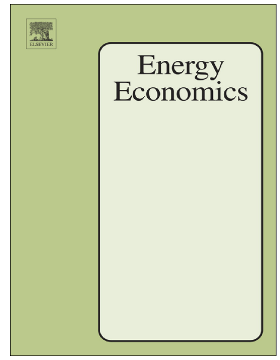

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Household Carbon Footprints Inequality in China：Drivers, Components and Dynamics

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Abstract

The significant achievements in economic growth and urbanization in China have recently led to substantial increases of and great inequality in household carbon footprints (HCFs). To achieve efficiency and justice in emissions reduction, policymakers need to fully understand the sources of HCFs and identify the major causes of carbon inequality. By applying the Unconditional Quantile Regression (UQR) model and decomposition method to the Chinese household survey data, this paper investigates the distributional features of HCFs and their determinants. We find that HCFs are unevenly distributed due to differences in the volume and pattern of consumption, which are further determined by household characteristics and lifestyles. The intertemporal lifestyle changes have played a major role in the rise of HCFs inequality measured by various quantile emissions differentials. In addition, considerable increases in HCFs come from the high carbon emission groups, and most of the HCFs inequality stems from the 90-50 emissions differential. To transform the current carbon-intensive economy, policies are required to enhance environmental equity and encourage low-carbon lifestyles.

Keywords

household carbon footprints; inequality; lifestyle; unconditional quantile regression; China

JEL classification: Q52; Q54; Q56; D10

1. Introduction

With the global consensus on pursuing sustainable and inclusive economic growth, climate justice has become a focus when striving to attain emission reduction targets, and mitigating climate change and reducing inequality have become global actions (Mi et al., 2020). Climate change and economic inequality are inextricably linked because the poorest people are the least responsible for causing climate change but tend to be the most vulnerable and least prepared for its consequences. In particular, the poor and vulnerable are being hardest hit by the pandemic. Recently, countries are generally concerned more about the equality of income distribution during the pandemic period, but it does not mean that the equality of household carbon emissions can be ignored. Given that emissions abatement responsibility has strong welfare and economic effects, ensuring fair responsibility in emissions abatement is an instrument to encourage more parties, such as countries, households and individuals, to participate in climate initiatives (Peters and Hertwich, 2008). Meanwhile, designing mitigation policies according to different situations and driving factors of HCFS are essential (Vogt-Schilb et al., 2019; Wang et al., 2020).

In China, notable achievements in economic growth and urbanization over the past two decades have been accompanied by substantial increases of and wide disparities in household carbon footprints (HCFs). The mitigation policies in China have tried to address the significant social inequality by mandating the wealthier regions with more mitigation responsibilities and making mitigation policies pro-poor

(Mi et al., 2020). Significant attempts have been made to quantify the HCFs inequality in China based on aggregated data classified by household income recently (Wiedenhofer et al., 2017; Mi et al., 2020). A few studies have explored the major influencing factors of the HCFs inequality in China with urban survey data (Golley and Meng, 2012; Han et al., 2015; Xu et al., 2016; Yang and Liu, 2017). However, the aggregated data or the urban survey data may not display the full picture of HCFs distribution. Meanwhile, the Gini coefficient or Lorenz curve, which is commonly used in measuring inequality, cannot provide detailed information on HCFs inequality. In particular, few studies have investigated the role of lifestyle changes in the dynamic evolution of HCFs inequality recently.

In this paper, the HCFs differences over quantiles are used to describe the HCFs inequality in China. Moreover, the Unconditional Quantile Regression (UQR) and Oaxaca-Blinder (OB) decomposition method further provide a novel way to assess the role of the intertemporal change of households' demographics and lifestyles in the dynamic evolution of HCFs inequality. The study on the feature, dynamic changes and drivers of HCFs inequality is of vital importance for governments to formulate policies to mitigate HCFs and the associated inequality and to enhance the fairness and effectiveness of HCFs reduction actions.

This paper contributes to the existing literature over three aspects: (1) Presenting a theoretical framework to analyze the driving factors of and dynamic changes in HCFs inequality. Specifically, it stresses that besides household demographics, household lifestyle changes may also be important in the evolution of HCFs inequality, which is usually overlooked in the literature. (2) Revealing the features of and dynamic changes in HCFs inequality by comparing HCFs per capita over different quantiles. Compared with the OLS, the UQR and the OB decomposition method provide a practical way to investigate the driving forces of HCFs as well as the changes in HCFs inequality. (3) Providing empirical evidence that lifestyle changes play an important role in the changes of HCFs inequality in China, which provides a useful reference for the design of mitigation policies in China and other developing countries.

The main findings of this paper are: (1) The Gini coefficient shows that there is a weak expansion trend in the HCFs inequality in China from 2012 to 2018. The HCFs over different quantiles further show that HCFs inequality is mainly caused by households with HCFs at the top 25% quantile, and they also have higher growth rate of HCFs. (2) The effects of various driving factors on HCFs are heterogeneous over different quantiles and for different years. (3) The contributions of the intertemporal lifestyle changes are the main cause of the dynamic changes of HCFs inequality, especially for households with HCFs at high quantiles.

The rest of the paper is organized as follows. Section 2 briefly summarizes the literature on the description of HCFs inequality and its driving factors. Section 3 presents the methodology and data. Section 4 reports the distributional features of HCFs and compares HCFs per capita from different dimensions. Section 5 analyzes the driving factors of HCFs per capita, and identifies the underlying sources of HCFs inequality from the perspectives of household's demographics and lifestyle changes. Section 6 concludes and provides some policy implications.

2. Literature review

Many literature have shown that HCFs account for a major part of the total carbon dioxide emissions and are unevenly distributed over households (Bin and Dowlatabadi, 2005; Lee and Lee, 2014; Ivanova et al., 2016; Allinson et al., 2016; Zhang and Wang, 2017), and the related literature on HCFs inequality are increasing. They can be roughly grouped into two categories: (1) Description of HCFs inequality. (2) Analyses on the driving factors of HCFs and the related HCFs inequality.

Some researchers have explored the HCFs inequality within one single country or among multiple countries (Hertwich and Peters, 2009; Ivanova et al., 2016). Hubacek et al. (2017) and Oswald et al. (2020) evaluated the HCFs inequality across many nations and aggregate world regions. Sommer and Kratena (2017), Ivanova et al. (2017), and Ivanova & Wood (2020) investigated the HCFs inequality in the European Union. They all found that there exists serious HCFs inequality in different countries. In addition, scholars compared the differences of HCFs among regions or income groups. Gill and Moeller (2018) found that there is no significant difference in HCFs among different cities in Germany, while Tomás et al. (2020) found that the HCFs of the large and medium-sized cities in Spain are lower than that of the small cities. Kennedy et al. (2014) studied the HCFs inequality of five income groups in

Canada and found that HCFs per capita of the highest income group is 2.2 times of the lowest one. This ratio is 4.25 times for the eight income groups in Germany (Miehe et al., 2016) and 2.6 times for the nine income groups in the United States (Feng et al., 2021).

In China, many studies found that HCFs per capita in urban areas is much higher than that in rural areas (Shi et al., 2020; Zhang et al., 2020). Serious HCFs inequality exists among different regions (Zheng et al., 2011; Marasseni et al., 2016). The highest income group in urban areas accounting for 5% of the total population holds almost 20% of the total HCFs (Wiedenhofer et al., 2017; Mi et al., 2020). Using the household survey data of urban areas, Golley and Meng (2012), Han et al. (2015) and Yang and Liu (2017) also found that there is significant HCFs inequality in China. In general, most studies have revealed that unequal distribution of HCFs does exist.

As for the driving factors of HCFs or HCFs inequality, there is a broad consensus that household income is one of the main determinants of HCFs in the long run (Duarte et al., 2010, Lyons et al., 2012), and income gap is the decisive factor leading to HCFs inequality (López et al., 2020). However, the impacts of household income on HCFs are highly heterogeneous among different regions and households (Ivanova et al., 2017; Ravallion et al., 2000). The inverted "U" Carbon Kuznets Curve (CKC) in both developed and developing countries is a representation of the nonlinear relationship between HCFs and household income (Grossman and Krueger, 1995; Chancel, 2014; Seriño and Klasen, 2015; Irfany and Klasen, 2017; Zhang et al., 2020).

Therefore, the impact of income gap on HCFs inequality may be nonlinear and highly heterogeneous among different regions.

Meanwhile, by using household survey data, empirical studies found that household energy consumption, housing type, and demographics (family size, age, education level, and marital status of the household head, etc.) have different impacts on HCFs for different households (Baiocchi et al., 2010; Golley and Meng, 2012; Büchs and Schnepf, 2013; Qu et al., 2013; Han et al., 2015; Choi and Zhang, 2017; Lévay et al., 2021). Moreover, some literature have proved that social-economic and environmental factors may induce the changes of lifestyle and consumption behavior (Carter, 2011; Brounen et al., 2013), which have become the key factors in designing mitigation pathways (van den Berg et al., 2019). Some studies indicated that individual consumption tastes, preferences, values and motivation may transform the household lifestyles, which have a further impact on household expenditures and HCFs inequality (Parag and Darby, 2009; Chitnis et al., 2012; Oxfam, 2015).

Our previous research have compared the consumer spending in each category of expenditure (Zhang et al., 2020), and found that richer households spend much more on the carbon-intensive mix of goods and services, such as housing, articles for the daily usages and services, transportation and communication services. This means that the consumption structure of richer households is likely to be more carbon-intensive than that of the low-income ones. Another recent study (Oswald et al., 2020) also pointed out that the increasing expenditure inequality can cause larger inequality in energy consumption, which resulted in the similar emission inequality in China's case (Guan, 2017). As a result, the heterogeneous effects of lifestyle changes may lead to larger HCFs inequality.

While significant attempts have been made to investigate HCFs inequality recently, there are some limitations in the existing research: (1) Many analyses have assumed that income and other demographics variables are the main cause of HCFs, which is not sufficient to describe and analyze the influencing factors of HCFs and HCFs inequality. (2) Many literature use aggregated data to carry out the empirical analysis. There are limited studies on HCFs inequality and its driving factors using large-scale household survey data, especially in the context of developing countries. (3) The popular indicators for HCFs inequality, such as statistical variance and the Gini coefficient, ignore the probabilistic distribution of HCFs and cannot identify clearly the sources of dynamic changes in HCFs inequality.

To better understand the causes of HCFs inequality in China, it is necessary to go beyond the commonly used statistical measures and the ordinary least squares (OLS) regression. By applying the UQR and OB decomposition method to household survey data, this paper aims to fill these gaps by studying the features, dynamic changes and driving factors of the HCFs inequality in China. We focused on the heterogeneous effects of the driving factors of HCFs as well as the specific contributions of these factors and the lifestyle changes to the dynamic changes in HCFs inequality.

3. Methodology and Data

In this part, we first present a framework to analyze the driving factors of and dynamic changes in HCFs inequality, then introduce the UQR model and OB decomposition method, and finally provide the data sources and data processing method.

3.1 The analytical framework of the dynamic changes in HCFs inequality

The literature review has shown that HCFs are determined by household consumption patterns, which are shaped by two key factors of the socio-economic development: household demographics and lifestyles.

As suggested by consumer behavioral economics, the decision-making of individual consumption is affected not only by personal income and other demographics, but also by social-economic and environmental factors. For example, the infrastructure construction, social institutions and legal foundation, have been continuously shaping and reinforcing lifestyles through changes in values, motivations, consumption preferences and patterns of individuals and families, then further affect household consumption patterns as well as quantities and changes in the associated HCFs (Schipper, 1989; Lutzenhiser and Gossard, 2000; Kahneman and Tversky, 2018). The household demographics include households' income, family features, such as location, family size, fuel type and housing type, and individual's characteristics, such as age, the marital status and education level of the household head. The features and dynamic changes of household demographics can be observed and quantified. However, the values, awareness, motivations and preferences of the individuals or household consumption generally fall into the category of lifestyles, which are not easy to be observed or quantified but can lead to substantial changes in consumption patterns and the associated HCFs. Consequently, lifestyle changes may have a significant effect on HCFs (Druckman and Jackson, 2009).

Taking China as an example, China is entering a rapid transition period to a middle-income country, and a considerable number of households have stepped into the upper-income groups while a large part of the population is just shaking off poverty. The households with different levels of HCFs are unlikely to be equally sensitive to the changes in household demographics and social-economic transformations. Many important explanations for the observed changes have specific implications for specific parts of the HCFs distribution, and some factors may only affect households at the bottom or top of the HCFs distribution. To sum up, it is crucial to better integrate lifestyle changes in the analysis on HCFs, and Fig. 1 shows the analytical framework explaining the mechanism for the dynamic changes of HCFs and HCFs inequality.

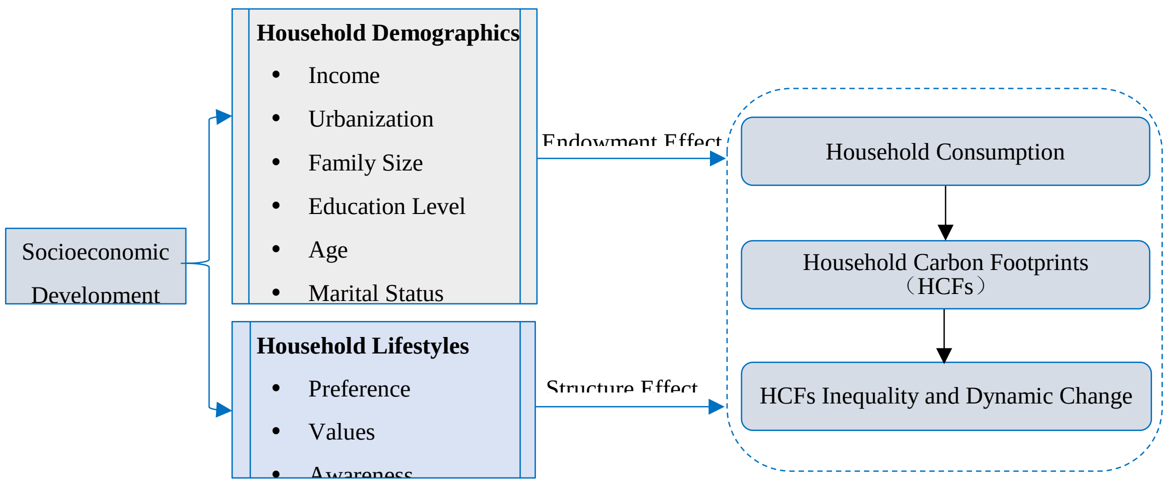


Figure 1. The analytical framework of the dynamics of HCFs inequality

The heterogeneities of demographics and lifestyles among households are the key factors in explaining the distribution and inequality of HCFs at a particular time. When the demographics and lifestyles of households change along with the development of socio-economics, the consumption patterns and HCFs of the households will change accordingly, which lead to the redistribution of HCFs and the dynamic changes of HCFs inequality. In this paper, with the Oaxaca-Blinder (OB) decomposition method we can calculate the contribution of household demographics to the dynamic changes in HCFs inequality (endowment effect) and the contribution of household lifestyles to the dynamic changes in HCFs inequality (structure effect).

3.2 UQR for the determinants of HCFs

In order to propose policies to mitigate HCFs inequality, we first need to know the driving factors of HCFs. Moreover, policymakers should design targeted mitigation policies according to the heterogeneous effects of household characteristics on HCFs. We apply the UQR approach to analyze the driving factors of HCFs. Compared with the OLS, the common Conditional Quantile Regression (CQR) approach provides a practical way to discern the differential effects of the covariates on the dependent variable at different points of the probability distribution of the dependent variable. However, the estimation results from the CQR are often not easy to interpret, especially for policymakers. In contrast, the UQR approach proposed by Firpo et al. (2009) does not have the limitations of the CQR approach. Using the UQR approach, we can explain the estimation results directly as the OLS approach. As in Firpo et al. (2009), we define the influence function (IF) as following:

$$\mathrm{IF}(y;v(F))=\lim_{\varepsilon\to 0}\frac{[v((1-\varepsilon)\cdot F+\varepsilon\cdot\delta_y)-v(F)]}{\varepsilon}\ ,\qquad 0\le\varepsilon\le 1$$

(1)

where y is the dependent variable and F is the cumulative distribution function of y. $\mathrm{IF}(y;v(F))$ is the influence function corresponding to an observed y for the distributional statistic of interest, $v(F)$.

Then, we define re-centered influence function (RIF) as:

$$\mathrm{RIF}(y;v)=v(F)+\mathrm{IF}(y;v)$$

(2)

In the case of quantiles, we have:

$$\mathrm{IF}(y;q_\tau)=(\tau-I\{Y\le q_\tau\})/f_Y(q_\tau)$$

(3)

where q_τ is the τth quantile of the unconditional distribution of Y, $f_Y(q_\tau)$ represents the density function of the marginal distribution of Y, and $I\{Y\le q_\tau\}$ is an indicator function. Then we have:

$$\mathrm{RIF}(y;q_\tau)=q_\tau+\mathrm{IF}(y;q_\tau)$$

(4)

As in Firpo et al. (2009), we can model the conditional expectation of $\mathrm{RIF}(y;q_\tau)$ as a function of explanatory variables, that is, $E[\mathrm{RIF}(Y;q_\tau)\,|\,X]=X\gamma$, where the parameter γ can be obtained from the OLS, and a RIF regression can be viewed as a UQR.

In this paper, we can get a series of coefficients of the driving factors at different quantiles of the HCFs through UQR. The comparison of these coefficients on different levels of HCFs and in different years can provide some preliminary conclusions of the sources of HCFs inequality and the associated dynamic changes.

3.3 Oaxaca-Blinder decomposition of the dynamic changes in HCFs inequality: endowment effect and structure effect

Usually, there are multiple decomposition methods to decompose the target variable into sum of various changes in the relevant variables and identify the contribution of each variable to the changes of the target variable, and they can fall under two distinct but related categories: index decomposition analysis (IDA) and input-output structural decomposition analysis (SDA).Ang and Zhang (2000) and Ang (2004) presented a comprehensive survey of IDA in energy and environmental studies; Hoekstra and van den Bergh (2002) gave a literature review on SDA and examined the theoretical aspects of SDA; Moreover, some literature compared and analyzed the similarities and differences between IDA and SDA (Hoekstra and van der Bergh, 2003; Wang et al., 2017; de Boer and Rodrigues, 2020; Wei et al., 2020). All these decomposition methods are commonly used when the relevant driving factors or determinants are available and the drivers of observed changes of energy and environmental impacts over time can be identified. However, as can be seen from the aforementioned theoretical framework, the dynamic changes in HCFs not only depend on household demographics, but also are the results of evolving aggregate preferences or environmental policies that change the relative supply and demand for carbon-intensive goods. Empirically, the latter is difficult to quantify and the commonly used decomposition methods become more or less inapplicable.

The OB decomposition is a standard tool quantifying the contributions of explained and unexplained effects to the differences between any two groups in labor economics and is more and more widely used in other fields (Oaxaca, 1973; Blinder, 1973). The most important development of this method is to extend the decomposition methods to distributional parameters other than the mean. For example, through the RIF regression method, the OB decomposition can be performed for any distributional statistics, not only for the quantiles of the unconditional distribution of the outcome variable but also the Gini coefficient (Firpo and Pinto, 2016; Firpo et al., 2018; Fortin et al., 2011), which is an attempt to better understand the underlying factors driving the inequality growth.

By applying the RIF regression and OB decomposition method, we distinguish the endowment effect with the structure effect, and demonstrate the contributions of driving factors to the dynamic changes of the HCFs inequality. Moreover, we estimate the HCFs inequality by comparing HCFs per capita at different quantiles, and analyze the dynamic changes of HCFs inequality between the year 2012 and 2018. For comparison, we also give the decomposition results of the Gini coefficient.

Firstly, for the differences among the various quantiles of HCFs per capita in two years, the coefficient of the UQR of each year is:

$$\hat{\gamma}_{g,\tau} = \left(\sum_{i\in G} X_i \cdot X_i^T\right)^{-1} \sum_{i\in G} \widehat{RIF}(X_{g_i}; q_{g,\tau}) \cdot X_i, \qquad g = 2012, 2018 \tag{5}$$

where X is the vector of covariates.

We can write the equivalent of the OB decomposition, which is used to decompose the dynamic changes over time, for any unconditional quantile as below:

$$\begin{aligned}\hat{\Delta}_O^\tau &= (\overline{X}_{2018} - \overline{X}_{2012})\hat{\gamma}_{2012,\tau} + \overline{X}_{2018}(\hat{\gamma}_{2018,\tau} - \hat{\gamma}_{2012,\tau}) \\ &= \hat{\Delta}_X^\tau + \hat{\Delta}_S^\tau\end{aligned} \tag{6}$$

where $\hat{\Delta}_O^\tau$ in Eq. (6) is the overall difference of HCFs per capita in the percentile between the year 2018 and 2012, $q_\tau(Y_{2018}) - q_\tau(Y_{2012})$.

The first term $\hat{\Delta}_X^\tau$ in the second line of Eq. (6) is named as "explained effect" or "endowment effect" in OB decomposition. It can be rewritten in terms of the sum of the contribution of the change of each covariate as:

$$\hat{\Delta}_X^\tau = \sum_{k=1}^{K}\left(\bar{X}_{2018,k} - \bar{X}_{2012,k}\right)\hat{\gamma}_{2012,k,\tau} \tag{7}$$

As shown in Eq. (7), the "endowment effect" indicates that when fixing the consumption preference in the year 2012, the changes of HCFs in the percentile over years are expected to obtain as a result of changes in household income and other demographics, which can be observed or quantified.

The second term $\hat{\Delta}_S^\tau$ in the second line in Eq. (6) is named as "unexplained effect" or "structure effect", which can be rewritten in terms of the sum of contribution of the change of each coefficient as:

$$\hat{\Delta}_S^\tau = \sum_{k=1}^{K} \left(\hat{\gamma}_{2018,k} - \hat{\gamma}_{2012,k}\right) \bar{X}_{2018,k} + \hat{\Delta}_C^\tau \tag{8}$$

As shown in Eq. (8), the "structure effect" measures the contribution of the differences in the coefficients of all the variables including the intercept $\hat{\Delta}_C^\tau$ in the τth percentile over the two years assuming that household income or demographics are unchanged. The changes of the coefficients may be caused by changes in household consumption pattern which is not relevant to the household income or demographics. The "structure effect" is based on the following counter-factual exercise: what would be the distribution of HCFs for 2018 if the distribution of the covariates for 2012 is the same as for 2018? In this paper, we attribute the underlying factors driving the consumption pattern evolution to the effects of the intertemporal lifestyle changes, such as the values, awareness, motivations and preferences of the individuals or household consumption generally fall into the category (Zhang et al., 2020). The "structure effect" is not easy to be observed or quantified but can lead to substantial changes in consumption patterns and the associated HCFs.

The HCFs inequality in 2012 and 2018 can be expressed as $q_{\tau_h}(Y_{2012}) - q_{\tau_l}(Y_{2012})$ and $q_{\tau_h}(Y_{2018}) - q_{\tau_l}(Y_{2018})$ respectively. Compared with 2012, the increase or decrease in inequality in 2018 can be determined by Eq. (9), which can be rewritten as $\hat{\Delta}_X + \hat{\Delta}_S$.

$$\begin{aligned}
&\left[q_{\tau_h}(Y_{2018}) - q_{\tau_l}(Y_{2018})\right] - \left[q_{\tau_h}(Y_{2012}) - q_{\tau_l}(Y_{2012})\right] \\
&= \left[q_{\tau_h}(Y_{2018}) - q_{\tau_h}(Y_{2012})\right] - \left[q_{\tau_l}(Y_{2018}) - q_{\tau_l}(Y_{2012})\right] \\
&= (\hat{\Delta}_X^{\tau_h} + \hat{\Delta}_S^{\tau_h}) - (\hat{\Delta}_X^{\tau_l} + \hat{\Delta}_S^{\tau_l}) \\
&= (\hat{\Delta}_X^{\tau_h} - \hat{\Delta}_X^{\tau_l}) + (\hat{\Delta}_S^{\tau_h} - \hat{\Delta}_S^{\tau_l}) \\
&= \hat{\Delta}_X + \hat{\Delta}_S
\end{aligned} \tag{9}$$

In addition, when the Gini coefficient is used to measure HCFs inequality, the dynamic changes of HCFs inequality can still be decomposed to the endowment effect and the structure effect using the RIF regression and OB decomposition method.

3.4 Data and data processing

The datasets used in this paper are the same as the paper of Shi et al. (2020) and Zhang et al. (2020). The datasets include: (i) a nationally representative survey data of Chinese households from Chinese Family Panel Studies (CFPS); (ii) China's Input-Output Tables and total CO_2 emissions of China's 35 production sectors from the World Input-Output Database (WIOD); In this paper, we select income, consumption expenditures and households' demographics of each household from CFPS for 2012 and 2018. The expenditures and income values for the two years are adjusted based on the 2007 prices according to the CPI sub-indices for both urban and rural regions published by the National Bureau of Statistics (NBS).

It is generally believed that the total HCFs per capita for an individual household consist of two parts: the direct HCFs per capita and the indirect HCFs per capita. The direct HCFs is the emissions per capita from a household's direct consumption of fossil fuels, such as coal, gas and oil and can be calculated using the emissions coefficient method (ECM). There are three expenditure items in the CFPS related to the energy that the households consume directly and are converted into physical quantities according to the average price of a certain energy source in different provinces and in the corresponding year. The direct HCFs can be obtained with Eq. (10).

$$E_{direct\_k} = \sum_i f_i \, Energy_{ik} \tag{10}$$

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

The indirect HCFs are the emissions embodied in the goods and services consumed by households and can be calculated using the input-output model, which is widely adopted in the literature (Munksgaard et al., 2000; Qu et al., 2013; Wiedenhofer et al., 2017). With the dataset in WIOD, we can derive the Leontief inverse matrix induced from the Input-Output Table and the emissions intensities coefficients for each sector. After aggregating the consumption-side detailed household expenditure items in CFPS into the production-side Leontief inverse matrix and emissions intensities, we estimate the indirect carbon footprints of each surveyed household in 2012 and 2018. We can calculate the indirect CO_2 emissions for a specific household k with Eq. (11).

$$E_{indirect\_k} = D(I - A)^{-1} Exp_k \tag{11}$$

where D is the row vector of sectoral direct emissions intensities; $(I - A)^{-1}$ is the Leontief inverse matrix; Exp_k is the column vector of expenditure per capita of household k. A detailed explanation of the calculation is presented in Zhang et al. (2020).

We use national IO table to calculate the Leontief inverse matrix and estimate the indirect HCFs for each surveyed household from household consumption expenditure, 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 without considering its country-of-origin or province-of-origin. Despite the limitations, it still has been applied in other recent studies (Markaki et al., 2017; Salo et al., 2021; Yu et al., 2022) as it is the best available approach to understand the changes in households' consumption patterns defined by national production technology and emissions intensities, which can make the analysis focus on investigating the effects of income, demographics and lifestyles on the change of HCFs.

The household demographic characteristics include urban or rural, regions, family sizes, household head's ages, education levels and marital status. In order to address the bias that might arise from the survey data and to calculate the Gini coefficient of the HCFs, we keep the sample weight in the datasets. To reduce bias due to outliers, the 1% of observations with the highest and lowest income groups and the corresponding HCFs are neglected. The final sample sizes are 12,277 for 2012 and 13,424 for 2018, respectively. Thus, we get a consolidated datum providing a single record to show the HCFs in China with the demographic characteristics in 2012 and 2018.

As shown in table 1, HCFs per capita in 2012 is 2.335 tons and increases to 4.145 tons in 2018 with an annual average growth rate of 10.037%, while that of the household income per capita is 12.741%, suggesting that HCFs may be decoupling from household income, which is desirable. The family size decreases to 3.385 in 2018 from 3.706 in 2012. The average age of the household heads decreases slightly, and more households' heads have higher education degrees and are married. In 2018, more households live in urban, east areas and in apartments, and the consumption of Coal Gas/LNG/Natural gas and electricity increases in 2018.

Table 1. Descriptive statistics

	2012		2018	
Variable	Mean	Std. Error	Mean	Std. Error

HCFs per capita (tons)	2.335	1.823	4.145	3.490
Income per capita (10^4 Yuan RMB)	1.048	1.118	2.152	2.086
Urban (pop.)	0.514	0.500	0.621	0.485
Family size	3.706	1.674	3.385	1.775
Head of Household				
Higher Education (pop.)	0.243	0.429	0.322	0.467
Age	50.367	13.561	49.270	15.009
Married (pop.)	0.870	0.336	0.896	0.306
Region (pop.)				
East	0.354	0.478	0.382	0.486
Central	0.261	0.439	0.239	0.427
West	0.252	0.434	0.238	0.426
Northeast	0.132	0.339	0.140	0.347
House Type (pop.)				
Apartment	0.235	0.424	0.303	0.459
Low-rise Building	0.223	0.417	0.126	0.331
Bungalow/ Courtyard	0.421	0.494	0.375	0.484
Villa/Townhouse	0.005	0.068	0.003	0.054
Others	0.115	0.319	0.193	0.395
Fuel Type (pop.)				
Solar energy or Marsh gas	0.014	0.117	0.003	0.052
Coal Gas/ LPG/Natural gas	0.408	0.492	0.548	0.498
Coal	0.058	0.233	0.024	0.152
Firewood/Straw	0.281	0.450	0.170	0.376
Electricity	0.239	0.427	0.255	0.436
N	12277		13424	

Notes: 1. Values are calculated using sample weight.

2. Lower education includes under primary education, primary education, junior secondary education; Higher education includes senior secondary education, college and above.

4. Comparisons of HCFs per capita from different dimensions

To have a general understanding of the HCFs inequality in China, it is necessary to know the HCFs per capita for different groups. In this part, we compare the average HCFs per capita from different dimensions (income, urban and rural areas, regions, etc.).

4.1 HCFs per capita by urban and rural areas, and regions

As is known to all, there exists great disparity in income and HCFs per capita among regions, and between urban and rural areas in China. Fig. 2 presents the HCFs per capita between urban and rural areas as well as among the East, the Central, the West and the Northeast.

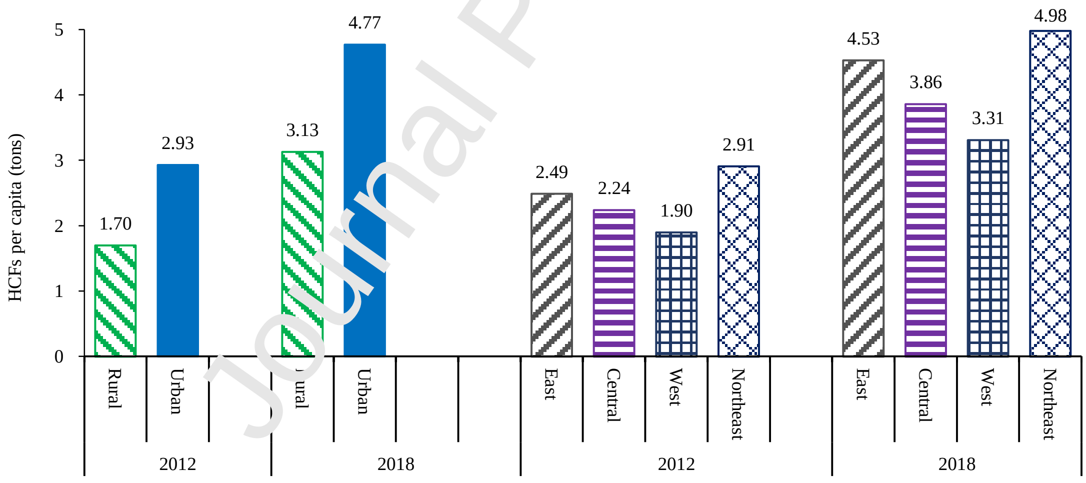


Figure 2. HCFs per capita of urban and rural areas, and regions

As can be seen from Fig. 2, households in urban areas tend to have higher HCFs per capita than their counterparts in rural areas. In 2018, HCFs per capita in urban areas is 4.77 tons, while it is 3.13 tons in rural areas. We can also see that HCFs per capita has increased since 2012 for both urban and rural areas. Meanwhile, the overall

HCFs per capita ratio of urban/rural decreased from 1.72 in 2012 to 1.52 in 2018, which means that the urban-rural HCFs inequality is slightly decreased over the period. In addition, Fig. 2 shows that HCFs per capita in four regions have increased over the period, however, the inequality has barely changed.

4.2 HCFs per capita by provinces

As China is a big country, to have a more detailed picture of the HCFs in China, Fig. 3 shows the HCFs per capita by provinces.

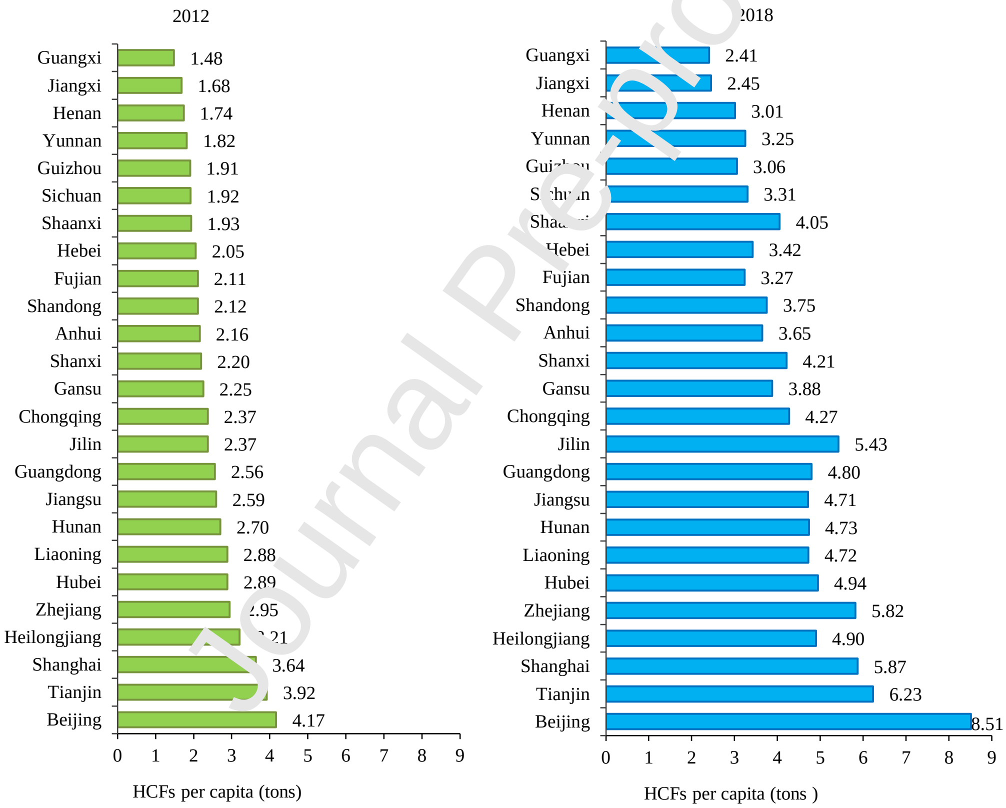


Figure 3. The HCFs per capita of the provinces in China

As shown in Fig. 3, in 2012 and 2018, the provinces with low HCFs per capita are Guangxi, Jiangxi, Henan, Yunnan and Guizhou, and all of them are underdeveloped provinces located in the western or central regions of China.[1] The

[1] Six provinces with small sample size are removed.

HCFs per capita of Guangxi province in 2012 and 2018 are 1.48 tons and 2.41 tons respectively. In 2012, the provinces with high HCFs per capita are Beijing, Tianjin, Shanghai, Heilongjiang and Zhejiang, while in 2018, the provinces with high HCFs per capita are Beijing, Tianjin, Shanghai, Zhejiang and Jilin. Of the six high HCFs provinces in 2012, Heilongjiang and Jilin are located in Northeast China, where the heating costs in the long winter are one of the important causes for the high HCFs. The other four provinces are the most developed provinces in China, suggesting that economic development is likely to be one of the key drivers of HCFs per capita. Meanwhile, the HCFs inequality among provinces in China is increasing. Compared with 2012, the HCFs per capita in all provinces increased significantly in 2018. For example, the HCFs per capita in Beijing are 4.17 tons in 2012 and 8.51 tons in 2018, which are 2.82 times and 3.53 times of the provinces with the lowest HCFs respectively. Moreover, the average HCFs growth rate of provinces above the median value is higher than those below the median value. The growth rates of Jilin, Shaanxi, Beijing, Zhejiang and Shanxi are the highest. Besides the climate reason for Jilin and economic reasons for Beijing and Zhejiang, the fast growth of HCFs in Shaanxi and Shanxi may be due to their rich endowments in coal resources.

4.3 HCFs per capita by different income groups

It is believed that HCFs per capita is highly correlated to income, we further divide the urban and rural households in China into five groups according to income levels and present their HCFs per capita. Fig. 4 shows the results of the average HCFs per capita sorted by the income level.

As can be seen from Fig. 4, HCFs per capita increases with the growth of income for all income groups. To be more specific, we can see that the average HCFs per capita of the group with the highest 20% income in urban areas is 4.27 tons in 2012, and increased to 7.87 tons in 2018, with a growth rate of 84.3%. The average HCFs per capita of the group with the lowest 20% income in rural areas is 1.42 tons in 2012 and increased to 2.13 tons in 2018 with a growth rate of 49.5%. The average HCFs per capita of households with the highest income of 20% in rural areas is 2.2 tons in 2012 and increased to 5.43 tons in 2018 with the largest growth rate of 144.8%. The ratio of HCFs per capita between the highest income group and the lowest one increased to 3.7 in2018 from 3.0 in 2012, which indicates that HCFs inequality has worsened in 2018.

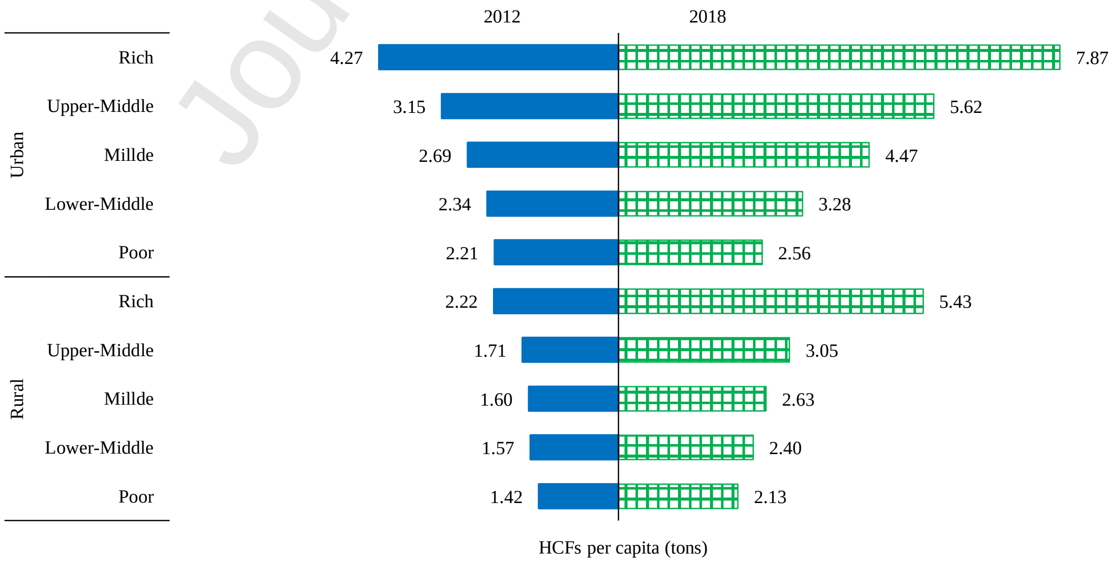


Figure 4. The HCFs per capita of different income groups

4.4 HCFs per capita over different quantiles

Before analyzing the determinants of HCFs per capita by using UQR, we give the logarithmic HCFs per capita over different quantiles in 2012 and 2018 as in Fig. 5.

Fig. 5 demonstrated that the trends of the quantile logarithmic HCFs per capita in the two years are almost the same. We can also see that the gap of the logarithmic HCFs per capita between 2012 and 2018 is stable between the 20th quantile and the 75th quantile, while it is growing with the increase of the quantile before the 20th quantile and after the 75th quantile. In addition, the gap of the logarithmic HCFs per capita reaches the peak at the 97th quantile, which indicates that the HCFs per capita in 2018 is more polarized than that in 2012 and the overall HCFs inequality is exacerbated to some extent. The fact that the gap of the HCFs per capita in the middle of the distribution (between the 20th quantile and the 75th quantile) remains stable leads to only a slight increase in the HCFs inequality in 2018.

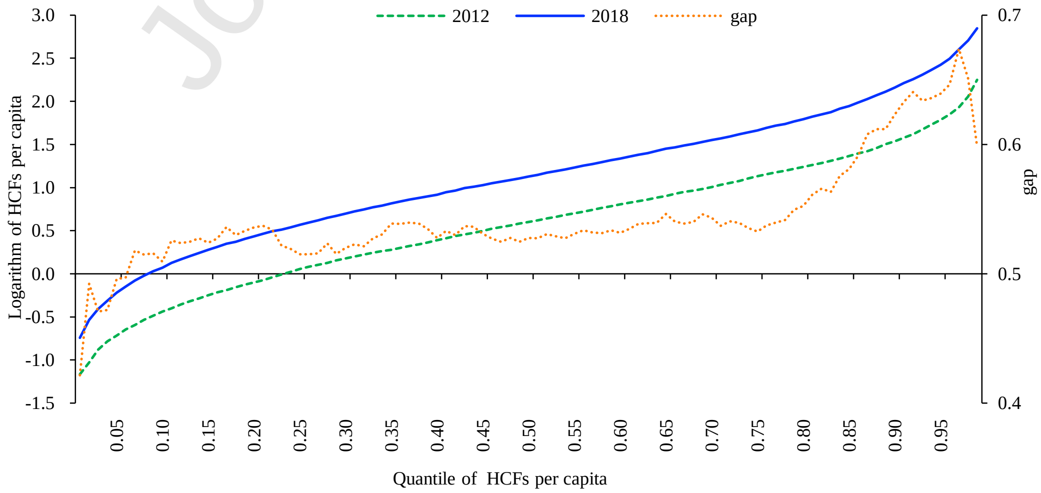


Figure 5. The Logarithmic HCFs per capita at different quantiles

It is shown that the changes of HCFs per capita in different groups (urban and rural areas, regions, provinces and different income groups) are uneven, which means that the distribution of HCFs per capita over the two years has changed. However, we cannot determine whether this change has exacerbated or slowed down the HCFs inequality in the whole society. Moreover, the dynamic changes of the HCFs per capita across the different HCF quantiles not only show that the HCFs inequality in 2018 is more serious, but also show that the cause could be the larger gap between the top 25% households and the bottom 20% ones.

Based on the comparison of HCFs per capita from different dimensions above, we can see that there exists remarkable difference in HCFs per capita from different perspectives, and we can compare the results with other relevant studies. For example, Maraseni et al. (2015) compared HCFs among China, Canada, and UK and showed that though average HCFs per capita in China is still much lower than that of Canada and UK, it is experiencing the highest growth in HCFs. Irfany and Klasen (2017) found that there are significant differences in HCFs between different affluence levels, regions and education levels in Indonesia. Yu et al. (2022) compared HCFs per capita between China and Japan and showed that HCFs in China is much less than that in Japan. Maraseni et al. (2016) also argued that HCFs from urban areas are higher than those from rural areas, and the rural areas of northern China have significantly higher HCFs than those from southern China. Mi et al. (2020) showed that the top 5% of income earners are responsible for 17% of the national HCFs in 2012. Wei et al.

(2021) found that the rising middle class assume more responsibility for carbon emissions. All these suggest that though HCFs per capita in China is lower than that in developed countries, it is growing rapidly and shows great differences in many aspects, and therefore it is necessary to go deep into the driving forces of HCFs and identify the underlying sources of HCFs inequality in China.

5. Determinants of HCFs and the Dynamic Change of HCFs Inequality

In this part, we analyze the dynamic changes of HCFs inequality and its underlying drivers through three steps. Firstly, the UQR model is used to compare the impacts of driving factors (observable household demographics) on HCFs at different quantiles on HCFs per capita at the same year as well as the same quantile difference between the two years (the results of three quantiles of 10th, 50th and 90th are listed). Secondly, the OB decomposition model is used to analyze the impacts and contributions of households' demographics and lifestyles on HCFs over the same quantiles between different years (the endowment effect and the structure effect). Finally, we analyze the impacts and contributions of the dynamic changes of the HCFs inequality together from the endowment effect and the structure effect perspective

5.1 Determinants of HCFs per capita through unconditional quantile regression

The UQR over 19 different quantiles (from the 5th to the 95th) are calculated, and the selected UQR regression results (10th, 50th and 90th) are presented by columns (1)-(3) for 2012 and columns (5)-(7) for 2018 in Table 2. Moreover, for comparison, the OLS regression results for the two years are also listed in column (4) and (8), respectively. The coefficients of income and other major households' demographics with OLS and UQR estimates are also reported.

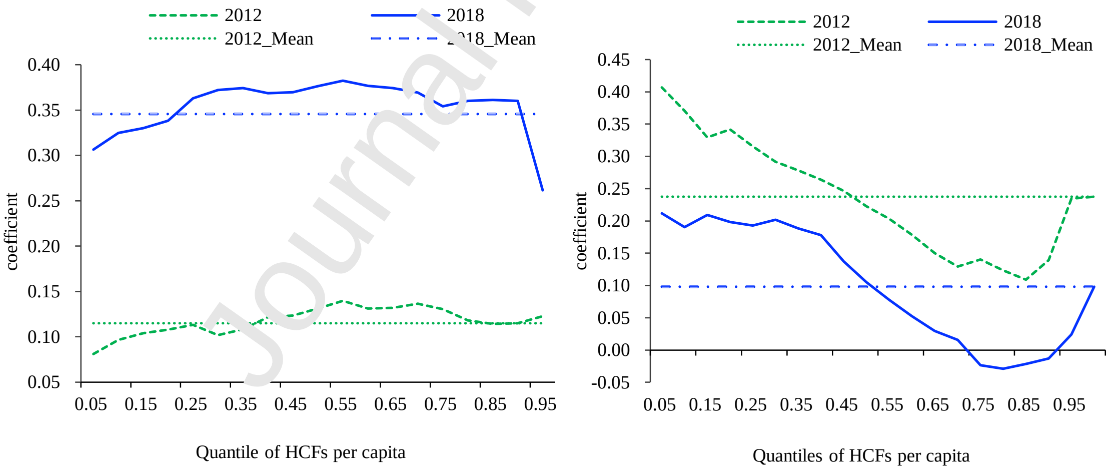
Table 2. Results of the UQR and OLS regression

	2012				2018			
	Uq10	Uq50	Uq90	Mean	Uq10	Uq50	Uq90	Mean
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Income	0.097***	0.131***	0.115***	0.115***	0.326***	0.376***	0.360***	0.346***
	(0.014)	(0.011)	(0.013)	(0.005)	(0.02[illegible])	(0.013)	(0.025)	(0.007)
Urbanization	0.371***	0.223***	0.139***	0.2[illegible]8***	0.195***	0.105***	-0.013	0.098***
	(0.031)	(0.027)	(0.029)	(0.01[illegible])	(0.041)	(0.025)	(0.040)	(0.013)
Family size	-0.400***	-0.429***	-0.390**	-0.390***	-0.190***	-0.343***	-0.439***	-0.314***
	(0.035)	(0.024)	(0.0[illegible]2)	(0.013)	(0.030)	(0.019)	(0.037)	(0.011)
Education	0.031	0.157**	0.128***	0.113***	-0.020	0.165***	0.124**	0.106***
	(0.028)	(0.027)	(0.041)	(0.014)	(0.027)	(0.027)	(0.051)	(0.013)
Age	-0.248***	0.15[illegible]***	-0.216***	-0.200***	-0.166***	-0.109***	-0.295***	-0.155***
	(0.047)	(0.038)	(0.053)	(0.020)	(0.041)	(0.034)	(0.065)	(0.018)
Marital status	0.[illegible]9***	0.190***	-0.027	0.136***	0.177***	0.053	-0.073	0.055***
	(0.049)	(0.034)	(0.048)	(0.018)	(0.058)	(0.037)	(0.069)	(0.018)
East	0.095***	0.143***	0.125***	0.117***	0.029	0.076***	0.051	0.041***
	(0.033)	(0.027)	(0.037)	(0.015)	(0.034)	(0.025)	(0.042)	(0.014)
West	0.025	0.032	0.002	0.023	-0.051	-0.007	0.027	-0.021
	(0.041)	(0.031)	(0.035)	(0.016)	(0.042)	(0.029)	(0.053)	(0.015)
Northeast	0.073*	0.192***	0.084	0.134***	0.189***	0.193***	-0.015	0.147***
	(0.038)	(0.035)	(0.053)	(0.019)	(0.037)	(0.040)	(0.069)	(0.018)
Low-rise Building	0.086***	-0.210***	-0.210***	-0.137***	-0.091*	-0.155***	-0.023	-0.105***
	(0.033)	(0.036)	(0.057)	(0.019)	(0.054)	(0.040)	(0.059)	(0.020)
Bungalow/ Courtyard	-0.026	-0.409***	-0.395***	-0.289***	0.003	-0.137***	-0.033	-0.073***
	(0.032)	(0.035)	(0.050)	(0.018)	(0.038)	(0.034)	(0.060)	(0.016)
Villa/Townhouse	0.183*	0.384***	0.303	0.240***	0.448***	-0.318**	-0.268***	-0.131
	(0.103)	(0.107)	(0.340)	(0.082)	(0.140)	(0.148)	(0.082)	(0.097)

Coal gas/ LNG/Natural gas	0.20***	0.296***	0.104***	0.209***	0.244***	0.196***	0.139***	0.202***
	(0.032)	(0.030)	(0.037)	(0.015)	(0.037)	(0.026)	(0.042)	(0.014)
Coal	0.331***	0.585***	0.438***	0.473***	0.748***	0.752***	0.611***	0.716***
	(0.056)	(0.052)	(0.069)	(0.026)	(0.063)	(0.061)	(0.101)	(0.036)
Firewood/Straw	-0.178***	0.003	0.084***	-0.033**	-0.204***	0.207***	0.270***	0.137***
	(0.048)	(0.031)	(0.030)	(0.016)	(0.059)	(0.031)	(0.044)	(0.017)
_cons	0.552***	1.473***	2.910***	1.620***	0.397**	1.489***	3.545***	1.659***
	(0.191)	(0.158)	(0.230)	(0.086)	(0.183)	(0.154)	(0.286)	(0.080)
Adjust R^2	0.116	0.250	0.107	0.339	0.143	0.313	0.140	0.430
N			12277				13424	

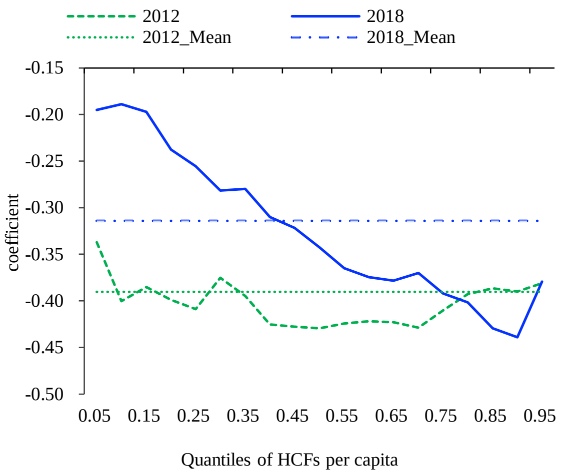
Notes: ***, **, * are statistically significant at the 1%, 5%, 10% level.
Standard error in parenthesis.

The 19 different quantiles are illustrated in the subplots (a) - (i) of Fig. 6, which illustrate the heterogeneous impacts of the driving factors on HCFs over different quantiles and their changes in different years.

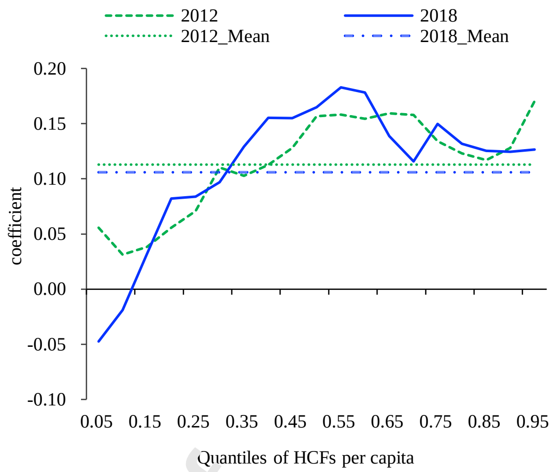


(a) Income

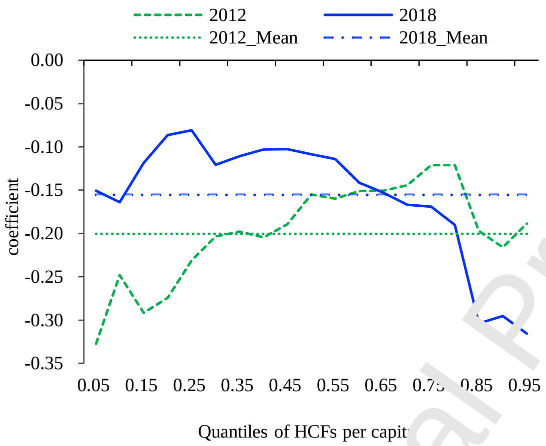
(b) Urbanization (rural=0)



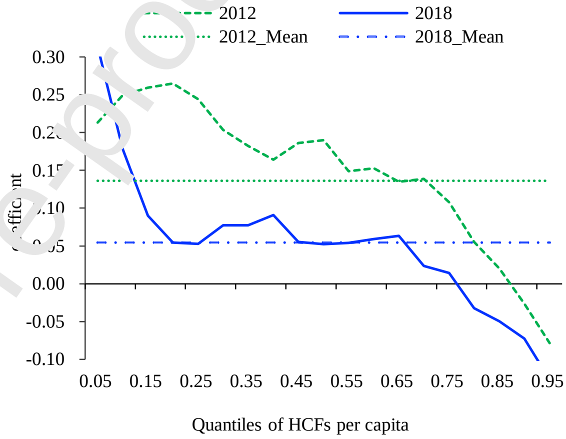
(c) Family size



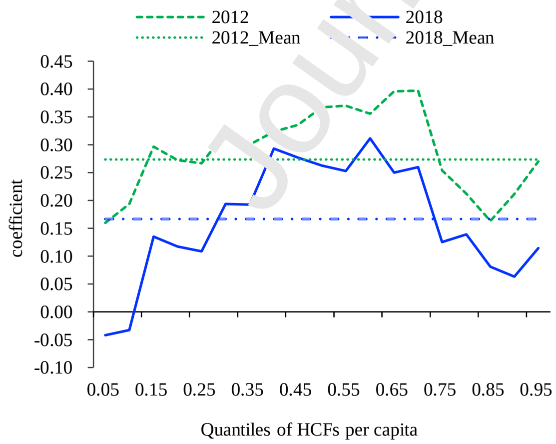
(d) Education (low education=0)



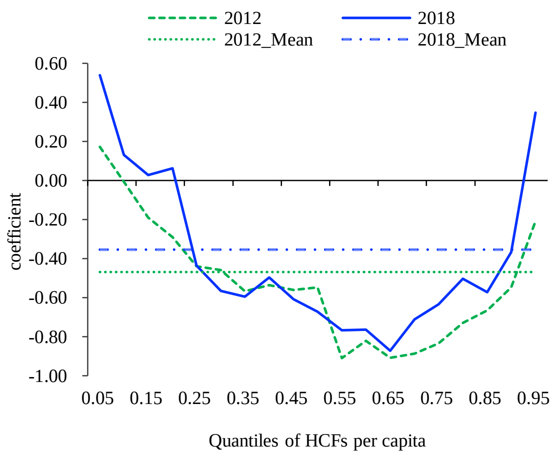
(e) Age



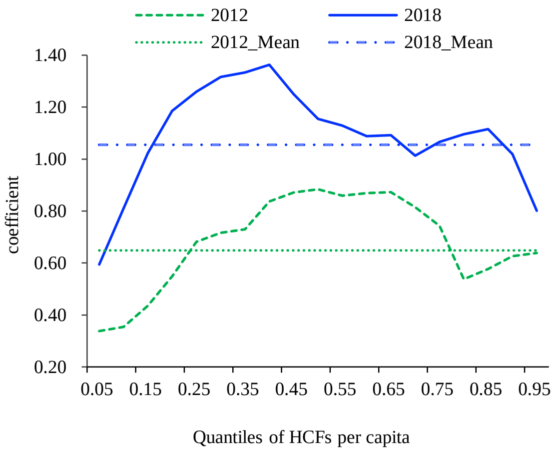
(f) Marital status (single=0)



(g) Regions (central=0)



(h) House type (apartment=0)



(i) Fuel type (electricity=0)

Figure 6. The effects of the households' demographics on HCFs per capita over different quantiles

As is shown in Table 2 and Fig. 6, the coefficients of all the variables, such as income, urbanization, family size and the features of households' heads, etc., are quite diverse over different quantiles in different years. The impacts of the driving factors from UQR are highly non-monotonic. Compared with the OLS regression, the UQR presents more comprehensive information about the heterogeneity of the driving factors' impacts on HCFs per capita over different quantiles of HCFs. As a result, the heterogeneous impacts may aggravate or alleviate the HCFs inequality.

(1) Income

The HCFs per capita is positively correlated with income, and the effect of income on HCFs per capita in 2018 is much greater than that in 2012. In addition, with the rise of the quantile of HCFs per capita, the effects of income are inverse U-shaped for the years 2012 and 2018. The uneven effects at different quantiles may lead to the dynamic changes of the HCFs inequality.

Firstly, as can be seen from Table 2 and Fig. 6(a), the OLS results show that one percent increase in income leads to 0.115 percent increase in the average HCFs in 2012 and leads to 0.346 percent increase in 2018. This means that for households in 2018, an increase of one percent in income will increase the average HCFs by an additional 0.212 percentage compared with 2012. In addition, the impacts of income on HCFs are quite uneven for HCFs at different quantiles. In 2012, one percent increase in income leads to 0.097 percent, 0.131 percent, and 0.115 percent increase in HCFs per capita for the households with HCFs at the 10th, 50th and 90th quantile respectively. While in 2018, there are 0.326 percent, 0.376 percent and 0.360 percent increases in HCFs per capita for households with HCFs at the same quantiles respectively. Moreover, Fig. 6(a) shows that the income coefficients of all quantiles in 2018 are higher than those in 2012 except for the 95th quantile, which means that the same increase in income can has a greater impact on HCFs in 2018.

Secondly, the effects of income with the increase of the quantile of HCFs per capita both are inverse U-shaped for the years 2012 and 2018. It can be seen from Fig. 6(a) that the coefficients of income increase from the 5th quantile and reach the highest point at the 55th quantile and then decline in the two years. However, the declining trend of income coefficients in 2018 is more obvious from the 55th quantile to the 75th quantile and t hen drop to the lowest point at the 95th quantile.

The result of the positive and inverse U-shaped effect of income on HCFs provides the new evidence for the Carbon Kuznets Curve (CKC). But greater coefficients in 2018 show that HCFs will increase at a faster rate even if the income growth rate remains unchanged. Moreover, the change of income and the heterogeneous effects of income on HCFs may lead to the dynamic changes of the HCFs inequality.

(2) Urbanization

The urbanization process in China leads to the increase of the HCFs per capita in urban areas but the effect is much lower in 2018 than that in 2012. In addition, the effects of urbanization on HCFs per capita at different quantiles are both U-shaped in 2012 and 2018. As shown in Fig. 6(b), the OLS regression results in 2012 and 2018 are 0.238 and 0.098, and the curve of coefficients for UQR of 2018 always lies below that of 2012. In addition, the coefficients for UQR in the two years both decrease monotonically before the 80th quantile and then increase. As a result, we may conclude that urbanization in China leads to higher HCFs per capita of urban households, however, the impacts of urbanization on HCFs decline obviously in 2018. In particular, among the households between the 75th and 90th quantiles of the HCFs, the HCFs of the rural households are even higher than those of the urban ones in 2018.

(3) Family size

Family size has a negative impact on HCFs per capita and it decreases with the rise of HCFs quantiles, and especially decreases rapidly in 2018. Table 2 and Fig. 6(c) show that the coefficients from both the OLS regression and the UQR in 2012 and

2018 are negative, which means that the increase of family member tends to have lower HCFs per capita. Fig. 6 (c) also shows that the coefficients curve in 2018 is higher and steeper, indicating that compared to 2012, the impact of family size on HCFs becomes weak and significantly decreases.

(4) Education level

On average, the effects of education level on HCFs per capita are positive, and with the rise of the quantile of HCFs per capita, the effects are inverse U-shaped for the years 2012 and 2018. Table 2 and Fig. 6(d) show that the coefficients of the education level from the OLS regression and UQR are positive in the two years except those below the 10th quantile in 2018. Moreover, the coefficient curves are close in the two years and are inverse U shaped, the inflection points are at about 60th quantile. The features of the two curves imply that the households whose heads have higher education levels tend to generate more carbon emissions and the promoting effect is more obvious for the households with middle and high HCFs.

(5) Age

The age of the household head has a negative effect on HCFs per capita, and with the rise of the quantile of HCFs per capita the effects are inverse U-shaped for the two years. Table 2 and Fig. 6 (e) show that the coefficients of age from the OLS regression and UQR in the two years are negative, which means that the household with an older head is conducive to the reduction of HCFs per capita. Moreover, for 2012, the reducing effect of household heads' ages on HCFs gets weak for the households with higher HCFs, while it is the opposite for the year 2018. Therefore, at present, we can conclude that the process of population aging in China does not exert additional pressure on the increase of HCF.

(6) Marital status

That the households' head are married has a positive effect on HCFs per capita and the effects tend to decrease with the rise of HCFs per capita for the two years, and the coefficient curve of 2018 lies below that of 2012. Table 2 shows that the average impacts of the marital status on the HCFs in 2012 and 2018 are 0.136 and 0.055 respectively, however, Fig. 6 (f) shows that the effect is weakening with the increase of the HCFs quantile, and turns to be negative at about the 85th quantile. In addition, the coefficients of the marital status for almost all the quantiles in 2018 are lower than those in 2012, which reflects that the impact of the marital status on the increase of HCFs in 2018 gets weak.

For other variables, as shown in Fig. 6(g)-Fig. 6(i), we can see that regions, housing types and fuel types all have significant impacts on the HCFs per capita, and the impacts on HCFs at different HCFs quantiles and in different years are also highly heterogeneous.

In summary, the OLS regression results show that in 2012 and 2018, the household demographics of income, urbanization, education level, marital status, and “using coal gas/LNG/natural gas/ coal/firewood/ straw as the main fuel" all lead to the increase of HCFs per capita, while family size, age, living in the western region, living in low rise building/bungalow/courtyard reduce the HCFs. Similar results can be found in the existing studies. For instance, Zhang et al. (2015) investigated the drivers of HCFs and found that income level, household size, education, time, housing conditions and other factors have important influences on HCFs. Lévay et al. (2021) found that income, household size, age and education significantly affect HCFs. Li et al. (2022) found that income is the most significant driving forces of food consumption-related carbon footprints in Japan. Moreover, the results of the UQR demonstrate that these determinants of HCFs have different effects on HCFs at different parts of the HCFs distribution and these effects are changing over time even for households at the same points of the HCFs distribution[2].

We have shown that the rapid growth of HCFs at higher quantiles in 2018 exacerbates the HCFs inequality, and the heterogeneity of UQR coefficients at different quantiles and different years can be considered as an important cause. However, the decomposition model needs to be used to further establish the quantitative relationship between the changes of the driving factors, the changes of the UQR coefficients and the changes of the HCFs inequality in the two years.

[2] Some literature (Han et al., 2015; Rong et al., 2018) applied CQR to study on HCFS and its determinants, however, the interpretation of the coefficients from CQR is still limited, leading to the results not generalizable or interpretable in a policy or population context (Borah and Basu, 2013).

5.2 Households' demographics and lifestyles and the quantile differentials in HCFs overtime

According to Eq. (6) - (9), we decompose the differentials of HCFs per capita at the same quantiles between the two years. Table 3 lists the decomposition results of three important quantiles (10th, 50th and 90th).

It can be seen from Table 3 that the differences between the logarithmic HCFs per capita in the three quantiles are 0.509, 0.527 and 0.624 respectively. Assuming that the UQR regression coefficients remain unchanged, the logarithmic HCFs in the three quantiles from 2012 to 2018 increase by 0.265, 0.296 and 0.249 due to the changes of driving factors, which means that the endowment effects account for 52.1%, 56.2% and 39.9% of the total changes of HCFs per capita at the three quantiles respectively. In contrast, assuming that the driving factors remain unchanged, the HCFs in the three quantiles from 2012 to 2018 increase by 0.245, 0.231 and 0.376 respectively due to the changes of the UQR regression coefficients. In other words, the structure effects account for 48.1%, 43.8% and 60.3% of the total changes of HCFs per capita at the three quantiles respectively.

Table 3. Decomposition results of the quantile differentials in the HCFs

Percentile difference	**Uq10** (1)	**Uq50** (2)	**Uq90** (3)	**Mean** (4)
Overall group (t_0=*2012*)	-0.439***	0.601***	1.538***	0.574***
Overall group (t_1=*2018*)	0.070***	1.128***	2.163***	1.118***
Total Percentile difference (t_1-t_0)	0.509*** (0.020)	0.527*** (0.016)	0.624*** (0.023)	0.543*** (0.012)
Total Endowment	0.265***	0.296***	0.249***	0.265***

effect	(0.011)	(0.009)	(0.012)	(0.008)
Income	0.143***	0.174***	0.163***	0.158***
	(0.010)	(0.007)	(0.010)	(0.006)
Urbanization	0.032***	0.019***	0.007***	0.019***
	(0.003)	(0.002)	(0.003)	(0.002)
Family size	0.039***	0.053***	0.058***	0.048***
	(0.003)	(0.003)	(0.004)	(0.003)
Education	0.002	0.015***	0.012***	0.010***
	(0.002)	(0.002)	(0.003)	(0.001)
Age	0.008***	0.005***	0.010***	0.007***
	(0.001)	(0.001)	(0.002)	(0.001)
Marital Status	0.006***	0.004***	0.000	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
Region	0.003***	[illegible]	0.003**	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
House type	[illegible]	0.016***	0.011***	0.008***
	(0.004)	(0.003)	(0.004)	(0.002)
Fuel type	0.040***	0.007*	-0.014***	0.009***
	(0.005)	(0.004)	(0.004)	(0.003)
Total Structure effect	0.245***	0.231***	0.376***	0.278***
	(0.022)	(0.016)	(0.022)	(0.011)
Income	0.011***	0.013***	0.011***	0.012***
	(0.003)	(0.002)	(0.003)	(0.002)
Urbanization	-0.101***	-0.068***	-0.087***	-0.081***
	(0.029)	(0.021)	(0.028)	(0.015)
Family size	0.238***	0.095***	-0.061	0.083***
	(0.053)	(0.035)	(0.056)	(0.026)
Education	-0.016	0.001	-0.003	-0.004
	(0.011)	(0.011)	(0.018)	(0.007)
Age	0.316	0.179	-0.308	0.173
	(0.242)	(0.197)	(0.323)	(0.137)
Marital Status	-0.065	-0.122***	-0.041	-0.073**
	(0.067)	(0.044)	(0.074)	(0.033)
Region	-0.028	-0.034	-0.034	-0.037**

	(0.032)	(0.025)	(0.037)	(0.017)
House type	0.018	0.154***	0.205***	0.127***
	(0.029)	(0.033)	(0.055)	(0.021)
Fuel type	0.026	-0.002	0.060*	0.039**
	(0.037)	(0.026)	(0.035)	(0.018)
_cons	-0.154	0.016	0.636*	0.039
	(0.264)	(0.221)	(0.367)	(0.153)

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

Standard error in parenthesis.

Fig. 7 further shows that the endowment effect rises slightly from the 10th quantile to the 55th quantile and then decreases significantly after the 55th quantile, while the structure effect increases significantly after the 55th quantile and exceeds the endowment effect after the 75th quantile. This result means that the changes of income and other household characteristics lead to higher promoting effects on HCFs per capita at the lower quantiles, while the structure effect has a greater impact on HCFs per capita at the higher quantiles. Especially, for the households at the top 25th quantiles of HCFs, the intertemporal changes of household lifestyles are the dominant factors of the dynamic changes of HCFs per capita.

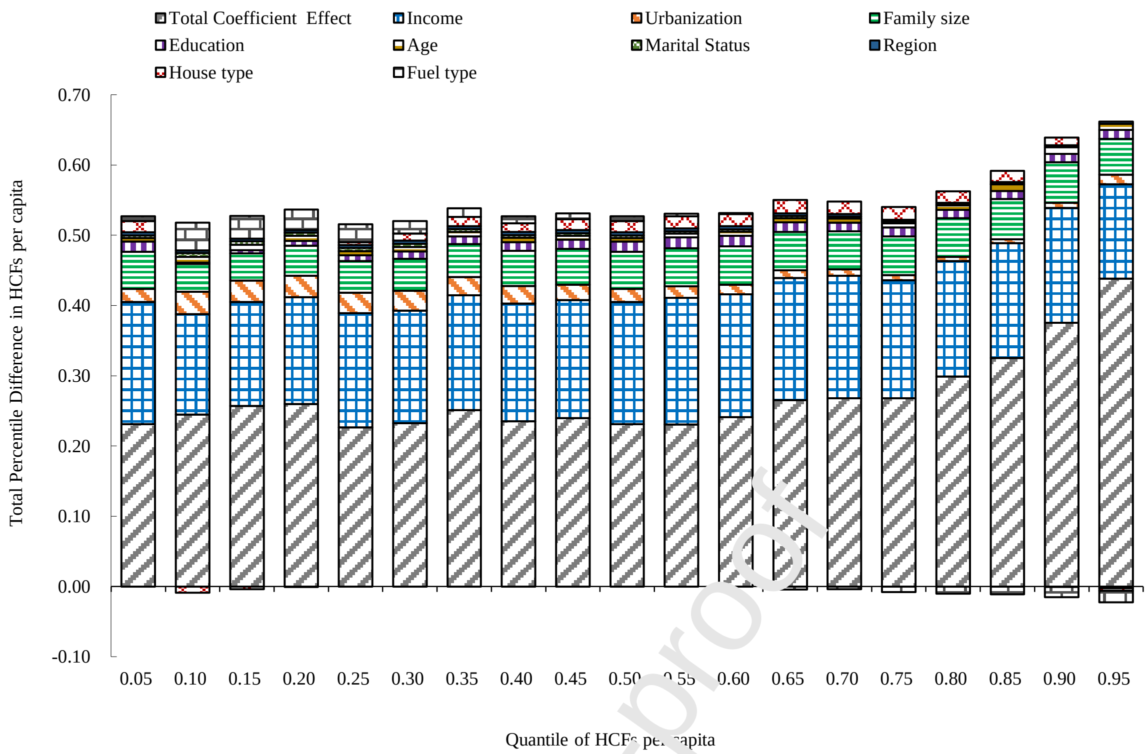


Figure 7. The endowment effect and the structure effect to the HCFs per capita

Furthermore, for the contribution of dynamic changes in driving factors to the dynamic changes of HCFs, it can be seen from Fig. 7 that income is the most important factor leading to the dynamic changes of HCFs between 2012 and 2018, accounting for over 50% of the total endowment effects, followed by family size, urbanization, the education levels of the household head, fuel types and house types. The effects of the change of the household head's ages, regions and household head's marital status are very small.

As for the contributions of driving factors at each quantile between 2012 and 2018, Fig. 7 shows that the effects of the dynamic changes of income, the education level of the household head and housing type are inverse U-shaped, which means that the growth of income, the improvement of the education level of household head and the change of housing type lead to a greater increase of HCFs at the middle quantiles in 2018 than that at low and high quantiles. While the urbanization process and the change of fuel type have an obvious promoting effect on the HCFs in the low quantiles and the effects get weak with the increase of quantiles. In particular, the changes in fuel types reduced HCFs per capita after the 65th quantile in 2018.

Combining the results from Table 3 and Fig. 7, we can see that the intertemporal changes of household lifestyles have an important contribution to the dynamic changes of HCFs, especially for the higher HCFs, which exacerbated the HCFs inequality in 2018. The reduction of HCFs from the households with higher ones is the key to reduce the total HCFs and the related inequality. However, if the abatement policies only focus on the effect of income and other household characteristics on the HCFs without considering the remarkable effects of the intertemporal changes of household lifestyles, it will not only weaken the emissions reduction effect of the policies but also is not conducive to the reduction of the HCFs inequality.

5.3 Decomposition of the dynamic changes in HCFs inequality

In this section, we first choose the differences of HCFs per capita between the main quantiles (Uq90-Uq10, Uq90-Uq50, and Uq50-Uq10) as well as the Gini coefficient as the measures of HCFs inequality[3] and evaluate the changes in HCFs inequality over time. Then we identify the main factors leading to the changes in the HCFs inequality over time with the unconditional quantile decomposition method.

[3] Gini coefficients are calculated based on the original value of CO2, that is, there is no logarithmic treatment.

Finally, we quantify the contributions of each covariate to the endowment effect and the structure effect. The results are shown in Table 4.

Table 4. Results of the decomposition of the dynamics changes in the HCFs inequality

Percentile difference	**Uq90-Uq10** (1)	**Uq90-Uq50** (2)	**Uq50-Uq10** (3)	**Gini index** (4)
Overall group (t_0=*2012*)	1.979	0.937	1.042	0.395
Overall group (t_1=*2018*)	2.089	1.032	1.056	0.415
Total Percentile difference (t_1-t_0)	0.109	0.095	0.014	0.021
Total Endowment Effect	-0.011	-0.055	0.044	-0.008
Income	0.014	-0.011	0.024	0.001
Urbanization	-0.025	-0.009	-0.016	-0.002
Family size	-0.001	-0.004	0.003	-0.002
Education	0.008	-0.002	0.010	0.001
Age	-0.001	0.002	-0.003	0.000
Married Status	-0.007	-0.005	-0.002	-0.002
Region	0.001	-0.001	0.002	0.000
House type	0.047	0.005	0.041	0.004
Fuel type	-0.047	-0.031	-0.016	-0.008
Total structure effect	0.120	0.150	-0.030	0.030
Income	0.004	0.000	0.004	-0.006
Urbanization	0.021	-0.019	0.040	-0.013
Family size	-0.274	-0.142	-0.133	-0.03
Education	0.011	-0.007	0.018	-0.002
Age	-0.633	-0.509	-0.124	-0.138
Marital Status	0.027	0.083	-0.056	0.023
Region	-0.006	0.003	-0.010	0.004
House type	0.179	0.053	0.126	0.009
Fuel type	0.019	0.063	-0.044	0.000
_cons	0.772	0.625	0.148	0.181

We find that:

(1) The rise of the HCFs inequality from 2012 to 2018 mainly comes from the gap between the top quantile (uq90) and the median quantile (uq50). As is shown in Table 4, the HCFs gap between the 90th quantile and the 10th quantile in 2012 is 1.979, which rises to 2.089 in 2018, resulting in an increase of 0.109. In 2018, the gap of the HCFs between the 90th quantile and the 50th quantile increases by 0.095, while it only increases by 0.014 between the 50th quantile and the 10th quantile. Meanwhile, the Gini coefficient of the HCFs is 0.395 in 2012 and rises to 0.415 in 2018. The dynamic changes of the HCFs gap over different quantiles and the dynamic changes of the Gini coefficients show the widening of the HCFs inequality from 2012 to 2018, and mainly comes from the gap between the top quantile (uq90) and the median quantile (uq50).

(2) The total endowment effect is helpful in decreasing the HCFs gap between the top quantile (uq90) and the 10th quantile (uq10) from 2012 to 2018. Though the endowment effect reduces the HCFs inequality between the top quantile (uq90) and the median quantile (uq50), it increase the HCFs inequality between the 50th quantile and the 10th quantile, leading to a decrease of 0.011 in the HCFs gap between the 90th quantile (uq90) and the 10th quantiles (uq10). Specifically, the endowment effect leads to a significant decrease (-0.055) in the HCFs gap between the top quantile (uq90) and the median quantile (uq50), and with a significant increase (0.044) in the HCFs gap between the median quantile (uq50) and the 10th quantile (uq10). That is to

say, changes of the household demographics reduce the HCFs inequality between the household with high and low levels of HCFs.

As for the detailed endowment effects of the household demographics, the contributions to the two types of HCFs inequality (Uq90-Uq50 and Uq50-Uq10) are quite different. In general, from 2012 to 2018, changes in income, regions that households living, housing type and education level of household heads enlarge the HCFs inequality, while changes in urbanization, family size, fuel type and the age and married status of household heads are helpful in reducing the HCFs inequality.

(3) The structure effect plays a dominant role in the rise of the HCFs inequality. While keeping the driving factors unchanged, the structure effect leads to an increase of the HCFs gap between the top and the median quantile (Uq90-Uq50) by 0.150, and it decreases the HCFs gap between the median and the low quantile (Uq50-Uq10) by 0.030. Ultimately, the total structure effect becomes 0.120. In other words, HCFs inequality at the top of the distribution of HCFs (the 90-50 quantiles differential) contributes much more to the overall HCFs inequality than at the bottom (the 50-10 quantiles differential). Moreover, the total structure effect is opposite to that of the endowment effect, and becomes the main cause of the increase in HCFs inequality. Therefore, we may conclude that the changes of lifestyles become the main source of the rise in HCFs inequality between households with the high and the median HCFs and eventually lead to the increase of the HCFs inequality between the households at the top (uq90) and the bottom quantile (uq10).

In summary, this paper confirmed the existence of significant emissions disparities among households over time (Xu et al., 2016; Yang and Liu, 2017; Li et al., 2019), and demonstrated that HCFs inequality increases from 2012 to 2018. It also showed that structure effect accounts for a large part of the increases of the HCFs inequality, especially for HCFs inequality between households at the top and the median quantile. As structure effect can be regarded as the impacts of lifestyle changes, this validates the theoretical results that intertemporal lifestyle changes play an important role in the increase of the HCFs inequality in China.

This conclusion makes us have a new understanding for the changes in intertemporal lifestyle and carbon footprint inequality. The reason why the carbon footprints of households with higher HCFs grow faster is not from changes in income and other demographics, but from changes in lifestyle. China's rapid development and transformation of social economy over the past 40 years has increased the income of residents, moved more people into cities, provided better education and cleaner fuel, etc. At the same time, it is constantly shaping the personal and households' lifestyle. It is obvious that the households with higher HCFs are stepping towards higher carbonization lifestyle leading to the aggravation of HCFs inequality.

Apart from the commonly used driving factors of HCFs, some studies have pointed out lifestyle changes could exert an import impact on household energy consumption and carbon emissions (Chen et al., 2019; Zhang et al., 2020). A few studies have investigated the relationship between awareness and HCFs (Wilson et al., 2013; Andersson et al., 2014; Li et al., 2019). Wei et al. (2021) also found that the rising middle class assume more responsibility for carbon emissions. However, few studies investigated the relationship between HCFs inequality and lifestyle changes. We found that the effects of lifestyle changes on HCFs are different across households and provide evidence that intertemporal lifestyle changes also play an important role in the increased HCFs inequality, which is not fully addressed in the past research works.

5.4 Robustness test

As a robustness test, we also use provinces instead of regions as the dummy variables in all regressions, the results are shown in Appendix A-E. As can been from the Appendix A-E, for the quantile regression and OLS regression models, some of the coefficients on provinces are significant, reflecting the heterogeneity of provinces. However, the coefficients of all other demographic variables have barely changed. The signs and the significance of coefficients for all other demographic variables remain unchanged. The trend of change with the quantiles for all these coefficients is also similar. When we decompose the effects affecting HCFs inequality with the OB method, the results and the conclusions also remain unchanged, which indicates that the results are robust.

6. Conclusions and policy implications

The UQR are useful in indicating which factors are important in explaining changes in HCFs and the OB decomposition are good at quantifying the contributions of various factors to a difference in an accounting sense, which provide a reliable basis for policy implications and measures to mitigate HCFs and HCFs inequality especially for different populations and unobservable influencing factors. With application of the UQR and decomposition method in the survey data in China for 2012 and 2018, this paper focuses on studying the diverse effects of various driving factors on HCFs over quantiles and identifying the major causes of HCFs inequality over time. We find that there are great emission disparities among households over time. Income and other covariates are found to affect HCFs heterogeneously. We also show that the HCFs inequality at the top of the HCFs distribution (the 90-50 quantiles differential) contributes much more to the overall HCFs inequality than the HCFs inequality at the bottom (the 50-10 quantiles differential). More importantly, according to the results of OB decomposition, we discover that intertemporal lifestyle changes have played a dominant role in the increase of HCFs inequality.

It is of critical importance for the Chinese government to tackle the growing HCFs and the associated inequality without detrimentally impacting the steadily improving living standards. However, it is also a great challenge for the developing countries since the increase of carbon emissions usually go hand in hand with the growth of economy and improvement of well-being. In addition, neglecting the remarkable role of the intertemporal lifestyle changes may underestimate the challenges in emissions growth in the future from the household sector and undermine the effectiveness of policies to reduce HCFs inequality. Hence, the policymakers need to pay much more attention to the effect of lifestyles on HCFs and inequality and implement policies to avoid household consumption pattern continuous moving towards carbon-intensive lifestyles when encouraging the households to pursue higher living standards and boosting economic growth, especially the ones with higher HCFs.

Firstly, encouraging the formation of green consumerism and low carbon lifestyles. Policies should be taken to strengthen the residents' awareness of the relations of household consumption, carbon emissions and climate change risks, and cultivate residents' concept of low-carbon lifestyles. Meanwhile, to stimulate low-carbon consumption behavior and meet the consumption demand, the government should provide more low-carbon infrastructure, such as convenient public transport, and introduce carbon tax, energy saving and low-carbon subsidies, efficiency standards, carbon labels, etc., to encourage firms to produce more low-carbon and affordable products (Shi, 2013; 2015).

Secondly, designing differentiated mitigation policies for different households. For example, the government may design and implement the carbon tax recycling mechanism, which has been proved useful both in the reduction of HCFs inequality and in the improvement on the fairness and feasibility of climate policy. In addition, a personal carbon permit trading scheme could also be used to push high HCFs groups to reduce their HCFs.

Thirdly, promoting a low carbon city development model and enhancing the HCFs equality during urbanization. Since the urbanization in China contributes a lot in the increase of the HCFs at all quantiles, especially for the top ones, it is necessary to promote low carbon city models which can reduce HCFs without compromising the urban services. Rational urban layout, convenient public transport system, clean heating system, net zero carbon emissions buildings, zero carbon community and more green spaces are essential for the reduction of HCFs and the formation of low-carbon lifestyles.

The paper has some limitations and shortcomings, some of which could be addressed in future studies. Firstly, due to data availability, we only have a survey dataset with a span of 6 years to work with. We believe that additional data can make the results more trustable. Secondly, to maintain the data consistency, we use the national WIOD Input-Output Table instead of the world multi-regional Input-Output Table or China multi-regional IO table to calculate the HCFs, which may lead to some bias in the estimation of the HCFs. Thirdly, we have concluded that intertemporal lifestyle changes may play a dominant role in the evolution of the HCFs inequality in China, but we have not analyzed the mechanism of how intertemporal lifestyle changes impacts HCFs and the associated inequality. Future studies can extend the analysis in this paper to provide more robust and more detailed analysis as well as policy recommendations.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Inclusion and Diversity

We worked to ensure that the study questionnaires were prepared in an inclusive way. The author list of this paper includes contributors from the location where the research was conducted who participated in the data collection, design, analysis, and/or interpretation of the work.

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References

Allinson, D., Irvine, K.N., Edmondson, J.L., Tiwary, A., Hill, G., Morris, J., Bell, M., Davies, Z.G., Firth, S.K., Fisher, J., Gaston, K.J., Leake, J.R., McHugh, N., Namdeo, A., Rylatt, M., Lomas, K., 2016. Measurement and analysis of household carbon: The case of a UK city. Appl. Energy 164, 871–881. https://doi.org/10.1016/j.apenergy.2015.11.054

Andersson, D., Nässén, J., Larsson, J., Holmberg, J., 2014. Greenhouse gas emissions and subjective well-being: An analysis of Swedish households. Ecol. Econ. https://doi.org/10.1016/j.ecolecon.2014.03.018

Ang, B.W., 2004. Decomposition analysis for policymaking in energy: Which is the preferred method? Energy Policy. https://doi.org/10.1016/S0301-4215(03)00076-4

Ang, B.W., Zhang, F.Q., 2000. A survey of index decomposition analysis in energy and environmental studies. Energy. https://doi.org/10.1016/S0360-5442(00)00039-6

Baiocchi, G., Minx, J., Hubacek, K., 2010. The Impact of social factors and consumer behavior on carbon dioxide emissions in the United Kingdom. J. Ind. Ecol. https://doi.org/10.1111/j.1530-9290.2009.00216.x

Bin, S., Dowlatabadi, H., 2005. Consumer lifestyle approach to US energy use and the related CO2 emissions. Energy Policy. https://doi.org/10.1016/S0301-4215(03)00210-6

Blinder, A.S., 1973. Wage Discrimination: Reduced Form and Structural Estimates. J. Hum. Resour. 8, 436–455.

Borah, B.J., Basu, A., 2013. Highlighting differences between conditional and unconditional quantile regression approaches through an application to assess medication adherence, in: Health Economics (United Kingdom). https://doi.org/10.1002/hec.2927

Büchs, M., Schnepf, S. V., 2013. Who emits most? Associations between socio-economic factors and UK households' home energy, transport, indirect and total CO2 emissions. Ecol. Econ. https://doi.org/10.1016/j.ecolecon.2013.03.007

Carter, D.M., 2011. Recognizing the role of positive emotions in fostering environmentally responsible behaviors. Ecopsychology. https://doi.org/10.1089/eco.2010.0071

Chancel, L., 2014. Are younger generations higher carbon emitters than their elders? Inequalities, generations and CO2emissions in France and in the USA. Ecol. Econ. https://doi.org/10.1016/j.ecolecon.2014.02.009

Chen, C., Liu, G., Meng, F., Hao, Y., Zhang, Y., Casazza, M., 2019. Energy consumption and carbon footprint accounting of urban and rural residents in Beijing through Consumer Lifestyle Approach. Ecol. Indic. https://doi.org/10.1016/j.ecolind.2018.11.049

Chitnis, M., Druckman, A., Hunt, L.C., Jackson, T., Milne, S., 2012. Forecasting scenarios for UK household expenditure and associated GHG emissions: Outlook to 2030. Ecol. Econ. https://doi.org/10.1016/j.ecolecon.2012.09.016

Choi, K., Zhang, M., 2017. The impact of metropolitan, county, and local land use on driving emissions in US metropolitan areas: Mediator effects of vehicle travel characteristics. J. Transp. Geogr. https://doi.org/10.1016/j.jtrangeo.2017.09.004

de Boer, P., Rodrigues, J.F.D., 2020. Decomposition analysis: when to use which method? Econ. Syst.

Res. https://doi.org/10.1080/09535314.2019.1652571

Druckman, A., Jackson, T., 2009. The carbon footprint of UK households 1990-2004: A socio-economically disaggregated, quasi-multi-regional input-output model. Ecol. Econ. https://doi.org/10.1016/j.ecolecon.2009.01.013

Duarte, R., Mainar, A., Sánchez-Chóliz, J., 2010. The impact of household consumption patterns on emissions in Spain. Energy Econ. https://doi.org/10.1016/j.eneco.2009.08.007

Feng, K., Baiocchi, G., Hubacek, K., Sun, L., Muñoz Castillo, R., Xue, J., 2017. Global carbon inequality. Energy, Ecol. Environ. https://doi.org/10.1007/s40974-017-0072-9

Feng, K., Hubacek, K., Song, K., 2021. Household carbon inequality in the U.S. J. Clean. Prod. https://doi.org/10.1016/j.jclepro.2020.123994

Firpo, B.S., Fortin, N.M., Lemieux, T., 2009. Unconditional Quantile Regressions. Econometrica 77, 953–973. https://doi.org/10.3982/ecta6822

Firpo, S., Pinto, C., 2016. Identification and Estimation of Distributional Impacts of Interventions Using Changes in Inequality Measures. J. Appl. Econom. https://doi.org/10.1002/jae.2448

Firpo, S.P., Fortin, N.M., Lemieux, T., 2018. Decomposing wage distributions using recentered influence function regressions. Econometrics. https://doi.org/10.3390/econometrics6020028

Fortin, N., Lemieux, T., Firpo, S., 2011. Decomposition Methods in Economics, Handbook of Labor Economics. https://doi.org/10.1016/S0169-7218(11)00407-2

Gill, B., Moeller, S., 2018. GHG Emissions and the Rural-Urban Divide. A Carbon Footprint Analysis Based on the German Official Income and Expenditure Survey. Ecol. Econ. https://doi.org/10.1016/j.ecolecon.2017.09.004

Golley, J., Meng, X., 2012. Income inequality and carbon dioxide emissions: The case of Chinese urban households. Energy Econ. https://doi.org/10.1016/j.eneco.2012.07.025

Grossman, G.M., Krueger, A.B., 1995. Economic Growth and the Environment. Q. J. Econ. https://doi.org/10.2307/2118443

Guan, D., 2017. An index of inequality in China. Nat. Energy. https://doi.org/10.1038/s41560-017-0013-z

Han, Liyan, Xu, X., Han, Lu, 2015. Applying quantile regression and Shapley decomposition to analyzing the determinants of household embedded carbon emissions: Evidence from urban China. J. Clean. Prod. https://doi.org/10.1016/j.jclepro.2014.08.078

Hertwich, E.G., Peters, G.P., 2009. Carbon footprint of nations: A global, trade-linked analysis. Environ. Sci. Technol. https://doi.org/10.1021/es803496a

Hoekstra, R., Van Den Bergh, J.C.J.M., 2002. Structural decomposition analysis of physical flows in the economy. Environ. Resour. Econ. https://doi.org/10.1023/A:1021234216845

Hoekstra, R., van der Bergh, J.J.C.J.M., 2003. Comparing structural and index decomposition analysis.

Energy Econ. https://doi.org/10.1016/S0140-9883(02)00059-2

Irfany, M.I., Klasen, S., 2017. Affluence and emission tradeoffs: Evidence from Indonesian households' carbon footprint. Environ. Dev. Econ. https://doi.org/10.1017/S1355770X17000262

Ivanova, D., Stadler, K., Steen-Olsen, K., Wood, R., Vita, G., Tukker, A., Hertwich, E.G., 2016. Environmental Impact Assessment of Household Consumption. J. Ind. Ecol. https://doi.org/10.1111/jiec.12371

Ivanova, D., Vita, G., Steen-Olsen, K., Stadler, K., Melo, P.C., Wood, R., Hertwich, E.G., 2017. Mapping the carbon footprint of EU regions. Environ. Res. Lett. https://doi.org/10.1088/1748-9326/aa6da9

Ivanova, D., Wood, R., 2020. The unequal distribution of household carbon footprints in Europe and its link to sustainability. Glob. Sustain. https://doi.org/10.1017/sus.2020.12

Kahneman, D., Tversky, A., 2018. Prospect theory: An analysis of decision under risk, in: Experiments in Environmental Economics. pp. 143–172. https://doi.org/10.2307/1914185

Kennedy, E.H., Krahn, H., Krogman, N.T., 2014. Egregious Emitters: Disproportionality in Household Carbon Footprints. Environ. Behav. https://doi.org/10.1177/0013916512474986

Lee, S., Lee, B., 2014. The influence of urban form on GHG emissions in the U.S. household sector. Energy Policy. https://doi.org/10.1016/j.enpol.2014.01.024

Lévay, P.Z., Vanhille, J., Goedemé, T., Verbist, G., 2021. The association between the carbon footprint and the socio-economic characteristics of Belgian households. Ecol. Econ. https://doi.org/10.1016/j.ecolecon.2021.107065

Li, J., Zhang, D., Su, B., 2019. The Impact of Social Awareness and Lifestyles on Household Carbon Emissions in China. Ecol. Econ. 160, 145–155. https://doi.org/10.1016/j.ecolecon.2019.02.020

Li, X., Ouyang, Z., Zhang, Q., Shang, W. long, Huang, L., Wu, Y., Gao, Y., 2022. Evaluating food supply chain emissions from Japanese household consumption. Appl. Energy. https://doi.org/10.1016/j.apenergy.2021.118080

López, L.A., Arce, G., Serrano, M., 2020. Extreme Inequality and Carbon Footprint of Spanish Households. Environ. Footprints Eco-Design Prod. Process. 35–53. https://doi.org/10.1007/978-981-13-7916-1_2

Lutzenhiser, L., Gossard, M.H., 2000. Lifestyle, status and energy consumption. Proc. Am. Counc. an Energy Effic. Econ. Washington, DC. https://doi.org/10.4236/epe.2015.710045

Lyons, S., Pentecost, A., Tol, R.S.J., 2012. Socioeconomic distribution of emissions and resource use in Ireland. J. Environ. Manage. 112, 186–198. https://doi.org/10.1016/j.jenvman.2012.07.019

Maraseni, T.N., Qu, J., Yue, B., Zeng, J., Maroulis, J., 2016. Dynamism of household carbon emissions (HCEs) from rural and urban regions of northern and southern China. Environ. Sci. Pollut. Res. https://doi.org/10.1007/s11356-016-7237-5

Maraseni, T.N., Qu, J., Zeng, J., 2015. A comparison of trends and magnitudes of household carbon emissions between China, Canada and UK. Environ. Dev. https://doi.org/10.1016/j.envdev.2015.04.001

Markaki, M., Belegri-Roboli, A., Sarafidis, Mirasgedis, S., 2017. The carbon footprint of Greek households (1995–2012). Energy Policy 100, 206–215. https://doi.org/10.1016/j.enpol.2016.10.031

Mi, Z., Zheng, J., Meng, J., Ou, J., Hubacek, K., Liu, Z., Coffman, D., Stern, N., Liang, S., Wei, Y.-M., 2020. Economic development and converging household carbon footprints in China. Nat. Sustain. 1–9. https://doi.org/10.1038/s41893-020-0504-y

Miehe, R., Scheumann, R., Jones, C.M., Kammen, D.M., Finkbeiner, M., 2016. Regional carbon footprints of households: a German case study. Environ. Dev. Sustain. https://doi.org/10.1007/s10668-015-9649-7

Munksgaard, J., Pedersen, K.A., Wien, M., 2000. Impact of household consumption on CO2 emissions. Energy Econ. https://doi.org/10.1016/S0140-9883(99)00033-X

Oaxaca Ronald, 1973. Male-Female Wage Differentials in Urban Labor Markets. Int. Econ. Rev. (Philadelphia). https://doi.org/10.1080/00420980020080431

Oswald, Y., Owen, A., Steinberger, J.K., 2020. Large inequality in international and intranational energy footprints between income groups and across consumption categories. Nat. Energy. https://doi.org/10.1038/s41560-020-0579-8

Oxfam, 2015. Extreme Carbon Inequality. URL https://www-cdn.oxfam.org/s3fs-public/file_attachments/mb-extreme-carbon-inequality-021215-en.pdf

Parag, Y., Darby, S., 2009. Consumer-supplier-government triangular relations: Rethinking the UK policy path for carbon emissions reduction from the UK residential sector. Energy Policy. https://doi.org/10.1016/j.enpol.2009.04.044

Peters, G.P., Hertwich, E.G., 2008. Post-Kyoto greenhouse gas inventories: Production versus consumption. Clim. Change. https://doi.org/10.1007/s10584-007-9280-1

Qu, J., Zeng, J., Li, Y., Wang, Q., Maraseni, T., Zhang, L., Zhang, Z., Clarke-Sather, A., 2013. Household carbon dioxide emissions from peasants and herdsmen in northwestern arid-alpine regions, China. Energy Policy. https://doi.org/10.1016/j.enpol.2012.12.065

Ravallion, M., Heil, M., Jalan, J., 2000. Carbon emissions and income inequality. Oxf. Econ. Pap. https://doi.org/10.1093/oep/52.4.651

Rong, P., Zhang, L., Qin, Y., Chen, S., Sun, Y., 2018. The influencing factors of urban household embedded carbon emissions based on quantile regression, in: Energy Procedia. https://doi.org/10.1016/j.egypro.2018.09.238

Salo, M., Savolainen, H., Karhinen, S., Nissinen, A., 2021. Drivers of household consumption expenditure and carbon footprints in Finland. J. Clean. Prod. https://doi.org/10.1016/j.jclepro.2020.125607

Schipper, L., 1989. Linking Life-Styles And Energy Use: A Matter Of Time. Annu. Rev. Energy Environ. https://doi.org/10.1146/annurev.energy.14.1.273

Seriño, M.N. V., Klasen, S., 2015. Estimation and determinants of the Philippines' household carbon footprint. Dev. Econ. https://doi.org/10.1111/deve.12065

Shi, X., 2015. Application of best practice for setting minimum energy efficiency standards in technically disadvantaged countries: Case study of Air Conditioners in Brunei Darussalam. Appl. Energy. https://doi.org/10.1016/j.apenergy.2015.07.071

Shi, X., 2013. Spillover effects of carbon footprint labelling on less developed countries: The example of the east asia summit region. Dev. Policy Rev. 31, 239–254. https://doi.org/10.1111/dpr.12005

Shi, X., Wang, K., Cheong, T.S., Zhang, H., 2020. Prioritizing driving factors of household carbon emissions: An application of the LASSO model with survey data. Energy Econ. https://doi.org/10.1016/j.eneco.2020.104942

Sommer, M., Kratena, K., 2017. The Carbon Footprint of European Households and Income Distribution. Ecol. Econ. https://doi.org/10.1016/j.ecolecon.2016.12.008

Tomás, M., López, L.A., Monsalve, F., 2020. Carbon footprint, municipality size and rurality in Spain: Inequality and carbon taxation. J. Clean. Prod. https://doi.org/10.1016/j.jclepro.2020.121798

van den Berg, N.J., Hof, A.F., Akenji, L., Edelenbosch, O.Y., van Sluisveld, M.A.E., Timmer, V.J., van Vuuren, D.P., 2019. Improved modelling of lifestyle changes in Integrated Assessment Models: Cross-disciplinary insights from methodologies and theories. Energy Strateg. Rev. https://doi.org/10.1016/j.esr.2019.100420

Vogt-Schilb, A., Walsh, B., Feng, K., Di Capua, L., Liu, Y., Zuluaga, D., Robles, M., Hubaceck, K., 2019. Cash transfers for pro-poor carbon taxes in Latin America and the Caribbean. Nat. Sustain. 2, 941–948. https://doi.org/10.1038/s41893-019-0385-0

Wang, H., Ang, B.W., Su, B., 2017. Assessing drivers of economy-wide energy use and emissions: IDA versus SDA. Energy Policy. https://doi.org/10.1016/j.enpol.2017.05.034

Wang, Z., Wang, X., Peng, S., Ming, L., Cui, C., Niu, B., 2020. Interactions between households and industrial sectors in embodied carbon emission networks. J. Clean. Prod. https://doi.org/10.1016/j.jclepro.2020.123809

Wei, L., Li, C., Wang, J., Wang, X., Wang, Z., Cui, C., Peng, S., Liu, Y., Yu, S., Wang, L., Shi, Z., 2020. Rising middle and rich classes drove China's carbon emissions. Resour. Conserv. Recycl. 159, 104839. https://doi.org/10.1016/j.resconrec.2020.104839

Wei, L., Li, M., Zuo, J., Wang, X., Wang, Z., Wang, J., Yan, H., Liu, S., Peng, S., Hong, S., Lenzen, M., 2021. Carbon spillover and feedback effects of the middle class in China. J. Clean. Prod. 329, 129738. https://doi.org/10.1016/j.jclepro.2021.129738

Wiedenhofer, D., Guan, D., Liu, Z., Meng, J., Zhang, N., Wei, Y.M., 2017. Unequal household carbon footprints in China. Nat. Clim. Chang. https://doi.org/10.1038/nclimate3165

Wilson, J., Tyedmers, P., Spinney, J.E.L., 2013. An exploration of the relationship between socioeconomic and well-being variables and household greenhouse gas emissions. J. Ind. Ecol. https://doi.org/10.1111/jiec.12057

Xu, X., Han, L., Lv, X., 2016. Household carbon inequality in urban China, its sources and determinants. Ecol. Econ. https://doi.org/10.1016/j.ecolecon.2016.04.015

Yang, T., Liu, W., 2017. Inequality of household carbon emissions and its influencing factors: Case study of urban China. Habitat Int. 70, 61–71. https://doi.org/10.1016/j.habitatint.2017.10.004

Yu, F., Dong, H., Geng, Y., Fang, A.S., Li, H., 2022. Uncovering the differences of household carbon footprints and driving forces between China and Japan. Energy Policy 165, 112990. https://doi.org/10.1016/j.enpol.2022.112990

Zhang, H., Shi, X., Wang, K., Xue, J., Song, L., Sun, Y., 2020. Intertemporal lifestyle changes and carbon emissions: Evidence from a China household survey. Energy Econ. 86, 104655. https://doi.org/10.1016/j.eneco.2019.104655

Zhang, X., Luo, L., Skitmore, M., 2015. Household carbon emission research: An analytical review of measurement, influencing factors and mitigation prospects. J. Clean. Prod. 103, 873–883. https://doi.org/10.1016/j.jclepro.2015.04.024

Zhang, X., Wang, Y., 2017. How to reduce household carbon emissions: A review of experience and policy design considerations. Energy Policy 102, 116–124. https://doi.org/10.1016/j.enpol.2016.12.010

Zheng, S., Wang, R., Glaeser, E.L., Kahn, M.E., 2011. The greenness of China: Household carbon dioxide emissions and urban development. J. Econ. Geogr. https://doi.org/10.1093/jeg/lbq031

Appendix A.

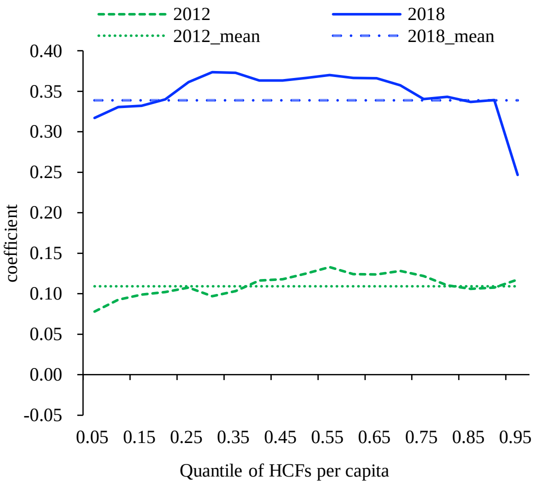
Table A1. Results of the UQR and OLS regression with province dummy

	2012				2018			
	Uq10	Uq50	Uq90	Mean	Uq10	Uq50	Uq90	Mean
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Income	0.093***	0.125***	0.108***	0.109***	0.330***	0.366***	0.339***	0.339***
	(0.014)	(0.011)	(0.013)	(0.005)	(0.021)	(0.013)	(0.025)	(0.007)
Urbanization	0.380***	0.209***	0.131***	0.231***	0.187***	0.105***	-0.021	0.094***
	(0.031)	(0.027)	(0.029)	(0.013)	(0.041)	(0.026)	(0.039)	(0.013)
Family size	-0.394***	-0.444***	-0.406***	-0.399***	-0.184***	-0.341***	-0.435***	-0.310***
	(0.036)	(0.024)	(0.033)	(0.013)	(0.030)	(0.019)	(0.036)	(0.011)

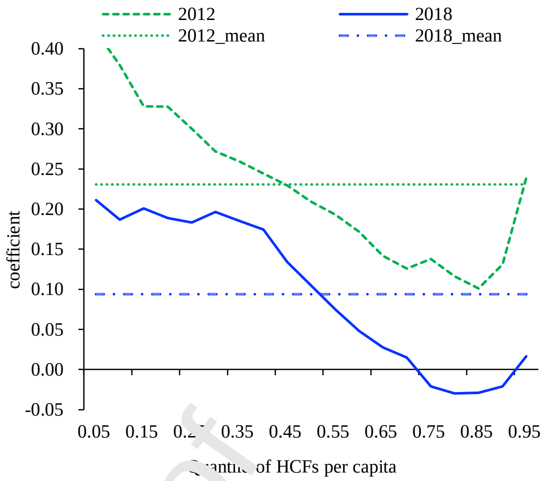
Education	0.036	0.161***	0.132***	0.116***	-0.024	0.156***	0.115**	0.096***
	(0.029)	(0.027)	(0.042)	(0.014)	(0.027)	(0.027)	(0.050)	(0.013)
Age	-0.232***	-0.161***	-0.232***	-0.203***	-0.178***	-0.113***	-0.292***	-0.160***
	(0.048)	(0.038)	(0.053)	(0.020)	(0.041)	(0.034)	(0.064)	(0.018)
Marital status	0.248***	0.207***	-0.016	0.148***	0.164***	0.045	-0.075	0.047***
	(0.048)	(0.034)	(0.048)	(0.018)	(0.057)	(0.037)	(0.067)	(0.018)
Low-rise Building	0.070**	-0.197***	-0.196***	-0.129***	-0.022	-0.117***	-0.039	-0.069***
	(0.034)	(0.037)	(0.058)	(0.019)	(0.055)	(0.041)	(0.059)	(0.020)
Bungalow/Courtyard	-0.034	-0.364***	-0.354***	-0.256***	0.012	-0.120***	-0.031	-0.061***
	(0.032)	(0.036)	(0.051)	(0.018)	(0.039)	(0.034)	(0.059)	(0.017)
Villa/Townhouse	0.104	0.381***	0.290	0.226***	0.515***	-0.280*	-0.324***	-0.096
	(0.105)	(0.105)	(0.339)	(0.082)	(0.148)	(0.148)	(0.104)	(0.096)
Coal gas/LNG/Natural gas	0.221***	0.302***	0.111***	0.211***	0.237***	0.216	0.155***	0.213***
	(0.035)	(0.031)	(0.039)	(0.016)	(0.0[illegible]8)	(0.028)	(0.050)	(0.015)
Coal	0.358***	0.566***	0.446***	0.468***	0.62[illegible]**	0.672***	0.623***	0.641***
	(0.058)	(0.052)	(0.069)	(0.026)	(0.0[illegible]4)	(0.062)	(0.102)	(0.036)
Firewood/Straw	-0.184***	0.007	0.099***	-0.03[illegible]**	-0.232***	0.211***	0.291***	0.139***
	(0.049)	(0.032)	(0.032)	(0.0[illegible]6)	(0.061)	(0.032)	(0.048)	(0.017)
_cons	0.622***	1.499***	2.966***	1.[illegible]46***	0.566***	1.515***	3.397***	1.660***
	(0.191)	(0.159)	(0.231)	(0.086)	(0.187)	(0.156)	(0.288)	(0.080)
Province Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjust R^2	0.120	0.263	0.111	0.352	0.150	0.321	0.151	0.441
N		12277				13424		

Notes: ***, **, * are statistically significant at the 1%, 5%, 10% level.
Standard error in parenthesis.

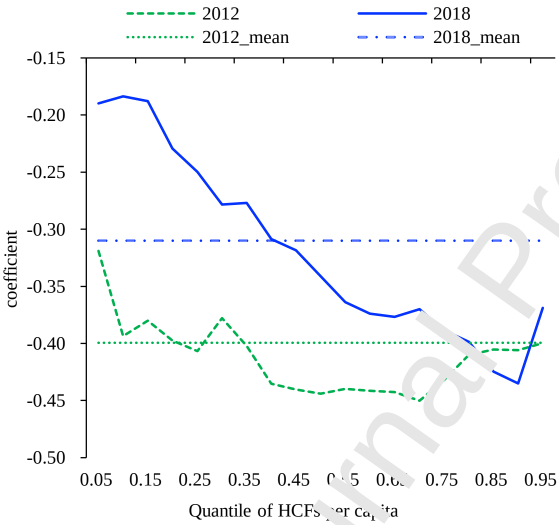
Appendix B.



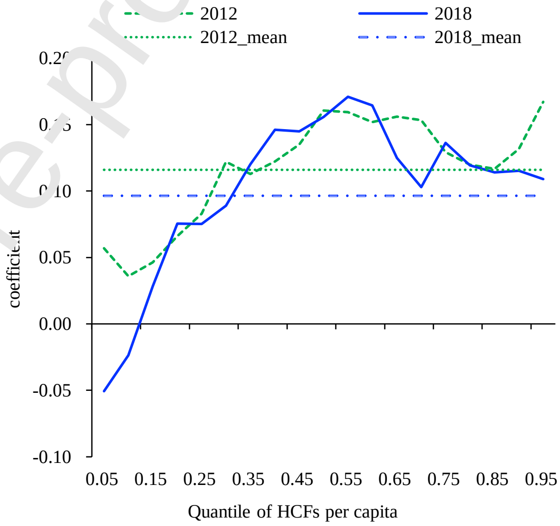
(a) Income



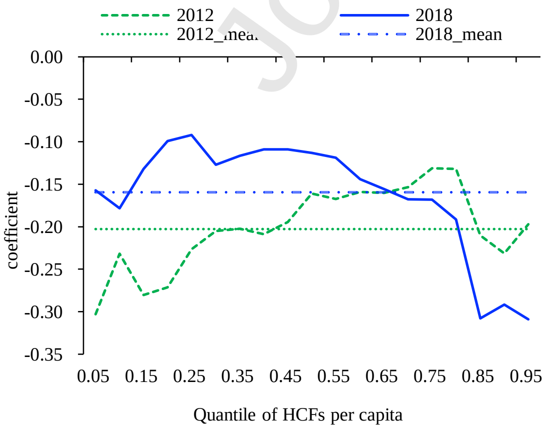
(b) Urbanization (rural=0)



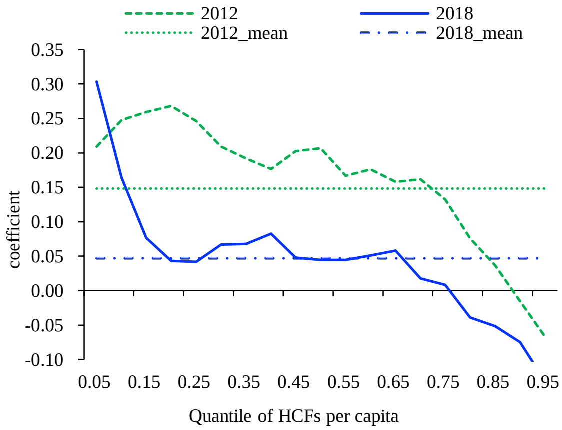
(c) Family size



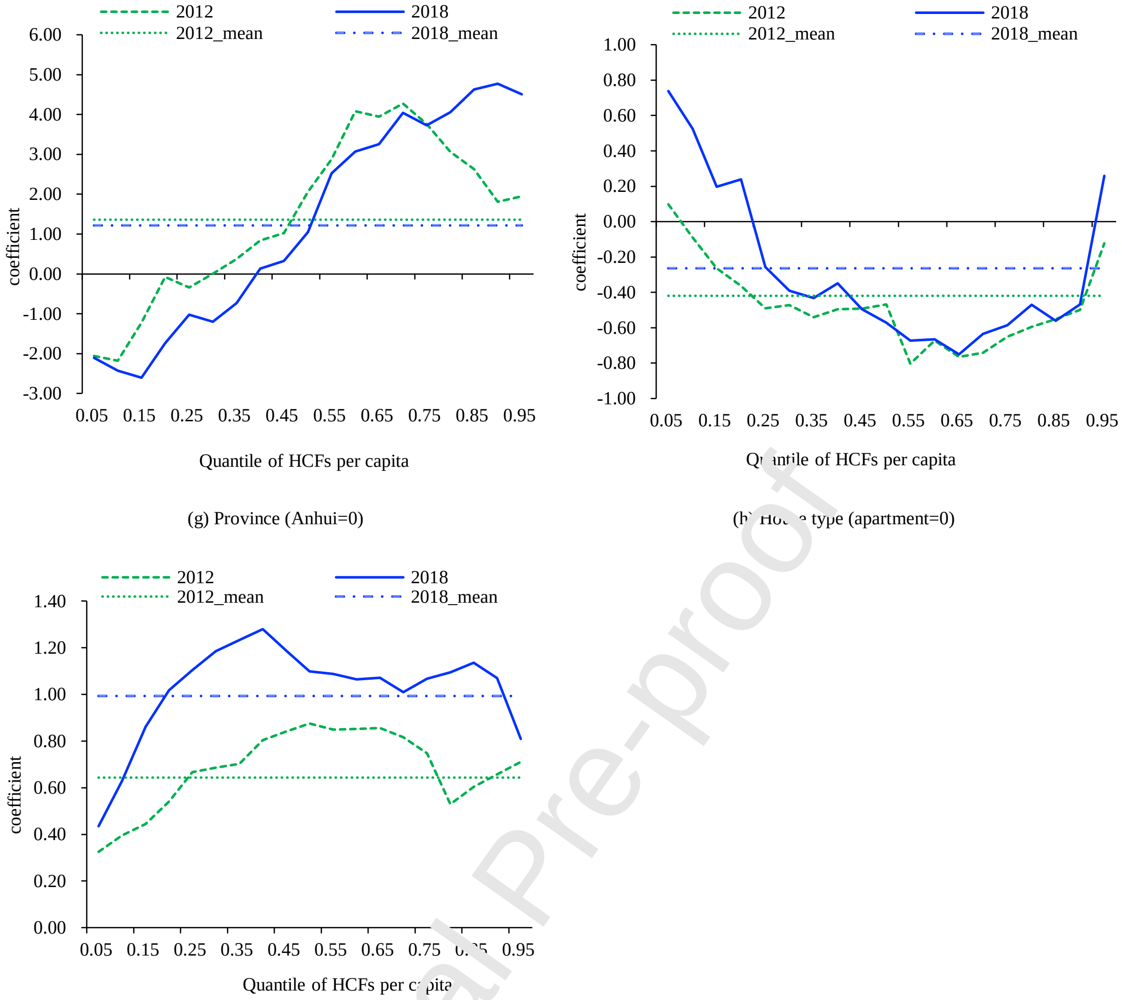
(d) Education (low education=0)



(e) Age



(f) Marital status (single=0)



(g) Province (Anhui=0)

(h) House type (apartment=0)

(i) Fuel type (electricity=0)

Figure A1. The effects of the households' demographics on HCFs per capita over different quantiles with province dummy

Appendix C.

Table A2. Decomposition results of the quantile differentials in the HCFs with province dummy

Percentile difference	**Uq10** (1)	**Uq50** (2)	**Uq90** (3)	**Mean** (4)
Overall group (t_0=*2012*)	-0.439^{***}	0.601^{***}	1.538^{***}	0.574^{***}
Overall group (t_1=*2018*)	0.070^{***}	1.128^{***}	2.163^{***}	1.118^{***}
Total Percentile difference	0.509^{***}	0.527^{***}	0.624^{***}	0.543^{***}
(t_1-t_0)	(0.020)	(0.016)	(0.023)	(0.012)
Total Endowment effect	0.259^{***}	0.284^{***}	0.237^{***}	0.255^{***}
	(0.011)	(0.009)	(0.013)	(0.008)
Income	0.141^{***}	0.165^{***}	0.151^{***}	0.150^{***}
	(0.010)	(0.007)	(0.010)	(0.006)
Urbanization	0.031^{***}	0.018^{***}	0.007^{***}	0.018^{***}
	(0.003)	(0.002)	(0.003)	(0.002)
Family size	0.038^{***}	0.053^{***}	0.058^{***}	0.048^{***}
	(0.003)	(0.003)	(0.004)	(0.003)
Education	0.002	0.014^{***}	0.011^{***}	0.010^{***}
	(0.002)	(0.002)	(0.003)	(0.001)
Age	0.008^{***}	0.005^{***}	0.010^{***}	0.007^{***}
	(0.001)	(0.001)	(0.002)	(0.001)
Marital Status	0.006^{***}	0.004^{***}	0.000	0.003^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
Province	0.000	0.004^{**}	0.008^{***}	0.003^{**}
	(0.002)	(0.002)	(0.002)	(0.001)
House type	-0.008^{**}	0.013^{***}	0.010^{***}	0.006^{***}
	(0.004)	(0.003)	(0.004)	(0.002)
Fuel type	0.043^{***}	0.008^{**}	-0.017^{***}	0.010^{***}
	(0.005)	(0.004)	(0.004)	(0.003)
Total Structure effect	0.250^{***}	0.243^{***}	0.387^{***}	0.288^{***}
	(0.022)	(0.016)	(0.022)	(0.011)
Income	0.013^{***}	0.015^{***}	0.012^{***}	0.014^{***}
	(0.003)	(0.003)	(0.003)	(0.002)
Urbanization	-0.110^{***}	-0.060^{***}	-0.087^{***}	-0.079^{***}
	(0.029)	(0.021)	(0.028)	(0.015)
Family size	0.238^{***}	0.115^{***}	-0.038	0.099^{***}
	(0.053)	(0.035)	(0.056)	(0.026)
Education	-0.018	-0.003	-0.006	-0.007
	(0.011)	(0.011)	(0.018)	(0.007)
Age	0.205	0.183	-0.234	0.166
	(0.245)	(0.196)	(0.321)	(0.136)
Marital Status	-0.074	-0.144^{***}	-0.053	-0.090^{***}
	(0.066)	(0.044)	(0.073)	(0.033)
Province	0.010	-0.028	0.116^{**}	0.008
	(0.055)	(0.045)	(0.057)	(0.030)
House type	0.040	0.145^{***}	0.177^{***}	0.120^{***}
	(0.029)	(0.033)	(0.055)	(0.021)
Fuel type	0.003	0.004	0.067^{*}	0.043^{**}
	(0.039)	(0.027)	(0.040)	(0.019)
_cons	-0.057	0.016	0.432	0.014
	(0.267)	(0.223)	(0.369)	(0.153)

Notes: ***, **, * are statistically significant at the 1%, 5%, 10% level.
Standard error in parenthesis.

Appendix D.

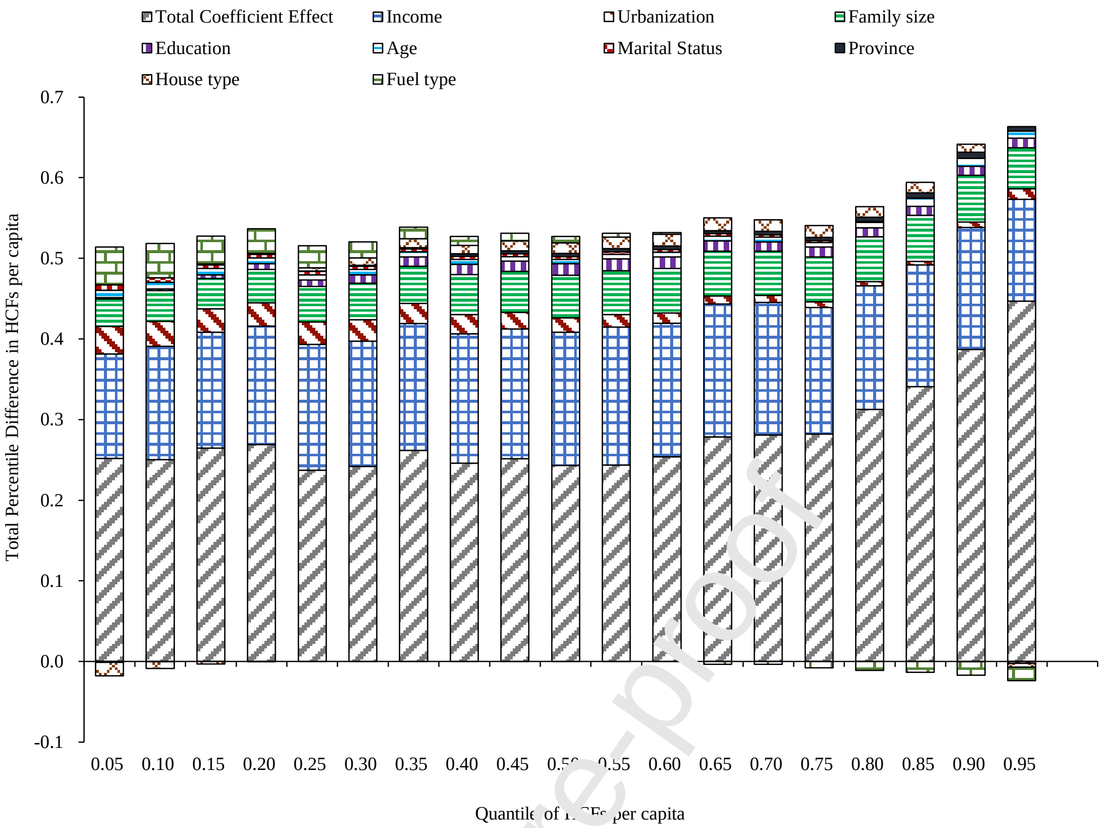


Figure A2. The endowment effect and the structure effect with province dummy

Appendix E.

Table A3. Results of the decomposition of the dynamics changes in the HCFs inequality with province dummy

Percentile difference	**Uq90-Uq10** (1)	**Uq90-Uq50** (2)	**Uq50-Uq10** (3)	**Gini index** (4)
Overall group (t_0=*2012*)	1.978	0.936	1.042	0.395
Overall group (t_1=*2018*)	2.089	1.031	1.057	0.417
Total Percentile difference (t_1-t_0)	0.111	0.096	0.015	0.021
Total Endowment Effect	-0.014	-0.057	0.042	-0.008
Income	0.011	-0.011	0.022	0.001
Urbanization	-0.027	-0.008	-0.018	-0.002
Family size	-0.002	-0.004	0.006	-0.001
Education	0.008	-0.002	0.010	0.001
Age	0.000	0.002	-0.002	0.000
Married Status	-0.007	-0.006	-0.001	-0.002
Province	0.009	0.002	0.008	0.001
House type	0.040	0.004	0.036	0.003
Fuel type	-0.048	-0.033	-0.018	-0.008
Total structure effect	0.125	0.152	-0.027	0.029
Income	0.004	-0.003	0.001	-0.007
Urbanization	0.030	-0.029	0.058	-0.014
Family size	-0.257	-0.139	-0.117	-0.027
Education	0.013	-0.006	0.019	-0.002
Age	-0.466	-0.439	-0.027	-0.122
Marital Status	0.019	0.093	-0.074	0.023
Province	0.091	0.137	-0.046	0.015
House type	0.133	0.036	0.097	0.003
Fuel type	0.047	0.065	-0.018	-0.001
_cons	0.511	0.438	0.080	0.159

Credit Author Statement

Keying Wang: Writing-Original draft preparation, Data curation, Methodology, Software, Visualization, Validation, Writing- Reviewing and Editing

Yongyan Cui: Data curation, Visualization, Validation

Hongwu Zhang: Writing-Original draft preparation, Methodology, Software, Validation, Writing-Reviewing and Editing

Xunpeng Shi: Conceptualization, Validation, Writing-Reviewing

Jinjun Xue: Conceptualization, Validation, Writing-Reviewing

Zhao Yuan: Editing, Validation, Writing- Reviewing

Inclusion and Diversity

We worked to ensure that the study questionnaires were prepared in an inclusive way. The author list of this paper includes contributors from the location where the research was conducted who participated in the data collection, design, analysis, and/or interpretation of the work.

Highlights

- Unconditional quantile regression is used to investigate the distributional features of HCFs.
- HCFs are unequally distributed due to differences in the scale and pattern of consumption.
- Intertemporal lifestyle changes account for a major part of the rise of HCFs inequality.
- Policies are needed to enhance environmental equity and encourage low-carbon lifestyles.