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Physical consumption data reveals hidden carbon inequalities beyond monetary-based accounting

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A R T I C L E I N F O

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A B S T R A C T

Understanding how carbon footprints differ across households is essential for designing fair and effective carbon pricing mechanisms. However, such assessments can vary depending on whether carbon footprints are allocated based on the monetary value of goods and services purchased or physical quantities consumed, because expenditure differences may reflect not only differences in consumption volumes but also differences in product characteristics, quality, and prices. Here, using micro-level data from China's Household Survey linked with an environmentally extended input–output database, we compare monetary- and physical-based carbon accounting for consumption categories with information on both expenditures and physical quantities and examine the implications for carbon taxation. We find systematic differences in estimated emissions across household groups, ranging from −9% to +7% at the expenditure-quintile level. Differences are larger within individual categories, reaching −54% to +59% for footwear. These differences substantially alter the estimated distribution of carbon tax burdens across household groups. Physical-based accounting indicates higher carbon tax burdens for the poorest quintile, especially for essential goods such as food and residential energy. The comparison demonstrates how accounting choices shape assessments of carbon tax burdens and climate policy fairness.

1. Introduction

Household consumption drives a large share of global greenhouse gas (GHG) emissions through both direct energy use and supply-chain effects (Bruckner et al., 2022; Creutzig et al., 2018). These consumption-based emissions are unequally distributed across population groups, reflecting disparities in income levels, consumption patterns, and lifestyles (Chancel, 2022; Guan et al., 2025). Addressing climate change, therefore, requires not only reducing emissions but also ensuring that mitigation policies are socially equitable (Cap et al., 2025; Creutzig et al., 2018, 2022). Understanding who contributes more to emissions and who bears the costs of mitigation is key to the pursuit of effective and equitable climate policy (Büchs et al., 2023; Chancel et al., 2024; Du et al., 2024; Oswald et al., 2020). Such strategies increasingly involve carbon pricing, which aims to reduce emissions while addressing social inequality through compensatory measures (Hubacek and Feng, 2016; Vogt-Schilb et al., 2019; Wood et al., 2018). However, the effectiveness and fairness of such instruments depend critically on how emissions are measured and attributed across different population groups (Chancel et al., 2024; Oswald et al., 2023).

Most existing household-level carbon footprint studies rely on monetary expenditure data, assuming that a household's spending proportionally reflects its carbon emissions (André et al., 2024; Pottier, 2022; Girod and De Haan, 2010; Goldstein et al., 2024). This

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assumption allows household budget data to be integrated readily with environmentally extended input–output (EEIO) models, which allocate consumption-based emissions across households with different income/expenditure levels by linking detailed budget surveys with aggregated household final demand data (Guan et al., 2025; Oswald et al., 2020; Tian et al., 2024). EEIO models are widely adopted due to their compatibility with national economic and environmental accounts and the relative ease of accessing monetary data (Ali et al., 2026; Miao et al., 2023; van Ewijk et al., 2023).

However, this monetary-based perspective has important limitations: it assumes that embodied emissions scale proportionally with household expenditure within each consumption category. This assumption may not fully capture heterogeneity in product quality, materials, production technologies, supply chains, and market prices (André et al., 2024; Goldstein et al., 2024; Kilian et al., 2023). In many economies, particularly in developing and emerging countries, substantial price heterogeneity arises from market segmentation, brand stratification, and subsidies (Kilian et al., 2023; Regmi and Seale, 2010; Vringer and Blok, 1997). Households may also acquire goods through non-market channels or targeted subsidy schemes, such as China's appliances and electronics replacement initiatives (China Daily, 2025), potentially weakening the relationship between monetary expenditure and the physical quantities consumed (André et al., 2024; Girod and De Haan, 2010). As a result, households with similar monetary expenditures may consume vastly different physical quantities. Expenditure-based allocation may allocate relatively more emissions to wealthier households, who often purchase higher-priced or luxury goods, while allocating fewer emissions to poorer households that rely more on lower-priced or subsidized consumption (André et al., 2024; Guan et al., 2025). The resulting differences can affect estimates across consumption domains, including footwear, food, mobility, housing, and durable goods, thereby influencing the interpretation of carbon footprints and carbon inequality across income classes (André et al., 2024; Leferink et al., 2023).

While many studies have widely acknowledged the limitations of carbon accounting approaches based on monetary expenditures (Enlund et al., 2023; Kilian et al., 2023; Pottier, 2022), empirical evaluations remain limited. To date, only a handful of studies have compared monetary-based and physical-based carbon estimates, and these focus on high-income countries such as the Netherlands (Vringer and Blok, 1997), Switzerland (Girod and De Haan, 2010), and France (André et al., 2024). Much less is known about how these differences play out in developing and emerging countries, despite their potentially different economic structures, wider price variations, and higher degrees of income inequality. In these contexts, monetary expenditure may be even more poorly aligned with physical consumption, potentially affecting estimates of carbon inequality and the evaluation of mitigation strategies. Moreover, the above studies adopt a narrow product focus (e.g., cooking oils (André et al., 2024)), missing broader patterns in total household carbon footprints and inequality.

These measurement issues are not merely methodological, since they shape how emission responsibility and vulnerability are understood in climate policy. Carbon taxation is adopted to internalise climate costs and shape consumer behavior by imposing higher costs on higher emitters (The World Bank, 2025). Yet if carbon inequality is mismeasured, carbon taxation may place undue burdens on those least responsible for emissions, undermining their political acceptability. However, no study to date has systematically assessed how the choice of accounting methods affects the design and fairness of carbon taxes. This leaves a critical gap in our understanding of how carbon responsibilities can be assigned equitably across populations (Steckel et al., 2021).

To fill these gaps, we conduct a systematic comparison of monetary- and physical-based carbon accounting approaches using household consumption categories with information on both expenditure and physical quantities. Our primary objective is to examine how the accounting approaches influence estimates of carbon inequality and the distribution of carbon tax burdens. China, as an emerging economy with wide income disparities, large variation in the prices of goods, and uneven access to basic resources such as energy and infrastructure, offers a critical context for this analysis. We use a large-scale household survey dataset from the 2015 China's Household Survey (Guan et al., 2025; National Bureau of Statistics, 2023; Zhang et al., 2023b), covering 47,188 households across ten provinces and 218 consumption items. Among them, 94 products across six key consumption categories (i.e., food, footwear, durable goods, private vehicles, transport fuels, and residential energy) have both expenditure and physical-quantity data. By linking these data with China's 2018 input–output table, we estimate carbon footprints by household income quintiles, compare the resulting inequality patterns, and assess their implications for carbon tax design. We show that the accounting method considerably affects estimates of emissions, carbon inequality, and the distribution of carbon tax burdens, thereby reshaping perceptions of who emits most, who is most vulnerable to carbon pricing, and who should bear mitigation costs. How emissions are measured is therefore not a simple methodological decision, but a fundamental factor shaping the perception of fairness and effectiveness of carbon taxation policies.

2. Methods

2.1. Overview

In this study, we link the micro-level household survey data to an environmentally extended input–output (EEIO) model to assess household consumption inequality and the distributional impacts of carbon taxation under monetary- and physical-based carbon accounting. First, we use detailed household consumption data from the 2015 China's Household Survey (CHS) to evaluate inequality in consumption patterns across household groups. We then estimate the national household carbon footprint using the 2018 single-region IO table for China and sectoral greenhouse gas emissions data. Assuming the same carbon intensities for a given product across households, we allocate national household carbon footprints to five expenditure quintiles based on their consumption structures derived from the CHS under both accounting approaches. Finally, we model a hypothetical uniform carbon tax scenario to examine the potential distributional consequences across expenditure groups. Data sources and processing are provided. Assumptions and uncertainties for all calculations are also given.

2.2. Data sources and processing

2.2.1. China input-output table

We use China's single-region input–output (SRIO) table published by the National Bureau of Statistics for the year 2018, representing the most recent pre-COVID benchmark year (National Bureau of Statistics, 2024). The 2018 IO table records intersectoral monetary flows among 153 economic sectors at 2018 purchasers' prices. The SRIO table is compiled under a competitive import framework, in which imports are treated according to the standard accounting conventions embedded in the national IO table.

2.2.2. Household consumption data and processing

Household consumption data are collected from the 2015 China's Household Survey (CHS), which was conducted by the National Bureau of Statistics of China (Zhang and Yang, 2025). Formerly known as China's Urban/Rural Household Income and Expenditure Survey (UHIES/RHIES), the CHS was integrated into a unified urban-rural survey after 2013. The CHS adopts a stratified, multistage random sampling design and survey weights to improve the representativeness of household-level estimates (National Bureau of Statistics, 2023). The 2015 CHS dataset is the most recent CHS available containing both detailed monetary expenditure and physical consumption information.

The survey data used in this study cover 47,188 households and

123,345 individuals from ten provinces (i.e., Beijing, Shanghai, Zhejiang, Guangdong, Liaoning, Sichuan, Hubei, Shaanxi, Anhui, and Gansu). These provinces include diverse economic development levels, geographical regions, and resource endowments, including both highly developed metropolitan regions and less-developed inland provinces. For each household, the CHS records detailed demographic and housing information (e.g., household size, income, dwelling characteristics), along with expenditures on 218 consumption items. Among these, 94 products have information on both monetary expenditure (in Chinese Yuan) and physical quantities (e.g., rice in kilograms, electricity in kilowatt-hours). Prior to analysis, households with missing information required for the monetary- and physical-based accounting analyses were excluded. To ensure consistency and comparability between the two accounting approaches, the analysis focuses on the 94 products for which both monetary and physical data are available. The selected categories mainly include food, footwear, durable goods, private vehicles, transportation fuels, and residential energy. Service-related categories without directly comparable physical-unit information are not fully covered. A number of studies have recently used this dataset for household consumption and inequality analyses (Zha et al., 2024; Zhang and Yang, 2025; Zhang et al., 2023b). A full list of the 94 products is provided in Table S1 in the Supplementary Information 2 (SI2).

The 2015 household consumption structure was linked to the 2018 IO table and emission inventories, assuming that relative household consumption patterns remained broadly stable between 2015 and 2018. We further constructed a binary (0–1) bridging matrix linking the 218 household consumption items reported in the CHS to the 153 sectors in China's IO table based on product descriptions, sector definitions, and the primary economic activity classifications defined in ISIC Rev.4 and GB/T 4754–2017 (see Table S2 in SI2), thereby ensuring consistency between survey products and IO sectors. Although such mapping procedures inevitably introduce uncertainty, particularly for heterogeneous or aggregated product categories, the same framework was consistently applied to both monetary- and physical-based accounting approaches.

2.2.3. Greenhouse gas emissions data and processing

Sectoral CO_2 and CH_4 emissions are obtained from the Carbon Emission Accounts & Datasets (CEADs), which provide detailed emissions inventories for China based on localized energy statistics and country-specific emission factors, covering fossil fuel combustion, agricultural activities, and waste management (Guan et al., 2021; Xu et al., 2024). The dataset covers 47 economic sectors and 26 fossil fuel types, allowing more detailed characterization of sectoral and household direct emissions, including those from residential heating, cooking, cooling, and private mobility.

Emissions of other greenhouse gases (i.e., N_2O, F-gases) are obtained from the Emissions Database for Global Atmospheric Research (EDGAR), which offers comprehensive sector-level estimates across a broad range of anthropogenic sources, ensuring consistency and comparability across emission categories (Crippa et al., 2024). Combining CEADs and EDGAR enables the integration of China-specific CO_2 and CH_4 inventories with more comprehensive multi-gas emission accounts in the EEIO framework. Different greenhouse gases were converted into CO_2-equivalent emissions using 100-year global warming potentials (GWPs) based on IPCC AR5 values, including $CO_2 = 1$, $CH_4 = 28$, and $N_2O = 265$.

To integrate emission data with the EEIO analysis, we construct binary (0–1) mapping matrices linking emission sectors from CEADs and EDGAR to the 153-sector classification used in China's IO table (see Table S3 and Table S4 in SI2). The sector classifications across CEADs, EDGAR, and the IO table are not fully identical, and the mapping is therefore not strictly one-to-one. The bridging matrices were constructed based on sector definitions, product descriptions, and economic activities. Each row of the matrix corresponds to an emission source sector, and each column to an IO sector, with a value of 1 indicating a mapping relationship. These matrices enable the alignment of environmental accounts with the economic sector classification used in the EEIO analysis.

2.3. Household consumption inequality

We assess household consumption inequality using the Lorenz curve as a visual tool and Gini coefficient for quantification (Oswald et al., 2020; Wang et al., 2025). The analysis compares monetary- and physical-based measures for the 94 products reported in the 2015 China's Household Survey.

Because products are reported in different physical units (e.g., kilograms, liters, pieces), we construct a category-level structural consumption indicator for each household. For the monetary-based accounting, product-level consumption is represented directly by household expenditures. For the physical-based accounting, household consumption of each product is first expressed as a share of total physical consumption and then rescaled using the aggregate monetary expenditure of that product. This procedure preserves the observed expenditure structure across products while allowing products with heterogeneous physical units to be aggregated consistently within each consumption category. Detailed equations and calculation procedures are provided in the Supplementary Information 1 (SI1).

2.4. Household carbon footprints

2.4.1. National-level EEIO calculation

We estimated household carbon footprint (**CF**) at the national level using an environmentally extended input–output (EEIO) model (Chancel, 2022; Zhong et al., 2024; Tong et al., 2026). As shown in eq. (1), **CF** is defined as the sum of direct emissions from households ($\mathbf{CF}^d$) (e.g., fossil fuel use for heating, cooking, and private transport) and indirect emissions ($\boldsymbol{\varepsilon}(I-A)^{-1}\widehat{\mathbf{Y}}$) embodied in the production of goods and services consumed by households along upstream supply chains

$$\boldsymbol{CF} = \boldsymbol{\varepsilon}(I-A)^{-1}\widehat{\boldsymbol{Y}} + \boldsymbol{CF}^d \tag{1}$$

where $\boldsymbol{\varepsilon}$ is a row vector of sectoral carbon coefficient, representing emissions per unit of economic output for 153 sectors represented in China's IO table. $L = (I-A)^{-1}$, the Leontief inverse, reflects total upstream production required to meet final demand. A is the technological coefficient matrix, where elements capture the intersectoral economic linkages. I is an identity matrix with the same size as A. **Y** is the column vector of final demand. As this study focuses on household consumption, emissions associated with government consumption, capital investment, and exports are excluded from the analysis. Therefore, **Y** covers only household consumption.

2.4.2. Allocation to quintiles based on consumption structure

We then allocate the national **CF** to five expenditure quintiles according to household consumption patterns from the 2015 CHS, assuming that the carbon coefficient of a given product is the same across household groups.

The 47,188 surveyed households were ranked by per-capita expenditure (total household expenditure divided by household size) and divided into quintiles, each representing 20% of the population. For both the monetary- and physical-based accounting, we constructed quintile-level consumption structures by calculating, for each of the surveyed products, the proportion of national consumption attributable to each quintile, aggregated from household-level data. Using the physical-based accounting as an example, product quantities reported in the CHS were aggregated within quintiles to determine their share of the national total. The 218 products were then mapped to the 153 sectors in the 2018 IO table via a bridging matrix (see Table S2 in SI2), ensuring consistency between survey categories and IO sectors. National sectoral **CF** were subsequently allocated to quintiles in proportion to these consumption shares.

2.5. Carbon taxation scenario

To assess the potential distributional impacts of carbon pricing, we modelled a hypothetical carbon taxation scenario in which a uniform tax rate of 100 CNY per ton CO_2e is applied to household direct and indirect emissions.

Although China currently operates pilot emission trading systems (ETS) in seven cities, with carbon prices ranging between 4 CNY and 103 CNY per ton CO_2e from 2014 to 2024 (The World Bank, 2025), we adopted a single uniform rate of 100 CNY per ton CO_2e for comparability and simplicity. The main purpose of this scenario is not to predict the long-term effects of carbon taxation, but to compare how different accounting approaches influence the estimated distribution of household carbon tax burdens under a consistent policy framework.

The tax burden for each expenditure quintile was calculated by multiplying its allocated carbon footprint by the assumed tax rate, following previous studies (Kang et al., 2026; Oswald et al., 2023; Vogt-Schilb et al., 2019). This simplified scenario represents the additional costs households would pay under carbon pricing, assuming no changes in household consumption patterns, technological progress, enterprise mitigation, or declining carbon intensities in response to the price signal (Dietsch, 2024; Steckel et al., 2021). In reality, long-term behavioral adjustments and technological adaptation may partially mitigate the regressive effects of carbon taxation. However, because low-income households allocate a larger share of expenditure to essential goods with relatively inelastic demand, the unequal burden patterns identified in this study may still persist, particularly in the short term. The resulting distribution of tax burdens enables a direct comparison of the relative financial impacts of carbon taxation under both monetary- and physical-based carbon accounting measures.

3. Results

3.1. Household consumption inequality under monetary- and physical-based accounting

To assess how accounting approaches affect estimates of household consumption inequality, we compare consumption distribution across product categories using both monetary and physical data (Fig. 1). Because physical consumption is reported in heterogeneous units (e.g., kilograms, liters, and cubic metres), products within a category cannot be aggregated directly. For the category-level inequality analysis, we therefore converted physical consumption into a comparable structural consumption index based on households' shares of total product consumption and the aggregate expenditure of each product (see Methods).

We find that inequality estimates diverge notably between the two

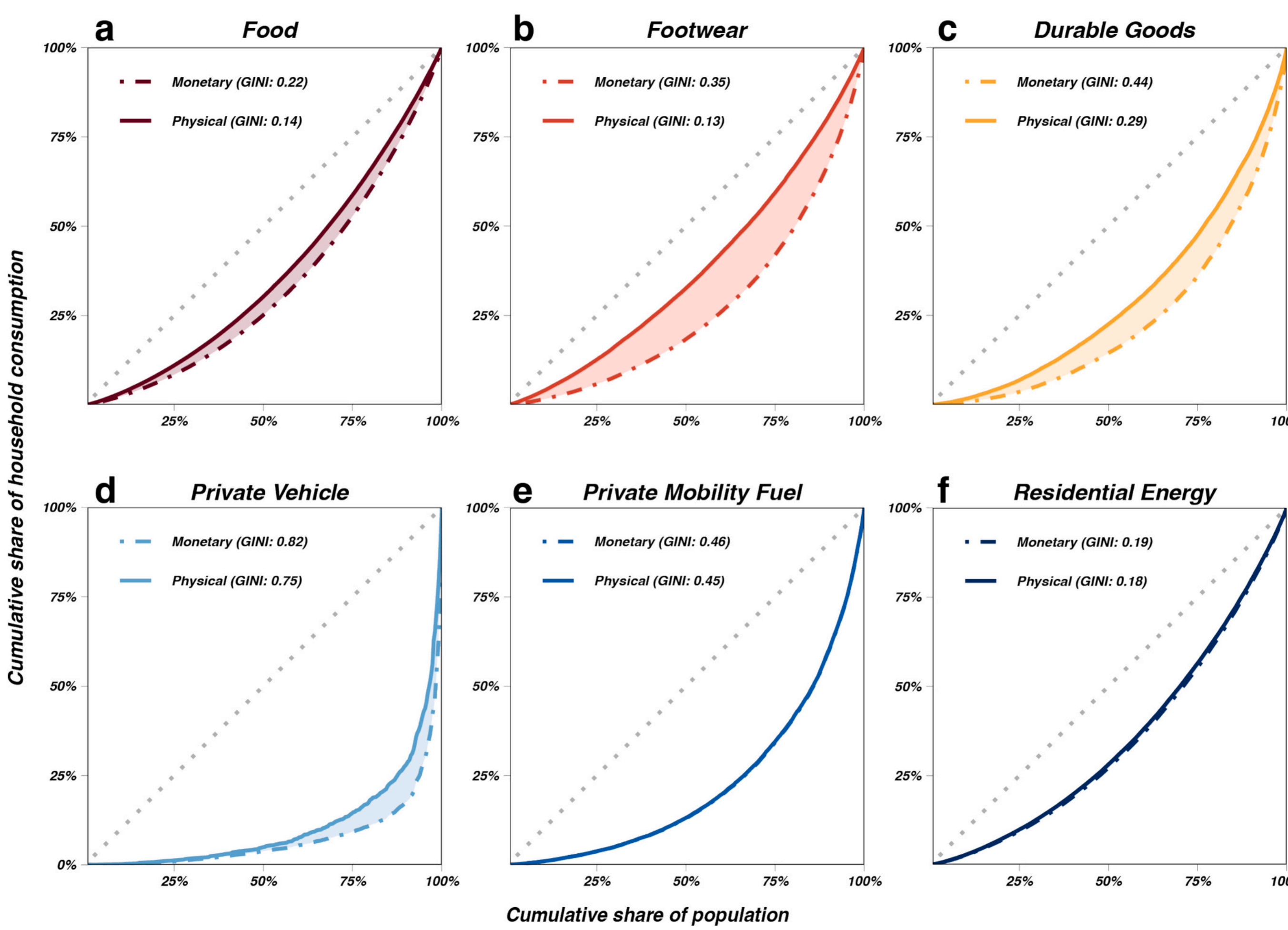

Fig. 1. Household consumption inequality in China under monetary- and physical-based accounting approaches. The x-axis shows the cumulative population share, ranked by per capita annual total expenditure. The y-axis represents the cumulative share of household consumption. For the physical-based accounting, household consumption of each product is first expressed as a share of total physical consumption and then rescaled using the aggregate monetary expenditure of that product. This procedure preserves the observed expenditure structure across products while allowing products with heterogeneous physical units to be aggregated consistently within each consumption category (see details in the Supplementary Information 1). Gini coefficients (shown in the legend) are widely used to assess inequality, ranging from 0 (perfect equality) to 1 (perfect inequality), with higher values indicating greater disparity in consumption across households.

units in categories with high price heterogeneity, such as footwear, durable goods, and private vehicles (Fig. 1 b, c, and d). In these categories, monetary-based measures show higher inequality than physical-based ones. This gap arises because wealthier households are more likely to purchase premium or higher-priced variants, which increases monetary spending without necessarily implying proportional differences in the physical amount consumed. As a result, monetary-based approaches tend to attribute a larger share of embodied emissions to richer household groups and produce higher inequality estimates. For example, the top 10% of households account for over 25% of total footwear expenditure under monetary-based accounting (Gini coefficient = 0.35), but only 14% under the physical-based accounting (Gini = 0.13).

By contrast, inequality estimates are more closely aligned for essential or energy-related goods, namely food, residential energy and mobility fuels (Fig. 1 a, e, and f). For example, the Gini coefficients for residential energy consumption are 0.19 under the monetary-based approach and 0.18 under the physical one. This convergence reflects China's regulated pricing policies, which constrain price variation across regions. In June 2025, for example, the retail price of gasoline and diesel ranged from 8835 to 9270 Chinese Yuan per ton across 24 provinces, with a coefficient of variation below 1% (National Development and Reform Commission (NDRC), 2025). In such cases, monetary- and physical-based approaches produce consistent inequality estimates.

Provincial-level results reveal that the divergence between monetary- and physical-based inequality measures is widespread across provinces and varies considerably across consumption categories, with the discrepancy being largest for footwear (0.10–0.27) and durable goods (0.07–0.15), while remaining below 0.004 for private mobility fuels and residential energy. To facilitate comparisons across provinces and product categories with different baseline inequality levels, Fig. 2 presents min–max normalized Gini indices. The relative differences between monetary- and physical-based measures remain consistent with those observed in the original Gini coefficients. Among the ten provinces analysed, Beijing and Shanghai show the smallest discrepancies between the two approaches across all six categories. In these two highly developed metropolitan areas, inequality in necessities (i.e., food and fuel) is lower than in other provinces under both measures, and differences for non-essential goods are smaller than in less developed regions. Possible explanations include more integrated retail markets, greater access to standardized goods and services, and less reliance on informal or subsidized consumption channels (Blekking et al., 2023; Z. Wu et al., 2023). In less developed provinces, variation in product quality and market access, differences in access to subsidized goods, and urban-rural differences in consumption structures may further weaken the relationship between monetary expenditure and physical consumption (Lei et al., 2022; X. Wu and Xiong, 2023; Zhu et al., 2026). For energy-related goods such as residential fuels and mobility fuels (**Fig. 2**e and f), the two measures yield nearly identical inequality estimates across all provinces, consistent with regulated energy pricing and relatively limited regional variation in energy prices (Zhang and Rui, 2025). Although these interprovincial differences are moderate, they highlight the role of local market structures in shaping measurement differences.

3.2. Household carbon footprints under monetary- and physical-based accounting

We further examine how different accounting approaches influence estimates of household carbon footprints across groups. Fig. 3 compares per capita carbon footprints in 2018 for five expenditure quintiles in China, based on household-level data reported in either monetary or

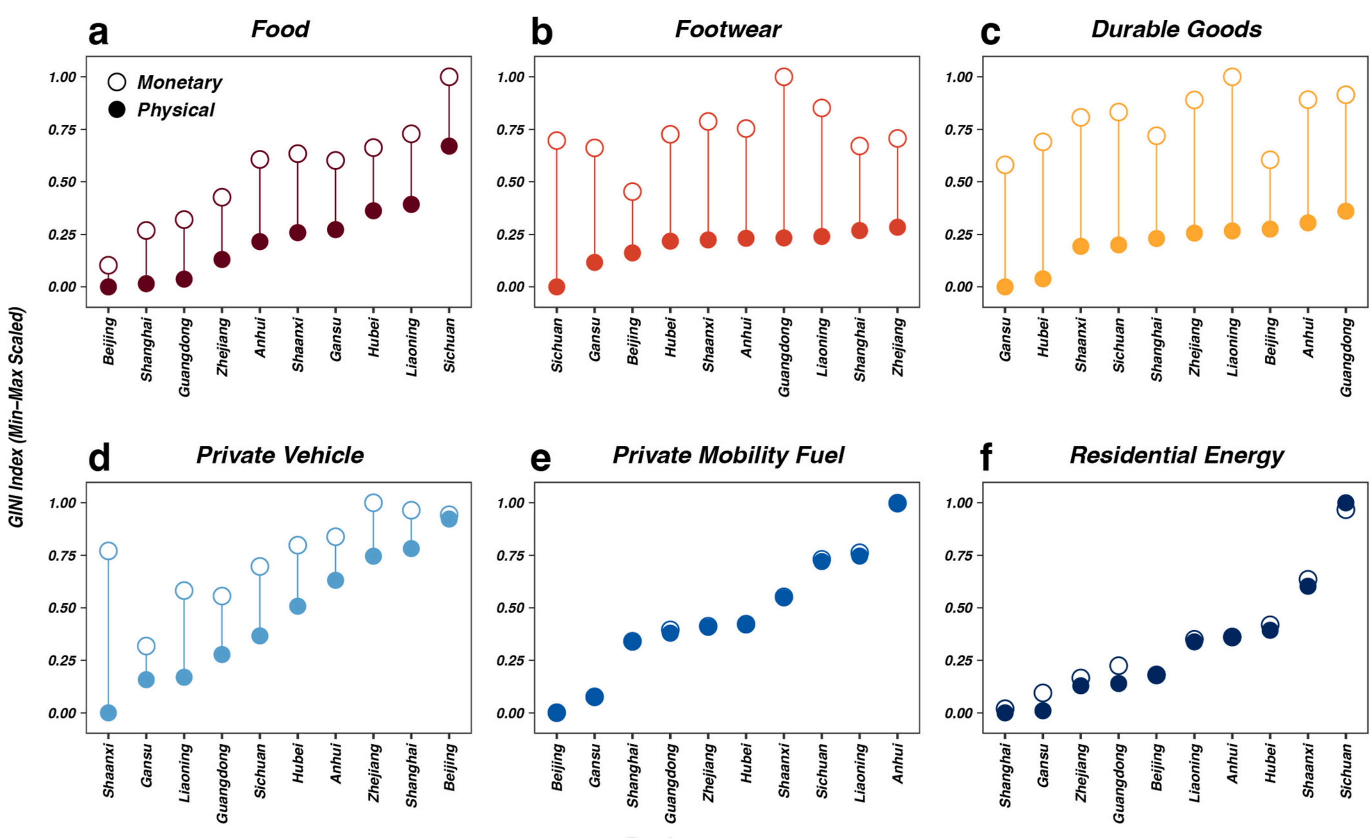

Fig. 2. Gini-based inequality in household consumption under monetary- and physical-based accounting approaches across six product categories and ten Chinese provinces. The y-axis shows min–max normalized Gini indices for each province within each product category. The physical-based Gini is calculated using a structural consumption index that accounts for individuals' shares of physical consumption within each product, rescaled to the aggregate expenditure level of that product to enable aggregation across heterogeneous physical units within each consumption category (see details in the Supplementary Information 1).

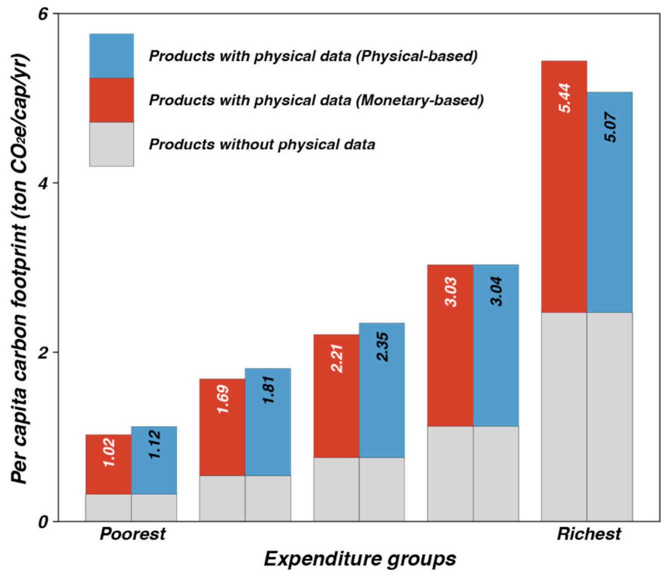

Fig. 3. Household carbon footprint across China's expenditure quintiles under monetary- and physical-based accounting approaches in 2018. The footprints are derived by allocating national household consumption-based GHG emissions using China's Household Survey (CHS) data. Products with physical data include items for which both physical quantities and monetary expenditures are reported in the survey. For products without physical quantity information, the same monetary-based allocation structure is applied in both accounting approaches.

physical units. Carbon footprints calculated with monetary data range from 1.0 (poorest expenditure group) to 5.4 (richest group) tons CO_2e per capita per year, whereas physical-based estimates are slightly narrower at 1.1 to 5.1 tons CO_2e. Compared with physical-based accounting, monetary-based carbon footprint calculations produce higher estimates for higher-expenditure households and lower estimates for lower-expenditure groups. While overall differences appear modest (−9% to +7%), these averages mask more substantial discrepancies within specific product categories and population groups.

To reveal the contributors of these aggregate differences, we decompose carbon footprints by product category across expenditure quintiles (Fig. 4). Among the poorer households, taking the poorest quintile (i.e., the bottom 20% population) in **Fig. 4**a as an example, physical-based GHG estimates exceed monetary-based ones by 100 kg CO_2e per capita or 9.0%, primarily due to food (62 kg CO_2e) and residential energy use (22 kg CO_2e). These households tend to allocate a larger share of their consumption to essential goods with relatively low prices. Because monetary expenditure reflects both consumption amount and price levels, expenditure-based allocation may assign relatively fewer emissions to these categories compared with physical-based allocation. In contrast, for the richest quintile (**Fig. 4**e, the top 20% population), the pattern is reversed: monetary-based estimates exceed physical ones by 366 kg CO_2e, with food (136 kg CO_2e) and residential energy (157 kg CO_2e) driving nearly 80% of the gap. The 4th quintile (**Fig. 4**d) shows smaller or mixed differences. Although price variation and inequality differences are relatively limited for food and residential energy, these categories account for a large share of total household emissions. Small differences between the two accounting approaches can therefore accumulate into sizeable absolute differences in household carbon footprints.

When we take a closer look at the relative differences across consumption categories, systematic patterns emerge across the expenditure spectrum (Fig. 5). The major discrepancies appear in non-essential goods such as footwear and private vehicles. For example, in the top expenditure quintile, footwear-related emissions are estimated to be 59% higher under monetary metrics, while they are 54% lower in the bottom quintile under monetary-based accounting. Durable goods also show lower estimates among poorer households under monetary-based accounting, likely reflecting purchases via secondhand markets or access to subsidized items like home appliances. By contrast, essential goods such as food and residential energy show smaller and more consistent differences across household groups. This pattern reflects limited price variation and centralized pricing mechanisms in China.

Across most categories, the direction of differences shifts systematically from lower estimates in lower-expenditure households to higher estimates in wealthier households under monetary-based accounting. This pattern reflects the combined influence of household consumption structures, product characteristics, and price heterogeneity. For instance, relatively uniform prices for essentials such as food and residential energy generate smaller differences between the two approaches, whereas broad price dispersion and quality-based differentiation in non-essential and luxury items such as footwear, vehicles, and durables lead to larger discrepancies. Wealthier households are also more likely to purchase premium or branded products through formal retail channels, where higher expenditures may reflect differences in product quality, branding, and market segmentation rather than physical consumption volumes alone.

3.3. Accounting approaches shape the distribution of household carbon tax burdens

Carbon inequality assessments based on different accounting approaches may lead to different interpretations of emission responsibility and exposure to carbon pricing, particularly for essential goods consumed by lower-income households.

To evaluate how measurement methods affect the distributional implications of carbon taxation, we simulate a simplified uniform carbon price scenario of 100 Chinese Yuan (CNY) per ton CO_2e, within the range of China's ETS pilot prices in 2024 (i.e., 26–103 CNY per ton CO_2e). The scenario is intended to compare the distribution of household carbon tax burdens under a consistent policy framework, rather than to predict the long-term effects of carbon taxation. Fig. 6 compares the carbon tax burdens (defined as carbon tax payments as a share of household disposable income) across five expenditure quintiles, using monetary- and physical-based accounting. Our results show that across categories, physical-based accounting generally estimates a higher carbon tax burden for poorer households, indicating that accounting choices affect the estimated distribution of carbon tax burdens.

For basic goods such as food and residential energy (**Fig. 6**a), the carbon tax burden appears significantly more regressive when measured using physical quantities. Among the poorest quintile, carbon taxes from food consumption account for 0.5% of household disposable income under the physical measure, compared to 0.4% under the monetary one. A similar pattern holds for residential energy. These differences reflect the tendency of low-income households to rely on essential, carbon-intensive goods that account for a larger share of their consumption, whose consumption patterns may be represented differently under monetary- and physical-based approaches. Because such goods constitute a substantial portion of poorer households' budgets and offer limited substitution options in the short term, even moderate price increases from carbon taxation can disproportionately affect their living standards.

Patterns diverge further for non-essential categories (**Fig. 6**b). For footwear, the physical-based measure reveals a greater burden on the poorest group, contrary to conventional expectations that carbon taxes on such goods affect all consumer groups equally. For durable goods, using different measurement units reverses the apparent progressivity: while monetary-based estimates suggest an increasing burden with expenditure levels, the physical-based estimates reveal a flatter or even regressive distribution. For private vehicles, both units yield broadly progressive distributions, with higher burdens concentrated in wealthier households.

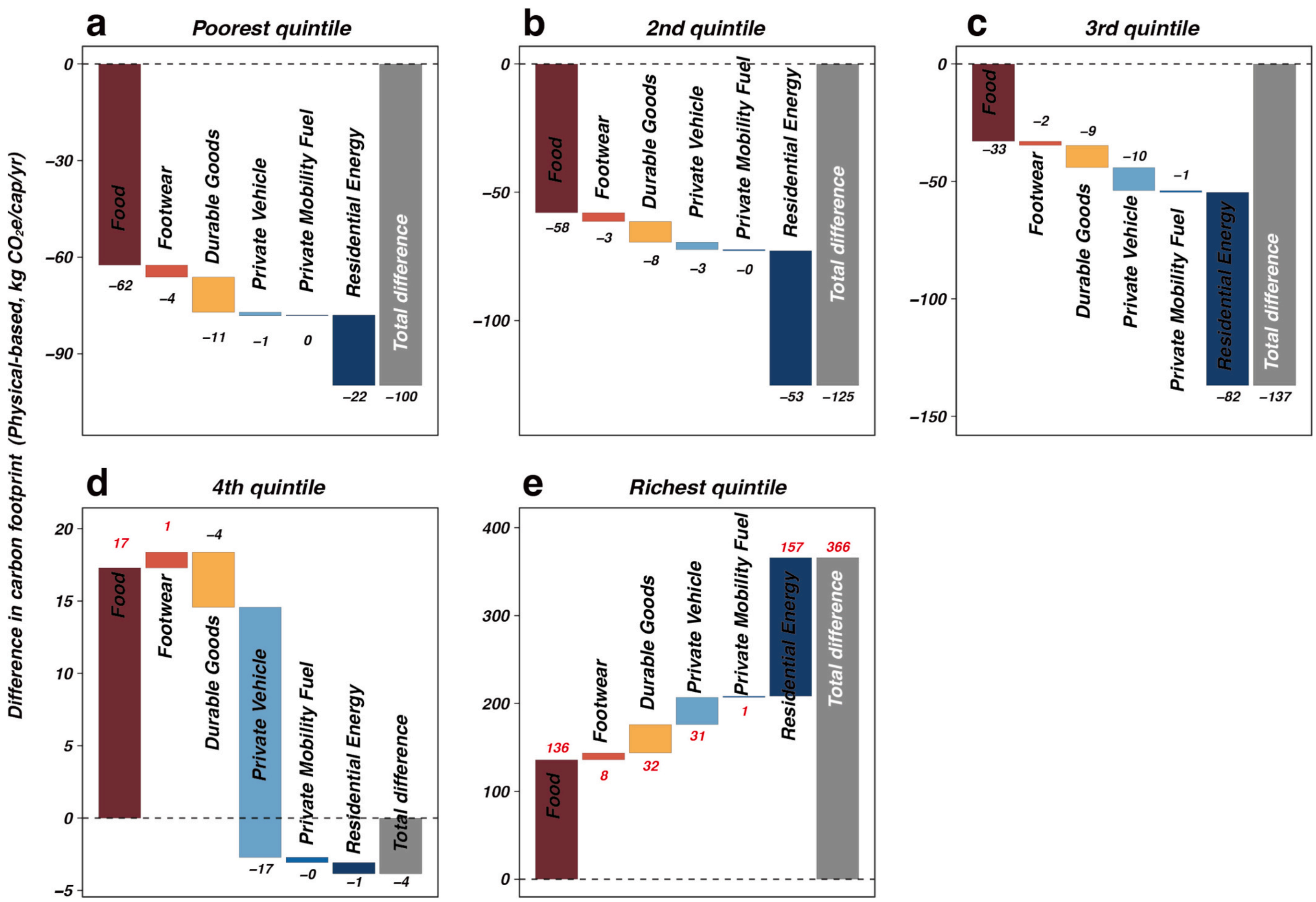

Fig. 4. Absolute differences in household carbon footprints between monetary- and physical-based accounting approaches across expenditure quintiles. Each panel displays the per capita difference in category-level emissions between the two approaches. Positive values indicate higher estimates under the monetary-based approach, while negative values indicate higher estimates under the physical-based approach. Bars are disaggregated by six product categories; grey bars show the total difference for each quintile.

4. Discussion

This study examines how monetary- and physical-based accounting affect estimates of household carbon footprints, carbon inequality, and carbon tax burdens. Drawing on household survey data from China, we find that the two approaches produce systematically different estimates: monetary-based accounting assigns relatively fewer emissions to lower-expenditure households and more emissions to higher-expenditure households.

Total carbon footprint estimates differ by −9% (poorest quintile) to +7% (richest), while category-level differences range from −54% to +59%. Physical-based accounting assigns higher emissions and tax burdens for essential goods, particularly food and residential energy, to poorer households, who devote a larger share of their expenditure to these carbon-intensive necessities and have fewer opportunities for substitution. Monetary-based accounting tends to allocate relatively more emissions to wealthier groups for goods with substantial price dispersion, especially footwear (Willis et al., 2022). Wealthier households may purchase premium or branded products through formal retail channels, including department stores and online platforms, where higher expenditures may reflect differences in product quality, branding, and market segmentation rather than greater physical use (Kurt and Gino, 2023; Walasek and Brown, 2016). At the same time, more expensive products may carry higher embodied emissions due to the use of higher-quality or more material-intensive inputs, more complex supply chains, and more energy-intensive manufacturing processes, although existing evidence suggests that the increase in embodied emissions is often smaller than implied by direct expenditure-based allocation approaches. By contrast, lower-income households may rely more heavily on informal or second-hand markets for certain durable goods and footwear, further increasing differences between expenditure-based and physical-based estimates.

The differences between the two accounting approaches reflect the distinct assumptions underlying each method. Monetary-based accounting assumes that emissions scale with expenditure, whereas physical-based accounting assumes homogeneous carbon intensities within product categories. Neither assumption is fully valid in reality. Product heterogeneity may arise from differences in materials, production technologies, durability, energy efficiency, and supply chains, while expenditure differences may reflect product quality, branding, and market segmentation rather than differences in physical consumption alone. Therefore, the two approaches provide complementary perspectives on household carbon footprints, and findings that are consistent across both approaches are likely to be more robust. In our analysis, both approaches consistently show that higher-expenditure households contribute more emissions in absolute terms, while lower-income households face relatively greater carbon burdens from essential consumption categories such as food and residential energy. Similar concerns regarding product and price heterogeneity in expenditure-based carbon accounting have also been raised in previous studies (André et al., 2024; Leferink et al., 2023).

These differences in accounting outcomes have important

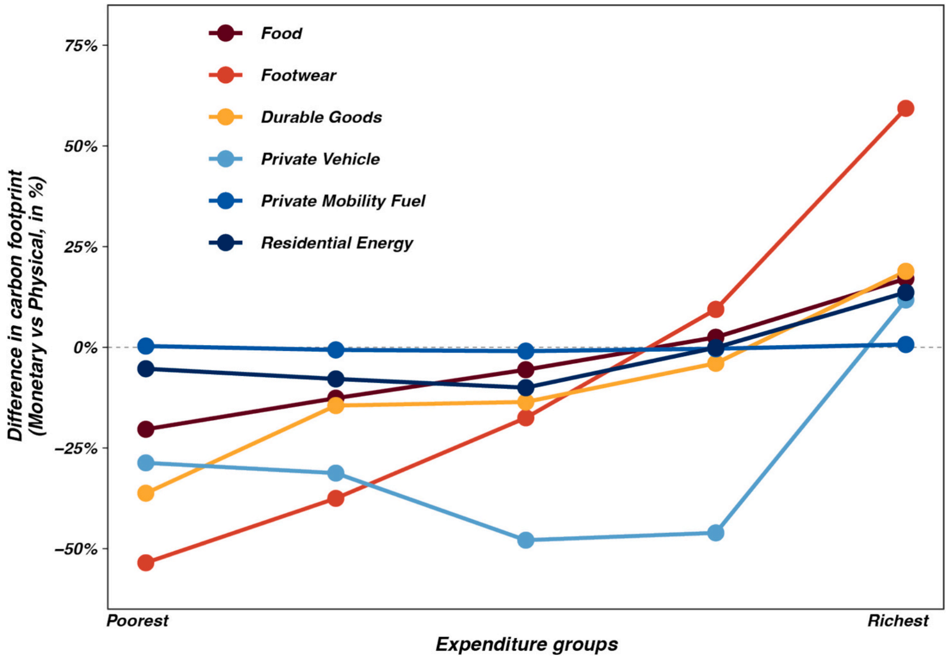

Fig. 5. Relative differences in household carbon footprints between monetary- and physical-based accounting approaches by category and expenditure group. The figure shows the percentage difference in per capita emissions between the two approaches across five expenditure quintiles. Positive values indicate higher estimates under monetary-based accounting, whereas negative values indicate higher estimates under physical-based accounting.

implications for the interpretation of carbon pricing policies. According to a recent World Bank report (The World Bank, 2025), in 2024, direct carbon pricing instruments cover around 28% of global emissions and generate over 100 billion USD in annual revenue. Carbon pricing instruments are increasingly used to reduce emissions while addressing distributional concerns through revenue recycling and compensatory measures (Malerba et al., 2022; Vogt-Schilb et al., 2019). However, the equity implications of such policies depend on how emission responsibility and exposure to carbon costs are assessed. Our findings suggest that relying solely on monetary-based measures may not fully capture the distribution of climate-related costs, particularly in emerging and developing economies where income inequality, price variation, and unequal access to infrastructure create differences between expenditure-based estimates and physical-based estimates. In practice, carbon pricing revenues are often redistributed through lump-sum transfers or green subsidies, which may not always reach the most vulnerable (Feng et al., 2023; Oswald et al., 2023). For example, in the United States, nearly 60% of clean energy subsidies under the Inflation Reduction Act have gone to the top-income quintile, while the bottom three quintiles have received only around 10% (Borenstein and Davis, 2025). In China, subsidies for electric vehicles and energy-efficient appliances may also be less accessible to households facing income and energy constraints (Nie et al., 2022a; Nie et al., 2022b).

Such potential mismatches between emission responsibility, exposure, and policy benefits raise broader concerns for climate policy fairness (Gatto and Chepeliev, 2024; Wood et al., 2018). If low-income households experience a heavier burden while receiving fewer tangible benefits, public acceptance of carbon pricing may further erode (Dietsch, 2024; Woerner et al., 2024). This is particularly salient in low-income countries, where direct and indirect energy costs constitute a large share of household expenditure and where even modest price increases can threaten basic livelihoods (Guan et al., 2023; Zhang et al., 2023a). Although long-term behavioral adjustments and technological progress may partially mitigate the regressive effects of carbon pricing, low-income households often face relatively inelastic demand and limited substitution options for essential goods such as food and residential energy. As a result, unequal burden patterns are likely to persist, particularly in the short term. Ensuring that carbon pricing mechanisms consider physical consumption information alongside monetary-based approaches is therefore important for improving policy effectiveness and political sustainability (The World Bank, 2025).

Several limitations should be acknowledged. First, the sectoral classification in the EEIO models remains aggregated and may mask variation in carbon intensities within broad sectors, despite the use of China's most detailed available input–output table (153 sectors). The national single-region IO framework does not capture regional production heterogeneity and interregional trade. A multi-regional IO framework would address these issues more directly but was not feasible given the limited provincial coverage of the household survey data.

Second, both monetary- and physical-based accounting are subject to uncertainty. A robustness analysis introducing expenditure-group-specific carbon intensity indicates that the main conclusions remain stable under alternative assumptions (see Supplementary Information 1). Nevertheless, product heterogeneity, data quality, and reporting errors remain sources of uncertainty (André et al., 2024; Goldstein et al., 2024; Leferink et al., 2023). Physical-quantity data may be particularly prone to measurement and recall errors for frequently purchased items, while expenditure data may also contain reporting uncertainties.

Third, our analysis relies on the 2015 CHS, which provides detailed monetary expenditures and physical quantity data but may not fully represent more recent consumption patterns. Linking the 2015 survey to the 2018 IO table and emission inventories through bridging matrices introduces temporal and sector-mapping uncertainty, particularly for absolute carbon footprint estimates. However, because the same framework was applied to both accounting approaches, the relative comparison between them is expected to be less sensitive to this uncertainty. In addition, the comparison is limited to 94 of 218 CHS consumption items for which both monetary and physical data are available. Services, which account for a growing share of expenditure among higher-income households, are not fully covered because such categories typically lack directly comparable physical-unit information. Their exclusion may affect estimates of total household carbon footprints and inequality. For service-related items such as school accommodation fees, monetary expenditure data were used as proxies for

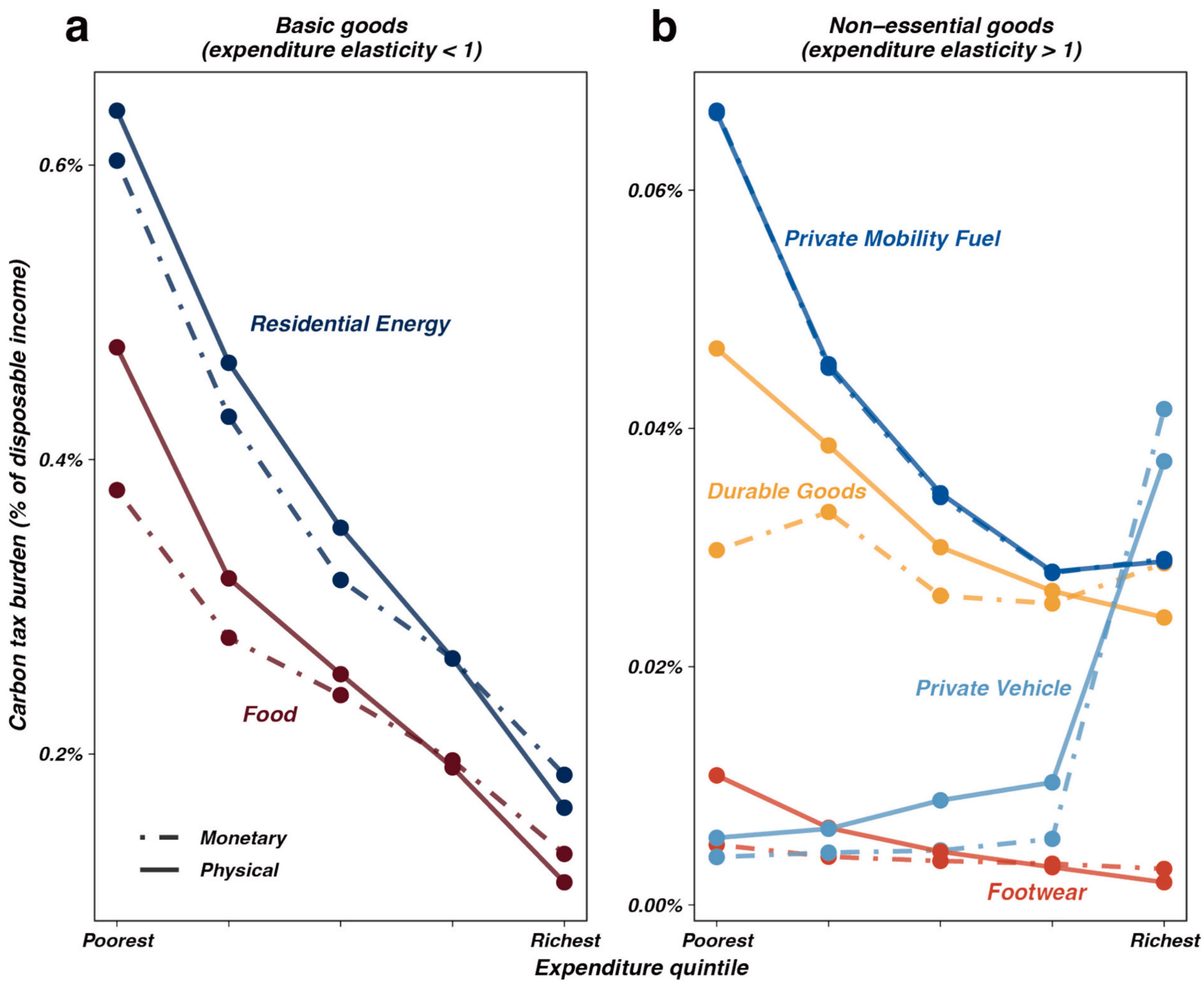

Fig. 6. Comparison of household carbon tax burden under monetary- and physical-based measures across expenditure quintiles and product categories. Subplots show the carbon tax burden, defined as the share of household disposable income allocated to carbon taxes, for each product category under a uniform carbon scenario (100 CNY/ton CO_2e). Subplot a includes basic goods with low expenditure elasticity ($\varepsilon < 1$), and subplot b includes non-essential goods with high elasticity ($\varepsilon > 1$).

physical consumption, following previous studies (Girod and De Haan, 2010; Zhang et al., 2023a, 2023b). Furthermore, using per capita expenditure assumes proportional allocation of household consumption across members and does not explicitly account for economies of scale within households.

Finally, the carbon tax analysis represents a static short-term scenario and considers only the price effect of taxation. Changes in product-level carbon intensities over time (André et al., 2024), and behavioral responses such as consumption adjustment or product substitution are not included due to data limitations (Guan et al., 2023; Oswald et al., 2023). Demand elasticity, consumption substitution, and long-term technological change would likely reduce the estimated regressivity of carbon taxation. However, because lower-income households devote a larger share of expenditure to inelastic necessities such as food and residential energy, unequal burden patterns may persist, although their magnitude may be smaller than estimated in this static scenario.

5. Conclusions

The choice of accounting approach substantially affects the estimated distribution of household carbon footprints and carbon tax burdens. Within a consistent analytical framework, monetary- and physical-based allocation can lead to different interpretations of household emission responsibility.

Both approaches identify higher absolute emissions among higher-expenditure households, but they differ substantially across consumption categories. Accounting choices are especially consequential for food and residential energy, which strongly shape the distributional effects of carbon pricing.

Accounting choices should therefore be considered explicitly when evaluating household carbon inequality and designing equitable climate policy. Using monetary- and physical-based approaches together can provide a more complete assessment of household emissions and support a fairer low-carbon transition.

CRediT authorship contribution statement

Yuru Guan: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Yang Wang:** Writing – review & editing, Investigation. **Ruoqi Li:** Writing – review & editing. **Ye Hang:** Writing – review & editing. **Yuli Shan:** Writing – review & editing, Supervision, Project administration, Funding acquisition. **Miaomiao Liu:** Writing – review & editing, Resources. **Peipei Tian:** Writing – review & editing. **Jun Bi:** Writing – review & editing, Resources. **David Andersson:** Writing – review & editing, Investigation, Conceptualization. **Klaus Hubacek:** Writing – review & editing, Supervision, Project administration, Investigation, Conceptualization.

Declaration of competing interest

The authors declare no competing interests.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.spc.2026.07.025.

Data availability

Household consumption data are collected from the 2015 China's Household Survey (CHS), provided by co-author M.L. China input-output table is obtained from the National Bureau of Statistics (2024). Sectoral CO_2 and CH_4 emissions are obtained from the Carbon Emission Accounts & Datasets (ceads.net). Emissions of other greenhouse gases (e.g., N_2O, F-gases) are taken from the Emissions Database for Global Atmospheric Research (EDGAR) (Crippa et al., 2024). More detailed results are available from the corresponding author on reasonable request.

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