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RESEARCH ARTICLE

A hybrid study of multiple contributors to per capita household CO_2 emissions (HCEs) in China

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Abstract Given the large expenditures by households on goods and services that contribute a large proportion of global CO_2 emissions, increasing attention has been paid to household CO_2 emissions (HCEs). However, compared with industrial CO_2 emissions, efforts devoted to mitigating HCEs are relatively small. A good understanding of the effects of some driving factors (i.e., urbanization rate, per capita GDP, per capita income/disposable income, Engel coefficient, new energy ratio, carbon intensity, and household size) is urgently needed prior to considering policies for reducing HCEs. Given this, in the study, the direct and indirect per capita HCEs were quantified in rural and urban areas of China over the period 2000–2012. Correlation analysis and gray correlation analysis were initially used to identify the prime drivers of per capita HCEs. Our results showed that per capita income/disposable income, per capita GDP, urbanization rate, and household size were the most significantly correlated with per capita HCEs in rural areas. Moreover, the conjoint effects of the potential driving factors on per capita HCEs were determined by performing principal component regression analysis for all cases. Based on the combined analysis strategies, alternative polices were also examined for controlling and mitigating HCEs growth in China.

Keywords Household CO_2 emissions (HCEs) · Driving factors · Correlation analysis (CA) · Gray correlation analysis (GCA) · Principle component regression (PCR)

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Introduction

Global warming is one of the most serious climate change problems that may strongly affect human society, the economy, and the environment (Liang et al. 2013). and human activities can also exert substantial influence on climate change. According to the Intergovernmental Panel on Climate Change (IPCC) fifth assessment report, it was reported that most (above 50 %) of the global average surface temperature rise since the 1950s is extremely likely (more than 95 % possibility) to be caused by human activities (IPCC 2013). For now, greenhouse gas (GHG) emissions and their negative impacts on the environment have become a major concern due to the challenging problem of global warming (Antanasijević et al. 2014). Global GHG emissions from 2000 to 2010 grew more quickly (2.2 %/year) than in each of the three previous decades (1.3 %/year) and reached 49(±4.5)Gt CO_2e/year in 2010 (IPCC 2014). especially in some rapidly developing countries, such as China and India, where large amounts of infrastructure and consumption are needed (Liu et al. 2011).

Since 1979, China's real GDP increased by approximately 10 % per year, which may have resulted from China's opening-up policy, creating a free market economy accessible to foreign trade and investment. The rapid development made China the world's largest trading economy and manufacturer and the second largest economy and destination for direct foreign investment (Morrison 2013). However, this rocketing

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progress has been associated with costs such as unprecedented environmental pollution, as well as huge energy consumption and the associated carbon emissions, in China (Zhang 2010). which has been ranked first among nations in terms of emissions since 2007 and in terms of energy consumption since 2010 (Morrison 2013). It was projected by the International Energy Agency that, by 2035, China will consume 70 % more energy than the second largest energy-consuming country, the USA (IEA-WEO 2012). China has been under international pressure to reduce its energy consumption and carbon emissions intensity. In the Copenhagen Climate Change Conference in 2009, China made two strong commitments: By 2020, the non-fossil energy share of energy consumption will increase to 15 %, and carbon emissions per unit of GDP will decrease by 40–45 % of the value for 2005 (Wang et al. 2015).

To accomplish those commitments, a series of aggressive policies on new energy, coals, and fuel economy standards for passenger vehicles have been adopted by Chinese governments. Currently, China is the world leader in hydro (45 % of the world's total), wind, and solar power generation (Climate Council 2014). Moreover, China is implementing annual non-binding caps on coal consumption and domestic coal production at 4 and 3.9 billion tons, respectively (AGCCA 2014). which reduces the emissions intensity from electricity generation in China by 16 % (Climate Council 2014). Additionally, fuel economy standards for passenger vehicles in three major cities of China have been implemented, and the standards are expected to be expanded to cover more cities (AGCCA 2014).

Based on the aforementioned analysis, substantial efforts have been devoted to mitigating CO_2 emissions, with most focusing on industrial emissions due to its majority share of total energy consumption and CO_2 emissions. In comparison, the household CO_2 emissions (HCEs) are more likely to be paid less attention because of their smaller contribution to total CO_2 emissions. Some studies quantified these studies and reported the proportion of household energy consumption to the total national energy consumption: 52 % in South Korea (Park and Heo 2007). over 80 % in USA (Bin and Dowlatabadi 2005). 75 % in India (Pachauri and Spreng 2002). and 11.06 % in China (Wei et al. 2006).

Although the household sector in China accounts for a minor portion of the total CO_2 emissions, the total amount is still massive due to the large size of China's population. Additionally, the rapidly rising household incomes promote the increase in consumption that will pose a great challenge to the mitigation of HCEs (Qu et al. 2013a, b; Song et al. 2011). Therefore, in recent years, some efforts have been devoted to investigating HCEs. Das and Paul (2014) performed a decomposition analysis on CO_2 emissions from household consumption in India in 1993–1994 and 2006–2007, and the results indicated that the activity, structure, and population effects were the main causes of increased CO_2 emissions from household fuel consumption. Kerkhof et al. (2009) quantified the CO_2 emissions of households in the Netherlands, the UK, Sweden, and Norway in the vicinity of the year 2000 by combining a hybrid approach of process analysis and input–output analysis with data on household expenditures, and they showed that average households in the Netherlands and the UK had higher CO_2 emissions than households in Sweden and Norway. Moreover, CO_2 emission intensities of household consumption decreased with increasing income in the Netherlands and the UK. However, a positive correlation between CO_2 emission intensities of household consumption and income can be found in Sweden and Norway. Additionally, the national comparison at the product level indicated that country characteristics (such as energy supply, population density, and the availability of district heating) influence variations in household CO_2 emissions between and within countries (Kerkhof et al. 2009). Feng et al. (2011) used a gray model to compare the relationship between energy consumption, consumption expenditure, and CO_2 emissions for different lifestyles, which showed that direct energy consumption was diverse for urban households and simple for rural households in China. Büchs and Schnepf (2013) investigated how household characteristics such as income, household size, education, gender, unemployment, and rural or urban location were associated with all types of emissions. It was found that, although these associations vary considerably across emission domains, high emissions were more likely to be from low income, unemployed, and elderly households. Chitnis and Hunt (2012) estimated that CO_2 attributable to households would not fall by 29 % (or 40 %) by 2020 compared with that in 1990. Rosas-Flores et al. (2011) focused on the estimation of energy consumption, energy savings, and reduction of emissions of CO_2 related to the use of urban and rural household appliances in Mexico between 1996 and 2021, which can be useful to policy makers as well as household appliance users.

As reported in the literature discussed above, large studies have been performed with regards to HCEs. Based on the scientific research, some policies and programs that relate to promoting GDP growth and to meeting emissions intensity reduction obligations might be proposed. In the effort to develop effective policies, some other potential driving factors should be examined. Given differences in incomes, lifestyles, and access to different types of fuels, the patterns of consumption of goods and services, and thus the related CO_2 emissions, could differ significantly between rural and urban households (Das and Paul 2014; Kerkhof et al. 2009). A comparison of the patterns of direct and indirect consumption of goods and services and the associated emissions between the urban and rural areas will be very helpful for developing targeted policies and programs for these areas. Thus, direct and indirect per capita HCEs in rural and urban areas of China, which are a more accurate metric for comparing emissions between these two regions, were chosen as the research object in this study.

This study aims to qualitatively and quantitatively assess the impact of some driving factors on per capita HCEs, such as urbanization rate, per capita GDP, per capita income/disposable income, Engel coefficient, new energy ratio, carbon intensity, and household size. Using various goods and services consumed by households, direct and indirect per capita HCEs were quantified in rural and urban areas of China over the period 2000–2012. The main contributions of this study are as follows: (1) Correlation analysis and gray correlation analysis were initially used to identify the prime drivers of per capita HCEs, and (2) the conjoint effects of the potential driving factors on per capita HCEs were also determined by performing principle component regression analysis for all cases. The results yield deep insights into the influence of some micro driving factors on the per capita HCEs, which can be an effective strategy for peer researchers promoting scientific research and understanding and for policy makers formulating CO_2 reduction policies.

Methods and available data

Brief introduction to methods

To examine and evaluate the multiple contributors to per capita household CO_2 emissions in China, this study applies three methods: correlation analysis (CA), gray correlation analysis (GCA), and principal component regression (PCR).

In statistics, a scatter plot is the simplest way to qualitatively examine the correlation of two variables. To quantify the degree of correlation, the correlation coefficient R developed by Pearson (1895) is usually calculated, giving a value between −1 and +1 inclusive, where −1 represents total negative correlation, 0 is no correlation, and +1 is total positive correlation.

Another analysis named gray correlation analysis (GCA) is developed from the gray system theory, which analyzes the geometric proximity between different discrete sequences within a system. The proximity is described by the gray relational degree, which is a measure of the similarities of discrete data that can be arranged in sequential order (Jia et al. 2010; Qin et al. 2014). The gray correlation degree quantitatively represents the correlation between different driving factors. If the gray degree is higher, the major factor and the subfactor are more relevant. Similar to the correlation efficient, a positive value means that the subfactors will enhance the major factor. Otherwise, it will weaken the major factor (Zhang and Zhang 2007). Detailed information about GCA can be referenced to (Jia et al. 2010; Qin et al. 2014).

Additionally, PCA is a non-parametric but simple method that can extract relevant information from confusing datasets, and it has been applied largely in different areas (Rajab et al. 2013; Olvera et al. 2012; Shi et al. 2009). Because PCA optimizes spatial patterns and removes possible complexities caused by multicollinearity, the new combined factors become ideal predictors for further multi-linear regression analysis. It is necessary to locate the loadings concerning the certain correlations between original and combined factors (Muller et al. 2008). Herein, the combined factors should be representative of the underlying process that created the correlations among original factors.

Estimation of direct and indirect per capita HCEs

For measuring per capita HCEs, two essential parts are included: direct CO_2 emissions and indirect CO_2 emissions. The sources of direct CO_2 emissions mainly stem from the consumption of different types of fossil fuels, such as raw/washed/molded/cooking coals, coke, or other fuels (e.g., gasoline, kerosene, diesel, LPG, and natural gas), and the consumption of electricity in the household. According to the IPCC's reference method (see Eq. (1)), the direct CO_2 emissions can be calculated (IPCC 2006):

$$E_D = \sum_{i=1}^{i=n} (f_i \times e_i \times c_i \times o_i) \times 44/12 \times 10^{-4} \tag{1}$$

where E_D (t) denotes the total direct CO_2 emissions, f_i is the fuel consumption of the household (i=1,2,…,n), and n is the number of fuel types. Herein, e_i (TJ/Gg), c_i (kg C/GJ), and o_i (percent) are the net calorific value (NCV), the CO_2 emission factor (CEF), and the fraction of oxidized CO_2 (COF) of the corresponding fuel type i. The constant 44/12 represents the ratio of the molecular weights of CO_2 to C. The detailed coefficients of each fuel type are listed in Table 1.

As for indirect CO_2 emissions that are related to the consumption of household goods and services, they can be estimated through input–output analysis, which is a quantitative economic technique representing the interdependencies between different sectors (Zhu et al. 2012). and it has been widely used by other researchers (Qu et al. 2013a, b; Zhu et al. 2012). In fact, the estimation of indirect CO_2 emissions is still of great challenge due to the difficulty in data availability of indirect goods and services in China. The household indirect CO_2 emissions are estimated by household consumption multiplied by household CO_2 emission factors (see Eq. (2)), which are available in the China Statistical Yearbook and China's input–output table:

Table 1 Detailed coefficients of each fuel type used in China

Fossil fuel type	Net calorific value (e_i) (TJ/ten thousand t)	CO_2 emission factor (c_i) (tC/TJ)	Fraction of CO_2 oxidized (o_i)
Raw coal	209.08	26.37	0.94
Washed coal	94.09	25.41	0.90
Moulded coal	147.60	33.60	0.90
Cooking coal	284.35	29.50	0.93
Coke oven gas	173.54	13.58	0.99
Other gas	182.74	12.20	0.99
Gasoline	430.70	18.90	0.98
Kerosene	430.70	19.60	0.98
Diesel	426.52	20.20	0.98
LPG	501.79	17.20	0.98
Natural gas	389.31	15.30	0.98

$$E_I = \sum_{d=1}^{d=n} \left(I_d \times C_d \times 10^{-3} \right) \quad (2)$$

where n is the number representing the type of household consumption, E_I (t) denotes the total indirect CO_2 emissions, I_d (RMB) is the consumption of household goods and services, and C_d (kg CO_2/RMB) is the CO_2 emissions from the consumption of goods and services. The CO_2 emission factors of specific goods and services are given in Table 2.

Available driving factors

In this study, the household consumption of different types of goods and services, GDP, household size, population, total national CO_2 emissions, per capita income, proportion of renewable energy, food expenditure, and total income are all collected for further analysis. The detailed source information for those data is listed in Table 3.

This work is implemented with the information regarding urban–rural structures, economic/technological levels, consumption levels/structures, and household size. Some potential driving factors that represent the above information are collected, including urbanization rate (UR), per capita gross domestic product (PCGDP), per capita income/per capita disposable income (PCI/PCDI),[1] Engel coefficient (EC), new energy ratio (NER), carbon intensity (CI), and household size (HHS).

UR is an index that can be quantified in terms of the urban population relative to the overall population, and it is closely linked to modernization, industrialization, and the sociological process of rationalization. The rapid growth of urbanization in China might result from the lure of economic opportunities and the entertainment attractions in urban areas during the process of industrialization and economic development. PCGDP is the average value of goods and service produced in a country. More products manufactured results in more energy consumption. PCI/PCDI, as a measure of the prosperity or living standard of a country, represents the average income or disposable income of the people in China. As the wealth increases, the consumption level increases, which leads to the energy consumption of goods and services. Another factor, EC, which is the proportion of income spent on food, reflects the living standard of a country. As the income rises, consumers decrease their proportion of food expenditure but significantly increase their expenditures on other services. NER refers to the proportion of new energy accounting for the total energy production. Herein, new energy refers to energy from alternative energy, free energy, renewable energy, etc., such as biofuel energy, wind power, nuclear power, hydrogen energy, and solar energy. As expected, the larger the value of NER is, the less traditional energy is consumed, which inevitably leads to decreases in CO_2 emissions. CI measures the total CO_2 emissions per unit of GDP. An increasing CI reflects a decreased use of energy carriers with lower emission factors, which means that the technical level increases in the country. The last driving factor that was considered in this study is HHS. Clearly, the per capita HCEs increase as HHS falls.

Results and discussion

For now, the responses of per capita HCEs to other urban–rural structures, economic/technological levels, consumption levels/structures, and household size have not been addressed well quantitatively and comprehensively. In this study, some representative driving factors (UR, PCGDP, PCI/PCDI, EC, NER, CI, and HHS) that might be closely related to per capita HCEs have been examined. Specifically, UR, PCGDP, NER, and CI are seen as key factors reflecting the state's overall level of economy and technology. In terms of EC, HHS, and PCI/PCDI, however, there is a significant difference between

[1] Due to the unavailability of data, PCI and PCDI are applied in rural and urban areas, respectively.

Table 2 CO_2 emission factors for various types of goods and services

Items/sectors	CO_2 emission factors (kg CO_2/RMB)
Food	0.095
Clothing	0.126
Reside	0.192
Household equipment	0.156
Transportation and communication	0.160
Cultural and educational entertainment	0.177
Medical care	0.159

Source: (NBSC 1996–2012)

rural and urban areas. Thus, the potential driving factors are classified into the national overall level (UR, PCGDP, NER, and CI) and the urban/rural distinctive level (EC, HHS and PCI/PCDI).

Results of GCA

GCA is mainly used for analyzing the dynamic relationships among various driving factors, as well as the changes with time and their features, to identify the main factors of the system (Song et al. 2011). That is to say, GCA was used to numerically and quantitatively examine the prime factors that influence the per capita HCEs. Herein, the four types of HCEs are selected as the reference dataset. The corresponding gray correlation degree and the correlational order were calculated and listed in Table 4. From Table 4, we can tell that the direct and indirect per capita HCEs in rural areas are closely related to the UR, PCGDP, NER, CI, EC, HHS, and PCI, with gray correlation degrees of 0.6906, 0.8963, 0.6660, 0.6228, 0.6173, 0.6310, 0.8996, and 0.7220 (direct), and 0.9361, 0.6862, 0.6327, 0.6252, 0.6425, and 0.9013 (indirect), respectively. In urban areas, regarding the effects of potential drivers on the direct and indirect per capita HCEs, the gray correlation degrees are 0.8869, 0.7347, 0.8251, 0.7457, 0.7516, 0.7558, and 0.6596 (direct) and 0.6872, 0.8946, 0.6535, 0.5955, 0.5970, 0.6007, and 0.7727 (indirect), respectively.

Specifically, among all of those potential driving factors, PCI and PCGDP turn out to be the first two prime factors affecting direct and indirect per capita HCEs, as they are the economic levels that play the leading role in HCEs. At the same time, the roles played by UR, NER, HHS, CI, and EC cannot be underrated. In urban areas, the effects of the driving factors on per capita HCEs show significant differences. UR and NER are the top two drivers for direct per capita HCEs, followed by HHS, EC, CI, PCGDP, and PCDI. For indirect per capita HCEs, the economic levels PCGDP and PCDI contribute the most to per capita HCEs, followed by UR, NER, HHS, EC, and CI.

Results of CA

Table 5 lists the correlation coefficients ρ between per capita HCEs and the potential driving factors. As seen from Table 5, the ρ values of per capita HCEs versus UR, PCGDP, NER, and PCI/PCDI are positive, which implies that those factors contribute to the household CO_2 emissions. The ρ values of per capita HCEs versus CI, EC, and HHS are negative, which indicates that the above three factors play a positive role in reducing per capita HCEs. Specifically, per capita HCEs are very strongly linearly (positive or negative) correlated with UR, PCGDP, HHS, and PCI/PCDI, with the absolute values of coefficients approaching or exceeding 0.95. Comparatively, the linear correlations between per capita HCEs and NER and CI are relatively poor, with the absolute values of ρ falling in the range 0.6685–0.8501. There is a significant discrepancy between rural and urban areas in the correlations of per capita HCEs and EC, an index representing the income elasticity of the demand for food. In rural areas, the proportion of income spent on food shows much stronger negative effects on per capita HCEs than that in urban areas. This implies that rural

Table 3 Sources for the related data

Data	Sources
Household consumption of different types of direct and indirect goods and services	China Statistical Yearbook (NBSC, 2000–2012); China Energy Statistics Yearbooks (NBSC, 2000–2012);
Household size; Engel coefficient;	China Statistical Yearbook (NBSC, 2000–2012)
per capita (disposable) income; per capita GDP; urbanization rate	World Bank (2013)
New energy ratio	China Statistical Yearbook (NBSC, 2000–2012)
Carbon intensity	International Education Association (IEA)

Table 4 Gray correlation degree and the correlation order (per capita HCEs versus potential driving factors)

Per capita HCEs	National overall level				Urban/rural distinctive level		
Emission type	UR	PCGDP	NER	CI	EC	HHS	PCI/PCDI
I: Rural direct	0.6906	0.8963	0.6660	0.6228	0.6173	0.6310	0.8996
	$r_{PCI}>r_{PCGDP}>r_{UR}>r_{NER}>r_{HHS}>r_{CI}>r_{EL}$						
II: Rural indirect	0.7220	0.9361	0.6862	0.6327	0.6252	0.6425	0.9013
	$r_{PCGDP}>r_{PCI}>r_{UR}>r_{NER}>r_{HHS}>r_{CI}>r_{EL}$						
III: Urban direct	0.8869	0.7347	0.8251	0.7457	0.7516	0.7558	0.6596
	$r_{UR}>r_{NER}>r_{HHS}>r_{EL}>r_{CI}>r_{PCGDP}>r_{PCDI}$						
IV: Urban indirect	0.6872	0.8946	0.6535	0.5955	0.5970	0.6007	0.7727
	$r_{PCGDP}>r_{PCDI}>r_{UR}>r_{NER}>r_{HHS}>r_{EL}>r_{CI}$						

UR urbanization rate, *PCGDP* per capita gross domestic product, *NER* new energy ratio, *CI* carbon intensity, *EC* Engel coefficient, *HHS* household size, *PCI/PCDI* per capita income/per capita disposable income

per capita HCEs are far more sensitive to the proportion of income spent on food. That discrepancy might be mainly due to an asymptote or already balanced food consumption demand in urban areas. In rural areas, such a demanding space is much greater, which could easily produce more variable food consumption, which is a key source of household CO_2 emissions. Those trends can be intuitively expressed by Figs. 1 and 2, which present the scatter plots of per capita HCEs and the potential driving factors as well as the fitted linear equations and the goodness of fit (R^2). The negative and positive signs of the regression model slopes agree with those of the correlation coefficients.

Figure 1a shows a scatter plot of the urbanization against four types of per capita HCEs. According to the regression model, under realistic conditions, a 1 % increase in urbanization rate could result in an increase in the per capita HCEs of 0.0305, 0.0260, 0.0194, and 0.0656 (tons) for the rural direct, rural indirect, urban direct, and urban indirect emission types, respectively. Clearly, the effect of urbanization on urban indirect HCEs is relatively large compared with that of the other three emission types. Similarly, the same trends can be found in Fig. 1b, c. The rural direct, rural indirect, urban direct, and urban indirect per capita HCEs can be increased by 0.0002, 0.0002, 0.0001, and 0.0005 (tons), respectively, for every one dollar increase in per capita GPD. Nonetheless, Fig. 1c clearly shows a positive relationship between per capita HCEs and new energy ratio (NER). Such a positive correlation is contradictory to the expected result as the new energy ratios increase: The per capita HCEs might decrease. This could be due to the dominant percentages of traditional energy consumption. Although China has been devoted to developing new energy, the portion accounts for only 6.1 to 8.6 % at present. Moreover, the average annual growth rate of different types of per capita HCEs (4.67–10.80 %) is larger than that of NER (3.26 %), and this continuous increasing trend in per capita HCEs cannot be inverted but is mitigated by the current new energy share. The promise of new energy is that it is sustainable and environmentally friendly, and the results of more devotion to it would inevitably slow down the currently increasing rate of per capita HCEs, both in rural and urban areas. Figure 1d exhibits the correlation between the per capita HCEs and carbon intensity (CI)—CO_2 emissions divided by GDP, a measure of how efficiently countries use their polluting energy resources. That is to say, CI is a key factor to measuring a state's technological level. A higher level of technology means a higher energy efficiency, which will reduce CO_2 emission. From Fig. 1d, although CI falls, the per capita HCEs still rise. On one hand, the decrease in CI reflects that China has been developing energy-efficient technologies to improve the quality of GDP, by weakening its dependence on fossil energy consumption. The gradual increase of per capita HCEs, on the other hand, reflects that people diversify

Table 5 Correlation coefficients ρ (per capita HCEs versus potential driving factors)

Emission type	National overall level				Urban/rural distinctive level		
	UR	PCGDP	NER	CI	EC	HHS	PCI/PCDI
I: Rural direct	0.9901	0.9985	0.7965	−0.8398	−0.9542	−0.9853	0.9860
II: Rural indirect	0.9842	0.9969	0.8201	−0.8501	−0.9515	−0.9814	0.9905
III: Urban direct	0.9815	0.9638	0.6685	−0.7313	−0.7510	−0.9610	0.9448
IV: Urban indirect	0.9946	0.9973	0.7964	−0.8450	−0.7320	−0.9403	0.9931

UR urbanization rate, *PCGDP* per capita gross domestic product, *NER* new energy ratio, *CI* carbon intensity, *EC* Engel coefficient, *HHS* household size, *PCI/PCDI* per capita income/per capita disposable income

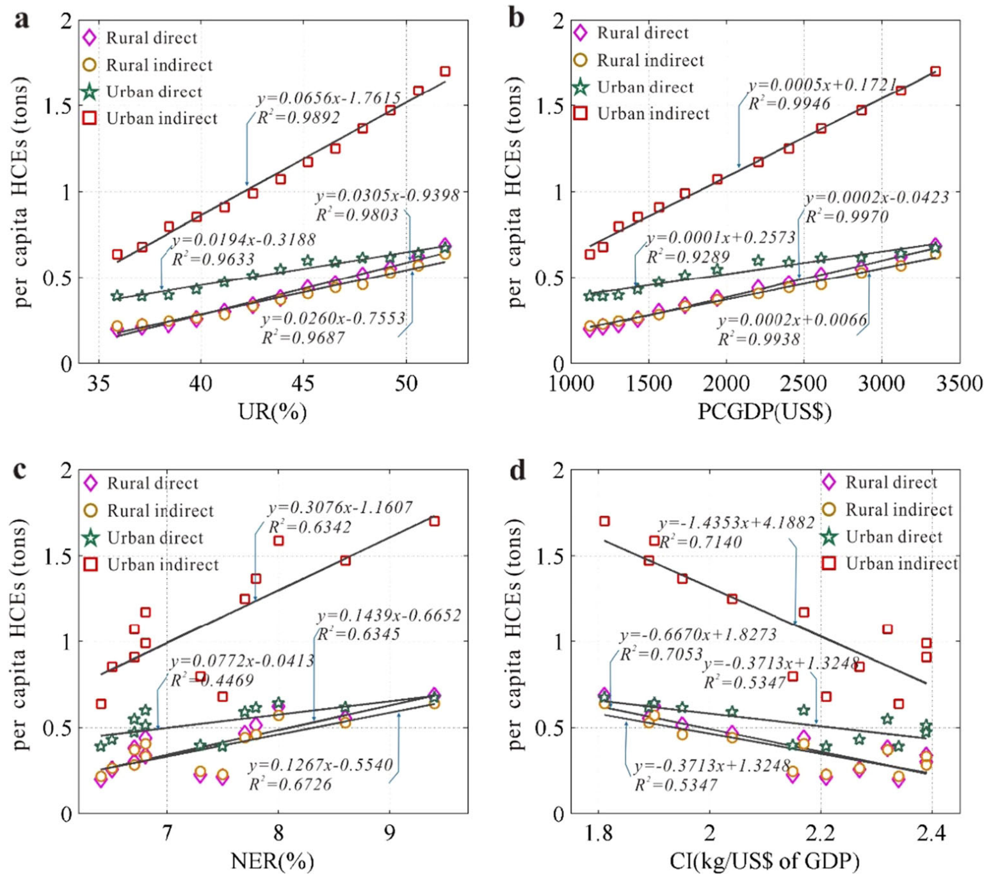

Fig. 1 Scatter plots of per capita HCEs and the potential driving factors (national overall level) as well as the fitted linear equations and goodness of fit (R^2): **a** UR versus four types of per capita HCEs; **b** PCGDP versus four types of per capita HCEs; **c** NER versus four types of per capita HCEs; **d** CI versus four types of per capita HCEs

more in household consumption in terms of purchasing, automobile, transportation, energy, housing, etc.

Figure 2 presents the scatter plots of per capita HCEs and the potential distinctive driving factors in rural and urban areas. As EC and HHS increase, the per capita HCEs decrease, whereas the rising of PCI drives increases in per capita HCEs. Specifically, assuming that other driving factors remain unchanged, a 1 % increase in the proportion of income spent on food, an increase in HHS by 1, or a 1000 (Yuan) decrease in PCI/PCDI would lead to a decrease in the per capita HCEs of (in tons) 0.05, 0.0427, 0.0716, and 0.2333; 1.6563, 1.4119, 1.1305, and 3.7002; or 0.09, 0.07, 0.2, and 0.06 in rural direct, rural indirect, urban direct, and urban indirect types, respectively. It can be concluded that those effects differ in rural and urban areas. In rural areas, the driving factors (EC, HHS, PCI) have stronger effects on direct emissions; but in urban areas, the opposite behavior is observed. That is, the indirect HCEs are more sensitive to the increasing or decreasing of the driving factors. An explanation might be that people in rural areas concentrate more on direct CO_2 emission sources, i.e., coal, LPG, and gas, due to their basic needs like heating and transportation most likely provided by themselves; in urban areas, however, much better infrastructure and service, plus higher incomes, can satisfy a more variety of consumption, such as food, clothing, entertainment, education, and medical care. It reflects that rural households emit more direct CO_2 emission than urban areas, but contrary for indirect CO_2 emission (Wu et al. 2014).

Results of PCR analysis

Defining the form of a regression equation is critical to the examination of the conjoint effects of different drivers (i.e., UR, PCGDP, PCI/PCDI, EC, NER, CI, and HHS) on the per capita HCEs. Then, a novel scheme in the regression model for the driving factor analysis is formulated in this section. In this subsection, we take one case (type I: rural direct) to illustrate this process in detail.

Multicollinearity test

Given that the performance of a regression model depends on the number of input variables and data representation, too many inputs might result in multicollinearity, with its definition being the mutual effects of interdependence on predictors of the dependency relationship whose parameters are desired. Multicollinearity poses threats, such as inducing over-fitting modeling and reducing the model's generalization and

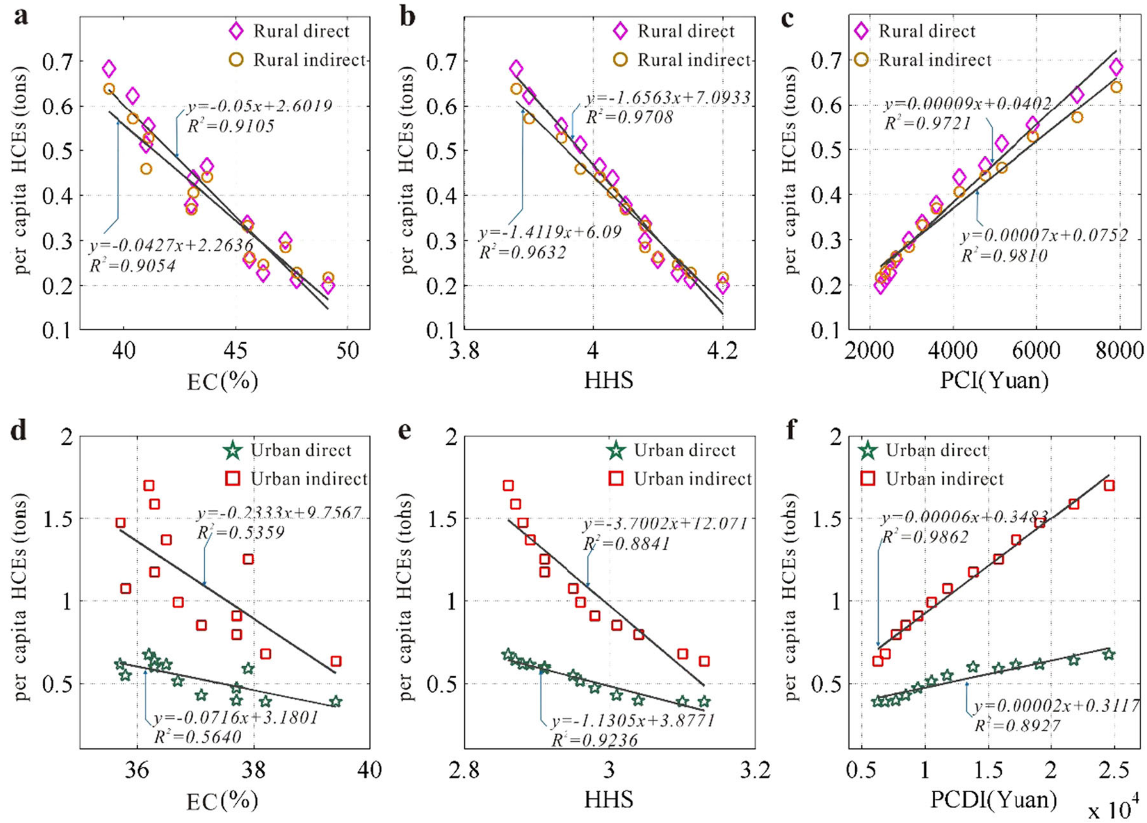

Fig. 2 Scatter plots of per capita HCEs and the potential driving factors (urban/rural distinctive level), as well as the fitted linear equations and goodness of fit (R^2): **a** EC versus type I–II per capita HCEs; **b** HHS versus type I–II per capita HCEs; **c** PCI versus type I–II per capita HCEs; **d** EC versus type III–IV per capita HCEs; **e** HHS versus type III–IV per capita HCEs; **f** PCDI versus type III–IV per capita HCEs

explanatory performance, both to the proper specification and to the effective estimation of the type of structural relationships commonly sought through the use of regression techniques (Farrar and Glauber 1967). The main reason might be that the least squares regression model is not well equipped to deal with interdependent explanatory variables, and the correlated data could confuse the model fitting (Farrar and Glauber 1967; Antanasijević et al. 2014). Furthermore, a high level of multicollinearity can also prevent computer software packages from performing the matrix (Antanasijević et al. 2014).

Table 6 gives the results of collinearity diagnostics of the driving factors. As the dimension increases, the eigenvalues approach zero, whereas for the conditional index, the tendency gradually increases to greater than 30. Moreover, the tolerance values are very small. Some scholars proposed that there is a strong collinearity when the tolerance values are smaller than 0.1. Another index variance inflation factor (VIF) equals the reciprocal of the tolerance; the larger the value of this index, the more serious the multicollinearity is. Usually, the VIF should never be larger than 10. As seen from Table 6, the small values of tolerance and the larger values of VIF indicate that the multicollinearity among those driving factors is strong. Specifically, for each principle component, if the variance proportion of two or more driving factors is large (larger than 0.5), then collinearity exists among those factors. For example, in the eighth component, the variance proportions of UR, PCGDP, HHS, and PCI are 0.76, 0.59, 0.98, and 0.63, respectively. In a word, the direct multiple linear regression will be unsatisfactory in dealing with regression analysis with serious multicollinearity. Thus, a principle component analysis is performed in the next step.

PCA

As described above, the core point of PCA is to reduce the dimensionality of the predictor variables with multicollinearity, while retaining the information contained in the variables as much as possible. After using PCA, a small number of PCs, which can explain a majority of the total variation in the predictor variables, is obtained. Generally, followed by a varimax rotation, the PCA procedure is implemented, which produces a ranked series of factors (Rajab et al. 2013). The first three PC score coefficient matrices are given in Table 7, which also lists the corresponding eigenvalues, respective variance, and cumulative variance explained by the extracted PCs. As seen from Table 7, the first three extracted PCs account for more than

Table 6 Results of multicollinearity diagnostics of the driving factors (type I: rural direct)

Dim.	Eigenvalue	Condition index	Variance proportions							
			Constant	UR	PCGDP	NER	CI	EC	HHS	PCI
1	7.766	1.000	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2	0.226	5.863	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
3	0.006	36.752	0.00	0.00	0.00	0.11	0.01	0.00	0.00	0.00
4	0.002	66.175	0.00	0.00	0.01	0.05	0.02	0.01	0.00	0.10
5	0.000	125.744	0.00	0.00	0.00	0.40	0.24	0.11	0.00	0.00
6	0.000	224.110	0.00	0.00	0.05	0.07	0.02	0.67	0.00	0.07
7	0.000	466.159	0.00	0.24	0.35	0.23	0.40	0.22	0.02	0.19
8	0.000	2317.828	1.00	0.76	0.59	0.14	0.32	0.00	0.98	0.63
	Tolerance			0.001	0.001	0.081	0.036	0.052	0.008	0.003
	VIF			848.876	1545.1	12.394	27.452	19.114	130.286	356.639

UR urbanization rate, *PCGDP* per capita gross domestic product, *NER* new energy ratio, *CI* carbon intensity, *EC* Engel coefficient, *HHS* household size, *PCI/PCDI* per capita income/per capita disposable income, *VIF* variance inflation factor

98 % of the cumulative variation. Specifically, the first components have eigenvalues larger than 1 and explain approximately 90.9 % of the total variance. PC1 accounts for a large proportion of the variance and is dominated by the positive loadings of UR, PCDGP, NER, and PCI and the negative loadings of CI, EC, and HHS, with values of 0.3848, 0.3920, 0.3467, and 0.3906 and of −0.3617, −0.3797, and −0.3879, respectively. Variation in PC2, accounting for 6.4 % of the total variance, is mainly associated with NER and CI, showing absolute values of factor loadings larger than 0.5. Variation in PC3 accounts for a small amount of the total variance (only 1.4 %), which is mainly associated with CI.

PCR

Table 8 presents the results of the PCR analysis that were used to match PCs to dependent variable, per capita HCEs. Using the first three PCs yields strong adjusted coefficients, with the asset values being 0.9901, 0.9888, 0.9642, and 0.9953 for types I–IV, respectively. The coefficients of the regressions in the majority were statistically highly significant, and the *p* values for estimated coefficients were less than 0.05. Nonetheless, there were two exceptions. The test results show that the *p* values of PC3 for type I and of PC2 for type IV (marked in red) are 0.0724 and 0.1081, respectively, which indicates that neither PC is statistically significant and that they should be eliminated in the regression equations. Thus, those PCs with significant coefficients are incorporated into the multiple regression analysis, and the regression equations are given in Table 8 as well. By substituting the corresponding PCs shown in Table 7 into the estimated regression equations, the combined effects reflected by regression equations that relate to the original driving factors and per capita HCEs can be obtained, as shown in Table 9.

Regression models have allowed the estimation of the conjoint contributions of those potential driving factors to different types of per capita HCEs. It is characteristic that the contributions of UR, PCGDP, and PCI/PCDI to per capita HCEs

Table 7 The first three PCs, together with loadings for each factor, the eigenvalues, variance per component, and cumulative variance for different types of HCEs (type I: rural direct)

PC	Coefficients of driving factors:							Eigenvalue	Var.[a]	C-Var.[b]
	UR	PCGDP	NER	CI	EC	HHS	PCI			
PC1	0.3848	0.3920	0.3467	−0.3617	−0.3797	−0.3879	0.3906	6.3664	90.9485	90.9485
PC2	−0.3312	−0.1791	0.6728	−0.5087	0.2843	0.2548	−0.0327	0.4488	6.4121	97.3606
PC3	0.1034	0.0966	0.4459	0.6536	0.4787	−0.1640	0.3131	0.1010	1.4422	98.8028

UR urbanization rate, *PCGDP* per capita gross domestic product, *NER* new energy ratio, *CI* carbon intensity, *EC* Engel coefficient, *HHS* household size, *PCI/PCDI* per capita income/per capita disposable income

[a] Variance per component

[b] Cumulative variance

Table 8 PCR estimation results: regression equations, significant test, R^2, and adjusted R^2

Emission Type	Criteria	Constant	PC1	PC2	PC3	R^2	Adj-R^2
I:	Coeff[a]	0.3993	0.0629	−0.0353	0.0297	0.9926	0.9901
Rural direct	*t* value	89.6347	34.2344	−5.1055	2.0347		
	p value	0.0000	0.0000	0.0006	0.0724		
	R-eq[b]	y=0.3993+0.0629PC1−0.0353PC2					
II:	Coeff[a]	0.3839	0.0540	−0.0226	0.0323	0.9916	0.9888
Rural indirect	*t* value	94.6413	32.2764	−3.5808	2.4323		
	p value	0.0000	0.0000	0.0059	0.0378		
	R-eq	y=0.3839+0.0540PC1−0.0226PC2+0.0323PC3					
III:	Coeff[a]	0.5299	0.0404	−0.0213	0.0452	0.9732	0.9642
Urban direct	*t* value	97.9009	17.3234	−3.4326	3.8055		
	p value	0.0000	0.0000	0.0075	0.0042		
	R-eq	y=0.5299+0.0404PC1−0.0213PC2+0.0452PC3					
IV:	Coeff[a]	1.1155	0.1418	−0.0135	0.0773	0.9965	0.9953
Urban indirect	*t* value	169.8356	50.0734	−1.7842	5.3677		
	p value	0.0000	0.0000	0.1081	0.0005		
	R-eq	y=1.1155+0.1418PC1+0.0773PC3					

Significant level: 0.05

[a] Coefficients

[b] Regression equation

were positive, whereas the contribution of HHS was negative for all cases. Specifically, a 1 % increase in UR (the other potential drivers remain stable) will lead to an increase of 0.0069, 0.0060, 0.0060, and 0.0151 (tons) in direct and indirect per capita HCEs in rural and urban areas. A \$1000 increase in PCGDP (the other potential drivers remain stable) will contribute to a growth of 0.0411, 0.0376, 0.0370, and 0.1033 (tons) in direct and indirect per capita HCEs in rural and urban areas. Similarly, a 1000 (Yuan) increase in PCI/PCDI is predicted to result in increases of 0.0139, 0.0172, 0.0044, and 0.0129 CO_2 (tons) for direct and indirect emission types in rural and urban areas. Conversely, a one person increase in each family will lead to a decrease of 0.3480, 0.3334, 0.4195, and 0.8955 CO_2 (tons) in terms of direct and indirect emission types in rural and urban areas. This demonstrates that extended families are more CO_2 friendly than nuclear families. As for NER, CI, and EC, their contributions to the four different types of HCEs are not appreciable. The driving loads for NER are negative (−0.0022 and −0.0193) and positive (0.0201 and 0.0162) values for direct and indirect emissions types, respectively. For example, a growth of 1 % in NER will lead to decreases of 0.0022 and 0.0193 CO_2 (tons) in direct per capita HCEs and increases of 0.0201 and 00162 in indirect per capita HCEs, which indicates that direct emission sources are negatively correlated with NER. Direct emission sources mainly include various coals, gases, or other fossil fuels, and more usage of new energy will decrease the consumption of those high emission fuels, which reduces per capita HCEs. Regarding EC, it plays a reverse role in rural and urban per capita HCEs. In rural areas, EC contributes to the decrease in direct and indirect HCEs, with driving loads being −0.0110 and −0.0037, respectively. In urban areas, however, EC contributes to increases of 0.0043 and 0.0079 in direct and indirect per capita HCEs. One unit of increase in CI values will force decreases of 0.0235 and 0.1849 in rural direct and urban indirect per capita HCEs, but it will also force growth of 0.0643 and 0.0156 CO_2 (tons) in rural indirect and urban direct HCEs.

Table 9 Combined effects of different driving factors on per capita HCEs

Emission type	Regression equations:
I: Rural direct	$y_{\mathrm{I}} = 1.9139 + 0.0069\mathrm{UR} + 0.0411\mathrm{PCGDP} - 0.0022\mathrm{NER} - 0.0235\mathrm{CI} - 0.0110\mathrm{EC} - 0.3480\mathrm{HHS} + 0.0139\mathrm{PCI}$
II: Rural indirect	$y_{\mathrm{II}} = 1.1942 + 0.0060\mathrm{UR} + 0.0376\mathrm{PCGDP} + 0.0201\mathrm{NER} + 0.0643\mathrm{CI} - 0.0037\mathrm{EC} - 0.3334\mathrm{HHS} + 0.0172\mathrm{PCI}$
III: Urban direct	$y_{\mathrm{III}} = 1.3230 + 0.0060\mathrm{UR} + 0.0370\mathrm{PCGDP} - 0.0193\mathrm{NER} + 0.0156\mathrm{CI} + 0.0043\mathrm{EC} - 0.4195\mathrm{HHS} + 0.0044\mathrm{PCDI}$
IV: Urban indirect	$y_{\mathrm{IV}} = 2.7028 + 0.0151\mathrm{UR} + 0.1033\mathrm{PCGDP} + 0.0162\mathrm{NER} - 0.1849\mathrm{CI} + 0.0079\mathrm{EC} - 0.8955\mathrm{HHS} + 0.0129\mathrm{PCDI}$

UR urbanization rate, *PCGDP* per capita gross domestic product, *NER* new energy ratio, *CI* carbon intensity, *EC* Engel coefficient, *HHS* household size, *PCI/PCDI* per capita income/per capita disposable income

Conclusions and policy recommendations

Conclusions

This paper presents a qualitative and quantitative individual and conjoint analysis of the potential driving factors on per capita HCEs, drawing on a comprehensive dataset of direct and indirect emissions in rural and urban areas of China. Some conclusions are drawn:

1. Through the gray correlation analysis, the main contributors to per capita HCEs have been examined. To be specific, in rural areas, both direct and indirect per capita HCEs are most strongly correlated with PCI/PCDI, PCGDP, and UR, which are also the first three significant factors correlated with indirect HCEs in the urban areas of China. This result agrees with the correlation analysis.
2. Based on the correlation analysis and individual regression analysis, however, for direct per capita HCEs in urban areas, the prime drivers are UR (0.8869), NER (0.8251), and HHS (0.7558) based on GCA and are UR (0.9815), PCGDP (0.9638), and HHS (−0.9610) based on CA. This difference can be explained by the non-linear and linear characteristic analysis of GCA and CA, respectively. In case III (urban direct), per capita HCEs show stronger non-linear relationships with the driving factor NER, and they lead to a higher gray correlation degree but a smaller correlation coefficient. Moreover, UR, PCGDP, NER, and PCI/PCDI have positive correlations with per capita HCEs, and CI, EC, and HHS have negative correlations with per capita HCEs.
3. Over the conjoint estimation analysis, the maximum of absolute affecting loads for HHS implies that the effect of HHS (one person increase or decrease in each family) is relatively large compared with the effects of other drivers. Given that the HHS remains relatively stable, however, it contributes little to changes in per capita HCEs. NER plays positive and negative roles in direct and indirect per capita HCEs both in rural and urban areas of China. Although the growth of NER did not hamper increases in per capita HCEs, it did mitigate the growth rate of per capita HCEs. This implies that Chinese families are more likely to gain access to low carbon energy products and decrease the usage of direct emission sources. UR is another driver that contributes to CO_2 emissions. The Chinese rural population was approximately 635 million by the end of 2013 (UN-DESA-PD 2014), and more than 82 million people lived below the poverty line (Iaccino 2014). The theme of the Expo 2010 in Shanghai, China, was “Better City-Better Life.” Therefore, to comprehensively build a Xiaokang society in China, urbanization or rural modernization should be continued. As PCI rises, more products are consumed, which increases per capita HCEs. However, these consumption behaviors are significantly distinctive in rural and urban areas of China. In rural areas, people use considerable portions of their incomes to meet their food needs and other basic needs. In urban areas, however, consumption behaviors shift toward indirect goods and services because of their high income level. According to comprehensive evaluation results, the decreasing EC values would help to improve and reduce per capita HCEs in rural and urban areas of China, respectively.

Policy recommendations

Household CO_2 emissions of China play a significant role in national CO_2 emissions, and their contributions tend to be increasing gradually. Over the following decades, China’s GDP will keep growth, which contributes to increases in CO_2 emissions up to achieving the emission peak. Therefore, promoting GDP quality through more aggressive action regarding energy efficiency and upgrading energy structure with increasing the share of new energy in the total energy market is a necessary strategy for reducing carbon emissions per unit of GDP and for approaching the 40–45 % carbon intensity reduction goal. Given the proportion of the household CO_2 emissions over the total and the large size of China’s population, however, the importance of addressing problems with the household CO_2 emissions has become increasingly recognized by policy makers within China. As the rapid industrialization and urbanization progress, and living standards and income levels increase in China, on one hand, it is needed to guide the residents of China toward healthier, greener, and more sustainable consumption and lifestyle. Specifically, for the urban residents of China, it is necessary to promote their environmental awareness toward using clean energy with low carbon emissions and carbon friendly products. As for people in rural areas, providing high-quality energy products for those residents is of prime necessary. On the other hand, although the HCEs of China are lower than those of the developed countries, China cannot follow the similar emissions trajectory as the developed countries did. It is suggested to accelerate the establishment of a carbon emission trade system or other incentive mechanisms, which will reduce the carbon cost of household consumption through making the products with lower carbon and increasing the proportion of renewable and clean energy accounting for electricity and direct consumption energy.

To sum up, this analysis provides evidence and insight into the driving factors to per capita HCE increases and decreases, and the corresponding driving loads. And, some alternative polices are also presented to improve the household CO_2 emission reduction policy framework both in rural and urban areas of China. Hopefully, this work will lead to a likely precondition for controlling and mitigating HCE growth in China.

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