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PAPER

Who emits as we age? Drivers and mitigation potentials of mid-to late-life carbon footprints across intergenerational, socioeconomic, and climatic dimensions

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Abstract

Residential consumption is a major source of greenhouse gas emissions, and rapid population aging is reshaping how these emissions are generated and distributed. In aging societies, later-life carbon outcomes are influenced not only by income and consumption needs but also by intergenerational support, housing conditions, digital access, and climatic exposure. China provides an important setting because population aging, strong family support systems, and large cross-city climatic differences coexist with substantial heterogeneity in household living conditions. However, micro-level evidence remains limited regarding how carbon-footprint heterogeneity varies across adjacent later-life cohorts and across these multiple dimensions. Here we show, by linking an environmentally extended multi-regional input–output framework to data for 15 243 individuals in 104 Chinese cities, that assigned per-capita household consumption-based carbon footprints differ systematically between adults aged 45–64 years and those aged 65 years and older, and that the nonlinear associations with key socioeconomic factors also vary across cohorts: income exhibits a U-shaped association, whereas assets and intergenerational support exhibit inverted-U associations, with these relationships differing in strength between the two groups. Model-implied scenario contrasts indicate that the largest predicted differentials arise across climate-related settings, reaching 407.95 kg-CO_2/cap for cold-versus-temperate conditions and 190.87 kg-CO_2/cap for hot-versus-temperate conditions. In addition, a reduction in durable-goods expenditure among high-income adults aged 45–64 years is associated with a predicted decline of 112.6 kg-CO_2/cap, of which vehicle outlays account for the largest share. These findings suggest that later-life carbon heterogeneity is shaped not only by affluence but also by cohort–specific consumption patterns and climate-related living environments, thereby providing a more differentiated basis for mitigation design in aging societies.

1. Introduction

1.1. Background

Residential activities—accounting for 72% of global greenhouse-gas emissions (Hertwich and Peters 2009)—are a critical source of carbon dioxide (CO_2) emissions and thus an important target for further climate mitigation in China. Economic growth has shifted household consumption from subsistence-oriented to quality-oriented patterns, fueling upgrades in durable goods, expanding demand for medical and eldercare services through social insurance, and diversifying energy use through digital platforms. At the same time, China's population is aging rapidly, with the share of people aged 65 and above rising from 4.0% in 1960 to 13.7% in 2022 (Peng 2023), thereby reshaping residents' lifestyles. Aging

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influences the consumption–carbon nexus through two opposing mechanisms: older cohorts typically allocate a larger share of spending to essentials, thereby reducing carbon footprints (CF) (Wang and Liu 2024); conversely, increased longevity raises demand for social care and medical services, partially offsetting these reductions (Fan *et al.* 2021). Moreover, newly emerging elderly cohorts may exhibit consumption behaviors distinct from those of earlier elderly cohorts because of intergenerational turnover. Consumption habits tend to remain stable over the life course; hence, as middle-aged individuals enter later life, their material demands may remain relatively high (Menz and Welsch 2012). Although residents' CF in China follows an inverted-U age profile—peaking in midlife before declining in older age (Zhang *et al* 2023)—imminent generational turnover may reverse this trend in the absence of effective intervention, causing future elderly cohorts to exhibit higher per-capita CF. Consequently, early micro-level analysis of consumption behavior among elderly and middle-aged cohorts—the latter constituting the source of intergenerational turnover—is essential for rigorously assessing the demographic implications for consumption-based emissions and for informing forward-looking policy frameworks.

Households in China bear the primary responsibility for eldercare (Zhang and Lei 2025), as more than 40% of older adults co-reside with their adult children and approximately 34% live nearby (Lei *et al* 2015). Intergenerational support—encompassing financial transfers, practical assistance, and emotional companionship—helps secure older adults' economic and care needs while increasing their disposable resources and reducing reliance on market services (Levine *et al* 2010, Wu *et al* 2018). By promoting social engagement and greater spending on experiential goods, such support may alter both the scale and the composition of older adults' CF.

1.2. Literature review

Most studies of resident CF remain macro-oriented and make limited use of micro-level data, which limits the ability to link residential lifestyles to the socioeconomic determinants of CF (Ivanova *et al* 2016, Xia *et al* 2019, Salo *et al* 2021, Peng *et al* 2023, Lian *et al* 2024). Although econometric methods—especially regression analysis—are widely used to identify the socioeconomic and behavioral factors associated with CF, this line of research still faces several important limitations.

First, despite the growing availability of large-scale microdata, many studies still rely on aggregated statistics, thereby introducing systematic bias and obscuring individual- or household-level mechanisms. For example, Wiedenhofer *et al* (2013) examined socioeconomic drivers of residential energy demand in Australia using district-level expenditure data, while Jiang *et al* (2020) relied on city-averaged indicators to analyze household emissions in Japan. Wakefield and Lyons (2010) further argue that hierarchical and spatial models cannot recover the granularity lost through aggregation, and Jones and Kammen (2014) likewise show that microdata can reveal patterns concealed in macro-level analyses, underscoring the importance of fine-scale evidence for targeted mitigation. In spatially heterogeneous economies such as China, Ahmad *et al* (2021) therefore stress the need for disaggregated assessments rather than national averages. This limitation is also evident in recent survey-based studies. Using household survey data from two Chinese cities, Cao *et al* (2025) show that household energy use and associated CO_2 emissions vary with local housing and household conditions. Wang *et al* (2025) similarly show that population aging affects residential energy demand and emissions through channels such as housing space and shrinking household size. However, these studies remain at the household level, rather than extending the analysis to individual-level assigned CF and cohort–specific heterogeneity within aging populations.

Second, data constraints and model simplification often lead to incomplete sets of explanatory variables. Most regressions of resident CF still focus on conventional socioeconomic variables such as income and education (Hernández and Vita 2022, Zen *et al* 2022, Almulhim *et al* 2024). Yet Lévay *et al* (2023) show that parsimonious models can substantially overestimate income elasticity, whereas broader specifications improve model fit and reduce residual variance. The socioeconomic dimension itself is also more complex than often assumed. Tian *et al* (2025) show that carbon inequality in China is shaped not only by income differences but also by disparities in capital ownership, indicating that asset-related factors should be considered alongside income in empirical analyses. Zhang *et al* (2025) further show that aging and affluence jointly shape household CO_2 emissions in China, suggesting that the carbon implications of population aging should be interpreted together with broader economic conditions. Climatic conditions likewise deserve more explicit attention. De Cian *et al* (2025) show that air-conditioning adoption substantially increases household electricity consumption, with effects varying by weather conditions, income, and country context, thereby highlighting the carbon implications of cooling demand. Hu *et al* (2025) further show that residential electricity use and mitigation potential in aging buildings are highly sensitive to temperature change, indicating that climatic exposure can materially affect residential carbon outcomes through heating and cooling needs. Intergenerational transmission is another dimension that remains insufficiently incorporated into regression-based analyses of resident

CF. Zhao *et al* (2025) show that financial support for elderly care affects rural households' adoption of clean cooking energy through labor allocation and social-network diffusion, while Gan *et al* (2025) find that adult children's education significantly reduces elderly parents' energy poverty through intergenerational financial transfers, the digital divide, and social capital. Together, these studies suggest that intergenerational transmission operates not only through co-residence or household structure but also through support flows and energy-related household decisions. However, such mechanisms are still rarely incorporated into regression-based analyses of resident CF, especially in ways that distinguish adjacent later-life cohorts.

1.3. Research purpose

Global population aging raises a more focused question than whether older adults emit less than younger adults on average: as middle-aged cohorts transition into later life, which observed lifestyle patterns, intergenerational relationships, and climatic conditions are associated with differences in resident CF, and to what extent can these differences be translated into age-stratified comparative mitigation relevance? Rather than treating middle-aged and older adults as one homogeneous group, this study focuses on two adjacent later-life cohorts—residents aged 45–64 years (45–64 s) and those aged 65 years and older (65 s–)—to capture how CF heterogeneity evolves during the transition into old age within an aging society.

This study makes three main contributions. First, by linking Chinese microdata to a provincial environmentally extended multi-regional input–output (MRIO) framework, we construct cohort-stratified, individually assigned estimates of resident CF. This approach moves beyond aggregate and household-level analyses and enables a more fine-grained examination of later-life carbon heterogeneity. Second, within an extended micro-level regression framework, we examine how multidimensional CF heterogeneity is associated with observed differences in economic conditions, demographic characteristics, living habits, social support, household assets, living conditions, and climatic exposure, with particular attention to the age-differentiated roles of intergenerational support and digitalization. In doing so, we show that the carbon implications of aging are shaped not only by affluence but also by cohort–specific lifestyle adaptation, family support structures, and residential climatic exposure. Third, we translate the estimated association structure into standardized scenario-based predicted differences that provide a comparative basis for assessing the relative mitigation relevance of selected behavioral, socioeconomic, and climate-related contrasts across age cohorts. Throughout, our empirical strategy is explicitly associational rather than causal. The regression results are used to characterize later-life CF heterogeneity and to derive comparative predicted differences within a maintained regression framework, rather than to identify the causal effects of realized behavioral change, residential relocation, or policy intervention.

2. Data and methods

We first describe the data sources and variable construction, then present descriptive statistics on heterogeneity in resident CF, and finally outline the methodological framework, including the CF estimation procedure and the regression design.

2.1. Key variables and data

Table 1 reports the variables used in the regression analysis, together with their definitions and data sources. The dependent variable, resident CF, is a consumption-based measure estimated from household expenditure vectors using data from the 2018 wave of the China health and retirement longitudinal study (CHARLS), whereas most explanatory variables are drawn from the same survey. At the individual level, we relate estimated CF to a broad set of economic, demographic, and lifestyle characteristics, together with detailed city-level climatic indicators. After data cleaning—including individual–household linkage, integration of the CHARLS data with the MRIO table to estimate the dependent variable, and processing of variables across all domains (see section S1.2 of the supplementary information (SI))—the final analytical dataset comprises 15 243 individuals from 104 cities. Although the most recent CHARLS wave was conducted in 2020, pandemic-related disruptions affected both lifestyles and survey conditions. We therefore use the 2018 wave to retain a pre-pandemic socioeconomic baseline.

We treat the economic dimension as the primary domain and include three core indicators—income, assets, and intergenerational support—to capture consumption capacity, durable-goods purchasing potential, and intra-household transfers. The demographic domain extends beyond conventional variables such as age to incorporate life-course experiences, including participation in the send-down movement, thereby providing a richer characterization of how individual attributes are associated with CF.

Table 1. Descriptive statistics: cross-sectional data for 2018.

Variable	Full sample		45–64 s		65 s–		Explanation	Reference
	Obs.	Mean	Obs.	Mean	Obs.	Mean		
Explained								
ln(*Total_CF*)	15 194	6.025	9081	6.145	6113	5.848	CF/cap for all goods and services	Estimated based on the raw data of CHARLS with the provincial MRIO table and CEADs apparent emissions data
ln(*Food_CF*)	15 194	3.027	9081	3.144	6113	2.853	CF/cap for food	
ln(*Electricity_CF*)	15 194	5.574	9081	5.699	6113	5.389	CF/cap for electricity	
ln(*Gas_CF*)	15 194	−0.14	9081	−0.028	6113	−0.305	CF/cap for gas	
ln(*Water_CF*)	15 194	−3.605	9081	−3.496	6113	−3.767	CF/cap for water	
ln(*Durablegoods_CF*)	15 194	2.303	9081	2.419	6113	2.131	CF/cap for durable-goods	
ln(*Consumablegoods_CF*)	15 194	3.493	9081	3.604	6113	3.329	CF/cap for consumable-goods	
ln(*Education_CF*)	15 194	0.836	9081	0.952	6113	0.665	CF/cap for education	
ln(*Medicals_CF*)	15 194	−1.678	9081	−1.581	6113	−1.823	CF/cap for medicals	
ln(*Transportation_CF*)	15 194	3.246	9081	3.354	6113	3.086	CF/cap for transportation	
ln(*Catering_CF*)	15 194	−0.349	9081	−0.219	6113	−0.542	CF/cap for catering services	
ln(*Entertainment_CF*)	15 194	−1.945	9081	−1.805	6113	−2.154	CF/cap for entertainment	
ln(*Financerealestate_CF*)	15 194	1.171	9081	1.288	6113	0.996	CF/cap for finance and real estate	
ln(*Other_CF*)	15 194	3.568	9081	3.682	6113	3.399	CF/cap for others	
Explanatory								
ln(*Income*)	15 243	8.49	9092	8.484	6151	8.499	Income-level	CHARLS
ln(*Asset*)	15 243	9.122	9092	9.34	6151	8.799	Asset-level	
ln(*Child_support*)	15 243	6.37	9092	5.764	6151	7.266	Intergenerational support from adult children.	
Age	15 012	62.15	9092	55.50	5920	72.37	Age (years)	CHARLS
Marriage	15 243	0.859	9092	0.935	6151	0.746	Marital status	
Household_size	15 243	5.494	9092	5.755	6151	5.109	Household size	
Self_education	15 243	4.897	9092	5.688	6151	3.729	Respondent's educational attainment	
Children_education	15 243	3.423	9092	3.861	6151	2.776	Children's educational attainment	
Health_status	14 195	2.934	8640	2.828	5555	3.099	Self-assessed general health	
Chronic_disease	15 243	0.464	9092	0.427	6151	0.519	Chronic disease status (dummy)	
Lifetime_work	15 243	0.635	9092	0.768	6151	0.439	Lifetime labor-force participation (dummy)	
Subsistence_allowance	15 243	0.072	9092	0.056	6151	0.095	Low-income subsidy receipt (dummy)	
Sent_down_to_countryside	15 243	0.025	9092	0.019	6151	0.034	Send-down movement participation (dummy)	

(Continued.)

Table 1. (Continued.)

Smoking	15 243	0.044	9092	0.046	6151	0.041	Smoking status (dummy)	CHARLS
Drinking	15 243	0.265	9092	0.293	6151	0.225	Drinking status (dummy)	
Mobile_payments	15 243	0.075	9092	0.115	6151	0.016	Mobile-payment usage (dummy)	
Medical_insurance	15 243	0.972	9092	0.976	6151	0.966	Health insurance enrollment (dummy)	CHARLS
Pension_insurance	15 243	0.852	9092	0.855	6151	0.847	Pension scheme participation (dummy)	
Community_eldercare	15 243	0.113	9092	0.034	6151	0.23	Local eldercare-program participation (dummy)	
ln(*Automobile*)	15 243	1.192	9092	1.788	6151	0.312	Automobile expenditure	CHARLS
ln(*Electric_bicycle*)	15 243	3.058	9092	3.608	6151	2.244	Electric-bicycle expenditure	
ln(*Refrigerator*)	15 243	4.927	9092	5.417	6151	4.204	Refrigerator expenditure	
ln(*Washing_machine*)	15 243	4.078	9092	4.644	6151	3.242	Washing machine expenditure	
ln(*Television*)	15 243	4.953	9092	5.29	6151	4.456	Television expenditure	
ln(*Computer*)	15 243	1.147	9092	1.582	6151	0.505	Computer expenditure	
House_age	15 242	19.647	9092	17.992	6150	22.095	Dwelling age	CHARLS
Property_registration	15 243	0.814	9092	0.851	6151	0.759	Land-title registration (dummy)	
Gas_supply	15 242	0.215	9092	0.211	6150	0.22	Municipal gas connection (dummy)	
Heating_supply	15 242	0.14	9092	0.141	6150	0.138	Central heating connection (dummy)	
Internet_supply	15 242	0.465	9092	0.562	6150	0.321	Internet connectivity (dummy)	
Air_satisfaction	14 108	2.852	8614	2.871	5494	2.821	Indoor air-quality rating	
Air_purification	15 242	0.025	9092	0.027	6150	0.023	Air-purifier installation (dummy)	
HDD	15 243	71.709	9092	73.816	6151	68.593	Annual heating degree days	China Meteorological Administration, and Meteorological Data Center of the China Meteorological Administration
CDD	15 243	75.366	9092	73.702	6151	77.825	Annual cooling degree days	

In addition, Gaussian kernel density estimates of mean-centered CF indicate that controlling for demographic characteristics reduces heterogeneity, offering distribution-level support for the inclusion of more refined explanatory variables (figure A1). The living-habits domain captures discretionary behaviors, such as mobile-payment use, that may shape CF by altering the frequency and composition of consumption. The social-security domain includes medical insurance, pension participation, and community eldercare to examine how risk protection and care arrangements are associated with CF. The household-ownership domain emphasizes the long-term emissions implications of durable goods, including the life-cycle carbon consequences of digital products. The living-conditions domain captures housing and infrastructure characteristics, such as internet access, that may create long-run lock-in effects on household energy demand. Finally, climatic conditions are represented by heating degree days (HDD) and cooling degree days (CDD), which capture exogenous variation in heating and cooling demand across cities. Table 2 summarizes the variables selected for the CF analysis and their expected coefficient signs, while sections S1.3 and S1.4 of the SI provide the detailed literature background, rationale, and hypotheses underlying variable selection.

Resident CF, the dependent variable in this study, refers to the indirect CO_2 emissions embodied in electricity and heat use, as well as in the supply chains of consumed goods and services (Huang *et al* 2022). We estimate resident CF by linking China's 2017 provincial MRIO table—covering 42 sectors across 31 provinces (Zheng *et al* 2020)—to household expenditure data from the 2018 wave of CHARLS. Rather than assigning a single carbon coefficient to aggregate household expenditure, we map CHARLS consumption items into province–sector consumption vectors and embed them within an environmentally extended MRIO framework that traces emissions throughout the full supply chain. The resulting CF estimates therefore reflect not only the scale of expenditure but also expenditure composition, province- and sector-specific carbon intensities, regional production heterogeneity, and interregional supply-chain linkages. This framework captures both the spatial heterogeneity of CF and the intersectoral linkages through which regional production, consumption, and trade are connected (Wakiyama *et al* 2020). Although the expenditure data are drawn from the 2018 wave of CHARLS, the household expenditure module relies on weekly, monthly, and annual recall questions designed to capture consumption in the period preceding the interview. Once annualized, these expenditure data can be aligned consistently with the 2017 MRIO benchmark.

2.2. Estimation framework for resident CF

Applying the environmentally extended MRIO framework to CHARLS microdata, we estimate resident CF while combining top-down and bottom-up validation to reduce aggregation bias and capture behavioral heterogeneity. The basic structure is given by equations (1) and (2) (Peters and Hertwich 2009),

$$\boldsymbol{C} = \boldsymbol{K}(\boldsymbol{I} - \boldsymbol{A})^{-1} y \tag{1}$$

$$\boldsymbol{C} = \begin{bmatrix} \boldsymbol{C}^1 \\ \boldsymbol{C}^2 \\ \vdots \\ \boldsymbol{C}^n \end{bmatrix}, \boldsymbol{K} = \begin{bmatrix} \boldsymbol{k}^1 \\ \boldsymbol{k}^2 \\ \vdots \\ \boldsymbol{k}^n \end{bmatrix}, \boldsymbol{A} = \begin{bmatrix} \boldsymbol{A}^{11} & \boldsymbol{A}^{12} & \cdots & \boldsymbol{A}^{1n} \\ \boldsymbol{A}^{21} & \boldsymbol{A}^{22} & \cdots & \boldsymbol{A}^{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \boldsymbol{A}^{n1} & \boldsymbol{A}^{n2} & \cdots & \boldsymbol{A}^{nn} \end{bmatrix},$$
$$\boldsymbol{y} = \begin{bmatrix} \boldsymbol{y}^{11} & \boldsymbol{y}^{12} & \cdots & \boldsymbol{y}^{1n} \\ \boldsymbol{y}^{21} & \boldsymbol{y}^{22} & \cdots & \boldsymbol{y}^{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \boldsymbol{y}^{n1} & \boldsymbol{y}^{n2} & \cdots & \boldsymbol{y}^{nn} \end{bmatrix} \tag{2}$$

where $\boldsymbol{C}$ is the CF from resident consumption. $\boldsymbol{K}$ is a vector of the carbon intensities for all economic sectors, obtained from the carbon emission accounts and datasets (Guan *et al* 2021). $\boldsymbol{I}$ is the identity matrix. The technical coefficient submatrix $\boldsymbol{A}^{rs} = (a_{ij}^{rs})$ is given by $a_{ij}^{rs} = \frac{z_{ij}^{rs}}{x_j^s}$, where z_{ij}^{rs} represents the intersectoral monetary flows from sector i in province r to sector j in province s. $y^{rs} = (y_i^{rs})$ is the resident consumption in province r of goods from sector i imported from province s. i and $j = 1 \cdots 42$ denote all economic sectors, while r and $s = 1 \cdots 31$ denote the 31 provinces. After determining province- and sector-specific carbon intensities, we reconciled discrepancies between the provincial MRIO table

Table 2. Selected explanatory variables and expected coefficients used for estimating resident CF.

Domains	Indicator	Predicted effect	Reasoning	References
Economics	*Income*	+	Increasing income enhances consumption capacity.	(Golley and Meng 2012).
	Asset	+	Asset endowments represent the ability to acquire and maintain carbon-intensive durable goods.	(Starr *et al* 2023)
	Child_support	±	Intergenerational support raises income, boosting emissions while reducing energy use via intra-household sharing	(Damman and van Duijn 2017, Zhou *et al* 2023)
Demographics	*Age*	−	Elderly cohorts exhibit lower life-cycle CF than younger cohorts.	(Ottelin *et al* 2018, Shigetomi *et al* 2014)
	Marriage *Household_size*	+	Married households have higher incomes and stronger consumption demand.	(Cao *et al* 2024)
	Self_education *Children_education*	+	Educational attainment correlates positively with income levels.	(Lin *et al* 2023, Zen *et al* 2022).
	Health_status *Chronic_disease*	+	Declining health and chronic illness intensify medical expenditures.	(Herrmann *et al* 2017, Zeeshan *et al* 2021).
	Lifetime_work	—	Extended labor-force participation strengthens human capital, fostering environmental awareness.	(Wulandari 2022)
	Subsistence_allowance	±	Subsistence allowances curb CF through consumption constraints but raise them via increased marginal consumption.	(Fan *et al* 2012, Wei *et al* 2024)
	Sent_down_to_countryside	+	Later-life CF is amplified by compensatory consumption and multigenerational households.	(Chen *et al* 2020)
Living habits	*Smoking* *Drinking*	+	Smoking and drinking impose carbon-intensive burdens, intensified by frequent socializing.	(Hallström *et al* 2018, Zafeiridou *et al* 2018)
	Mobile_payments	±	Mobile-payment convenience increases purchase frequency.	(Chen *et al* 2025)
Social security	*Medical_insurance* *Pension_insurance*	+	Enhanced social security mitigates income shocks and smooths lifetime consumption.	(Galiani *et al* 2016, Nansai *et al* 2020)
	Community_eldercare	—	By centralizing care in shared facilities and leveraging public infrastructure, economies of scale lower per-capita energy use.	

(Continued.)

Table 2. (Continued.)

Domains	Indicator	Predicted effect	Reasoning	References
Household ownership	*Automobile* *Electric_bicycle* *Refrigerator* *Washing_machine* *Television* *Computer*	+	Use-phase emissions arise from transport—automobiles and e-bikes—and the continuous operation of appliances—refrigerators, washing machines, computers, and TVs—with rapid computer turnover further amplifying life-cycle CF.	(Grottera *et al* 2018, Hertwich and Roux 2011, Shigetomi *et al* 2021)
Living conditions	*House_age*	−	Older homes have smaller floor areas and undergo less frequent equipment upgrades.	(Aksoezen *et al* 2015)
	Property_registration	−	Property registration secures tenure and return-expectations, spurring energy-efficiency retrofits.	(Zhao *et al* 2023)
	Gas_supply *Heating_supply* *Internet_supply*	+	Natural gas and centralized heating intensify carbon-intensive thermal energy use, while internet connectivity continually elevates electricity demand.	(Du *et al* 2024; Li *et al* 2020)
	Air_satisfaction *Air_purification*	+	Maintaining high indoor air-quality via continuous air purification raises electricity demand.	(Wilson *et al* 2013, Vita *et al* 2020,)
Climatic Conditions	*HDD* *CDD*	+	HDD and CDD measure heating and cooling demands; higher values indicate greater space-conditioning energy use.	(Ivanova *et al* 2017; Wiedenhofer *et al* 2013)

and CHARLS by mapping CHARLS consumption items to MRIO sectors and applying an optimization algorithm to recover sectoral consumption estimates (Shigetomi *et al* 2014). Accordingly, individually assigned CF in this study is derived from sectorally and regionally differentiated consumption vectors embedded in interregional supply chains, rather than from a simple proportional transformation of aggregate expenditure.

2.3. Empirical specification for the regression of resident CF

Building on the literature and our spatially resolved estimates of resident CF, we employ ordinary least squares (OLS) regression to examine how resident CF heterogeneity is associated with a broad range of observed characteristics (Wiedenhofer *et al* 2017, Ivanova and Wood 2020). This multidimensional specification is designed to characterize the conditional relationships between CF and observed covariates across individuals. Given the cross-sectional nature of the data, all estimates are interpreted as associations rather than causal effects. The baseline regression model is specified as follows:

$$\begin{aligned}\ln(C_t) = {} & \alpha_0 + \sum_{k=1}^{3}\beta_{k1}\text{Economics}_{tk} + \sum_{k=1}^{3}\beta_{k2}\text{Economics}_{tk}{}^{2} + \sum_{kD=1}^{10}\alpha_{kD}\text{Demographics}_{tkD} \\ & + \sum_{kLH=1}^{3}\alpha_{kLH}\text{Living habits}_{tkLH} + \sum_{kS=1}^{3}\alpha_{kS}\text{Social security}_{tkS} \\ & + \sum_{kH=1}^{6}\alpha_{kH}\text{Household ownership}_{tkH} + \sum_{kLC=1}^{7}\alpha_{kLC}\text{Living conditions}_{tkLC} \\ & + \sum_{kC=1}^{2}\alpha_{kC}\text{Climatic conditions}_{tkC} + \varepsilon_t \end{aligned} \tag{3}$$

where subscripts t and k denote the individual and variable indices, respectively, and $\ln(C_t)$ indicates the individual's CF in logarithmic form. Economics_{tk}, $\text{demographics}_{tkD}$, $\text{living habits}_{tkLH}$, $\text{social security}_{tkS}$, $\text{household ownership}_{tkH}$, $\text{living conditions}_{tkLC}$, and $\text{climatic conditions}_{tkC}$ represent the seven domains. Moreover, we transformed income, assets, intergenerational support, durable-goods expenditure, and resident CF by taking their natural logarithms. Note that, in the aforementioned procedure, to avoid undefined values arising from zero observations and to maintain a consistent baseline for the rate-of-change analysis, we added one before the logarithmic transformation, following Wooldridge (2016) and Tsagris *et al* (2016). To elucidate intersectoral heterogeneity in CF, we further consolidated the 42 sectors into 13 broader categories (see table A1 for the corresponding mappings).

For the category-specific regressions, some dependent variables contain a non-trivial share of zero observations, particularly gas, water, and entertainment CF. Although the $\ln(x+1)$ transformation is retained for consistency with the baseline specification, it may distort the distribution near zero and generate scale-sensitive marginal effects when zeros are frequent (Bellemare and Wichman 2020, Mullahy and Norton 2024). We therefore conduct an additional robustness check using Poisson pseudo-maximum likelihood (PPML), which accommodates non-negative outcomes with a mass at zero without requiring logarithmic transformation of the dependent variable (Silva and Tenreyro 2006).

2.4. Methods for estimating scenario-based CF differentials

To derive scenario-based predicted differences in resident CF within the maintained regression framework, we proceed as follows. Let Q denote resident CF, x the explanatory variable of interest, and $\hat{\beta}$ the corresponding estimated regression coefficients. For a standardized contrast in x of magnitude Δx, while other observed covariates are held at their specified values, the model-implied difference in predicted CF (ΔQ) can be derived from the baseline regression equations below. Consistent with the associational interpretation of the regression framework, these quantities are reported as model-implied predicted differentials.

2.4.1. Scenario-based absolute predicted CF differentials

For discrete variables, we construct standardized scenario contrasts based on the observed dummy indicators. Specifically, *Internet_supply, Air_purification, Community_eldercare, Chronic_disease*, and *Mobile_payments* represent internet connectivity, air-purifier installation, participation in community eldercare, chronic disease status, and mobile-payment use, respectively. In each case, the indicator is shifted by one unit (i.e. $|\Delta x| = 1$) to derive the corresponding model-implied difference in predicted CF,

$$\Delta Q = \hat{\beta}\bar{Q}\Delta x = -\left|\hat{\beta}\right|\bar{Q} \tag{4}$$

where $\bar{Q}$ is the sample mean of the resident CF. A positive or negative contrast in x is selected according to the sign of $\hat{\beta}$ so that the resulting model-implied differential corresponds to a lower predicted CF (i.e. $\Delta Q < 0$). We also derive predicted CF differentials associated with stylized climatic contrasts between colder or hotter settings and a temperate setting using equation (5):

$$\Delta Q = \bar{Q}\hat{\beta}\Delta x \tag{5}$$

where $\hat{\beta}$ denotes the estimated coefficient for x (i.e. HDD or CDD), and Δx represents the stylized climate contrast. In figure 1, these differentials are benchmarked using stylized comparisons between a colder setting with HDD levels comparable to Hulunbuir, a hotter setting with CDD levels comparable to Shenzhen, and a temperate setting with HDD and CDD levels comparable to Zhengzhou. Environmental data were calculated using 5 °C as the threshold for HDD and 25 °C as the threshold for CDD (Zhu *et al* 2013), as shown in equations (6) and (7),

$$\text{HDD} = \sum_{d=1, t<5^{\circ}\text{C}}^{365} (5 - t) \tag{6}$$

$$\text{CDD} = \sum_{d=1, t>25^{\circ}\text{C}}^{365} (t - 25) \tag{7}$$

where d and t denote the day index and the temperature, respectively. Specifically, $d, t < 5^{\circ}$C (or $t >$ 25°C) indicates a day when the temperature falls below 5 °C (or rises above 25 °C).

2.4.2. Scenario-based relative predicted CF differentials

We next construct standardized scenario contrasts for continuous variables. For income, we consider a downward adjustment of RMB 10 000 (USD 1069). Because Income is measured in yuan, this corresponds to $\Delta x = \Delta\text{Income} = -10,000$. Since $\ln Q$ is quadratic in $\ln x$, the following approximation applies:

$$\Delta Q = \bar{Q}\bar{x}^{-1}\left(\hat{\beta}_1 + 2\hat{\beta}_2 \ln\bar{x}\right)\Delta x = -10,000\bar{Q}\bar{x}^{-1}\left(\hat{\beta}_1 + 2\hat{\beta}_2 \ln\bar{x}\right) \tag{8}$$

where $\hat{\beta}_1$ and $\hat{\beta}_2$ are the estimated coefficients for $\ln(\text{Income}) = \ln x$ and $\{\ln(\text{Income})\}^2 = (\ln x)^2$, and $\bar{x}$ is the sample mean of the income.

Similarly, for intergenerational support we consider an increase of RMB 10 000 (USD 1069), so that $\Delta x = \Delta\text{Child}_{\text{support}} = +10\,000$. The corresponding approximation is:

$$\Delta Q = \bar{Q}\bar{x}^{-1}\left(\hat{\beta}_1 + 2\hat{\beta}_2 \ln\bar{x}\right)\Delta x = 10\,000\bar{Q}\bar{x}^{-1}\left(\hat{\beta}_1 + 2\hat{\beta}_2 \ln\bar{x}\right) \tag{9}$$

where $\hat{\beta}_1$ and $\hat{\beta}_2$ are the estimated coefficients for $\ln(\text{Child\_support}) = \ln x$ and $\{\ln(\text{Child\_support})\}^2 = (\ln x)^2$, and $\bar{x}$ is the sample mean of intergenerational support.

We also assess the comparative relevance of durable-goods expenditure by contrasting high-income spending levels with the corresponding low-income benchmark. For each durable good—automobiles, washing machines, computers, refrigerators, and electric bicycles—we divide the sample into high- and low-income groups, calculate the mean expenditure gap between them, and estimate the corresponding predicted CF differential under a standardized contrast that removes this observed gap. Specifically, the expenditure contrasts are RMB 153 912 (USD 16 454) for automobiles, RMB 1149 (USD 123) for washing machines, RMB 3319 (USD 355) for computers, RMB 2131 (USD 228) for refrigerators, and RMB 2751 (USD 294) for electric bicycles. Because $\ln Q$ is linear in $\ln x$, the approximation is:

$$\Delta Q_j = \bar{Q}\bar{x}^{-1}\hat{\beta}\Delta x_j \tag{10}$$

$$\Delta x_j = \bar{x}_j^{\text{high}} - \bar{x}_j^{\text{low}} \tag{11}$$

where $\hat{\beta}$ is the estimated coefficient for $\ln x$ and $\bar{x}$ is the sample mean of x. The average expenditure for high- ($\bar{x}_j^{\text{high}}$) and low-income ($\bar{x}_j^{\text{low}}$) groups on each of the five durable goods is drawn from our compilation of the CHARLS sample data ('Equipments, consumption durables, and valuables' section).

3. Results and discussion

3.1. Regression analysis of resident CF across later-life cohorts

Based on equation (3), we examine the factors associated with resident CF among China's later-life population. Column 1 of table 3 presents the baseline OLS estimates, most of which are statistically significant. Low variance inflation factors (mean = 1.64; table A2) indicate no material multicollinearity, a conclusion further supported by the correlation matrix of the resident CF indicators (table S1 in section S1.1 of the SI). Columns 2 and 3 of table 3 report subgroup estimates for the 45–64 s and the 65 s–, respectively.

Income exhibits a U-shaped association with CF, whereas assets and intergenerational support display inverted-U associations. Elasticity estimates evaluated at the sample mean (table A3, col. 1) are positive for income and assets but negative for intergenerational support. In the full sample, the turning point for log-income is 6.08; because the mean log-income is 8.49, most individuals lie on the emissions-increasing segment of the curve. The turning point for log-assets is 11.58, whereas the mean log-assets is 9.12, indicating that further accumulation remains positively associated with CF for most of the sample. By contrast, the association between intergenerational support and CF becomes negative beyond a log value of 3.16; the sample mean of 6.37 therefore lies within the CF-decreasing range. The subgroup estimates indicate that these nonlinear economic associations differ across the two later-life cohorts. For the 45–64 s, the income–CF U-shaped relationship is flatter, while the asset terms do not indicate a clearly defined inverted-U pattern. For the 65 s–, the income–CF relationship is steeper, the turning point of the asset–CF relationship shifts leftward, and the inverted-U association for intergenerational support is stronger. Thus, the two cohorts differ not because the nonlinear patterns reverse, but because the strength and turning-point structure of these associations vary across age groups.

Health status and digital behaviors are also associated with CF heterogeneity. Among the 65 s–, better health is positively associated with CF (0.0272^{**}), whereas among the 45–64 s, chronic disease is positively associated with CF (0.0936^{***}). Digitalization likewise shows cohort–specific associations. Mobile-payment use is positively associated with CF among the 45–64 s (0.112^{***}), but it is not statistically significant among the 65 s–. By contrast, internet access is positively associated with CF in both cohorts, with a larger coefficient among the 65 s—(0.336^{***}) than among the 45–64 s (0.229^{***}).

Durable-goods ownership and housing infrastructure are likewise associated with resident CF. The coefficient on automobile expenditure is largest among the 45–64 s (0.0299^{***}), whereas the coefficient on washing machine expenditure is largest among the 65 s—(0.0242^{***}). Electric bicycle expenditure is modestly but significantly positively associated with CF among the 45–64 s ($0.004\,91^{*}$), and computer expenditure is also positively associated with CF in this cohort (0.0206^{***}). Housing infrastructure is similarly associated with higher CF. Access to heating systems is positively associated with CF in the full sample and in both cohorts, with the largest coefficient among the 65 s—(0.308^{***}). Air purifiers are also positively associated with CF in the full sample and in both subgroups.

Climatic factors are also associated with cross-city differences in resident CF. In the baseline specification, the coefficient on HDD is approximately 1.71 times as large as that on CDD, indicating that colder climatic settings are associated with larger observed CF differentials than hotter settings. The coefficients on both HDD and CDD are positive and statistically significant in the full sample and in both cohorts, with the coefficient on HDD being slightly larger among the 65 s—than among the 45–64 s.

3.2. Robustness checks

3.2.1. Estimation of resident CF by domain

Table 4 reports nine nested OLS specifications, in which control variables are added sequentially until the final column reaches the preferred model. Across all specifications, the coefficients on the principal economic variables—ln(*Income*), ln(*Asset*), and ln(*Child_support*)—retain stable signs and remain statistically significant at conventional levels. Specifically, ln(*Income*) is consistently negative, whereas ln(*Asset*) and ln(*Child_support*) are consistently positive when entered linearly. None of these coefficients changes sign or loses significance as additional covariates are introduced, and their magnitudes remain broadly stable, indicating that the core associations are not driven by a narrow set of controls. At the same time, model fit improves substantially as additional domains are incorporated. The R^2 rises from 0.067 in the initial specification to 0.324 in the fully controlled model, while the BIC is lowest for the full specification. Taken together, the stability of the principal coefficients and the improvement in model fit support the robustness of the main empirical patterns and identify the full model as the preferred specification for estimating resident CF.

Table 3. Regression results for resident CF using OLS estimates.

Variables		Base regression	Regression for 45–64 s	Regression for 65 s–
Economics	ln(*Income*)	−0.562***	−0.517***	−0.517***
		(−10.13)	(−8.00)	(−4.89)
	ln(*Income*)^2	0.0462***	0.0414***	0.0480***
		(13.35)	(10.20)	(7.38)
	ln(*Asset*)	0.264***	0.130*	0.421***
		(4.33)	(1.66)	(4.15)
	ln(*Asset*)^2	−0.0114***	−0.004 88	−0.0197***
		(−3.64)	(−1.22)	(−3.66)
	ln(*Child_support*)	0.0763***	0.0616***	0.109***
		(7.96)	(5.40)	(5.91)
	ln(*Child_support*)^2	−0.0121***	−0.009 89***	−0.0172***
		(−11.10)	(−7.54)	(−8.64)
Demographics	*Age*	−0.008 47***	−0.007 67***	−0.0108***
		(−8.25)	(−3.95)	(−4.29)
	Marriage	0.239***	0.183**	0.275***
		(4.00)	(2.38)	(3.03)
	Household_size	−0.191***	−0.190***	−0.194***
		(−10.38)	(−8.35)	(−6.76)
	Self_education	0.0227***	0.0156***	0.0340***
		(9.95)	(5.62)	(8.49)
	Children_education	0.005 38***	0.005 86***	0.006 33**
		(3.98)	(3.72)	(2.34)
	Health_status	0.0335***	0.0344***	0.0272**
		(4.34)	(3.67)	(2.03)
	Chronic_disease	0.0904***	0.0936***	0.0759***
		(6.07)	(5.13)	(3.01)
	Lifetime_work	−0.216***	−0.200***	−0.225***
		(−12.35)	(−8.91)	(−8.00)
	Subsistence_allowance	−0.0436	−0.116***	0.0381
		(−1.44)	(−2.74)	(0.88)
	Sent_down_to_countryside	0.194***	0.178***	0.168***
		(4.80)	(3.08)	(2.94)
Living habits	*Smoking*	0.0693**	0.0397	0.112*
		(1.96)	(0.94)	(1.78)
	Drinking	0.0253	0.0390**	0.00 109
		(1.57)	(2.02)	(0.04)
	Mobile_payments	0.0555**	0.112***	−0.136
		(2.11)	(4.03)	(−1.41)
Social security	*Medical_insurance*	0.0371	0.0206	0.0395
		(0.82)	(0.37)	(0.54)
	Pension_insurance	0.0345	0.0130	0.0687*
		(1.58)	(0.49)	(1.81)
	Community_eldercare	−0.0956***	−0.0186	−0.128***
		(−3.87)	(−0.39)	(−4.44)
Household ownership	*Automobile*	0.0256***	0.0299***	0.0204***
		(11.22)	(12.39)	(2.63)
	Electric_bicycle	0.002 18	0.004 91*	−0.00319
		(1.01)	(1.91)	(−0.80)
	Refrigerator	0.007 30**	0.0102**	0.003 31
		(2.14)	(2.22)	(0.65)
	Washing_machine	0.0211***	0.0170***	0.0242***
		(6.25)	(3.82)	(4.70)
	Television	0.000 749	−0.002 57	0.00 584
		−0.21	(−0.57)	−1.03
	Computer	0.0172***	0.0206***	0.0174**
		(5.60)	(6.12)	(2.37)

(Continued.)

Table 3. (Continued.)

Living conditions	*House_age*	−0.001 53***	−0.001 10	−0.00 199**
		(−2.73)	(−1.45)	(−2.38)
	Property_registration	−0.0682***	−0.118***	−0.00 752
		(−3.44)	(−4.63)	(−0.24)
	Gas_supply	0.0892***	0.0772***	0.0917***
		(4.65)	(3.37)	(2.69)
	Heating_supply	0.242***	0.196***	0.308***
		(9.96)	(6.84)	(7.02)
	Internet_supply	0.270***	0.229***	0.336***
		(16.44)	(11.57)	(11.40)
	Air_satisfaction	0.0384***	0.0405***	0.0275*
		(4.40)	(3.85)	(1.81)
	Air_purification	0.223***	0.217***	0.216***
		(5.64)	(4.63)	(2.96)
Climatic Conditions	*HDD*	0.004 60***	0.004 55***	0.004 61***
		(19.66)	(15.88)	(11.29)
	CDD	0.002 69***	0.002 59***	0.002 87***
		(10.23)	(8.00)	(6.41)
	Constant	6.344***	7.076***	5.233***
		(17.04)	(15.21)	(7.67)
	Observations	13 890	8,601	5,289
	R-squared	0.324	0.302	0.336
	BIC	34 549.061	20 741.639	13 898.713

Note: Robust t-statistics in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. BIC is the Schwarz Bayesian information criterion.

3.2.2. Estimation of resident CF by consumption category

We further decompose each individual's total CF (C_t) into thirteen consumption categories, such that $C_t = \sum_i C_{ti}$. This disaggregation allows us to assess whether the associations between key covariates and CF vary systematically across consumption categories, rather than merely scaling total CF proportionally. The corresponding OLS results are reported in table 5.

Income, assets, and intergenerational support exhibit significant nonlinear associations across the thirteen consumption categories, with both magnitudes and turning points varying by category. This heterogeneity indicates that the relationship between economic variables and total CF does not simply reflect a fixed proportional scaling of overall expenditure. First, income has significantly negative linear coefficients across categories (for example, electricity: −0.631***; transportation: −0.626***), alongside positive quadratic terms (0.046***–0.057***), consistent with a carbon-Kuznets-type relationship. In energy-related categories, the turning point beyond which CF begins to increase occurs at lower income levels than in discretionary categories such as entertainment. Second, assets have positive linear coefficients in most categories and negative quadratic coefficients in several of them, suggesting that asset accumulation is initially associated with higher CF, while this positive association weakens at higher asset levels. However, this curvature should be interpreted cautiously, as its robustness is weaker under alternative estimators. Third, intergenerational support exhibits a pronounced inverted-U association across categories: moderate transfers are associated with higher CF, whereas larger transfers are associated with lower CF.

Demographic and institutional variables also show category-specific patterns. Age is negatively associated with CF across all categories, with coefficients ranging from −0.021*** to −0.006***. Participation in medical insurance shows only small and statistically insignificant associations, including in the medical category, suggesting that insurance expansion alone is not strongly associated with observable differences in consumption-related emissions. By contrast, community eldercare is associated with lower CF in several categories, including food, medical care, and other services. Climatic variables likewise display distinct category-specific patterns, especially for electricity, gas, and water. HDD shows the largest elasticity for electricity, followed by water and gas, whereas CDD exhibits relatively stronger associations with gas and water than with electricity.

We also estimate Zellner's seemingly unrelated regression (SUR) model for the thirteen consumption categories, with the results presented in table A4. The SUR results are broadly consistent with the OLS estimates. The signs and significance levels of ln(*Income*), ln(*Asset*), and ln(*Child_support*), including their squared terms, remain largely unchanged, and none of the principal regressors reverses sign or

Table 4. Results of an OLS stepwise regression analyzing resident CF across seven domains.

	(1)			(2)	(3)	(4)	(5)	(6)	(7)
	Economics								
Variables	Income	Asset	Intergenerational support	Demographics	Living conditions	Social security	Living habits	Household ownership	Climatic conditions
ln(*Income*)	−0.853***	−0.756***	−0.853***	−0.649***	−0.580***	−0.576***	−0.572***	−0.546***	−0.562***
	(−14.81)	(−13.49)	(−14.53)	(−11.11)	(−10.22)	(−10.15)	(−10.07)	(−9.71)	(−10.13)
ln(*Income*)^2	0.0626***	0.0550***	0.0682***	0.0544***	0.0483***	0.0481***	0.0478***	0.0452***	0.0462***
	(17.83)	(16.05)	(18.66)	(14.96)	(13.65)	(13.58)	(13.50)	(12.88)	(13.35)
ln(*Asset*)		0.283***	0.280***	0.339***	0.402***	0.403***	0.414***	0.345***	0.264***
		(4.41)	(4.45)	(5.43)	(6.62)	(6.63)	(6.82)	(5.63)	(4.33)
ln(*Asset*)^2		−0.00588*	−0.00638*	−0.0121***	−0.0169***	−0.0168***	−0.0176***	−0.0156***	−0.0114***
		(−1.77)	(−1.96)	(−3.75)	(−5.36)	(−5.36)	(−5.60)	(−4.93)	(−3.64)
ln(*Child_support*)			0.0924***	0.100***	0.0942***	0.0934***	0.0931***	0.0871***	0.0763***
			(9.17)	(9.95)	(9.63)	(9.56)	(9.53)	(8.96)	(7.96)
ln(*Child_support*)^2			−0.0162***	−0.0157***	−0.0143***	−0.0142***	−0.0142***	−0.0131***	−0.0121***
			(−14.15)	(−13.81)	(−12.86)	(−12.80)	(−12.78)	(−11.90)	(−11.10)
Age				−0.0171***	−0.0132***	−0.0120***	−0.0118***	−0.00872***	−0.00847***
				(−17.88)	(−13.53)	(−11.85)	(−11.56)	(−8.41)	(−8.25)
Marriage				0.245***	0.259***	0.254***	0.253***	0.255***	0.239***
				(3.89)	(4.21)	(4.13)	(4.13)	(4.18)	(4.00)
Household_size				−0.190***	−0.187***	−0.186***	−0.186***	−0.196***	−0.191***
				(−9.77)	(−9.88)	(−9.85)	(−9.82)	(−10.46)	(−10.38)
Self_education				0.0473***	0.0317***	0.0311***	0.0292***	0.0276***	0.0227***
				(20.78)	(13.99)	(13.71)	(12.58)	(11.96)	(9.95)
Children_education				0.008 35***	0.006 63***	0.006 48***	0.006 06***	0.005 21***	0.005 38***
				(5.89)	(4.85)	(4.75)	(4.39)	(3.79)	(3.98)
Health_status				0.008 39	0.0208***	0.0194**	0.0213***	0.0265***	0.0335***
				(1.04)	(2.64)	(2.45)	(2.69)	(3.37)	(4.34)
Chronic_disease				0.124***	0.111***	0.114***	0.112***	0.114***	0.0904***
				(7.89)	(7.27)	(7.47)	(7.35)	(7.57)	(6.07)
Lifetime_work				−0.340***	−0.233***	−0.232***	−0.238***	−0.235***	−0.216***
				(−19.21)	(−13.13)	(−13.07)	(−13.27)	(−13.18)	(−12.35)
Subsistence_allowance				−0.0986***	−0.0415	−0.0381	−0.0400	−0.0252	−0.0436
				(−3.06)	(−1.32)	(−1.21)	(−1.28)	(−0.81)	(−1.44)

(Continued.)

Table 4. (Continued.)

Sent_down_to_countryside	0.270***	0.197***	0.200***	0.197***	0.211***	0.194***
	(6.24)	(4.83)	(4.92)	(4.86)	(5.17)	(4.80)
Smoking				0.0568	0.0590*	0.0693**
				(1.56)	(1.65)	(1.96)
Drinking				0.0316*	0.0308*	0.0253
				(1.91)	(1.88)	(1.57)
Mobile_payments				0.0914***	0.0433	0.0555**
				(3.40)	(1.62)	(2.11)
Medical_insurance			0.0511	0.0535	0.0454	0.0371
			(1.10)	(1.15)	(0.98)	(0.82)
Pension_insurance			0.0154	0.0162	0.0111	0.0345
			(0.68)	(0.72)	(0.49)	(1.58)
Community_eldercare			−0.118***	−0.116***	−0.116***	−0.0956***
			(−4.72)	(−4.66)	(−4.67)	(−3.87)
Automobile					0.0271***	0.0256***
					(11.75)	(11.22)
Electric_bicycle					0.00 949***	0.00 218
					(4.40)	(1.01)
Refrigerator					0.00 640*	0.00 730**
					(1.85)	(2.14)
Washing_machine					0.0199***	0.0211***
					(5.84)	(6.25)
Television					−0.001 19	0.000 749
					(−0.33)	(0.21)
Computer					0.0161***	0.0172***
					(5.17)	(5.60)

(Continued.)

Table 4. (Continued.)

	(1)			(2)	(3)	(4)	(5)	(6)	(7)
	Economics								
Variables	Income	Asset	Intergenerational support	Demographics	Living conditions	Social security	Living habits	Household ownership	Climatic conditions
House_age					−0.00140**	−0.00143**	−0.00145**	−0.000 999*	−0.001 53***
					(−2.40)	(−2.45)	(−2.48)	(−1.71)	(−2.73)
Property_registration					−0.0378*	−0.0381*	−0.0357*	−0.0632***	−0.0682***
					(−1.88)	(−1.89)	(−1.78)	(−3.12)	(−3.44)
Gas_supply					0.0405**	0.0424**	0.0381*	0.0305	0.0892***
					(2.07)	(2.17)	(1.95)	(1.58)	(4.65)
Heating_supply					0.438***	0.438***	0.439***	0.434***	0.242***
					(19.51)	(19.51)	(19.55)	(19.60)	(9.96)
Internet_supply					0.310***	0.310***	0.306***	0.261***	0.270***
					(19.01)	(19.01)	(18.62)	(15.62)	(16.44)
Air_satisfaction					0.0368***	0.0367***	0.0357***	0.0363***	0.0384***
					(4.10)	(4.08)	(3.98)	(4.07)	(4.40)
Air_purification					0.265***	0.264***	0.263***	0.230***	0.223***
					(6.57)	(6.55)	(6.57)	(5.76)	(5.64)
HDD									0.004 60***
									(19.66)
CDD									0.002 69***
									(10.23)
Constant	8.650***	6.303***	6.491***	7.420***	6.513***	6.371***	6.291***	6.428***	6.344***
	(37.05)	(16.85)	(17.47)	(19.39)	(17.38)	(16.91)	(16.67)	(17.07)	(17.04)
Observations	15 194	15 194	15 194	13 981	13 890	13 890	13 890	13 890	13 890
R-squared	0.067	0.122	0.152	0.235	0.285	0.286	0.287	0.301	0.324
BIC	42 828.052	41 927.504	41 413.039	36 327.890	35 202.424	35 205.171	35 217.392	35 009.470	34 549.061

Note: Robust t-statistics in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. BIC is the Schwarz Bayesian information criterion.

Table 5. Regression results for resident CF by consumption category in OLS estimates.

Variables	(1) Food	(2) Electricity	(3) Gas	(4) Water	(5) Durable goods	(6) Consumable goods	(7) Education	(8) Medical	(9) Transportation	(10) Catering services	(11) Entertainment	(12) Finance and real estate	(13) Other
ln(*Income*)	−0.630***	−0.631***	−0.652***	−0.599***	−0.581***	−0.651***	−0.661***	−0.524***	−0.626***	−0.569***	−0.648***	−0.560***	−0.570***
	(−10.32)	(−11.01)	(−8.09)	(−8.13)	(−9.55)	(−10.39)	(−10.15)	(−6.26)	(−10.26)	(−7.52)	(−7.36)	(−8.22)	(−9.60)
ln($Income$)^2	0.053***	0.051***	0.056***	0.052***	0.049***	0.054***	0.057***	0.047***	0.053***	0.049***	0.056***	0.049***	0.046***
	(13.87)	(14.31)	(11.18)	(11.30)	(12.75)	(14.04)	(14.03)	(8.96)	(14.01)	(10.44)	(10.19)	(11.62)	(12.56)
ln(*Asset*)	0.319***	0.251***	0.240***	0.247***	0.208***	0.151**	0.264***	0.220**	0.087	0.274***	0.265***	0.291***	0.267***
	(4.74)	(3.99)	(2.74)	(3.12)	(3.08)	(2.27)	(3.77)	(2.48)	(1.32)	(3.26)	(2.74)	(3.95)	(4.10)
ln($Asset$)^2	−0.012***	−0.010***	−0.008*	−0.008**	−0.008**	−0.003	−0.009**	−0.008*	−0.000	−0.009**	−0.012**	−0.010**	−0.011***
	(−3.49)	(−2.96)	(−1.82)	(−2.03)	(−2.23)	(−0.83)	(−2.50)	(−1.72)	(−0.08)	(−2.02)	(−2.29)	(−2.55)	(−3.40)
ln(*Child_support*)	0.091***	0.082***	0.090***	0.069***	0.072***	0.109***	0.099***	0.114***	0.074***	0.111***	0.110***	0.094***	0.075***
	(8.54)	(8.36)	(6.36)	(5.31)	(6.66)	(10.22)	(8.74)	(7.95)	(7.02)	(8.15)	(7.10)	(7.94)	(7.32)
ln($Child\_support$)^2	−0.015***	−0.013***	−0.016***	−0.012***	−0.012***	−0.017***	−0.017***	−0.016***	−0.014***	−0.017***	−0.017***	−0.015***	−0.012***
	(−12.24)	(−11.46)	(−9.86)	(−8.46)	(−9.72)	(−14.34)	(−12.96)	(−9.84)	(−11.46)	(−10.72)	(−9.47)	(−11.52)	(−10.69)
Age	−0.014***	−0.011***	−0.016***	−0.015***	−0.012***	−0.017***	−0.016***	−0.018***	−0.013***	−0.020***	−0.021***	−0.018***	−0.006***
	(−13.35)	(−11.23)	(−11.47)	(−12.43)	(−11.31)	(−16.64)	(−14.57)	(−12.77)	(−13.03)	(−16.14)	(−14.40)	(−16.10)	(−5.84)
Marriage	0.229***	0.268***	0.374***	0.042	0.241***	0.123*	0.183***		0.223***	0.051	0.260***	0.141*	0.154**
	(3.39)	(4.42)	(4.31)	(0.55)	(3.55)	(1.84)	(2.64)		(3.45)	(0.64)	(2.81)	(1.96)	(2.43)
Household_size	−0.188***	−0.203***	−0.209***	−0.110***	−0.199***	−0.150***	−0.165***	−0.111***	−0.186***	−0.140***	−0.201***	−0.158***	−0.160***
	(−9.01)	(−10.87)	(−7.79)	(−4.72)	(−9.51)	(−7.30)	(−7.73)	(−10.08)	(−9.35)	(−5.70)	(−7.03)	(−7.10)	(−8.22)
Self_education	0.045***	0.026***	0.039***	0.033***	0.030***	0.041***	0.036***	0.038***	0.036***	0.041***	0.057***	0.049***	0.025***
	(18.31)	(11.56)	(11.78)	(11.32)	(12.51)	(17.00)	(13.91)	(11.59)	(15.20)	(13.40)	(15.85)	(18.31)	(10.27)
Children_education	0.008***	0.008***	0.008***	0.004**	0.004**	0.007***	0.008***	0.007***	0.006***	0.003	0.012***	0.005***	0.005***
	(5.40)	(5.52)	(4.03)	(2.31)	(2.48)	(4.94)	(5.11)	(3.24)	(3.97)	(1.46)	(5.53)	(2.90)	(3.13)
Health_status	0.019**	0.030***	0.018	0.042***	0.020**	0.049***	0.031***	0.098***	0.024***	0.046***	0.123***	0.018*	0.046***
	(2.17)	(3.84)	(1.55)	(4.13)	(2.40)	(5.65)	(3.47)	(8.51)	(2.87)	(4.35)	(9.92)	(1.94)	(5.60)
Chronic_disease	0.108***	0.078***	0.148***	0.103***	0.109***	0.121***	0.100***	0.204***	0.094***	0.154***	0.097***	0.159***	0.103***
	(6.47)	(5.08)	(6.66)	(5.15)	(6.61)	(7.27)	(5.75)	(9.22)	(5.70)	(7.45)	(4.02)	(8.68)	(6.47)
Lifetime_work	−0.341***	−0.252***	−0.273***	−0.229***	−0.297***	−0.291***	−0.315***	−0.294***	−0.274***	−0.318***	−0.320***	−0.316***	−0.190***
	(−18.25)	(−14.24)	(−10.81)	(−10.14)	(−15.89)	(−15.50)	(−15.78)	(−11.71)	(−14.73)	(−13.62)	(−11.58)	(−15.22)	(−10.23)

(Continued.)

Table 5. (Continued.)

Subsistence_allowance	−0.087**	−0.055*	0.023	−0.150***	−0.068**	−0.054	−0.150***		−0.147***	−0.093**			−0.078**
	(−2.57)	(−1.80)	(0.52)	(−3.77)	(−2.01)	(−1.62)	(−4.26)		(−4.51)	(−2.24)			(−2.48)
Sent_down_ to_countryside	0.296***	0.209***	0.189***	0.377***	0.212***	0.286***	0.416***	0.598***	0.298***	0.399***	0.411***	0.457***	0.179***
	(6.31)	(5.02)	(2.91)	(6.52)	(4.54)	(6.35)	(8.24)	(9.23)	(6.25)	(7.35)	(6.40)	(8.59)	(4.13)
Smoking							0.091**				0.087		0.061
							(2.20)				(1.60)		(1.64)
Drinking							0.066***			0.033	−0.080***		0.051***
							(3.47)			(1.50)	(−3.05)		(2.93)
Mobile_payments	0.209***						0.201***			0.271***	0.324***		0.055*
	(7.11)						(6.42)			(7.20)	(7.37)		(1.93)
Medical_insurance								0.065					0.021
								(0.97)					(0.41)
Pension_insurance								0.055*					0.026
								(1.73)					(1.11)
Community_eldercare	−0.066**							−0.207***					−0.094***
	(−2.40)							(−5.69)					(−3.60)
Automobile					0.035***				0.038***				0.027***
					(13.57)				(15.54)				(11.10)
Electric_bicycle		0.002			0.001				−0.005**				0.006***
		(0.94)			(0.43)				(−2.15)				(2.62)
Refrigerator	0.021***	0.006*			0.013***								0.012***
	(6.40)	(1.73)			(3.38)								(3.22)
Washing_machine		0.021***			0.027***								0.024***
		(6.15)			(7.26)								(6.55)
Television		0.002			0.002								−0.002
		(0.51)			(0.59)								(−0.56)
Computer		0.028***			0.035***								0.013***

(Continued.)

Table 5. (Continued.)

Variables	(1) Food	(2) Electricity	(3) Gas	(4) Water	(5) Durable goods	(6) Consumable goods	(7) Education	(8) Medical	(9) Transportation	(10) Catering services	(11) Entertainment	(12) Finance and real estate	(13) Other
		(9.01)			(10.49)								(3.85)
House_age		−0.002***	−0.003***	−0.005***									−0.001
		(−3.13)	(−4.41)	(−6.41)									(−1.14)
Property_registration		−0.050**	−0.007	−0.043*									−0.095***
		(−2.43)	(−0.25)	(−1.67)									(−4.55)
Gas_supply		0.064***	0.241***										0.195***
		(3.32)	(8.55)										(9.50)
Heating_supply			0.132***										0.165***
			(3.29)										(6.30)
Internet_supply		0.273***											0.288***
		(16.17)											(16.41)
Air_satisfaction													0.044***
													(4.70)
Air_purification		0.256***											0.267***
		(6.08)											(5.99)
HDD		0.009***	0.003***	0.006***									0.002***
		(38.82)	(10.95)	(22.78)									(7.68)
CDD		0.007***	0.009***	0.009***									0.000
		(24.37)	(28.15)	(29.44)									(1.59)
Constant	4.275***	5.901***	0.738	−3.349***	3.854***	5.603***	2.399***	−0.662	5.603***	0.990*	−0.176	2.348***	3.965***
	(10.43)	(15.52)	(1.38)	(−6.99)	(9.42)	(13.77)	(5.61)	(−1.23)	(13.87)	(1.95)	(−0.30)	(5.20)	(9.90)
Observations	13 981	13 980	13 980	13 980	13 981	13 981	13 981	13 981	13 981	13 981	13 981	13 981	13 890
R-squared	0.215	0.349	0.185	0.193	0.225	0.190	0.199	0.117	0.216	0.157	0.133	0.184	0.281
BIC	37 994.916	35 612.726	46 134.421	43 027.804	37 817.680	38 092.567	39 416.736	46 155.786	37 752.284	43 992.339	48 328.946	40 823.982	36 397.147

Note: Robust *t*-statistics in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. BIC is the Schwarz Bayesian information criterion.

loses significance. Although some coefficient magnitudes differ slightly from the OLS estimates and the SUR framework yields marginally lower R^2 values, these differences are quantitatively small and do not alter the substantive interpretation. Overall, the SUR estimates provide additional support for the stability of the category-level findings across alternative specifications.

As an additional robustness check, we re-estimate all thirteen category regressions using PPML, and the resulting estimates are reported in table A5. The results are broadly consistent with the OLS estimates. The U-shaped association between income and CF and the inverted-U association between intergenerational support and CF are preserved across all categories, and the signs of age, chronic disease, and lifetime work remain unchanged. One notable difference is that the inverted-U pattern for assets becomes substantially weaker under PPML, as the quadratic asset term is no longer statistically significant in most categories. This suggests that the curvature of the asset–CF relationship is less stable than that of income and intergenerational support when alternative estimators are applied to outcomes with zero observations. Taken together, these results indicate that the main category-level findings are robust, while the nonlinear asset pattern should be interpreted with greater caution.

3.2.3. Further robustness checks via alternative regression specifications

Table 6 reports six additional specifications designed to assess the robustness of the main findings. Columns 1–6 correspond to: (1) the baseline mo (2) a specification excluding statistically insignificant controls; (3) a sample restricted to respondents aged 85 years or younger; (4) a model in which income is winsorized at the 98th percentile; (5) a specification including city fixed-effects; and (6) a specification that re-estimates the baseline model with standard errors clustered at the household level. Across these specifications, the estimated coefficients on ln(*Income*), ln(*Asset*), and ln(*Child_support*), together with their squared terms, retain their signs and statistical significance, indicating that the core economic patterns do not depend on any single modeling choice. Overall, the results in table 6 indicate that the main empirical findings are robust to alternative samples, outlier treatment, controls for city-level heterogeneity, and within-household error correlation.

In Column 5, the inclusion of city fixed-effects leaves most coefficients broadly unchanged but reverses the signs of HDD and CDD relative to the baseline specification. This reversal indicates that the positive climate coefficients in the baseline model are identified primarily from between-city climatic variation and therefore reflect not only climatic exposure itself but also correlated city-level characteristics, such as heating infrastructure, the energy mix, and other persistent place-based features. This interpretation is consistent with the climate econometrics literature, which shows that cross-sectional climate estimates can capture long-run spatial differences and adaptation patterns while remaining vulnerable to confounding from time-invariant regional heterogeneity (Dell *et al* 2014, Mendelsohn and Massetti 2017, Kolstad and Moore 2020). The two specifications therefore identify distinct quantities: with city fixed-effects, HDD and CDD are identified only from residual within-city variation, whereas without such fixed-effects, the model captures a longer-run cross-city climate–environment association in the Ricardian cross-sectional sense (Mendelsohn and Nordhaus 1999). Accordingly, the climate-related CF differentials reported below should be interpreted as associational, model-implied comparative estimates under long-run climate–environment contrasts, rather than as causally identified gains from migration or relocation.

As an additional check, Column 6 re-estimates the baseline model with standard errors clustered at the household level to account for within-household correlation in the residuals arising from shared consumption infrastructure and living arrangements. By construction, the point estimates are identical to those in the baseline regression. Relative to heteroskedasticity-robust standard errors, household clustering moderately increases the standard errors, and the t-statistics for the principal economic regressors decline by approximately 15%–25%. Importantly, however, the core variables—including ln(*Income*), ln(*Asset*), ln(*Child_support*), and their quadratic terms—remain statistically significant at conventional levels, and the main nonlinear patterns are preserved. The only exception is refrigerator, whose coefficient falls below the 10% significance threshold under household clustering. Given that refrigerator expenditure more clearly reflects shared household durable-goods consumption than individual-level variation, this change does not affect the substantive conclusions of our study.

3.3. Scenario-based comparisons of predicted CF differentials

Figures 1 and 2 present scenario-based predicted differentials in resident CF associated with selected lifestyle and socioeconomic contrasts across the 45–64 s and the 65 s–. These values are derived from the regression coefficients reported in table 3 and are evaluated at the sample mean to account for model nonlinearity. Discrete variables are used to construct predicted absolute differentials, whereas continuous variables are used to construct predicted relative differentials. The variables included in this exercise are

Table 6. Results of additional robustness checks.

Variables	(1) Baseline regression	(2) Exclusion of non-significant comparisons	(3) Sample restricted to respondents aged ⩽85 years	(4) Income winsorized at the 98th percentile	(5) Inclusion of city fixed effects	(6) Household-clustered SE
ln(*Income*)	−0.562***	−0.543***	−0.559***	−0.562***	−0.498***	−0.562***
	(−10.13)	(−9.68)	(−10.03)	(−10.13)	(−9.13)	(−7.91)
ln(*Income*)^2	0.046***	0.045***	0.046***	0.046***	0.042***	0.046***
	(13.35)	(12.87)	(13.22)	(13.35)	(12.22)	(10.45)
ln(*Asset*)	0.264***	0.367***	0.271***	0.264***	0.218***	0.264***
	(4.33)	(6.03)	(4.42)	(4.33)	(3.63)	(3.70)
ln(*Asset*)^2	−0.011***	−0.017***	−0.012***	−0.011***	−0.010***	−0.011***
	(−3.64)	(−5.26)	(−3.75)	(−3.64)	(−3.08)	(−3.11)
ln(*Child_support*)	0.076***	0.088***	0.075***	0.076***	0.068***	0.076***
	(7.96)	(9.02)	(7.76)	(7.96)	(7.31)	(6.12)
ln(*Child_support*)^2	−0.012***	−0.013***	−0.012***	−0.012***	−0.011***	−0.012***
	(−11.10)	(−11.97)	(−10.86)	(−11.10)	(−10.37)	(−8.57)
Age	−0.008***	−0.009***	−0.009***	−0.008***	−0.009***	−0.008***
	(−8.25)	(−8.70)	(−8.25)	(−8.25)	(−8.67)	(−6.73)
Marriage	0.239***	0.260***	0.220***	0.239***	0.189***	0.239***
	(4.00)	(4.27)	(3.62)	(4.00)	(3.22)	(3.41)
Household_size	−0.191***	−0.195***	−0.185***	−0.191***	−0.178***	−0.191***
	(−10.38)	(−10.35)	(−9.84)	(−10.38)	(−9.85)	(−8.69)
Self_education	0.023***	0.028***	0.023***	0.023***	0.020***	0.023***
	(9.95)	(12.28)	(9.84)	(9.95)	(8.67)	(9.48)
Children_education	0.005***	0.005***	0.005***	0.005***	0.003**	0.005***
	(3.98)	(3.52)	(3.97)	(3.98)	(2.15)	(3.04)
Health_status	0.034***	0.024***	0.033***	0.034***	0.024***	0.034***
	(4.34)	(3.04)	(4.25)	(4.34)	(3.27)	(4.01)
Chronic_disease	0.090***	0.114***	0.091***	0.090***	0.095***	0.090***
	(6.07)	(7.57)	(6.09)	(6.07)	(6.62)	(5.92)
Lifetime_work	−0.216***	−0.226***	−0.216***	−0.216***	−0.185***	−0.216***
	(−12.35)	(−12.82)	(−12.29)	(−12.35)	(−10.83)	(−11.36)
Subsistence_allowance	−0.044		−0.042	−0.044	−0.106***	−0.044
	(−1.44)		(−1.36)	(−1.44)	(−3.51)	(−1.14)
Sent_down_to_countryside	0.194***	0.205***	0.194***	0.194***	0.098**	0.194***
	(4.80)	(5.01)	(4.80)	(4.80)	(2.42)	(4.44)

(Continued.)

Table 6. (Continued.)

Variables	(1) Baseline regression	(2) Exclusion of non-significant comparisons	(3) Sample restricted to respondents aged ⩽85 years	(4) Income winsorized at the 98th percentile	(5) Inclusion of city fixed effects	(6) Household-clustered SE
Smoking	0.069**	0.064*	0.066*	0.069**	0.045	0.069**
	(1.96)	(1.79)	(1.89)	(1.96)	(1.33)	(1.97)
Drinking	0.025		0.026	0.025	0.037**	0.025
	(1.57)		(1.59)	(1.57)	(2.38)	(1.63)
Mobile_payments	0.055**	0.040	0.058**	0.055**	0.015	0.055**
	(2.11)	(1.49)	(2.20)	(2.11)	(0.57)	(2.00)
Medical_insurance	0.037		0.038	0.037	0.041	0.037
	(0.82)		(0.82)	(0.82)	(0.91)	(0.75)
Pension_insurance	0.035		0.031	0.035	0.065***	0.035
	(1.58)		(1.41)	(1.58)	(3.03)	(1.37)
Community_eldercare	−0.096***	−0.113***	−0.096***	−0.096***	−0.040*	−0.096***
	(−3.87)	(−4.53)	(−3.83)	(−3.87)	(−1.67)	(−3.41)
Automobile	0.026***	0.026***	0.026***	0.026***	0.027***	0.026***
	(11.22)	(11.53)	(11.18)	(11.22)	(12.07)	(8.41)
Electric_bicycle	0.002		0.002	0.002	0.008***	0.002
	(1.01)		(1.03)	(1.01)	(3.50)	(0.76)
Refrigerator	0.007**	0.007**	0.007**	0.007**	0.009***	0.007
	(2.14)	(2.15)	(1.97)	(2.14)	(2.64)	(1.64)
Washing_machine	0.021***	0.020***	0.021***	0.021***	0.024***	0.021***
	(6.25)	(5.99)	(6.09)	(6.25)	(7.19)	(4.78)
Television	0.001		0.001	0.001	−0.003	0.001
	(0.21)		(0.21)	(0.21)	(−0.76)	(0.16)
Computer	0.017***	0.017***	0.018***	0.017***	0.014***	0.017***
	(5.60)	(5.38)	(5.70)	(5.60)	(4.83)	(4.20)
House_age	−0.002***	−0.001**	−0.002***	−0.002***	−0.001**	−0.002**
	(−2.73)	(−1.96)	(−2.70)	(−2.73)	(−2.44)	(−2.10)
Property_registration	−0.068***	−0.062***	−0.061***	−0.068***	−0.064***	−0.068***
	(−3.44)	(−3.06)	(−3.07)	(−3.44)	(−3.32)	(−2.69)

(Continued.)

Table 6. (Continued.)

Variables	(1) Baseline regression	(2) Exclusion of non-significant comparisons	(3) Sample restricted to respondents aged ⩽85 years	(4) Income winsorized at the 98th percentile	(5) Inclusion of city fixed effects	(6) Household-clustered SE
Gas_supply	0.089***	0.026	0.094***	0.089***	0.147***	0.089***
	(4.65)	(1.34)	(4.87)	(4.65)	(7.22)	(3.57)
Heating_supply	0.242***	0.429***	0.242***	0.242***	0.207***	0.242***
	(9.96)	(19.43)	(9.93)	(9.96)	(8.16)	(7.61)
Internet_supply	0.270***	0.266***	0.268***	0.270***	0.257***	0.270***
	(16.44)	(15.98)	(16.31)	(16.44)	(16.08)	(12.54)
Air_satisfaction	0.038***	0.037***	0.038***	0.038***	0.032***	0.038***
	(4.40)	(4.10)	(4.33)	(4.40)	(3.78)	(4.12)
Air_purification	0.223***	0.231***	0.229***	0.223***	0.220***	0.223***
	(5.64)	(5.82)	(5.79)	(5.64)	(5.74)	(4.29)
HDD	0.005***		0.005***	0.005***	−0.080***	0.005***
	(19.66)		(19.71)	(19.66)	(−2.70)	(14.97)
CDD	0.003***		0.003***	0.003***	−0.126***	0.003***
	(10.23)		(10.20)	(10.23)	(−2.81)	(7.83)
Constant	6.344***	6.375***	6.304***	6.344***	22.07***	6.344***
	(17.04)	(17.05)	(16.84)	(17.04)	(4.08)	(14.18)
City FE					√	
Observations	13 890	13 890	13 776	13 890	13 890	13 890
R-squared	0.324	0.299	0.324	0.324	0.391	0.324
BIC	34 549.061	34 977.457	34 243.204	34 549.061	34 083.379	

Note: Robust t-statistics in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Column (6) reports the baseline specification with household-clustered standard errors. Its point estimates are identical to those in Column (1) by construction; only the t-statistics change. City fixed effects are included only in Column (5). BIC is not reported for Column (6).

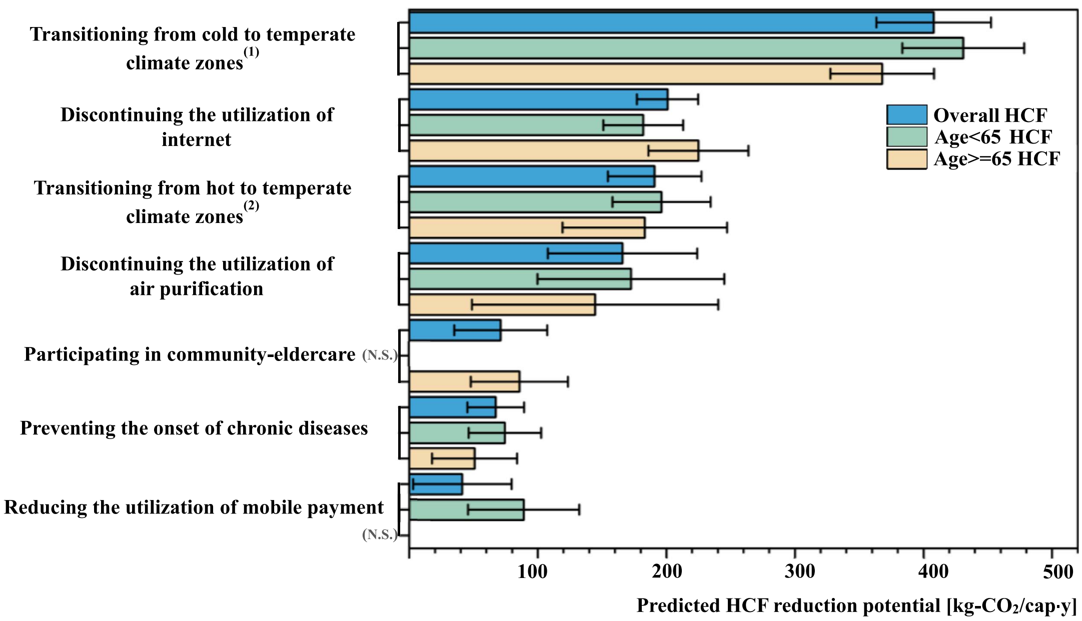

Figure 1. Scenario-based absolute predicted CF differentials with respect to selected lifestyle and socioeconomic contrasts. Note: bars without error bars represent estimates that are not statistically significant (N.S.), indicating insufficient evidence to reject the null hypothesis at the 5% significance level. The error bars correspond to 95% confidence intervals around the estimated values, providing a measure of the precision of the estimates. (1) A stylized contrast between a colder climatic setting with HDD levels comparable to Hulunbuir and a temperate setting represented by Zhengzhou. (2) A stylized contrast between a hotter climatic setting with CDD levels comparable to Shenzhen and a temperate setting represented by Zhengzhou.

selected on the basis of statistical significance and support in the literature (Wynes and Nicholas 2017, Ivanova *et al* 2020, Shigetomi *et al* 2021). Because the underlying regression is cross-sectional, these values should be interpreted as associational, model-implied comparative estimates under standardized contrasts, rather than as realized effects of policy or behavioral interventions.

3.3.1. Absolute scenario-based predicted CF differentials

Figure 1 shows that climate-related contrasts generate the largest predicted differentials in resident CF. In the baseline specification, residence in a more temperate climate-related environment is associated with substantially lower predicted CF than residence in colder or hotter environments. The estimated differential is 407.95 kg-CO_2/cap for the HDD-based contrast and 190.87 kg-CO_2/cap for the CDD-based contrast. Consistent with the interpretation of the baseline climate coefficients discussed above, these values are more appropriately understood as comparative predicted differences across long-run climate-related urban environments than as directly realizable mitigation gains from migration or relocation. As such, they likely reflect not only climatic exposure itself but also adaptation and place-based conditions associated with local heating and cooling contexts. The corresponding predicted differentials are larger for the 45–64 s than for the 65 s–, especially for HDD (430.90 versus 367.83 kg-CO_2/cap).

Digitalization-related variables are also associated with sizable predicted differentials in resident CF. Within the maintained regression framework, a change from internet access to no access corresponds to a predicted decrease of 200.93 kg-CO_2/cap in the full sample, with larger predicted differentials for the 65 s—(224.96 kg-CO_2/cap) than for the 45–64 s (181.99 kg-CO_2/cap). Likewise, a change from mobile-payment use to non-use among the 45–64 s corresponds to a predicted decrease of 89.01 kg-CO_2/cap, whereas no statistically significant association is observed for the 65 s–. These patterns suggest that the carbon implications of digitalization differ across cohorts, with internet connectivity more strongly associated with CF among the 65 s—and mobile-payment use more strongly associated with CF among the 45–64 s. Health- and indoor-environment-related variables also show notable predicted differentials. A change from air purifier installation to no installation corresponds to a predicted decrease of 172.45 kg-CO_2/cap among the 45–64 s, while the absence of chronic disease is associated with a predicted decrease of 67.28 kg-CO_2/cap. Participation in community eldercare is associated with a predicted decrease of 71.15 kg-CO_2/cap in the full sample and 85.70 kg-CO_2/cap among the 65 s–. Taken together, these results indicate that later-life CF heterogeneity is shaped not only by economic resources and climate-related living environments but also by digitalization, health-related needs, indoor-environment management, and the organization of care, with these channels displaying clear cohort–specific differences.

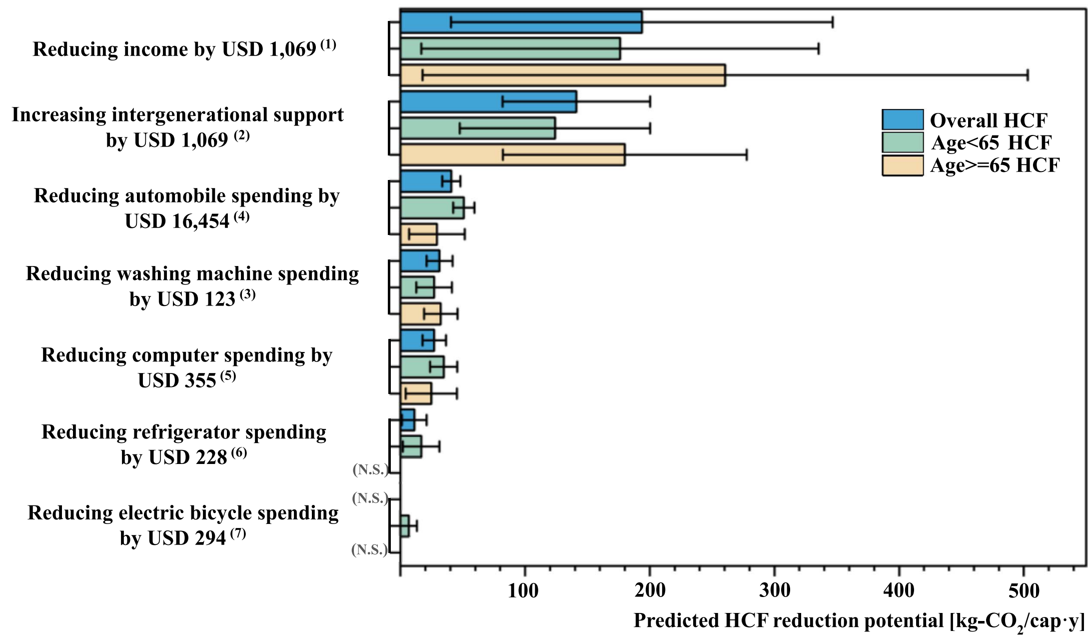

Figure 2. Scenario-based relative predicted CF differentials with respect to selected socioeconomic and durable-goods expenditure contrasts. Note: bars without error bars represent estimates that are not statistically significant (N.S.), indicating insufficient evidence to reject the null hypothesis at the 5% significance level. The error bars correspond to 95% confidence intervals around the estimated values, providing a measure of the precision of the estimates. To aid international interpretation, all RMB-denominated amounts were converted to USD using the 2018 annual average RMB–USD exchange rate derived from currency data compiled by the international monetary fund (IMF) (International monetary fund 2018). (1)–(2) For comparison, income and intergenerational support are reported in units of RMB 10 000 (USD 1069). (3)–(7) Each amount—calculated based on CHARLS microdata—denotes the expenditure margin associated with carbon reduction for each respective durable good, originally reported in RMB and converted to USD as follows: the margins were RMB 153 912 (USD 16 454) for automobiles; RMB 1149 (USD 123) for washing machines; RMB 3319 (USD 355) for computers; RMB 2131 (USD 228) for refrigerators; and RMB 2751 (USD 294) for electric bicycles.

3.3.2. Relative scenario-based predicted CF differentials

We next evaluate relative predicted CF differentials along two dimensions: economic resources—represented by income and intergenerational support—and durable-goods expenditure, represented by expenditure on automobiles, washing machines, computers, refrigerators, and electric bicycles (figure 2). Building on section 3.1, which shows that higher income is positively associated with resident CF at the sample mean whereas greater intergenerational support is negatively associated with resident CF, we construct two standardized contrasts: a reduction in annual income of RMB 10 000 and an equivalent increase in intergenerational support. In addition, following the logic of demand substitutability and discretionary overconsumption (Nielsen *et al* 2021, Creutzig *et al* 2022), we estimate the predicted CF differentials associated with reducing durable-goods expenditure among the high-income group to the corresponding benchmark observed for the low-income group. For each durable good, the relevant expenditure contrast is defined as the mean spending gap between the high- and low-income groups in the baseline sample.

The predicted differentials associated with income variation are substantially larger than those associated with intergenerational support, underscoring the stronger association between income and resident CF. Under the standardized contrast, a USD 1069 reduction in income is associated with a predicted decrease of 260.48 kg-CO_2/cap among the 65 s–, approximately 1.5 times the corresponding estimate for the 45–64 s. This pattern suggests that CF among the 65 s—is more closely tied to current budget constraints, with less scope to buffer income changes through savings or asset reallocation. Conversely, a USD 1069 increase in intergenerational support is associated with a predicted decrease of 179.98 kg-CO_2/cap among the 65 s–, compared with 123.99 kg-CO_2/cap for the 45–64 s. This contrast is consistent with the view that additional transfers in later life are more strongly associated with lower-carbon expenditure patterns, as transferred resources are more likely to support health maintenance and basic living needs than material acquisition.

The durable-goods expenditure contrasts also reveal distinct age-specific patterns. Automobile-related expenditure is associated with the largest predicted differential overall (40.84 kg-CO_2/cap): among high-income 45–64 s, eliminating the observed vehicle-expenditure gap relative to the low-income benchmark corresponds to a predicted CF differential of 50.93 kg-CO_2/cap, compared with 29.28 kg-CO_2/cap for the

65 s–. By contrast, the standardized contrast for washing-machine expenditure is associated with a larger predicted differential among the 65 s—(32.39 kg-CO_2/cap), consistent with more frequent laundering linked to health and home-care needs. Similarly, eliminating the observed computer-expenditure gap corresponds to a predicted CF differential of 34.7 kg-CO_2/cap among the 45–64 s and 24.7 kg-CO_2/cap among the 65 s–, consistent with more intensive multi-device use and faster replacement among the 45–64 s. By contrast, refrigerators and electric bicycles are more strongly associated with predicted differentials among the 45–64 s, suggesting more limited discretionary expenditure margins among the 65 s—in these categories.

3.4. Research limitations

This study is subject to several limitations. First, because CHARLS reports expenditure at the household rather than individual level, the dependent variable analyzed here is not a directly observed individual CF but an assigned per-capita household CF constructed under an equal-allocation rule. The estimated coefficients should therefore be interpreted as conditional associations between individual characteristics and the corresponding per-capita household consumption-based CF, rather than as evidence of purely autonomous individual consumption behavior. Second, given the cross-sectional nature of the data and the reliance on observed covariates, the empirical findings remain associational. Accordingly, the scenario-based predicted differentials reported in section 3.3 should be understood as comparative estimates derived within a maintained regression framework, rather than as causal effects of realized behavioral change, relocation, or policy intervention. This caution is especially important for the climate-related contrasts, which may still reflect time-invariant city-level characteristics that co-vary with climatic conditions. Third, CHARLS reports direct household energy use only in aggregated form across broad fuel categories, which constrains precise fuel-specific carbon accounting. This limitation may introduce measurement error into some energy-related components of CF, although it does not alter the broader multidimensional framework through which CF heterogeneity is characterized in this study.

4. Conclusions and policy implications

This study provides a micro-level perspective on how population aging is associated with heterogeneity in consumption-based CF. Focusing on two adjacent later-life cohorts—the 45–64 s and the 65 s—we show that resident CF is associated not only with income and asset conditions but also with intergenerational support, digitalization, durable-goods ownership, housing infrastructure, and climatic exposure. In doing so, the study moves beyond the simple view that CF decline automatically with age and shows instead that later-life carbon heterogeneity is structured by cohort–specific differences in consumption patterns and residential environments.

The results reveal several salient patterns. First, the associations between economic resources and resident CF are nonlinear: income exhibits a U-shaped association, whereas assets and intergenerational support exhibit inverted-U associations. Second, these relationships differ across the 45–64 s and the 65 s–, indicating that adjacent later-life cohorts do not share a uniform carbon-footprint structure. Third, scenario-based predicted differentials suggest that the largest comparative differences are associated with climate-related contrasts, while digitalization, durable-goods expenditure, and intergenerational support also display clear cohort–specific relevance. Taken together, these findings suggest that later-life carbon heterogeneity is associated not only with affluence but also with age-differentiated consumption structures and residential environments.

These results provide an indicative basis for comparing the relative relevance of different mitigation domains in aging societies. Within the economic and consumption domain, the findings suggest that progressive green-consumption taxes and carbon surcharges on highly discretionary durable-goods expenditure may help shift high-income consumption toward lower-carbon alternatives. Within the intergenerational support domain, tax deductions or other incentives that encourage lower-carbon forms of caregiving and intergenerational support may represent one possible policy direction. Within the digitalization domain, the results suggest that policies should be differentiated by cohort: for the 45–64 s, digital-consumption nudges may help moderate carbon-intensive convenience consumption, whereas for the 65 s–, digital inclusion strategies may need to focus more on the carbon implications of home-based connectivity and service use.

The climate-related findings also imply that mitigation in aging societies should be approached less as a matter of individual choice and more as a problem of place-based system design. For later-life populations, a substantial share of CF heterogeneity appears to be conditioned by the thermal and infrastructural environments in which daily life is embedded. This suggests that effective mitigation will depend not only on influencing household behavior but also on reducing the carbon intensity of routine adaptation to cold and heat through improvements in housing quality, neighborhood services, and the local provision of heating and cooling. In this sense, spatial planning and infrastructure policy are not merely complementary to household-level mitigation, but part of its institutional foundation. A more effective policy approach would therefore integrate aging policy with housing, energy, and urban governance so that low-carbon transition strategies can better reflect the climatic constraints and everyday living conditions of later-life populations.

Data availability statement

The data cannot be made publicly available upon publication because they are not available in a format that is sufficiently accessible or reusable by other researchers. The data that support the findings of this study are available upon reasonable request from the authors.

Supplementary data 1 available at https://doi.org/10.1088/2515-7620/ae68e5/data1.

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Conflict of interest

The authors declare no conflict of interest.

Informed consent statement

This study did not involve human participants or their data; therefore, ethical approval and informed consent were not required.

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Appendix

Table A1. List of sector classifications included in 2017 provincial MRIO table with the corresponding categories in OLS regression.

No.	Consumption categories in OLS regression	No.	Sector classification of provincial MRIO table
1	Food	01	Agriculture, forestry, animal husbandry and fishery
		02	Food and tobacco processing
2	Electricity & heating	03	Production and distribution of electric power and heat power
3	Gas	04	Production and distribution of gas
4	Water	05	Production and distribution of tap water
5	Durable goods	06	Mining and processing of metal ores
		07	Mining and processing of nonmetal and other ores
		08	Processing of timber and furniture
		09	Manuf. of non-metallic mineral products
		10	Smelting and processing of metals
		11	Manufacture of metal products
		12	Manufacture of general-purpose machinery
		13	Manufacture of special-purpose machinery
		14	Manufacture of transport equipment
		15	Manufacture of electrical machinery and equipment
		16	Manufacture of communication equipment, computers and other electronic equipment
		17	Other manufacturing
6	Consumable goods	18	Mining and washing of coal
		19	Extraction of petroleum and natural gas
		20	Textile industry
		21	Manufacture of leather, fur, feather and related products
		22	Processing of petroleum, coking, processing of nuclear fuel
		23	Manufacture of chemical products
7	Education	24	Manufacture of paper, printing and articles for culture, education and sport activity
		25	Manufacture of measuring instruments
		26	Scientific research and polytechnic services
		27	Education
8	Medicals	28	Health care and social work
		29	Public administration, social insurance, and social organizations
9	Transportation	30	Transport, storage, and postal services
10	Catering services	31	Accommodation and catering
11	Entertainment	32	Culture, sports, and entertainment
12	Finance and real estate	33	Finance
		34	Real estate
		35	Leasing and commercial services
13	Other	36	Waste resources
		37	Repair of metal products, machinery and equipment
		38	Construction
		39	Wholesale and retail trades
		40	Information transfer, software and information technology services
		41	Administration of water, environment, and public facilities
		42	Resident, repair and other services

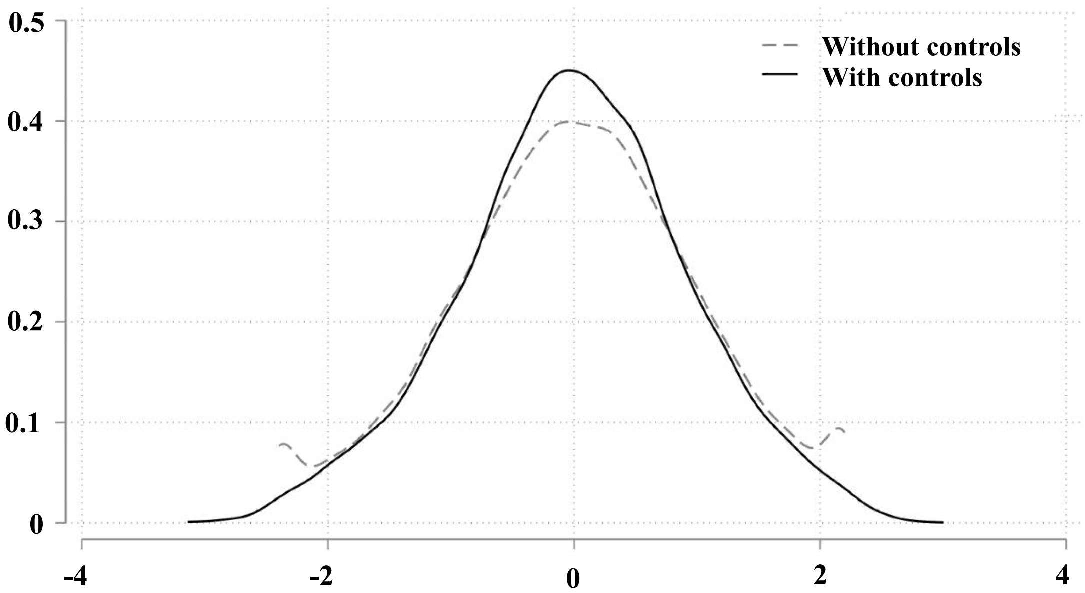

Figure A1. Heterogeneity in resident CF. Note: this figure presents kernel-density estimates of mean-centered CF using a Gaussian kernel. To satisfy census disclosure-avoidance requirements, CF values were winsorized at the 2nd and 98th percentiles. The gray dashed line shows the unconditional kernel density of log-transformed CF, whereas the black solid line depicts the density after adjusting for observable resident characteristics. These covariates (see table 3 in the main text) include: respondents' age (*age*); marital status (*marriage*); number of co-residing household members (*household_size*); respondent's education level (*self_education*); children's education level (*children_education*); self-rated health status (*health_status*); presence of chronic disease (*chronic_disease*); lifetime work history (*lifetime_work*); receipt of subsistence allowance (*subsistence_allowance*); and experience of the sent-down policy (*sent_down_to_countryside*).

Table A2. Collinearity test results for independent variables: variance inflation factors (VIF).

	VIF	1/VIF
ln(*Income*)	1.37	0.73
ln(*Asset*)	1.483	0.674
ln(*Child_support*)	1.409	0.71
Age	1.783	0.561
Marriage	6.603	0.151
Household_size	6.612	0.151
Self_education	1.419	0.705
Children_education	1.073	0.932
Health_status	1.204	0.831
Chronic_disease	1.108	0.902
Lifetime_work	1.338	0.748
Subsistence_allowance	1.06	0.943
Sent_down_to_countryside	1.073	0.932
Smoking	1.032	0.969
Drinking	1.084	0.922
Mobile_payments	1.221	0.819
Medical_insurance	1.036	0.965
Pension_insurance	1.057	0.946
Community_eldercare	1.123	0.89
Automobile	1.256	0.796
Electric_bicycle	1.191	0.84
Refrigerator	1.617	0.618
Washing_machine	1.618	0.618
Television	1.455	0.687
Computer	1.384	0.723
House_age	1.098	0.91
Property_registration	1.097	0.912
Gas_supply	1.306	0.766
Heating_supply	1.427	0.701
Internet_supply	1.373	0.728
Air_satisfaction	1.044	0.958
Air_purification	1.063	0.941
HDD	2.481	0.403
CDD	2.307	0.433
Mean VIF	1.641	—

Table A3. Elasticities of resident CF at mean levels of income, asset, and intergenerational support.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	All	Food	Electricity	Gas	Water	Durable goods	Consumable goods	Education	Medicals	Transportation	Catering services	Entertainment	Finance and real estate	Other
Income	0.303***	0.357***	0.326 ***	0.400***	0.369***	0.329 ***	0.368***	0.405 ***	0.347***	0.370***	0.356***	0.399 ***	0.361***	0.299***
	(−10.13)	(−10.32)	(−11.01)	(−8.09)	(−8.13)	(−9.55)	(−10.39)	(−10.15)	(−6.26)	(−10.26)	(−7.52)	(−7.36)	(−8.22)	(−9.60)
Asset	0.020***	0.060***	0.045***	0.063***	0.068***	0.041***	0.090**	0.070***	0.050**	0.081	0.086***	0.019***	0.083***	0.023***
	(4.33)	(4.74)	(3.99)	(2.74)	(3.12)	(3.08)	(2.27)	(3.77)	(2.48)	(1.32)	(3.26)	(2.74)	(3.95)	(4.10)
Child_support	−0.139***	−0.171***	−0.146***	−0.190***	−0.152***	−0.140***	−0.199***	−0.195***	−0.171***	−0.168***	−0.184***	−0.185***	−0.180***	−0.146***
	(7.96)	(8.54)	(8.36)	(6.36)	(5.31)	(6.66)	(10.22)	(8.74)	(7.95)	(7.02)	(8.15)	(7.10)	(7.94)	(7.32)

Note: In our analysis, the income-elasticity of residents CF is defined as $\widehat{\beta}_1 + 2\widehat{\beta}_2 \ln(\text{Income})$, where $\widehat{\beta}_1$ and $\widehat{\beta}_2$ are the estimated coefficients on ln(Income) and $\{\ln(\text{Income})\}^2$, respectively, from regression equation (3) in the main text. This formulation reflects the logarithmic transformation of CF as the dependent variable and is evaluated at the sample mean of *Income*. The same methodological framework is applied to compute corresponding elasticities for *asset* and *Child_support* (i.e. intergenerational support).

Table A4. Zellner SUR results for resident CF by consumption category.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Variables	Food	Electricity	Gas	Water	Durable goods	Consumable goods	Education	Medical	Transportation	Catering services	Entertainment	Finance and real estate	Other
ln(*Income*)	−0.622***	−0.681***	−0.705***	−0.591***	−0.624***	−0.646***	−0.668***	−0.523***	−0.675***	−0.577***	−0.655***	−0.555***	−0.666***
	(−10.17)	(−12.15)	(−8.62)	(−8.08)	(−10.27)	(−10.50)	(−10.37)	(−6.38)	(−11.12)	(−7.61)	(−7.40)	(−8.18)	(−11.49)
ln(*Income*)^2	0.052***	0.056***	0.060***	0.051***	0.053***	0.054***	0.057***	0.046***	0.057***	0.050***	0.056***	0.049***	0.055***
	(13.71)	(16.10)	(11.73)	(11.21)	(13.89)	(14.08)	(14.25)	(9.07)	(15.03)	(10.53)	(10.18)	(11.54)	(15.22)
ln(*Asset*)	0.342***	0.270***	0.067	0.254***	0.270***	0.152**	0.241***	0.238***	0.070	0.250***	0.239**	0.292***	0.244***
	(5.11)	(4.39)	(0.75)	(3.17)	(4.07)	(2.26)	(3.43)	(2.66)	(1.05)	(3.02)	(2.47)	(3.94)	(3.84)
ln(*Asset*)^2	−0.013***	−0.009***	0.001	−0.009**	−0.009**	−0.003	−0.008**	−0.009*	0.002	−0.007*	−0.010*	−0.010**	−0.007**
	(−3.63)	(−2.69)	(0.28)	(−2.16)	(−2.50)	(−0.82)	(−2.06)	(−1.91)	(0.49)	(−1.65)	(−1.93)	(−2.53)	(−2.22)
ln(*Child_support*)	0.090***	0.085***	0.077***	0.084***	0.077***	0.108***	0.099***	0.115***	0.081***	0.109***	0.109***	0.092***	0.087***
	(8.38)	(8.68)	(5.35)	(6.58)	(7.21)	(10.05)	(8.77)	(8.00)	(7.64)	(8.25)	(7.05)	(7.80)	(8.58)
ln(*Child_support*)^2	−0.014***	−0.014***	−0.015***	−0.014***	−0.013***	−0.017***	−0.016***	−0.016***	−0.015***	−0.016***	−0.016***	−0.015***	−0.015***
	(−11.96)	(−12.54)	(−8.99)	(−9.72)	(−10.76)	(−14.05)	(−12.94)	(−9.85)	(−12.24)	(−10.91)	(−9.37)	(−11.32)	(−12.98)
Age	−0.016***	−0.017***	−0.016***	−0.018***	−0.017***	−0.017***	−0.017***	−0.020***	−0.015***	−0.021***	−0.022***	−0.018***	−0.015***
	(−16.23)	(−18.18)	(−11.54)	(−15.26)	(−16.85)	(−16.90)	(−15.65)	(−14.52)	(−15.36)	(−16.89)	(−15.09)	(−16.18)	(−15.10)
Marriage	0.235***	0.237***	0.322***	−0.026	0.230***	0.112***	0.167***		0.205***	0.045	0.244***	0.136***	0.115***
	(5.28)	(5.51)	(4.62)	(−0.59)	(4.95)	(2.90)	(4.04)		(4.48)	(0.93)	(3.81)	(3.33)	(2.77)
Household_size	−0.184***	−0.189***	−0.197***	−0.094***	−0.184***	−0.146***	−0.161***	−0.110***	−0.179***	−0.140***	−0.198***	−0.157***	−0.145***
	(−12.42)	(−13.43)	(−8.85)	(−6.02)	(−12.07)	(−10.84)	(−11.28)	(−10.45)	(−11.89)	(−8.30)	(−9.28)	(−10.87)	(−10.51)
Self_education	0.049***	0.039***	0.040***	0.033***	0.037***	0.041***	0.041***	0.040***	0.038***	0.046***	0.062***	0.049***	0.042***
	(20.43)	(17.51)	(12.46)	(11.36)	(15.41)	(17.12)	(15.94)	(12.32)	(15.89)	(15.47)	(17.68)	(18.33)	(18.40)
Children_education	0.009***	0.009***	0.010***	0.004*	0.005***	0.007***	0.009***	0.007***	0.007***	0.003*	0.013***	0.005***	0.007***
	(5.58)	(6.43)	(4.79)	(1.89)	(3.48)	(4.78)	(5.48)	(3.22)	(4.54)	(1.70)	(5.78)	(2.79)	(5.01)
Health_status	0.016*	0.016**	0.021*	0.047***	0.011	0.049***	0.028***	0.101***	0.022***	0.041***	0.119***	0.019**	0.034***
	(1.89)	(2.04)	(1.84)	(4.68)	(1.35)	(5.82)	(3.18)	(9.05)	(2.62)	(3.94)	(9.89)	(2.01)	(4.30)
Chronic_disease	0.108***	0.087***	0.126***	0.121***	0.108***	0.121***	0.104***	0.199***	0.091***	0.155***	0.099***	0.160***	0.111***
	(6.47)	(5.69)	(5.64)	(6.06)	(6.52)	(7.25)	(5.96)	(8.93)	(5.50)	(7.49)	(4.10)	(8.65)	(7.01)
Lifetime_work	−0.342***	−0.339***	−0.331***	−0.244***	−0.316***	−0.289***	−0.307***	−0.292***	−0.275***	−0.302***	−0.310***	−0.314***	−0.291***
	(−18.47)	(−19.87)	(−13.27)	(−11.00)	(−17.16)	(−15.57)	(−15.75)	(−11.80)	(−15.01)	(−13.16)	(−11.53)	(−15.33)	(−16.53)
Subsistence_allowance	−0.078***	−0.086***	0.001	−0.121***	−0.074***	−0.055***	−0.153***		−0.136***	−0.087***			−0.123***
	(−4.62)	(−4.38)	(0.04)	(−5.19)	(−3.97)	(−3.33)	(−7.92)		(−8.32)	(−4.55)			(−6.77)
Sent_down_to_countryside	0.310***	0.280***	0.266***	0.401***	0.213***	0.286***	0.422***	0.594***	0.279***	0.408***	0.416***	0.456***	0.261***
	(6.05)	(5.97)	(3.88)	(6.54)	(4.19)	(5.55)	(7.83)	(8.66)	(5.50)	(6.42)	(5.61)	(8.04)	(5.39)

(Continued.)

Table A4. (Continued.)

Smoking				0.008				0.018	−0.008
				(0.49)				(0.54)	(−0.68)
Drinking				0.028***			−0.042***	−0.133***	0.019***
				(3.87)			(−4.70)	(−8.29)	(3.37)
Mobile_payments	0.012			−0.003			0.044***	0.075**	0.006
	(1.20)			(−0.23)			(2.78)	(2.54)	(0.62)
Medical_insurance					0.013				−0.010
					(0.47)				(−0.67)
Pension_insurance					−0.040***				0.006
					(−3.18)				(0.95)
Community_eldercare	−0.023***				−0.022				−0.014*
	(−3.28)				(−1.54)				(−1.74)
Automobile			0.006***			0.004***			0.003***
			(6.08)			(4.33)			(3.37)
Electric_bicycle		0.002*	−0.001*			−0.004***			0.006***
		(1.93)	(−1.69)			(−4.68)			(7.90)
Refrigerator	0.001	−0.003*	0.006***						0.001
	(1.10)	(−1.88)	(4.76)						(0.89)
Washing_machine		0.001	−0.001						0.002**
		(0.76)	(−0.76)						(2.08)
Television		0.001	−0.000						−0.001
		(0.95)	(−0.03)						(−1.19)
Computer		0.008***	0.003**						−0.001
		(6.33)	(2.34)						(−0.70)

(Continued.)

Table A4. (Continued.)

Variables	(1) Food	(2) Electricity	(3) Gas	(4) Water	(5) Durable goods	(6) Consumable goods	(7) Education	(8) Medical	(9) Transportation	(10) Catering services	(11) Entertainment	(12) Finance and real estate	(13) Other
House_age		−0.001***	−0.001***	0.000									0.000
		(−4.03)	(−3.17)	(0.69)									(1.12)
Property_registration		0.045***	0.073***	0.057***									0.003
		(5.07)	(4.41)	(4.27)									(0.49)
Gas_supply		−0.114***	−0.055***										0.032***
		(−13.63)	(−3.62)										(4.81)
Heating_supply			−0.108***										−0.015*
			(−6.14)										(−1.88)
Internet_supply		0.008											0.021***
		(1.14)											(3.67)
Air_satisfaction													0.007**
													(2.53)
Air_purification		0.023											0.047***
		(1.21)											(2.93)
HDD		0.009***	0.009***	0.006***									0.003***
		(95.14)	(47.62)	(44.95)									(34.65)
CDD		0.008***	0.012***	0.014***									0.002***
		(67.50)	(58.85)	(83.35)									(27.64)
Constant	4.260***	6.229***	1.067**	−3.804***	3.922***	5.578***	2.559***	−0.554	5.880***	1.164**	0.000	2.325***	4.739***
	(10.58)	(16.88)	(1.98)	(−7.91)	(9.81)	(13.82)	(6.05)	(−1.03)	(14.74)	(2.34)	(0.00)	(5.22)	(12.42)
Observations	13 890	13 890	13 890	13 890	13 890	13 890	13 890	13 890	13 890	13 890	13 890	13 890	13 890
R-squared	0.210	0.314	0.155	0.168	0.202	0.189	0.196	0.114	0.205	0.154	0.130	0.183	0.226

Robust t-statistics in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A5. PPML regression results for resident CF by consumption category.

Variables	(1) Food	(2) Electricity	(3) Gas	(4) Water	(5) Durable goods	(6) Consumable goods	(7) Education	(8) Medical	(9) Transportation	(10) Catering services	(11) Entertainment	(12) Finance and real estate	(13) Other
ln(*Income*)	−0.539***	−0.553***	−0.467***	−0.544***	−0.491***	−0.584***	−0.592***	−0.515***	−0.548***	−0.566***	−0.550***	−0.522***	−0.525***
	(−8.54)	(−9.00)	(−5.51)	(−7.70)	(−7.50)	(−8.82)	(−8.36)	(−5.85)	(−9.05)	(−6.46)	(−5.56)	(−6.99)	(−8.33)
ln(*Income*)^2	0.045***	0.044***	0.041***	0.046***	0.041***	0.047***	0.050***	0.043***	0.046***	0.048***	0.046***	0.044***	0.041***
	(11.55)	(11.77)	(7.96)	(10.71)	(10.25)	(11.83)	(11.62)	(8.02)	(12.38)	(9.04)	(7.55)	(9.70)	(10.75)
ln(*Asset*)	0.188**	0.142*	0.143	0.227***	0.123	0.036	0.154*	0.142	0.055	0.046	0.201*	0.155*	0.159**
	(2.46)	(1.92)	(1.44)	(2.68)	(1.60)	(0.49)	(1.86)	(1.38)	(0.76)	(0.44)	(1.72)	(1.71)	(2.03)
ln(*Asset*)^2	−0.006	−0.004	−0.004	−0.007*	−0.004	0.003	−0.004	−0.004	0.001	0.002	−0.007	−0.004	−0.006
	(−1.50)	(−1.11)	(−0.71)	(−1.72)	(−0.92)	(0.69)	(−0.94)	(−0.78)	(0.14)	(0.40)	(−1.14)	(−0.77)	(−1.46)
ln(*Child_support*)	0.073***	0.072***	0.078***	0.079***	0.060***	0.089***	0.089***	0.106***	0.059***	0.132***	0.075***	0.093***	0.058***
	(6.67)	(6.92)	(5.41)	(6.27)	(5.14)	(7.94)	(7.23)	(6.69)	(5.58)	(7.98)	(4.12)	(7.13)	(5.27)
ln(*Child_support*)^2	−0.012***	−0.011***	−0.013***	−0.012***	−0.010***	−0.014***	−0.014***	−0.014***	−0.011***	−0.019***	−0.011***	−0.014***	−0.010***
	(−9.55)	(−9.30)	(−8.03)	(−9.02)	(−7.54)	(−11.51)	(−10.68)	(−8.22)	(−9.45)	(−10.19)	(−5.47)	(−9.95)	(−7.96)
Age	−0.011***	−0.008***	−0.014***	−0.013***	−0.009***	−0.014***	−0.011***	−0.015***	−0.009***	−0.015***	−0.014***	−0.015***	−0.005***
	(−9.73)	(−7.36)	(−8.72)	(−10.02)	(−7.12)	(−12.00)	(−8.81)	(−9.24)	(−7.88)	(−9.87)	(−8.05)	(−11.34)	(−3.74)
Marriage	0.242***	0.285***	0.395***	0.003	0.263***	0.079	0.125*		0.169***	0.069	0.300***	0.141*	0.098
	(3.91)	(4.96)	(4.79)	(0.04)	(3.92)	(1.17)	(1.77)		(2.70)	(0.84)	(3.42)	(1.94)	(1.46)
Household_size	−0.210***	−0.223***	−0.242***	−0.126***	−0.218***	−0.163***	−0.169***	−0.133***	−0.195***	−0.164***	−0.217***	−0.187***	−0.164***
	(−11.03)	(−12.78)	(−9.74)	(−5.33)	(−10.65)	(−7.96)	(−7.89)	(−11.77)	(−10.15)	(−6.57)	(−8.00)	(−8.43)	(−7.94)
Self_education	0.039***	0.023***	0.028***	0.023***	0.026***	0.034***	0.032***	0.035***	0.030***	0.035***	0.045***	0.047***	0.018***
	(14.76)	(8.96)	(7.79)	(7.45)	(9.30)	(12.63)	(10.57)	(9.27)	(11.49)	(8.61)	(10.66)	(15.04)	(6.40)
Children_education	0.006***	0.004***	0.004	0.002	0.001	0.006***	0.006***	0.003	0.004**	0.003	0.007***	0.004*	0.002
	(4.03)	(2.70)	(1.63)	(1.27)	(0.70)	(3.83)	(3.45)	(1.55)	(2.24)	(1.27)	(2.71)	(1.85)	(1.47)
Health_status	0.015	0.025***	−0.005	0.046***	0.021**	0.047***	0.029***	0.077***	0.019**	0.065***	0.088***	0.013	0.043***
	(1.56)	(2.86)	(−0.43)	(4.31)	(2.08)	(4.82)	(2.73)	(5.58)	(2.03)	(4.65)	(5.93)	(1.13)	(4.44)
Chronic_disease	0.101***	0.081***	0.116***	0.071***	0.097***	0.104***	0.088***	0.164***	0.088***	0.102***	0.097***	0.146***	0.089***
	(5.60)	(4.73)	(4.82)	(3.45)	(5.17)	(5.62)	(4.35)	(6.62)	(4.93)	(3.89)	(3.37)	(6.81)	(4.89)
Lifetime_work	−0.325***	−0.216***	−0.264***	−0.211***	−0.270***	−0.273***	−0.303***	−0.310***	−0.264***	−0.216***	−0.307***	−0.322***	−0.183***
	(−16.36)	(−10.85)	(−9.59)	(−9.15)	(−12.80)	(−13.36)	(−13.34)	(−11.31)	(−13.25)	(−7.42)	(−9.22)	(−13.38)	(−8.64)
Subsistence_allowance	−0.120***	−0.078**	−0.086*	−0.139***	−0.076*	−0.124***	−0.168***		−0.222***	−0.109*			−0.154***
	(−3.03)	(−2.01)	(−1.72)	(−3.01)	(−1.77)	(−3.19)	(−3.71)		(−5.76)	(−1.76)			(−3.95)
Sent_down_to_countryside	0.176***	0.073*	0.026	0.208***	0.087*	0.147***	0.291***	0.394***	0.164***	0.216***	0.101	0.298***	0.066
	(3.89)	(1.76)	(0.39)	(4.40)	(1.75)	(3.19)	(5.76)	(6.55)	(3.63)	(3.59)	(1.44)	(5.53)	(1.50)

(Continued.)

Table A5. (Continued.)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Variables	Food	Electricity	Gas	Water	Durable goods	Consumable goods	Education	Medical	Transportation	Catering services	Entertainment	Finance and real estate	Other
Smoking							0.081*				−0.028		0.050
							(1.74)				(−0.45)		(1.18)
Drinking							0.041*			−0.044	−0.066**		0.037*
							(1.86)			(−1.63)	(−2.05)		(1.86)
Mobile_payments	0.171***						0.159***			0.207***	0.234***		0.050*
	(5.83)						(4.81)			(5.14)	(4.97)		(1.66)
Medical_insurance								0.049					0.014
								(0.65)					(0.25)
Pension_insurance								−0.004					−0.020
								(−0.11)					(−0.76)
Community_eldercare	−0.039							−0.129***					−0.052*
	(−1.28)							(−2.87)					(−1.66)
Automobile					0.037***				0.038***				0.031***
					(14.37)				(15.45)				(11.82)
Electric_bicycle		−0.007***			−0.008***				−0.010***				0.002
		(−2.84)			(−3.12)				(−4.13)				(0.74)
Refrigerator	0.011***	−0.001			0.001								0.000
	(2.93)	(−0.31)			(0.23)								(0.04)
Washing_machine		0.021***			0.028***								0.023***
		(4.88)			(6.18)								(4.91)
Television		0.003			−0.001								−0.004
		(0.74)			(−0.30)								(−0.81)
Computer		0.023***			0.023***								0.007*
		(7.17)			(6.34)								(1.94)

(Continued.)

Table A5. (Continued.)

House_age		−0.002**	−0.001	−0.006***									−0.000
		(−2.44)	(−1.53)	(−6.91)									(−0.62)
Property_registration		−0.067***	−0.008	−0.030									−0.080***
		(−3.10)	(−0.27)	(−1.18)									(−3.56)
Gas_supply		0.084***	0.173***										0.156***
		(4.05)	(5.55)										(6.77)
Heating_supply			0.107***										0.105***
			(2.69)										(3.85)
Internet_supply		0.252***											0.257***
		(12.52)											(12.06)
Air_satisfaction													0.044***
													(4.13)
Air_purification		0.155***											0.209***
		(4.04)											(4.85)
HDD		0.008***	0.006***	0.006***									0.002***
		(24.72)	(14.20)	(18.01)									(6.45)
CDD		0.005***	0.008***	0.007***									0.000
		(12.53)	(16.88)	(20.07)									(1.11)
Constant	5.172***	6.839***	1.512**	−2.551***	4.470***	6.487***	3.169***	0.710	5.990***	2.647***	0.571	3.641***	4.982***
	(11.45)	(15.78)	(2.51)	(−5.11)	(9.76)	(14.54)	(6.36)	(1.15)	(13.92)	(4.31)	(0.80)	(6.71)	(10.94)
Observations	14 009	14 008	14 008	14 008	14 009	14 009	14 009	14 009	14 009	14 009	14 009	14 009	13 918
R-squared	0.180	0.272	0.121	0.147	0.189	0.160	0.161	0.087	0.212	0.103	0.082	0.140	0.229

Note: Robust z-statistics in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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