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Expansion of social networks and household carbon emissions: Evidence from household survey in China

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ABSTRACT

As a factor influencing household consumption behavior, the expansion of social networks has an important impact on household carbon emissions (HCEs). Based on survey data from the China Family Panel Studies from 2014 to 2018, we explored the impacts of the expansion of social networks on HCEs and its mechanism. We further analyzed the heterogeneous effects of household income level and characteristics of household heads on HCEs, including age and education level. Our results show that the expansion of social networks can increase HCEs through enlarging consumption quantity and upgrading consumption structure, which is motivated by the comparison behavior based on status-seeking. In addition, the expansion of social networks has a bigger impact on HCEs when the head of household is younger, the head of household has a higher level of education, and the per capita income of the household is higher. These findings suggest that adjusting consumer behavior through the expansion of social networks, cultivating green consumption concepts, and promoting the consumption of low-carbon products may become important strategies to mitigate HCEs.

1. Introduction

The climate crisis is the most urgent threat of our time. There is a fifty-fifty chance that global warming will exceed 1.5 °C in the next two decades unless there are immediate, rapid and large-scale reductions in GHG emissions (UNEP, 2020). China has approximately one-fifth of the world's population, and its carbon emissions in 2019 were roughly 9.8 billion tons, representing about 28% of global carbon emissions, with consumption-side carbon emissions accounting for nearly 52% of China's total carbon emissions (Friedlingstein et al., 2019). And China's continued industrialization and urbanization have led to a constant increase in total carbon emissions in 2020 (Guan et al., 2021). China is aiming to reach carbon peaking by 2030 and achieve carbon neutrality by 2060 (3060 goals), which is not only a central objective of China's climate change mitigation efforts, but also a necessary step for global emissions to peak. Green consumption concepts and lifestyle changes are considered necessary for long-term greenhouse gas emission reduction. Over the past two decades, China has focused mainly on how to reduce carbon emissions from the productive sector but not attach importance to households' carbon emissions, which are the ultimate drivers of carbon emissions in the productive sector (Jun Li et al., 2019).

China's household carbon emissions will climb close to the peak as China's household income and energy consumption increase. At the global level, about two-thirds of global emissions are linked to private household activities according to consumption-based accounting (UNEP, 2020). China's final consumption expenditure accounts for 56% of the country's GDP, and the corresponding percentages for the US, Japan, Germany, and the UK are 81.2%, 74.3%, 72.2%, and 83.1%, respectively.[1] Compared with developed countries, there is still plenty of room for China's final consumption to increase. The indirect carbon emissions from household consumption, compared with 2008, increased by 83.43%–2401 million tons in 2020 and will increase by 55% from 2020 to 2030, reaching 3735 million tons (Xia et al., 2019). However, China's household energy consumption level is at a low level in the world, only 1/3 of the United States and 1/2 of the United Kingdom (Zheng, 2016). At present, China is still in the stage of deepening urban-

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ization, and per capita energy consumption and carbon emissions are still not at their peak.

Household carbon emissions can be driven by many factors. The existing literature found that income, education, demographic structure, and household lifestyle can influence HCEs (Han et al., 2015; Li et al., 2019; Lyu et al., 2019; Zhang et al., 2015; Sager, 2019). However, given that social networks have a significant effect on residents' daily life (Liu et al., 2019), household carbon emissions can also be influenced by the expansion of social networks which can make households pay more attention to others' consumption and cause a comparison behavior. Several researchers have argued that people are constantly exposed to information about others and may be pushed to compare themselves, regardless of whether they choose to (Stapel and Blanton, 2004; Wood, 1996). Social network expansion, that is, the increase of engagement and connection with others, opens up a wide range of opportunities for social comparison, and these comparisons are automatically motivated by intrinsic characteristics such as human self-esteem, self-evaluation and social identity (Hogg, 2000; Vogel et al., 2014; Sabatini and Sarracino, 2016). The need for the class identity of the consumer will not only encourage households to consume more but also make household consumption more inclined to conspicuous goods, which may lead to higher carbon emissions. Achieving 3060 goals is a broad and profound economic and social systemic change for China. The expansion of social networks has an important influence on the formation of green consumption concepts, which ultimately affect carbon emissions and is part of a social systemic transformation under the 3060 goals. Therefore, it is necessary to explore the impact of the expansion of social networks on HCEs.

Based on the data from the China Family Panel Studies (CFPS) in 2014, 2016, and 2018, we explored the impact of the expansion of social networks on HCEs. The results showed that the expansion of social networks had significantly increased HCEs. Further analysis showed that the expansion of social networks increased HCEs by household comparison consumption behavior based on social status-seeking motivation. In addition, heterogeneity analysis showed that the expansion of social networks had a bigger impact on HCEs of the households with a young head, households with a high-educated head and high-income households.

The main contributions of this paper include the following. First, based on China's Household Panel Study and World Input–Output Database (WIOD), we calculated the direct HCEs using the emissions coefficient method and indirect HCEs using input–output modeling (IOM). Second, our study investigates the impact of the expansion of social networks on household carbon emissions by using microdata from China. Existing studies mainly examine the influencing factor of household carbon emissions from the perspective of income, lifestyle, policy, and demographic structure (Li et al., 2019; Zhang et al., 2015; Sager, 2019). There is no research that pays attention to the impact of the expansion of social networks on household carbon emissions at the micro-level. Third, Our research verifies the intermediary mechanism of comparison consumption between social network expansion and household carbon emissions. The existing studies on the impact of household carbon emissions mainly come from income and credit constraint channels (Fan et al., 2021; Zhang et al., 2020), but we considered the comparison behavior based on status-seeking motivation.

The paper proceeds as follows: Section 2 states the hypotheses analysis. Section 3 describes data and methodology. Section 4 presents the empirical analysis. Section 5 illustrates our analysis of heterogeneous effects. Section 6 discusses findings and presents a conclusion with policy implications.

2. Theoretical framework and hypothesis

Psychological research showed that an individual's happiness was determined by relative consumption compared with the surrounding groups (Liu and Wang, 2020). Relative consumption is important because it is closely related to social status. Mattan et al. (2017) showed that social status was the ranking of individuals or groups generally recognized in society. An important basis for ranking status is household wealth, which should be revealed through consumption (Nelissen and Meijers, 2011). The main reasons why individuals seek social status are as follows: First, the improvement of relative status can show ability, enhance self-esteem and self-confidence, and obtain greater spiritual satisfaction. Second, it is easier to gain the trust and respect of others if you join a higher social class, so you can get more indirect returns in many aspects such as business, job hunting, mate selection, and so on. Therefore, the comparison behavior is induced by the intrinsic motivation of human beings to pursue social status.

The expansion of social networks may have an impact on HCEs through comparison behavior based on status-seeking motivation. Social networks allow contact between people and function as a means of communicating and exchanging information and provide a basis for the realization of status-seeking. Existing literature finds that the expansion of social networks can improve households' status-seeking motivation, and the external expression of internal status-seeking motivation is comparison consumption (Gao et al., 2016; Sabatini and Sarracino, 2016). With the expansion of social networks, an individual's motivation for status-seeking is often stronger (Liu et al., 2019). First, driven by the upward comparison behavior, the expansion of social networks may increase the amount of household consumption, thereby resulting in more HCEs. When the household social network expands, the household may pay more attention to the consumption of the surrounding groups, resulting in comparison psychology (Duesenberry, 1949). In the context of comparative effects based on status-seeking motivation, households may tend to be in line with the consumption of high-status households, thereby increasing their consumption, which brings more HCEs. Second, the expansion of social networks may promote the upgrading of household consumption structure, thus increasing high carbon consumption. Class identity is an important factor in maintaining social networks (Park et al., 2015). The need for class identity may also encourage households to consume more hedonically, such as by buying large cars and buying high-end gifts, and lead to higher household carbon consumption (Tian et al., 2016). According to the research on China's household consumption data, Yuan et al. (2015) shows that consumption upgrading will significantly increase HCEs. Although consumption upgrading often looks more environmentally friendly, its high carbon attribute is more embodied on the production side.

In summary, the expansion of social networks can increase the quantity and upgrade the structure of household consumption through comparative behavior, thereby increasing HCEs. Therefore, we proposed Hypothesis 1 and 2.

Hypothesis 1. The expansion of social networks can increase HCEs.

Hypothesis 2. The expansion of social networks can increase HCEs through comparison behavior.

Different age characteristics of household heads may affect the impact of social network expansion on HCEs. Existing studies show that household consumption expenditure decreases with the increase of the age of the head of household (Zhang and Guo, 2020). Households with an elder head tend to be more rational and cautious in the face of consumption. However, under the influence of comparative behavior, households with a young head are more likely to consume on impulse, which may enhance the influence of comparison behavior (Kim et al., 2014). Therefore, we proposed hypothesis 3.

Hypothesis 3. Compared with households that had an old head, the expansion of social networks has a bigger impact on HCEs among households with a young head.

The impact of social network expansion on HCEs may show heterogeneity among households with a head who had different educational levels. Individuals with higher education often have a higher subjective class identity, which can enable them to obtain material or spiritual satisfaction (Easterbrook et al., 2020). From the perspective of self-esteem, the education level is closely related to subjective social status since an individual can obtain self-esteem from identities that can provide them with a sense of social status (Becker et al., 2014; Easterbrook and Vignoles, 2012). This makes them have a higher tendency of comparison to maintain their class or join a higher class. Therefore, we proposed hypothesis 4.

Hypothesis 4. Compared with households that had a low-educated head, the expansion of social networks has a bigger impact on HCEs with households with a high-educated head.

Different income characteristics of households may affect the impact of social network expansion on HCEs. Since the income status of households will affect the budget constraints supporting the comparison behavior, the expansion of social networks has a much greater positive effect on household consumption in high-income households than in low-income households (Arun et al., 2016). Even if low-income households are willing to consume more or have more expenses for high-carbon goods, they may be put off by budget constraints, which weaken the influence of the comparison behavior. Therefore, we proposed Hypothesis 5.

Hypothesis 5. Compared with low-income households, the expansion of social networks has a greater impact on HCEs among high-income households.

3. Data and methodology

3.1. Data

3.1.1. Data processing

Our datasets had three main components: household data from the China Family Panel Studies, China's input–output table from the World Input-Output Database (WIOD), and carbon emissions of China's 35 sectors from the WIOD. We calculated direct HCEs based on household fuel consumption expenditure, and the rest of the consumption expenditure was used to calculate indirect HCEs. Therefore, we added up direct HCEs and indirect HCEs to get total HCEs.

The household data used in this paper were derived from the China Family Panel Studies (CFPS) carried out nationwide by the Institute of Social Science Survey of Peking University, which has five rounds of surveys, occurring in 2010, 2012, 2014, 2016 and 2018. The sample surveys nearly 15,000 households each year, covering 31 provinces in China. To maintain the consistency of the data, we obtained all the information on income, consumption, and demographic data of each household from the CFPS dataset for 2014, 2016, and 2018.[2] The CFPS collects 26 categories of consumption expenditure data. After excluding the Financial Support for relatives, others, and social donations, we obtained 23 categories of consumption expenditure. Although China is a typical "relationship" society, using our sample can still reflect the relationship between social network expansion and household carbon emissions to a certain extent. Firstly, resident social network expansion is common in different cultural contexts (Adler and Kwon, 2002; Woolcock, 2010). Albeit Chinese residents' tendency to pursue social network expansion is partly influenced by traditional cultures, such as Confucianism, some scholars believe that it is institutionally driven, since the higher the degree of economic development and the greater the maturity of the institutions, the fewer people will be included to use informal ties (Batjargal et al., 2013; Ren et al., 2009). This means that utilizing samples from China to study the impact of social network expansion on household carbon emissions is instructive to countries with different institutional backgrounds. Secondly, in terms of the mediation mechanism of comparison behavior, the intrinsic property of human beings, such as self-esteem, self-evaluation, and social identity, are the main drivers that generate social comparisons, as well as some scholars have shown that these internal drivers have an impact on the economic lives of residents from various cultural backgrounds (Hogg, 2000; Vogel et al., 2014).

Fig. 1 presents the changes in household consumption structure over years. Food expenditure accounted for the highest proportion of household consumption expenditure, although the percentage showed a downward trend from 32% to 30%. The second highest was transportation and communication expenditure, which showed an upward trend from 17% to 19%. The percentage of housing expenditure was the third. The percentage of entertainment and education expenditure was increasing from 9% to 11%. The percentage of health care and clothing expenditure did not change remarkably. In contrast, there was a dramatic increase in the percentage of daily necessities expenditure in 2016 and fell back in 2018. The expenditure on other goods and services, the least percentage of household consumption expenditure, showed an upward trend in these years.

3.1.2. Direct HCEs

Following the literature (Wiedenhofer et al., 2017; Zhang et al., 2020), we calculated the direct HCEs using the emissions coefficient method (ECM) from the IPCC (2022). The formula is as follows:

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

Where f_i represents the CO2 emissions factor of energy source i, $Energy_{ik}$ represents the quantity of energy i consumed by household k. According to the provincial fuel price of that year, we converted the consumption expenditure of electricity, coal, petrol, LNG and PNG of each household in CFPS into the direct energy consumption of physical units.[3] IPCC provides the carbon emissions per unit of energy consumption of five fuels. Therefore, we weighted the carbon emissions of five energy consumption of households to obtain the direct HCEs. Fig. 2 showed the changing trend of household direct carbon emission structure in three years. Electricity consumption was the main source of direct HCEs, accounting for about 50%. The percentage of gasoline consumption in household direct HCEs increased sharply in 2016 and decreased in 2018. The percentage of direct HCEs from household coal consumption showed a downward trend over years, which may be related to the Chinese government's policy of banning residents from burning coal in recent years. The percentage of the other two categories of direct HCEs was increasing over years, but the percentage is small.

3.1.3. Indirect HCEs

We used the I–O method to estimate indirect HCEs by combining household consumption expenditure into I–O tables (Dai et al., 2012; Ding et al., 2017; Duarte et al., 2010; Golley and Meng, 2012; Zhang et al., 2020). The WIOD provides two datasets: China Input-Output Tables and CO2 emissions for 35 sectors. These two datasets have the same department classification, which reduces the possible deviation in the process of data matching. Because WIOD provides carbon emission intensity data of various departments in China, it can better avoid errors caused by inconsistent selection of energy emission coefficients. Based on these two datasets, we derived the Leontief inverse matrix induced

[2] Since the categories of household consumption expenditure in the questionnaire before and after 2012 are quite different, we choose the data of 2014, 2016 and 2018 to maintain the comparability.

[3] Electric: Electric fuel; Petrol: Petrol fuel; Coal: Coal fuel; LNG: Liquified natural gas; PNG: Pipeline natural gas.

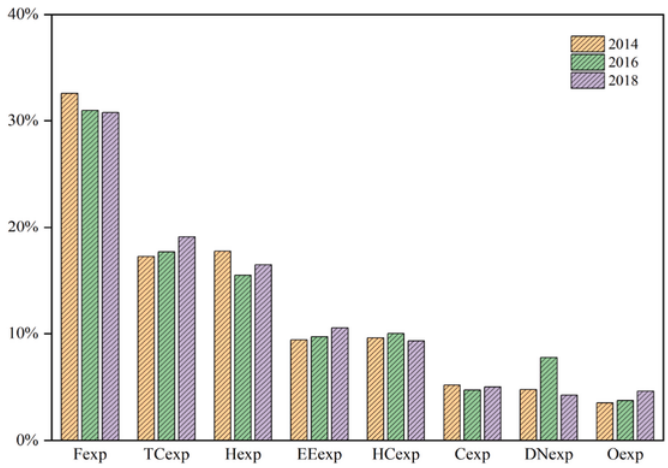

Fig. 1. Consumption structure changes over time. Notes: Eight types of consumption: Food expenditure (Fexp), Transportation and communication expenditure (TCexp), Housing expenditure (Hexp), Entertainment and education expenditure (EEexp), Health care expenditure (HCexp), Expenditure on daily necessities (DNexp), Clothing expenditure (Cexp), Other expenditure (Oexp).

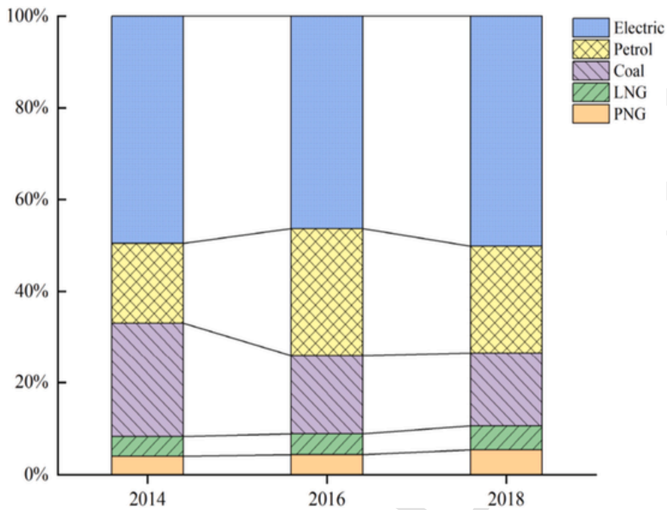

Fig. 2. The components of direct HCEs.

from the I–O table and per-Yuan CO_2 emissions intensities coefficients for each sector. This is the basis for our calculation of indirect HCEs.

The matching between household consumption expenditures and I–O categories is one of the possible sources of uncertainty in the analysis. Before decomposing household consumption expenditure, we preprocessed the data (Zhang et al., 2020). Since CFPS and WIOD used different classification methods,[4] to obtain the CO_2 emissions contained in the specific goods and services consumed by each household, we created two indices to match the consumption items in CFPS with the sectors in WIOD and split the expenditures into more categories to match the items in WIOD. The first concordance is the I–O table released by the National Bureau of Statistics of China (NBS) to match household consumption expenditures and the total emission intensity of each sector. The second concordance is the household consumption expenditure classification table released by the NBS in 2013 to match categories in household consumption expenditure and I–O tables.

The matching process was as follows: First, we integrated the sectoral categories of the 2007[5] national input–output table of NBS following the "Classification of National Economic Activities Industry (GB/T 4754–2017)" issued by the NBS. Second, we divided the consumer expenditure categories in CFPS and the sectors in the NBS input–output table into eight categories to match. Third, we used the weights of the urban and rural household consumption ratios of different industries in the I–O table to split the consumption expenditures. Finally, after aggregating the consumption-side detailed household expenditure items in the CFPS into a production-side Leontief inverse matrix and CO_2 emissions intensities, we estimated the indirect CO_2 emissions for every surveyed household spread over the three years according to Eq. (2).

$$HCE_{indirect\_k} = E_k D (1 - A)^{-1} \tag{2}$$

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

3.1.4. HCEs

We added up direct HCEs and indirect HCEs to get total HCEs. Fig. 3 shows the quantity and trend of direct HCEs and indirect HCEs. Both direct and indirect HCEs showed an upward trend over years. Direct HCEs increased from 3.76 in 2014 to 3.94 in 2018, and indirect HCEs increased from 11.99 in 2014 to 15.61 in 2018. Indirect HCEs were the main source of HCEs, and their amount was about four times that of direct HCEs. In recent years, the growth rate of indirect HCEs was much faster than that of direct HCEs.

3.2. Variables

3.2.1. Dependent variable

Considering the need to correct errors by changes in household size, we used per capita household carbon emissions rather than total household carbon emissions as the dependent variable. On the one hand, the family size of the same household ID will change in different years. On the other hand, there are significant differences in the household size between different household IDs. The per capita value can be used to measure the change in household carbon emissions more accurately.

3.2.2. Independent variables

The expansion of social networks refers to the relatively stable relationship formed by the interaction between social individuals. Considering that the breadth of social networks is often closely related to an individual's implicit and explicit characteristics, we selected the household owner's popularity, trust index and the importance of obtaining information through others as the internal factors affecting the expansion of social networks (Kawachi et al., 1999; Lin, 2005). We also chose the household head's local income level, social status level and monthly communication cost as the external factors affecting the expansion of social networks (Liu et al., 2021; Bian et al., 2005). As shown in Table 1, we selected the above six sub-variables as the driving factors and generated the expansion of social networks variable by using the factor analysis method (Cao et al., 2015). Before using factor analysis, we found that Kaiser-Meyer-Olkin (KMO) value was 0.60 and the Bartlett test of sphericity was acceptable in this study.

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

[5] Since the China Input-Output table and sectoral carbon emission intensity data in WIOD database are updated to 2009, in order to maintain the consistency between WIOD and NBS data, we selected the data of 2007 for consolidation.

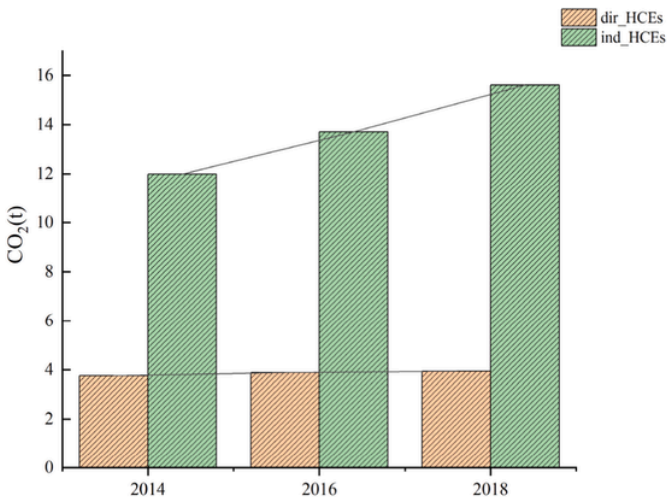

Fig. 3. Direct HCEs and indirect HCEs change over time.

Table 1
Constituent variables of the expansion of social networks.

Social Networks	Internal factors	The popularity of the head of household	The values range from 0 to 10.0 represents poor popularity and 10 represents good popularity.
		Trust index	The values range from 0 to 35.0 means very distrust and 35 means very trust[a].
		The importance of obtaining information through others	The values range from 1 to 5.1 means very unimportant and 5 means very important.
	External factors	Local ranking of household head's income	The values range from 1 to 5.1 means very low and 5 means very high.
		The social status of the head of household in the local ranking	The values range from 1 to 5.1 means very low and 5 means very high.
		Monthly communication cost	Monthly mobile phone charge.

[a] The CFPS surveyed individuals' trust in six groups: parents, neighbors, doctors, officials, strangers and Americans. According to the difference order model theory, individuals' trust in different groups varies greatly. Generally, individuals' trust in their parents is high, while their trust in people from different countries is low. Therefore, we used the weight method to calculate the comprehensive trust index. The formula was as follows: Trust index = 1/6*trust_parents + 2/6*trust_neighbor + 3/6*trust_doctor + 4/6*trust_official + 5/6*trust_stranger + 1*trust_American.

3.2.3. Control variables

We controlled for the following variables about the head of household: age, gender, marital status, education, health status, migration status, working status, and household register. We also controlled for household characteristic variables: household size, per capita income, household location, the proportion of children, the proportion of the elderly, and the proportion of migrant workers. Furthermore, we controlled regional characteristic variables: regional economic development level, regional industrial structure, and population growth rate. Table 2 shows the definitions and summary statistics of the above-mentioned variables.

3.3. Model setting

We used model (3) to examine the impact of the expansion of social networks on HCEs as follows:

Table 2
The definitions and summary statistics of variables.

Variables	Variable Description	Obs	Mean	SD	Min	Max
HCEs	Per capita household carbon emissions	20,066	5.7521	7.8035	0.0078	214.4428
Ind_HCEs	Per capita indirect household carbon emissions	20,066	4.5071	7.1091	0.0078	212.9279
Dir_HCEs	Per capita direct household carbon emissions	20,066	1.2450	1.8522	0.0000	80.1878
Social_Network	The expansion of social networks	20,066	0.0047	0.5812	−2.1597	7.5378
Humangift_Exp	Gift expenditure	20,066	2.6531	1.3201	1.0000	5.0000
Age	Householder age	20,066	48.7904	13.4479	16.0000	93.0000
Gender	Householder gender, male:1, female:0	20,066	0.5401	0.4984	0.0000	1.0000
Education	Householder education years, illiterate or semi-literate:1, primary school:2, junior high school:3, senior high school/professional high school/higher vocational school:4, junior college:5, undergraduate:6, master:7, doctor:8	20,066	2.8221	1.3815	1.0000	8.0000
Marriage	Marital status of head of household, married:1, others:0	20,066	0.8543	0.3528	0.0000	1.0000
Familysize	Household size	20,066	3.6669	1.7711	1.0000	17.0000
Lnincome	The logarithm of disposable income per capita	20,066	9.2481	1.2877	−1.3863	13.8279
Teenratio	Proportion of population under 14 years old in total household population	20,066	0.1378	0.1818	0.0000	0.8333
Oldratio	Proportion of population over 65 years old in total household population	20,066	0.1399	0.2816	0.0000	1.0000
Dagongratio	Proportion of the migrant workers	20,066	0.1007	0.2029	0.0000	1.0000
Health	Householder health condition. From healthy to unhealthy, it is sorted from 1 to 5	20,066	3.0954	1.1900	1.0000	5.0000
Emigrate	Migration status, emigrant:1, no emigrant:0	20,066	0.0185	0.1347	0.0000	1.0000
Work	Working status, have a job:1, no job:0	20,066	0.7899	0.4074	0.0000	1.0000
Hukou	Household registration type, urban hukou:1, rural hukou:0	20,066	0.3047	0.4603	0.0000	1.0000
Urban	Household location, city dwellers:1, rural dwellers:0	20,066	0.5023	0.5000	0.0000	1.0000
Lngdp	The logarithm of local gross domestic production	20,066	10.0981	0.7174	7.8136	11.5124
Industry	Regional industrial structure	20,066	0.4096	0.0601	0.1654	0.5278
Popgrowth	Population growth rate	20,066	4.5841	2.6628	−1.0000	11.0800

$$HCE_{kt} = \alpha_0 + \alpha_1 Social\ network_{kt} + \alpha_4 X_{kt} + \zeta_t + \eta_j + \varepsilon_{kt} \quad (3)$$

Where HCE_{kt} represents per capita carbon emissions of household k in year t. $Social\ network_{kt}$ represents the expansion of social networks of households k in year t. X_{kt} represents a series of control variables, including household head characteristic variables, household characteristic variables and regional characteristic variables. The ζ_t represents year fixed effect. The η_j represents county fixed effect. The ε_{kt} represents a random disturbing term.

4. Empirical results

4.1. Baseline results

Table 3 shows the impact of the expansion of social networks on HCEs, indirect HCEs and direct HCEs. We only included the expansion of social networks in columns (1), (3), and (5), but included other control variables in columns (2), (4), and (6). The results showed that the coefficient of the expansion of social networks was significantly positive, indicating that the expansion of social networks can increase HCEs, indirect HCEs and direct HCEs in China. Furthermore, we found that the expansion of social networks has a bigger impact on indirect HCEs than direct HCEs. These results support Hypothesis 1.

Our results also showed that HCEs tended to decrease with the age of the household head since older individuals have more frugal consumption habits. There was a positive correlation between the education level of the household head and HCEs (Zhang et al., 2020). The HCEs of married-headed households and large households were low, which may be related to the sharing of high carbon-intensive goods within the household. The high-incomed households had more HCEs since consumption was an important factor to increase HCEs. We further found that the higher proportion of children and the elderly reduced HCEs, but the lower health level of the head of household can increase HCEs. In addition, households with migration experience and urban hukou have higher HCEs.

4.2. Robustness testing

To confirm the robustness of the results, we conducted robustness tests by: (1) using the instrumental variable method; (2) using the

Table 3
The impact of the expansion of social networks on per capita HCEs.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	HCEs	HCEs	Ind_HCEs	Ind_HCEs	Dir_HCEs	Dir_HCEs
Social_Network	1.582***	1.372***	3.287***	2.867***	0.825***	0.729***
	(12.093)	(10.500)	(7.790)	(6.780)	(11.899)	(10.310)
Age		−0.038***		−0.091***		−0.017***
		(-7.645)		(-6.485)		(-4.227)
Gender		0.079		−0.288		−0.053
		(0.721)		(-0.945)		(-0.665)
Education		0.533***		1.341***		0.207***
		(10.027)		(9.958)		(6.318)
Marriage		−1.003***		0.617		−0.030
		(-5.207)		(1.419)		(-0.308)
Familysize		−0.594***		1.807***		0.549***
		(-19.052)		(16.968)		(19.627)
Lnincome		0.545***		1.107***		0.061
		(9.734)		(6.655)		(1.338)
Teenratio		−1.853***		−3.026***		−0.524**
		(-6.416)		(-3.236)		(-2.294)
Oldratio		−0.403*		−0.910		−0.400***
		(-1.646)		(-1.624)		(-2.935)
Dagongratio		−0.281		−3.213***		−0.809***
		(-0.821)		(-5.206)		(-4.410)
Health		0.147***		0.513***		−0.036
		(3.774)		(4.817)		(-1.097)
Emigrate		1.465**		1.837		0.982*
		(2.502)		(1.577)		(1.894)
Work		−0.634***		−0.917**		−0.377***
		(-4.240)		(-2.317)		(-3.944)
Hukou		0.597***		1.572***		0.811***
		(3.835)		(3.772)		(6.473)
Urban		−0.004		0.590*		−0.453***
		(-0.028)		(1.667)		(-4.436)
Lngdp		0.852		1.986		0.782
		(1.182)		(1.347)		(1.536)
Industrystructure		5.383		5.728		6.579*
		(1.047)		(0.554)		(1.847)
Popgrowth		0.100		0.178		−0.080*
		(1.303)		(0.906)		(-1.725)
Constant	5.747***	−7.024	13.881***	−26.722*	3.865***	−8.051
	(113.230)	(-1.033)	(100.664)	(-1.871)	(110.872)	(-1.597)
Control Variables	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,066	20,066	20,066	20,066	20,066	20,066
R-Squared	0.164	0.219	0.104	0.143	0.098	0.138

Notes: t values are in parentheses, and *, ** and *** indicate significant levels at 10%, 5% and 1%, respectively.

propensity score matching method; (3) using the alternative indicator of social networks expansion; (4) using the method of dropping some control variables.

4.2.1. Instrumental variable method

The endogenous problems caused by the above-mentioned reverse causality could have influenced the correction of our conclusions. Thus, to eliminate the endogenous problem caused by reverse causality, we used the instrumental variable method.

We employed the mean of the expansion of social networks of other households in the same county as an instrumental variable. Referring to the instrumental variable selection idea of Fu et al. (2016), the expansion of one household social network is affected by the expansion of other household social networks in the same county, while the expansion of other households' social networks did not directly affect the carbon emissions level of this household, so the instrumental variable satisfied the principles of correlation and exogeneity. Columns (1) in Table 4 is the results of the first-stage regression and show a significant negative correlation between the instrumental variable and the expansion of social networks. Columns (2) in Table 4 show the regression results of the instrumental variable method. The coefficients for the expansion of social networks were significantly positive, which was consistent with our baseline model. Furthermore, the Anderson canon. corr. LM statistic results show that there is no problem of insufficient identification, and the Cragg-Donald Wald F statistics is bigger than the Stock-Yogo threshold at the significant level of 10%, indicating our instrumental variable is valid.

4.2.2. Propensity score matching method

Given the possible sample self-selection issue, we used the propensity score matching method to mitigate the estimated bias (Churchill and Smyth, 2021). To ensure the robustness of the results, we used four matching methods: one-to-one matching, nearest neighbor matching, radius matching and kernel matching. Before matching, we divided the sample into three groups according to the size of the expansion of social networks: high, medium and low. The samples of the highest group were defined as the treatment group, and the rest of the two groups were defined as the control group. We successively used the above four matching methods to test and found that all results were significantly positive at the level of 1% (Table 5), which indicated that after eliminating the sample selection deviation, the pure effect of the expansion of social networks on HCEs was still significantly positive. We also conducted a balance test after matching. The results showed that the standard deviation of the control variables by the four methods was significantly reduced and passed the balance test, indicating that our findings are robust.

Table 4
Regression results with the instrumental variable method.

VARIABLES	(1) Social network	(2) HCEs
Average	−2.500***	
	(-33.710)	
Social_Network		1.665***
		(4.227)
Control Variables	Yes	Yes
Year FE	Yes	Yes
County FE	Yes	Yes
Anderson Canon. Corr. Lm Statistic	1098.111	
Cragg-Donald Wald F Statistic	1136.442	
Observations	20,066	
R-Squared	0.079	

Notes: t values are in parentheses, and *, ** and *** indicate significant levels at 10%, 5% and 1%, respectively.

Table 5
Results from five propensity score matching methods.

Matching method	Test group	Control group	ATT	Standard error	t value
One-to-one match	7.10	5.83	7.26	0.18	40.33
Neighbor matching	7.10	5.82	8.66	0.15	57.73
Radius match	7.10	5.84	9.12	0.14	65.14
Local linear matching	7.10	5.91	6.78	0.18	37.67

4.2.3. Construct alternative independent variable

In the baseline model, we used the factor analysis method to construct the expansion of social networks. Considering that the economic interaction between households often measures the level of "strong relationship" in the household, we used gift expenditures as an alternative indicator of social networks to verify the impact of the expansion of social networks on HCEs (Chen et al., 2021; Huang and Fang, 2021). Table 6 shows the regression results. The results indicated that the expansion of social networks had a significant positive impact on HCEs, the regression results were consistent with the conclusions of the baseline model, indicating that our findings are robust.

4.2.4. Dropping control variables

Some control variables seemed to have no impact on household carbon footprint in baseline regression. In this section, we drop these variables and then conduct regression to examine the robustness of the conclusions in this study. The regression results are reported in Table 7. The results are consistent with the baseline regression, which shows that social network expansion still has a significantly positive effect on HCEs and our findings are robust.

4.3. Mechanism analysis

In this subsection, we attempted to reveal the impact mechanism of social network expansion on HCEs. The theoretical analysis showed that the expansion of social networks can affect the consumption quantity and consumption structure through comparison behavior based on status-seeking motivation, thereby impacting on HCEs.

4.3.1. Increasing consumption quantity under the comparison behavior

To confirm the existence of the comparison behavior based on status-seeking motivation, we divided the sample households into high and low social status groups, as measured by responses to the following question: "How high is your social status in the local area?" Answers ranged from 1 to 5; the lower the score, the lower the social status. We investigate whether the consumption of high social status households in the same county will have an impact on the expansion of social networks and HCEs of low social status households to verify the existence of comparable consumption based on status-seeking motivation. The model is as follows:

Table 6
Replacing core explanatory variables.

VARIABLES	(1) HCEs	(2) Ind_HCEs	(3) Dir_HCEs
Gift_Exp	1.1640***	2.9339***	0.7496***
	(16.310)	(17.504)	(16.898)
Constant	−16.6890**	−50.6935***	−14.1736***
	(-2.467)	(-3.639)	(-2.809)
Control Variables	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Observations	20,066	20,066	20,066
R-Squared	0.229	0.154	0.149

Notes: t values are in parentheses, and *, ** and *** indicate significant levels at 10%, 5% and 1%, respectively.

Table 7
Dropping some control variables.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	HCEs	HCEs	Ind_HCEs	Ind_HCEs	Dir_HCEs	Dir_HCEs
Social_Network	1.582***	1.371***	3.287***	2.856***	0.825***	0.729***
	(12.093)	(10.491)	(7.790)	(6.763)	(11.899)	(10.374)
Age		−0.038***		−0.094***		−0.018***
		(-7.687)		(-6.858)		(-4.502)
Education		0.538***		1.321***		0.203***
		(10.397)		(10.191)		(6.190)
Marriage		−1.011***		0.613		−0.027
		(-5.238)		(1.406)		(-0.272)
Familysize		−0.594***		1.804***		0.548***
		(-19.095)		(16.941)		(19.589)
Lnincome		0.548***		1.113***		0.063
		(9.801)		(6.704)		(1.392)
Teenratio		−1.864***		−2.984***		−0.511**
		(-6.505)		(-3.213)		(-2.252)
Oldratio		−0.398		−0.937*		−0.400***
		(-1.627)		(-1.666)		(-2.927)
Dagongratio		−0.306		−3.267***		−0.818***
		(-0.891)		(-5.303)		(-4.502)
Health		0.143***		0.521***		−0.034
		(3.706)		(4.935)		(-1.062)
Emigrate		1.447**		1.814		0.970*
		(2.475)		(1.560)		(1.882)
Work		−0.618***		−0.979**		−0.387***
		(-4.173)		(-2.503)		(-4.041)
Hukou		0.592***		1.573***		0.811***
		(3.802)		(3.773)		(6.466)
Urban		−0.010		0.601*		−0.448***
		(-0.077)		(1.703)		(-4.420)
_Cons	5.747***	4.237***	13.881***	−3.477*	3.865***	2.165***
	(113.230)	(7.048)	(100.664)	(-1.897)	(110.872)	(4.331)
Control Variables	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,066	20,066	20,066	20,066	20,066	20,066
R-Squared	0.164	0.219	0.104	0.143	0.098	0.137

Notes: t values are in parentheses, and *, ** and *** indicate significant levels at 10%, 5% and 1%, respectively.

$$HCE_{kt} = \beta_0 + \beta_1 Social\ network_{kt} + \beta_2 Social\ network_{kt} \times Expence_{kt} + \beta_3 Expence_{kt} + \beta_4 X_{kt} + \zeta_t + \eta_j + \varepsilon_{kt} \tag{4}$$

Where $\mathrm{Expence}_{kt}$ represents the average consumption expenditure of high-status households in the same county. Columns (1) and (2) of Table 8 show that the coefficient of $Social\ network_{kt} \times Expence_{kt}$ were significantly positive in both columns, indicating that the expansion of social networks increased household consumption through the comparison behavior under the motivation of status-seeking, and then affect HCEs, supporting Hypothesis 2.

We further examine the impact of comparative behavior on different categories of household consumption expenditure. According to the consumption classification issued by NBS, we divided household consumption into 8 categories.[6] Table 9 shows the regression results. We found that the comparative behavior of the expansion of social networks was mainly reflected in the expenditure on food, entertainment and other goods, which increases HCEs and indirect HCEs. However, comparative consumption has no significant impact on the direct HCEs from household consumption expenditures.

Table 8
The number of consumptions under the comparison behavior.

	(1)	(2)	(3)
VARIABLES	HCEs	Ind_HCEs	Dir_HCEs
Social_Network	1.600***	3.431***	0.883***
	(7.727)	(4.760)	(9.346)
Social × Expence	0.885***	2.596***	0.153
	(2.758)	(2.938)	(0.990)
Expence	0.140	0.234	−0.158
	(0.594)	(0.342)	(-0.895)
Control Variables	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Observations	13,887	13,887	13,887
R-Squared	0.216	0.158	0.132

Notes: t values are in parentheses, and *, ** and *** indicate significant levels at 10%, 5% and 1%, respectively.

4.3.2. Upgrading of the consumption structure under the comparison behavior

The expansion of social networks may boost the structure upgrading of household consumption by status-seeking incentives, thereby increasing HCEs. Following the literature Wang et al. (2021), we divided consumption into three levels: basic, middle-end and high-end consumption. Specifically, food expenditure belongs to basic consumption, daily necessities and services belong to middle-end consumption, educational expenditure and entertainment expenditure belong to high-end

[6] Food, clothing, entertainment and education, daily necessities and services, housing, health care, transportation and communication, and others.

consumption. Finally, the proportion of different types of consumption expenditure was calculated and weighted to obtain the upgrading rate of consumption structure. The formula is as follows:

$$Expupgrade = 1 * food/6 + 2 * daily/6 + 3 * ee/6 \tag{5}$$

Where *food* represents the expenditure on food, *daily* represents the expenditure on daily necessities and services, and *ee* represents the expenditure on education and entertainment. In the consumption expenditure, the more cultural and entertainment expenditure means the higher consumption upgrading. On the contrary, more food expenditure means lower consumption upgrading. Therefore, the bigger the indicator value, the higher the consumption upgrading level. To verify the existence channel of consumption structure upgrading based on status-seeking motivation, we investigate whether the upgrading of consumption structure of high social status households in the same county will have an impact on the expansion of social networks and HCEs of low social status households. As described in this subsection, we used the following model to verify Hypothesis 2:

$$\begin{aligned} HCE_{kt} = \gamma_0 + \gamma_1 Social\ network_{kt} \\ + \gamma_2 Social\ network_{kt} \times Upgrade_{kt} \\ + \gamma_3 Upgrade_{kt} + \gamma_4 X_{kt} + \zeta_t + \eta_j + \varepsilon_{kt} \end{aligned} \tag{6}$$

Where $Upgrade_{kt}$ represents the average consumption upgrading of high-status households in the same county. Column (1) and (2) of Table 10 shows that the coefficient of $Social\ network_{kt} \times Upgrade_{kt}$ were significantly positive in both columns, indicating that the expansion of social networks affected HCEs through the upgrading of consumption structure caused by the comparison behavior based on the motivation of status-seeking, supporting Hypothesis 2.

5. Heterogeneity analysis

Groups' characteristics may affect their HCEs. Fig. 4 shows the differences in expenditure among the eight consumption categories grouped by age[7] and educational background of households' heads,[8] and household income level.[9] After grouping by age of household head, we found that the top three consumption proportions of households with a young head were food expenditure, transportation and communication expenditure and housing expenditure. However, food expenditure, medical care expenditure and housing expenditure account for a higher proportion of household consumption expenditure in households with an old head. Compared with households with an old head, households with a young head have higher expenditure on transportation and communication and entertainment. Households with an old head spent more on health care. After grouping by the educational level of the household head, we found that food expenditure, housing expenditure and transportation and communication expenditure accounted for the top three in both groups of household consumption expenditure. Households with a high-educated head spend more on transportation, communication and entertainment education. Households with a low-educated head spend more on health care. After grouping by household income, we found that food expenditure, housing expenditure and transportation and communication expenditure accounted for the top three in both groups of household consumption expenditure. Compared with low-income households, high-income households had higher expenditure on food and transportation and communication. The low-income households spent more on health care.

Table 9
Different consumption categories.

VARIABLES	(1) HCEs	(2) Ind_HCEs	(3) Dir_HCEs
Social_Network	1.600***	1.280***	0.320***
	(7.660)	(6.476)	(9.249)
Social × Fexp	0.687**	0.694**	−0.007
	(2.207)	(2.415)	(-0.110)
Fexp_Group	0.051	0.052	−0.001
	(0.233)	(0.260)	(-0.023)
Social_Network	1.617***	1.296***	0.320***
	(7.789)	(6.604)	(9.343)
Social × Cexp	0.119	0.132	−0.014
	(0.410)	(0.495)	(-0.274)
Cexp_Group	0.085	0.081	0.004
	(0.530)	(0.569)	(0.080)
Social_Network	1.612***	1.292***	0.320***
	(7.861)	(6.666)	(9.379)
Social × Eeexp	0.296***	0.296***	−0.000
	(3.312)	(3.622)	(-0.007)
Eeexp_Group	−0.027	−0.015	−0.011
	(-0.548)	(-0.413)	(-0.397)
Social_Network	1.616***	1.295***	0.321***
	(7.723)	(6.536)	(9.377)
Social × Dnexp	0.197	0.236	−0.038
	(1.032)	(1.322)	(-1.046)
Dnexp_Group	−0.112	−0.094	−0.018
	(-0.988)	(-0.916)	(-0.544)
Social_Network	1.614***	1.292***	0.322***
	(7.968)	(6.769)	(9.442)
Social × Hexp	0.138	0.209	−0.071**
	(0.527)	(0.834)	(-1.976)
Hexp_Group	0.180*	0.161*	0.019
	(1.922)	(1.839)	(0.844)
Social_Network	1.618***	1.297***	0.321***
	(7.808)	(6.619)	(9.417)
Social × Hcexp	0.040	0.073	−0.034
	(0.239)	(0.477)	(-1.269)
Hcexp_Group	0.092	0.075	0.017
	(1.071)	(0.946)	(0.899)
Social_Network	1.617***	1.296***	0.320***
	(7.780)	(6.594)	(9.380)
Social × Tcexp	0.220	0.250	−0.030
	(0.974)	(1.226)	(-0.653)
Tcexp_Group	−0.144	−0.144	0.000
	(-0.979)	(-1.077)	(0.003)
Social_Network	1.611***	1.291***	0.320***
	(7.860)	(6.664)	(9.330)
Social × Oexp	0.222*	0.213*	0.009
	(1.723)	(1.788)	(0.353)
Oexp_Group	−0.014	−0.035	0.020
	(-0.203)	(-0.537)	(1.066)
ControlVariables	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Observations	13,887	13,887	13,887

Notes: t values are in parentheses, and *, ** and *** indicate significant levels at 10%, 5% and 1%, respectively.

Since the embodied carbon of each category of goods is different, the differences in the consumption structure of each type will also affect the HCEs. Fig. 5 shows the comparison of direct and indirect HCEs according to different types. Households with a young head had higher HCEs than households with an old head. Households with a high-educated head had higher HCEs. The indirect HCEs of households with a high-educated head were about twice more than households with a low-educated head. High-income households had higher HCEs than low-income households. The indirect HCEs of low-income households were about two-thirds of those of high-income households.

[7] Households with a head under the age of 60 were defined as young group, and the rest were defined as the old group.

[8] Households with a head who had not got a bachelor's degree were defined as low-educated group, and the rest were defined as high-educated group.

[9] Households with per capita income in the bottom 50% of the whole sample were defined as low-income group, and the rest were defined as high-income group.

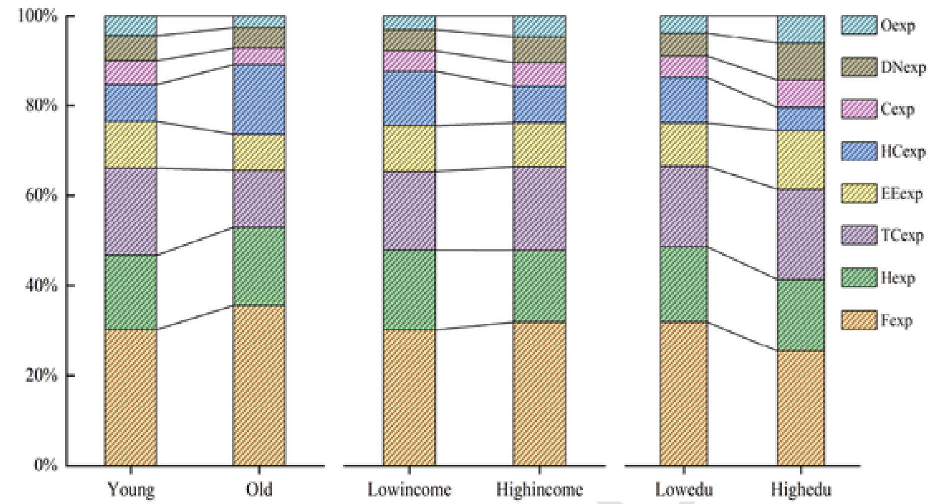

Fig. 4. Different consumption structures of various groups.

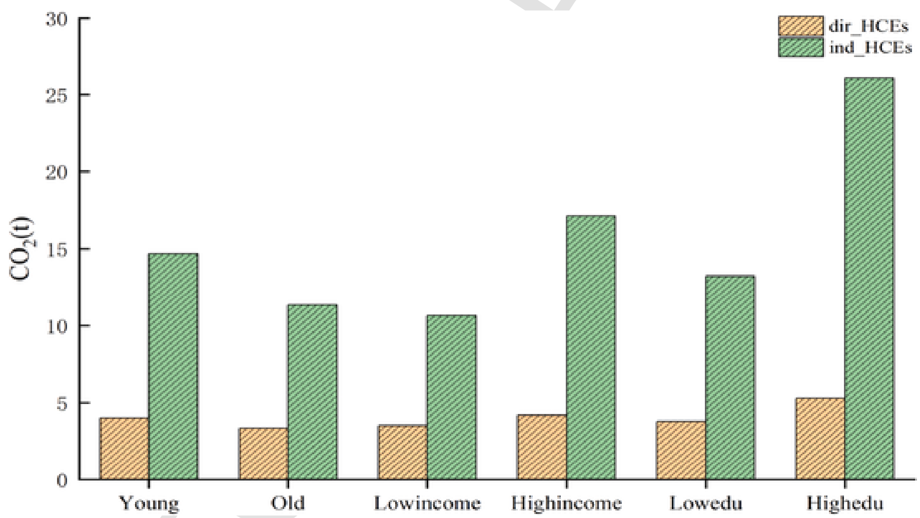

Fig. 5. The difference in HCEs of each group.

We also compared the differences in the composition of direct HCEs among these groups in Fig. 6. We found that the direct HCEs from electricity consumption accounted for the largest proportion in both groups. Households with a young head had higher direct HCEs from gasoline consumption than households with an old head, while households with an old head had higher direct HCEs from coal consumption than households with a young group. We further found that the direct HCEs of households with a high-educated head are much higher than households with a low-educated head in gasoline and natural gas consumption, while the direct HCEs of households with a low-educated head were much higher than households with a high-educated head in coal consumption. In addition, we found that electricity consumption is the largest source of direct HCEs in both groups. High-income households produce higher direct HCEs in gasoline and natural gas consumption than low-income households, while low-income households produce higher direct HCEs in coal consumption than high-income households.

5.1. Effects of the age of household head

The impact of the expansion of social networks on HCEs may vary with the age of the head of household. We used the following model to verify hypothesis 3:

$$HCE_{kt} = \delta_0 + \delta_1 Social\ network_{kt} + \delta_2 Social\ network_{kt} \times Young + \delta_3 Y$$

Where *Young* represents the households with a young head. Households with a head under the age of 60 were defined as the young group. We converted the grouped variable into a dummy variable not only to more intuitively reflect the difference between different variables' attributes on the impact of social network expansion on household carbon emissions, but also to effectively avoid the problem of reducing parameter estimation accuracy due to the group's too small sample (Li et al., 2019; Miller and Erickson, 1974). Furthermore, for the following reasons, we used the Interaction term regression method to assess group heterogeneity: First, the positive and negative coefficients of the interaction term can be used to examine the substitution or complementary effects of grouped variables in the relationship between social network expansion and household carbon emissions. Second, because this method is based on the whole sample, it avoids the problem of insufficient sample sizes caused by group regression, which improves estimation accuracy (Minier, 2007; Zuur et al., 2009). As a result, we selected this method to verify heterogeneity. Column (1) in Table 11 reported the regression results. The result shows that the coeffi-

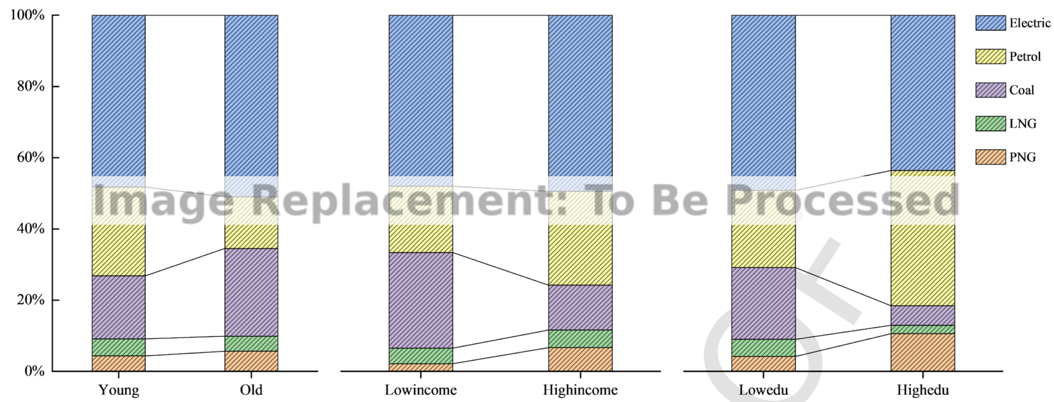

Fig. 6. Differences in the structure of direct HCEs among different groups.

Table 10
Consumption upgrade under the effect of comparison.

	(1)	(2)	(3)
VARIABLES	HCEs	Ind_HCEs	Dir_HCEs
Social_Network	1.607***	1.288***	0.319***
	(7.857)	(6.662)	(9.299)
Social × Upgrade	11.399*	10.407*	0.992
	(1.753)	(1.729)	(0.791)
Upgrade_Group	−3.956	−3.129	−0.827
	(-1.323)	(-1.157)	(-1.063)
Control Variables	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Observations	13,887	13,887	13,887
R-Squared	0.216	0.198	0.132

Notes: t values are in parentheses, and *, ** and *** indicate significant levels at 10%, 5% and 1%, respectively.

Table 11
Heterogeneity analysis.

	(1)	(2)	(3)
VARIABLES	HCEs	HCEs	HCEs
Social_Network	0.607***	1.256***	0.769***
	(2.967)	(9.474)	(7.167)
Social × Young	1.001***		
	(4.055)		
Young	−0.282		
	(-1.393)		
Social × High Educated		1.714**	
		(2.168)	
High Educated		1.375***	
		(3.370)	
Social × High Income			1.210***
			(4.993)
High Income			0.435***
			(3.196)
Control Variables	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Observations	20,066	20,066	20,066
R-Squared	0.221	0.222	0.222

Notes: t values are in parentheses, and *, ** and *** indicate significant levels at 10%, 5% and 1%, respectively.

cient of $Social\ network_{kt} \times Young$ was significantly positive, indicating that households with a young head are more likely to be affected by the comparison behaviors in the expansion of social networks. The possible reason for the above result is that the impulsive tendency of households with a young head in consumption promotes the impact of social network expansion in increasing HCEs through comparison behavior. The results verify our Hypothesis 3.

5.2. Effects of the education level of household heads

The impact of the expansion of social networks on HCEs may vary with the education level of the household head. To test hypothesis 4, we constructed the following model:

$$\begin{aligned} HCE_{kt} = & \varepsilon_0 + \varepsilon_1 Social\ network_{kt} \\ & + \varepsilon_2 Social\ network_{kt} \times High\_educated \\ & + \varepsilon_3 High\_educated + \varepsilon_4 X_{kt} + \zeta_t + \eta_j + \varepsilon_{kt} \end{aligned} \quad (8)$$

Where *High educated* represents the households with a high-educated head. When the educational level of the head of household is equal or higher than college, we defined it as a high-educated group. The regression result was reported in column (1) of Table 11. The coefficient of $Social\ network_{kt} \times high\_educated$ was significantly positive, which means that households with a high-educated head were more vulnerable to the impact of comparative behavior brought by the expansion of social networks than households with a low-educated head. The possible reason for the above result is that households with a high-educated head have higher class identity which promotes the impact of social network expansion in increasing HCEs through comparison behavior. The results confirm our Hypothesis 4.

5.3. Effects of household income level

Theoretically, income levels may affect the impact of the expansion of social networks on HCEs. We used the following model to verify hypothesis 5:

$$\begin{aligned} HCE_{kt} = & \theta_0 + \theta_1 Social\ network_{kt} \\ & + \theta_2 Social\ network_{kt} \times High\_income \\ & + \theta_3 High\_income + \theta_4 X_{kt} + \zeta_t + \eta_j + \varepsilon_{kt} \end{aligned} \quad (9)$$

Where *high_income* represents the high-income household group. When the per capita income of the household is in the top 50% of the whole sample, we defined it as the high-income group. Column (3) in Table 11 reported the regression results. The result shows that the coefficient of $Social\ network_{kt} \times High\_income$ was significantly positive, indicating that high-income households are more vulnerable to the impact of comparative consumption brought by the expansion of social networks than low-income households. The possible reason for the above result is that high-income households have fewer budget constraints, which promotes the impact of social network expansion on HCEs. The results verify our Hypothesis 5.

6. Conclusions and policy implications

Based on the data of a large-scale household survey in China from 2014 to 2018, we estimate the impact of the expansion of social networks on HCEs. The empirical results show that the expansion of social networks can significantly increase HCEs, which is more obvious in indirect HCEs. Further, the expansion of social networks increases HCEs by comparison behavior based on status-seeking motivation. In addition, our results show that the impact of the expansion of social networks on HCEs varies among the age and the education level of the household head and the income level of the households. Compared with older and lower education levels of the household head and households with lower income levels, younger and higher education levels of the household head and households with higher income levels can promote the impact of the expansion of social networks on HCEs.

In order to achieve the 3060 goals, the government must pay attention to carbon emissions from household consumption, which is an important driver of carbon emissions in the production process. Based on the results, we propose the following policy implications: First, by providing timely and frequent feedback on household carbon emission records, the government can utilize social comparison psychology to mitigate household greenhouse gas emissions. For example, send residents a household energy comparison report that includes the information of energy use of the community to provide comparable information on each household's energy consumption. Second, the government can promote establishment the statistical evaluation system for individual carbon emissions and then use the social network between households to publicize the green consumption information. Third, the government should reduce the information asymmetry of consumers on the embodied carbon of commodities by pasting carbon footprint labels and providing consumers with the choice of consuming low-carbon commodities. The carbon footprint label will promote the enterprises to produce more low-carbon products, speed up the green transformation in the production process, and form a positive interaction with households.

The main limitation of this paper is the availability of data, and due to the late establishment of China's household micro survey database, our study used cross-sectional data from 2014, 2016 and 2018. With further disclosure of micro-household data later, subsequent studies can use longer-period panel data to further investigate the impact of social network expansion on household carbon emissions.

Credit author statement

Weilu Meng: Conceptualization, Validation, Formal analysis, Writing – original draft. Gecheng Yuan: Data curation, Empirical analysis, Writing - Empirical results. Yongping Sun: Conceptualization, Methodology, Formal analysis, Writing – review & editing.

Uncited references

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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.

Data availability

Data will be made available on request.

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