Supplementary Information for

From individual carbon inequality to equitable provincial mitigation effort-sharing in China

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1.1 Data collection and processing

This study utilizes micro-level household data from the China Family Panel Studies (CFPS), a nationally representative longitudinal survey conducted by the Institute of Social Science Survey (ISSS) at Peking University (https://www.isss.pku.edu.cn/cfps/). The CFPS provides comprehensive data on Chinese households' income, wealth, expenditure, and a range of demographic, economic, and social characteristics. It has been widely used in empirical studies on household economics, energy use, and carbon emissions in China[1-6]. The CFPS is conducted biennially and includes a sample size of approximately 16,000 households per wave. It covers 26 provincial-level administrative regions in China, excluding Qinghai, Inner Mongolia, Tibet, Ningxia, Hainan, Hong Kong, Macao, and Taiwan.

Household income in CFPS is the sum of five major components: wage income, business income, property income, transfer income, and other income. Household wealth is measured as net household assets, calculated as the difference between total household assets and total household liabilities. Total assets include land, housing, financial assets, productive fixed assets, and durable consumer goods; liabilities include housing-related and non-housing-related debts. All income and wealth indicators are reported in the current year's prices. In this study, we adjust these values to constant 2015 prices using the consumer price index (CPI) published by the National Bureau of Statistics of China. Unless otherwise specified, all monetary values in the remainder of this paper are expressed in real 2015 prices.

We used the 2018 wave of the CFPS dataset to fit the distribution functions of provincial-level individual income and wealth for the year 2017. As the CFPS is designed at the household level, we derived individual-level income and wealth by dividing the total household income and wealth equally among all household members based on household size. To reduce the potential bias caused by extreme outliers in the distribution fitting process, we followed the approach in ref. [6] and excluded the top 0.5% of the sample in terms of income or wealth.

Unlike income, household wealth may be negative. Therefore, the common assumption of non-negative values, which is reasonable for income distribution modeling, may not be directly applicable to wealth distribution fitting[7]. In this study, individual wealth plays an important role in the allocation of regional investment-related carbon emission responsibility (as discussed in the Supplementary Information Section 3). Specifically, individual wealth is used as the baseline indicator in allocating the total investment-based emissions. This allocation must satisfy the following rules: 1) Individuals with greater wealth should bear more investment-related carbon responsibility than those with less wealth; 2) The allocated responsibility for everyone must be non-negative; 3) The sum of all individual investment-related emissions should be equal to the regional total investment-related emissions (mass conservation principle). However, when individual wealth values are negative (e.g., when household liabilities exceed assets), the allocation model may yield negative emission responsibility values, violating the rules. To ensure the logical validity and numerical stability of the model, we apply the following treatment to the wealth data: 1) Set all negative wealth values to zero. This guarantees that all assigned responsibilities remain non-negative, and assigns minimal responsibility to individuals with zero or negative net wealth. In practice, negative wealth typically reflects high indebtedness and low investment capacity; such individuals should reasonably bear minimal investment-based carbon responsibility. 2) Shift all wealth values upward by a fixed amount (500 units) during the distribution fitting process. This ensures all wealth values are positive and prevents computational issues during logarithmic transformation. A modest positive shift also moves values away from zero, avoiding numerical instability. The transformation preserves the relative differences among individuals, maintaining fairness in the allocation process. 3) After distribution fitting, shift the fitted wealth function back to its original position. This step restores the wealth distribution to its pre-shift values, ensuring that the fitted distribution remains consistent with the original data. Consequently, the final allocation results retain the same interpretability as if no transformation had been applied.

1.2 Distribution function fitting

In modeling the income and wealth distributions of residents across Chinese provinces, we first examine their fundamental statistical characteristics. Existing literature indicates that income and wealth distributions generally exhibit pronounced skewness, heavy tails, and heterogeneity. Income distributions are typically right-skewed, with most individuals concentrated in the low- and middle-income brackets, while a small number of high-income earners disproportionately raise the mean[8]. After logarithmic transformation, income distributions in many countries and regions can be approximated by a normal distribution, although some degree of asymmetry may still remain[9]. Wealth distributions are even more extreme than income: they tend to have longer right tails and greater concentration, with a small proportion of high-net-worth individuals holding a substantial share of total wealth. As a result, even the log-transformed wealth data often exhibit significant skewness and fat tails[8,10]. Moreover, due to vast regional disparities in socioeconomic development, income and wealth distributions vary greatly across provinces[11]. Given these complexities, relying on a single distribution model is insufficient to comprehensively capture the diverse distributional features across provinces. Therefore, we adopt a comparative modeling approach involving multiple classical empirical distributions, enabling us to select the most appropriate functional form for each province and laying a robust foundation for further comparative analysis.

1.2.1 Empirical distribution functions

Following prior studies[12-17], we select eight empirical distribution functions that are widely used in the modeling of income and wealth: the lognormal distribution, gamma distribution, exponential distribution, skew-normal distribution, log-skew-normal distribution, Weibull distribution, generalized Pareto distribution (GPD), and beta distribution. These distribution families are applicable under different income or wealth distribution scenarios and can capture a wide range of empirical shapes, including various degrees of skewness and tail behavior. This multi-distribution strategy enhances the coverage and robustness of our model-fitting process. The mathematical formulations and parameter definitions for each of these distributions are presented below.

1) Lognormal distribution

The lognormal distribution is commonly used to describe personal income, particularly suitable for modeling the distribution among middle- and low-income groups. Its underlying assumption is that if the logarithm of a variable follows a normal distribution, then the variable itself follows a lognormal distribution. This reflects a multiplicative process of income generation, which aligns with many economic phenomena. It is a two-parameter distribution. The probability density function (PDF) and cumulative distribution function (CDF) are given in formulas (1) and (2), respectively:

$$f(x;\mu,\sigma)=\frac{1}{x\sigma\sqrt{2\pi}}e^{-\frac{(\ln x-\mu)^2}{2\sigma^2}},\quad x>0 \tag{1}$$

$$F(x;\mu,\sigma)=\Phi\left(\frac{\ln x-\mu}{\sigma}\right) \tag{2}$$

where μ denotes the mean of the log–transformed data and determines the location of the distribution, while $\sigma>0$ is the standard deviation of the log-transformed data, governing the spread and skewness. $\Phi(\square)$ is the cumulative distribution function of the standard normal distribution.

2) Gamma distribution

The gamma distribution is widely used to model skewed, non-negative data, such as individual income or expenditure. It is especially useful in describing distributions that exhibit a peak and long right tail. The gamma distribution is a two-parameter function. Its PDF and CDF are shown in formulas (3) and (4), respectively:

$$f(x;k,\theta)=\frac{1}{\Gamma(k)\theta^k}x^{k-1}e^{-x/\theta},\quad x>0 \tag{3}$$

$$F(x;k,\theta)=\frac{\gamma(k,x/\theta)}{\Gamma(k)} \tag{4}$$

where k is the shape parameter, which controls the skewness and peakedness of the distribution, and $\theta > 0$ is the scale parameter, which controls the horizontal stretch of the distribution. $\Gamma(k)$ denotes the gamma function, and $\gamma(k, x)$ is the lower incomplete gamma function.

3) Exponential distribution

The exponential distribution is a special case of the gamma distribution with the shape parameter $k = 1$. It models the time between events in a Poisson process and serves as a baseline model for positively skewed data. This is a one-parameter distribution, and its PDF and CDF are given in formulas (5) and (6):

$$f(x; \lambda) = \lambda e^{-\lambda x}, \quad x \geq 0 \tag{5}$$

$$F(x; \lambda) = 1 - e^{-\lambda x} \tag{6}$$

where $\lambda > 0$ is the rate parameter, and $1/\lambda$ is the mean of the distribution.

4) Skew-Normal distribution

The skew-normal distribution extends the normal distribution by introducing a shape parameter to allow skewness. It is suitable for modeling income or wealth data that is approximately normal but exhibits asymmetry. This is a three-parameter distribution. The PDF is given in formula (7), and the CDF is expressed in terms of the standard normal functions in formula (8):

$$f(x; \xi, \omega, \alpha) = \frac{2}{\omega} \phi\left(\frac{x - \xi}{\omega}\right) \Phi\left(\alpha \cdot \frac{x - \xi}{\omega}\right) \tag{7}$$

$$F(x; \xi, \omega, \alpha) = \int_{-\infty}^{x} f(t; \xi, \omega, \alpha)\ dt \tag{8}$$

where ξ is the location parameter, $\omega > 0$ is the scale parameter, and α is the shape parameter controlling the degree of skewness. $\phi(\square)$ and $\Phi(\square)$ represent the standard normal PDF and CDF, respectively.

5) Log-skew-normal distribution

This distribution is particularly effective for modeling wealth data, which tends to exhibit more extreme skewness and heavy tails than income. Even after logarithmic transformation, wealth may still be right-skewed. The log-skew-normal distribution is defined as the exponential of a skew-normal variable and inherits its parameters. The PDF and CDF are given in formulas (9) and (10):

$$f(y;\xi,\omega,\alpha)=\frac{2}{y\omega}\phi\left(\frac{\ln y-\xi}{\omega}\right)\Phi\left(\alpha\cdot\frac{\ln y-\xi}{\omega}\right),\quad y>0 \tag{9}$$

$$F(y;\xi,\omega,\alpha)=\int_0^y f(t;\xi,\omega,\alpha)\ dt \tag{10}$$

where $y = exp(X)$, and $X \sim Skew - Normal(\xi, \omega, \alpha)$. The parameters retain their original interpretations from the skew-normal distribution.

6) Weibull distribution

The Weibull distribution is flexible in modeling various types of skewed data and can represent different shapes depending on the value of its parameters. It is frequently used for modeling income with adjustable tail thickness. It is a two-parameter distribution, as shown in formulas (11) and (12):

$$f(x;\lambda,k)=\frac{k}{\lambda}\left(\frac{x}{\lambda}\right)^{k-1}e^{-(x/\lambda)^k},\quad x\geq 0 \tag{11}$$

$$F(x;\lambda,k)=1-e^{-(x/\lambda)^k} \tag{12}$$

where $\lambda > 0$ is the scale parameter and $k > 0$ is the shape parameter, which determines the skewness and kurtosis of the distribution.

7) Generalized pareto distribution (GPD)

The generalized Pareto distribution is widely used to model the tail behavior of wealth distributions, particularly for capturing extreme values and heavy right tails. It is a three-parameter distribution defined by formulas (13) and (14):

$$f(x;\xi,\sigma,\mu)=\frac{1}{\sigma}\left(1+\xi\frac{x-\mu}{\sigma}\right)^{-1/\xi-1},\quad x\geq\mu \tag{13}$$

$$F(x;\xi,\sigma,\mu)=1-\left(1+\xi\frac{x-\mu}{\sigma}\right)^{-1/\xi} \tag{14}$$

where ξ is the shape parameter controlling the tail heaviness, $\sigma > 0$ is the scale parameter, and μ is the location parameter indicating the minimum value.

8) Beta distribution

The beta distribution is defined on a finite interval [0, 1], making it especially suitable for normalized income or wealth data. It can model both symmetric and skewed shapes. It is a two-parameter distribution, with the PDF and CDF given in formulas (15) and (16):

$$f(x;\alpha,\beta)=\frac{x^{\alpha-1}(1-x)^{\beta-1}}{B(\alpha,\beta)},\quad 0<x<1 \tag{15}$$

$$F(x;\alpha,\beta) = \frac{B_x(\alpha,\beta)}{B(\alpha,\beta)} \tag{16}$$

where $\alpha > 0$ and $\beta > 0$ are the shape parameters, and $B(\alpha,\beta)$ is the Beta function. $B_x(\alpha,\beta)$ is the incomplete beta function evaluated at x.

1.2.2 Fitting method

We applied the maximum likelihood estimation (MLE) method to fit the eight candidate distributions to each province's data on residents' income or wealth. For the skew-normal and log-skew-normal distributions, which are not directly supported by standard statistical software, we implemented custom probability density functions (PDFs) and manually specified initial parameter values to ensure estimation accuracy and algorithm convergence. For the other distributions, we utilized built-in MATLAB functions such as *mle*, *wblfit*, and *expfit*.

Regarding data preprocessing, we performed the procedures described in Supplementary Information Section 1.1, including logarithmic transformations when necessary and normalization to the [0, 1] interval for fitting the Beta distribution.

1.2.3 Selection of the optimal fitting distribution

After fitting all candidate models, we evaluated the goodness-of-fit using probability–probability (P–P) plots. In a P–P plot, the theoretical CDF values are plotted on the x-axis, while the empirical CDF values are plotted on the y-axis. If the model fits the data perfectly, all points should lie along the 45° diagonal line. Compared to quantile–quantile (Q–Q) plots, which emphasize tail fitting, P–P plots are more sensitive to the overall fit, especially around the median region. Given that our goal is to capture the overall distribution shape of residents' income and wealth, rather than focusing solely on extreme values, using P–P plots as the primary criterion for model selection is both reasonable and intuitive. Ultimately, for each province, we selected the distribution whose P–P plot showed the closest alignment with the diagonal line as the best-fitting model.

Taking Hunan province as an example, Fig. 1 and 2 display the P–P plots for the fitted income and wealth distributions, respectively. It can be observed that the optimal income distribution is the Gamma distribution, $\mathrm{Gamma}(k = 1.191,\ \theta = 17{,}194)$, and the optimal wealth distribution is the Generalized Pareto Distribution, $\mathrm{GPD}(\xi = 0.172,\ \sigma = 152{,}885,\ \mu = 500)$. The fitted histograms and the corresponding probability density curves are shown in Fig. 3. As evident, both income and wealth distributions in Hunan exhibit a pronounced right-skewed pattern, though with different degrees of skewness. The wealth distribution has a longer tail, indicating a higher level of inequality. Similar patterns are observed across all other provinces, and the detailed fitting results are presented in Table 1.

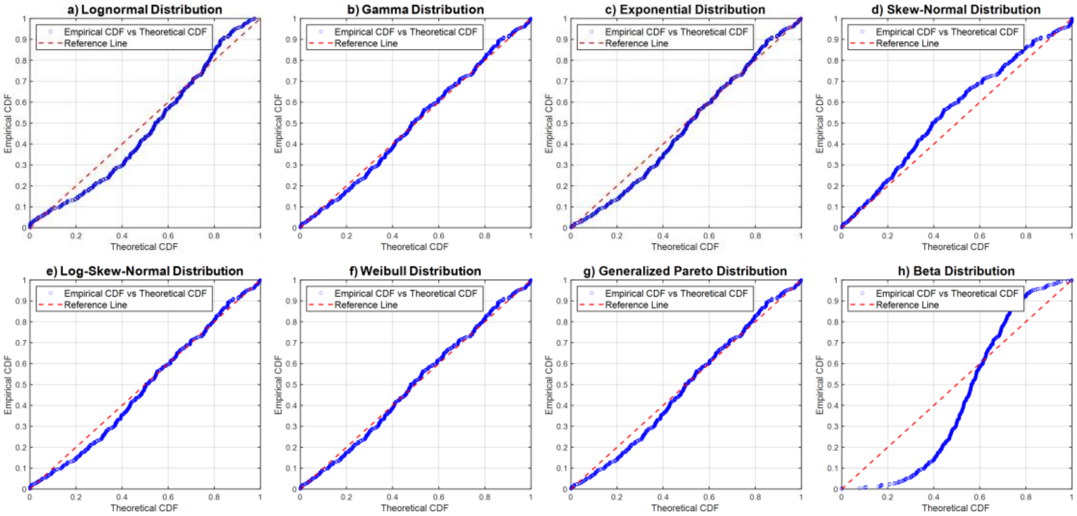

Fig. 1. P–P plot of individual income distribution in Hunan province, 2017

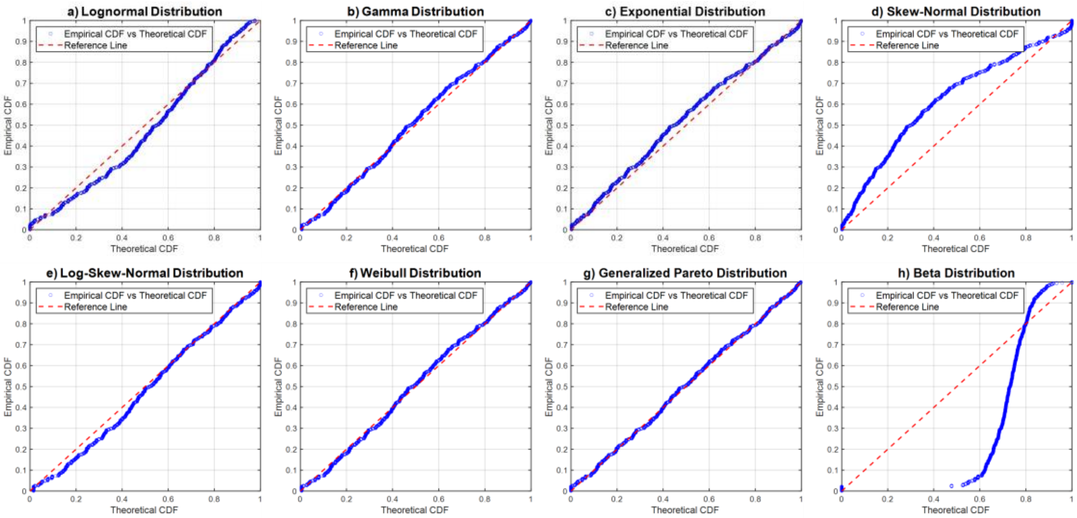

Fig. 2. P–P plot of individual wealth distribution in Hunan province, 2017

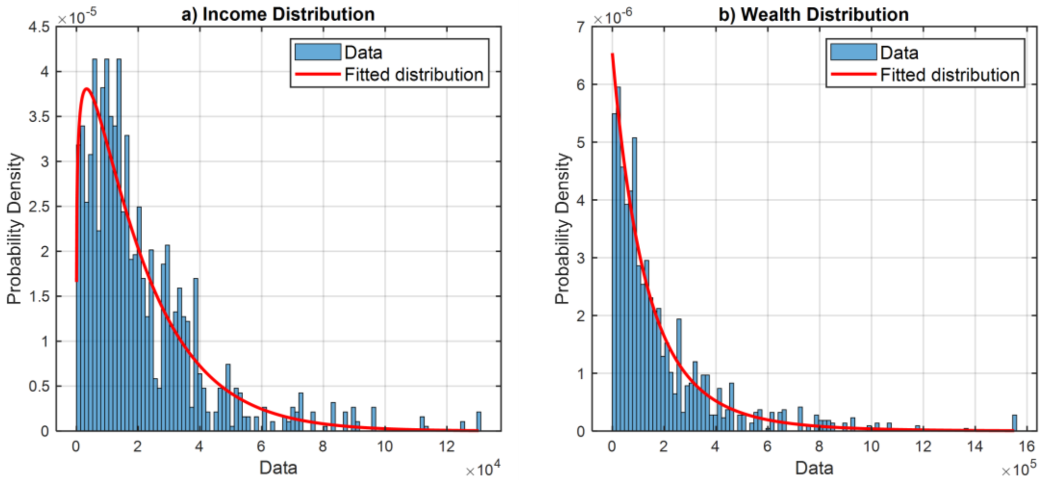

Fig. 3. Histogram and fitted curve of individual income and wealth distribution in Hunan province, 2017

Table 1. Optimal fitting results of provincial household income and wealth distributions

Province	Optimal income distribution	Optimal wealth distribution
Beijing*	$\mathrm{Lognormal}(\mu = 10.759, \sigma = 0.824)$	$\mathrm{GPD}(\xi = 0.067, \sigma = 1{,}242{,}685, \mu = 500)$
Tianjin	$\mathrm{Lognormal}(\mu = 9.827, \sigma = 1.091)$	$\mathrm{Lognormal}(\mu = 12.285, \sigma = 1.096)$
Hebei*	$\mathrm{Gamma}(k = 1.192, \theta = 10{,}774)$	$\mathrm{GPD}(\xi = 0.349, \sigma = 89{,}326, \mu = 500)$
Shanxi*	$\mathrm{Log-Skew-Normal}(\xi = 10.093, \omega = 1.493, \alpha = -2.75)$	$\mathrm{GPD}(\xi = 0.265, \sigma = 67{,}012, \mu = 500)$
Liaoning*	$\mathrm{GPD}(\xi = -0.079, \sigma = 21{,}392, \mu = 48.25)$	$\mathrm{GPD}(\xi = 0.197, \sigma = 98{,}408, \mu = 500)$
Jilin*	$\mathrm{Gamma}(k = 1.242, \theta = 11{,}789)$	$\mathrm{GPD}(\xi = 0.169, \sigma = 74{,}511, \mu = 500)$
Heilongjiang*	$\mathrm{Weibull}(\lambda = 21{,}418, k = 1.241)$	$\mathrm{GPD}(\xi = 0.148, \sigma = 69{,}429, \mu = 500)$
Shanghai*	$\mathrm{Gamma}(k = 2.419, \theta = 18546)$	$\mathrm{Gamma}(k = 1.218, \theta = 955{,}653)$
Jiangsu*	$\mathrm{Gamma}(k = 1.122, \theta = 26{,}098)$	$\mathrm{GPD}(\xi = 0.202, \sigma = 267{,}532, \mu = 500)$
Zhejiang*	$\mathrm{Weibull}(\lambda = 35{,}839, k = 1.365)$	$\mathrm{GPD}(\xi = 0.162, \sigma = 288{,}159, \mu = 500)$
Anhui*	$\mathrm{Gamma}(k = 1.28, \theta = 14{,}115)$	$\mathrm{Exponential}(\lambda = 154{,}613)$
Fujian*	$\mathrm{Weibull}(\lambda = 14{,}968, k = 1.061)$	$\mathrm{GPD}(\xi = 0.23, \sigma = 119{,}510, \mu = 500)$
Jiangxi*	$\mathrm{Weibull}(\lambda = 14{,}639, k = 1.225)$	$\mathrm{GPD}(\xi = 0.115, \sigma = 99{,}767, \mu = 500)$
Shandong*	$\mathrm{Gamma}(k = 1.513, \theta = 11{,}296)$	$\mathrm{GPD}(\xi = 0.221, \sigma = 137{,}151, \mu = 500)$
Henan*	$\mathrm{Gamma}(k = 1.2651, \theta = 10{,}470)$	$\mathrm{Log-Skew-Normal}(\xi = 12.166, \omega = 1.663, \alpha = -1.764)$
Hubei*	$\mathrm{Gamma}(k = 1.286, \theta = 19{,}723)$	$\mathrm{Lognormal}(\mu = 11.906, \sigma = 1.157)$
Hunan*	$\mathrm{Gamma}(k = 1.191, \theta = 17{,}194)$	$\mathrm{GPD}(\xi = 0.172, \sigma = 152{,}885, \mu = 500)$
Guangdong*	$\mathrm{Gamma}(k = 1.053, \theta = 17{,}658)$	$\mathrm{GPD}(\xi = 0.444, \sigma = 112{,}985, \mu = 500)$
Guangxi*	$\mathrm{Gamma}(k = 1.239, \theta = 8{,}292)$	$\mathrm{GPD}(\xi = 0.178, \sigma = 64{,}404, \mu = 500)$
Chongqing*	$\mathrm{Gamma}(k = 0.998, \theta = 17{,}208)$	$\mathrm{GPD}(\xi = 0.399, \sigma = 83{,}850, \mu = 500)$

Sichuan*	Weibull($\lambda = 11{,}249, k = 0.969$)	GPD($\xi = 0.316, \sigma = 58{,}894, \mu = 500$)
Guizhou*	Weibull($\lambda = 10{,}637, k = 0.991$)	GPD($\xi = 0.431, \sigma = 49{,}077, \mu = 500$)
Yunnan*	Gamma($k = 0.988, \theta = 12{,}194$)	GPD($\xi = 0.131, \sigma = 89{,}857, \mu = 500$)
Shaanxi*	Gamma($k = 1.217, \theta = 13{,}771$)	GPD($\xi = 0.195, \sigma = 100{,}860, \mu = 500$)
Gansu*	Gamma($k = 1.245, \theta = 8{,}875$)	GPD($\xi = 0.367, \sigma = 49{,}964, \mu = 500$)
Xinjiang*	Gamma($k = 1.399, \theta = 18{,}720$)	GPD($\xi = 0.202, \sigma = 140{,}936, \mu = 500$)

Notes: the "*" indicates provinces whose wealth data contained negative values and were thus shifted for processing. The original values are restored when extracting the fitted data, so no information bias is introduced. For details of the processing procedure, see Supplementary Information Section 1.1.

1.3 Estimation of income and wealth distributions for data-deficient provinces

As noted in Supplementary Information Section 1.1, the CFPS does not cover four provinces—Inner Mongolia, Hainan, Qinghai, and Ningxia—in terms of individual-level income and wealth data. To address this data gap, we identified the most similar provinces from the remaining 26 regions with available data, and imputed the missing income and wealth distributions based on those comparable provinces. We further tested the sensitivity of this proxy selection by replacing the identified similar provinces with geographically neighboring provinces. The results of this robustness test are presented in Supplementary Information Section 7.

Below, we describe the main procedure used to identify similar provinces and impute the missing distributions. Specifically, we first identified the key factors that influence income and wealth distribution across provinces. According to refs. [18-24], inter-provincial variation in household income and wealth is typically shaped by multiple dimensions, including the level of economic development, industrial structure, rural–urban income gaps, education attainment, government expenditure patterns, degree of marketization, and infrastructure quality. We selected 10 representative indicators (listed in Table 2) to capture these dimensions. Using these indicators, we conducted a clustering analysis to identify the provinces most similar to each data-deficient province. Based on the assumption that provinces with similar socioeconomic profiles exhibit comparable income and wealth distributions, we used the fitted distributions of the matched provinces to infer the likely distributional forms in the missing regions. Furthermore, to improve the alignment with observed conditions, we adjusted the inferred distributions to match the actual average income and average wealth values reported for the missing provinces.

The data for all quantitative indicators in Table 2 refer to the year 2017. The per capita capital stock is estimated using the perpetual inventory method and represents the material capital stock of each province; the estimates are drawn from ref. [25]. Average years of schooling refer to the mean years of education for the population aged 15 and above, while the proportion of higher education corresponds to the number of individuals with tertiary education per 100,000 people. Both education indicators are obtained from the Bulletin of the Seventh National Population Census of China[26]. All other indicators are sourced from the China Statistical Yearbook (2018). The provincial data for all 10 indicators are provided in Supplementary Data 2.

Table 2. Determinants of household income and wealth distribution across provinces

Dimension	Indicator	Explanation
Level of economic development	Per capita GDP (RMB/person)	A basic indicator for measuring the level of regional economic development.
Industrial structure	Ratio of tertiary sector value added to secondary sector value added	Industrial structure has a significant impact on income and wealth distribution. Empirical findings from refs. [27,28] suggest that the shift from secondary to tertiary industries tends to exacerbate regional inequality.
Urban–rural gap	Ratio of per capita disposable income between urban and rural residents	The income disparity between urban and rural populations is a key factor influencing the distribution of household income and wealth.
	Urbanization rate	Reflects the extent of population concentration in urban areas, influencing the distribution of household income and wealth.
Capital stock	Per capita capital stock (RMB 10,000/person)	Capital formation contributes to future investment activities, but its impact on income and net wealth inequality remains ambiguous. On one hand, regions with higher capital stock are better positioned to create employment opportunities and raise household income. On the other hand, the returns on capital tend to disproportionately benefit wealthier groups, thereby exacerbating income and wealth disparities.
Education	Average years of schooling	Higher educational attainment enhances workers' ability to generate income through improved skills and productivity.
	Share of population with higher education	The proportion of the population with higher education in a region influences the formation of high-income groups.
Policy factors	Share of public expenditures on social protection, healthcare, and education in total government expenditure	Educational spending enhances human capital and reduces opportunity disparities; healthcare spending alleviates the financial burden of illness and lowers the risk of poverty caused by medical expenses; and social security improves the income levels of low-income groups through direct transfer payments. Together, these expenditures help narrow income gaps and promote social equity.
Degree of marketization	The proportion of self-employed individuals and private-sector workers	The impact of marketization on income and wealth inequality is multifaceted. On the one hand, the development of the non-public sector during the marketization process has created a large number of

	relative to employees in state-owned or institutional work units	employment opportunities, reduced unemployment and poverty, and contributed to narrowing the income gap. On the other hand, the privatization of assets in a market economy may lead to uneven distribution of income and net wealth, thereby further widening the gap between the rich and the poor.
Infrastructure	Density of public roads per capita (km/10,000 persons)	The development of transportation infrastructure contributes to improving the welfare of all social groups. On the one hand, enhanced infrastructure can provide more employment and development opportunities for low- and middle-income or low-wealth populations. On the other hand, infrastructure often serves as a productive input that complements private capital, potentially increasing returns for the wealthy and thereby exacerbating inequality.

1.3.1 Hierarchical clustering

To estimate the income and wealth distributions of provinces with missing data, we first identify provinces with similar characteristics from the set of provinces with available data. The estimation is then based on the observed distributional features of these comparable provinces. Given the large number of selected indicators—each with different units and scales—it is challenging to directly compare the raw indicator values across provinces. Hierarchical clustering is an unsupervised learning algorithm that generates a tree-like structure by recursively merging (or splitting) data points based on their similarity. Therefore, we adopt a hierarchical clustering approach to group provinces based on the 10 indicators in Table 2. The steps are as follows:

1) Data standardization

All indicators are standardized using Z-scores to eliminate the influence of differing units and magnitudes. The standardization formula is given as:

$$Z_{ij} = \frac{X_{ij} - \mu_j}{\sigma_j} \tag{17}$$

where X_{ij} is the original value of indicator j for province i, μ_j is the mean value of indicator j, and σ_j is the standard deviation of indicator j.

2) Distance metric

To quantify the similarity between provinces, we use Euclidean distance as the distance metric. The formula for Euclidean distance is as follows:

$$d(X_i, X_j) = \sqrt{\sum_{k=1}^{n} (X_{ik} - X_{jk})^2} \tag{18}$$

where X_i and X_j represent the feature vectors of provinces i and j, respectively. X_{ik} denotes the value of indicator k in province i. n is the total number of indicators. The Euclidean distance reflects the overall difference between two provinces across multiple indicators. A smaller distance indicates a higher degree of similarity between the provinces.

3) Linkage method

Hierarchical clustering requires the specification of a linkage method to define the distance between two groups of data points. In this study, we adopt Ward's method, which aims to minimize the within-cluster sum of squares (WCSS) when merging clusters. Specifically, the core idea of Ward's method is to iteratively merge the pair of clusters that leads to the minimum increase in within-cluster variance. The formula is as follows:

$$\Delta\,\mathrm{WCSS} = \mathrm{WCSS}_{\mathrm{new}} - (\mathrm{WCSS}_A + \mathrm{WCSS}_B) \tag{19}$$

where WCSS_A and WCSS_B are the within-cluster sum of squares for clusters A and B, respectively. $\mathrm{WCSS}_{\mathrm{new}}$ is the within-cluster sum of squares after merging clusters A and B. The advantage of the Ward method is that by minimizing the within-cluster variance after each merge, the resulting clusters are more compact and can more accurately reflect the underlying structure of the data. This is particularly important when dealing with high-dimensional data.

4) Dendrogram generation

To visually present the similarity and clustering structure among provinces, we used MATLAB's dendrogram function to generate a dendrogram (Fig. 4). The horizontal axis represents the names of the provinces, while the vertical axis indicates the distance between merged clusters (measured by Euclidean distance). The dendrogram illustrates the hierarchical relationships between provinces, allowing for flexible grouping by selecting a cutoff height.

5) Determining the number of clusters

The number of clusters was determined based on the structure of the dendrogram branches. Typically, a natural division can be found by cutting the dendrogram where a sudden increase in linkage distance occurs. In this study, we divided the 30 provinces into five clusters by truncating the dendrogram to ensure that provinces within each group share similar characteristics across multiple socioeconomic and infrastructure indicators (Fig. 4). Cluster 1 consists of Guizhou, Yunnan, and Gansu; Cluster 2 includes Shanxi, Liaoning, Heilongjiang, Henan, Hunan, Sichuan, and Shaanxi; Cluster 3 covers Hebei, Jilin, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Shandong, Hubei, Guangdong, Guangxi, Hainan, and Chongqing; Cluster 4 comprises Inner Mongolia, Qinghai, Ningxia, and Xinjiang; and Cluster 5 includes Beijing, Tianjin, and Shanghai.

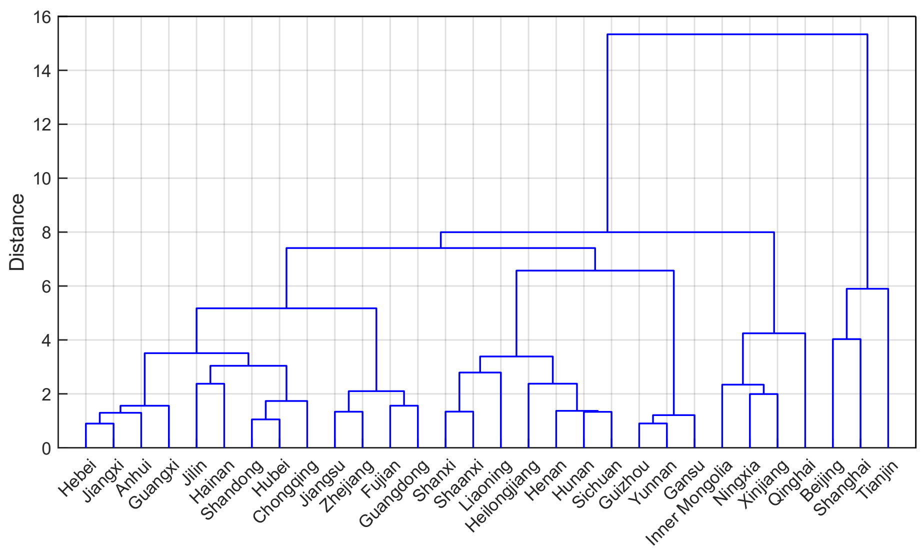

Fig. 4. Hierarchical clustering dendrogram

1.3.2 Identifying the most similar province

In hierarchical clustering, the target province is grouped with other provinces into the same cluster. However, noticeable differences may still exist within the cluster. Therefore, we further refine the matching process by identifying the most similar province based on intra-cluster distance. The specific steps are as follows:

1) Intra-cluster filtering

Based on the target province's cluster assignment from the hierarchical clustering results, we extract all provinces within the same cluster.

2) Intra-cluster distance calculation

For all provinces within the same cluster, we compute the Euclidean distance between the target province and each other province. The formula used is identical to the formula (18). Here, X_i is the standardized feature vector of the target province, and X_j is the feature vector of another province within the same cluster.

3) Similarity ranking

The calculated distances are ranked in ascending order, with smaller values indicating greater similarity to the target province. We identify the three provinces with the smallest distances as the “most similar provinces” to the target province. For Inner Mongolia, the three most similar provinces were Ningxia (distance: 2.127), Xinjiang (2.383), and Qinghai (3.258). However, since Ningxia is also a data-deficient province, Xinjiang was selected as the most similar province. For Hainan, the closest provinces were Jilin (2.375), Hebei (2.492), and Jiangxi (2.521), with Jilin chosen as the proxy. In the case of Qinghai, the most similar provinces were Inner Mongolia (3.258), Xinjiang (3.407), and Ningxia (4.311); as Inner Mongolia also lacks data, Xinjiang was again selected. Similarly, for Ningxia, the closest provinces were Xinjiang (1.992), Inner Mongolia (2.127), and Qinghai (4.311), and Xinjiang was ultimately chosen due to data availability.

1.3.3 Estimation of income and wealth distributions

1) Distribution based on similar provinces

The income and wealth distributions of the most similar provinces are used as the initial distributional estimates for the provinces with missing data.

2) Per capita income adjustment

To align the distribution with the actual income level of the target province, a linear adjustment is applied based on the ratio of average income between the target province and the matched similar province. Specifically, the adjustment is performed using the following formulas:

$$x_{\text{adjusted}} = x_{\text{similar}} \cdot \frac{\overline{x_{\text{target}}}}{\overline{x_{\text{similar}}}} \tag{20}$$

$$w_{\text{adjusted}} = w_{\text{similar}} \cdot \frac{\overline{x_{\text{target}}}}{\overline{x_{\text{similar}}}} \tag{21}$$

where x_{adjusted} and w_{adjusted} represent the adjusted income and wealth values for the target province. x_{similar} and w_{adjusted} denote the original income and wealth values from the matched similar province. $\overline{x_{\text{target}}}$ and $\overline{x_{\text{similar}}}$ are the average per capita incomes of the target and similar provinces, respectively.

2 Provincial carbon footprints

2.1 Extended multi-regional input–output model

In this study, we apply an environmentally extended multi-regional input–output (EE-MRIO) model to calculate the consumption-based carbon emissions (or carbon footprints, CFs) for each Chinese province. The MRIO framework enables a detailed depiction of production activities within regions, interregional transfers, and final consumption flows. It is widely used to quantify regional CFs due to its ability to capture supply chain linkages across regions.

Under a non-competitive MRIO framework, the fundamental linear equation for a given region r is expressed as:

$$x^r = \sum_s A^{rs} x^s + \sum_s y^{rs} \tag{22}$$

where x^r is a column vector representing the total output in region r; $A^{rs} = (a_{ij}^{rs})$ is the input coefficient matrix, where each element $a_{ij}^{rs} = z_{ij}^{rs}/x_j^s$, with z_{ij}^{rs} denoting the interregional monetary flow from sector i in region r to sector j in region s, and x_j^s being the total output of sector j in region r. The term y^{rs} represents the final consumption of goods and services produced in region r and consumed in region s. In particular, y^{rr} refers to the goods and services that are produced and finally consumed within region r. The final demand vector y includes rural household consumption, urban household consumption, government expenditure, capital formation, and changes in inventories.

Assuming there are m regions and each region contains n sectors, formula (22) can be expanded into the following form:

$$\begin{bmatrix} x^1 \\ x^2 \\ \vdots \\ x^m \end{bmatrix} = \begin{bmatrix} A^{11} & A^{12} & \cdots & A^{1m} \\ A^{21} & A^{22} & \cdots & A^{2m} \\ \vdots & \vdots & \ddots & \vdots \\ A^{m1} & A^{m2} & \cdots & A^{mm} \end{bmatrix} \begin{bmatrix} x^1 \\ x^2 \\ \vdots \\ x^m \end{bmatrix} + \sum_s \begin{bmatrix} y^{1s} \\ y^{2s} \\ \vdots \\ y^{ms} \end{bmatrix} \tag{23}$$

which can be simplified and expressed in the following compact form:

$$X = AX + Y \tag{24}$$

Based on formula (24), we have $X = (I - A)^{-1} Y$, where I is the identity matrix with the same dimensions as matrix A. This formulation can be further simplified as:

$$X = LY \tag{25}$$

where L is the Leontief inverse matrix, representing the total output response of all sectors—both direct and indirect—resulting from a unit change in final demand. The matrix L can be expanded as follows:

$$L = \left(I - \begin{bmatrix} A^{11} & A^{12} & \cdots & A^{1m} \\ A^{21} & A^{22} & \cdots & A^{2m} \\ \vdots & \vdots & \ddots & \vdots \\ A^{m1} & A^{m2} & \cdots & A^{mm} \end{bmatrix} \right)^{-1} = \begin{bmatrix} L^{11} & L^{12} & \cdots & L^{1m} \\ L^{21} & L^{22} & \cdots & L^{2m} \\ \vdots & \vdots & \ddots & \vdots \\ L^{m1} & L^{m2} & \cdots & L^{mm} \end{bmatrix} \tag{26}$$

In general, provincial CFs consist of the following components: emissions from goods and services produced and consumed locally, embodied emissions in goods and services imported from other provinces, and direct emissions from household energy use[29,30]. To calculate provincial CFs, we employ the EE-MRIO model. The EE-MRIO model builds upon the standard

MRIO framework by introducing a matrix E that contains sector-specific emission intensities for each province. It allows for quantifying both the direct and indirect carbon emissions across provinces and sectors driven by changes in final demand. The structure of matrix E is as follows:

$$E = \begin{bmatrix} E^1 & 0 & \cdots & 0 \\ 0 & E^2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & E^m \end{bmatrix} \tag{27}$$

in which,

$$E^r = \begin{bmatrix} e_1^r & 0 & \cdots & 0 \\ 0 & e_2^r & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & e_n^r \end{bmatrix} \tag{28}$$

is a diagonal matrix composed of the carbon emission intensities of different sectors in region r (i.e., direct carbon emissions per unit of output). e_i^r represents the direct carbon emissions per unit output of sector i in region r.

The MRIO model enables the quantification of monetary flows between sectors across different regions. Accordingly, in the EE-MRIO model, carbon emission transfers corresponding to these monetary flows can be calculated using the following formula:

$$\begin{aligned} CT &= \begin{bmatrix} CT^{11} & CT^{12} & \cdots & CT^{1m} \\ CT^{21} & CT^{22} & \cdots & CT^{2m} \\ \vdots & \vdots & \ddots & \vdots \\ CT^{m1} & CT^{m2} & \cdots & CT^{mm} \end{bmatrix} \\ &= \begin{bmatrix} E^1 & 0 & \cdots & 0 \\ 0 & E^2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & E^m \end{bmatrix} \begin{bmatrix} L^{11} & L^{12} & \cdots & L^{1m} \\ L^{21} & L^{22} & \cdots & L^{2m} \\ \vdots & \vdots & \ddots & \vdots \\ L^{m1} & L^{m2} & \cdots & L^{mm} \end{bmatrix} \begin{bmatrix} y^{11} & y^{12} & \cdots & y^{1m} \\ y^{21} & y^{22} & \cdots & y^{2m} \\ \vdots & \vdots & \ddots & \vdots \\ y^{m1} & y^{m2} & \cdots & y^{mm} \end{bmatrix} \end{aligned} \tag{29}$$

where CT^{rs} represents the embodied carbon emissions in goods and services imported by province s from province r. Specifically, CT^{rr} denotes the embodied carbon emissions from goods and services that are both produced and consumed within province r. Accordingly, the CF of province r can be calculated using the following formula:

$$CF^r = \sum_{s,s\neq r} CT^{sr} + CT^{rr} + CE_h^r \tag{30}$$

where CE_h^r denotes the direct carbon emissions from household energy consumption in province r. This activity does not generate value-added and thus cannot be captured within the EE-MRIO model, yet it results in carbon emissions. Therefore, it is incorporated into formula (30) to account for this portion of emissions (by attributing it to the "household consumption" component of final demand).

2.2 Data sources

China's MRIO tables are not updated on an annual basis, with the most recent version available for the year 2017. We obtained the 2012 and 2017 MRIO tables of China from the China Emission Accounts and Datasets (CEADs) database[31], which consist of 42 industrial sectors and 31 provinces. In addition, constructing the carbon emission intensity matrix E requires province-level carbon emission inventories by sector. We also obtained historical carbon emission inventories for 42 sectors across all provinces from CEADs[32]. It is important to note that the sector classifications in the emission inventories differ slightly from those in the 2012 and 2017 MRIO tables. Therefore, we aggregated all sectors into 8 broader categories, as shown in Table 3.

Table 3. Sector aggregation

CEADs carbon emission inventories	CEADs 2012 MRIO table	CEADs 2017 MRIO table	This paper
1. Farming, Forestry, Animal Husbandry, Fishery and Water Conservancy	1. Agriculture, Forestry, Animal Husbandry and Fishery	1. Agriculture, Forestry, Animal Husbandry and Fishery	1. Agriculture
2. Coal Mining and Dressing 3. Petroleum and Natural Gas Extraction 4. Ferrous Metals Mining and Dressing 5. Nonferrous Metals Mining and Dressing 6. Nonmetal Minerals Mining and Dressing 7. Other Minerals Mining and Dressing	2. Mining and washing of coal 3. Extraction of petroleum and natural gas 4. Mining and processing of metal ores 5. Mining and processing of nonmetal and other ores	2. Mining and washing of coal 3. Extraction of petroleum and natural gas 4. Mining and processing of metal ores 5. Mining and processing of nonmetal and other ores	2. Mining

8. Logging and Transport of Wood and Bamboo 9. Food Processing 10. Food Production 11. Beverage Production 12. Tobacco Processing 13. Textile Industry 14. Garments and Other Fiber Products 15. Leather, Furs, Down and Related Products 16. Timber Processing, Bamboo, Cane, Palm Fiber & Straw Products 17. Furniture Manufacturing 18. Papermaking and Paper Products 19. Printing and Record Medium Reproduction 20. Cultural, Educational and Sports Articles	6. Food and tobacco processing 7. Textile industry 8. Manufacture of leather, fur, feather and related products 9. Processing of timber and furniture 10. Manufacture of paper, printing and articles for culture, education and sport activity	6. Food and tobacco processing 7. Textile industry 8. Manufacture of leather, fur, feather and related products 9. Processing of timber and furniture 10. Manufacture of paper, printing and articles for culture, education and sport activity	3. Light Industry

21. Petroleum Processing and Coking 22. Raw Chemical Materials and Chemical Products 23. Medical and Pharmaceutical Products 24. Chemical Fiber 25. Rubber Products 26. Plastic Products 27. Nonmetal Mineral Products 28. Smelting and Pressing of Ferrous Metals 29. Smelting and Pressing of Nonferrous Metals 30. Metal Products 31. Ordinary Machinery 32. Equipment for Special Purposes 33. Transportation Equipment 34. Electric Equipment and Machinery 35. Electronic and Telecommunications Equipment 36. Instruments, Meters, Cultural and Office Machinery 37. Other Manufacturing Industry 38. Scrap and waste	11. Processing of petroleum, coking, processing of nuclear fuel 12. Manufacture of chemical products 13. Manuf. of non -metallic mineral products 14. Smelting and processing of metals 15. Manufacture of metal products 16. Manufacture of general-purpose machinery 17. Manufacture of special purpose machinery 18. Manufacture of transport equipment 19. Manufacture of electrical machinery and equipment 20. Manufacture of communication equipment, computers and other electronic equipment 21. Manufacture of measuring instruments 22. Other manufacturing 23. Comprehensive use of waste resources	11. Processing of petroleum, coking, processing of nuclear fuel 12. Manufacture of chemical products 13. Manuf. of non -metallic mineral products 14. Smelting and processing of metals 15. Manufacture of metal products 16. Manufacture of general-purpose machinery 17. Manufacture of special purpose machinery 18. Manufacture of transport equipment 19. Manufacture of electrical machinery and equipment 20. Manufacture of communication equipment, computers and other electronic equipment 21. Manufacture of measuring instruments 22. Other manufacturing and waste resources	4. Heavy Industry

39. Production and Supply of Electric Power, Steam and Hot Water	24. Production and distribution of electric power and heat power	23. Production and distribution of electric power and heat power	5. Production and Supply of Electricity and Steam
40. Production and Supply of Gas 41. Production and Supply of Tap Water	25. Production and distribution of gas 26. Production and distribution of tap water	24. Production and distribution of gas 25. Production and distribution of tap water	6. Production and Distribution of Gas and Water
42. Construction	27. Construction	26. Construction	7. Construction

43. Transportation, Storage, Post and Telecommunication Services 44. Wholesale, Retail Trade and Catering Services 45. Others	28. Repair of metal products, machinery and equipment 29. Wholesale and retail trades 30. Transport, storage, and postal services 31. Accommodation and catering 32. Information transfer, software and information technology services 33. Finance 34. Real estate 35. Leasing and commercial services 36. Scientific research and polytechnic services 37. Administration of water, environment, and public facilities 38. Resident, repair and other services 39. Education 40. Health care and social work 41. Culture, sports, and entertainment 42. Public administration, social insurance, and social organizations	27. Repair of metal products, machinery and equipment 28. Wholesale and retail trades 29. Transport, storage, and postal services 30. Accommodation and catering 31. Information transfer, software and information technology services 32. Finance 33. Real estate 34. Leasing and commercial services 35. Scientific research 36. Polytechnic services 37. Administration of water, environment, and public facilities 38. Resident, repair and other services 39. Education 40. Health care and social work 41. Culture, sports, and entertainment 42. Public administration, social insurance, and social organizations	8. Service Industry

46.	Urban	N/A	N/A	N/A
47.	Rural			

Note: in the CEADs carbon emission inventories, "Urban" and "Rural" represent the direct carbon emissions from household energy consumption in urban and rural areas, respectively. These activities do not generate value-added and therefore cannot be captured by the EE-MRIO model. However, they are important sources of CFs at the provincial level. As a result, they are temporarily excluded from the input-output calculations, but as shown in formula (30), they are included when calculating the provincial CFs (by attributing it to the “household consumption” component of final demand).

2.3 Results

Based on the methodology described above, we calculated the consumption-based carbon emissions (CFs) for each Chinese province for the years 2017 and 2012. The provincial CFs were further disaggregated by final demand categories into household consumption CF (HCCF), government consumption CF (GCCF), and capital formation CF (CFCF) (Fig. 5). In particular, HCCF accounts not only for the indirect emissions estimated through the EE-MRIO model but also for the direct emissions from household energy use as reported in carbon emission inventories. Due to data limitations, CFs associated with international exports were not included in the analysis.

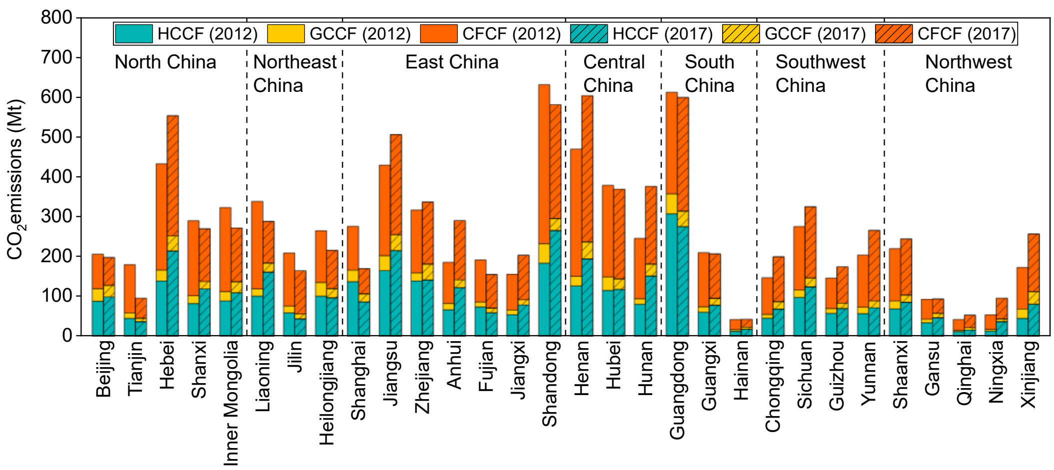

Fig. 5. Composition of consumption-based carbon emissions (CFs) for each province in 2017 and 2012

Note: HCCF refers to household consumption CF, GCCF refers to government consumption CF, and CFCF refers to capital formation CF.

3 Individual carbon footprints

By integrating the fitted provincial-level individual income and wealth distributions derived from micro-level household surveys with the province-level CFs data obtained from the macro-level EE-MRIO model, we enable an effective downscaling of CFs from the provincial scale to the individual scale. This process is crucial for understanding the distribution of carbon responsibility across different income groups. Ref. [33] proposed a systematic method to allocate national-level

CFs to the individual level, which has been successfully applied to over 100 countries worldwide. This method establishes a mapping between macro-level CF data and micro-level income or wealth distributions based on the elasticity of CFs with respect to income or wealth. It enables the disaggregation of household consumption CF, government consumption CF, and capital formation CF from the national level to individuals across different income brackets. The core logic and technical pathway of this method are also applicable at the provincial level in China.

For analytical purposes, individuals in each province are grouped into 100,000 income percentiles, with individuals within each percentile treated as homogeneous. Accordingly, for any given province, the CF composition of individuals in percentile i can be expressed as follows:

$$CF_i^{\mathrm{tot}} = CF_i^{\mathrm{cons}} + CF_i^{\mathrm{gov}} + CF_i^{\mathrm{inv}} \tag{31}$$

where CF_i^{tot}, CF_i^{cons}, CF_i^{inv}, CF_i^{gov} represent the per capita total CF, household consumption CF, capital formation CF, and government consumption CF, respectively, for percentile i. In the following sections, we develop downscaling models corresponding to each of these three CF components.

3.1 Household consumption carbon footprint

The sum of household consumption CFs across all individuals in a province should be equal to the province-level household consumption CF. Meanwhile, individual household CFs are primarily influenced by their income levels—meaning that differences in CFs across income groups are largely driven by income disparities[33]. Accordingly, for a given province, the downscaling model for household consumption CF can be formulated as follows:

$$\begin{cases} CF_1^{\mathrm{cons}} = k^{\mathrm{cons}} CF^{\mathrm{cons}} \cdot {Y_1}^{\alpha} \\ CF_2^{\mathrm{cons}} = k^{\mathrm{cons}} CF^{\mathrm{cons}} \cdot {Y_2}^{\alpha} \\ \qquad\qquad \vdots \\ CF_N^{\mathrm{cons}} = k^{\mathrm{cons}} CF^{\mathrm{cons}} \cdot {Y_N}^{\alpha} \\ \sum_{i=1}^{N} CF_i^{\mathrm{cons}} = N \cdot CF^{\mathrm{cons}} \end{cases} \tag{32}$$

where CF^{cons} denotes the per capita household consumption CF of the province, Y_i is the average income of individuals in income percentile i, α represents the income elasticity of household consumption CF, and N is the number of percentile groups, i.e., 100,000.

It can be observed that an individual's household consumption CF is determined not only by the province's overall household consumption CF, but also by the income elasticity of household CF, denoted as α. Previous studies have shown that α typically ranges between 0.6 and 1.0, indicating that an additional unit of income generates less carbon emissions for the rich than for the poor[33,34]. This implies a trade-off between poverty alleviation (or reducing income inequality) and climate mitigation. According to findings from refs. [33-35], the value of α varies across regions and tends to be higher in more developed areas compared to less developed ones.

To reflect interprovincial differences, this study estimates province-specific elasticity coefficients between income and household consumption CF based on observed data. First, we calculate the growth rates of per capita income and per capita household consumption CF for each province. These growth rates are then used to derive initial elasticity estimates. To ensure consistency with the empirically supported range (0.6–1.0), the initial elasticity values are mapped onto this interval to obtain the final province-specific elasticity coefficients. This method provides a reasonable adjustment of provincial elasticity estimates based on limited empirical data and helps reveal region-specific carbon emission patterns across different levels of economic development. It also offers both empirical support and a theoretical basis for formulating targeted regional carbon mitigation policies. Details are provided as follows:

First, the initial elasticity estimate for province i is calculated using the following formula:

$$\alpha_i^{\text{initial}} = \frac{\left(\dfrac{HCCF_{i,2017} - HCCF_{i,2012}}{HCCF_{i,2012}}\right)}{\left(\dfrac{Y_{i,2017} - Y_{i,2012}}{Y_{i,2012}}\right)} \tag{33}$$

where $HCCF_{i,2017}$ and $HCCF_{i,2012}$ represent the per capita household consumption CFs of province i in 2017 and 2012, respectively, and $Y_{i,2017}$ and $Y_{i,2012}$ denote the per capita income of province i in 2017 and 2012, respectively. The provincial per capita income data are obtained from the national and provincial statistical yearbooks.

Then, after estimating the initial elasticity values for all provinces, the elasticity coefficient for province i is obtained by mapping its initial elasticity estimate into the theoretical range of 0.6 to 1.0, as shown in the following formula:

$$\alpha_i = 0.6 + 0.4 \times \frac{\alpha_i^{\text{initial}} - \alpha_{min}^{\text{initial}}}{\alpha_{max}^{\text{initial}} - \alpha_{min}^{\text{initial}}} \tag{34}$$

where $\alpha_{min}^{\text{initial}}$ and $\alpha_{max}^{\text{initial}}$ denote the minimum and maximum values, respectively, of the initial elasticity estimates across all provinces.

Fig. 6 presents the estimated income elasticity coefficients of household consumption CF for each province. In addition, the same estimation method was applied at the national level, yielding an elasticity value of 0.76, which is consistent with the estimates reported in refs. [33,36,37]. We take the estimated provincial income elasticity coefficients as the baseline scenario. In Supplementary Information Section 7, we also calculate the provincial CF results under extreme scenarios, where the elasticity coefficients are uniformly set to the upper and lower bounds of their typical range (0.6 and 1.0, respectively).

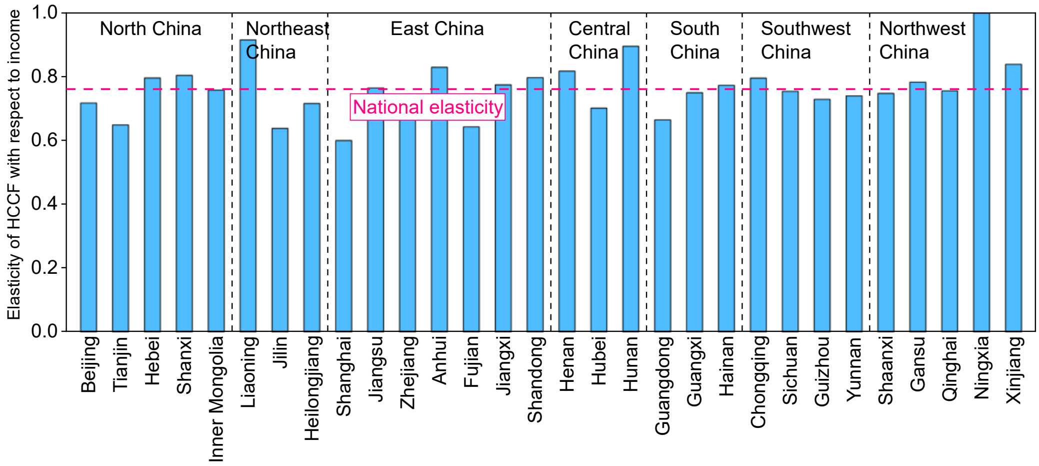

Fig. 6. Income elasticity of household consumption CF (HCCF) across provinces (from 2012 to 2017)

Note: the red dashed line indicates the national-level elasticity value (0.76).

3.2 Government consumption carbon footprint

Unlike household consumption CFs, provincial-level government consumption CFs in this study are equally distributed among all individuals within each province. This approach has been adopted in global inequality studies[33,38], based on the implicit assumption that government expenditures primarily serve the general population, and thus the associated emissions should be equally borne by everyone. This assumption is generally regarded as both reasonable and conservative in international research.

Although some scholars have pointed out that public service provision in China is characterized by significant inequality[39]—suggesting that government consumption emissions should not be equally allocated—Fig. 5 shows that government consumption emissions account for only a small share of total CFts in China. Therefore, adopting alternative allocation approaches would have only a limited impact on the overall carbon inequality results and would not significantly alter the main conclusions.

Therefore, for a given province, the government consumption CF of individuals in income percentile i is calculated as follows:

$$CF_i^{\mathrm{gov}} = CF^{\mathrm{gov}} \tag{35}$$

where CF^{gov} denotes the per capita government consumption CF of the province.

3.3 Capital formation carbon footprint

The allocation of provincial capital formation CFs to individuals follows a similar approach to that of household consumption CFs, but uses wealth rather than income as the allocation basis, as shown in the following formula:

$$\begin{cases} CF_1^{\text{inv}} = k^{\text{inv}} CF^{\text{inv}} \cdot {W_1}^{\beta} \\ CF_2^{\text{inv}} = k^{\text{inv}} CF^{\text{inv}} \cdot {W_2}^{\beta} \\ \qquad \vdots \\ CF_N^{\text{inv}} = k^{\text{inv}} CF^{\text{inv}} \cdot {W_N}^{\beta} \\ \sum_{i=1}^{N} CF_i^{\text{inv}} = N \cdot CF^{\text{inv}} \end{cases} \tag{36}$$

where CF^{inv} denotes the per capita household consumption CF of the province, W_i is the average wealth of individuals in income percentile i, β represents the wealth elasticity of capital formation CF.

For the elasticity coefficient β, we set its value to 1, assuming that the capital formation CF borne by individuals within a province is proportional to their wealth. This assumption is supported by several empirical studies. Ref. [40], based on analyses of France and Germany, found elasticity values of approximately 1.1 and 0.95, respectively, indicating that wealth and the capital formation CF are roughly linearly related in magnitude. Ref. [33] further argued that in most countries lacking micro-level asset-based carbon data, assuming unit elasticity is an acceptable and widely adopted approach in studies on cross-national carbon inequality and responsibility allocation. We take $\beta = 1$ as the baseline scenario. In Supplementary Information Section 7, we also calculate individual CF results under extreme scenarios ($\beta = 0.9$ and 1.1).

The average wealth W_i of individuals in income percentile i cannot be directly derived from the fitted provincial income and wealth distribution functions, as individuals in income percentile i do not necessarily fall into the same wealth percentile. Micro-level data from provincial household surveys reveal a highly complex and nonlinear relationship between income and wealth. First, income and wealth distributions differ substantially: income typically exhibits a right-skewed distribution, whereas wealth is even more heavily right-skewed. Second, the dependence between income and wealth is nonlinear; individuals with similar income levels may possess vastly different levels of wealth, and the structure of wealth distribution varies across income groups. This is understandable—for instance, some high-income individuals may not have accumulated substantial wealth, while certain low-income individuals may own considerable assets. Therefore, assuming a one-to-one correspondence between income and wealth percentiles (e.g., equating the bottom 1% in income with the bottom 1% in wealth) leads to significant distortion and fails to reflect the actual statistical patterns observed in the data. To address this issue, we propose a percentile-based method for estimating the joint distribution of income and wealth. The steps are as follows:

1) Fitting the empirical wealth distribution function

This step has already been completed in Supplementary Information Section 1. Here, we denote the optimal cumulative distribution function of wealth as $F_W(w)$. This distribution captures the marginal characteristics of the wealth data and serves as the basis for estimating individual wealth values in the subsequent steps.

2. Exploring the relationship between income and wealth based on their joint distribution

A Copula model is used to fit the joint distribution of income percentiles and wealth percentiles, capturing the nonlinear dependence between the two variables. The conditional distribution derived from the joint distribution is used to estimate the correspondence between income percentiles and wealth percentiles. Based on this, wealth percentile values are generated for each sample within different income groups. The details are as follows:

First, we introduce the Copula model. Copula is a method used to construct multivariate joint distributions by separating marginal distributions from their dependence structure. Its core idea is expressed as:

$$C(u,v) = P(U \leq u, V \leq v) \tag{37}$$

where $U = F_X(x)$ and $V = F_Y(y)$ are marginal distributions standardized to the interval [0, 1], and $C(u,v)$ is the Copula function that describes the dependence structure between U and V. This approach is particularly well-suited for modeling the complex and nonlinear relationship between income and wealth because it allows for the combination of arbitrary marginal distributions $F_X(x)$ and $F_Y(y)$, preserving the original distributional characteristics of each variable, while separately constructing the dependence structure $C(u,v)$, thereby enabling the capture of nonlinear relationships.

Then, we proceed with model selection and fitting. Before that, the sample income and wealth data are first transformed into percentile values:

$$U = F_X(x) = \frac{\mathrm{rank(income)}}{n}, \quad V = F_Y(y) = \frac{\mathrm{rank(wealth)}}{n} \tag{38}$$

where $U = F_X(x)$ and $V = F_Y(y)$ are the normalized percentile values of income and wealth, respectively. Here, $\mathrm{rank(income)}$ and $\mathrm{rank(wealth)}$ denote the rank orders of income and wealth within the sample, and n is the total number of observations. This transformation maps the original data to the [0, 1] interval, producing uniform marginal distributions required for Copula fitting.

After transforming the data into percentile form, we proceed to select the most appropriate

Copula type. We fit several commonly used Copula families, including Gaussian, t, Clayton, and Gumbel Copulas, and identify the best-fitting model based on the Akaike information criterion (AIC), as defined by the following formula:

$$\mathrm{AIC} = -2 \cdot \mathrm{loglik} + 2 \cdot \mathrm{num\_params} \tag{39}$$

where loglik denotes the log-likelihood of the fitted Copula model, and $\mathrm{num\_params}$ is the number of estimated parameters. The Copula model with the lowest AIC value is considered the best-fitting model.

Then, based on the fitted Copula model, joint distribution samples (U_i, V_i) of income and wealth percentiles can be generated to capture the complex correspondence between income percentiles and wealth percentiles.

Furthermore, we can proceed to estimate the wealth percentiles corresponding to each income percentile. For each fixed income percentile u, multiple corresponding wealth percentiles v are generated based on the conditional distribution. The conditional distribution of a Copula is given by the following formula:

$$C_{V|U=u}(v) = \frac{\partial C(u,v)}{\partial u} \Big/ \frac{\partial C(u,1)}{\partial u} \tag{40}$$

where $C_{V|U=u}(v)$ denotes the conditional distribution function of V given $U = u$. The numerator $\frac{\partial C(u,v)}{\partial u}$ represents the partial derivative of the Copula function with respect to u, capturing the cumulative dependence up to percentile v. The denominator $\frac{\partial C(u,1)}{\partial u}$ serves as a normalization term, ensuring that the conditional distribution integrates to 1 over the range of v. This formulation allows us to generate conditional samples of wealth percentiles for a given income percentile using the estimated Copula function. The specific form of the conditional distribution varies depending on the type of Copula used. For example, for the Gaussian Copula, the conditional mean and variance are given by:

$$\mu = \rho \cdot z_u, \quad \sigma^2 = 1 - \rho^2 \tag{41}$$

where $z_u = \Phi^{-1}(u)$ is the inverse of the standard normal distribution, and ρ is the dependence parameter.

Finally, the generated wealth percentile v is substituted into the inverse of the fitted empirical wealth distribution function $F_W(w)$ to obtain the corresponding wealth value:

$$w = F_W^{-1}(v) \tag{42}$$

The above describes our proposed percentile-based method for estimating the joint distribution of income and wealth. This percentile-mapping approach offers two key advantages. First, it ensures consistency: the estimated wealth values preserve the original wealth distribution in the sample. Second, it retains the complexity of the relationship between income and wealth: the mapping between income percentiles and wealth percentiles is derived from the joint distribution observed in the original micro-level data, accurately reflecting the nonlinear dependence between the two variables.

4 Individual carbon footprints in 2030 under the BAU scenario

In the preceding sections, the calculation of individual CFs for each province in 2017 included emissions from household consumption, government consumption, and capital formation. Emissions from exports were excluded due to the lack of province-level data. We calculated the share of these three sectors in China's total carbon emissions in 2017 and found that they accounted for 80.66% of the national total. This indicates that the individual CFs we computed cover the majority of total emissions. Therefore, we reasonably upscale the individual carbon footprints by a factor corresponding to this proportion (80.66%) to match the national total emissions. This adjustment ensures consistency between the aggregated individual footprints and the national inventory, which is necessary for estimating provincial mitigation efforts, which must be assessed relative to the national total carbon emissions.

Furthermore, we assume that under the business-as-usual (BAU) scenario, China's national carbon intensity in 2030 will remain at its current level, and the distribution of individual carbon footprints within each province will also remain unchanged. Based on these assumptions, we estimate the individual CFs for each province in 2030 under the BAU scenario, which will serve as the reference line for evaluating future provincial mitigation efforts.

1) Provincial population and CF projections for 2030

For provincial population projections, this study first refers to the medium-growth scenario of China's population growth rate from the United Nations' World Population Prospects to estimate China's total population in 2030[41]. Based on this estimate, we assume that each province's share of the national population in 2024 remains constant through 2030, allowing us to derive provincial population estimates for 2030. Population data are obtained from the China Statistical Yearbook.

For provincial CF projections, we assume that each province's share of national CF in 2017 remains unchanged. Under this assumption, provincial CFs in 2030 can be derived from the projected national total. In the BAU scenario, China's carbon intensity in 2030 is assumed to remain at the 2024 level; therefore, national carbon emissions in 2030 are determined by the projected GDP.

Considering recent economic slowdowns due to weak domestic demand and external trade pressures, China's current GDP growth rate has stabilized around 5%. The average annual growth rate over the next five years is expected to range between 3% and 5%. To reflect this uncertainty, we define three GDP growth scenarios: a high-growth scenario (annual average of 4.5% from 2025 to 2030), a medium-growth scenario (4.0%), and a low-growth scenario (3.5%). Based on these assumptions, we calculate the projected national and provincial BAU carbon emissions in 2030 under each growth scenario (Table 4). The GDP data are sourced from the China Statistical Yearbook.

2) Individual CF for 2030 under the BAU scenario

Based on the assumption that the distribution of individual CFs within each province in 2030 under the BAU scenario remains consistent with that of 2017, and combined with the projected population and total CF values for each province in 2030, we can calculate the provincial-level individual CFs under the BAU scenario.

Table 4. Projected national and provincial CFs in 2030 under the BAU Scenario

Region	CF in 2017 (Mt)	Low GDP growth scenario (Mt)	Medium GDP growth scenario (Mt)	High GDP growth scenario (Mt)
Beijing	244.6	318.2	327.6	337.1
Tianjin	118.2	153.8	158.3	162.9
Hebei	685.9	892.3	918.4	945.3
Shanxi	334.2	434.8	447.5	460.6
Inner Mongolia	336.9	438.2	451.1	464.3
Liaoning	357.1	464.5	478.2	492.1
Jilin	203.7	265.0	272.8	280.7
Heilongjiang	267.2	347.5	357.7	368.2
Shanghai	210.6	273.9	281.9	290.2
Jiangsu	627.6	816.4	840.3	864.9
Zhejiang	417.7	543.3	559.2	575.6
Anhui	360.1	468.5	482.2	496.3
Fujian	191.9	249.6	256.9	264.4
Jiangxi	252.2	328.1	337.7	347.5
Shandong	720.0	936.6	964.1	992.3

Henan	748.9	974.2	1002.8	1032.0
Hubei	457.5	595.2	612.6	630.5
Hunan	466.5	606.9	624.7	642.9
Guangdong	743.2	966.7	995.1	1024.1
Guangxi	255.8	332.7	342.5	352.5
Hainan	52.4	68.2	70.2	72.3
Chongqing	247.0	321.2	330.7	340.3
Sichuan	402.8	524.0	539.3	555.1
Guizhou	216.0	281.0	289.3	297.7
Yunnan	329.1	428.1	440.7	453.6
Shaanxi	302.7	393.8	405.3	417.2
Gansu	115.5	150.2	154.6	159.2
Qinghai	65.7	85.4	87.9	90.5
Ningxia	118.5	154.1	158.6	163.3
Xinjiang	318.0	413.6	425.7	438.2
China	10167.7	13226.0	13614.0	14011.5

Note: all the CF values have been upscaled from 80.66% to 100% of total emissions.

5 China's national carbon emissions target for 2030

In 2020, China announced an updated and enhanced NDC, committing to reduce carbon intensity by more than 65% from the 2005 level by 2030. Based on this target, and using the GDP growth scenarios defined in Supplementary Information Section 4, we derive the corresponding national total carbon emissions targets.

To account for uncertainties in the level of target achievement, we define three mitigation scenarios: low, medium, and high, corresponding to carbon intensity reduction rates of 60%, 65%, and 70%, respectively. Combining the three GDP growth scenarios (low, medium, and high) with the three mitigation scenarios yields a matrix of nine national carbon emissions target scenarios: LL (low GDP growth + low mitigation), LM (low GDP growth + medium mitigation), LH (low GDP growth + high mitigation), ML (medium GDP growth + low mitigation), MM (medium GDP growth + medium mitigation), MH (medium GDP growth + high mitigation), HL (high GDP growth + low mitigation), HM (high GDP growth + medium mitigation), and HH (high GDP growth + high mitigation).

Table 5 presents the total national carbon emissions targets associated with each of these scenarios. As shown, the LH scenario represents the most stringent climate target, allowing emissions of only 8.43 billion tons of CO_2 by 2030. In contrast, the HL scenario is the most lenient, allowing emissions up to 11.9 billion tons of CO_2. This study focuses on the MM scenario, where the national carbon emissions target is 10.12 billion tons, as the central case for analyzing provincial mitigation efforts. Results under the other scenarios are also calculated and serve as benchmarks for comparison with the MM scenario.

Table 5. National carbon emissions targets under different GDP growth and mitigation scenarios

GDP growth scenario	Mitigation scenario	Emission target (Mt)
Low	Low	11234.9
Low	Medium	9830.5
Low	High	8426.2
Medium	Low	11564.5
Medium	Medium	10118.9
Medium	High	8673.4
High	Low	11902.1
High	Medium	10414.4
High	High	8926.6

Note: the low, medium, and high GDP growth scenarios correspond to national average annual GDP growth rates of 3.5%, 4.0%, and 4.5% from 2025 to 2030, respectively. The low, medium, and high mitigation scenarios correspond to reductions in carbon intensity by 60%, 65%, and 70% by 2030 relative to 2005 levels.

6 Individual carbon footprints based on decent living standards (DLS)

Unlike most existing studies that focus solely on carbon emissions related to household consumption, this study defines an individual's CF as the sum of emissions associated with three final demand components: household consumption, government consumption, and capital formation. Traditional estimations of decent living standards (DLS)-based emissions typically concentrate on essential household consumption categories—such as food, clothing, housing, transport, education, health, water, and cooking—while neglecting the latter two sources.

Building on household consumption-based DLS CFs, this study further incorporates minimum emission thresholds from government consumption and capital formation to construct a comprehensive, full-scope DLS CF floor covering all three final demand components. Specifically, we calculate household DLS-related CFs based on provincial-level energy demands for key consumption categories. For capital formation, we set the 25th percentile of individual capital-related CFs within each province as the minimum level of investment required to support a decent life. Given the relatively small share of government consumption, we assume that maintaining current levels of per capita government consumption CFs is sufficient to meet basic public service needs. The resulting individual-level DLS CF comprises these three components and serves as a floor reference for subsequent effort-sharing analysis.

Household consumption-related DLS CFs in this study are calculated based on estimated DLS energy demand and the carbon intensity per unit of energy use. Regarding DLS energy demand, ref. [42] developed an evaluation system covering both direct and indirect energy consumption, and estimated per capita DLS energy use at the provincial level for 2017. Specifically, their study builds upon the general DLS framework proposed by ref. [35], while adapting it to China's national context by incorporating regional development levels, cultural norms, and lifestyle patterns. The framework defines DLS thresholds for eight consumption categories: food, clothing, housing, transport, education, health, water, and cooking. For example, the food intake standard is adjusted based on the Dietary Reference Intakes for Chinese Residents (2013 Edition); heating standards in the housing category reflect the temperature differences between northern and southern regions; and the transport category assumes that private urban travel is replaced by public transportation under DLS conditions. Furthermore, ref. [42] applied the EE-MRIO model to quantify provincial DLS energy consumption under the specified thresholds. This includes both direct and indirect energy use. Direct energy consumption covers three categories: transport, housing, and cooking, while indirect energy consumption spans all eight categories mentioned above. The detailed calculation process is provided in Table 6.

For the carbon emission factor per unit of energy consumption, we use the most recent (2021) provincial-level data on energy consumption and carbon emissions in China to calculate province-specific emission coefficients. The relevant data are obtained from the China Energy Statistical Yearbook. By combining the estimated DLS energy demand with these carbon intensity factors, we derive the per capita household consumption DLS CFs for each province. Finally, by summing up the household consumption, government consumption, and capital formation components of DLS-related CFs, we obtain the individual DLS CF for each province. In addition, to test robustness, we adjust the capital formation component of individual DLS CF from the 25th percentile to the 40th and 10th percentiles of the provincial individual capital-related CF distribution, constructing the upper and lower bounds of the individual DLS CF. The values and variation range of individual DLS CF under these scenarios are shown in Fig. 7.

Table 6. Provincial DLS energy estimation method

Category	DLS material threshold	Energy type	Calculation logic
Food	Daily caloric intake per person is set based on the Dietary Reference Intakes for Chinese Residents, differentiated by gender and age. Provincial annual caloric demand is calculated based on the population structure.	Indirect	• Using the EE-MRIO to extract the indirect energy use associated with household consumption in the "Food and Tobacco" sector. • Calculating the energy intensity per kcal = total indirect energy / actual total caloric intake (kJ/kcal). • Multiplying this intensity by the DLS-based caloric demand for each province to estimate food-related indirect energy consumption under DLS.

Clothing	Annual clothing weight is set for men, women, and children based on temperature zones, ensuring adequate insulation during the coldest months.	Indirect	• Using EE-MRIO to obtain the indirect energy embodied in the "Textile, Garment, and Leather Products" sectors due to household consumption. • Calculating the unit energy intensity per gram = total energy / total national clothing weight consumed. • Multiplying this by the clothing weight defined under DLS for each province to obtain DLS clothing energy use.
Transportation	In DLS scenario, urban residents use only public transport; rural residents use a combination of public and private transport. Total travel distance (passenger-km) is assumed the same as in 2017.	Direct + Indirect	• Direct energy: replacing urban private transport with public modes. Applying energy use coefficients (MJ/passenger-km) for different transport modes from national/international data. Multiplying by travel distance by mode to compute direct transport energy use. • Indirect energy: using EE-MRIO to extract household-induced energy use from the "Transport, Storage, and Postal Services" sector. Computing energy intensity per passenger-km and multiply by DLS travel demand to obtain indirect energy.
Housing – Cooling	Each household is assumed to own one 1.5 horsepower energy-efficient air conditioner. Cooling is activated when the outdoor temperature exceeds 26°C. Operating time is 8 hours per day on weekdays and 10 hours on weekends.	Direct + Indirect	• Direct energy: for each climate zone, representative cities are selected to estimate daily household cooling load. Multiplying cooling energy per household by number of households in each province. • Indirect energy: multiplying DLS cooling electricity demand by the unit indirect energy coefficient of the "Electricity and Heat Supply" sector derived from EE-MRIO.
Housing – Heating	Central heating is applied in northern urban areas; air conditioners are used for heating in southern and rural regions. Heating area and duration are set based on climate zones and housing standards.	Direct + Indirect	• Direct energy: estimating heating demand by region using standard indoor temperature thresholds and heating days. Considering energy sources (coal, electricity, heat), efficiency, and distribution losses. • Indirect energy: multiplying DLS coal, electricity, and heat consumption by their respective indirect energy intensities derived from EE-MRIO sectors.
Housing – Lighting	Lighting is considered for living rooms and bedrooms only. Lighting power is set based on area (in square meters) and standard lighting power density (W/m²). Lighting duration is determined by daylight hours.	Direct + Indirect	• Direct energy: multiplying room lighting area by power density and estimated lighting time per day. Multiplying by number of households to obtain total electricity use for lighting. • Indirect energy: multiplying DLS lighting electricity consumption by the electricity sector's indirect energy intensity from EE-MRIO.
Housing – Appliances	Each household owns one refrigerator (0.33 kWh/day), one TV (3 kWh/year), and each person owns one mobile phone (0.2 kWh/year).	Direct + Indirect	• Direct energy: multiplying number of devices by annual electricity consumption per device unit. Estimating at provincial level using population and household size. • Indirect energy: multiplying DLS appliance electricity consumption by the electricity sector's indirect energy coefficient from EE-MRIO.
Water	Each person consumes 100 liters of water per day, consistent with the national standard for basic residential water supply.	Indirect	• Using EE-MRIO to extract the indirect energy use associated with household consumption in the "Water Production and Supply" sector. • Computing per-liter indirect energy intensity = total sector energy consumption/ total actual water supplied nationally (kJ/L).

			• Multiplying by DLS water demand per province to get indirect energy use.
Health Care	Annual per capita expenditure is set at ¥4614.96, equivalent to the median value for basic health coverage.	Indirect	• Using EE-MRIO to extract the indirect energy use induced by household consumption in the "Health and Social Work" sector. • Computing per-yuan energy intensity based on the national actual health expenditure (kJ/CNY). • Multiplying this by DLS-based per capita health expenditure to obtain DLS energy use for health services.
Education	DLS requires completion of nine-year compulsory education, with primary school expenditure set at ¥6939.79 and junior secondary at ¥10409.68.	Indirect	• Due to lack of a dedicated "Education" sector in EE-MRIO, use "Other Services" as a proxy. • Extracting indirect energy use associated with household education consumption. • Computing energy intensity per yuan from "Other Services" sector in EE-MRIO and multiplying by DLS educational spending to estimate energy use.
Cooking	Only electricity and gas are allowed as fuels. Their proportion is determined by actual provincial fuel use patterns. Cooking energy demand is set equal to the actual thermal need, with fuel switching and efficiency adjustments.	Direct + Indirect	• Direct energy: calculating cooking fuel required = thermal demand / fuel efficiency (75% for electricity, 60% for gas). • Indirect energy: multiplying DLS cooking electricity and gas consumption by the indirect energy intensities of the "Electricity and Heat Supply" and "Coal Mining and Processing" sectors in EE-MRIO.

Source: ref. [42].

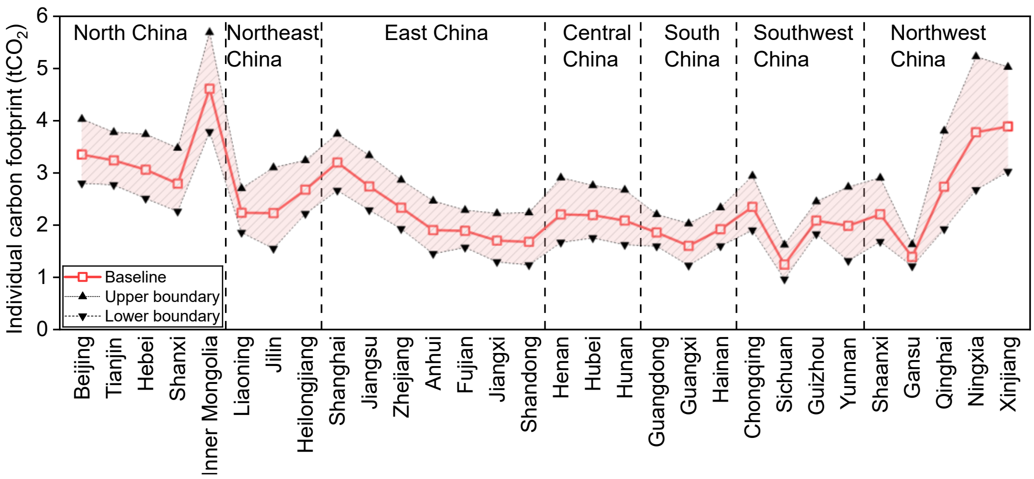

Fig. 7. Individual carbon footprint for DLS

7 Robust tests

First, for the estimation of provincial individual income and wealth distributions, four provinces—Inner Mongolia, Ningxia, Qinghai, and Hainan—lack sufficient data and were thus estimated using a cluster analysis to identify the most similar provinces, which were then used as proxies for estimation (Supplementary Information 1.3). Similarly, refs. [43,44] faced the same issue and addressed it by assuming that data-deficient provinces share income distribution patterns with neighboring provinces, directly adopting the latter as proxies. Compared to this straightforward approach, our cluster-based proxy selection is arguably more systematic and scientifically justified. Nevertheless, to test the robustness of our method, we also employed neighboring provinces as alternative proxies, following the same adjustment procedure with our cluster-based approach: the matched distributions were linearly scaled to align with the observed average income and wealth levels of the target provinces. We then recalculated the individual CFs for different income groups under these alternative assumptions and compared the results with our original estimates.

Specifically, Shanxi—a neighboring coal-producing province—was used as a proxy for Inner Mongolia; Gansu was selected for both Ningxia and Qinghai, given their geographic proximity and similar economic development levels; and Guangxi, a neighboring province with a more similar economic development level, was used for Hainan. The recalculated individual CFs for each income group are presented in Fig. 8. The results show no substantial differences across the income groups, indicating that alternative choices of proxies have minimal impact on our findings and thereby supporting the robustness of the adopted method.

Second, in estimating individual CFs, income and wealth elasticity coefficients serve as key parameters linking individual income and wealth to household consumption and investment CFs, and it is necessary to assess the sensitivity of the results to their values. For income elasticity (α), we assigned province-specific values based on empirical data and theoretical ranges provided in previous studies (refs. [33,34]; 0.6 to 1.0), as described in Supplementary Information Section 3.1. Here, we consider two extreme scenarios where α is set to the lower and upper bounds of its typical range (0.6 and 1.0) and recalculate individual CFs accordingly. As shown in Table 7, increasing α amplifies carbon inequality: individual CFs moderately increase for the top 1%, slightly increase for the next 9%, remain largely unchanged for the middle 40%, and slightly decrease for the bottom 50%. In other words, for the vast majority of individuals across all provinces, CFs are not highly sensitive to variations in α, indicating that the estimated provincial CFs are robust to the choice of income elasticity estimation.

For wealth elasticity (β), we set the baseline value at 1.0, following the approach in ref. [33], due to the lack of empirical evidence at the Chinese provincial level (Supplementary Information Section 3.3). To assess the robustness of our results to this assumption, we follow ref. [33] by introducing two extreme scenarios for β: an upper bound of 1.1 and a lower bound of 0.9. We then examine the impact of these scenarios on individual CFs across income groups in each province. Similar to α, an increase in β leads to higher individual CFs for the top 1% and the next 9% income groups, while the middle 40% remains largely unaffected and the bottom 50% experiences a slight decrease (Table 8). This is expected, as a higher β implies a more unequal allocation of capital-related emissions across income groups—assigning more responsibility to high-income individuals and less to low-income individuals, with middle-income groups relatively unaffected. Importantly, the variations in individual CFs under these extreme elasticity assumptions are minor across all provinces and income groups. These changes do not materially alter the overall patterns of carbon inequality or the main conclusions of this study.

Third, in the construction of individual DLS CFs, the capital formation component was previously set as the 25th percentile of the individual capital-related CF distribution within each province. To test the robustness of this assumption, we apply a ±15 percentile point variation, constructing lower- and upper-bound scenarios corresponding to the 10th and 40th percentiles, respectively. Based on these extreme cases, we recalculate the individual DLS CF values (Fig. 7). At the national level, this adjustment does not affect the overall climate target, as the target itself does not rely on the specific definition of individual DLS CF. However, it does cause slight variations in the individual CF ceilings (Fig. 9). Under the baseline DLS CF scenario, the individual CF ceilings for the low, medium, and high mitigation scenarios are 16.4 tCO_2, 11.2 tCO_2, and 8.3 tCO_2, respectively (as shown in Fig. 4 of the main text). When applying the lower-bound scenario (10th percentile), the ceilings become 16.5 tCO_2, 11.3 tCO_2, and 8.3 tCO_2, respectively; under the upper-bound scenario (40th percentile), they become 16.1 tCO_2, 11.1 tCO_2, and 8.2 tCO_2. These results indicate that even under extreme assumptions, the variation in individual DLS CF has only a limited effect on national-level mitigation indicators. At the provincial level, the estimated mitigation efforts under the baseline, lower-bound, and upper-bound DLS CF scenarios are shown in Fig. 5e-h of the main text, Fig. 10, and Fig. 11, respectively. The results show that across all mitigation scenarios (low, medium, and high), provincial emission reductions, reduction contributions, and reduction rates exhibit minimal changes. Combined with the earlier finding that whether or not DLS CF is considered to have negligible impact on national and provincial climate targets, these results are fully in line with expectations.

Finally, since China's climate targets are defined in terms of carbon intensity rather than absolute emission levels, uncertainty in GDP growth directly affects the actual mitigation effort. The preceding analysis is based on the medium GDP growth scenario, which assumes an average annual growth rate of 4% from 2025 to 2030. To assess the impact of GDP fluctuations, we further calculate the national and provincial emission reduction rates under the low (3.5%) and high (4.5%) GDP growth scenarios. The associated uncertainty ranges are illustrated by error bars in Fig. 12. The results show that changes in GDP growth scenarios have a relatively small effect on emission reduction rates, and this pattern holds consistently across all mitigation scenarios. In contrast, variations in mitigation scenarios—i.e., different carbon intensity reduction targets—have a significant impact on emission reduction rates. This indicates that policy ambition itself is the primary driver of differences in mitigation intensity. Therefore, at both the national and provincial levels, the design of climate targets has a much greater influence on reduction rates than the uncertainty in economic growth trajectories.

8 Additional tables and figures

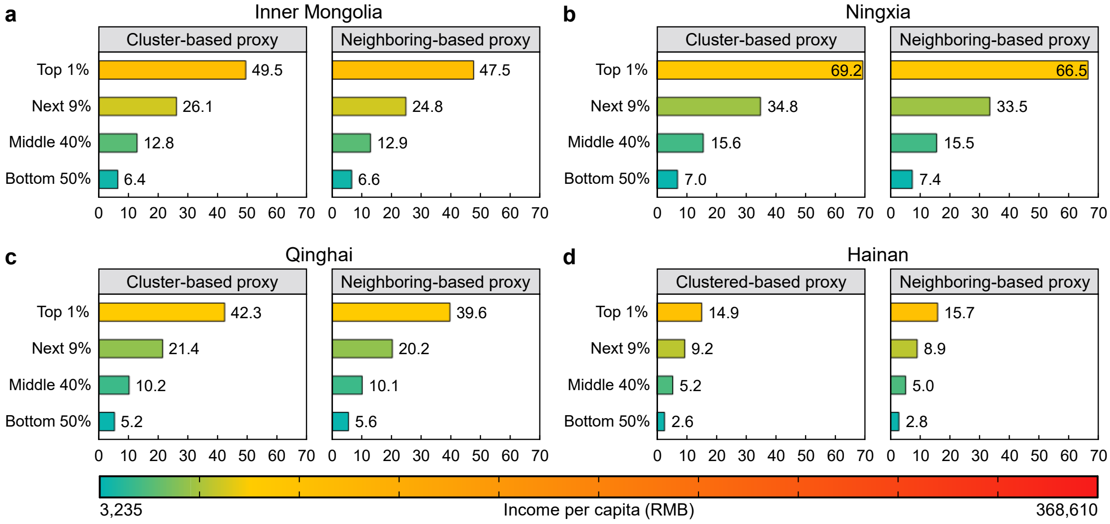

Fig. 8. Per capita carbon footprints by income group in data-deficient provinces under different proxy approaches

Note: **a,** Per capita carbon footprints by income group for Inner Mongolia under different proxy approaches. The cluster-based and neighboring-based proxies are Xinjiang and Shanxi, respectively. **b,** Per capita carbon footprints by income group for Ningxia. The cluster-based and neighboring-based proxies are Xinjiang and Gansu, respectively. **c,** Per capita carbon footprints by income group for Qinghai. The cluster-based and neighboring-based proxies are Xinjiang and Gansu, respectively. **d,** Per capita carbon footprints by income group for Hainan. The cluster-based and neighboring-based proxies are Jilin and Guangxi, respectively.

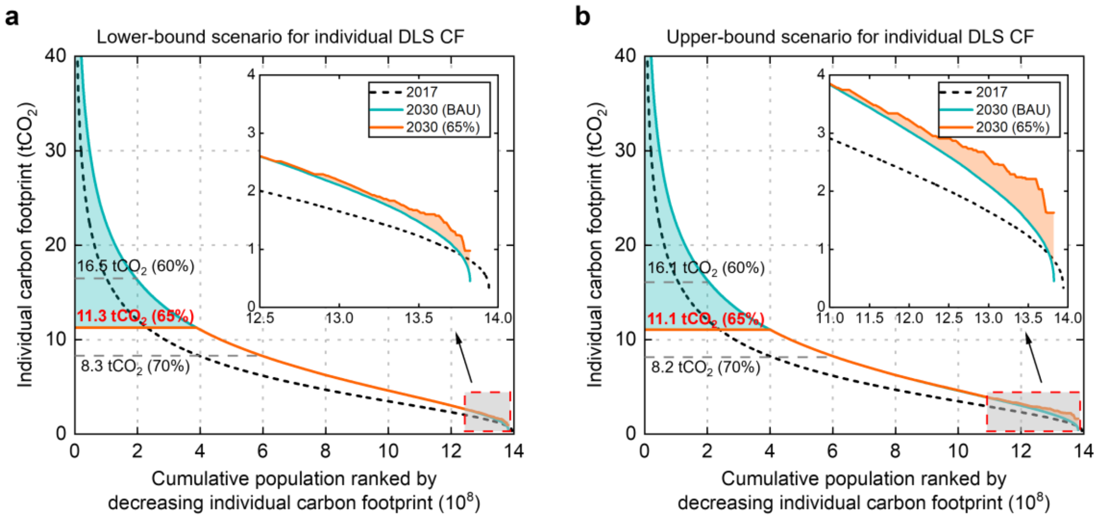

Fig. 9. National population in 2030 (1.38 billion), sorted by decreasing individual carbon footprint under the lower-bound (a) and upper-bound (b) scenario for individual DLS CF

Note: The cyan and orange curves represent the BAU and 65% mitigation scenarios in 2030, respectively, with national emissions of 13.61 $GtCO_2$ and 10.12 $GtCO_2$. The black dashed line shows the 2017 baseline (10.2 $GtCO_2$). The shaded areas indicate the total CFs to be reduced (cyan) or increased (orange) relative to the 65% target. The upper and lower grey horizontal dashed lines represent the individual CF ceilings under the 60% and 70% mitigation scenarios, respectively.

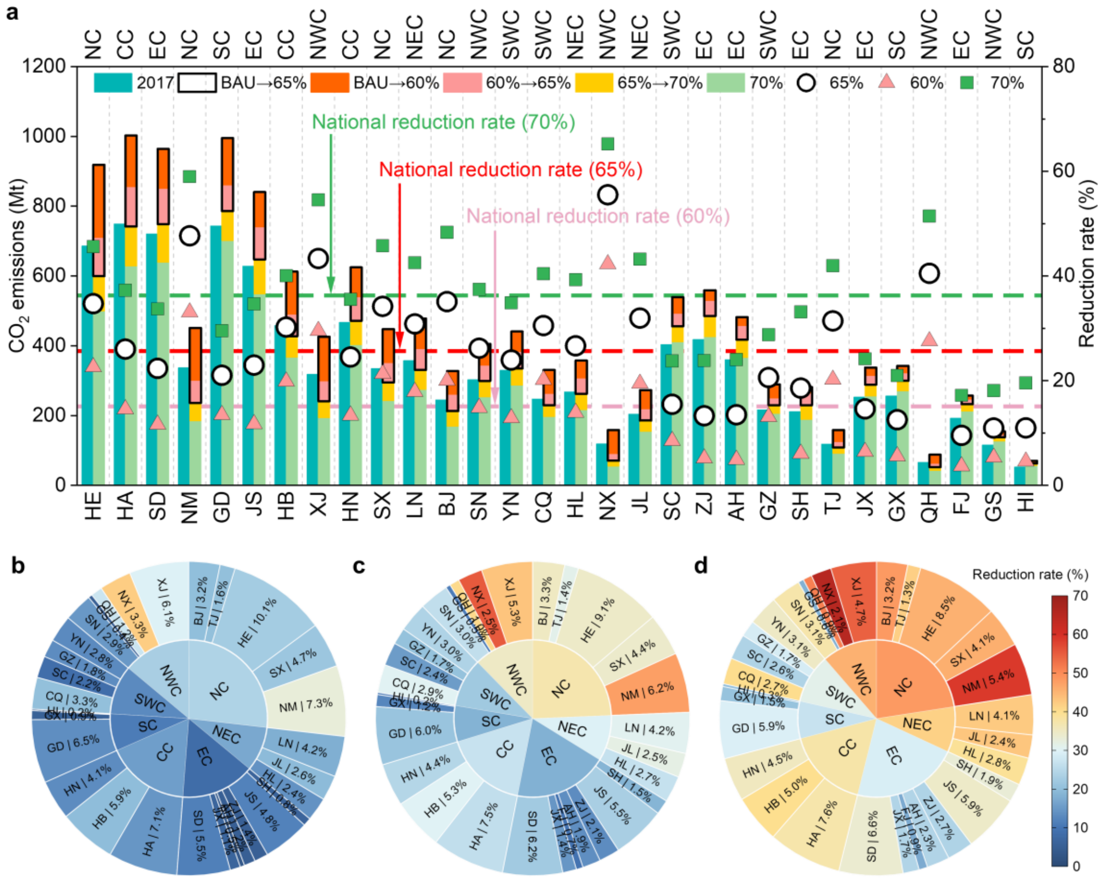

Fig.10. Provincial mitigation efforts in 2030 under the lower-bound scenario for individual DLS CF

Note: **a,** Emission reductions (bars, Mt) and reduction rates (dots, %) across provinces under different mitigation scenarios, with provinces ordered from left to right by emission reductions in the medium scenario. Dashed lines represent national reduction rates under each scenario. Reduction rate is calculated as the emission reduction divided by the province's BAU emissions. **b–d,** Emission reduction contributions across provinces under the low, medium, and high reduction scenarios. The color of each sector represents the province's emission reduction rate. The full names of acronyms are as follows: BJ: Beijing, TJ: Tianjin, HE: Hebei, SX: Shanxi, NM: Inner Mongolia, LN: Liaoning, JL: Jilin, HL: Heilongjiang, SH: Shanghai, JS: Jiangsu, ZJ: Zhejiang, AH: Anhui, FJ: Fujian, JX: Jiangxi, SD: Shandong, HA: Henan, HB: Hubei, HN: Hunan, GD: Guangdong, GX: Guangxi, HI: Hainan, CQ: Chongqing, SC: Sichuan, GZ: Guizhou, YN: Yunnan, SN: Shaanxi, GS: Gansu, QH: Qinghai, NX: Ningxia, XJ: Xinjiang, North China: NC, Northeast China: NEC, East China: EC, Central China: CC, South China: SC, Southwest China: SWC, Northwest China: NWC.

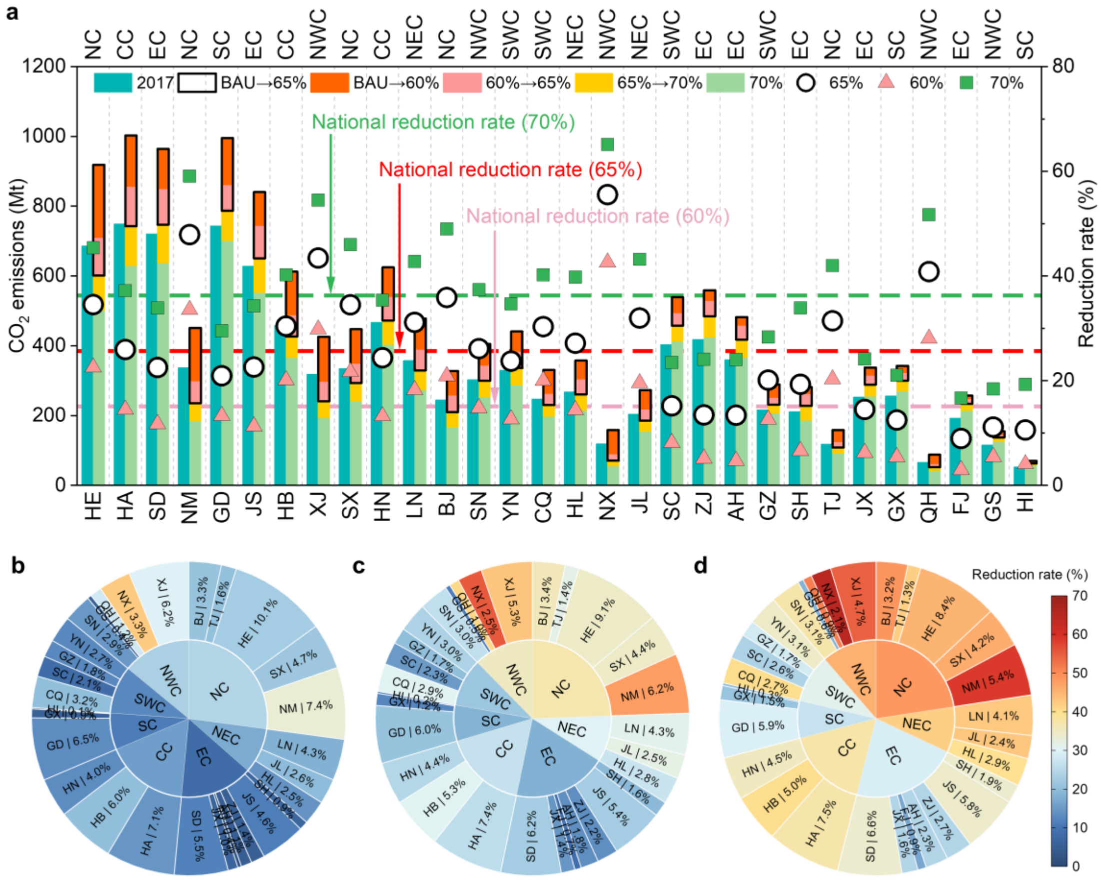

Fig.11. Provincial mitigation efforts in 2030 under the upper-bound scenario for individual DLS CF

Note: **a,** Emission reductions (bars, Mt) and reduction rates (dots, %) across provinces under different mitigation scenarios, with provinces ordered from left to right by emission reductions in the medium scenario. Dashed lines represent national reduction rates under each scenario. Reduction rate is calculated as the emission reduction divided by the province's BAU emissions. **b–d,** Emission reduction contributions across provinces under the low, medium, and high reduction scenarios. The color of each sector represents the province's emission reduction rate. The full names of acronyms are as follows: BJ: Beijing, TJ: Tianjin, HE: Hebei, SX: Shanxi, NM: Inner Mongolia, LN: Liaoning, JL: Jilin, HL: Heilongjiang, SH: Shanghai, JS: Jiangsu, ZJ: Zhejiang, AH: Anhui, FJ: Fujian, JX: Jiangxi, SD: Shandong, HA: Henan, HB: Hubei, HN: Hunan, GD: Guangdong, GX: Guangxi, HI: Hainan, CQ: Chongqing, SC: Sichuan, GZ: Guizhou, YN: Yunnan, SN: Shaanxi, GS: Gansu, QH: Qinghai, NX: Ningxia, XJ: Xinjiang, North China: NC, Northeast China: NEC, East China: EC, Central China: CC, South China: SC, Southwest China: SWC, Northwest China: NWC.

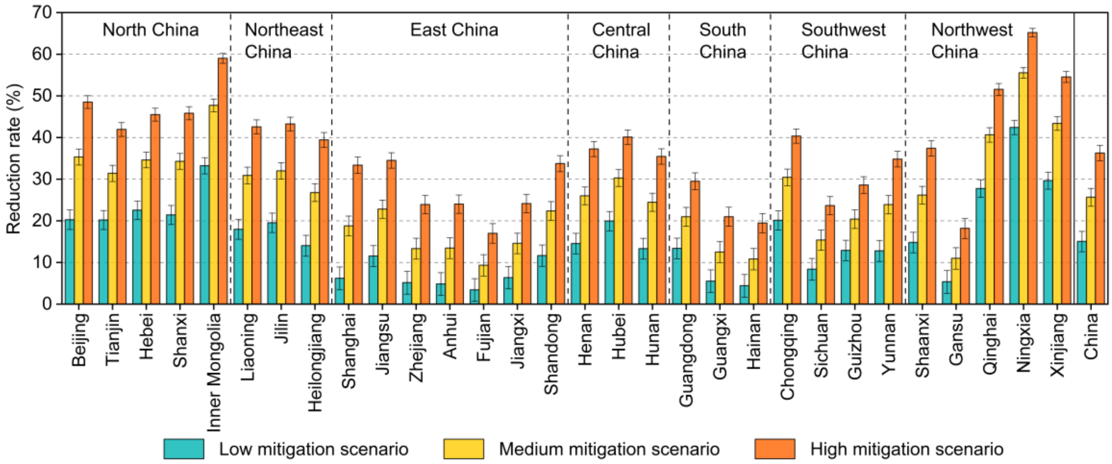

Fig. 12. Emission reduction rates across China and its provinces under different mitigation scenarios

Note: each bar represents the emission reduction rate under the medium GDP growth scenario (average annual growth of 4% from 2025 to 2030). The error bars indicate the uncertainty range resulting from GDP growth variations: the upper and lower bounds correspond to the high (4.5%) and low (3.5%) GDP growth scenarios, respectively.

Table 7. Provincial per-capita carbon footprint by income group in 2017 under different income elasticity scenarios

Province	Scenario	Per-capita carbon footprint (tCO_2)			
		Top 1%	Next 9%	Middle 40%	Bottom 50%
Beijing	$\alpha = 0.72$ (Baseline)	32.2	18.7	10.6	5.5
	$\alpha = 0.6$	28.7	17.7	10.6	5.8
	$\alpha = 1$	43.5	21.4	10.6	4.8
Tianjin	$\alpha = 0.65$ (Baseline)	35	16.3	7.8	3.7
	$\alpha = 0.6$	33.5	15.9	7.8	3.8
	$\alpha = 1$	49.2	18.7	7.5	3.2
Hebei	$\alpha = 0.8$ (Baseline)	39.1	17.7	8.7	4
	$\alpha = 0.6$	36.3	16.6	8.7	4.3
	$\alpha = 1$	42.6	18.9	8.7	3.7
Shanxi	$\alpha = 0.8$ (Baseline)	34	17.7	8.9	4.3
	$\alpha = 0.6$	30.7	16.4	8.9	4.7
	$\alpha = 1$	37.9	19	8.9	4
Inner Mongolia	$\alpha = 0.76$ (Baseline)	49.5	26.1	12.8	6.4
	$\alpha = 0.6$	46.4	24.8	12.7	6.8
	$\alpha = 1$	55.1	28.1	12.9	5.9
Liaoning	$\alpha = 0.92$ (Baseline)	31	17.1	8.1	3.2
	$\alpha = 0.6$	25.4	14.7	8	3.8
	$\alpha = 1$	32.8	17.7	8.1	3
Jilin	$\alpha = 0.64$ (Baseline)	22.3	13.7	7.7	3.9
	$\alpha = 0.6$	22.1	13.5	7.7	4
	$\alpha = 1$	25.7	14.9	7.8	3.6
Heilongjiang	$\alpha = 0.72$ (Baseline)	22.6	13.4	7.5	3.8
	$\alpha = 0.6$	21.3	12.8	7.4	4
	$\alpha = 1$	26.1	14.8	7.5	3.5
Shanghai	$\alpha = 0.6$ (Baseline)	14.8	11.4	8	5
	$\alpha = 0.6$	14.8	11.4	8	5
	$\alpha = 1$	19.3	13.3	8.2	4.4
Jiangsu	$\alpha = 0.76$ (Baseline)	20.9	12.9	7.2	3.5
	$\alpha = 0.6$	18.8	12	7.2	3.7
	$\alpha = 1$	24.6	14.2	7.2	3.2
Zhejiang	$\alpha = 0.69$ (Baseline)	14.4	9.6	6.4	3.8
	$\alpha = 0.6$	13.8	9.3	6.3	3.9

	$\alpha = 1$	17.1	10.7	6.5	3.5
Anhui	$\alpha = 0.83$ (Baseline)	14.9	9.5	5.6	3.1
	$\alpha = 0.6$	12.7	8.6	5.5	3.4
	$\alpha = 1$	16.9	10.2	5.6	3
Fujian	$\alpha = 0.64$ (Baseline)	12.2	7.5	4.4	2.5
	$\alpha = 0.6$	11.9	7.4	4.4	2.5
	$\alpha = 1$	15.1	8.6	4.4	2.2
Jiangxi	$\alpha = 0.77$ (Baseline)	16.4	9.6	5.3	2.8
	$\alpha = 0.6$	15.2	9.1	5.2	2.9
	$\alpha = 1$	18.2	10.3	5.3	2.6
Shandong	$\alpha = 0.8$ (Baseline)	21.1	12.5	6.9	3.4
	$\alpha = 0.6$	18.7	11.5	6.8	3.7
	$\alpha = 1$	24.2	13.6	6.9	3.2
Henan	$\alpha = 0.82$ (Baseline)	21.5	12.6	7.1	3.9
	$\alpha = 0.6$	19.4	11.7	7.1	4.1
	$\alpha = 1$	23.5	13.3	7.1	3.7
Hubei	$\alpha = 0.7$ (Baseline)	36.4	15.7	7.1	3.3
	$\alpha = 0.6$	35.5	15.3	7.1	3.4
	$\alpha = 1$	39.6	16.9	7.1	3
Hunan	$\alpha = 0.9$ (Baseline)	25.2	13.8	6.7	3
	$\alpha = 0.6$	21.7	12.5	6.6	3.4
	$\alpha = 1$	26.7	14.3	6.7	2.9
Guangdong	$\alpha = 0.66$ (Baseline)	34.2	12.1	5.6	2.5
	$\alpha = 0.6$	33.5	11.8	5.6	2.6
	$\alpha = 1$	38.9	13.8	5.6	2.1
Guangxi	$\alpha = 0.75$ (Baseline)	15.7	8.7	4.9	2.6
	$\alpha = 0.6$	14.6	8.2	4.8	2.8
	$\alpha = 1$	17.9	9.4	4.9	2.5
Hainan	$\alpha = 0.77$ (Baseline)	14.9	9.2	5.2	2.6
	$\alpha = 0.6$	13.5	8.7	5.2	2.7
	$\alpha = 1$	17.1	10	5.2	2.4
Chongqing	$\alpha = 0.8$ (Baseline)	39.9	16.2	7.1	3.3
	$\alpha = 0.6$	37.5	15.2	7.1	3.5
	$\alpha = 1$	42.9	17.1	7.1	3.1
Sichuan	$\alpha = 0.75$ (Baseline)	18.9	9.1	4.6	2.1
	$\alpha = 0.6$	17.6	8.5	4.6	2.3

	$\alpha = 1$	21.5	9.9	4.6	1.9
Guizhou	$\alpha = 0.73$ (Baseline)	24.9	11.2	5.1	2.6
	$\alpha = 0.6$	23.6	10.7	5	2.7
	$\alpha = 1$	28.2	12.3	5	2.4
Yunnan	$\alpha = 0.74$ (Baseline)	19.4	11.6	6.5	3.7
	$\alpha = 0.6$	18.2	11.2	6.4	3.8
	$\alpha = 1$	22	12.5	6.4	3.5
Shaanxi	$\alpha = 0.75$ (Baseline)	22	13.2	7.5	3.7
	$\alpha = 0.6$	20.5	12.6	7.4	3.9
	$\alpha = 1$	25.1	14.3	7.5	3.5
Gansu	$\alpha = 0.78$ (Baseline)	14.9	8.3	4.3	2.2
	$\alpha = 0.6$	13.4	7.6	4.3	2.3
	$\alpha = 1$	17.2	9.1	4.3	2
Qinghai	$\alpha = 0.76$ (Baseline)	42.3	21.4	10.2	5.2
	$\alpha = 0.6$	40.6	20.7	10.1	5.5
	$\alpha = 1$	45.6	22.6	10.2	4.9
Ningxia	$\alpha = 1$ (Baseline)	69.2	34.8	15.6	7
	$\alpha = 0.6$	59.3	31	15.4	8
	$\alpha = 1$	69.2	34.8	15.6	7
Xinjiang	$\alpha = 0.84$ (Baseline)	48.3	24.7	11.7	5.9
	$\alpha = 0.6$	44.8	23.3	11.6	6.3
	$\alpha = 1$	51.1	25.6	11.7	5.7

Table 8. Provincial per-capita carbon footprint by income group in 2017 under different wealth elasticity scenarios

Province	Scenario	Per-capita carbon footprint (tCO_2)			
		Top 1%	Next 9%	Middle 40%	Bottom 50%
Beijing	Baseline	32.2	18.7	10.6	5.5
	$\beta = 0.9$	30.9	18.3	10.6	5.6
	$\beta = 1.1$	33.5	19.1	10.6	5.4
Tianjin	Baseline	35	16.3	7.8	3.7
	$\beta = 0.9$	31.9	15.7	7.8	3.8
	$\beta = 1.1$	38.4	16.9	7.7	3.5
Hebei	Baseline	39.1	17.7	8.7	4
	$\beta = 0.9$	35.1	17	8.8	4.2
	$\beta = 1.1$	43.7	18.3	8.7	3.8
Shanxi	Baseline	34	17.7	8.9	4.3
	$\beta = 0.9$	31.3	17.1	9	4.5
	$\beta = 1.1$	37.2	18.3	8.9	4.2
Inner Mongolia	Baseline	49.5	26.1	12.8	6.4
	$\beta = 0.9$	44.9	25.1	12.9	6.6
	$\beta = 1.1$	54.5	27.1	12.7	6.2
Liaoning	Baseline	31	17.1	8.1	3.2
	$\beta = 0.9$	29.1	16.7	8.2	3.3
	$\beta = 1.1$	33.1	17.5	8.1	3.1
Jilin	Baseline	22.3	13.7	7.7	3.9
	$\beta = 0.9$	20.6	13.1	7.7	4.1
	$\beta = 1.1$	24.2	14.2	7.7	3.8
Heilongjiang	Baseline	22.6	13.4	7.5	3.8
	$\beta = 0.9$	21	13	7.5	3.9
	$\beta = 1.1$	24.3	13.8	7.4	3.8
Shanghai	Baseline	14.8	11.4	8	5
	$\beta = 0.9$	14.4	11.2	8	5.1
	$\beta = 1.1$	15.2	11.6	8	5
Jiangsu	Baseline	20.9	12.9	7.2	3.5
	$\beta = 0.9$	19.7	12.6	7.2	3.6
	$\beta = 1.1$	22.3	13.2	7.2	3.4
Zhejiang	Baseline	14.4	9.6	6.4	3.8
	$\beta = 0.9$	13.7	9.4	6.4	3.9

	$\beta = 1.1$	15.1	9.8	6.4	3.8
Anhui	Baseline	14.9	9.5	5.6	3.1
	$\beta = 0.9$	14.4	9.3	5.6	3.2
	$\beta = 1.1$	15.5	9.7	5.6	3.1
Fujian	Baseline	12.2	7.5	4.4	2.5
	$\beta = 0.9$	11.4	7.3	4.4	2.5
	$\beta = 1.1$	13	7.7	4.4	2.4
Jiangxi	Baseline	16.4	9.6	5.3	2.8
	$\beta = 0.9$	15.2	9.3	5.3	2.8
	$\beta = 1.1$	17.6	9.9	5.2	2.7
Shandong	Baseline	21.1	12.5	6.9	3.4
	$\beta = 0.9$	19.9	12.2	6.9	3.5
	$\beta = 1.1$	22.5	12.9	6.8	3.3
Henan	Baseline	21.5	12.6	7.1	3.9
	$\beta = 0.9$	20.1	12.2	7.2	4
	$\beta = 1.1$	22.9	13	7.1	3.8
Hubei	Baseline	36.4	15.7	7.1	3.3
	$\beta = 0.9$	31.7	15	7.2	3.5
	$\beta = 1.1$	41.6	16.5	7	3.1
Hunan	Baseline	25.2	13.8	6.7	3
	$\beta = 0.9$	23.4	13.4	6.7	3.1
	$\beta = 1.1$	27.2	14.3	6.7	2.9
Guangdong	Baseline	34.2	12.1	5.6	2.5
	$\beta = 0.9$	29.4	11.7	5.7	2.6
	$\beta = 1.1$	39.7	12.5	5.5	2.4
Guangxi	Baseline	15.7	8.7	4.9	2.6
	$\beta = 0.9$	14.5	8.4	4.9	2.7
	$\beta = 1.1$	17.1	8.9	4.9	2.6
Hainan	Baseline	14.9	9.2	5.2	2.6
	$\beta = 0.9$	14.1	9	5.2	2.6
	$\beta = 1.1$	15.8	9.5	5.2	2.5
Chongqing	Baseline	39.9	16.2	7.1	3.3
	$\beta = 0.9$	34.6	15.5	7.2	3.4
	$\beta = 1.1$	46.1	16.8	7	3.1
Sichuan	Baseline	18.9	9.1	4.6	2.1
	$\beta = 0.9$	17.1	8.8	4.7	2.2

	$\beta = 1.1$	21	9.4	4.6	2
	Baseline	24.9	11.2	5.1	2.6
Guizhou	$\beta = 0.9$	22	10.7	5.1	2.7
	$\beta = 1.1$	28.3	11.7	5	2.5
	Baseline	19.4	11.6	6.5	3.7
Yunnan	$\beta = 0.9$	18.1	11.2	6.5	3.8
	$\beta = 1.1$	20.8	12	6.4	3.6
	Baseline	22	13.2	7.5	3.7
Shaanxi	$\beta = 0.9$	20.5	12.8	7.5	3.8
	$\beta = 1.1$	23.6	13.7	7.5	3.6
	Baseline	14.9	8.3	4.3	2.2
Gansu	$\beta = 0.9$	13.9	8	4.3	2.2
	$\beta = 1.1$	16.1	8.5	4.3	2.1
	Baseline	42.3	21.4	10.2	5.2
Qinghai	$\beta = 0.9$	37.8	20.4	10.3	5.4
	$\beta = 1.1$	47.3	22.4	10.1	5
	Baseline	69.2	34.8	15.6	7
Ningxia	$\beta = 0.9$	63.2	33.5	15.7	7.3
	$\beta = 1.1$	76	36.2	15.5	6.7
	Baseline	48.3	24.7	11.7	5.9
Xinjiang	$\beta = 0.9$	43.5	23.6	11.8	6.1
	$\beta = 1.1$	53.6	25.7	11.6	5.7

Note: the baseline scenario represents $\beta = 1$, is the basis for the empirical analysis in this study.

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