J. Geogr. Sci. 2018, 28(10): 1467-1484
DOI: https://doi.org/10.1007/s11442-018-1556-z

Assessment and determinants of per capita household CO_2 emissions (PHCEs) based on capital city level in China

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Abstract: Household CO_2 emissions were increasing due to rapid economic growth and different household lifestyle. We assessed per capita household CO_2 emissions (PHCEs) based on different household consuming demands (including clothing, food, residence, transportation and service) by using provincial capital city level survey data in China. The results showed that: (1) there was a declining trend moving from eastward to westward as well as moving from northward to southward in the distribution of PHCEs. (2) PHCEs from residence demand were the largest which accounted for 44% of the total. (3) Correlation analysis and spatial analysis (Spatial Lag Model (SLM) and Spatial Error Model (SEM)) were used to evaluate the complex determinants of PHCEs. Per capita income (PI) and household size (HS) were analyzed as the key influencing factors. We concluded that PHCEs would increase by 0.2951% and decrease by 0.5114% for every 1% increase in PI and HS, respectively. According to the results, policy-makers should consider household consuming demand, income disparity and household size on the variations of PHCEs. The urgency was to improve technology and change household consuming lifestyle to reduce PHCEs.

Keywords: household CO_2 emissions (HCEs); determinants; capital city level; China

1 Introduction

China has become the world's largest CO_2 emitter (Guan *et al.*, 2009). Since 2007, the Chinese government has proposed the 'ecological civilization' to reduce its carbon emissions. At the Copenhagen Climate Conference in 2009, the Chinese government established a 40%–45% reducing CO_2 emissions intensity target by 2020 based on the level in 2005 due to fast growing CO_2 emissions. During the APEC (Asia-Pacific Economic Cooperation) Sum-

Received: 2017-02-24 **Accepted:** 2017-09-28
Foundation: National Key Research and Development Program, No.2016YFA0602803; National Natural Science Foundation of China, No.41371537; The Fundamental Research Funds for the Central Universities, No.lzujbky-2016-257; The Fundamental Research Funds for the Central Universities, No.lzu-jbky-2017-it106
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mit in 2014, China pledged that emissions would peak around 2030 and pledge to peak early. On the one hand, global warming, which was mainly caused by anthropogenic CO_2 emissions, affected the sustainable development both in China and in other countries (IPCC, 2006; Dietz *et al*., 2009). On the other hand, China, as the largest developing country in the world, faced the great pressures on reducing carbon emissions (Liu *et al*., 2016). As such reasons, studies concerning the nexus between climate change, carbon emissions and the related impacts have been undertaken in the world (Liu *et al*., 2016; Shen *et al*., 2016).

Studies of CO_2 emissions were concentrated on the industrial sector, but recently, the researches on CO_2 emissions reduction have turned to the household sector (Wei *et al*., 2007; Qu *et al*., 2013; Wiedenhofer *et al*., 2017). Vringer and Bolk (1995) first calculated household CO_2 emissions from direct and indirect household energy usage in the Netherlands based on the statistical data. After this study, various scholars focused on carbon emissions from residential uses, e.g., that analyzed in Australia (Lenzen, 1998), European Union countries (Reinders *et al*., 2003; Kerkhof *et al*., 2009), Brazil (Cohen *et al*., 2005), USA (Bin and Dowlatabadi, 2005; Underwood, 2013), India (Kadian *et al*., 2007) and China (Wei *et al*., 2007; Liu *et al*., 2011; Zhu *et al*., 2012; Tian *et al*., 2014; Qu *et al*., 2015; Wiedenhofer *et al*., 2017; Liu *et al*., 2017). From what mentioned above, a variety of assessment methods for CO_2 emissions from household consumption were established, including the IPCC's Reference Approach (IPCC, 2006; Kadian *et al*., 2007), the Input-Output Analysis (Liu *et al*., 2011; Qu *et al*., 2013), and the Consumer Lifestyle Approach (Bin and Dowlatabadi, 2005; Wei *et al*., 2007). More and more emissions from human activity were due to the accelerated economic and fast-growth living standards which attributed to the use of more energy both in direct and indirect household consumption (Liu *et al*., 2011; Zhu *et al*., 2012; Tian *et al*., 2014). Tian *et al*. (2014) showed that CO_2 emissions from household sector accounted for 35% of the total in China. Low-carbon consumption and low-carbon lifestyle were crucial ways to achieve its sustainable consumption and sustainable development. It was why transforming household lifestyle was essential to reduce its carbon emission (Wiedenhofer *et al*., 2017). However, these studies, dating from statistical macro-consumption data, only reflected the difference between regions or nations but they did not reflect the difference among different households (Qu *et al*., 2013).

Weber and Matthews (2008) found that income and expenditure were the key predictors of CO_2 emissions by using the United States' consumer expenditure survey data. Fahmy *et al*. (2011) first offered the integrated analysis on household CO_2 emissions (HCEs) according to entirely nationally representative survey data including household, private cars, public transportation and the domestic and international aviation energy usage in the UK. Their work demonstrated that CO_2 emissions from household energy usage varied in different socio-economic and demographic conditions (Fahmy *et al*., 2011). Qu *et al*. (2013) assessed HCEs of arid areas and explored the determinants such as income, family size in China. They reported that HCEs increased with rising income and decreased with larger household size (Qu *et al*., 2013). Xu *et al*. (2015) pointed out that income, demography and consuming behavior were the key determinants on urban HCEs by analyzing the questionnaire survey data in the Yangtze River Delta. Li *et al*. (2016) showed that per capita income and carbon intensity were the main impacts on HCEs in Northwest China. Household, as the basic unit of society, better reflected the inequalities for their differences in consuming demand, income and demographic factors (Qu *et al.*, 2013).

Recently, researchers have turned to focus on the analysis of determinants and mitigation measures on HCEs including LMDI (Logarithmic Mean Divisia Index) model (Zha *et al.*, 2010; Wang *et al.*, 2015; Zhu *et al.*, 2015), STIRPAT (Stochastic Impacts by Regression on Population, Affluence and Technology) model (Wang *et al.*, 2014; Wang *et al.*, 2016), Shapley decomposition (Han *et al.*, 2015), SDA (Structural Decomposition Analysis) model (Yuan *et al.*, 2015), AWD (Adaptive Weighting Divisia) model (Fan *et al.*, 2013), SOFM (self-organizing feature map) model (Fan *et al.*, 2014), and EPDM (Econometric Panel Data Models) (Li *et al.*, 2015; Hao *et al.*, 2016), etc. Various researchers explored the determinants of HCEs based on national, regional, and one city scale. Cities, considered as the main contributors to CO_2 emissions, accounted for about 85% of the total in China (Shan *et al.*, 2017). However, previous studies neglected the issue on the determinants of city level HCEs from the spatial regression analysis. Assessment of cities' HCEs based on survey data was needed for designing related policies and providing effective measures on CO_2 emission reduction from different households.

In China, most spatial analysis on CO_2 emissions concentrated on energy carbon emissions. Chuai *et al*. (2012) pointed out that the trend of global spatial autocorrelation on CO_2 emissions increased during the 1997–2009 period. Cheng *et al*. (2014) showed that there was a growing spatial agglomeration in China's carbon intensity. Energy usage and CO_2 emissions from household sector accounted for 27% and 17% of the total amount at the global level, respectively (Nejat *et al*., 2015). Moreover, CO_2 emissions from household sector accounted for 35% of the total in China (Tian *et al*., 2014). It was vital to explore the impact mechanism of HCEs for setting the carbon reduction targets. In China, urban area, as production and habitation center, was gradually replacing rural area. Many scholars searched for effective carbon mitigation strategies by analyzing urban settlements' energy consumption patterns (Fan *et al*., 2012; Golley and Meng, 2012). This paper aimed to further understand the determinants of city level PHCEs by using Spatial Lag Model (SLM) and Spatial Error Model (SEM) based on 31 provincial capital cities' survey data in China.

Two key questions were addressed. (1) What was the current distribution of PHCEs from provincial capital cities in China? We answered this question through calculating HCEs at per capita indicator based on different household consuming demand. (2) Which factor influenced the distribution of PHCEs? We answered this question in two ways: the first was the correlation analysis comparing the correlation coefficients between PHCEs and the explanatory variables; the second was the spatial regression models (SLM and SEM) evaluating the impacts of different determinants (such as, per capita income (PI), household size (HS), total population (TP), urban and rural structure (UR), education level (EL)) on PHCEs.

The main contributions of this work were as follows: (1) we collected 3543 household survey data by using a simple random sampling technique; (2) we divided PHCEs into five parts based on different household consuming demand including clothing, food, residence, transportation and service; (3) we explored the determinants of PHCEs both with correlation analysis and spatial regression analysis. The results including assessment and determinants of PHCEs yielded deep insights into impacts on PHCEs, which gave certain policy implications to policy-makers and scientific researchers for making a long-term carbon reduction strategy and climate change mitigation.

The remainder of this study was organized as follows. Section 2 presented the study area and methodology. Section 3 gave the assessment of PHCEs from provincial capital cities and discussed the related determinants. Sections 4 and 5 offered discussion and conclusions.

2 Data and methodology

2.1 Data

In this work, we chose 31 provincial capital cities in China as our study area. Three key issues were addressed: (1) we used a simple random sampling technique to select survey samples. Face-to-face interviews were conducted to obtain questionnaire survey data in each provincial capital city. (2) We chose a sampling ratio of 1/20,000 as the criterion in each provincial capital city. This sampling ratio looked small but the samples could give the characteristics of household energy usage and household consuming demand in the research area. The samples were enough for this benchmarking study. (3) We used reliability and validity test to give the availability of data used in this work. Cronbach's alpha coefficient was 0.73, which was calculated by using Software SPSS22. This showed that the survey data used in this work was reliable.

Based on the aforementioned three questions, 3543 households survey data were analyzed in different provincial capital cities between the end of 2011 and early 2013. Since the data gathered in this work were mostly in 2012, the year 2012 was set as the research period. Interview survey data included: (1) household energy usage and household consumption data consisting of clothing (clothing consumption), food (food consumption), residence (the usage of coal, gas and the consumption of electricity, heating, water and household facilities), transportation (the usage of oil and the consumption of transportation and communication) and service (the consumption of education, culture and recreation, and health and medical services) based on different household consuming demands. (2) The related influencing factors data consisting of per capita income (PI), total population (TP), urban and rural structure (UR), household size (HS), education level (EL) and age structure (AS) were shown in Figure 1. The survey households provided a good representation of the target samples.

Provincial capital city, as one of the most significant cities, had its own unique identity. In the process of accelerated urbanization, energy usage and carbon emissions varied considerably in the future. It was a long-term task for energy conservation and carbon emissions reduction, especially in household sector (Qu *et al*., 2013; Li *et al*., 2015). How to reduce CO_2 emissions was crucial for administrators and policy-makers in the context of fast-growth urbanization. This work was a pioneering effort to choose provincial capital cities in China as study objectives to examine assessment and determinants on PHCEs.

2.2 Estimation of HCEs

Qu *et al.* (2013) gave a definition of "Household CO_2 emissions" both including direct and indirect emissions from direct household usage and indirect household consumption. Same as the previous studies, household CO_2 emissions in this work also included direct and indirect emissions from the household sector. However, the difference was that we divided household CO_2 emissions into five parts by comparing different household consuming demand including clothing, food, residence, transportation and service in this work (Figure 2)

Name	Per capita income (10^4 yuan/person)	Total population (person)	Urban and rural structure (%)	Household size (person/household)	Education level (%)	Age structure (%)
Beijing	4.4	908	83	2.5	51	51
Harbin	3.4	285	49	3.0	27	59
Hohhot	2.7	122	37	3.1	30	84
Jinan	5.3	257	59	2.9	47	59
Lhasa	2.8	90	47	3.1	23	64
Lanzhou	1.9	161	74	3.2	36	47
Shenyang	3.7	436	68	2.5	42	41
Shijiazhuang	3.2	324	42	3.4	39	53
Taiyuan	3.1	192	68	2.9	43	65
Tianjin	4.1	710	75	2.9	45	48
Urumqi	1.9	158	51	3.0	31	69
Xi'an	2.4	362	46	3.3	43	69
Xining	1.7	244	39	3.1	34	83
Yinchuan	1.4	114	83	3.7	20	76
Changchun	3.6	189	55	3.2	44	61
Zhengzhou	2.9	256	56	3.0	30	56
Chengdu	5.0	613	73	3.0	34	72
Fuzhou	3.2	391	50	3.7	40	59
Guangzhou	3.3	258	36	3.0	31	49
Guiyang	4.1	614	50	3.1	38	59
Haikou	4.8	125	81	3.4	42	93
Hangzhou	6.7	337	65	2.6	40	64
Hefei	3.4	218	50	3.1	44	65
Kunming	2.7	467	66	2.7	38	55
Nanchang	2.3	185	64	3.4	31	49
Nanjing	4.1	332	75	3.0	40	60
Nanning	2.2	204	20	3.7	26	60
Shanghai	5.6	895	85	2.8	43	51
Wuhan	3.8	224	44	2.9	30	67
Changsha	2.4	259	60	2.9	18	51
Chongqing	2.9	576	41	3.1	37	49
AVERAGE	3.8	339	58	2.97	36	61

Figure 1 The related impacts on per capita household CO_2 emissions

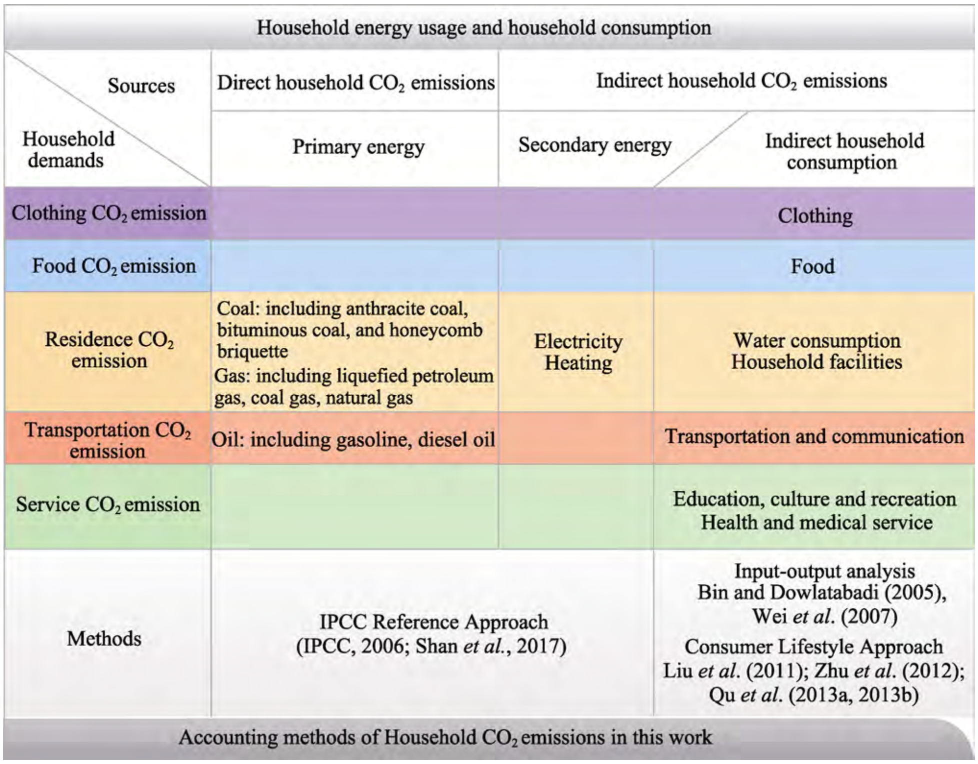

Figure 2 Accounting methods of household CO_2 emissions used in this work

(Jones *et al.*, 2011; Jones *et al.*, 2013). CPHCEs (per capita clothing household CO_2 emissions) represented PHCEs induced by household clothing consumption. FPHCEs (per capita food household CO_2 emissions) represented PHCEs induced by household food consumption. RPHCEs (per capita residence household CO_2 emissions) represented PHCEs induced in three ways: (1) household coal and gas usage; (2) household electricity and heating consumption and (3) household water and household facilities consumption. TPHCEs (per capita transportation household CO_2 emissions) represented PHCEs induced by two ways: (1) household oil including gasoline and diesel usage and (2) household transportation and communication consumption. SPHCEs (per capita service household CO_2 emissions) represented PHCEs induced by education, culture and recreation and health, medical service consumption. The formula of assessment on PHCEs was shown as below:

$$PHCEs = CPHCEs + FPHCEs + RPHCEs + TPHCEs + SPHCEs \tag{1}$$

where *PHCEs*, *CPHCEs*, *FPHCEs*, *RPHCEs*, *TPHCEs* and *SPHCEs* were the value of PHCEs from total, clothing, food, residence, transportation and service consumption, respectively (t CO_2/person).

Household CO_2 emissions from coal, oil, gas, electricity and heating were calculated based on the IPCC's Reference Approach (IPCC, 2006; Shan *et al*., 2017).

$$E_i = F_i \times NCV_i \times CC_i \times OF_i = F_i \times C_i \tag{2}$$

where F_i was the energy usage of household (10^4 t, 10^8 m^3) (i=coal, oil, gas); CC_i was the CO_2 emission factor of the ith fuel (t $CO_2/10^4$ t, 10^8 m^3).

$$E_{Elec} = F_{Elec} \times C_{Elec} \tag{3}$$

where F_{Elec} was the electric power consumption (MWh); C_{Elec} was the CO_2 emission factor of the electricity sector (t CO_2/MWh), which came from the Baseline Emission Factor for regional power grids in China.

$$E_{Heat} = M_{Heat} \times F_{Heat} \times C_{Heat} \times 10^{-3} \tag{4}$$

where M_{Heat} was the coal consumption per unit area for heating (kg/m^2); F_{Heat} was the heating areas (m^2); C_{Heat} was the CO_2 emission factor (kg CO_2/kg), which was derived from Zhang *et al*. (2013).

Household CO_2 emissions from household consumption were calculated by input-output analysis following Bin and Dowlatabadi (2005), Wei *et al*. (2007) and the consumer lifestyle approach following Liu *et al*. (2011), Zhu *et al*. (2012) and Qu *et al*. (2013).

$$E_{HCj} = \frac{Ej}{Pj} \times \left(I - A\right)^{-1} \times F_{HCj} = F_{HCj} \times C_{HCj} \tag{5}$$

where F_{HCj} was the jth consumption of household (10^4 yuan); C_{HCj} was the CO_2 emissions factor from jth household consumption (t $CO_2/10^4$ yuan); j was the jth household consumption.

Based on the formulas (2)–(5), *RPHCEs*, *TPHCEs* and *SPHCEs* were calculated as below:

$$RPHCEs = E_{Coal} + E_{Gas} + E_{Elec} + E_{Heat} + E_{Water} + E_{House} \tag{6}$$

where E_{Coal}, E_{Gas}, E_{Elec}, E_{Heat}, E_{Water} and E_{House} was PHCEs from household coal usage, gas usage, electricity usage, heating usage, water consumption and household facilities consumption, separately (t CO_2/person).

$$TPHCEs = E_{Oil} + E_{Trans} \tag{7}$$

where E_{Oil} and E_{Trans} were PHCEs from household oil usage and household transportation and communication consumption, separately (t CO_2/person).

$$SPHCEs = E_{Cul\&Edu} + E_{Medical} \tag{8}$$

where $E_{Cul\&Edu}$ and $E_{Medical}$ were PHCEs from household education, culture and recreation consumption and health and medical service consumption, separately (t CO_2/person).

Table 1 The CO_2 emission factors from the household sector used in this work

Items	Value	Unit	Source
Anthracite coal	2.1625	t $CO_2/10^4$ t	Data source: The People's Republic of China National Greenhouse Gas Inventory (NDRC, 2007); Calculated by IPCC Reference Approach (IPCC, 2006; Shan *et al*., 2017)
Bituminous coal	1.9518	t $CO_2/10^4$ t	
Honeycomb briquette	1.6366	t $CO_2/10^4$ t	
Gasoline	3.0425	t $CO_2/10^4$ t	
Diesel oil	3.1469	t $CO_2/10^4$ t	
Coal gas	2.9509	t $CO_2/10^4$ t	
Liquefied petroleum gas	7.0493	t $CO_2/10^4$ t	
Natural gas	21.6502	t $CO_2/10^8$ m^3	
Electricity	/	t CO_2/MWh	Data source: (CDMC, 2010)
Heating	/	t CO_2/m^2	Data source: Zhang *et al*., 2013
Food	0.77	t $CO_2/10^4$ yuan	Data source: China Energy Statistical Yearbook (NBSC, 2013) and Input-output Tables of China (NBSC, 2015); Calculated by input-output analysis (Bin and Dowlatabadi, 2005; Wei *et al*., 2007)
Clothing	1.20	t $CO_2/10^4$ Yuan	
Water	2.13	t $CO_2/10^4$ Yuan	
Transportation and communication	2.33	t $CO_2/10^4$ Yuan	
Education, culture, and recreation	1.09	t $CO_2/10^4$ Yuan	
Health care and medical services	2.13	t $CO_2/10^4$ Yuan	
Household facilities	2.44	t $CO_2/10^4$ Yuan	

Raw data for calculating CO_2 emission factors were taken from China Energy Statistical Yearbook 2012 (NBSC, 2013; NDRC, 2007) and Input-output Tables of China 2012 (NBSC, 2015). PHCEs parameters of household fossil fuel usage and household consumption were shown in Table 1.

2.3 Spatial econometric models

SLM and SEM were introduced to analyze the influencing factors of PHCEs (Anselin, 1992; Chuai *et al*., 2012; Cheng *et al*., 2014). SLM reflected the observed values of adjacent areas, whereas SEM emphasized the spatial diffusion effect with spatial autocorrelation in the error terms.

The formula of SLM was shown as below:

$$Y = \rho W_y + \beta X + \varepsilon \tag{9}$$

The formula of SEM was shown as below:

$$Y = \beta X + \varepsilon, \varepsilon = \lambda W_y \varepsilon + \mu \tag{10}$$

where Y represented the dependent variable; X represented the independent variables; W_y denoted the spatial weight matrix of $n \times n$; ρ and λ represented the spatial autoregressive and autocorrelative parameter, respectively; β was the coefficient of independent variables; ε and

μ were random errors, which were finally represented by a constant C.

Based on the aforementioned analysis, various variables were selected to estimate the relationship between them and PHCEs. Per capita income (PI), as a metric of economic affluence which had the most impact on PHCEs, was chosen in this study (Zha *et al*., 2010). Total population (TP), urban and rural structure (UR), household size (HS) and age structure (AS) were chosen to represent the demographic factors (Qu *et al*., 2013; Liu *et al*., 2017). Education level (EL), as a key factor influencing HCEs, was also identified (Qu *et al*., 2015; Li *et al*., 2016).

In this work, PI, TP, UR, HS, EL and AS were selected as the impact factors influencing PHCEs (Table 2). We gave the correlation coefficients between PHCEs and the related factors and then created SLM and SEM for evaluating their impacts on PHCEs in the following analysis.

Table 2 The factors influencing PHCEs used in this work

Variables abbreviations	Variables	Interpretation	Unit
PHCEs	Per capita household CO_2 emissions	Total household CO_2 emissions/ population	t CO_2/person
PI	Per capita income	Total income/population	10^4 yuan/person
TP	Total population	Urban population	Person
UR	Urban and rural structure	The proportion of urban population in total	%
HS	Household size	Average persons in each household	Person/household
EL	Education level	The proportion of population with college and higher-level education	%
AS	Age structure	The proportion of population aged 15–49	%

3 Results

3.1 Assessment of capital city level PHCEs in China

We analyzed the characteristics of annual average PHCEs for all capital cities in China according to the assessment results (Figure 3). The annual average PHCEs of all provincial

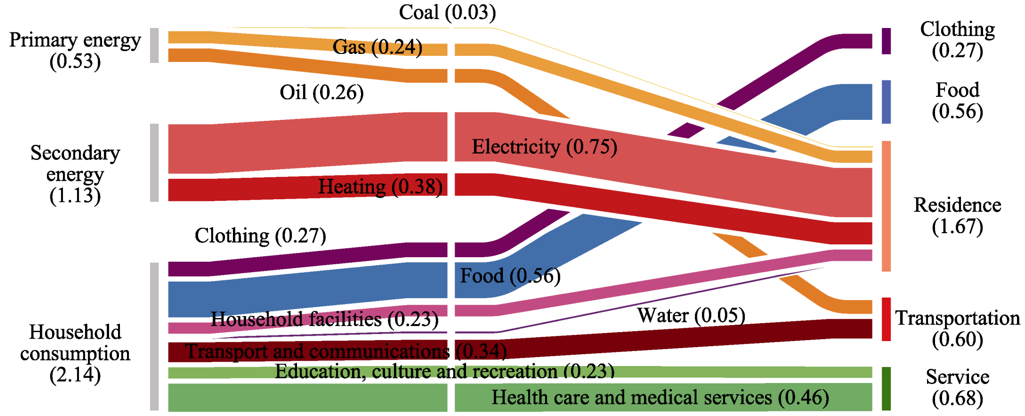

Figure 3 Annual average per capita household CO_2 emissions in all capital cities in China (t CO_2/person)

capital cities were 3.79 t CO_2/person, which was related to clothing, food, residence, transportation and service consuming demand, being 0.27 t CO_2/person, 0.56 t CO_2/person, 1.67 t CO_2/person, 0.60 t CO_2/person and 0.68 t CO_2/person, respectively. We found that PHCEs for residence consuming demand was the largest.

PHCEs of different provincial capital cities ranged from 2.38 t CO_2/person (Nanchang) to 4.99 t CO_2/person (Hangzhou), which differed by a factor of 2.10 times (Figures 4 and 5). We

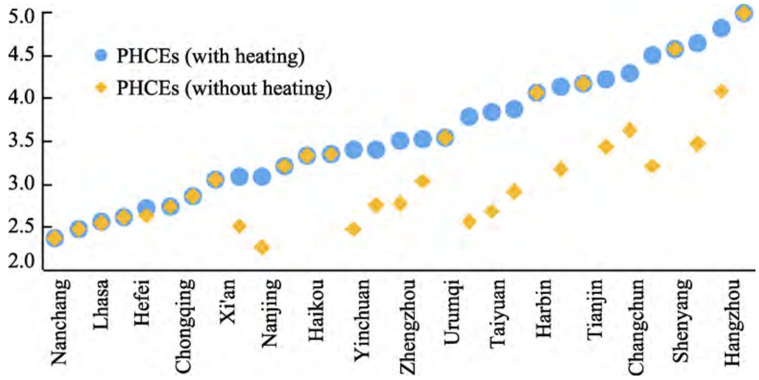

Figure 4 Comparing provincial capital city level PHCEs with heating and without heating consumption in China

found an interesting phenomenon that PHCEs decreased obviously in these provincial capital cities located in northern China (such as Xi'an, Lanzhou, Xining, Yinchuan and Urumqi located in Northwest China, Shijiazhuang, Zhengzhou, Taiyuan, Jinan, Tianjin, Beijing and Hohhot mainly located in Central and North China, Harbin, Changchun and Shenyang located in Northeast China) when we removed heating demand of PHCEs from the total. Because these cities needed the centralized heating usage in winter for keeping warm. That was why various provincial capital cities with the highest-group values of PHCEs located in North China.

We divided PHCEs into five groups in this work (Figure 5). The lowest-value group was less than 2.50 t CO_2/person, which was located in some developing capital cities – Nanchang and Nanning.

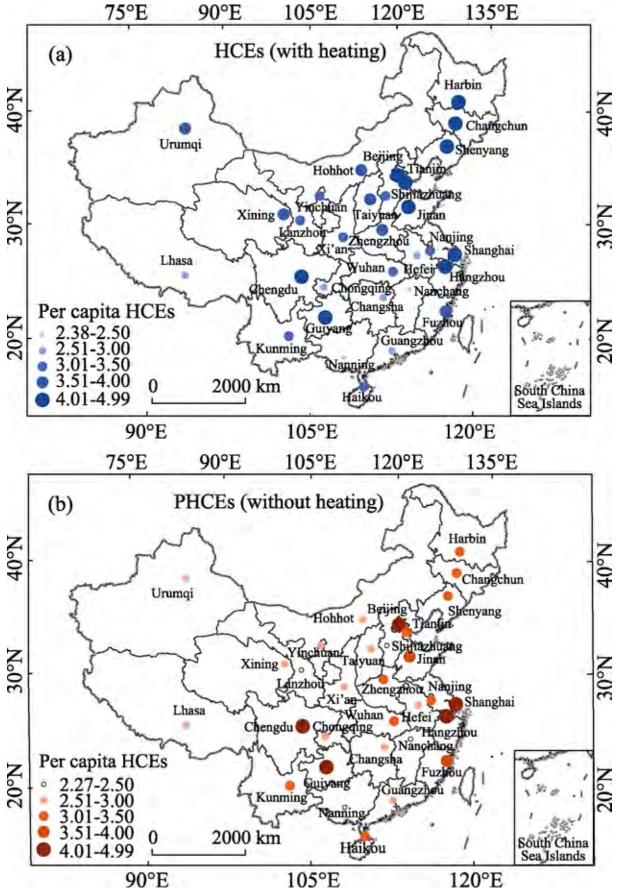

Figure 5 Comparing spatial distribution of PHCEs with heating and without heating in provincial capital cities in China

There were 10 provincial capital cities with the highest-value group (more than 4.01 t CO_2/person), which were located in Northeast China (Harbin, Changchun and Shenyang), the Bohai Rim Region (Beijing and Tianjin), Eastern China (Jinan), Yangtze River Delta Region (Shanghai and Hangzhou), and in Southwest China (Chengdu and Guiyang). Interestingly, PHCEs of Guangzhou and Chongqing were similar to that of Lhasa, Hefei and Changsha, ranging from 2.51 to 3.00 t CO_2/person. There were 14 provincial capital cities with the mid-value group (from 3.01 to 4.00 t CO_2/person), situated in North China (Shijiazhuang, Taiyuan and Hohhot), Central China (Zhengzhou and Wuhan), Eastern China (Nanjing and Fuzhou) and Northwest China (Urumqi, Xining, Yinchuan, Lanzhou and Xi'an) where people needed to burn more coal in winter to keep warm. We found a declining trend moving from the east toward the middle and to the west as well as from the north to the south by comparing the distribution of PHCEs in provincial capital cities. We also had an interesting finding that highest-value group of PHCEs was mainly distributed in the Bohai Rim Region, Yangtze River Delta Region and Southwest China (Chengdu and Guiyang). The highest value group of PHCEs with heating was found in Harbin, Changchun and Shenyang located in Northeast China, while, these areas changed into the mid-value group because we removed heating from the total (Figure 5). Household lifestyle and household demand between different residents who live between South China and North China played a vital role in the contribution of PHCEs.

As noted above, PHCEs were divided by clothing, food, residence, transportation and service based on different household consuming demands. The proportion of each item in total reflected the contribution of various consuming demands to PHCEs between different residents. It clearly showed that clothing consuming demand made the smallest contribution to PHCEs in all provincial capital cities, which with the ratio no more than 15%, especially in Urumqi, Shijiazhuang and Shenyang with the ratio no more than 5%. The ratio of food consuming demand in PHCEs was also small (around 20%); interestingly, the lowest ratio was no more than 10% in Harbin, Shijiazhuang, Shenyang and the highest ratio was more than 20% in Guangzhou, Nanning and Nanchang (Figure 6). Another interesting finding was that residence consuming behavior was the major contributor to PHCEs in all provincial

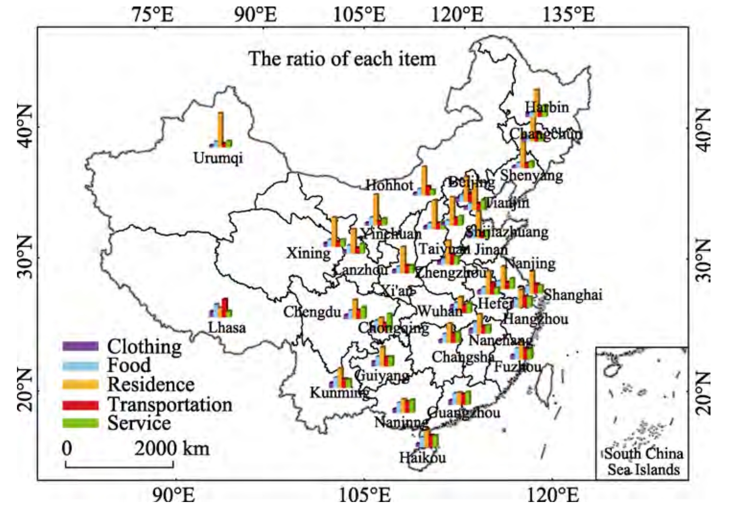

Figure 6 The ratio of each item to total per capita household CO_2 emissions from provincial capital cities in China

capital cities except Lhasa, Guangzhou and Chongqing. We found that the provincial capital cities with lower PHCEs were also with lower HCEs from residence consuming and with higher HCEs from food consuming.

3.2 Correlation analysis on the relationship between PHCEs and the explanatory variables

3.2.1 The impact of household consumption demand on PHCEs

To better understand the relationship between PHCEs and its consuming demand, in this work, we listed the correlation coefficients between the ratio of different consuming demands and PHCEs. The correlation coefficients of PHCEs versus the ratio of clothing, food, residence, transportation and service consuming demands were all positive, which implied that all these consuming demands contributed to CO_2 emissions increasing from household sector (Figure 7).

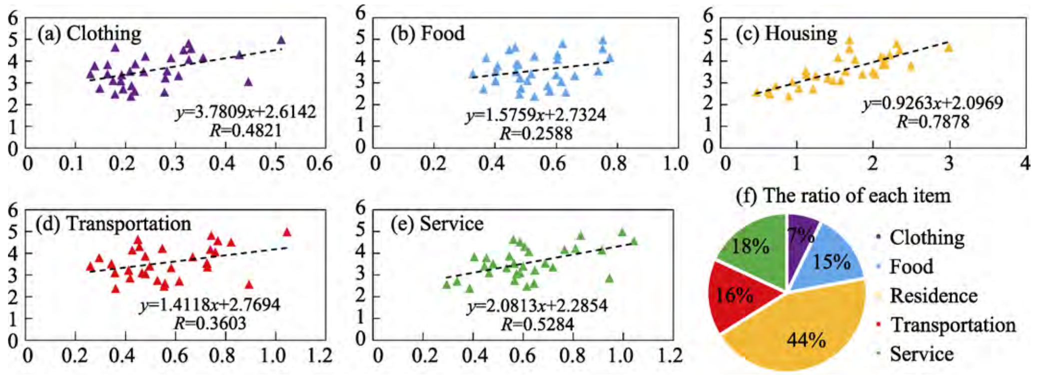

Figure 7 Scatter plots between PHCEs and from clothing (a), food (b), residence (c), transportation (d), service consuming demand (e), and the ratio of each item (f) in the total PHCEs

Comparing the correlation coefficients, we found that the relationships between food consuming demand, transportation consuming demand and PHCEs were rather weak. The relationships between clothing consuming demand, service consuming demand and PHCEs were a bit stronger, but were not very strong. As we expected, the correlation coefficient between PHCEs and residence consuming behavior was very strong, with R equal to 0.7878. That was why the provincial capital cities with lower PHCEs were also with lower HCEs from residence consuming behavior; the provincial capital cities with higher PHCEs were also with higher HCEs from residence consuming behavior. Those richer cities – Beijing, Tianjin, Xi'an, Harbin, Changchun and Shenyang with higher PHCEs also had higher HCEs from residence consuming behavior. However, Guangzhou and Chongqing were rich but had lower PHCEs, the main reason was that the household residents we interviewed had lower residence consuming demand. As for those not rich or poorer cities – Shijiazhuang, Hohhot, Taiyuan, Xining, Yinchuan and Urumqi, they were also with higher PHCEs than that in Guangzhou and Chongqing because the samples we collected had higher PHCEs from residence consuming demand, especially from heating demand in winter.

The ratio of clothing, food, residence, transportation and services consuming behavior to the total average PHCEs (Figure 7) was 7%, 15%, 44%, 16% and 18%, respectively. Moreover, PHCEs from gasoline accounted for 7% of the total PHCEs and occupy 43% in transportation by using private cars. We also found that the PHCEs from residence consuming behavior hold the biggest ratio of the total, while, 70% of them came from coal usage, heating usage and electricity usage. We deemed that PHCEs from housing consumption behavior were the most important driving force for the increased PHCEs of provincial capital cities according to the results of survey data above.

3.2.3 The impact of economic affluence and demographic factors on PHCEs

We listed the correlation coefficients between PHCEs and the related impacts (Figure 8). PI had the most significant positive effect on PHCEs by comparing the relationship between it and the related influencing factors. HS had a negative effect on PHCEs and AS almost had no relationship with PHCEs. TP, UR and EL also had a positive effect on PHCEs, but the importance was less than what PI showed.

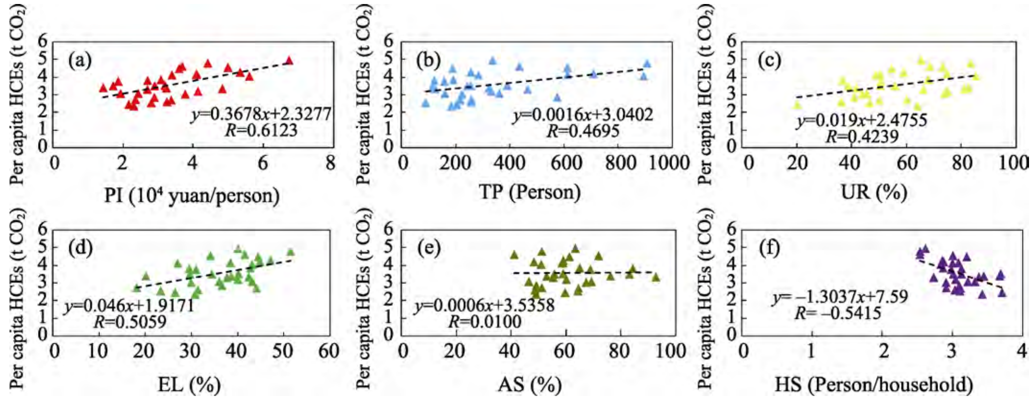

Figure 8 Scatter plots between PHCEs and PI-per capita income(a), TP-total population (b), UR-urban and rural structure (c), EL-education level (d), AS-age structure (e); HS-household size (f)

The results showed that CO_2 emissions varied due to age structure changes (Han *et al.*, 2015) and increased association with fast-growth urbanization (Li *et al.*, 2015) and high education level (Qu *et al.*, 2013). On the one hand, TP and UR directly impacted residents' lifestyle, i.e., more energy were used and more household products were purchased, which resulted in more HCEs. Li *et al.* (2015) pointed out that every 1% increase in urbanization accompanied with 2.9% and 1.1% increase in direct and indirect HCEs, separately. On the other hand, China was in the stage of rapid urbanization and industrialization, which brought more pressures on CO_2 emissions reduction. From EL scale, some scholars viewed that higher education level would produce more HCEs than lower education level (Liu *et al.*, 2017), while, others thought that groups with higher education reduced HCEs (Golley and Meng, 2012; Dai *et al.*, 2012). We found that EL had a moderate positive effect on PHCEs according to the results in Figure 8. Among these influential factors of PHCEs above, the coefficients of PI and HS were significant, which indicated that these factors exerted the most influence on PHCEs.

3.3 Spatial analysis on the determinants of PHCEs

First, we chose PI, TP, UR, HS, AS and EL as this work's significant influencing factors of PHCEs to create SLM and SEM for evaluating their impacts. Then we evaluated the equation of SLM and SEM by using the software GeoDa. In model SLM(i) and SEM(i), two most relevant variables – PI, HS– were included. In model SLM(ii) and SEM(ii), three most relevant variables –PI, HS, EL– were included. In model SLM (iii) and SEM (iii), we included all explanatory variables.

The values of R^2, Akaike information criterion (AIC), and Schwartz criterion (SC) (Wooldridge, 2010) were chosen to assess the model fitness (Table 3). Based on the values of R^2, AIC and SC between in SLM (i), SLM (ii) and SLM (iii) and in SEM (i), SEM (ii) and SEM (iii), we deemed that the models of SEM with explanatory variables were suitable to better explain the mechanism of PHCEs from provincial capital cities in China.

Table 3 Estimation of influencing factors on per capita household CO_2 emissions by SLM and SEM

Explanatory	**SLM**			**SEM**		
	SLM(i)	**SLM(ii)**	**SLM(iii)**	**SEM(i)**	**SEM(ii)**	**SEM(iii)**
ρ	–0.1126	–0.1413	–0.1797**			
C	5.5368***	4.9599***	4.1512***	3.8121***	3.6012***	3.5437***
PI	0.2693***	0.1893**	0.1132*	0.3818***	0.3633***	0.2951***
HS	–0.8135**	–0.7774**	–0.6680*	–0.4058	–0.4027	–0.5114*
EL		0.0230*	0.0173		0.0066	0.0042
TP			–0.0006			–0.0001
UR			–0.0018**			0.0004
AS			0.0133*			
γ				0.6847***	0.1559***	0.0102
R^2	0.47	0.52	0.59	0.59	0.59	0.61
AIC	55.88	55.26	55.66	49.85	–51.53	55.82
SC	61.62	62.43	67.14	54.15	57.26	65.85

* Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level

The fifth column in Table 3 provided the SEM (i) estimation results. We found that PI was the key positive factor influencing PHCEs and HS was the key negative factor influencing PHCEs. Considering how EL impacted PHCEs, we added the impact factor EL to SEM (ii). We found that the impact of HS on PHCEs was not significant. Considering how economic affluence, demographic factors and education level affected PHCEs, we included all explanatory variables in SEM (iii). Every 1% increase in PI was associated with 0.2951% increase in PHCEs when other impact factors remained unchanged. We deemed that the elastic coefficient of HS's spatial error was –0.5114, which implied the changes in HS in adjacent cities had negative influences on local PHCEs. HS was the key factor that had a negative effect on PHCEs. Every 1% increase in HS was associated with 0.5114% decrease in PHCEs when other influencing factors unchanged. The coefficients of EL, UR and AS were positive to PHCEs. Every 1% increase in EL, UR and AS could lead to 0.0042%, 0.0004% and 0.0102% increase in PHCEs, with this significant level being not obvious. The elastic coefficient of TP indicated that TP had a positive impact on PHCEs increasing, with the significant level being also not obvious.

4 Discussion

We discussed the analysing results of assessment and determinants of PHCEs based on capital city level in the following aspects.

(1) Residence consuming demand was the key contributor to PHCEs, which accounted for 44% of the total. An interesting finding from this survey was that provincial capital cities with lower PHCEs were also with lower ratio from residence consuming demand and vice versa. A declining trend moved from eastward to westward as well as from northward to southward by comparing the distribution of PHCEs based on capital city level. The results represented here were similar to Tian *et al*.'s study, whose work was analyzed from the perspective of production and consumption (Tian *et al*., 2014).

(2) In addition, we found Guangzhou and Chongqing's PHCEs were similar to Lhasa, Hefei and Changsha's, in the meanwhile, Chengdu, Guiyang's PHCEs were more than Guangzhou and Chongqing's. Why did this phenomenon occur? There were four reasons addressed here: 1) The main reason was that the households we interviewed in Guangzhou and Chongqing had lower household consumption and the households we interviewed in Chengdu and Guiyang had higher household consumption. 2) The samples we interviewed in Guangzhou and Chongqing might be a little bit less than that in other cities, as the results shown in Figure 1, the urbanization of Guangzhou and Chongqing was lower than the average value. 3) The characteristics of investigators and interviewees from different survey areas were also important, such as sexism, racism, marriage, and aging. The same questionnaire from different investigators might have different answers. 4) The consciousness of different samples was also important, e.g., some people were very rich, but they said they purchased less; others were very poor, whilst, they said they purchased more. These reasons induced PHCEs account in this work was not similar to the previous studies. Our work would continue to interview more households in these cities such as Guangdong, Chongqing, Guizhou, Chengdu to make further efforts to test the reality of PHCEs.

(3) Larger amounts of coal and heating were used for keeping warm in winter in northern provincial capital cities. Coal usage and heating usage were the main sources of PHCEs from residence consuming behavior. It was the primary cause of such a declining trend of PHCEs from northward to southward. Meanwhile, temperature difference between summer and winter as well as locational difference between northern China and southern China both had influence on household consuming behavior to a certain degree (Hao *et al*., 2016). Residents who lived in provincial capital cities of southern China always used electricity for keeping cool in summer, such as the utilization of air conditioners and fans. While, residents who lived in northern China always burned more coal in winter for keeping warm. PHCEs from coal usage, heating usage and electricity usage occupied 70% in the total from residence consuming behavior. Moreover, PHCEs from gasoline accounted for 7% of the total, of which, 43% were produced by private cars. Hence, individual, as the main consumer in the world, should change their ideas from luxurious activities to frugal lifestyle (Wei *et al*., 2007), such as, purchasing cars with low-gasoline consumption and low-carbon emissions as well as using more environmental-friendly appliances. Carbon labeled products should be considered, as Zhao *et al.* argued that, carbon labeling scheme took an effective place both in enterprises and industries (Zhao *et al*., 2016a; Zhao *et al*., 2016b).

(4) PI had a great impact on PHCEs. Feng *et al.* (2011) and Han *et al*. (2015) showed that per capita income had a significant positive effect on per capita CO_2 emissions. In normal conditions, household demand would be rapidly grown and household consumption would

be increased with the rapid economic growth. PHCEs increased as per capita income increased in provincial capital cities. The results showed that PI had a positive impact on PHCEs from the household sector which was similar to previous studies (Feng *et al*., 2011; Qu *et al*., 2013; Han *et al*., 2015). As shown in this paper, PI played the most important role in PHCEs from provincial capital cities in China. Under the background of economic development, consumers should change their lifestyle to reduce their carbon emissions. The progress of urbanization should be regulated by the government to ensure the sustainable development. Besides, policy-makers should provide suitable suggestions according to the local conditions, as Qu *et al*. (2013) suggested that, electricity usage and LPG usage in Northwest China would replace the coal usage and petrol usage in the years to come.

(5) HS took a negative role in the increased PHCEs from provincial capital cities in China. Every 1% increase in household size was associated with 0.06% decrease in PHCEs. Qu *et al*. (2013) pointed out that PHCEs decreased as the household size increased in Northwest China. It showed that large families especially extended families living together presented a promising way to save energy and reduce CO_2 emissions. What observation was discussed in China above was also found in U.S. (Underwood, 2013). A switch to a two-child policy has already begun in China. Would this policy bring more carbon emissions from household sector? On the one hand, we suspected that the total HCEs would increase but was only with a minor variation based on the aforementioned results, e.g., children shared their stuffs with their brothers or sisters, such as clothes, toys, books, etc., sustainable utilization could be achieved. On the other hand, we suspected that per capita or per household HCEs would decrease in the future. A family had more members than less, they could cook, travel and watch TV together, etc., which could save energy and cut carbon emissions.

However, some limitations also existed in this study: (i) we just had survey data in one year, which was a lack of continuous data for years; (ii) more and more living garbage was made in cities, yet in this work we did not conduct any analysis about it. Hence, we would continue to delve in PHCEs with the household garbage. Our future study aimed to explore the temporal and spatial determinants on PHCEs which gave more suggestions for policy-makers.

5 Conclusions

(1) In this work, we explored the spatial variations and determinants of PHCEs (per capita household CO_2 emissions) from provincial capital cities in China. The average PHCEs was 3.79 t CO_2/person, which ranged from 2.38 t CO_2/person to 4.99 t CO_2/person in different provincial capital cities. There was a declining trend from the east to the west as well as from the north to the south in the distribution of PHCEs. Meanwhile, residence consuming behavior was the major contributor which accounted for 44% of the total.

(2) Based on the correlation analysis and spatial analysis of PHCEs and the related factors, we found that per capita income and household size was the two main impacts on PHCEs. Every 1% increase in PI was associated with 0.2951% increase in PHCEs, whilst, every 1% increase in HS was associated with 0.5114% decrease in PHCEs when other influential factors remained unchanged.

(3) What we presented here is to assess the value of PHCEs and investigate the related impacts by correlation analysis and spatial regression model. Results offered some sugges-

tions and policy implications to support the green development and to make long-term mitigation strategies for coping with climate change.

We deemed that PHCEs varied in different household consuming demands by analyzing the survey data results of PHCEs according to capital city level in China. PHCEs was the largest from residence consuming demand. In the meanwhile, centralized heating usage in winter for keeping warm played an important role in PHCEs increasing. The matter of urgency was to improve coke quality and clean energy technology in heating department. Based on different groups of PHCEs such as Zhejiang and Beijing, these provincial capital cities with higher PHCEs should have more responsibility to reduce their emissions by taking the so-called common but different responsibilities. Per capita income had a great impact on PHCEs from the spatial analysis on the determination of PHCEs. Policy-makers should consider this disparity phenomenon that occurred between different income levels. Frugal lifestyle and consuming behavior needed to be promoted in household sector. More than that, individual, as an important consumer, should change his or her bad lifestyle into good habits, such as saving water, electricity, food and energy. Household size had a great negative impact on PHCEs. It was advisable to start an extended family, e.g., members of family had dinner together and watched TV together which could reduce food waste and also could reduce PHCEs.

Chinese government has pledged to cut its 40%–45% carbon intensity by 2020 based on the 2005 level as well as peaked its CO_2 emissions around 2030. Policy-makers should consider the provincial differences by considering the policies responded to climate change when made the related measures. More and more CO_2 emissions would be produced as China was at the stage of accelerated urbanization and industrialization. The pressing issue was to improve technology and change household consuming lifestyle to reduce carbon emissions from household sector.

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