2. Supplementary Information:

Item	Present?	Filename This should be the name the file is saved as when it is uploaded to our system, and should include the file extension. The extension must be .pdf	A brief, numerical description of file contents. i.e.: *Supplementary Figures 1-4, Supplementary Discussion, and Supplementary Tables 1-4.*
Supplementary Information	Yes	Supplementary information_NATSUSTAIN-19073894.pdf	Supplementary Tables 1-12, Supplementary Figures 1-3 and Supplementary references 1-4.
Reporting Summary	Yes	NATSUSTAIN-19073894_Reporting_Summary.pdf	

Economic development and converging household carbon footprints in China

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There are substantial differences in carbon footprints across households. This study applied an environmentally extended multiregional input-output (MRIO) approach to estimate household carbon footprints for 12 different income groups of China's 30 regions. Subsequently, carbon footprint Gini coefficients were calculated to measure carbon inequality for households across provinces. We found that the top 5% of income earners were responsible for 17% of the national household carbon footprints in 2012, while the bottom half of income earners caused only 25%. Carbon inequality declined with economic growth in China across space and time in two ways: first, carbon footprints were more similar in the wealthier coastal regions than in the poorer inland regions; second, China's national carbon footprint Gini coefficients declined from 0.44 in 2007 to 0.37 in 2012. We argue that economic growth not only increases income levels but also contributes to an overall reduction in carbon inequality in China.

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Mitigating climate change and reducing inequality are both critical goals for sustainable development. The seventeen United Nations sustainable development goals (SDGs) include both taking urgent action to combat climate change and reducing income inequality[1]. The carbon footprint, defined as the total carbon emissions caused directly and indirectly by an individual, organisation, event, or product, has been increasingly used to measure the impacts of human activity on global warming[2, 3]. An informed discussion of “fairness” or “justice” in processes of emissions reduction requires an understanding of the relation between emissions and income[4, 5]. Due to differences in income level, local conditions and lifestyle, there are great disparities in the average carbon footprint of households within and between countries[6]. This study aims to provide information to help policymakers understand some of the interactions and trade-offs between measures targeting inequality, poverty, and climate change mitigation. We do so by estimating the carbon footprint of different income groups in China.

Climate change mitigation and poverty alleviation provide mutual benefits. On the one hand, mitigating climate change, through reducing emissions, can have a positive effect on poverty alleviation[7] but might require pro-poor measures[8]. For example, the clean development mechanism (CDM) has created jobs for rural areas with a simultaneous increase in income, which helps the poor[9]. On the other hand, strategies and policies focused on the poor are of great significance for achieving emission-reduction targets[10], e.g., providing a daily living wage might have considerable carbon implications[11, 12]. There is growing understanding that the increase in income resulting from economic growth is not sufficient to reduce poverty and inequality if it is not inclusive and if it does not take careful account of the three key dimensions of sustainable development – economic, social and environmental[13].

China aims to consider social equality in its climate change actions by allocating more responsibilities for climate change mitigation to its wealthier regions[14]. The government has targeted a reduction in energy intensity and carbon intensity by 15% and 18%, respectively, during the 13th five-year period (2016-2020)[15], and wealthiest eastern provinces (such as Beijing, Shanghai, and Tianjin) are required to reduce their energy intensity by 17%, while the targets in some poorer western provinces (such as Tibet, Qinghai, and Xinjiang) are 10%. There are also many examples of making climate mitigation pro poor[16], especially with regard to removal of subsidies for fossil fuels[17]. In addition to studies of taxes and subsidies in developed countries, the politics of reform efforts in developing regions has been widely researched[18]. However, climate change researchers have rarely considered equality at the household level in China, and this needs to be explored and analysed[19].

Many studies have estimated the inequality of carbon emissions at national[20] or sub-national levels[21], while studies comparing household level carbon inequality are still limited[22]. Hubacek *et al*.[11, 23] estimated the carbon footprints of four household groups in 30 developed countries and 90 developing countries. The results show that the top 10% of income earners were responsible for 36% of global carbon emissions in 2010, while the bottom half of global income earners caused only approximately 13%. There are more studies at the national level. López *et al*.[24] compared the household carbon footprint for eight social groups in Spain and found that higher income households imported more carbon emissions compared to lower income households. However, most of the existing research at the national level is based on single region input-output tables, and thus ignores regional disparities in income, as well as significant regional differences in production technologies, fuel mix and economic structure. For example, Wiedenhofer *et al.*[4] measured national inequality of household carbon footprints across five rural income groups and eight urban income groups in China. We extended their research from both time and space perspectives, using multiregional input-output (MRIO) models. Specifically, we utilized the latest socioeconomic datasets to compile China's 2012 MRIO table and estimated household carbon footprints for twelve income groups (five rural and seven urban) in 30 Chinese provinces in 2007 and 2012. The inequality in the household carbon footprint was quantified with a carbon footprint Gini (CF-Gini) coefficient. Important findings are that while average per capita carbon footprints in most poor provinces increased and those in some wealthy provinces declined, carbon inequality declines with economic growth in China across space and time. Those interesting conclusions provide policy implications to understand the interactions and trade-offs between measures targeting inequality and climate change mitigation, which are both critical for sustainable development and an important focus of the UN SDGs.

Results

China's households contributed 34% of the national carbon footprint in 2012 (see Supplementary Table 1 and Supplementary Table 2 for consumption-based emissions of China's 30 provinces). The remainder was induced by government consumption (7%), fixed capital formation (57%), and inventory change (3%). We don't attempt to attribute to this 66% to households.

Carbon footprint. The proportion of carbon footprint attributed to households is relatively lower in China than developed countries. For example, the household shares of the carbon footprint in the USA and the UK were 70% and 69%, respectively, in 2012. There are significant differences in household carbon contributions across provinces in China. In Guangdong and Shanghai, for example, households were responsible for 48% and 47%, respectively, of the total carbon footprint in 2012. By comparison, the household shares of the carbon footprint were only 24% and 27%, respectively, in the two less-developed provinces Ningxia and Shanxi in western China.

At the national level, China's household carbon footprints increased by 27% or 2,113 million tonnes (Mt) of CO_2 between 2007 and 2012, with 72% of this increase being due to consumption in urban areas. The household carbon footprint increased much faster in poorer western regions than in wealthier eastern regions: specifically, it increased by 37%, 32%, and 21%, respectively, in western, central and eastern China. Although western China is relatively poor compared to eastern China, its growth rates in consumption and gross domestic product (GDP) have been much faster since the global financial crisis. At the provincial level, the household carbon footprint increased in most provinces. For example, the household carbon footprint of Guangxi and Shaanxi, two provinces in western China, increased by 39% and 37%, respectively, while the household carbon footprint in the three most affluent provinces – Tianjin, Beijing, and Shanghai – decreased by 22%, 6%, and 5%, respectively, mainly due to the decline (percentage changed in this ratio) in carbon intensity (i.e., CO_2 emissions per unit of economic output) and the effect of outsourcing pollution[25]. The carbon intensities of Beijing, Shanghai, and Tianjin declined by 53%, 32%, and 37%, respectively, between 2007 and 2012, and the share of low-carbon goods and services in household consumption increased in these provinces. Between 2007 and 2012, for example, the proportions of wholesale and retailing products, and of leasing and commercial services in Beijing's household expenditure increased by 2 and 3 percentage points, respectively.

Per capita carbon footprint. The per capita household carbon footprint varies greatly across China's provinces, but wealthy regions usually have a higher per capita carbon footprint than poor regions. In 2007, the per capita carbon footprint of three affluent eastern coastal provinces (Tianjin, Shanghai, and Beijing) was over 4.0 tonnes of CO_2 (tCO_2), while those in central and western provinces (Hainan, Guangxi, Henan, and Yunnan) were less than 1.0 tCO_2 (Fig. 1). For example, the per capita carbon footprint in Beijing, the capital of China, was 4.2 tCO_2, which was over five times that in Guangxi, a poorer western province. In 2012, Inner Mongolia was the province with the highest per capita household carbon footprint (4.4 tCO_2), which was four times that of the smallest one in Jiangxi (1.1 tCO_2). Inner Mongolia is a western province, and its household consumption increased rapidly between 2007 and 2012. In addition, Inner Mongolia is one of the main providers of coal-fired electricity, which has a higher carbon intensity. For example, Inner Mongolia provides large amounts of electricity to neighbouring regions, with 133 billion kilowatt hours (kWh) in net electricity exports in 2012. China's national average per capita carbon footprint increased by 23% from 1.6 tCO_2 in 2007 to 2.0 tCO_2 in 2012. Average per capita carbon footprints in most poorer provinces increased, while those in some wealthier provinces declined. Overall, China's regional carbon inequality declined between 2007 and 2012. We further explored whether conditional convergence exists in China. Our estimates show that provinces with the lowest per capita carbon footprint in 2007 were the provinces in which the carbon footprint grew the most from 2007 to 2012. By estimating convergences but differentiating between rural and urban households, results show that the convergence occurred more rapidly in urban households (see Supplementary Fig. 1).

Urban residents, accounting for 53% of China's population, induced 74% of the national household carbon footprint in 2012. The average per capita footprint of urban residents was 2.8 tCO_2 in 2012, which was 2.5 times that of rural residents (1.1 tCO_2), while the average per capita expenditure was 2.9 times that of rural residents. Fig. 2 shows per capita carbon footprint of 12 income groups in 30 of China's provinces in 2012. The per capita carbon footprint is much higher for urban residents than for rural residents across all provinces. The gap in per capita carbon footprints between urban and rural residents is much larger in poorer western China. For example, the per capita carbon footprint of urban residents in Guizhou (Fig. 2, row 6, column 5), whose GDP per capita was the smallest in China in 2012, was 2.7 times that of Guizhou's rural residents. By comparison, the per capita carbon footprints of urban residents in Beijing (Fig. 2, row 1, column 2) and Shanghai (Fig. 2, row 6, column 3), two of the most affluent regions in China, were in both cases 'only' 1.3 times of the footprint of their respective rural residents.

It is surprising that the income groups with the highest per capita household carbon footprint are mostly located in relatively poor provinces (see Supplementary Table 3). Per capita carbon footprints of very wealthy urban groups in Inner Mongolia, Heilongjiang, and Xinjiang were 16.9, 10.9, and 10.1 tCO_2 in 2012, respectively, which were similar to the estimated range for the USA (10.4 to 20 tCO_2)[4, 26, 27]. The per capita household expenditure of the top 10% in terms of urban income in Inner Mongolia was 45,246 yuan, and even higher than that of the top 10% of the urban income earners in Beijing (45,190 yuan) and Tianjin (41,214 yuan). Although the per capita household expenditure of the top 10% of the urban groups in Inner Mongolia and Beijing was almost equal, the two groups had a large gap in their per capita household carbon footprints (Fig. 2). This is mainly caused by the differences in their carbon intensity. The carbon intensity of Inner Mongolia was 149 g/yuan in 2012, which was the highest among the 30 Chinese provinces and approximately 10 times that in Beijing (15 g/yuan). One possible reason for this difference is the higher number of heating days and availability of natural resources influencing the fuel mix[28]. Additionally, relatively low administrative efficiency and loose environmental regulations result in high levels of carbon emissions. For example, Inner Mongolia struggles to design an appropriate path for economic development accompanied by a low carbon transition in consumption patterns[29]. The carbon intensities of Heilongjiang and Xinjiang were 79 and 129 g/yuan in 2012, respectively, which were also above China's national average (50 g/yuan). In addition to the carbon intensity, the different consumption pattern of households in poor and rich regions also plays an important role in the discrepancy (see Supplementary Table 4). For example, rural areas in relatively poor provinces in 2012, including Inner Mongolia (1.22 tCO_2), Shanxi (1.13 tCO_2) and Ningxia (1.07 tCO_2), show relatively high per capita carbon footprint in terms of residence expenditure, with this item closely related to high energy-consuming indirect sectoral emissions and direct household emissions. Simultaneously, the consumption from different sources (i.e., local production, domestic inflow, or international imports) can partially explain the discrepancy (see Supplementary Table 5). Households consumption in poorer provinces has a higher proportion of local production but lower proportions of both domestic inflow and international import.

The income groups with the lowest per capita household carbon footprint are also mostly located in relatively poor provinces (see Supplementary Table 6). The per capita carbon footprints of the poor rural income groups in Guangxi, Jiangxi, Hainan, and Yunnan were only 0.4 tCO_2 in 2012, which was less than half of the average in India in 2011 (0.9 tCO_2)[4]. This is mainly due to their lower household expenditure: per capita household expenditure for the poor rural income groups in these four provinces was approximately 3,000 yuan in 2012, which was only a quarter of China's national average (11,990 yuan).

Carbon inequality. We measure household carbon inequality using carbon footprint Gini (CF-Gini) coefficients, with zero representing perfect equality and one representing perfect inequality. Carbon inequality declines with economic growth in China. At the national level, China's CF-Gini coefficient declined from 0.44 in 2007 to 0.37 in 2012 (Fig. 3), while the officially released Gini coefficient for income dropped slightly from 0.48 in 2007 to 0.47 in 2012[30]. In 2012, the top 5% of income earners were responsible for 17% of the national household carbon footprint, while the bottom half of income earners caused only 25%. At the provincial level, the CF-Gini coefficients of the wealthier eastern coastal provinces were much lower than those of the poorer western provinces. In 2012, the four most affluent provinces (Tianjin, Beijing, Shanghai, and Jiangsu), whose GDP per capita was over 68,000 yuan in 2012, had the lowest CF-Gini coefficients (0.19, 0.16, 0.14, and 0.18, respectively). By comparison, the CF-Gini coefficients of Xinjiang and Guizhou, two western provinces, were 0.40 and 0.38, respectively, which were higher than China's national CF-Gini coefficient in 2012. Between 2007 and 2012, the CF-Gini coefficients of most provinces declined except for Jiangxi and Chongqing (see Supplementary Fig. 3), and the inequality in less-developed western provinces declined faster. For example, the CF-Gini coefficients of Sichuan and Qinghai declined by 0.21 and 0.20, respectively. Based upon these observations, it can be concluded that carbon inequality declines with economic growth in China across space and time (see Supplementary Table 7 for details).

The estimated CF-Gini declined across all expenditure categories of national, urban and rural households from 2007 to 2012, with a simultaneous decline of income Gini excluding rural education (Fig. 4), while changes in provincial CF-Gini varied among the expenditure categories during this period (see Supplementary Tables 8 and 9). This reflects the close linkage of carbon inequality with consumption volume (Supplementary Table 4) and expenditure pattern (Supplementary Table 5). To reduce the CF-Gini requires an increase in income of the poor, indicating the importance of eradicating poverty, and changes of lifestyles and consumption patterns and thus the reduction of carbon emissions of higher income households. To avoid larger consumption-based emissions appropriate carbon mitigation measures are needed; otherwise, a declining CF-Gini leads to larger overall emissions. By encouraging green lifestyles, especially among wealthy groups, carbon footprints can be reduced by changes in expenditure structures towards low-carbon goods and products, thereby, mitigating climate change. In addition, demographic change, e.g. a dynamic composition of population through rural-urban migration, can also influence. By moving of the rural poor to urban areas and climbing up the income (and thus consumption) ladder, the CF-Gini tends to decrease.

Conclusions

There are large inequalities between household carbon footprints within and across China's provinces. First, the per capita carbon footprint of urban residents is 2.5 times of the footprint of rural residents. China's economy has been growing rapidly, but there is still a visible urban-rural divide in the nation. This is one of the greatest challenges for China's sustainable development. Urban residents have much higher household incomes and more modern lifestyles, resulting in higher carbon footprints compared to rural residents.

Second, the per capita carbon footprint varies greatly across China's provinces. Generally, the per capita carbon footprint is larger in the wealthier coastal regions than in the poorer inland regions. From a production perspective, China's western region is more carbon intensive due to its reliance on coal-based heavy industry, relatively lower efficiency and weaker environmental regulations. From a consumption perspective, however, most of the high emissions-intensive goods produced in western China are consumed by residents in eastern China and more emissions are ultimately exported to other regions than locally consumed in the west. China has made great efforts to balance economic development among the provinces and to narrow the gap between the east and the west, such as with the Western Development Strategy. Since the global financial crisis, the growth in consumption and GDP has been faster in western China than in eastern China. As a result, the carbon footprint gap between the east and west declined between 2007 and 2012.

Third, the size of the carbon footprint varies across income groups in China. The per capita carbon footprint of the wealthiest groups in Mongolia, Heilongjiang, and Xinjiang was similar with the average level in the USA, while the per capita carbon footprint of the poorest groups in Guangxi, Jiangxi, Hainan and Yunnan was only 0.4 tCO_2, which was less than half of the average carbon footprint in India.

Carbon inequality has declined with economic growth in China. We argue that economic growth not only increases income levels but also contributes to higher shares of low-carbon consumption items in higher income groups and an overall reduction in carbon inequality in China. But overall, urban and wealthy regions tend to have a greater carbon footprint, as a high income drives a high carbon footprint lifestyle. Hence, with the income growth and economic development experienced in China from 2007 to 2012, the overall size of the carbon footprint increased. However, we emphasize the significance of studying changes in carbon inequality in addition to the overall levels. Decarbonizing domestic production contributes to the decline of carbon intensity in China. The decline of carbon footprints in rich households contributed to decarbonization in rich regions; thus, there is a need to decarbonize poor areas as well. Although richer households consume more goods and have higher carbon footprints than lower income groups, they tend to consume a larger share of less carbon intensive consumption items. Thus, the divergence declines. It is important to truly decarbonize consumption patterns to reduce overall carbon footprints.

According to our research, carbon inequality has improved during this time period and across provinces. Carbon footprints show less inequality in wealthier eastern coastal regions than in poorer western inland regions, and our results show that the income groups with the highest (and lowest) per capita carbon footprint are mostly located in relatively poor provinces. At the national level, China's CF-Gini coefficient declined from 0.44 in 2007 to 0.37 in 2012. At the provincial level, the CF-Gini coefficients of most provinces declined with only two exceptions (i.e., Jiangxi and Chongqing). China has managed to decrease both income and carbon inequality during the observed time period. There might be idiosyncratic and context specific differences among developing countries but the insights we gained achieving further decarbonization through changing the energy mix, improving carbon efficiencies in production and changes in consumption patterns should hold for other countries as well.

Governments need to pay more attention to inequality at the household level when considering climate change mitigation actions. Although China has considered regional equality in distributing climate change mitigation responsibilities, equality at the household or individual level is seldom considered. The carbon footprint and corresponding CF-Gini coefficient are useful indicators for climate mitigation. Based on the findings, the gap in carbon footprints can be narrowed by simultaneously increasing the income of the poor to eradicate poverty and changing the lifestyles of the wealthy to reduce the carbon intensity of their consumption patterns. Additionally, there is nothing automatic about declining environmental impacts associated with economic growth. Improvements can be induced with appropriate legislation, monitoring and enforcement, as well as inducing changes in consumption patterns with environmental taxation, information and eco-labels, and other policy tools. Carbon mitigation also does not automatically lead to a reduction in inequality as especially poorer households are often times more affected by increases in prices of environmental resources, e.g. through a carbon tax. In other words, carbon mitigation can be regressive, that is affecting poorer households with higher carbon intensity more than richer households who can afford to have a higher share of services and other lower carbon consumption items. Therefore, mitigation actions need to be designed with the poorest segments of society in mind.

Methods

This study applied an environmentally extended MRIO approach to estimate household carbon footprints for 12 different income groups of China's 30 regions. Carbon footprint Gini coefficients were calculated to measure carbon inequality for households.

Construction of MRIO tables. We compiled the 2012 MRIO table for China's 26 provinces and 4 cities, except Tibet, Hong Kong, Macao, and Taiwan (in total, 30 regions). The MRIO table was compiled using a gravity model based on the single regional input-output tables for China's provinces[31]. The MRIO table describes the economic linkages among 30 sectors in 30 Chinese regions. Final demand is divided into five categories, including rural household consumption, urban household consumption, government consumption, fixed capital formation, and changes in inventories.

To calculate carbon emissions embodied in imports, we connected China's MRIO tables to global MRIO models, which are based on version 9 of the GTAP database[32]. The GTAP database describes international trade connections for 57 economic sectors among 129 regions in 2007 and 140 regions in 2011. China's 2007 MRIO table was connected to the 2007 GTAP database, while China's 2012 MRIO table was connected to the 2011 GTAP database. All input-output tables are deflated to 2012 prices using the double-deflation method[33]. China is one of the regions in the GTAP database, so we disaggregated the China-related sections in the GTAP model into 30-region and 30-sector tables according to our Chinese MRIO models. The new global MRIO then includes 30 Chinese provinces and 128 (or 139) countries with 30 sectors for Chinese provinces and 57 sectors for foreign countries. For the final demand, there are five sectors for Chinese provinces and three sectors for foreign countries (investment, household consumption, and government consumption).

We choose the GTAP database because of the suitable region and sector classification. First, this study focuses on carbon footprint in China. The emissions embodied in bilateral trade between China and developing countries are critical to the results of this study. However, many developing regions have been aggregated to "Rest of the World" in WIOD and some other database such as OECD-ICIO, which introduces uncertainty. For example, the latest WIOD database covers forty-three countries, including 7 developing regions, while latest EXIOBASE database covers 8 developing regions. By contrast, the GTAP database covers 77 developing regions[34]. Eora database has a heterogeneous classification, which impedes the comparing of results between countries. The harmonized version has 26-sectors, which is much less than the GTAP database. Sector aggregation has great impact on MRIO uncertainty. The use of double deflation is to make the MRIO table in 2007 and 2012 in constant price and thus comparable without inflation bias.

Environmentally extended input-output analysis. The MRIO model describes the economic linkages among different sectors in different regions using linear equation systems. The basic linear equation is

$$X = (I - A)^{-1} F \,, \tag{1}$$

$$X = \begin{bmatrix} x^1 \\ x^2 \\ \vdots \\ x^n \end{bmatrix}, \quad A = \begin{bmatrix} a^{11} & a^{12} & \cdots & a^{1n} \\ a^{21} & a^{22} & \cdots & a^{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a^{n1} & a^{n2} & \cdots & a^{nn} \end{bmatrix}, \quad F = \begin{bmatrix} f^{11} & f^{12} & \cdots & f^{1n} \\ f^{21} & f^{22} & \cdots & f^{2n} \\ \vdots & \vdots & \ddots & \vdots \\ f^{n1} & f^{n2} & \cdots & f^{nn} \end{bmatrix}, \tag{2}$$

where $X = \left(x_i^s\right)$ is the vector of total output and x_i^s is the total output of sector *i* in region *s*. I is the identity matrix, and $(I - A)^{-1}$ is the Leontief inverse matrix. The technical coefficient submatrix $A^{rs} = \left(a_{ij}^{rs}\right)$ is given by $a_{ij}^{rs} = z_{ij}^{rs} / x_j^s$, in which z_{ij}^{rs} represents the intersectoral monetary flows from sector *i* in region *r* to sector *j* in region *s*, and x_j^s is the total output of sector *j* in region *s*. $F = \left(f_i^{rs}\right)$ is the final demand matrix, and f_i^{rs} is the final demand of region *s* for the goods of sector *i* from region *r*.

Carbon footprints are calculated using environmental extended input-output analysis. Based on the carbon intensity (i.e., CO_2 emissions per unit of economic output), the total carbon footprint is calculated by

$$C = K\left(I - A\right)^{-1} F \,, \tag{3}$$

where C is the total carbon footprint, and K is a vector of the carbon intensity for all economic sectors in all regions. Final demand (i.e., F) can be divided into rural household consumption, urban household consumption, government consumption, fixed capital formation, and changes in inventories. Therefore, the household carbon footprint can be calculated as follows:

$$C_h = K\left(I - A\right)^{-1} H \tag{4}$$

where C_h is the household carbon footprint, and H is the household consumption, including rural and urban household consumption. The H matrix in equation (4) is a diagonalized matrix by sections, differentiating between domestic and imported goods[35]. Because we use MRIO tables at the provincial level, the domestic and imported goods are further divided into the self-production, domestic inflow and international import.

The household carbon footprint estimated by the MRIO model is aggregated into eight major categories of consumption: food, clothing, residence, household facilities, transport, education, health care, and others[36]. Carbon emissions emitted from direct rural and urban household energy use are not included in equation (4) because the input-output model only estimates the carbon emissions indirectly emitted in economically productive sectors. In this study, directed energy-related emissions from direct household energy use of coal, natural gas and electricity are allocated to the category “residence” and oil emissions are allocated to “transport” to be incorporated into the household carbon footprint[4].

Construction of carbon emission inventories. We use the approach provided by the Intergovernmental Panel on Climate Change (IPCC) to calculate the CO_2 emissions from energy combustion based on China’s provincial energy statistics[29]:

$$C = E \times V \times F \times O, \tag{5}$$

where C refers to fossil fuel-related CO_2 emissions, E refers to the amount of energy consumption from different fuel types (in physical units), V refers to the net calorific value of different fuel types, F refers to the carbon content that represents CO_2 emissions when unit heat is released, and O refers to the oxygenation efficiency of different fuel types. To avoid missing emissions or double counting, we calculate the fossil fuel consumption as follows:

$$\begin{aligned} E = {} & \text{Total final consumption} + \text{Input for thermal power} + \text{Input for heating} \\ & - \text{Used as chemical material} - \text{Loss} \end{aligned}. \tag{6}$$

Calculations of Gini coefficients. The Gini coefficient was proposed by the Italian economist Gini to determine quantitatively the level of difference in the income distribution[37]. The range of Gini coefficient is from zero to one, indicating the income distribution changing from completely equal to absolutely unequal. The basic income Gini coefficient is calculated by

$$G = \sum_{i=1}^{n} D_i Y_i + 2\sum_{i=1}^{n} D_i (1 - T_i) - 1, \tag{7}$$

where G represents the Gini coefficient. D_i and Y_i are the proportions of the population and income of each group, respectively. T_i refers to the cumulative proportion of the income of each group, and i refers to ($i = 1, 2, 3, ..., n$) the number of groups. Similarly, the CF-Gini can be calculated by replacing the income with the carbon footprint in the equation (7).

China has a high level of income inequality. The Gini coefficient is a statistical measure of the income distribution of residents on a scale from complete equality (zero) to complete inequality (one)[38, 39]. China’s Gini coefficient is 0.55, compared with 0.5 for the United States and a global average of 0.44[40]. China’s income inequality is in large measure due to the rural-urban gap and to significant regional disparities. For example, per capita income in Beijing is twice that in Xinjiang and income of urban households is three times that of rural households[39]. In addition, in 2015, per capita income of the top 20% of households was over ten times that of the bottom 20% of households in China[41].

By 2012, China’s poverty alleviation policies included allocating financial payments of 300 billion yuan by the central government, launching 11 pilot projects of contiguous poverty-stricken areas, and achieving poverty-alleviating coverage of key national counties, thereby reducing the size of China’s rural poverty to 99 million[42]. Effective polices resulted in the simultaneous declines in both CF-Gini and income Gini in China from 2007 to 2012. According to our estimates (see Supplementary Table 10), if changes in consumption are the same (3.63%) for rural upper-middle group and urban very poor group, changes in carbon footprint of the former (2.18%) is significantly higher than the latter (1.28%); based on our simulations, we find that the urban very rich group would have to cut consumption, which is nearly twice that of the rural poor, to compensate for the increase in consumption associated with the increase in income of the poor. For example, the very rich urban consumers can reduce their very high carbon footprint, e.g. associated with air travel and transport by private cars, by changing modes of transport or reducing their demand for travel. In addition to the aforementioned static comparison, carbon inequality reduction, poverty alleviation and climate change mitigation require a dynamic perspective, given significant rural-urban migration, adoption of urban lifestyles, and changes in the age composition, family size and important demographic variables (see Supplementary Table 11)[43]. Partially affected by demographic trends, carbon inequality declined during the period of urbanization with for example the poorest segments of the rural population moving to urban areas adopting urban lifestyles.

Data sources. The 2012 China MRIO table is compiled by Mi *et al*.[31], and the 2007 China MRIO table is compiled by the Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences[44, 45]. The global MRIO tables are based on version 9 of the GTAP database[46]. The pricing data for China's IOTs were acquired from the China Statistics Yearbook[41], while the pricing data for China's imports and global MRIO tables were obtained from the National Accounts Main Aggregates Database[47].

We need energy consumption and emission factors (see Supplementary Table 12) to calculate CO_2 emission inventories for the 30 regions under study. The energy consumption data are obtained from the China Energy Statistical Yearbooks[48]. Emission factors are very important for calculating CO_2 emissions following the IPCC approach. The most widely used emission factors are the IPCC default values. However, recent studies have indicated that these default emission factors overestimate China's carbon emissions[49]. The low quality of China's coal is caused by the total moisture and high ash content but low carbon content. With the lower net heating values of China's coal, the carbon content for coal mines provided by IPCC is higher than samples from China. In this study, we use emission factors from our previous studies[49], which are measured based on 602 coal samples from the 100 largest coal-mining areas in China. The MRIO tables are online available[50], and carbon emission inventories can be sourced from the China Emission Accounts and Datasets[51].

All households are divided into 5 rural income groups, including poor (20%), lower-middle (20%), middle (20%), upper-middle (20%), and rich (20%), and 7 urban income groups, including very poor (10%), poor (10%), lower-middle (20%), middle (20%), upper-middle (20%), rich (10%), and very rich (10%). Notably, the proportions for each income group are calculated based on household numbers rather than population. Household consumption is divided into eight major categories: food, clothing, residence, household facilities, transport, education, health care, and others. The data on household consumption for each income group are obtained from the provincial statistical yearbooks, proportioned on the respective structures for the concordance of data at different levels. They provide data on per capita annual expenditure and average household size for each income group, so that we can calculate carbon footprint at both household and individual levels.

Household carbon footprints track how household consumption in a region causes carbon emissions elsewhere due to supply chains in the global economic network, taking into account interregional trade. It is important to better understand the uncertainty in order to deliver robust policy applications[52, 53]. The uncertainty in this study mainly lies in the economic data which includes the national accounts and interregional trade and emission inventories. Previous estimates reported the uncertainty of country consumption-based carbon accounts in the range 5-15%[54] and 2-16%[55]. There is a consensus that the major source of uncertainty in the calculation of carbon footprint is mainly associated with the emission inventories rather than the economic data, supported by the comparable uncertainty rage of production-based accounts and consumption-based accounts[56]. The sources of uncertainty of the emission inventories used in this study have been clearly explained by our previous study[49], which improved the Chinese emission accounting by using the emission factors based on the 602 coal samples from the 100 largest coal-mining areas in China. Moreover, the MRIO table used in China has also been validated by our previous study[50]. The understanding of uncertainties in the results is a key limiting factor, more efforts are needed to develop a standardized procedure for uncertainty estimation.

Data availability. The 2012 China MRIO table is compiled by Mi *et al.*[31] (https://doi.org/10.6084/m9.figshare.c.4064285), and global MRIO tables are from the GTAP database (https://www.gtap.agecon.purdue.edu/)[46]. Carbon emission inventories can be sourced from the China Emission Accounts and Datasets (http://www.ceads.net/)[51]. The data that support the findings of this study are available from the corresponding authors upon request.

Code availability. Requests for code developed in Matlab to process and analyse the primary data collected in this study will be reviewed and made available upon reasonable request.

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Additional Information

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Supplementary information is available in the online version of the paper.

Author Contributions

Z.M. designed the study and preformed calculations. Z.M. and J.Z. prepared the manuscript. J.O. and J.M. collected data on household expenditure and carbon emissions. All authors (Z.M., J.Z., J.M., J.O., K.H., Z.L., D.C., N.S., S.L., and Y.-M.W.) participated in performing the analysis and contributed to writing the manuscript. Y.-M.W. coordinated and supervised the project.

Declaration of Interests

The authors declare no competing interests.

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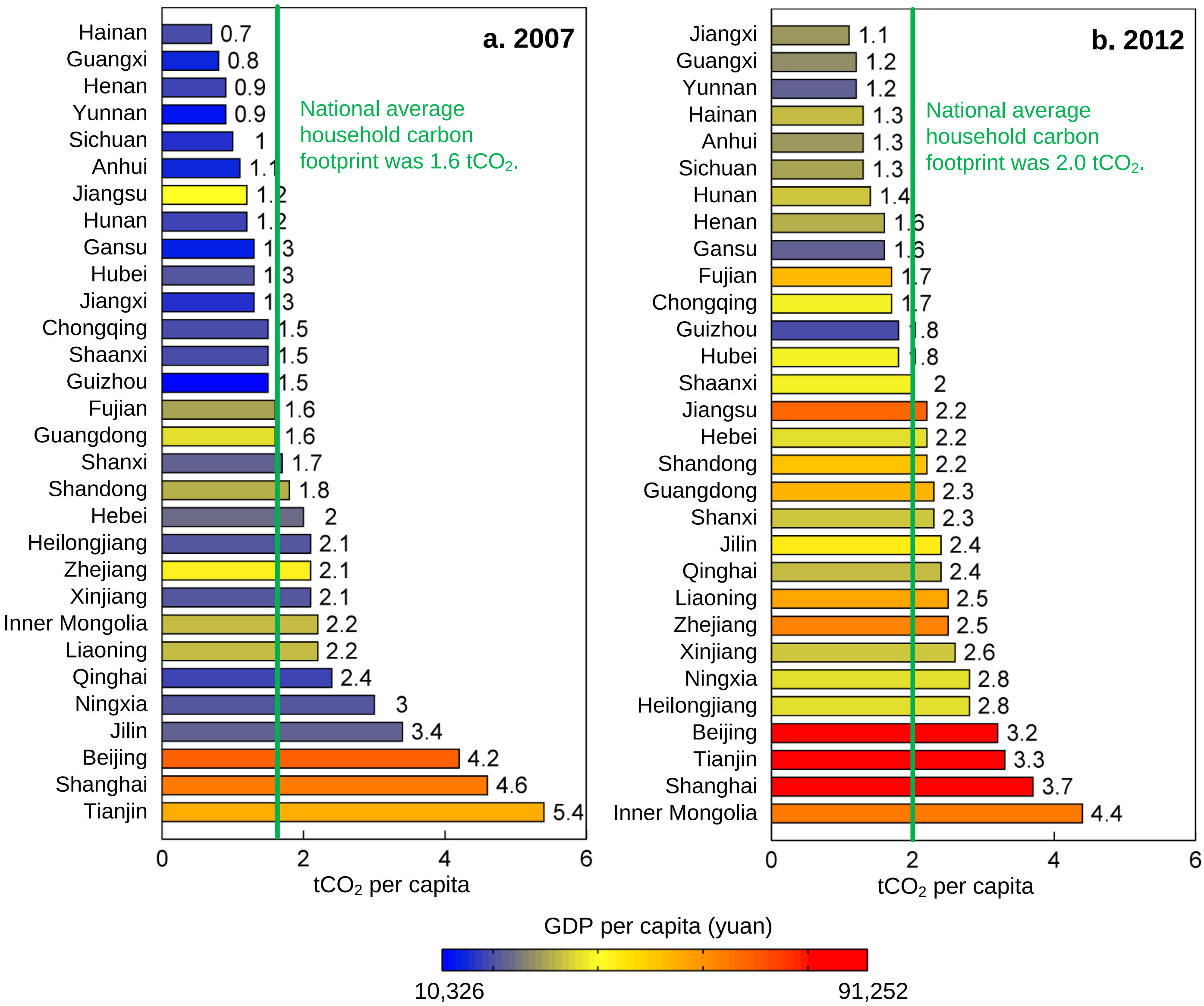
Figure legends

Fig. 1 Per capita carbon footprint of 30 of China's provinces in 2007 and 2012. The colour of the bars corresponds to the provincial GDP per capita, from the wealthiest provinces in red to the poorest provinces in blue (see scale).

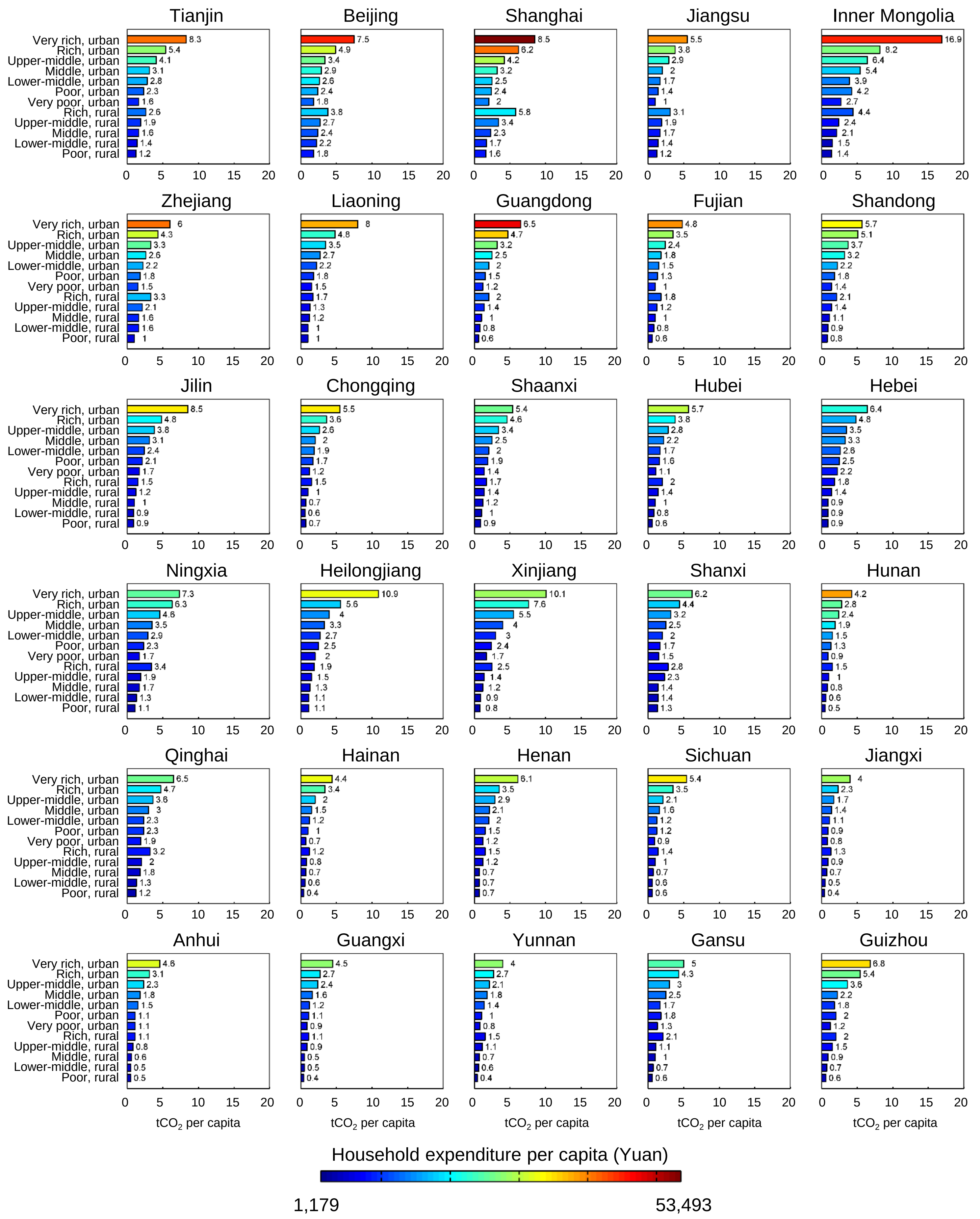
Fig. 2 The per capita carbon footprint of 12 income groups for 30 of China's provinces in 2012. The colour of the bars corresponds to the household expenditure per capita, from the wealthiest groups in red to the poorest groups in blue (see scale). All provinces are arranged based on GDP per capita, from the wealthiest province (Tianjin) located in the first row and first column to the poorest province (Guizhou) located in the sixth row and the fifth column. See Supplementary Fig. 2 for per capita carbon footprints of the 12 income groups for 30 of China's provinces in 2007.

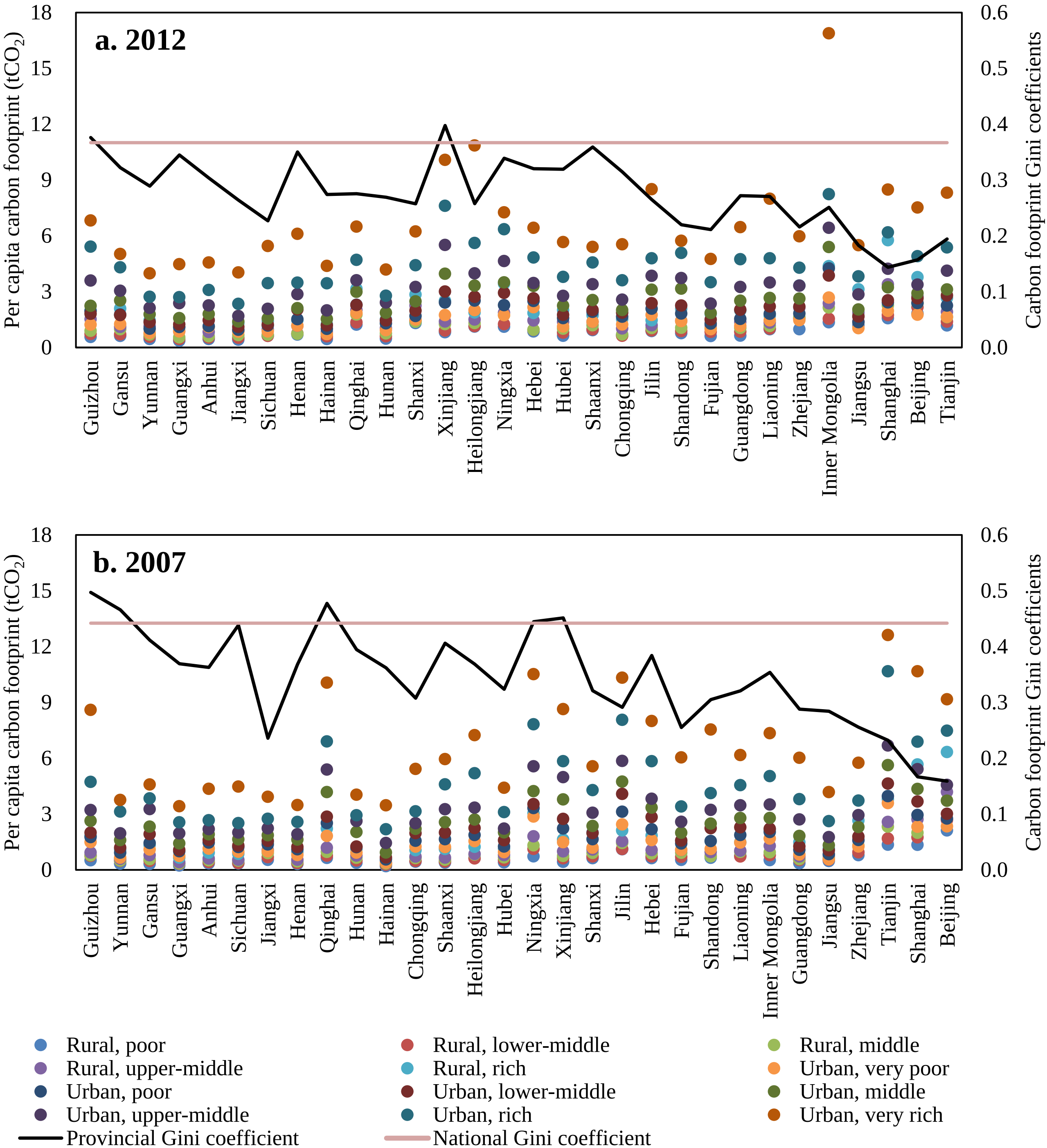
Fig. 3 Carbon footprint Gini coefficients and per capita carbon footprints of different income groups for 30 provinces in 2012 and 2007. All provinces are arranged based on GDP per capita (¥ per person), from the poorest provinces with the lowest GDP per capita starting from the left (Guizhou) to the wealthiest provinces with the highest GDP per capita at the right (Tianjin in 2012 and Beijing in 2007).

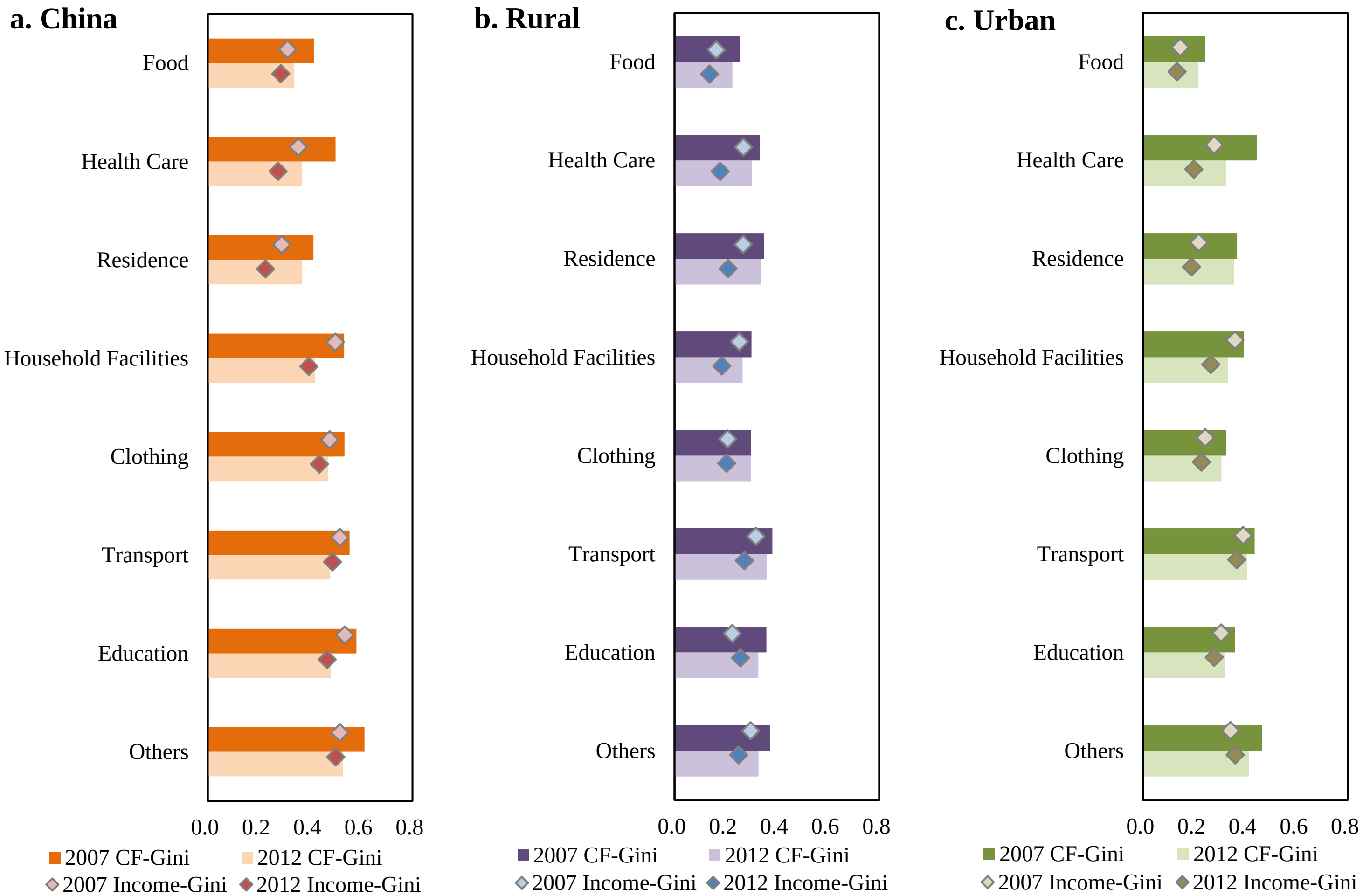
Fig. 4 The carbon footprint Gini and income Gini coefficients for 8 household expenditure categories in 2012 and 2007.



a. 2007
National average household carbon footprint was 1.6 tCO_2.
Hainan 0.7
Guangxi 0.8
Henan 0.9
Yunnan 0.9
Sichuan 1
Anhui 1.1
Jiangsu 1.2
Hunan 1.2
Gansu 1.3
Hubei 1.3
Jiangxi 1.3
Chongqing 1.5
Shaanxi 1.5
Guizhou 1.5
Fujian 1.6
Guangdong 1.6
Shanxi 1.7
Shandong 1.8
Hebei 2
Heilongjiang 2.1
Zhejiang 2.1
Xinjiang 2.1
Inner Mongolia 2.2
Liaoning 2.2
Qinghai 2.4
Ningxia 3
Jilin 3.4
Beijing 4.2
Shanghai 4.6
Tianjin 5.4
0 2 4 6
tCO_2 per capita
b. 2012
National average household carbon footprint was 2.0 tCO_2.
Jiangxi 1.1
Guangxi 1.2
Yunnan 1.2
Hainan 1.3
Anhui 1.3
Sichuan 1.3
Hunan 1.4
Henan 1.6
Gansu 1.6
Fujian 1.7
Chongqing 1.7
Guizhou 1.8
Hubei 1.8
Shaanxi 2
Jiangsu 2.2
Hebei 2.2
Shandong 2.2
Guangdong 2.3
Shanxi 2.3
Jilin 2.4
Qinghai 2.4
Liaoning 2.5
Zhejiang 2.5
Xinjiang 2.6
Ningxia 2.8
Heilongjiang 2.8
Beijing 3.2
Tianjin 3.3
Shanghai 3.7
Inner Mongolia 4.4
0 2 4 6
tCO_2 per capita
GDP per capita (yuan)
10,326
91,252


Very rich, urban
Rich, urban
Upper-middle, urban
Middle, urban
Lower-middle, urban
Poor, urban
Very poor, urban
Rich, rural
Upper-middle, rural
Middle, rural
Lower-middle, rural
Poor, rural
Tianjin 8.3 5.4 4.1 3.1 2.8 2.3 1.6 2.6 1.9 1.6 1.4 1.2
Beijing 7.5 4.9 3.4 2.9 2.6 2.4 1.8 3.8 2.7 2.4 2.2 1.8
Shanghai 8.5 6.2 4.2 3.2 2.5 2.4 2 5.8 3.4 2.3 1.7 1.6
Jiangsu 5.5 3.8 2.9 2 1.7 1.4 1 3.1 1.9 1.7 1.4 1.2
Inner Mongolia 16.9 8.2 6.4 5.4 3.9 4.2 2.7 4.4 2.4 2.1 1.5 1.4
Zhejiang 6 4.3 3.3 2.6 2.2 1.8 1.5 3.3 2.1 1.6 1.6 1
Liaoning 8 4.8 3.5 2.7 2.2 1.8 1.5 1.7 1.3 1.2 1 1
Guangdong 6.5 4.7 3.2 2.5 2 1.5 1.2 2 1.4 1 0.8 0.6
Fujian 4.8 3.5 2.4 1.8 1.5 1.3 1 1.8 1.2 1 0.8 0.6
Shandong 5.7 5.1 3.7 3.2 2.2 1.8 1.4 2.1 1.4 1.1 0.9 0.8
Jilin 8.5 4.8 3.8 3.1 2.4 2.1 1.7 1.5 1.2 1 0.9 0.9
Chongqing 5.5 3.6 2.6 2 1.9 1.7 1.2 1.5 1 0.7 0.6 0.7
Shaanxi 5.4 4.6 3.4 2.5 2 1.9 1.4 1.7 1.4 1.2 1 0.9
Hubei 5.7 3.8 2.8 2.2 1.7 1.6 1.1 2 1.4 1 0.8 0.6
Hebei 6.4 4.8 3.5 3.3 2.6 2.5 2.2 1.8 1.4 0.9 0.9 0.9
Ningxia 7.3 6.3 4.6 3.5 2.9 2.3 1.7 3.4 1.9 1.7 1.3 1.1
Heilongjiang 10.9 5.6 4 3.3 2.7 2.5 2 1.9 1.5 1.3 1.1 1.1
Xinjiang 10.1 7.6 5.5 4 3 2.4 1.7 2.5 1.4 1.2 0.9 0.8
Shanxi 6.2 4.4 3.2 2.5 2 1.7 1.5 2.8 2.3 1.4 1.4 1.3
Hunan 4.2 2.8 2.4 1.9 1.5 1.3 0.9 1.5 1 0.8 0.6 0.5
Qinghai 6.5 4.7 3.6 3 2.3 2.3 1.9 3.2 2 1.8 1.3 1.2
Hainan 4.4 3.4 2 1.5 1.2 1 0.7 1.2 0.8 0.7 0.6 0.4
Henan 6.1 3.5 2.9 2.1 2 1.5 1.2 1.5 1.2 0.7 0.7 0.7
Sichuan 5.4 3.5 2.1 1.6 1.2 1.2 0.9 1.4 1 0.7 0.6 0.6
Jiangxi 4 2.3 1.7 1.4 1.1 0.9 0.8 1.3 0.9 0.7 0.5 0.4
Anhui 4.6 3.1 2.3 1.8 1.5 1.1 1.1 1.1 0.8 0.6 0.5 0.5
Guangxi 4.5 2.7 2.4 1.6 1.2 1.1 0.9 1.1 0.9 0.5 0.5 0.4
Yunnan 4 2.7 2.1 1.8 1.4 1 0.8 1.5 1.1 0.7 0.6 0.4
Gansu 5 4.3 3 2.5 1.7 1.8 1.3 2.1 1.1 1 0.7 0.6
Guizhou 6.8 5.4 3.6 2.2 1.8 2 1.2 2 1.5 0.9 0.7 0.6
0 5 10 15 20
tCO2 per capita
Household expenditure per capita (Yuan)
1,179
53,493


a. 2012
b. 2007
Per capita carbon footprint (tCO_2)
Carbon footprint Gini coefficients
0
3
6
9
12
15
18
0.0
0.1
0.2
0.3
0.4
0.5
0.6
Guizhou
Gansu
Yunnan
Guangxi
Anhui
Jiangxi
Sichuan
Henan
Hainan
Qinghai
Hunan
Shanxi
Xinjiang
Heilongjiang
Ningxia
Hebei
Hubei
Shaanxi
Chongqing
Jilin
Shandong
Fujian
Guangdong
Liaoning
Zhejiang
Inner Mongolia
Jiangsu
Shanghai
Beijing
Tianjin
Guizhou
Yunnan
Gansu
Guangxi
Anhui
Sichuan
Jiangxi
Henan
Qinghai
Hunan
Hainan
Chongqing
Shaanxi
Heilongjiang
Hubei
Ningxia
Xinjiang
Shanxi
Jilin
Hebei
Fujian
Shandong
Liaoning
Inner Mongolia
Guangdong
Jiangsu
Zhejiang
Tianjin
Shanghai
Beijing
Rural, poor
Rural, lower-middle
Rural, middle
Rural, upper-middle
Rural, rich
Urban, very poor
Urban, poor
Urban, lower-middle
Urban, middle
Urban, upper-middle
Urban, rich
Urban, very rich
Provincial Gini coefficient
National Gini coefficient



a. China
b. Rural
c. Urban
Food
Health Care
Residence
Household Facilities
Clothing
Transport
Education
Others
0.0
0.2
0.4
0.6
0.8
2007 CF-Gini
2012 CF-Gini
2007 Income-Gini
2012 Income-Gini