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Intertemporal Lifestyle Changes and Carbon Emissions: Evidence from a China Household Survey

Hongwu Zhang [a], Xunpeng Shi [d,b,c], Keying Wang [b,c*], Jinjun Xue [b,c,e,f], Ligang Song[g], YongPing Sun[b,c]

[a] School of Economics, Zhongnan University of Economics and Law, China
[b] Center of Hubei Cooperative Innovation for Emissions Trading System, Hubei University of Economics, China
[c] School of Low Carbon Economics, Hubei University of Economics, China
[d] Australia-China Relations Institute, University of Technology Sydney, Australia
[f] Economics Research Center, Graduate School of Economics, Nagoya University, Japan
[g] Institute of Global Low-carbon Economy, University of International Business and Economics, China
[h] Crawford School of Public Policy, Australian National University, Australia

Highlights

- Decomposition of the intertemporal change of household carbon emissions (HCEs).
- Household-based Carbon Kuznets Curves (CKC) are observed in all sample periods.
- Income growth is not the main contributor to the increase in HCEs over time.
- Intertemporal lifestyle changes are the dominant source of increases in HCEs.

Abstract

This paper examines the endogenous evolution of household consumption patterns and household carbon emissions (HCEs) by integrating the analysis methods of income distribution with climate change. Based on a large-scale household survey spanning from 2012 to 2016 in China, we estimated the direct and indirect HCEs, observed inverse U-shaped Carbon Kuznets Curves (CKC) and significant changes in HCEs over the period at the household level. Applying the Oaxaca-Blinder method, we decomposed factors causing the changes in HCEs and found that income and demographic effects contribute only 25.1% to the total increase of HCEs. The other 74.9% remain unexplained and we define them as the effect of intertemporal lifestyle changes. Further analysis from multiple perspectives illustrates that the lifestyles of households across various social strata are becoming increasingly higher carbon-intensive over time even though the income remains unchanged. The findings indicate that existing modelling and projections of carbon emissions based on income and household characteristics may underestimate the future emissions pressure from the household sector. Hence, we conclude that in order to reach more meaningful results, the increasing effect of lifestyles should be taken into account when conducting climate change studies and formulating climate policies.

* Corresponding author: Keying Wang, E-mail address: wangkeying@126.com.

Key words: Household carbon emissions (HCEs); Intertemporal lifestyle changes; Household-based Carbon Kuznets Curves (CKCs); Oaxaca-Blinder decomposition method

JEL classification: Q56; D15

1 Introduction

Though most countries have been trying to apply the 2015 Paris Climate Accord and comprehend their promised targets of emissions reduction, global CO_2 emissions increased by 1.6% in 2017, having flattened out between 2014 and 2016. In 2018, it is projected to go up by more than 2% (Figueres et al., 2017). Therefore, we have to rethink the reasons behind the increase and find effective ways of carbon emissions reduction.

In the case of China, the largest carbon emitter in the world, the efforts to mitigate climate change are mainly on the production-side over the last two decades. Though significant progress has been achieved,[1] it tends to be partly offset by the consequences on the consumption side because the direct carbon emissions from the residential sector have increased significantly over the past forty years.[2] If the indirect household carbon emissions (HCEs) that are embodied in the production and distribution process of goods and services consumed by households are included, the increase is even higher (Li et al., 2015; Wei et al., 2007), and therefore further steps must be considered in order to cut the consumption-induced carbon emissions. However, before implementing any such steps, it is vitally important to fully understand the actual factors that drive the rapid growth of HCEs in China.

It can be expected that with continued rapid income growth in China, the direct and indirect emissions coming from households will continue to rise in the future and put extra pressure on carbon abatement. However, as shown in Figure 1, the large and extremely diverse households in China have been undergoing tremendous socioeconomic and environmental changes in recent decades, such as infrastructure construction, social institutions and legal foundation, which have been continuously

[1] The carbon intensity declined by about 46% in 2017 compared to 2015. http://www.chinanews.com/cj/2018/03-24/8475350.shtml.

[2] According to the CO_2 Emissions Factors listed by the IPCC (2006) and data from *China Energy Statistics Yearbooks*, we calculated the annual growth rate of direct household carbon emissions in China to be 6.3% from 2006 to 2016, while that of the total carbon emissions was 3.3% over the same period.

shaping and reinforcing individual and family lifestyles through encouraging or constraining behaviors, further affect household consumption patterns as well as the quantity and changes in the associated HCEs (Schipper, 1989; Wilhite and Lutzenhiser, 1999).

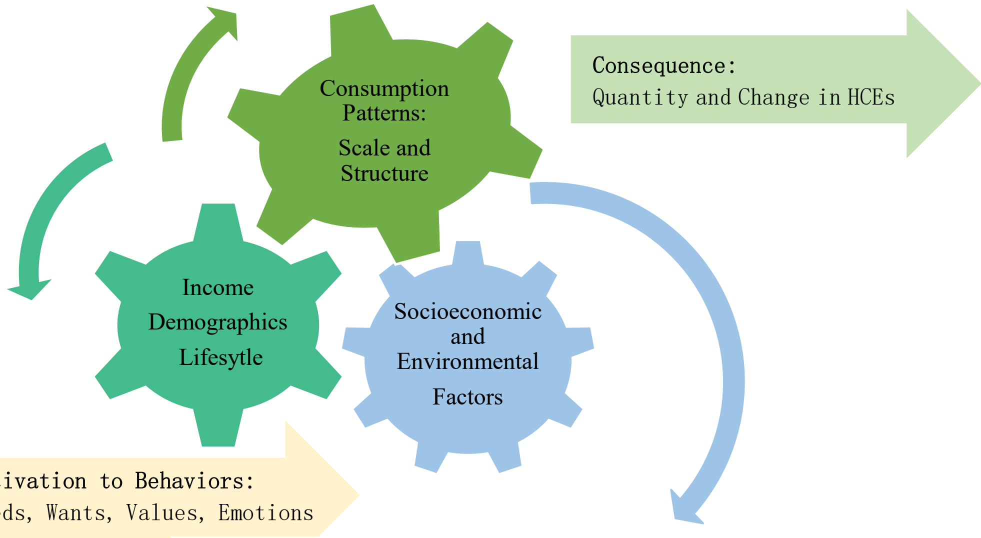

Figure 1: Conceptual Framework

Therefore, our central thesis in this paper is that for a country like China which is experiencing tremendous transformations in all aspects, the shape and underlying trend in HCEs is determined not only by changes in household incomes or demographics, but also by intertemporal lifestyle changes. In order to achieve the greatest potential carbon reductions, it is critically important for China's policy-makers to fully understand the evolution of household lifestyles and the associated emissions. Such studies can also help the global community in formulating climate change policies as China is the largest carbon emitter and its significant growth potential will shape the future trend of carbon emissions.

Although there is abundant research on HCEs and the relevant influencing factors in China, few has attempted to estimate indirect emissions over time with household level survey data. Moreover, the impacts of changing lifestyles on household consumption patterns and the related HCEs have been mentioned frequently, however, few studies have quantified them. In particular, there is still no study which quantifies the effect of intertemporal lifestyle changes on HCEs in China at the household level. Importantly, the conclusions from aggregate analysis may be incapable of providing enough evidence for policy design (Lenzen et al., 2006; Wilson et al., 2013), and the studies with cross-sectional data also cannot capture the dynamic properties of the HCEs.

Therefore, the main aims of this paper are to estimate the magnitude and dynamic changes in HCEs using large-scale household survey data, and to quantify the effects of income, demographics and intertemporal lifestyle changes on HCEs within an analytical framework. Moreover, we focus on the effects of intertemporal lifestyle changes on HCEs and these are relatively independent of the forces of incomes and demographics. Our contributions are threefold. Firstly, by applying the Oaxaca-Blinder decomposition method, we showed that there are three effects related to the dynamics of HCEs: total income growth effect, household demographic effect, and intertemporal lifestyle changes effect. As the intertemporal lifestyle changes effect is the dominant effect, we further explored the link between changes in intertemporal household lifestyles and the increase in HCEs from three perspectives: the allocation of resources across financial, material, and temporal activities. Secondly, the estimated direct and indirect household carbon emissions for 37,620 representative households in China for the latest available years provides a rich dataset for future research. Thirdly, we observed a set of Carbon Kuznets Curves (CKCs) at the household level and analyzed the significant changes in HCEs across households and over the period. We also explored the underlying reasons for the concavity of the CKCs.

The rest of the paper is organized as follows. Section 2 briefly explains driving factors for HCEs in the literature. Section 3 presents the methodology and data. Section 4 reports the total HCEs for each household in the sample, plots the income-carbon emissions curves to test the CKC hypothesis and examines the effects of impacting the dynamic evolution of HCEs. Section 5 explores the underlying reasons for the CKC and dynamic evolution of HCEs from the perspectives of changing consumption patterns and lifestyles in more details. Section 6 summarizes the main conclusions and provides policy implications.

2 Driving factors for household carbon emissions

There are many factors affecting household carbon emissions. Firstly, there is a broad consensus that income is one of the main determinants of HCEs in the long run (Duarte et al., 2010; Lyons et al., 2012). In China, households with the highest income also tend to have the highest CO_2 emissions (Han et al., 2015; Liu et al., 2011; Wiedenhofer et al., 2017). However, the relationship between income and HCEs was found to be nonlinear and Ravallion et al. (2000) stated that the heterogeneity of consumer preferences and consumption patterns between income groups is more likely the source of the nonlinearities. Empirical studies with aggregate data indicated that both the income elasticity of carbon emissions and the marginal propensity to emit decline as incomes rise and the inverse U-shaped Environmental Kuznets Curve (EKC) hypothesis could be valid (Chancel, 2014; Grossman and Krueger, 1995; Zhang et al., 2017). As for some developing countries and emerging economies, for instance China, the Philippines and Indonesia, there also exists an inverted U-shaped relationship between household income and carbon footprint (Golley and Meng, 2012; Irfany and Klasen, 2017; Seriño and Klasen, 2015; Zhu et al., 2018)

Moreover, many studies have found that there is a wide variation in HCEs at a given income level. This means that non-economic factors, namely, household characteristics such as family size, age, education level, marital status, dwelling type, occupation, the location of households, etc., could be statistically significant predictors of HCEs (Baiocchi et al., 2010; Büchs and Schnepf, 2013; Choi and Zhang, 2017; Golley and Meng, 2012; Long et al., 2018). In the case of China, some studies have found that energy consumption patterns and CO_2 emissions show remarkable disparity between urban and rural households due to differences in socio-economic development, government policies, habits and behaviors (Feng et al., 2011; Han et al., 2015; Maraseni et al., 2016; Wang and Zhang, 2016; Wang, 2014; Wiedenhofer et al., 2017).

While most studies acknowledge the fundamental roles of income and demographics in shaping the HCEs, some have shown that there is still a large part of carbon emissions that the mentioned factors fail to explain. Chitnis et al. (2012) argued that income itself is not even a particularly good predictor of a household's energy consumption. The changes in values, motivations, consumption preferences and patterns of individuals and families, which generally fall under "lifestyle", can lead to substantial changes in energy demand and HCEs even with small changes in income, particularly during the long-term (Parag and Darby, 2009; Schipper, 1989). Schipper (1989) found that in industrialized countries, energy prices and incomes will no longer drive significant changes in energy demand, and that lifestyle changes are becoming the dominant source of changes in energy demand. Chitnis et al. (2012) found that exogenous non-economic factors affect all of the household expenditure categories, and have a higher contribution to the changes in expenditures of high carbon-intensive categories in the UK. Levinson and O'Brien (2018) found that intertemporal changes in lifestyle contributed 39 to 76 percent to the change in pollutants in the US.

Following Axsen et al. (2012) who developed a conceptual framework for analyzing private low carbon consumption and lifestyle, some studies have estimated the effect of lifestyle on energy use or carbon emissions based on the method of scenario simulation and aggregated data. The results show that energy-saving or low-carbon lifestyles such as the deliberate purchasing of lower energy-intensity products and the use of energy in an efficient way, will obviously lead to energy-saving and CO_2 emission reductions even at given expenditure levels (Alfredsson, 2004; Carlsson-Kanyama et al., 2005; Vringer and Blok, 1995). Chitnis et al. (2012) found that exogenous non-economic factors (ExNEF), including tastes, consumer preferences, lifestyle and values have a relatively higher contribution in some high carbon-intensive expenditures. Applying the survey data on time-use, De Lauretis et al. (2017) and Wiedenhofer et al. (2018) found that there are large differences in the carbon intensity across residents' activities. In China, Feng et al. (2009) found that people's lifestyles changed and diversified dramatically between 1980 and 2002, and that the increasing resemblance to Western lifestyles is expected to lead to rapid increases in emissions. Wei et al. (2007) found that lifestyles have a noticeable impact on residents' total energy use and the related CO_2 emissions in urban and rural areas. Based on the BAU scenario, Wang et al. (2016) found that when eliminating the income differences, the household consumption propensity and consumption patterns have a significant impact on HCEs among different groups.

It can be seen that in addition to income and demographics, studies have noticed the impact of lifestyle on household energy consumption and carbon emissions, however, few quantify the intertemporal lifestyle effect on HCEs. The current modelling and predictions of carbon emissions based on income and household characteristics may miss the significant effect of lifestyle changes and underestimate the future emissions pressure from the household sector. In this paper, we plot the income-carbon emissions curves to examine the dynamic evolution of HCEs with a large-scale household survey data and apply the Oaxaca-Blinder decomposition method to quantify the intertemporal lifestyle effect on changes in HCEs over time, which cannot be captured by explanatory variables and are usually overlooked by existing related research. We show that understanding how the household's lifestyle changes may be the key to a better understanding of the plausible levels of future HCEs in China, the most populous country with rapid development and the largest emitter of carbon in the world.

3 Methodology and data

Following Levinson and O'Brien (2018), we first provide an analytical framework with a series of income-carbon emissions curves to demonstrate how income, demographics and intertemporal lifestyle changes can cause changes in household consumption patterns and HCEs. This is important in understanding the dynamic evolution of HCEs. Then in the empirical section, we estimate the direct and indirect HCEs for a total of 37,620 representative households in China for 2012, 2014 and 2016, using Input-Output Modeling (IOM) and the Emission Coefficient Method (ECM). We further employ the Oaxaca-Blinder decomposition method to reveal the three effects affecting the dynamic changes in HCEs.

3.1 Analytical framework

Based on the literature review, it seems that the differences in per capita HCEs across households and over time can be regarded as the result of the income effect, demographics effect, and intertemporal lifestyle changes effect on consumption patterns, as shown in Figure 2.

We assumed:

1) There is a possible non-linear income-HCEs relationship across households. If holding the consumers' preferences and other influencing factors constant, except income, i.e., comparing the HCEs of two different households with income per capita

y_1 and y_2 on curve L_1,[3] we may expect that emissions may rise proportionately to income and move along the straight line L_2 from point A to point B,[4] and that the increase of emissions e_1e_5 is usually referred to as scale effect of income.

However, there are some possible factors that may affect the expected linear relationship. Firstly, when a household's income increases, its consumption expenditures may not increase in proportion to income due to the law of diminishing marginal propensity to consume, thus leading to a non-linear relationship between HCEs and income. Secondly, with the increase in income, households will adjust the composition of goods and services consumed. This may lead to an increase or decline in carbon-intensive consumption structure. Such an increase or decline in carbon emissions is generally called the composition effect of income, which is e_5e_3. Thirdly, household demographics are often associated with income, such as household size, marital status, educational level, location, i.e., urban v.s. rural areas, etc., and will have influence on HCEs accompanied with income.[5] The shifts of the line from L_1 to L_4 or from L_1 to L_3 and the HCEs per capita e_4e_3 or e_3e_2 in Figure 2a reflect the impacts of household demographics heterogeneity on HCEs. From Figure 2a, we can conclude that when holding household demographics and other factors, the increase in per capita household incomes simply leads to the movement of the HCEs moving along L_1.

2) There is a possible non-linear income-HCEs relationship over time. As described in Part One, the lifestyles of individuals and households may change as a result of socioeconomic and environmental factors even if the income or demographics remain unchanged. Tremendous changes have taken place in all aspects of Chinese people's lifestyles over four decades of reform and opening up. Rapid and extensive infrastructure construction likely stimulated rapid acquisition of cars, and concomitantly more driving and traveling. The construction of centralized heating and gas pipelines in cities likely altered households' energy consumption structure. The increase of internet coverage, and the popularization of credit

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[3] As there is no theory or model indicating the exact form of the relationship between household income and HCEs, the inverse U-shaped curves in Figure 2 to Figure 4 are merely a postulate based on the existing empirical studies.

[4] The straight line L_2 is tangent to L_1 at point A.

[5] To some extent, income-HCEs curves are similar to the Engel curves that may also depend on demographic variables and other consumer characteristics (Lewbel, 2006).

payments and e-commerce likely spurred consumption and accelerated the upgrade of consumption structure. All of these have greatly increased the energy use and the associated environmental impact. Environmental regulations have served to strengthen people's environmental awareness, while urbanization and globalization have continually caused households to re-evaluate their lifestyle goals.

Intertemporal lifestyle changes are the result of multiple factors and the individual effect is not easily measurable. However, their existence may still be confirmed by the analysis, and it is important when it comes to understanding the underlying driving factors of expenditures and the associated carbon emissions (Chitnis et al., 2012).

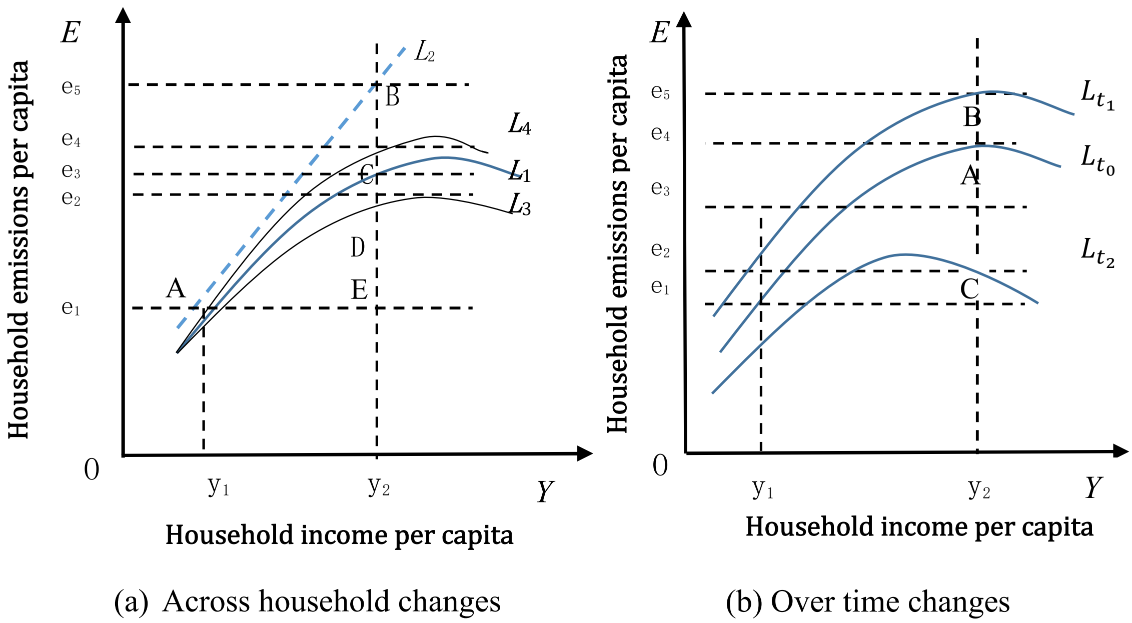

Figure 2. Theoretical Models of Income-HCEs Curves

Figure 2b demonstrates the dynamic changes in HCEs resulting from the transformation of consumption patterns over time. Point A on curve L_{t_0} represents a household with income per capita y_2 and the corresponding carbon emissions e_4 at time t_0. At time t_1, a household may consume less and reduce its carbon-intensive mix of goods and services to below $t_{0,}$. Though income and demographic characteristics do not change, HCEs may move down from point A to C, representing a trend towards low-carbon lifestyles. On the contrary, if a household changes its lifestyle and consumes a larger and more carbon-intensive mix of products, HCEs may move up from A to B. If all the households with different incomes behave in the same way as the household with income y_2, we may see the HCEs curve L_{t_0} shift down to L_{t_2} or up to L_{t_1} indicating that the whole society transits to a low-carbon economy or high-carbon economy. It should to be specially noted that when a household's lifestyle becomes more carbon intensive, the turning point of the income-HCEs curve is expected at a higher income and HCEs level. This makes it more difficult to cut carbon emissions from the residential sector.

3.2 Calculation of HCEs: direct and indirect HCEs

The total carbon emissions for an individual household k in our sample consist of two parts: indirect emissions $E_{indirect\_k}$, and direct emissions E_{direct_k}. The direct carbon emissions for household k are the emissions from the household's final consumption of fossil fuels, i.e., coal, oil and gas (Zhang et al., 2015). We calculated the direct carbon emissions for household k with the emissions coefficient method (ECM) from the IPCC (2006), as is widely done in the literature (Munksgaard et al., 2000; Qu et al., 2013; Wiedenhofer et al., 2017). The direct CO_2 emissions for household k are:

$$E_{direct\_k} = \sum_i f_i Energy_{ik} \tag{1}$$

where f_i is the CO_2 emissions factor of energy source i, and $Energy_{ik}$ is the quantities of energy source i consumed by household k.

The indirect HCEs are estimated with Input-Output modeling (IOM), which is a widely employed approach (Büchs and Schnepf, 2013; Dai et al., 2012; Ding et al., 2017; Duarte et al., 2010; Fan et al., 2012; Golley and Meng, 2012; Wiedenhofer et al., 2017). The calculation of the indirect CO_2 emissions for a specific household k is as follows:

$$E_{indirect\_k} = D(I - A)^{-1} Exp_k \tag{2}$$

where D is the row vector of direct emission intensities for each sector, $(I - A)^{-1}$ is the Leontief inverse matrix, which is the key to the application of input-output analysis; Exp_k is the column vector of household k's expenditure per capita on goods and services.

3.3 Oaxaca-Blinder (OB) decomposition methods

Widely used to examine discrimination in the labor market, the Oaxaca-Blinder decomposition methods (Blinder, 1973; Oaxaca, 1973) have been employed extensively as standard tools to identify and quantify the contribution of various factors in differences within a group (or region/time period), including household environmental behavior (Levinson and O'Brien, 2018; Long et al., 2018). Based on the demonstration of the analytical framework, we employed the Oaxaca-Blinder decomposition approach to identify the contribution of income growth, demographic characteristics and intertemporal lifestyle changes to the overall changes in per capita HCEs in China from 2012 to 2016.

We started by estimating a series of linear regressions with per capita HCEs on the left-hand side and income, income squared, and other covariates on the right-hand side:

$$E_{kt} = \alpha_t + \beta_t y_{kt} + \gamma_t y_{kt}^2 + X_{kt}\delta_t + \varepsilon_{kt}, \tag{3}$$

where E_{kt} and y_{kt} are total HCEs per capita and household income per capita at year t, so β_t and γ_t represent the marginal propensity to emit. X_{kt} is a vector containing other covariates, α_t is the estimated intercept and ε_{kt} is the error term, $E(\varepsilon_{kt}) = 0$. The coefficients are indexed by t because we ran separate regressions for each year. With the coefficients β_t, γ_t and the income of all households in the sample, we can obtain an estimated household-based income-HCEs curve for a given year.

Based on equation (3), we defined the average level of HCEs per capita in a given year:

$$\bar{E}_t = \alpha_t + \beta_t \bar{y}_t + \gamma_t \overline{y_t^2} + \bar{X}_t \delta_t \tag{4}$$

where $\bar{E}_t$ is the expected value of per capita HCEs for year t, $\bar{y}_t$ and $\overline{y_t^2}$ are average per capita household income and the squared term, and $\bar{X}_t$ is the average of other included covariates. The error term disappears because $\mathrm{E}(\varepsilon_t) = 0$ by assumption.

Then based on equation (4), the change in the expected value of HCEs per capita between any two years can be written as:

$$\begin{aligned}\bar{E}_{t_1} - \bar{E}_{t_0} = {} & (\alpha_{t_1} + \beta_{t_1}\bar{y}_{t_1} + \gamma_{t_1}\overline{y_{t_1}^2} + \bar{X}_{t_1}\delta_{t_1}) \\ & -(\alpha_{t_0} + \beta_{t_0}\bar{y}_{t_o} + \gamma_{t_0}\overline{y_{t_0}^2} + \bar{X}_{t_0}\delta_{t_0})\end{aligned} \tag{5}$$

To identify the sources of the overall differences in HCEs per capita, equation (5) can be rearranged, for example, between 2012 and 2016, as follows:

$$\begin{aligned}\bar{E}_{16} - \bar{E}_{12} = {} & [\beta_{12}(\bar{y}_{16} - \bar{y}_{12}) + \gamma_{12}(\overline{y_{16}^2} - \overline{y_{12}^2})] \\ & +(\bar{X}_{16} - \bar{X}_{12})\delta_{12} \\ & +[(\beta_{16} - \beta_{12})\bar{y}_{16} + (\gamma_{16} - \gamma_{12})\overline{y_{16}^2} + \bar{X}_{16}(\delta_{16} - \delta_{12}) + (a_{16} - a_{12})]\end{aligned} \tag{6}$$

The difference in HCEs between year 2012 and 2016 is divided into three components in equation (6). The terms of in the first line measure the income effect, while the term in the second line estimates the demographics effect. The sum of two effects is called the explained effect or endowment effect in OB decomposition, which indicate, when fixing the consumption preference in 2012, the differences in average HCEs are expected to have as a result of changes in incomes and all demographics. The income effect can be further decomposed to scale effect and composition effect. When assuming each household's consumption preference will not change with income growth, the average per capita HCEs will change at the same rate as the average household income per capita, and then change of HCEs of $\bar{E}_{12} \times \left(\frac{\bar{y}_{16}}{\bar{y}_{12}} - 1\right)$ is the scale effect of income. The difference between total income effect and the scale effect is the composition effect of income.

The sum of four terms in the third line measures the contribution of differences in the coefficients of all variables including the intercept over the two years when assuming that the income or demographics are unchanged. This is usually called the unexplained effect or coefficients effect. The changes in the coefficients may result from the changes in the consumption scale or structure and are independent of the income and demographics. We ascribe the underlying force which drives the consumption pattern evolution to the effect of intertemporal lifestyle changes.

Combining the Income-HCEs Curves in Figure 2 with the decomposed effects in equation (6), we find that the income effect measures how HCEs changed when using the income-HCEs curve in year t_0 to estimate a hypothetical level of HCEs in t_1. This resulted in a movement along the estimated curve, while the coefficients effect leads to a shift in curves. The two effects both cause dynamic changes in HCEs, but there is an important difference. Movements along the income-HCEs curve are mainly driven by the differences in consumption preferences and are merely due to differences in income. They are independent of any particular policy intervention since all households are facing the same external environment. In this sense, the movements may be predictive of future levels of HCEs under status quo carbon abatement policies if household incomes increase but nothing else changes. Moreover, the shifts in the income-HCE curves are caused by intertemporal lifestyle changes resulting from the continually evolving socioeconomic and environmental factors, including carbon abatement policies. In this context, policies aimed at encouraging low-carbon lifestyles and changing the relative demand and supply for carbon-intensive goods and services will be effective.

3.4 Data

Our datasets have three main components: (i) Samples of China households for the latest available years (2012, 2014 and 2016) from the *China Family Panel Studies* (CFPS); (ii) China's Input-Output table from *the World Input-Output Database* (WIOD); and (iii) Carbon emissions for China's 35 sectors in 2007 from the *WIOD*.

(1) The CFPS dataset: income, expenditure and demographics

The China Family Panel Studies (CFPS) is a national representative longitudinal survey of Chinese communities, families and individuals, which was launched in 2010 and implemented every two years thereafter by the Institute of Social Science Survey of Peking University (ISSS).[6] The sample covers almost 15 thousand households for one year and was spread over 25 provinces in 2010 and all 31 provinces in 2016. The CFPS has been widely used in studies on economic activities, education outcomes and family dynamics (Xie and Hu, 2014). Considering the consistency and quality of the data, we obtained all the information on income, consumption expenditures and demographic characteristics of each household from the CFPS dataset for 2012, 2014 and 2016.[7]

The data on household living expenditures is of critical importance when estimating direct and indirect carbon emissions. The CFPS collects 26 living expenditure categories of data, most of which have corresponding categories in the Chinese National Bureau of Statistics (NBS). After excluding the financial support given to non-resident relatives, social donations and other expenditures, we set the value of the "Mortgage Loan" and "Commercial Insurance" categories as zero since the two categories are treated as assets rather than living expenditures (CFPS, 2014).

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[6] Before doing the study, we made a comprehensive comparison of the main household survey data in China and found that the respondents in some surveys are inconsistent with this topic, and the time span, availability or expenditure items in some other surveys cannot meet the requirement in this paper. Therefore, for the current study in this paper, we think CFPS is the more appropriate dataset that we can use at the moment.

[7] In CFPS, baseline family members and their future siblings/adoptive children are the permanent respondents, however, the same family ID in different years may represent different family due to birth, marry, migration or death. So instead of applying a panel data model, we ran the cross-section model respectively for the three years and then decomposed the changes in HCEs into different components.

Thus, we obtained 22 categories of living expenditures. The adjusted household disposable income data was also collected from the CFPS. The expenditures and income values for the three years were adjusted to constant 2007 prices according to the CPI sub-indices for both urban and rural regions published by the NBS.

Besides income, we collected other household characteristics variables that have significant effects on consumption structure and HCEs from CFPS, including household size, household head's age, education level, marital status. We also collected the type of fuel to feature household's direct energy consumption structure. In view of the fact that the type of housing has an important impact on households' energy consumption and carbon emissions, we included the variable into the model. In addition, environment policies and regulations usually vary across China. Considering that provinces are the main authority of regional policy making, we included provincial dummy with urban or rural dummy into the analysis to reflect the difference in households' lifestyles and consumption patterns due to the development of socio-economics, geographical features and policy. These two dummy variables can helpful of in controlling the household groups fixed effects to a certain extent. In order to address the bias that might arise from the survey data, we kept the cross-section weight in our dataset.

In addition, we converted the direct energy consumption in physical unit with the three kinds of related expenditures on cooking, heating and personal driving from CFPS and the provincial prices for each type of fuel in that year,[8] and then calculated the direct HCEs according to equation (1). In this way, we had the direct carbon emissions of each household in the sample.

(2) Input-Output table, and sectorial CO_2 emissions intensity

We used I-O method to estimate HCEs by integrating household consumption expenditure into I-O tables. The WIOD (the first version was released in 2003) provides China Input-Output Tables and total CO2 emissions for 35 sectors. The same sectoral classification in two dataset and sectoral carbon emissions provided directly by WIOD greatly reduces the bias arising from the processing of data

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[8] Due to lack of provincial price of coal consumed by households, we estimated the direct HCEs under four coal prices setting scenarios and chose the most reasonable one according to some public information. The details of coal prices setting scenarios are presented in Appendix B.

matching and the bias due to inconsistency in the selection of energy emission factors when calculating the sectoral carbon emissions with energy use data. Based on the two datasets, we derived the Leontief inverse matrix induced from the I-O table and per-Yuan CO_2 emissions intensities coefficients for each sector.[9]

Before explaining how the indirect HCEs were calculated with equation (2), three points should be noted. Firstly, we employed CO_2 emission intensities and the I-O table in 2007 to all the expenditure data over the three years,[10] and assumed that the carbon-efficient and production technology remained unchanged. Although technological innovations are generally regarded as the most efficient way to cut carbon emissions from the industrial sectors, here we specialize in analyzing the causes of change in HCEs over the period from the perspective of consumption by holding other factors constant, including technology. In addition, although technological progress played an important role in reducing the emissions, if a household's consumption continues to become more carbon-intensive, the positive effects of technological improvements on emissions reduction will be offset by the increase in demand for carbon-intensive goods and services. Therefore, the overall emissions may be higher (Kaika and Zervas, 2013; Peters et al., 2007).

Secondly, we used the national IO table and emission intensities in each sector to estimate the indirect carbon emissions from China's household consumption expenditure without considering its country-of-origin, which means that we hold the assumption that all goods and services, including intermediate inputs, use the same technologies and have the same carbon emission intensities as made in China.

There will be some differences in HCEs between using the multiregional IO table from China or just using the national IO table. If China imports more low carbon-intensive products over time, the actual growth rate of HCEs will be lower than we have estimated, and vice versa. However, the underestimation is minimal given that during the period of 2000-2014, the average proportion of imports in China's final consumption expenditure by households was just 5.2% ~~(~~(Timmer et al., 2016)~~WIOD, 2016)~~. Moreover, as for the carbon emissions in the production process through imports, Su and Ang (2013) and Liu et al. (2017) found that China's total import-based embodied emissions are not as large as previously estimated. Hence,

[9] In RMB according to the exchange rate in 2007.

[10] Due to data constraints, we had to apply 2007 production technologies.

using the multiregional IO table or just national IO table has relatively little impact on the results. In addition, the difference in the proportion of imported products and the carbon intensity of these products consumed by different income households will have impacts on the shape of HCEs curve, however, as far as we know, there is no available dataset can be used to estimate the impacts at present. On the contrary, the use of the national IO table can help us better understand the changes in households' consumption patterns defined by China's production technology and emissions intensities and focus on the effects of income, demographics and lifestyles on the change of HCEs.

(3) The process of data matching

The matching between household consumption expenditure in the Survey and the IO categories is one of the possible sources of uncertainty in this type of analysis. Before disaggregating the household consumption expenditure, we have done some data pretreatment. Since CFPS and WIOD use different ways of classification,[11] to obtain indirect CO2 emissions embodied in specific goods and services consumed by each household, we created a concordance to match consumption items in CFPS with sectors in WIOD and split the expenditure into more categories to match the categories in WIOD. In the process of matching, firstly, the criteria for classification refers to the "Industrial classification for national economic activities (GB/T 4754-2017)" and IO table for 135 sectors, which are published by NBS. Secondly, we used weights to split the expenditure, and the weights are calculated according to the ratio of urban or rural households' consumption for different industries in IO table. (See Appendix A for details.)

After aggregating the consumption-side detailed household expenditure items in the CFPS into a production-side Leontief inverse matrix and CO_2 emissions intensities,[12] we estimated the indirect CO_2 emissions for every surveyed household spread over the three years according to equation (2). Combining the related information from the two datasets, we obtained consolidated datum providing a

[11] The WIOD was developed to classify industries based on the International Standard Industrial Classification revision 3 (ISIC Rev. 3) and the CFPS categorize goods and service based on consumption patterns.

[12] The National Economic Industry Classification (GB/T 4754-2011) and the Chinese Input-Output Table for 135 sectors in 2007 published by NBS were important references in the process of aggregating.

single record to show Chinese households' total carbon emissions, annual income, expenditure and demographic characteristics for each household spread across the three interview years. This was the starting point for our research.

Finally, to reduce bias caused by outliers, the 1% of households with the highest and lowest emissions and income were excluded. The sample sizes were 12,359, 12,396 and 12,865 for the year of 2012, 2014 and 2016, respectively.

4. Aggregated results: Household-based Carbon Kuznets Curve

4.1 Descriptive statistics

Table 1 presents key summary statistics for per capita household carbon emissions and income for 2012, 2014 and 2016.[13] Per capita HCEs were 2.32 tons in 2012 and increased to 3.37 tons in 2016, at an average annual growth rate of 9.77%,[14,15] while the corresponding real household income per capita increased by 7.8%.[16] These indicate that carbon emissions may expand rapidly with income growth. The summary statistics for household demographics are presented in Table 1, showing that the changes in household size and age of the household head between 2012 and 2016 were not significant and the proportion of married population declined slightly. From 2012 to 2016, more households used the electricity and Gas/LPG/Natural gas, and the share increased to 72.0% in 2016. The use of Coal and Firewood/Straw declined. Over the period, residents became better educated. In table 1 we present the distribution of households across four regions instead of across 31 provinces and found more residents likely to move out of the Northeast region. At the same time, the proportion of households living in urban areas increased from 51.3% in 2012 to 54.2% in 2016. This is in line with China's overall sustained increase in its urbanization rate.

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[13] We used household income per capita rather than household income since it can automatically correct for household size and the policy prescription based on it can be very defective (Datta and Meerman, 1980).

[14] The HCEs in the three years were estimated assuming all goods and services were produced applying 2007 production technologies.

[15] The value of per capita household CO_2 emissions in China are not always consistent in the literature due to differences in sample, time or method: 2.3 tons per capita for urban households in 2005 (Golley and Meng, 2012), 1.43 tons per capita for peasants and herdsmen in northwestern arid-alpine regions of China in 2008 and 2009 (Qu et al., 2013), 1.77 tons per capita in 2011 (Maraseni et al., 2015), and 1.72 per capita for China in 2012 (Wiedenhofer et al., 2017).

[16] Incomes are measured in 2007 yuan.

Table 1 Descriptive Statistics

Variable	2012		2014		2016	
	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.
	(1)	(2)	(3)	(4)	(5)	(6)
HCEs per capita	2.324	1.825	2.829	2.034	3.374	2.633
Household income per capita	1.039	1.117	1.236	1.227	1.403	1.360
Household size	3.708	1.675	3.716	1.813	3.712	1.860
Age of household head	50.370	13.580	49.030	14.460	49.270	15.080
Married (share of pop.)	0.870	0.336	0.853	0.354	0.830	0.375
Urban	0.513	0.500	0.532	0.499	0.542	0.498
Education of head (Share of pop.)						
Under primary education	0.184	0.387	0.175	0.380	0.165	0.371
Primary education	0.223	0.416	0.227	0.419	0.241	0.427
Junior secondary education	0.352	0.478	0.347	0.476	0.343	0.475
Senior secondary education	0.162	0.368	0.160	0.366	0.155	0.362
College and above	0.079	0.270	0.092	0.288	0.096	0.295
Type of fuel						
Solar energy	0.014	0.117	0.010	0.099	0.003	0.056
Electricity	0.229	0.420	0.222	0.416	0.249	0.432
Gas/Liquid/Natural gas	0.407	0.491	0.420	0.494	0.471	0.499
Coal	0.058	0.234	0.043	0.202	0.038	0.191
Firewood/Straw	0.281	0.450	0.260	0.439	0.230	0.421
Others	0.011	0.104	0.046	0.208	0.010	0.099
Type of housing						
Villa/Condominium villa	0.005	0.068	0.015	0.120	0.006	0.075
Apartment in a building	0.234	0.423	0.236	0.425	0.195	0.396
Low-rise house	0.223	0.416	0.231	0.422	0.249	0.433
Quadrangle courtyard	0.029	0.167	0.026	0.159	0.016	0.125
Bungalow	0.394	0.489	0.374	0.484	0.328	0.469
Others	0.116	0.320	0.118	0.322	0.207	0.405
Region (share of pop.)						
East	0.355	0.478	0.374	0.484	0.365	0.481
West	0.253	0.435	0.252	0.434	0.265	0.441
Center	0.260	0.439	0.246	0.431	0.252	0.434
Northeast	0.132	0.338	0.128	0.334	0.118	0.323
Observations	12359	12359	12396	12396	12865	12865

Notes: Values calculated using sample weights.

4.2 A household-based Carbon Kuznets Curve (CKC)

Based on the calculation results of HCEs, we plotted the HCEs per capita curves against per capita household income for the three years to explore the effects of income and other influencing factors on HCEs according to the shape and structure of the curves. To avoid blurring the trend due to the large sample size, we investigated the differences in HCEs by group. More concretely, we divided the households in 2012 into 50 groups according to the quantiles of household income per capita, where each group represented 2 percent of the overall households in 2012.[17] Then we calculated the average per capita HCEs and average household income per capita for each group. Plotting these 50 points with income on the horizontal axis and the HCEs on the vertical axis gives the household- based income-carbon emissions curve for 2012 in Figure 3. In the same way, we plotted the curves for 2014 and 2016. Through the shape and shift of the curves, we can observe the relationship between HCEs and income, and examine how the relationship may be evolving over time.

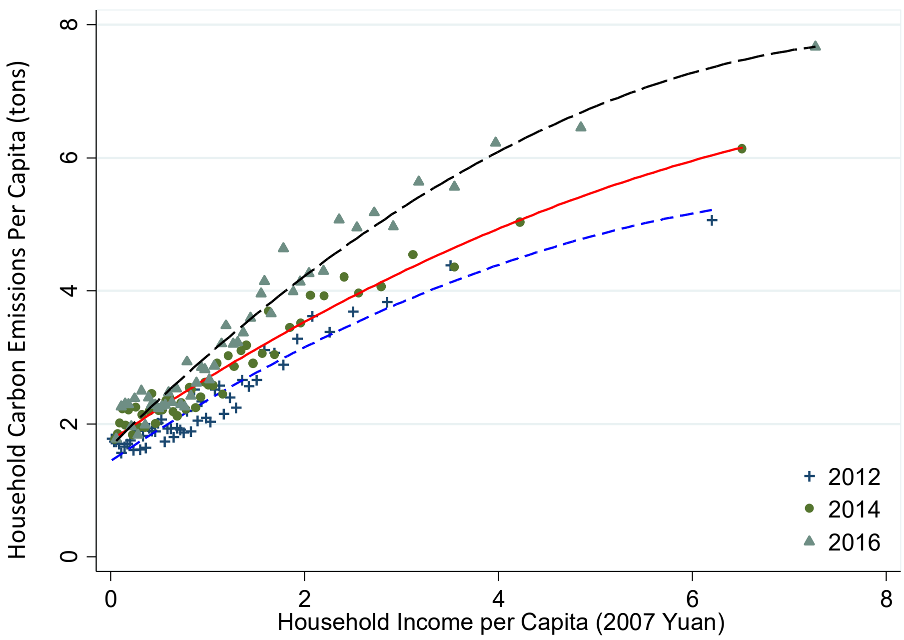

Figure 3. Household based Carbon Kuznets Curve

[17] We tried dividing the households into 100, 200 and more groups. There was almost no change in the shape and structure of the curves.

Two remarkable conclusions can be drawn from the sets of income-carbon emissions curves shown in Figure 3. Firstly, all curves are upward sloping and concave.[18] Not surprisingly, the HCEs rise with the increase in income. The richer households are responsible for more of the overall carbon emissions as they tend to consume more goods and services. However, the concavity indicates the slope of the curves, indicating that the per capita HCE intensity decreases with increases in income.[19] The upward sloping and concave curves verify the inverse U shaped EKC hypothesis on the HCEs at the household level in China, both in a year and over the span of years. Thus, they can be called household-based Carbon Kuznets Curves (CKC).

Secondly, it should be noted that Figure 3 suggests that the CKCs shift up over time. As shown in Figure 3, the shape and concavity are generally similar in the three years, but households represented by the CKC of 2016 are responsible for more carbon emissions than their 2012 and 2014 counterparts with similar real household income per capita. This means that households tend to consume a more carbon-intensive mix of goods and services over time even if they have the same real incomes as before. It also means that household lifestyles in China are steadily exhibiting high-carbon consumption patterns.

4.3 Decomposition results

The CKCs intuitively indicate that other factors, besides income, have significantly affected per capita HCEs. In this section, we turn to OLS regression and Oaxaca-Blinder decomposition methods to explore the effects of influencing factors on the dynamic evolution of HCEs.

4.3.1 OLS Regression between HCEs and influencing factors

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[18] The following empirical results show that the shape of the curves does not change even with the influence of changing household demographics.

[19] In fact, we had to assume that we slightly overestimated rich households' emissions. Hence, the income-carbon emission curves should be more concave in Figure 3 due to the "product quality problem" (Druckman and Jackson, 2009), i.e., richer households consume more expensive versions of the same goods and services, such as cars, refrigerators and airlines, but emit the same emissions (Girod and de Haan, 2010). For example, richer residents may pay more to enjoy business class seats in aircraft but the amount of carbon emissions created is exactly the same as those of less wealthy people who take economy class seats. Based on the results of other research, we can be confident of the upward trend.

Before running regressions of equation (3), to avoid possible exogeneity, collinearity, biases related to the omission of relevant variables and misspecification, we conducted some tests.

Almost all studies proved that income is the most important influencing factor of HCEs, and similar to the statement in Levinson and O'Brien (2018), the assumption that income is exogenous with respect to emission content of household consumption should be reasonable, because when people make efforts to earn income, they do not concern the carbon emissions embodied in the goods or services they consumed. Considering the relationships between some socio-economic variables and income may be endogenous, we estimated the usual variance inflation factors for the independent variables (VIF) and found that none of the VIFs is greater than 10, indicating that no harmful collinearity is detected in the model.

To avoid possible significant biases related to the omission of relevant variables, we applied the method put forward by Altonji et al. (2005) and refined by Oster (2019) to evaluate robustness to omitted variable bias under some restrictive assumptions about the relationship between observed and unobserved covariates. The results suggest that the regressions with household characteristics variables provide a reasonable estimate of the effect of income on HCEs, even after considering other observed and unobserved household characteristics.

Then we ran separate regressions of equation (3) for each year and obtained a set of annual coefficients (see Table 2). The results showed that the coefficients are significantly positive for all per capita income terms and negative for all the income squared terms in the three years whether or not there are household characteristics variables in the regressions. It is reassuring that the estimates are very similar, indicating that the results are not likely to be driven by omitted variables bias.[20] The regression results are consistent with the upward sloping and concave CKCs depicted in Figure 3, and the hypothesis of the inverse U shape showed in Figure 3 is also supported.

[20] Other nonlinear specifications such as cubic polynomials and logarithms of income yield similar results.

Table 2 Parametric estimates of household-based CKCs

	2012		2014		2016	
	(1)	(2)	(3)	(4)	(5)	(6)
Income	0.941***	0.518***	1.025***	0.634***	1.395***	0.964***
	(0.005)	(0.005)	(0.008)	(0.009)	(0.007)	(0.007)
Income squared	-0.048***	-0.022***	-0.052***	-0.025***	-0.073***	-0.041***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Household size		-0.205***		-0.177***		-0.201***
		(0.001)		(0.003)		(0.002)
Age		-0.004***		-0.002***		-0.002***
		(0.000)		(0.000)		(0.000)
Married		-0.079***		0.116***		-0.214***
		(0.008)		(0.013)		(0.011)
Urban		0.404***		0.563***		0.541***
		(0.005)		(0.010)		(0.008)
Education						
Under primary education		-0.197***		-0.183***		-0.324***
		(0.007)		(0.013)		(0.010)
Primary education		-0.121***		-0.095***		-0.102***
		(0.006)		(0.011)		(0.009)
Senior secondary education		0.028***		0.150***		0.083***
		(0.007)		(0.013)		(0.011)
College and above		0.686***		0.623***		0.472***
		(0.012)		(0.020)		(0.015)
Type of fuel						
Solar energy		-0.246***		0.195***		-0.004
		(0.013)		(0.039)		(0.045)
Gas/LPG/Natural gas		0.385***		0.486***		0.472***
		(0.006)		(0.012)		(0.010)
Coal		1.105***		1.416***		1.617***
		(0.013)		(0.027)		(0.022)
Firewood/Straw		0.013**		0.409***		0.471***
		(0.006)		(0.012)		(0.010)
Others		-0.501***		0.175***		-0.624***
		(0.021)		(0.027)		(0.035)
Type of housing						
Villa/Condominium villa		0.520***		0.225***		1.328***
		(0.044)		(0.046)		(0.065)
Low-rise house		-0.254***		-0.215***		-0.166***
		(0.009)		(0.015)		(0.013)
Quadrangle courtyard		-0.452***		-0.458***		-0.427***
		(0.014)		(0.026)		(0.023)
Bungalow		-0.511***		-0.346***		-0.276***
		(0.008)		(0.015)		(0.012)
Others		-0.352***		-0.386***		0.037***
		(0.011)		(0.020)		(0.013)
_cons	1.456***	2.618***	1.721***	1.777***	1.695***	2.242***
	(0.004)	(0.020)	(0.008)	(0.039)	(0.006)	(0.033)
province fixed effects	No	Yes	No	Yes	No	Yes
ADJ R^2	0.164	0.330	0.199	0.327	0.255	0.342
Observations	12359	12359	12396	12396	12865	12865

Notes: ***, ***, *Figures are statistically significant at the 1%, 5%, 10% level.

All demographic variables are significantly correlated with HCEs, and the overall results suggest that the households that live in urban areas, whose head has a high level of education, use the fossil energy as fuel and live in Villa/Condominium villa are responsible for more carbon emissions. It is not surprising to see that household size is negatively associated with per capita HCEs since it implies the economy of scale in carbon emissions for a household. The coefficients of age are negative implying the aged residents are likely emit less carbon emissions. The coefficients of married status of the household head were negative in 2012 and 2016, but positive in 2014. Their influences need to be further examined.

However, as shown in Table 2, the regression coefficients for income and the absolute value of the coefficients on income squared terms increased over the years, and the coefficients on demographics were different over the three years, further indicating that the lifestyle changes may result in the change of dynamic HCEs, but the regression model cannot quantify the magnitude of the effect.

4.3.2 Decomposing the effects of influencing factors

Appling the Oaxaca-Blinder decomposition method and equation (6), we decomposed the overall change in the average per capita HCEs over the years. Table 3 shows the endowment effects of each variable to the increase in HCEs per capita, and Table 4 groups the decomposed results into the income effect, demographics effect and intertemporal lifestyle changes effect.

Table 3 Increases in per capita HCEs resulting from the endowment effect (tons)

Variable	2012-2014	2014-2016	2012-2016
	(1)	(2)	(3)
Overall changes in HCEs	0.505***	0.545***	1.050***
	(0.006)	(0.007)	(0.005)
Income	0.108***	0.145***	0.269***
	(0.002)	(0.003)	(0.003)
Income squared	-0.016***	-0.028***	-0.046***
	(0.001)	(0.001)	(0.001)
Household size	-0.002	0.001	-0.001
	(0.001)	(0.001)	(0.001)
Age	0.004***	-0.001***	0.004***
	(0.000)	(0.000)	(0.000)
Married	0.000**	0.003***	0.006***
	(0.000)	(0.000)	(0.000)
Urban	0.008***	0.006***	0.014***
	(0.001)	(0.001)	(0.001)

Education	0.009***	0.003***	0.013***
	(0.001)	(0.001)	(0.001)
Type of Fuel	-0.021***	0.018***	-0.008***
	(0.001)	(0.001)	(0.001)
Type of Housing	0.011***	0.011***	0.021***
	(0.001)	(0.001)	(0.001)
Province	0.004***	-0.006***	-0.010***
	(0.001)	(0.001)	(0.001)

Notes: ***, ***, * Figures are statistically significant at the 1%, 5%, 10% level.

Table 4 Decomposition of the effect of average per capita HCEs

Decomposition effect	2012-2014		2014-2016		2012-2016	
	tons	share	tons	share	tons	share
HCEs Difference	0.505	100.0%	0.545	100.0%	1.050	100.0%
Total income effect (movement along CKC)	0.091	18.1%	0.117	21.5%	0.223	21.3%
Scale effect	0.441	87.3%	0.382	70.1%	0.814	77.5%
Composition effect	-0.350	-69.2%	-0.265	-48.6%	-0.591	-56.2%
Demographic effect	0.014	2.9%	0.035	6.5%	0.040	3.8%
Intertemporal lifestyle change effect (shift in CKC)	0.399	79.0%	0.392	72.0%	0.786	74.9%

Taking the results between 2012 and 2016 in Tables 3 and 4 as an example, the average HCEs per capita increased by 1.050 tons. We found 1) The income growth raised average HCEs by 0.223 tons (0.269 tons increase from income and 0.046 tons decrease from income squared). Furthermore, the scale effect of income led to an increase in average HCEs of 0.814 tons, accounting for 77.5 percent of the total difference.[21] However, a major part of these increases (0.591 tons, accounting for 56.2 percent of the total difference) from the scale effect were offset by the composition effect of income growth. As a result, the total income effect accounted for only 21.3 percent of the total difference in per capita HCEs from 2012 to 2016. Though the coefficients of income are all statistically significant in this paper and consistent with findings in the literature, our decomposed results suggest that income growth will not inevitably lead to a dramatic increase in average per capita

[21] The scale effect assumes that each household's consumption preference will not change with income growth, and the average per capita HCEs will rise at the same rate as the average household income per capita (annual growth rate 7.8% from 2012 to 2016).

HCEs in China because the concavity reduces the total contribution of income when HCEs simply move along the CKC.

2) Changes in demographics raise the average per capita HCEs by 0.040 tons, accounting for only 3.8 percent of the total increase in average HCEs (0.059 tons increase from age, marital status, urban location, education, type of housing and 0.019 tons decrease from household size, type of fuel, and province). Demographic changes played almost no role in the increase in HCEs between 2012 and 2016.

3) The main part of the increase in average HCEs (0.786 tons, accounting for 74.9 percent of the total difference) is attributed to the effect of intertemporal lifestyle changes. Similar results can be drawn for other periods in Table 4, though there are some differences between the two periods. The total income and demographics effects both increase in period of 2014-2016 compared with the last period, while the contribution of intertemporal lifestyle changes in the period of 2014-2016 drop from 79.0 percent to 72.0 percent but still was the dominant effect.

4.3 Robustness test

In this paper, we applied three methods to test the robustness of the above results: (1) We added cubic polynomials of income into the model. (2) We ran the regressions and decompositions with regional dummy (East, Central, West and Eastnorth) instead of provincial dummy. (3) We estimated the direct HCEs under four energy prices setting scenarios and applied the related total HCEs in our model respectively to evaluate the robustness of the results to the way of price setting. We found that the model with income squared terms is more suitable for the study, and the results of both the OLS regressions and OB decomposition change less with cubic polynomials of income, or with the regional dummy or under different energy price setting scenarios. The robust tests indicate that our results are relatively credible. The details of the robustness test are presented in Appendix B.

In summary, though we have observed the shift up of CKCs over period, the effect of income and demographics on the changes in HCEs is less than we expected. The coefficients of income are all statistically significant, which means the scale effect of income bring about more HCEs. However, the structure effect of income due to “the law of diminishing marginal propensity to consume” leads to the concavity of CKCs, which is the main reason that income growth will not inevitably lead to a dramatic increase in average per capita HCEs in China. In addition, we found that the demographics have significant impact on HCEs, however, some changes in demographics increase HCEs, such as moving to urban areas, while some of them decrease HCEs, such as reduction in coal use. Thus, the opposite effects among demographics lead to a lower aggregated contribution to the changes in HCEs.

As stated in the analytical framework, we assumed that the effects of intertemporal lifestyle changes are the result of evolving socio- economic and environmental factors, including policies. It makes sense that the effects play relatively little role over a short period as consumption structure and socio-economic situations are relatively stable in the developed countries. [22] However, as a developing country, China is undergoing fast urbanization and transformation in economy, society, culture and policy, which may have significant impacts on changes in consumption patterns even over a short period. Next, we will use detailed consumption data in CFPS and China's macro data to analyze the intertemporal changes in consumption patterns and lifestyle to explore the dominant effects of the changes on HCEs.

5 Detailed analysis: consumption patterns, intertemporal lifestyle changes and HCEs

5.1 Household consumption patterns and changes in HCEs

The differences in HCEs driven by household income, household demographics and lifestyle are all generated through changes in household consumption patterns, either consumption scale or structure. In this part, we classified the household expenditure items into 8 categories with the information in CFPS and analyzed the changes in the scale and structure of consumption across different income groups and across years when keeping the income constant[23]. The detailed classification can measure the change of HCEs due to changes among the 8 categories expenditures,

[22] Some researchers found lifestyle changes, exogenous non-economic factors or unexplained effect have a higher contribution to the changes in households' energy demand, carbon emissions or some air pollutants in some industrialized countries (Chitnis et al.,2012; Levinson and O'Brien, 2018; Schipper,1989).

[23] The classification is in line with that of NBS and is widely used in the literature (Fan et al., 2012; Golley and Meng, 2012; Wiedenhofer et al., 2017).

which allows us to deeply understand how income and consumption structure influence HCEs.

To this end, we first divided the households in the three years into ten groups according to household income per capita in 2012, and ensured that the same group in different years had roughly the same average income. Then we calculated the corresponding average household's carbon intensities and average propensity to consume for each group, as shown in Table 5. Moreover, to analyze the change in consumption patterns, we further aggregated the expenditure data in the CFPS into eight categories according to the principle of classification of the NBS and calculated the carbon intensity for each category, as shown in Figure 4.[24,25] The first four categories – Housing, Daily, Trco and Touring– are usually referred to as the high carbon-intensive mix, and the others, such as Health, ECC, Dress and Food are regarded as part of the low carbon-intensive mix.

Table 5 Average household carbon intensities and propensity to consume

	HCEs/Income (tons/ 10^4 Yuan)			Average propensity to consume		
	2012	2014	2016	2012	2014	2016
10%	28.97	25.65	24.73	6.93	5.99	6.00
20%	8.45	10.10	10.64	2.19	2.56	2.52
30%	4.91	5.88	6.14	1.52	1.66	1.64
40%	3.68	4.18	4.44	1.07	1.28	1.36
50%	2.76	3.36	3.38	0.91	1.07	1.09
60%	2.55	2.78	3.13	0.77	0.94	1.02
70%	2.11	2.48	2.78	0.68	0.87	0.95
80%	1.84	2.22	2.50	0.64	0.77	0.94
90%	1.77	1.92	2.29	0.59	0.71	0.80
100%	1.17	1.33	1.57	0.41	0.54	0.63
average	2.24	2.29	2.40	0.78	0.86	0.89

[24] The sectoral total carbon intensities calculated with the data from the WIOD show that the expenditure-associated Residence (Housing) embody the highest carbon emissions, followed by Articles for Daily Use and Service (Daily), Transport and Communications (Trco), Travel, Health Care (Health), Education, Culture and Recreation (ECC), Dress and Food.

[25] In order to present the results more clearly, the households were divided into five groups according to the same treatment.

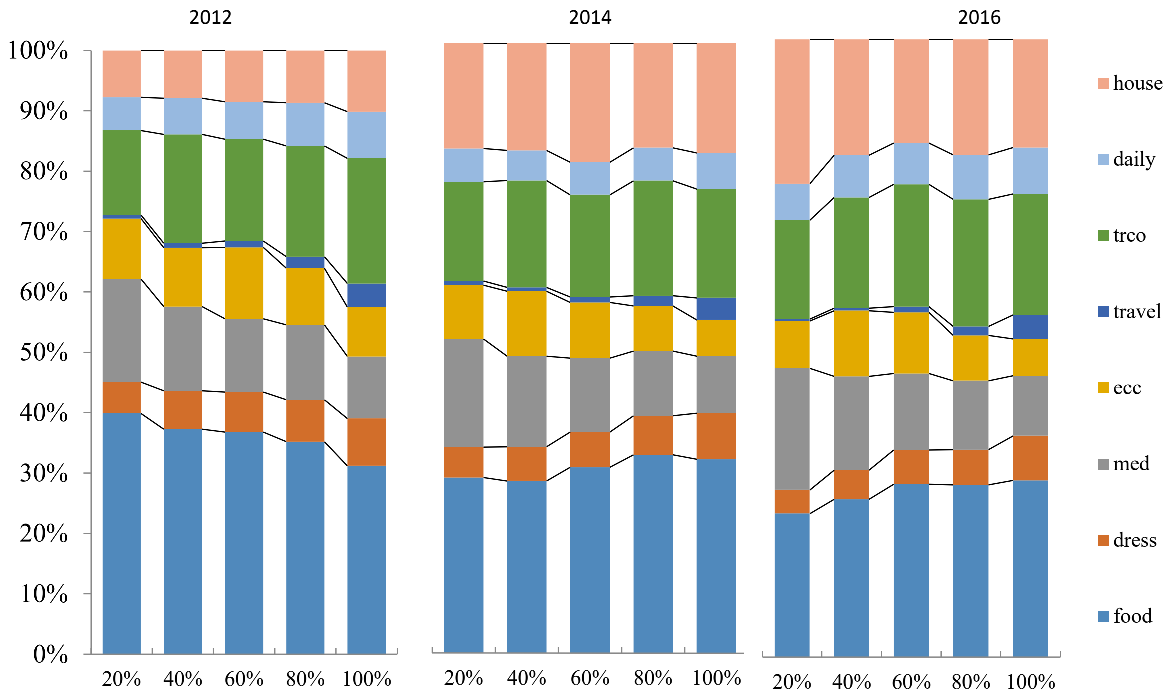

Figure 4. Consumption structure changes over time

Firstly, we can clearly see the changes in household consumption patterns across different income groups. Not surprisingly, consistent with the concave CKCs shown in Figure 3 and the law of diminishing marginal propensity to consume, the average propensity to consume declines with the increase in income in the three years, and the value of the highest group is less than 10% that of the lowest group, which leads to the disproportional increase in carbon emissions to the income growth. Thus, the law of diminishing marginal propensity to consume turns out to be an important explanation for composition effects of income. However, when taking a closer look at the consumption structure of different income groups in Figure 4, we found that the richer households spent much more on the high carbon-intensive mix in all of the sample periods. Taking year 2012 as an example, the proportion of consumption on high carbon-intensive goods and services for the 1st quintile income group was about 28 percent, which increased to 33 percent and 43 percent for the 3rd and the 5th quintile. Similar trends can be seen for the other two years.

Actually, the gentle slope of the per capita HCEs along with the income growth observed in Figure 3 is a combination of three factors: the increasing effect of consumption scale, the increasing effects of consumption structure and the decreasing effects of propensity to consume. The simple distinction between scale effect and composition effect of income masks the difference in consumption structure among different income groups. When considering the proportion of non-living expenditure, the conclusions derived from the concave CKC have changed: the decline of carbon intensities along the income growth in China does not mean that the higher income groups have less carbon-intensive lifestyles. On the contrary. So in that sense, the CKC may represent only a reduced-form model (Stern et al., 1996), with the low-carbon policy applying directly the result of the CKC regardless of the underlying reasons, and may not attain the expected effect.

Secondly, we proceed to the analysis of the intertemporal changes in household consumption patterns driven by lifestyle transformation. Comparing the carbon intensities of the same income group over the three years, we found that the carbon intensities increased year by year except for the lowest group. For example, the average carbon intensity of the median group in 2012 was 2.66 tons/10^4 Yuan, which increased to 3.07 tons/10^4 Yuan in 2014 and 3.26 tons/10^4 Yuan in 2016. This is consistent with the shift up of the CKCs over time in Figure 3.

First of all, Table 5 shows that the average propensity to consume increases over the years for most groups with the same average income, except the lowest 10% one. This means that most of the scale of households' consumption is expanding from 2012 to 2016 even with the income unchanged, and may lead to a shift up of CKC.

Moreover, Figure 4 shows that the consumption structures of households in the same income group were becoming more carbon intensive over the years. The proportion of consumption on high carbon-intensive goods and services in 2012 was 27.8 percent for the lowest income group, but increased to 39.7 percent in 2014 and 45.6 percent in 2016. The proportions were 32.6 percent, 42.6 percent and 44.2 percent, respectively, for the 3rd quintile, and 35.2 percent, 43.2 percent and 47.0 percent, respectively, for the highest income group. Similar results can also be seen for the other groups. The household consumption structure was developing towards high carbon-intensive, which caused a further shift up of the CKC. Therefore, the changes in both expenditure scale and structure showed that household consumption patterns were transforming towards high carbon-intensive. Since the income is fixed and the household characteristics effect is small, the underlying driving force of this transformation could only be attributed to changes in intertemporal lifestyles.

5.2 Link between intertemporal lifestyle changes and the increase in HCEs

From the categorized expenditure data, we have shown the changes in intertemporal lifestyles and their impacts on HCEs. However, we have only insights into what households have, what they are doing, how long and where. Ideally, we need more detailed information about households' lifestyle changes so that we can gain a better understanding of the real causes of the changes in household consumption patterns and the sharp rise in carbon emissions. Based on Schipper (1989), we present more specific information about intertemporal household lifestyle changes from three perspectives: the allocation of resources across financial, material, and temporal activities, namely household expenditures, the quantity of goods and services owned by households, and time use.

5.3.1 Household expenditures

The more detailed information relating to the expenditures of each household reveals how family members allocate their incomes among goods and services in a given year. From this we can obtain a rough idea of what people do and where. According to the analysis based on the 23 types of expenditure data found in the CFPS between 2012 and 2016, not surprisingly, we found that the proportion of total expenditures on food dropped in both urban and rural areas. This was even more obvious for rural households, while the proportion of eating out increased. As for housing expenditures, the proportion of heating and home repairs and decoration declined, while that of renting and property management increased. The proportion of durable goods, transportation, communication, tourism, fitness and cosmetics rose. Moreover, the proportions of water and electricity, fuel, education, entertainment, medical expenses increased in rural areas but fell in urban areas.[26]

It was observed that after the meeting of basic living needs, residents allocated much of their income to lifestyle improvements such as: more comfort (dwelling, furniture and appliances), more convenience (purchase and use of transportation

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[26] The drop in the proportion of water and electricity and education has much to do with the government's maintenance of the price of these public goods and services.

and communication tools), more leisure and more individual development (tourism, fitness and cosmetics). In the process of pursuing better lives, lifestyles shifted towards higher carbon intensities.

5.3.2 Quantity of goods and services

The quantity of goods and services consumed by households can further reveal the daily activities that household expenditures cannot. For example, we can derive more detailed information about housework methods, entertainment or travel by observing the ownership of appliances or passenger traffic. Household equipment ownership not only reveals current consumption patterns but also reflects the lifestyles of individuals and families in the future. According to data published by the NBS,[27] the average living space per capita was 45.8 m^2 in rural areas and 36.6 m^2 in urban areas in 2016, and increased by 8.7 m^2 and 3.3 m^2, respectively, compared to 2012. The average number of appliances, communication tools and private autos owned by per hundred households from 2013 to 2016 all increased dramatically in the rural areas, especially air conditioners, water-heaters, computers and cars. In urban areas, the growth rates of these commodities were all relatively low, except for air conditioners and cars.

Undoubtedly, the carbon emissions embodied in the production processes for the additional goods that households will acquire in the future will rise rapidly with the hypothesis of constant technology. Moreover, the general use of them will lead to more direct consumption of energy and encourage new relevant activities. From 2012 to 2016, household energy consumption per capita increased by 14.8 percent in urban areas, and 39.3 percent in rural areas. Indeed, the level in rural areas almost matched what it was in urban areas. Per capita residential consumption for electricity, LPG, natural gas and gasoline increased by 32.8 percent, 76.9 percent 29.1 percent and 74.5 percent, respectively (NBS, 2018). In addition, the number of tourists, especially those going overseas, rose sharply. There were also changes in the modes of transport for travel: more passengers were traveling by car, railways and air. Undoubtedly, the increased travel leads to more HCEs while the substitution

[27] As the CFPS does not provide data about household consumption quantity, our analysis is based on aggregated data in the *China Yearbook of Household Survey 2017* and *China Statistical Yearbook 2017* (NBS). Moreover, due to changes in the survey scope, method and caliber, the compared period was 2013 and 2016.

effect may have caused a disproportionate increase in HCEs, but this cannot be deduced from the aggregated expenditures data on travel or transportation.

5.3.3 Time-use

As consumption is modelled as an activity combining time and commodities, lifestyle changes will necessarily imply a shift in the patterns of time use. Due to large differences in the carbon intensity of activities reported by some literature, the trade-offs for individual time-use across different activities not only reflect the balance of multiple responsibilities for life, work, families, and themselves, but also shape lifestyles and affect HCEs (De Lauretis et al., 2017; Druckman et al., 2012; Wiedenhofer et al., 2018). Thus, besides household expenditures and quantity of goods and services, a survey of time-use is an approach for investigating the carbon implications of everyday life.

Regarding the data on time-use in China, the NBS conducted the first residential time-use survey in ten provinces in 2008. The second survey is still in progress and there is not yet any data available. Due to the typical dual economic structure, there are large gaps between the urban and rural areas of China. In the process of urbanization, rural areas have been catching up with cities in terms of infrastructure construction, economic development, social norms, consumption patterns and lifestyles. The time-use pattern of urban residents, to a certain extent, may represent the future trend for rural residents. Thus, given the shortage of data, it is reasonable to simultaneously describe the intertemporal lifestyles of rural residents with the differences in time-use between urban and rural areas.

The ways in which an average urban and rural adult (15 to 74 years of age) used his/her time in 2008 in China are shown in the appendix. The largest categories were personal time, both nearly 9 hours per day for sleeping and resting, and 0.9 and 0.8 hours, respectively, for personal care. The contracted time (working, studying and commuting) was 4.8 hours for urban adults and 6.8 hours for rural adults. The committed time used for family (meals and preparation, shopping, housework, care) was 4.7 hours and 4.2 hours, respectively. Free time (entertainment, socializing, sport, leisure and hobbies) was 4.6 hours and 3.1 hours, respectively. It is clear that the time allocation patterns of urban and rural residents varied considerably.

There is no estimation of the carbon emissions intensity of activities relating to Chinese residents' use of time. According to empirical research for the UK, Finland and France (De Lauretis et al., 2017; Jalas and Juntunen, 2015; Wiedenhofer et al., 2018), the total carbon emissions intensities are higher for commuting, personal care, eating and drinking, entertainment, meal preparation and clean-up and shopping, and lower for leisure and caring. Therefore, Chinese urban residents seem to allocate much more time to leisure, and less to working and studing. This seems to be conducive to reductions in HCEs. Howerver, since much more time is used for eating out, meal preparation and cleaning-up, shopping, and entertainment, it can be expected that HCEs will rise. Moreover, the reduction of time devoted to working and studying does not reduce the commuting time. For urban residents, the reallocation of time across activities resulted in an increase of 20 minutes in trips, with the time used on public transport and driving increasing by 14 minutes and 8 minutes, respectively. In addition, although urban residents spent much time watching TV and using the internet at home, compared to rural residents, each urban adult spent 68 more minutes outside (street or park, bank, store, hotel, eating and drinking places, and entertainment places,etc.). Moreover, even compared with the industrial sectors, the tertiary sector may not mean less carbon emissions. Applying input-output subsystems, Alcántara and Padilla (2009) found in Spain, besides transport, many other service activities, such as wholesale and retail trade, hotels and restaurants, real estate, renting and business activities and public administration services were the significant sources of the increase in CO_2 emissions in recent years.

Through deep analysis of households' expenditures, quantity of goods and services and time-use, we have new perspectives on intertemporal household lifestyles and carbon emissions. It is clear that changes in lifestyles are still significant, especially for rural households, and this is meaningful for HCEs. Naturally, households tend to seek larger dwellings, more comfortable home environments, more recreational activities, and more convenient travel and communication modes, and therefore allocate a large part of their income on their housing, and tend to own more equipment such as appliances and autos. The equipment ownership and wide usage of them in turn affect the time allocation, and the time formerly used for working, cooking and laundry is switched to leisure activities with lower carbon-intensities, but are accompanied by more time devoted to driving, shopping and outdoor activities.

In conclusion, over 40 years' rapid developments in China have laid the foundation for the expansion and upgrading of consumption. The fast transformation of socio-economics is continuously shaping the households' lifestyles, and the stimulating consumption policies have greatly released households' consumption potential in a short period, resulting in the growth of HCEs at a rate much faster than income. More important, the Chinese government is carrying out a new round of policies to stimulate consumption, and the ignorance of the remarkable unexplained effects may lead to a rapid increase in HCEs, hindering the implementation of China's emission reduction targets.

6 Conclusions and policy implications

China's rapid economic and social development over the past 40 years has led to radical changes in household consumption patterns and lifestyles. This paper studies the endogenous evolution of household consumption patterns and household carbon emissions (HCEs) by integrating the analysis methods of income distribution with climate change. Based on a large-scale household survey spanning 2012 to 2016 in China, we estimated the direct as well as indirect HCEs and constructed a set of upward and concave Carbon Kuznets Curves (CKC) at the household level to observe the significant changes in HCEs accompanying the rise in income over the period. However, when taking a closer look at the implicit influencing factors of the CKCs, the conclusions have changed: the decline in the carbon intensities along with the income growth in China does not mean that the higher income groups have less carbon-intensive lifestyles, but quite the opposite.

By applying the Oaxaca-Blinder method, we decomposed the influencing factors underlying the changes in HCEs and found that income and demographic effects contributed only 25.1% to the total increase of HCEs while 74.9% was attributed to intertemporal lifestyle change. These empirical results are further supported by detailed and multi-perspectives analysis about the link of "development of socio-economic and environment factors — intertemporal change in household consumption patterns and lifestyle—increase in HCEs" based on macro and survey data. For a country experiencing a fast transition, like China, the fast transformation of socio-economics is continuously shaping the households' lifestyle, the development of socio-economy, external environment and policies released a large amount of consumption demand, and led to the changes in lifestyle over time to be the dominant source of the increase in HCEs instead of income, which is often ignored or not quantified in present literatures.

At present, the expansion of domestic consumption is still regarded as an important way to boost China's economic growth. More important, a new round of policies have been developed by central and local governments to release the consumption potential. The dual effects of policy stimulus and improvement of consumption environment will lead to continuous rapid household consumption even in the case of slowing income growth. Despite of the continuous promotion of green and low carbon lifestyle, the release of the huge potential of households' consumption in short period will result in rapid rise of HCEs. Our findings indicate that the current modeling and predictions of carbon emissions based on income and household demographics may miss the significant effect of lifestyle changes and underestimate the challenges in emissions growth in the future from the household sector. The policymakers need to pay much more attention to the effect of lifestyles on HCEs and implement policies to avoid continuous moving towards carbon-intensive lifestyles when encouraging the households to pursue higher living standards and boosting economic growth.

Going forward, given the inevitable migration of the rural population to urban areas, and the increasing number of hours that people devote to leisure activities instead of work, adequate measures should be taken to reduce the expected increases in carbon emissions while maintain people's well-being. First, in order to achieve challenging carbon emissions reduction targets, policies should be implemented which guide households towards low-carbon lifestyles. Relevant policy support is needed to motivate the lifestyle shifts. Considering the large proportion of indirect HCEs and the fact that most consumers have little knowledge of the carbon content of the goods and services, green or low carbon labeling should be applied to influence consumers' purchasing choices.

Second, since household consumption decisions are strongly influenced by costs, taxes and fees, such as fuel taxes, congestion charges, carbon taxes and multi-stage electricity prices on high carbon products should be introduced to encourage households to purchase energy efficient products and also to change their consumption behavior.

Third, promote energy efficient housing and transportation. Energy efficient housing and travel infrastructure are the keys to lowering carbon emissions in almost all activities including commuting, housework and leisure. Compact housing, more convenient public transport systems, higher charges for private auto parking, shorter commuting distances, and more shuttle buses between work and living places are essential. In addition, urban planning should be optimized. Communities should assume more city functions, such that basic needs, such as shops, libraries, sanitation facilities, recreational facilities and public green areas are all situated within walking or bicycle distance.

At last, the estimation and analysis of HCEs in this paper is limited in some ways, which are possible topics for future studies. Firstly, the Input–output data are widely applied to estimate indirect emissions at the household level, however, they only provide emission estimates for broad consumption categories and are affected by lags in data availability. Secondly, in CFPS, for the reason of migration, marriage etc., the household with same ID in different years may have different family characteristics, we have to apply the cross-section data of three years rather than panel data. Thirdly, due to the lack of the survey data about household equipment ownership and the latest data of time use, we have to apply the macro-data or time use data of urban and rural areas in same year as the alternatives to reflect the evolution of household lifestyle. Further improvement of data quality is thus required to take research in this area forward. Furthermore, with the expansion of international trade, the deepening of the supply-chain, and the imbalance of technological development across countries, the use of multiregional IO table may be helpful to improve the accuracy of the estimation of HCEs, which we will study in future research. Finally, this paper analyzes the intertemporal lifestyle changes on average HCEs using all the households in the sample with a survey data of four years. Further studies can extend the analysis from the perspective of urban and rural areas or different income groups and with longer-term data so as to provide more detailed evidence and policy implications.

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