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The Impact of Psychosocial Factors on Household Carbon Footprints: The Roles of Environmental Evaluation, Well-Being, and Social Trust

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Abstract

Psychosocial factors can promote low-carbon consumption by shaping individual behavioral decisions. This paper focuses on three key psychosocial factors: environmental evaluation, well-being, and social trust. Using data from the China Family Panel Studies (CFPS) in 2018 and 2020, this study applies a mixed-effects model to empirically examine the impacts of psychosocial factors on Household Carbon Footprints (HCFs). Additionally, the study examines eastern-central-western and urban-rural heterogeneity. The study reveals several key findings: (1) Environmental evaluation significantly reduces HCFs. Social trust exhibits an inverted U-shaped relationship with HCFs, initially promoting but later inhibiting them. Well-being, however, has no significant effect on HCFs. (2) Environmental evaluation has a significant negative impact on HCFs in all regions, and the inverted "U" shape of social trust on HCFs is significant only in eastern, central and rural areas. Furthermore, based on these findings, the study proposes strategies to promote low-carbon household consumption, aiming to foster more sustainable practices.

Keywords

Environmental Evaluation, Well-Being, Social Trust, HCFs

1. Introduction

Climate change is a major challenge facing the global community, and low-carbon development has become a key international objective. China has actively participated in global emission reduction efforts and pledged to achieve the "dual-

carbon" targets of "carbon peaking" and "carbon neutrality". While significant progress has been made in reducing industrial carbon emissions, more attention should be directed toward the impact of household consumption on climate change. Studies indicate that direct emissions from fuel use and indirect emissions from consumption activities account for 65% of total global carbon footprints (Ivanova et al., 2015). Shifting consumption patterns is crucial for China to achieve the "dual-carbon" targets and promote green, high-quality development.

Reducing household carbon footprints (HCFs) requires promoting greener and low-carbon consumption patterns in scale, structure, and philosophy. Psychosocial factors, including awareness levels, values, and attitudes, play a crucial role in shaping low-carbon behaviors (Steg et al., 2005). On the one hand, these factors encourage energy-efficient practices and reduce dependence on fossil fuels, while on the other, they shape lifestyles that directly influence carbon emissions. Research has widely supported the role of psychosocial factors in driving low-carbon behaviors. For instance, Wang (2015a) highlighted how heightened psychological awareness fosters corresponding low-carbon consumption behaviors. Similarly, Yuan (2020) found that factors such as low-carbon travel attitudes, values, social roles, and safety preferences significantly influence urban residents' low-carbon travel intentions and behaviors.

Despite this, most studies on HCFs focus on demographic factors such as household size, age structure, and income levels. Few have integrated psychosocial factors into a unified framework to analyze their subjective drivers and evolutionary characteristics. This study addresses this gap by empirically examining the impact of psychosocial factors on HCFs, exploring the heterogeneity of this effect in different regions. This paper contributes in two key ways: (1) It investigates the impacts of environmental evaluation, well-being, and social trust on HCFs from a subjective perspective; (2) It examines the heterogeneity analysis.

2. Literature Review

Carbon emissions reduction efforts have gradually shifted from the industrial sector to households, which are increasingly recognized for their emission reduction potential and responsibility. HCFs include direct emissions from fuel use and indirect emissions from consumption activities. Academic research on this topic has primarily focused on two aspects: the measurement of HCFs and the factors influencing them.

First, the measurement of HCFs has constituted a central focus of academic research. Commonly used methods include the carbon emissions coefficient method, the input-output method, and the consumer lifestyle method. Most calculations rely on energy carbon emissions coefficients multiplied by corresponding energy consumption. For instance, Wang (2015b) applied this method using data from a Chinese household tracking survey to measure carbon footprints. The input-output method provides a standardized framework to assess carbon emissions across economic sectors and quantifies both direct and indirect household

energy consumption. Mi (2020) employed the environmentally extended multi-region input-output method to estimate carbon footprints for different income groups and eight consumption categories in China. The consumer lifestyle method combines the carbon emissions coefficient approach with input-output modeling to estimate residential carbon footprints. This method calculates the carbon footprint of each expenditure item by multiplying its consumption expenditure by the carbon intensity per unit output value. For example, Wei et al. (2007) applied the consumer lifestyle method to calculate direct and indirect HCFs for urban and rural residents.

Secondly, regarding the drivers of HCFs, some scholars have explored this topic from a macro-level perspective. For example, Li and Wang (2021) conducted an analysis of the primary drivers of HCFs among urban and rural Chinese households, indicating that per capita residential area and consumption expenditure are the most significant factors. In contrast, the energy intensity of household consumption and residences are the primary factors contributing to the reduction of HCFs growth. The study of Ji et al. (2016) shows that population, residential consumption level and energy consumption intensity have significant impacts on HCFs, the degree of impact varies significantly between urban and rural areas. Zhou et al. (2019) found that the impact of factors such as family size and labor force ratio on per capita household direct HCFs varies over time and there are provincial differences. Some scholars have also explored the driving factors of HCFs from the micro level, such as Sun (2022), who used data from the China Family Panel Studies to empirically analyze the factors influencing HCFs in China at the household level. The study revealed that a number of factors, including household economy, housing area, family size, urban/rural attributes, age, employment ratio, and education level, exert a significant influence on HCFs.

Existing studies have extensively explored HCFs accounting and its drivers, with a pre-dominant focus on external factors. However, the Theory of Planned Behavior posits that behavioral intentions are the strongest determinants of behavior, suggesting that individuals with positive attitudes toward environmental issues are more likely to exhibit pro-environmental behaviors (Ajzen, 1991). According to numerous studies, social awareness and environmental issues can motivate lifestyle changes (Gadenne et al., 2011), which subsequently influence consumption behaviors (Kaida, 2016). Bai (2013) investigated the link between low-carbon awareness and behavior among residents of Tianjin, China, uncovering a gap between awareness and actual behavior. Brounen et al. (2013) similarly highlighted the role of awareness in shaping sustainable practices. Wilson et al. (2013) explored the relationship between carbon footprints and subjective happiness in Canada, finding no significant correlation between the two. Li (2019) examined the impact of subjective variables on HCFs in China, revealing that well-being, a sense of social security, and adherence to traffic rules significantly reduced HCFs. Conversely, heightened concern for social issues was found to increase carbon footprints. Similarly, Zhao et al. (2019) studied the impact of social trust on

farmers' low-carbon production practices, demonstrating that both interpersonal and institutional trust significantly promoted such behavior. Building on these empirical findings, this paper investigates the relationship between environmental evaluation, well-being, social trust, and HCFs. By simultaneously considering these psychosocial dimensions, this study seeks to empirically evaluate the impact of subjective factors on the HCFs.

3. Data, Variables and Model

3.1. Data

The data used in this paper primarily includes information related to carbon footprint measurement factors, as well as household consumption expenditures across eight categories, household heads, and basic household characteristics. The sources of the data related to carbon emission factors are as follows: the output values of each sub-sector are obtained from the China Statistical Yearbook, the China Industrial Statistical Yearbook, and the China Economic Census Yearbook; the carbon emission factors for each type of energy are referenced from the IPCC guidelines. Data on the eight categories of household consumption expenditures, the household head, and basic household characteristics are sourced from the China Family Panel Studies (CFPS). The CFPS is a large-scale, nationally representative social survey dataset, conducted every two years since 2010, the most recent data updated to 2020. For this study, data from 2018 and 2020 are combined into a mixed cross-sectional dataset to increase the sample size and ensure the validity and stability of the parameter estimation results.

3.2. Variables

1) Dependent variable

In this paper, the dependent variable is the logarithmic value of HCFs. HCFs are classified into two categories: direct and indirect. The indirect category is a comprehensive indicator that is calculated based on the carbon footprints of the eight fundamental types of consumption. These include the carbon footprints generated in the production process of eight types of residents' daily consumption items. According to Equations (1)-(4), the direct and indirect carbon emissions coefficients in 2018 and 2020 are calculated respectively, and multiplied by the amount of the eight major categories of consumption of residents in the CFPS data to obtain the various types of HCFs, and the total HCFs are obtained by summing up the various types.

Direct energy consumed mainly includes coal, kerosene, liquefied petroleum gas, natural gas, town gas, gasoline, heat and electricity. The carbon emissions generated by heat and electricity are mainly in the process of production and transportation, which do not directly generate carbon footprints, and thus are not counted as household direct energy consumption. In this paper, we mainly use five types of direct energy, namely coal, kerosene, liquefied petroleum gas, natural gas and gas, to calculate the household direct carbon emission factor, and the

calculation method (Wang, 2015b) is as follows:

$$E_d = \sum_{i=1}^{5} \alpha_i \cdot d_i \tag{1}$$

$$d_i = NCV_i \cdot Q_i \tag{2}$$

where E_d is the direct carbon emissions generated by the household (kg), α_i is the carbon emission factor of standard coal (kg/KJ); d_i is the amount of heat generated by the first direct energy source consumed by the household ($KJ/yuan$). NVC_i is the average low-level calorific value of energy source i (KJ/kg), Q_i is the energy consumption of energy source i (kg).

$$\xi_d = \frac{E_d}{H} \tag{3}$$

where ξ_d is the household direct carbon emission factor (kg / $yuan$); H is the household residential consumption expenditure ($yuan$).

The household indirect carbon emission factor is calculated as follows (Hua & Shi, 2023):

$$\beta_m = \frac{\sum TE_{nj} \cdot CEF}{\sum PV_{nj}} \tag{4}$$

In the above equation, β_m is the indirect carbon emissions coefficient of the household's category m consumption ($kg/yuan$); TE_{nj} denotes the energy consumption of the category consumption corresponding to the nth production industry sector ($kg\ standard\ coal$); standard coal denotes the carbon emissions coefficient of the standard coal ($kg\ CO_2/kg\ standard\ coal$); and PV denotes the output value of the industry sector ($yuan$). Based on the National Economic Industry Classification (GB/T+4754-2017) published by the National Bureau of Statistics (NBS) in 2017 linking the main consumption items of households to different industrial production sectors, 25 relevant industry sectors were finally selected.

2) Independent variable

Because the household head is the decision maker of family economic behavior, we choose the psychosocial factors of the household head as independent variables. Refer to Li (2019), we adopt environmental evaluation, well-being and social trust as the indicators of psychosocial factors, and use the three questions in the questionnaire, "How serious do you think the environmental problems are in our country" (0 means very serious, 10 means not serious), "Are you happy in your life? (0 represents the lowest, 10 represents the highest) and "How much do you trust strangers" (0 represents very distrustful, 10 represents very trustful) in the questionnaire, corresponding to the variables of environmental evaluation, well-being and social trust, and all of them take the value of the discrete integer between 0 and 10.

3) Control variable

In addition, with reference to the relevant literature, this paper controls in the regression equation for household head characteristic variables, household

characteristic variables and macro control variables that may affect household consumption behavior. Household head characteristics variables include: gender (male = 1, female = 0), age, education (years), marital status (married = 1, other = 0), health status (self-rated from 1 - 5, a larger value indicates less healthy), in addition to social class (self-rated from 1 - 5, a higher value indicates a higher self-rating); household characteristics variables included: urban-rural attributes (urban = 1, rural = 0), family size, housing situation (owned home = 1, other = 0), and logarithmic value of household income. The definitions of the variables and the results of descriptive statistics are shown in Table 1.

Table 1. Descriptive statistics of variables.

Variable types	Variable	CFPS2018			CFPS2020		
		Sample size	Mean	Standard deviation	Sample size	Mean	Standard deviation
Dependent variable	HCF (log)	10851	8.441	0.988	9485	8.458	0.997
Independent variable	Well-being	10851	7.353	2.194	9485	7.350	2.118
	Social trust	10851	2.222	2.236	9485	2.380	2.245
	Environmental evaluation	10851	3.271	2.746	9485	3.749	2.848
Individual characteristic variable	Gender	10851	0.531	0.499	9485	0.564	0.496
	Age	10851	50.250	14.871	9485	48.896	14.529
	Education	10851	8.138	4.709	9485	8.596	4.899
	Marital status	10851	0.827	0.378	9485	0.824	0.381
	Health status	10851	3.132	1.198	9485	3.000	1.180
	Social class	10851	3.118	1.080	9485	3.089	1.044
Household characteristic variable	Urban	10851	0.521	0.500	9485	0.543	0.498
	Family size	10851	3.529	1.861	9485	3.626	1.924
	Housing situation	10851	0.793	0.405	9485	0.771	0.420
	Household income (log)	10851	10.853	1.144	9485	11.009	1.174

3.3. Model

Based on the above analysis, this paper focuses on examining the influence of psychosocial factors on HCFs, and the mixed OLS model is selected to construct the empirical equations as follows:

$$\ln carbon_{it} = \beta_0 + \beta_1 society_{it} + \beta_2 X_{master\_it} + \beta_3 X_{family\_it} + \beta_4 X_{region\_it} + \mu_m + \mu_t + \sigma_{it} \quad (5)$$

$\ln carbon_{it}$ denotes the logarithmic value of HCFs; $society_i$ for psychosocial factors, respectively, environmental evaluation, well-being and social trust; X_{master_it} for basic characteristics of the household head; X_{family_it} for basic characteristics of the household; μ_t for year fixed effects; μ_m for fixed effects of the region where the sample household is located; σ_{it} for the random error term. Considering the differences in consumption activities among households, this paper clusters the regression standard errors at the household level.

4. Baseline Regression

4.1. Impact of Psychosocial Factors on HCFs

Based on the previous analysis, this study conducts an empirical analysis to explore how psychosocial factors influence HCFs. Table 2 reports the effects of environmental evaluation, well-being, and social trust on HCFs, respectively.

Table 2. Impact of psychosocial factors on HCFs.

	HCFs				
	(1)	(2)	(3)	(4)	(5)
Environmental evaluation	−0.010***				
	(0.002)				
Well-being		0.000		0.004	
		(0.003)		(0.014)	
Well-being2				−0.000	
				(0.001)	
Social trust			0.000		0.016**
			(0.003)		(0.007)
Social trust2					−0.003**
					(0.001)
Gender	−0.036***	−0.036***	−0.036***	−0.036***	−0.037***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Age	−0.010***	−0.010***	−0.010***	−0.010***	−0.010***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Education	0.023***	0.023***	0.023***	0.023***	0.023***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Marital status	0.140***	0.142***	0.142***	0.142***	0.142***
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Health status	0.011**	0.011**	0.011**	0.011**	0.010**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Social class	0.005	0.004	0.004	0.004	0.005
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Urban	0.253***	0.254***	0.254***	0.254***	0.254***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Family size	0.066***	0.067***	0.067***	0.067***	0.067***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Housing situation	−0.105***	−0.106***	−0.106***	−0.106***	−0.106***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Household income	0.315***	0.316***	0.316***	0.316***	0.315***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Constant	4.979***	4.949***	4.950***	4.941***	4.945***
	(0.140)	(0.140)	(0.140)	(0.144)	(0.139)
Year fe	Yes	Yes	Yes	Yes	Yes
Region fe	Yes	Yes	Yes	Yes	Yes
Sample size	20336	20336	20336	20336	20336
Turning point					2.667

Note: Clustering robust standard errors are reported in parentheses; *, ** and *** indicate significance at the level of 10%, 5% and 1%, respectively, the same below.

The findings indicate that environmental evaluation has a significant negative effect on HCFs, where a 1% increase in environmental evaluation reduces HCFs by 1%. Conversely, well-being and social trust exhibit no significant direct effects on HCFs. To explore potential nonlinear relationships, quadratic terms for well-being and social trust are introduced, with results shown in Table 2, columns (4) and (5). While well-being does not exhibit a U-shaped relationship with HCFs, an inverted U-shaped relationship is observed for social trust, indicating that as social trust increases, HCFs initially rise and subsequently fall, with a turning point at 2.667. This means that social trust will initially promote the increase of household carbon emissions, and when social trust reaches 2.667, household carbon emissions will decrease. These results highlight several important conclusions. First, households with a stronger environmental evaluation are more likely to adopt low-carbon lifestyles and actively take measures to reduce carbon footprints. Second, while well-being does not directly influence HCFs, this does not diminish the relevance of carbon reduction to overall well-being. Future studies could explore more comprehensive well-being indices to better understand its relationship with HCFs. Finally, fostering greater social trust can encourage households to reduce their carbon footprints, thereby promoting a collective social commitment to environmental protection.

Moreover, analysis of the control variables reveals that both the individual characteristics of the household head and household-level attributes significantly influence HCFs. Specifically, the gender and age of the household head, as well as housing situation, are negatively associated with carbon footprints. On the other hand, the education level, marital status, health status, urban or rural location, family size, and household income have significant positive effects on HCFs.

4.2. Impact of Psychosocial Factors on Different Types HCFs

In this section, we examine the influence of psychosocial factors on HCFs across different types, building on the previous findings. We focus on the primary term of environmental evaluation and the secondary term of social trust, analyzing their effects on the carbon footprints of the survival, development, and enjoyment types. Additionally, given that well-being was found to have no significant impact on HCFs in the previous study, we incorporate both primary and secondary terms of well-being to explore their effects on various types of carbon footprints. In addition, survival-oriented carbon footprints include clothing, food and dwelling; Development-oriented include Household goods and services, other goods and services; Enjoyment-based include transportation and communication, education, culture and recreation, healthcare.

1) Impact of psychosocial factors on survival-oriented HCFs

Table 3 reports the effects of psychosocial factors use on survival-oriented HCFs. Environmental evaluation has a significant negative effect on survival-oriented HCFs, with a 1% increase in environmental evaluation decreasing survival-oriented HCFs by 1%, and this decrease comes mainly from clothing and dwelling carbon footprints. Social trust has no significant effect on survival-oriented HCFs, but there

is a significant inverted "U" shaped relationship with the clothing category of these emissions. Well-being also has no significant effect on survival-oriented HCFs, but the primary index is positive and the secondary index is negative for clothing and food emissions, indicating that the effect of well-being on clothing and food carbon footprints is firstly promoting and then inhibiting, showing an inverted "U" curve.

Table 3. Impact of psychosocial factors on survival-oriented HCFs.

	Survival-oriented		Clothing		Food		Dwelling	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Environmental evaluation	−0.010***		−0.019***		−0.004		−0.018***	
	(0.003)		(0.004)		(0.003)		(0.004)	
Well-being	−0.003	−0.020	0.010*	0.136***	0.003	0.033*	−0.007	−0.003
	(0.003)	(0.016)	(0.005)	(0.025)	(0.004)	(0.018)	(0.006)	(0.027)
Well-being^2		−0.000		−0.010***		−0.002*		−0.000
		(0.001)		(0.002)		(0.001)		(0.002)
Social trust		0.010		0.055***		0.012		0.007
		(0.008)		(0.013)		(0.009)		(0.014)
Social trust^2		−0.002*		−0.008***		−0.003*		−0.003
		(0.001)		(0.002)		(0.001)		(0.002)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample size	20336	20336	20336	20336	20336	20336	20336	20336

2) Impact of psychosocial factors on development-oriented HCFs

Table 4 reports the effect of psychosocial factors on development-oriented HCFs. Environmental evaluation has a significant negative effect on development-oriented HCFs; specifically, a 1% increase in environmental evaluation is associated with a 1.7% reduction in development-oriented HCFs. Well-being has no significant effect on development-oriented HCFs, but the effect of well-being on the category of other goods and services is a significant inverted "U" curve that first promotes and then inhibits. Social trust also has an inverted "U" curve on development-oriented HCFs.

Table 4. Impact of psychosocial factors on development-oriented HCFs.

	Development-oriented		Household goods and services		Other goods and services	
	(1)	(2)	(3)	(4)	(5)	(6)
Environmental evaluation	−0.017***		−0.020***		−0.015***	
	(0.004)		(0.004)		(0.004)	
Well-being	0.005	0.027	0.000	0.020	0.007	0.099***
	(0.005)	(0.022)	(0.006)	(0.024)	(0.006)	(0.025)
Well-being^2		−0.003**		−0.003		−0.007***
		(0.002)		(0.002)		(0.002)
Social trust		0.056***		0.051***		0.085***
		(0.012)		(0.014)		(0.014)
Social trust^2		−0.007***		−0.007***		−0.011***
		(0.002)		(0.002)		(0.002)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes
Sample size	20336	20336	20336	20336	20336	20336

3) Impact of psychosocial factors on enjoyment-based HCFs

Table 5 reports the impact of psychosocial factors on enjoyment-based HCFs. A 1% increase in environmental evaluation is associated with a 1.1% reduction in enjoyment-based HCFs. This reduction is primarily attributed to education, culture, recreation, and healthcare HCFs. While well-being has no significant effect on overall enjoyment-based HCFs, it exhibits an inverted "U" shaped relationship with education, culture, and entertainment HCFs, initially promoting and later inhibiting them. Similarly, social trust shows an inverted "U" shaped relationship with enjoyment-based HCFs, with its influence primarily stemming from education, culture, recreation, and medical care.

Table 5. Impact of psychosocial factors on enjoyment-based HCFs.

	Enjoyment-based		Transportation and communication		Education, culture and recreation		Healthcare	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Environmental evaluation	−0.011***		−0.004		−0.036***		−0.020***	
	(0.003)		(0.003)		(0.007)		(0.005)	
Well-being	−0.000	−0.009	−0.003	−0.006	0.005	0.119***	0.001	0.017
	(0.004)	(0.016)	(0.004)	(0.019)	(0.009)	(0.040)	(0.007)	(0.032)
Well-being^2		0.001		0.000		−0.009***		−0.001
		(0.001)		(0.001)		(0.003)		(0.002)
Social trust		0.025***		0.010		0.097***		0.061***
		(0.009)		(0.011)		(0.021)		(0.018)
Social trust^2		−0.004***		−0.003		−0.010***		−0.009***
		(0.001)		(0.002)		(0.001)		(0.002)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample size	20336	20336	20336	20336	20336	20336	20336	20336

4.3. Robustness check

1) Changing regression samples

The average age of household heads in the base regression sample is approximately 50 years, with 23.54% older than 60 and only 0.13% younger than 18. However, in some cases, the most suitable respondents for the questionnaires may not be household heads. This is particularly true for households with very young or very old heads, who may not be the primary decision-makers in household consumption activities. Therefore, excluding these households from the sample helps to ensure more robust conclusions.

Table 6. Changing regression samples.

	HCFs				
	(1)	(2)	(3)	(4)	(5)
Environmental evaluation	−0.009***				
	(0.003)				
Well-being		−0.002	−0.013		
		(0.003)	(0.015)		
Well-being^2			0.001		

Continued

			(0.001)		
Social trust				0.003	0.020**
				(0.003)	(0.008)
Social trust^2					−0.003**
					(0.001)
Control variable	Yes	Yes	Yes	Yes	Yes
Sample size	15132	15132	15132	15132	15132

In this study, we further refine the sample to include only households whose heads are aged between 18 and 60, resulting in an average age of approximately 43 years. After re-estimating the regression equations using the restricted sample, the results (Table 6) indicate that environmental evaluation has a significant negative effect on HCFs. Well-being, however, remains statistically insignificant. Additionally, social trust exhibits an inverted "U" shaped relationship with HCFs. These findings confirm the robustness of the results.

2) Changing the dependent variable

Secondly, we change the dependent variable HCFs into per capita HCFs and redo the regression. Table 7 presents the effects of psychosocial factors on per capita HCFs and reveals that environmental evaluation has a significant negative impact. Social trust exhibits an inverted "U" shaped relationship with per capita HCFs, initially increasing them before leading to a reduction. In contrast, the sense of well-being does not have a statistically significant effect on per capita HCFs. These findings align with the results of previous regression analyses, further confirming their robustness.

Table 7. Changing dependent variable.

	Per capita HCFs				
	(1)	(2)	(3)	(4)	(5)
Environmental evaluation	−0.009***				
	(0.002)				
Well-being		0.001	0.006		
		(0.003)	(0.014)		
Well-being^2			−0.000		
			(0.001)		
Social trust				0.002	0.015**
				(0.003)	(0.007)
Social trust^2					−0.002**
					(0.001)
Control variable	Yes	Yes	Yes	Yes	Yes
Sample size	20336	20336	20336	20336	20336

5. Heterogeneity Analysis

Heterogeneity analysis is performed taking into account regional differences in household distribution, including regional differences (eastern, central and western) and urban-rural differences (urban and rural). According to the above, the

impact of happiness on household carbon footprint is not statistically significant, so the heterogeneity of environmental evaluation and social trust on household carbon emissions is discussed. Table 8 Column 1-Column 3 shows the Eastern-Central-Western heterogeneity of psychosocial factors on HCFs. In general, environmental evaluation has a significant negative impact on HCFs in all regions, with the same impact on eastern and central households, and the least impact on western households. Social trust only has an inverted "U" shaped effect on HCFs in the eastern.

The results of rural-urban heterogeneity are shown in columns in Table 8, Column 4 and Column 5. In general, environmental evaluation has a significant negative impact on HCFs in both urban and rural areas, and has a greater impact on HCFs in urban areas. When environmental evaluation increases by 1%, household carbon emissions in urban areas decrease by 1.3%. The influence of social trust on rural households is an inverted "U" curve. There was no significant effect on urban households.

Table 8. Heterogeneity analysis results.

	Eastern	Central	Western	Urban	Rural
	(1)	(2)	(3)	(4)	(5)
Environmental evaluation	−0.010***	−0.010**	−0.008*	−0.013***	−0.006**
	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)
Social trust	0.022**	0.002	0.020	0.006	0.024**
	(0.010)	(0.014)	(0.014)	(0.010)	(0.010)
Social trust2	−0.003*	−0.002	−0.004*	−0.002	−0.003**
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)
Control variable	Yes	Yes	Yes	Yes	Yes
Sample size	9804	4826	5706	10798	9538

6. Conclusion and Recommendation

6.1. Conclusion

This paper focuses on three key factors: environmental evaluation, well-being, and social trust. It constructs a mixed-effects model to empirically analyze the impact of these psychosocial factors on HCFs and examines the heterogeneity of this effect in different regions. Several key findings have emerged: Environmental evaluation has a significant negative relationship with HCFs. Contrary to expectations, well-being has no significant effect on HCFs. This suggests that while well-being is a crucial aspect of well-being, it may not directly translate into environmental consciousness or actions. An inverted U-shaped relationship exists between social trust and HCFs. This implies that increasing social trust initially promotes pro-environmental behavior, but beyond a certain threshold, it may lead to complacency or reduced efforts in carbon reduction. The study reveals that Environmental evaluation has a significant negative impact on HCFs in all regions, and the inverted "U" shape of social trust on HCFs is significant only in eastern, central and rural areas. This highlights that households in different regions should

implement different carbon reduction policies.

6.2. Recommendation

The following are recommendations written from the conclusions:

Improve environmental evaluation to reduce HCFs. First of all, the government should increase its support for green buildings, promote the application of energy-saving and environmental protection materials and technologies, transform old residential areas, and improve the quality of the living environment. Secondly, strengthen environmental protection education, through community activities, publicity and incentive mechanisms, encourage residents to participate in energy conservation and emission reduction actions, and enhance their sense of identity and responsibility for environmental protection. This can not only improve the living environment, but also effectively reduce carbon emissions.

Build social trust and balance environmental efforts. The inverted "U" shaped relationship between social trust and HCFs suggests that higher levels of trust can encourage sustainable behavior. Community engagement initiatives, such as local environmental groups and participatory decision-making processes, can contribute to increased levels of social trust. By providing transparent information and opportunities for collaboration, governments can ensure that social trust is a motivating factor for sustaining environmental efforts over the long term.

Make different HCFs reduction plans according to different region households. In the eastern and central regions, households can be further encouraged to adopt a low-carbon lifestyle by strengthening environmental awareness education and upgrading the environmental evaluation system, especially by providing subsidies for energy-saving technologies and green products, to promote the optimization of household energy structure. In the western region, HCFs can be promoted by enhancing social trust and strengthening environmental protection cooperation among local communities. In addition, urban households can further reduce HCFs by promoting green buildings, energy-efficient appliances and low-carbon transportation. In rural areas, carbon reduction targets can be achieved by gradually changing the energy consumption habits of rural households by enhancing social trust and providing low-cost energy-saving technologies.

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Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

References

Ajzen, I. (1991). The Theory of Planned Behavior. *Organizational Behavior and Human Decision Processes, 50,* 179-211. https://doi.org/10.1016/0749-5978(91)90020-t

Bai, Y., & Liu, Y. (2013). An Exploration of Residents' Low-Carbon Awareness and

Behavior in Tianjin, China. *Energy Policy, 61,* 1261-1270. https://doi.org/10.1016/j.enpol.2013.06.014

Brounen, D., Kok, N., & Quigley, J. M. (2013). Energy Literacy, Awareness, and Conservation Behavior of Residential Households. *Energy Economics, 38,* 42-50. https://doi.org/10.1016/j.eneco.2013.02.008

Gadenne, D., Sharma, B., Kerr, D., & Smith, T. (2011). The Influence of Consumers' Environmental Beliefs and Attitudes on Energy Saving Behaviours. *Energy Policy, 39,* 7684-7694. https://doi.org/10.1016/j.enpol.2011.09.002

Hua, Y., & Shi, B. (2023). Internet Usage and Household Indirect Carbon Emissions Measurement and Impact Factor Analysis. *Journal of Chongqing University (Social Science Edition), 29,* 117-134.

Ivanova, D., Stadler, K., Steen-Olsen, K., Wood, R., Vita, G., Tukker, A. et al. (2015). Environmental Impact Assessment of Household Consumption. *Journal of Industrial Ecology, 20,* 526-536. https://doi.org/10.1111/jiec.12371

Ji, Z., Lai, X., & Jia, L. (2016). Measurement and Driving Factors of Carbon Emissions from Household Energy Consumption. *China Population, Resources and Environment, 26,* 64-72.

Kaida, N., & Kaida, K. (2016). Pro-Environmental Behavior Correlates with Present and Future Subjective Well-Being. *Environment, Development and Sustainability, 18,* 111-127. https://doi.org/10.1007/s10668-015-9629-y

Li, J., Zhang, D., & Su, B. (2019). The Impact of Social Awareness and Lifestyles on Household Carbon Emissions in China. *Ecological Economics, 160,* 145-155. https://doi.org/10.1016/j.ecolecon.2019.02.020

Li, Z., & Wang, J. (2021). Accounting and Driving Factors Analysis of Household Carbon Emissions in Urban and Rural China. *Statistics & Decision, 37,* 48-52. https://doi.org/10.13546/j.cnki.tjyjc.2021.20.010

Mi, Z., Zheng, J., Meng, J., Ou, J., Hubacek, K., Liu, Z. et al. (2020). Economic Development and Converging Household Carbon Footprints in China. *Nature Sustainability, 3,* 529-537. https://doi.org/10.1038/s41893-020-0504-y

Steg, L., Dreijerink, L., & Abrahamse, W. (2005). Factors Influencing the Acceptability of Energy Policies: A Test of VBN Theory. *Journal of Environmental Psychology, 25,* 415-425. https://doi.org/10.1016/j.jenvp.2005.08.003

Sun Y. (2022). Research on Household Carbon Emissions and It's lnfluencing Factors-An Empirical Analysis Based on the Perspective of the Family Life Cycle. *Population Journal, 44,* 86-98. https://doi.org/10.16405/j.cnki.1004-129X.2022.05.007

Wang, J. (2015a). The Dimensional Structure of Environmental Emotions and Its Impact on Consumers' Carbon Reduction Behavior. *Journal of Management World, 12,* 82-95. https://doi.org/10.19744/j.cnki.11-1235/f.2015.12.008

Wang, Q. (2015b). Effects of Household Size on Energy Consumption and Carbon Emissions. *Resources Science, 37,* 299-307.

Wei, Y., Liu, L., Fan, Y., & Wu, G. (2007). The Impact of Lifestyle on Energy Use and CO_2 Emission: An Empirical Analysis of China's Residents. *Energy Policy, 35,* 247-257. https://doi.org/10.1016/j.enpol.2005.11.020

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. *Journal of Industrial Ecology, 17,* 880-891. https://doi.org/10.1111/jiec.12057

Yuan Y. (2020). Psychologically Driven or Structurally Bound: Analysis of the Mechanism

of Resident's Low-Carbon Travel in Urban. *Journal of Arid Land Resources and Environment, 34,* 20-26. https://doi.org/10.13448/j.cnki.jalre.2020.61

Zhao, L., Nan, L., Li, X., Liu, M., & Li, M. (2019). Environmental Equity Perception, Social Trust and Farmers' Behavior of Low Carbon Production-Taking Plastic Film and Straw as An Example. *Chinese Journal of Agricultural Resources and Regional Planning, 40,* 91-100.

Zhou, J., Shi, X., Zhao, J., Wang, Y., & Sun, L. (2019). On Regional Difference and Influential Factors of Carbon Emissions from Direct Living Energy Consumption of Chinese Residents. *Journal of Safety and Environment, 19,* 954-963. https://doi.org/10.13637/j.issn.1009-6094.2019.03.032