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## 2. Supplementary Information:

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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>i.e.: Supplementary Figures 1-4, Supplementary Discussion, and Supplementary Tables 1-4.</i>
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	

# 3 Economic development and converging household carbon 4 footprints in China

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8

9 There are substantial differences in carbon footprints across households. This study  
10 applied an environmentally extended multiregional input-output (MRIO) approach to  
11 estimate household carbon footprints for 12 different income groups of China's 30  
12 regions. Subsequently, carbon footprint Gini coefficients were calculated to measure  
13 carbon inequality for households across provinces. We found that the top 5% of income  
14 earners were responsible for 17% of the national household carbon footprints in 2012,  
15 while the bottom half of income earners caused only 25%. Carbon inequality declined  
16 with economic growth in China across space and time in two ways: first, carbon  
17 footprints were more similar in the wealthier coastal regions than in the poorer inland  
18 regions; second, China's national carbon footprint Gini coefficients declined from 0.44  
19 in 2007 to 0.37 in 2012. We argue that economic growth not only increases income levels  
20 but also contributes to an overall reduction in carbon inequality in China.  
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23 Mitigating climate change and reducing inequality are both critical goals for sustainable  
24 development. The seventeen United Nations sustainable development goals (SDGs) include  
25 both taking urgent action to combat climate change and reducing income inequality<sup>1</sup>. The  
26 carbon footprint, defined as the total carbon emissions caused directly and indirectly by an  
27 individual, organisation, event, or product, has been increasingly used to measure the impacts  
28 of human activity on global warming<sup>2,3</sup>. An informed discussion of “fairness” or “justice” in  
29 processes of emissions reduction requires an understanding of the relation between emissions  
30 and income<sup>4,5</sup>. Due to differences in income level, local conditions and lifestyle, there are  
31 great disparities in the average carbon footprint of households within and between countries<sup>6</sup>.  
32 This study aims to provide information to help policymakers understand some of the  
33 interactions and trade-offs between measures targeting inequality, poverty, and climate change  
34 mitigation. We do so by estimating the carbon footprint of different income groups in China.

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

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

56 Many studies have estimated the inequality of carbon emissions at national<sup>20</sup> or  
57 sub-national levels<sup>21</sup>, while studies comparing household level carbon inequality are still  
58 limited<sup>22</sup>. Hubacek *et al.*<sup>11, 23</sup> estimated the carbon footprints of four household groups in 30  
59 developed countries and 90 developing countries. The results show that the top 10% of  
60 income earners were responsible for 36% of global carbon emissions in 2010, while the  
61 bottom half of global income earners caused only approximately 13%. There are more studies  
62 at the national level. López *et al.*<sup>24</sup> compared the household carbon footprint for eight social  
63 groups in Spain and found that higher income households imported more carbon emissions  
64 compared to lower income households. However, most of the existing research at the national  
65 level is based on single region input-output tables, and thus ignores regional disparities in  
66 income, as well as significant regional differences in production technologies, fuel mix and

67 economic structure. For example, Wiedenhofer *et al.*<sup>4</sup> measured national inequality of  
68 household carbon footprints across five rural income groups and eight urban income groups in  
69 China. We extended their research from both time and space perspectives, using multiregional  
70 input-output (MRIO) models. Specifically, we utilized the latest socioeconomic datasets to  
71 compile China's 2012 MRIO table and estimated household carbon footprints for twelve  
72 income groups (five rural and seven urban) in 30 Chinese provinces in 2007 and 2012. The  
73 inequality in the household carbon footprint was quantified with a carbon footprint Gini  
74 (CF-Gini) coefficient. Important findings are that while average per capita carbon footprints  
75 in most poor provinces increased and those in some wealthy provinces declined, carbon  
76 inequality declines with economic growth in China across space and time. Those interesting  
77 conclusions provide policy implications to understand the interactions and trade-offs between  
78 measures targeting inequality and climate change mitigation, which are both critical for  
79 sustainable development and an important focus of the UN SDGs.

## 81 **Results**

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

87  
88 **Carbon footprint.** The proportion of carbon footprint attributed to households is relatively  
89 lower in China than developed countries. For example, the household shares of the carbon  
90 footprint in the USA and the UK were 70% and 69%, respectively, in 2012. There are  
91 significant differences in household carbon contributions across provinces in China. In  
92 Guangdong and Shanghai, for example, households were responsible for 48% and 47%,  
93 respectively, of the total carbon footprint in 2012. By comparison, the household shares of the  
94 carbon footprint were only 24% and 27%, respectively, in the two less-developed provinces  
95 Ningxia and Shanxi in western China.

96 At the national level, China's household carbon footprints increased by 27% or 2,113  
97 million tonnes (Mt) of CO<sub>2</sub> between 2007 and 2012, with 72% of this increase being due to  
98 consumption in urban areas. The household carbon footprint increased much faster in poorer  
99 western regions than in wealthier eastern regions: specifically, it increased by 37%, 32%, and  
100 21%, respectively, in western, central and eastern China. Although western China is relatively  
101 poor compared to eastern China, its growth rates in consumption and gross domestic product  
102 (GDP) have been much faster since the global financial crisis. At the provincial level, the  
103 household carbon footprint increased in most provinces. For example, the household carbon  
104 footprint of Guangxi and Shaanxi, two provinces in western China, increased by 39% and  
105 37%, respectively, while the household carbon footprint in the three most affluent provinces –  
106 Tianjin, Beijing, and Shanghai – decreased by 22%, 6%, and 5%, respectively, mainly due to  
107 the decline (percentage changed in this ratio) in carbon intensity (i.e., CO<sub>2</sub> emissions per unit  
108 of economic output) and the effect of outsourcing pollution<sup>25</sup>. The carbon intensities of  
109 Beijing, Shanghai, and Tianjin declined by 53%, 32%, and 37%, respectively, between 2007  
110 and 2012, and the share of low-carbon goods and services in household consumption

111 increased in these provinces. Between 2007 and 2012, for example, the proportions of  
112 wholesale and retailing products, and of leasing and commercial services in Beijing's  
113 household expenditure increased by 2 and 3 percentage points, respectively.

114

115 **Per capita carbon footprint.** The per capita household carbon footprint varies greatly across  
116 China's provinces, but wealthy regions usually have a higher per capita carbon footprint than  
117 poor regions. In 2007, the per capita carbon footprint of three affluent eastern coastal  
118 provinces (Tianjin, Shanghai, and Beijing) was over 4.0 tonnes of CO<sub>2</sub> (tCO<sub>2</sub>), while those in  
119 central and western provinces (Hainan, Guangxi, Henan, and Yunnan) were less than 1.0 tCO<sub>2</sub>  
120 (Fig. 1). For example, the per capita carbon footprint in Beijing, the capital of China, was 4.2  
121 tCO<sub>2</sub>, which was over five times that in Guangxi, a poorer western province. In 2012, Inner  
122 Mongolia was the province with the highest per capita household carbon footprint (4.4 tCO<sub>2</sub>),  
123 which was four times that of the smallest one in Jiangxi (1.1 tCO<sub>2</sub>). Inner Mongolia is a  
124 western province, and its household consumption increased rapidly between 2007 and 2012.  
125 In addition, Inner Mongolia is one of the main providers of coal-fired electricity, which has a  
126 higher carbon intensity. For example, Inner Mongolia provides large amounts of electricity to  
127 neighbouring regions, with 133 billion kilowatt hours (kWh) in net electricity exports in 2012.  
128 China's national average per capita carbon footprint increased by 23% from 1.6 tCO<sub>2</sub> in 2007  
129 to 2.0 tCO<sub>2</sub> in 2012. Average per capita carbon footprints in most poorer provinces increased,  
130 while those in some wealthier provinces declined. Overall, China's regional carbon inequality  
131 declined between 2007 and 2012. We further explored whether conditional convergence exists  
132 in China. Our estimates show that provinces with the lowest per capita carbon footprint in  
133 2007 were the provinces in which the carbon footprint grew the most from 2007 to 2012. By  
134 estimating convergences but differentiating between rural and urban households, results show  
135 that the convergence occurred more rapidly in urban households (see [Supplementary Fig. 1](#)).

136 Urban residents, accounting for 53% of China's population, induced 74% of the national  
137 household carbon footprint in 2012. The average per capita footprint of urban residents was  
138 2.8 tCO<sub>2</sub> in 2012, which was 2.5 times that of rural residents (1.1 tCO<sub>2</sub>), while the average per  
139 capita expenditure was 2.9 times that of rural residents. Fig. 2 shows per capita carbon  
140 footprint of 12 income groups in 30 of China's provinces in 2012. The per capita carbon  
141 footprint is much higher for urban residents than for rural residents across all provinces. The  
142 gap in per capita carbon footprints between urban and rural residents is much larger in poorer  
143 western China. For example, the per capita carbon footprint of urban residents in Guizhou  
144 (Fig. 2, row 6, column 5), whose GDP per capita was the smallest in China in 2012, was 2.7  
145 times that of Guizhou's rural residents. By comparison, the per capita carbon footprints of  
146 urban residents in Beijing (Fig. 2, row 1, column 2) and Shanghai (Fig. 2, row 6, column 3),  
147 two of the most affluent regions in China, were in both cases 'only' 1.3 times of the footprint  
148 of their respective rural residents.

149 It is surprising that the income groups with the highest per capita household carbon  
150 footprint are mostly located in relatively poor provinces (see [Supplementary Table 3](#)). Per  
151 capita carbon footprints of very wealthy urban groups in Inner Mongolia, Heilongjiang, and  
152 Xinjiang were 16.9, 10.9, and 10.1 tCO<sub>2</sub> in 2012, respectively, which were similar to the  
153 estimated range for the USA (10.4 to 20 tCO<sub>2</sub>)<sup>4, 26, 27</sup>. The per capita household expenditure of  
154 the top 10% in terms of urban income in Inner Mongolia was 45,246 yuan, and even higher

155 than that of the top 10% of the urban income earners in Beijing (45,190 yuan) and Tianjin  
156 (41,214 yuan). Although the per capita household expenditure of the top 10% of the urban  
157 groups in Inner Mongolia and Beijing was almost equal, the two groups had a large gap in  
158 their per capita household carbon footprints (Fig. 2). This is mainly caused by the differences  
159 in their carbon intensity. The carbon intensity of Inner Mongolia was 149 g/yuan in 2012,  
160 which was the highest among the 30 Chinese provinces and approximately 10 times that in  
161 Beijing (15 g/yuan). One possible reason for this difference is the higher number of heating  
162 days and availability of natural resources influencing the fuel mix<sup>28</sup>. Additionally, relatively  
163 low administrative efficiency and loose environmental regulations result in high levels of  
164 carbon emissions. For example, Inner Mongolia struggles to design an appropriate path for  
165 economic development accompanied by a low carbon transition in consumption patterns<sup>29</sup>.  
166 The carbon intensities of Heilongjiang and Xinjiang were 79 and 129 g/yuan in 2012,  
167 respectively, which were also above China's national average (50 g/yuan). In addition to the  
168 carbon intensity, the different consumption pattern of households in poor and rich regions also  
169 plays an important role in the discrepancy (see [Supplementary Table 4](#)). For example, rural  
170 areas in relatively poor provinces in 2012, including Inner Mongolia (1.22 tCO<sub>2</sub>), Shanxi  
171 (1.13 tCO<sub>2</sub>) and Ningxia (1.07 tCO<sub>2</sub>), show relatively high per capita carbon footprint in  
172 terms of residence expenditure, with this item closely related to high energy-consuming  
173 indirect sectoral emissions and direct household emissions. Simultaneously, the consumption  
174 from different sources (i.e., local production, domestic inflow, or international imports) can  
175 partially explain the discrepancy (see [Supplementary Table 5](#)). Households consumption in  
176 poorer provinces has a higher proportion of local production but lower proportions of both  
177 domestic inflow and international import.

178 The income groups with the lowest per capita household carbon footprint are also  
179 mostly located in relatively poor provinces (see [Supplementary Table 6](#)). The per capita carbon  
180 footprints of the poor rural income groups in Guangxi, Jiangxi, Hainan, and Yunnan were  
181 only 0.4 tCO<sub>2</sub> in 2012, which was less than half of the average in India in 2011 (0.9 tCO<sub>2</sub>)<sup>4</sup>.  
182 This is mainly due to their lower household expenditure: per capita household expenditure for  
183 the poor rural income groups in these four provinces was approximately 3,000 yuan in 2012,  
184 which was only a quarter of China's national average (11,990 yuan).

185  
186 **Carbon inequality.** We measure household carbon inequality using carbon footprint Gini  
187 (CF-Gini) coefficients, with zero representing perfect equality and one representing perfect  
188 inequality. Carbon inequality declines with economic growth in China. At the national level,  
189 China's CF-Gini coefficient declined from 0.44 in 2007 to 0.37 in 2012 (Fig. 3), while the  
190 officially released Gini coefficient for income dropped slightly from 0.48 in 2007 to 0.47 in  
191 2012<sup>30</sup>. In 2012, the top 5% of income earners were responsible for 17% of the national  
192 household carbon footprint, while the bottom half of income earners caused only 25%. At the  
193 provincial level, the CF-Gini coefficients of the wealthier eastern coastal provinces were  
194 much lower than those of the poorer western provinces. In 2012, the four most affluent  
195 provinces (Tianjin, Beijing, Shanghai, and Jiangsu), whose GDP per capita was over 68,000  
196 yuan in 2012, had the lowest CF-Gini coefficients (0.19, 0.16, 0.14, and 0.18, respectively).  
197 By comparison, the CF-Gini coefficients of Xinjiang and Guizhou, two western provinces,  
198 were 0.40 and 0.38, respectively, which were higher than China's national CF-Gini coefficient

199 in 2012. Between 2007 and 2012, the CF-Gini coefficients of most provinces declined except  
200 for Jiangxi and Chongqing (see [Supplementary Fig. 3](#)), and the inequality in less-developed  
201 western provinces declined faster. For example, the CF-Gini coefficients of Sichuan and  
202 Qinghai declined by 0.21 and 0.20, respectively. Based upon these observations, it can be  
203 concluded that carbon inequality declines with economic growth in China across space and  
204 time (see [Supplementary Table 7](#) for details).

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

221

## 222 **Conclusions**

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

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

241 Third, the size of the carbon footprint varies across income groups in China. The per  
242 capita carbon footprint of the wealthiest groups in Mongolia, Heilongjiang, and Xinjiang was

243 similar with the average level in the USA, while the per capita carbon footprint of the poorest  
244 groups in Guangxi, Jiangxi, Hainan and Yunnan was only 0.4 tCO<sub>2</sub>, which was less than half  
245 of the average carbon footprint in India.

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

260 According to our research, carbon inequality has improved during this time period and  
261 across provinces. Carbon footprints show less inequality in wealthier eastern coastal regions  
262 than in poorer western inland regions, and our results show that the income groups with the  
263 highest (and lowest) per capita carbon footprint are mostly located in relatively poor  
264 provinces. At the national level, China's CF-Gini coefficient declined from 0.44 in 2007 to  
265 0.37 in 2012. At the provincial level, the CF-Gini coefficients of most provinces declined with  
266 only two exceptions (i.e., Jiangxi and Chongqing). China has managed to decrease both  
267 income and carbon inequality during the observed time period. There might be idiosyncratic  
268 and context specific differences among developing countries but the insights we gained  
269 achieving further decarbonization through changing the energy mix, improving carbon  
270 efficiencies in production and changes in consumption patterns should hold for other  
271 countries as well.

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



287 households who can afford to have a higher share of services and other lower carbon  
288 consumption items. Therefore, mitigation actions need to be designed with the poorest  
289 segments of society in mind.

290

## 291 **Methods**

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

295

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

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

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

327

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

331 
$$X = (I - A)^{-1} F, \quad (1)$$

332 
$$X = \begin{bmatrix} x^1 \\ x^2 \\ \vdots \\ x^n \end{bmatrix}, A = \begin{bmatrix} a^{11} & a^{12} & \dots & a^{1n} \\ a^{21} & a^{22} & \dots & a^{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a^{n1} & a^{n2} & \dots & a^{nm} \end{bmatrix}, F = \begin{bmatrix} f^{11} & f^{12} & \dots & f^{1n} \\ f^{21} & f^{22} & \dots & f^{2n} \\ \vdots & \vdots & \ddots & \vdots \\ f^{n1} & f^{n2} & \dots & f^{nm} \end{bmatrix}, \quad (2)$$

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

339 Carbon footprints are calculated using environmental extended input-output analysis.  
 340 Based on the carbon intensity (i.e., CO<sub>2</sub> emissions per unit of economic output), the total  
 341 carbon footprint is calculated by

342 
$$C = K (I - A)^{-1} F, \quad (3)$$

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

348 
$$C_h = K (I - A)^{-1} H \quad (4)$$

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

354 The household carbon footprint estimated by the MRIO model is aggregated into eight  
 355 major categories of consumption: food, clothing, residence, household facilities, transport,  
 356 education, health care, and others<sup>36</sup>. Carbon emissions emitted from direct rural and urban  
 357 household energy use are not included in equation (4) because the input-output model only  
 358 estimates the carbon emissions indirectly emitted in economically productive sectors. In this  
 359 study, directed energy-related emissions from direct household energy use of coal, natural gas

360 and electricity are allocated to the category “residence” and oil emissions are allocated to  
361 “transport” to be incorporated into the household carbon footprint<sup>4</sup>.

362

363 **Construction of carbon emission inventories.** We use the approach provided by the  
364 Intergovernmental Panel on Climate Change (IPCC) to calculate the CO<sub>2</sub> emissions from  
365 energy combustion based on China’s provincial energy statistics<sup>29</sup>:

$$366 \quad C = E \times V \times F \times O, \quad (5)$$

367 where  $C$  refers to fossil fuel-related CO<sub>2</sub> emissions,  $E$  refers to the amount of energy  
368 consumption from different fuel types (in physical units),  $V$  refers to the net calorific value of  
369 different fuel types,  $F$  refers to the carbon content that represents CO<sub>2</sub> emissions when unit  
370 heat is released, and  $O$  refers to the oxygenation efficiency of different fuel types. To avoid  
371 missing emissions or double counting, we calculate the fossil fuel consumption as follows:

$$372 \quad E = \text{Total final consumption} + \text{Input for thermal power} + \text{Input for heating} \quad (6)$$

– Used as chemical material – Loss

373

374 **Calculations of Gini coefficients.** The Gini coefficient was proposed by the Italian  
375 economist Gini to determine quantitatively the level of difference in the income distribution<sup>37</sup>.  
376 The range of Gini coefficient is from zero to one, indicating the income distribution changing  
377 from completely equal to absolutely unequal. The basic income Gini coefficient is calculated  
378 by

$$379 \quad G = \sum_{i=1}^n D_i Y_i + 2 \sum_{i=1}^n D_i (1 - T_i) - 1, \quad (7)$$

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

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

392 By 2012, China’s poverty alleviation policies included allocating financial payments of  
393 300 billion yuan by the central government, launching 11 pilot projects of contiguous  
394 poverty-stricken areas, and achieving poverty-alleviating coverage of key national counties,  
395 thereby reducing the size of China’s rural poverty to 99 million<sup>42</sup>. Effective policies resulted in  
396 the simultaneous declines in both CF-Gini and income Gini in China from 2007 to 2012.  
397 According to our estimates (see [Supplementary Table 10](#)), if changes in consumption are the  
398 same (3.63%) for rural upper-middle group and urban very poor group, changes in carbon  
399 footprint of the former (2.18%) is significantly higher than the latter (1.28%); based on our

400 simulations, we find that the urban very rich group would have to cut consumption, which is  
401 nearly twice that of the rural poor, to compensate for the increase in consumption associated  
402 with the increase in income of the poor. For example, the very rich urban consumers can  
403 reduce their very high carbon footprint, e.g. associated with air travel and transport by private  
404 cars, by changing modes of transport or reducing their demand for travel. In addition to the  
405 aforementioned static comparison, carbon inequality reduction, poverty alleviation and  
406 climate change mitigation require a dynamic perspective, given significant rural-urban  
407 migration, adoption of urban lifestyles, and changes in the age composition, family size and  
408 important demographic variables (see [Supplementary Table 11](#))<sup>43</sup>. Partially affected by  
409 demographic trends, carbon inequality declined during the period of urbanization with for  
410 example the poorest segments of the rural population moving to urban areas adopting urban  
411 lifestyles.

412  
413 **Data sources.** The 2012 China MRIO table is compiled by Mi *et al.*<sup>31</sup>, and the 2007 China  
414 MRIO table is compiled by the Institute of Geographic Sciences and Natural Resources  
415 Research, Chinese Academy of Sciences<sup>44, 45</sup>. The global MRIO tables are based on version 9  
416 of the GTAP database<sup>46</sup>. The pricing data for China's IOTs were acquired from the China  
417 Statistics Yearbook<sup>41</sup>, while the pricing data for China's imports and global MRIO tables were  
418 obtained from the National Accounts Main Aggregates Database<sup>47</sup>.

419 We need energy consumption and emission factors (see [Supplementary Table 12](#)) to  
420 calculate CO<sub>2</sub> emission inventories for the 30 regions under study. The energy consumption  
421 data are obtained from the China Energy Statistical Yearbooks<sup>48</sup>. Emission factors are very  
422 important for calculating CO<sub>2</sub> emissions following the IPCC approach. The most widely used  
423 emission factors are the IPCC default values. However, recent studies have indicated that  
424 these default emission factors overestimate China's carbon emissions<sup>49</sup>. The low quality of  
425 China's coal is caused by the total moisture and high ash content but low carbon content. With  
426 the lower net heating values of China's coal, the carbon content for coal mines provided by  
427 IPCC is higher than samples from China. In this study, we use emission factors from our  
428 previous studies<sup>49</sup>, which are measured based on 602 coal samples from the 100 largest  
429 coal-mining areas in China. The MRIO tables are online available<sup>50</sup>, and carbon emission  
430 inventories can be sourced from the China Emission Accounts and Datasets<sup>51</sup>.

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

442 Household carbon footprints track how household consumption in a region causes  
443 carbon emissions elsewhere due to supply chains in the global economic network, taking into

444 account interregional trade. It is important to better understand the uncertainty in order to  
445 deliver robust policy applications<sup>52, 53</sup>. The uncertainty in this study mainly lies in the  
446 economic data which includes the national accounts and interregional trade and emission  
447 inventories. Previous estimates reported the uncertainty of country consumption-based carbon  
448 accounts in the range 5-15%<sup>54</sup> and 2-16%<sup>55</sup>. There is a consensus that the major source of  
449 uncertainty in the calculation of carbon footprint is mainly associated with the emission  
450 inventories rather than the economic data, supported by the comparable uncertainty range of  
451 production-based accounts and consumption-based accounts<sup>56</sup>. The sources of uncertainty of  
452 the emission inventories used in this study have been clearly explained by our previous  
453 study<sup>49</sup>, which improved the Chinese emission accounting by using the emission factors based  
454 on the 602 coal samples from the 100 largest coal-mining areas in China. Moreover, the  
455 MRIO table used in China has also been validated by our previous study<sup>50</sup>. The understanding  
456 of uncertainties in the results is a key limiting factor, more efforts are needed to develop a  
457 standardized procedure for uncertainty estimation.

458

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

465

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

468

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473

### 474 **Additional Information**

475 Correspondence and requests for materials should be addressed to Z.M., J.M. or Y.-M.W.

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

477

### 478 **Author Contributions**

479 Z.M. designed the study and performed calculations. Z.M. and J.Z. prepared the manuscript.  
480 J.O. and J.M. collected data on household expenditure and carbon emissions. All authors  
481 (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  
482 the analysis and contributed to writing the manuscript. Y.-M.W. coordinated and supervised  
483 the project.

484

### 485 **Declaration of Interests**

486 The authors declare no competing interests.

487

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617  
618  
619

620    **Figure legends**

621

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

625

626 **Fig. 2** The per capita carbon footprint of 12 income groups for 30 of China's provinces in 2012.  
627 The colour of the bars corresponds to the household expenditure per capita, from the wealthiest  
628 groups in red to the poorest groups in blue (see scale). All provinces are arranged based on GDP  
629 per capita, from the wealthiest province (Tianjin) located in the first row and first column to the  
630 poorest province (Guizhou) located in the sixth row and the fifth column. See [Supplementary Fig.](#)  
631 [2](#) for per capita carbon footprints of the 12 income groups for 30 of China's provinces in 2007.

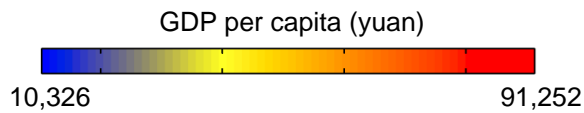
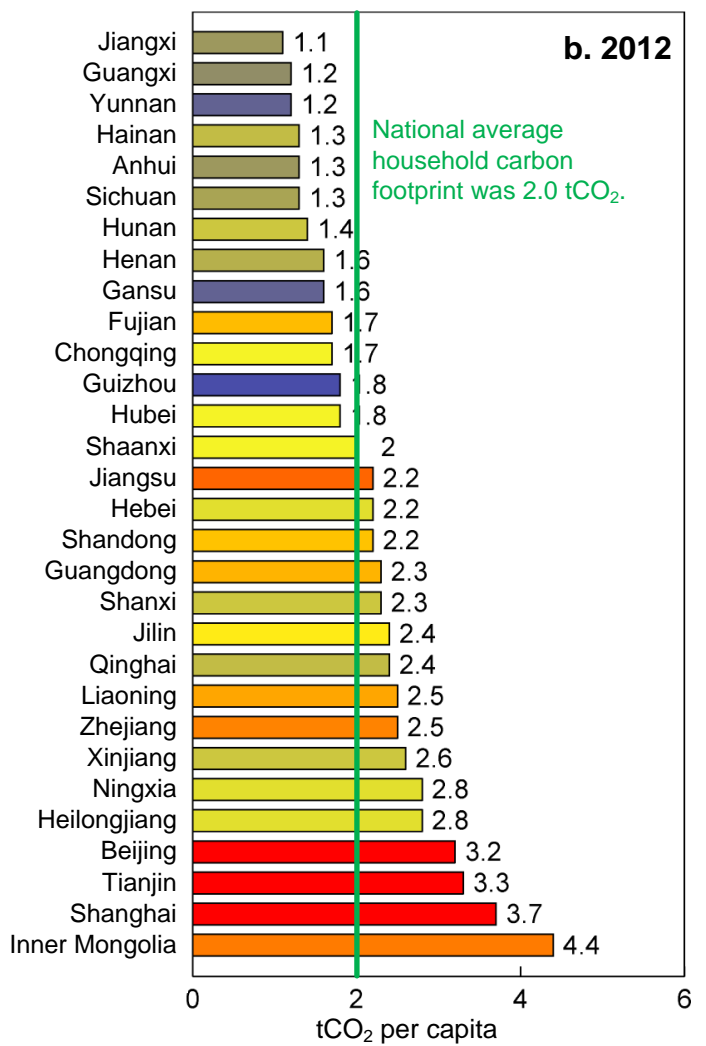
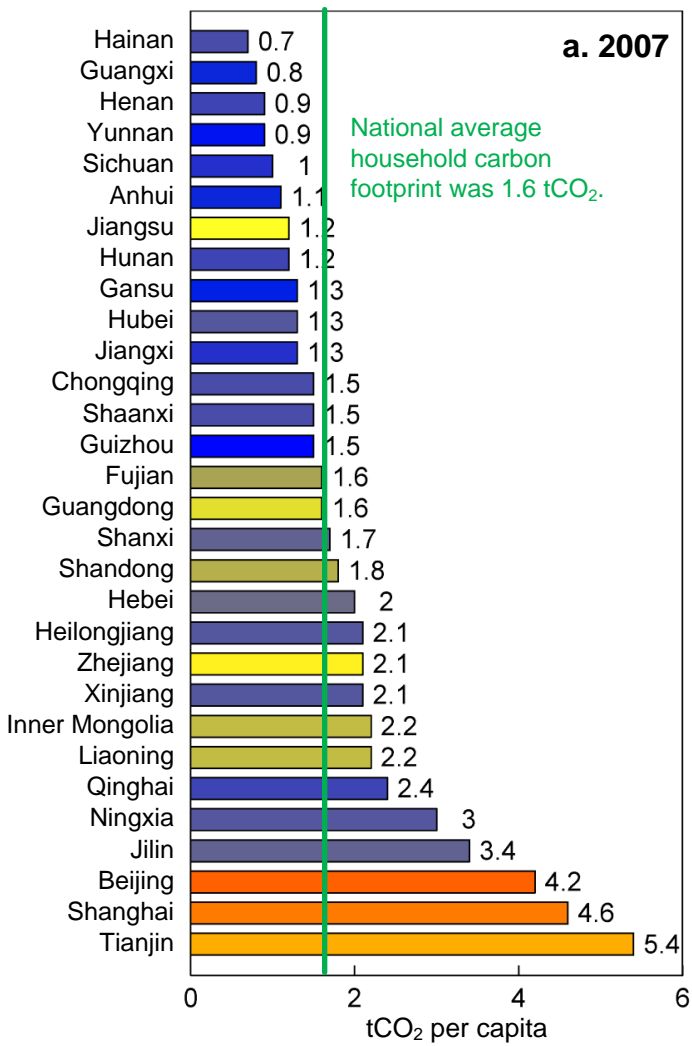
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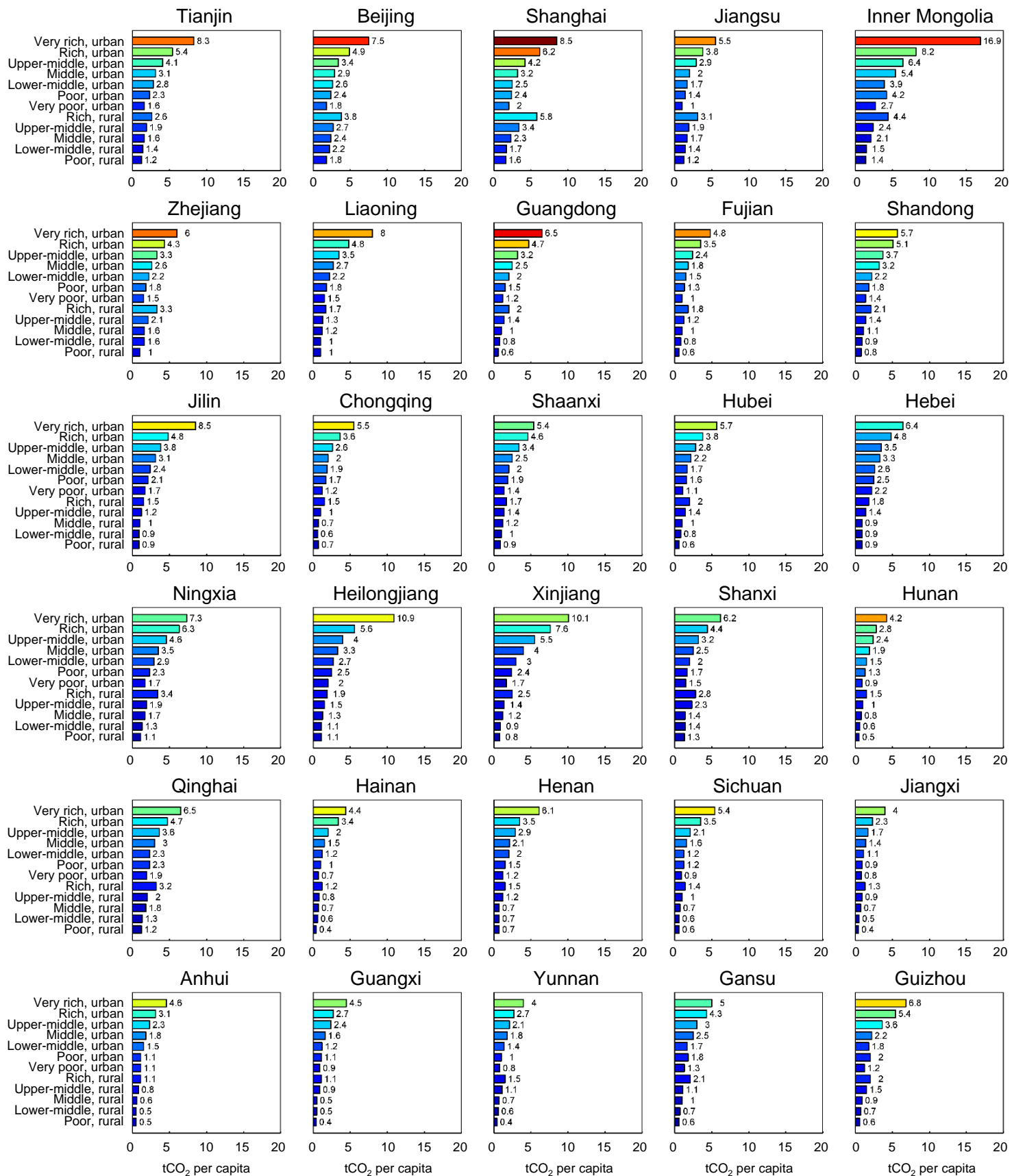
633 **Fig. 3** Carbon footprint Gini coefficients and per capita carbon footprints of different income  
634 groups for 30 provinces in 2012 and 2007. All provinces are arranged based on GDP per capita  
635 (¥ per person), from the poorest provinces with the lowest GDP per capita starting from the left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

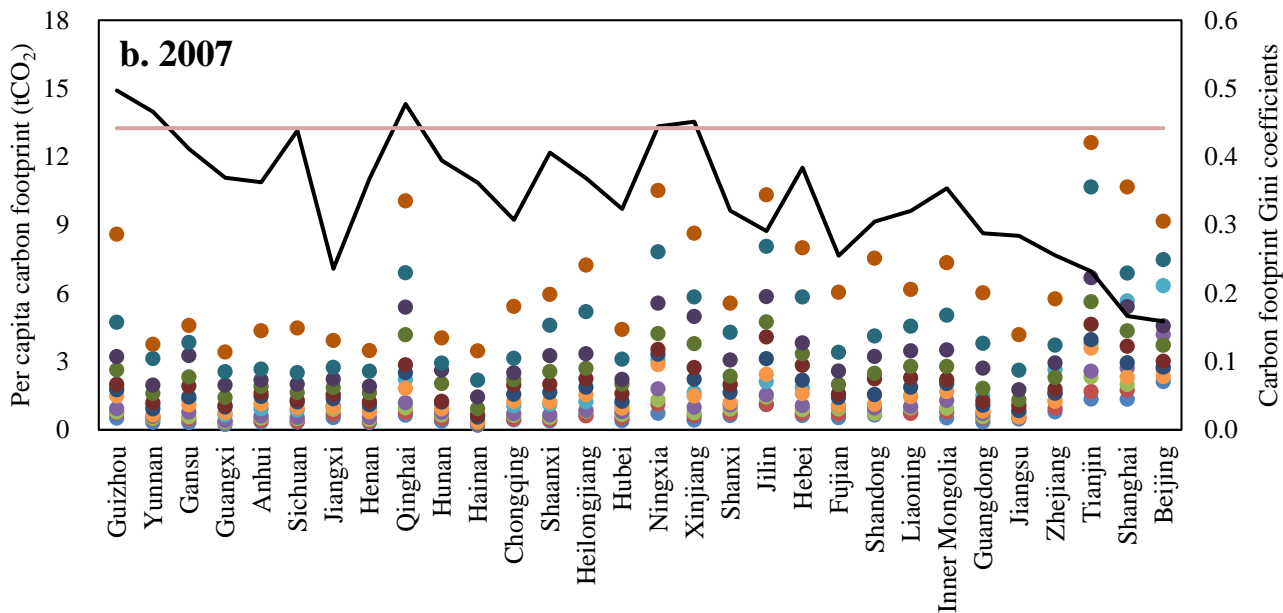
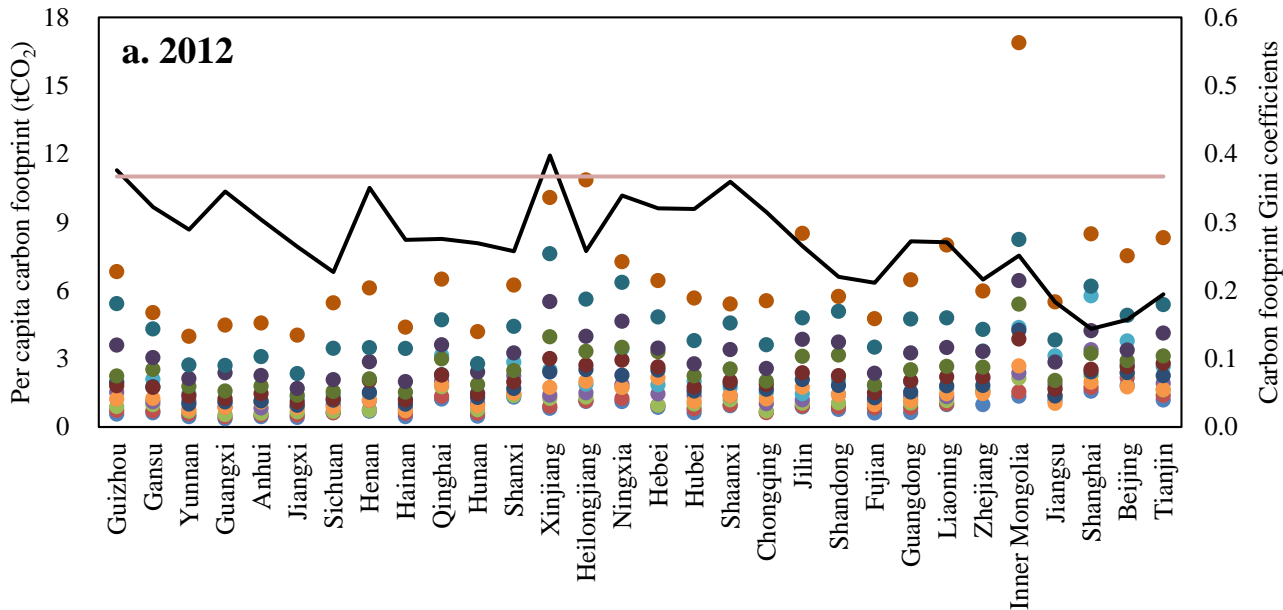
638

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

641

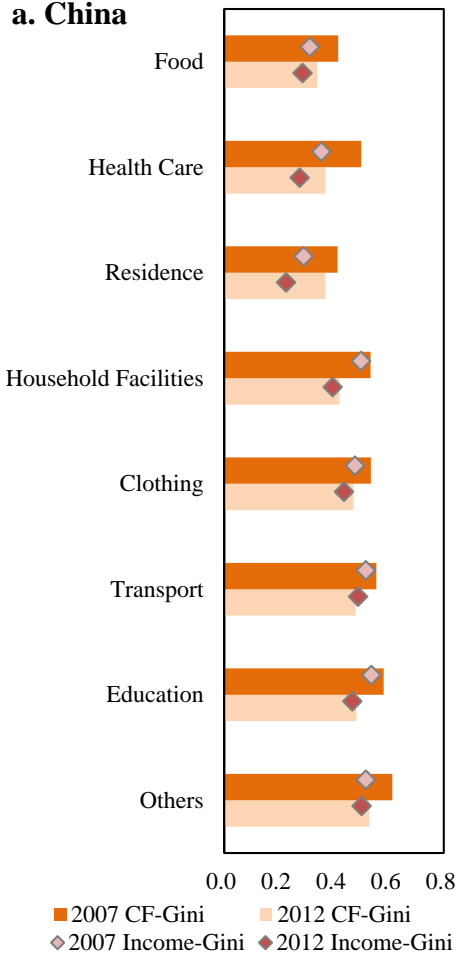




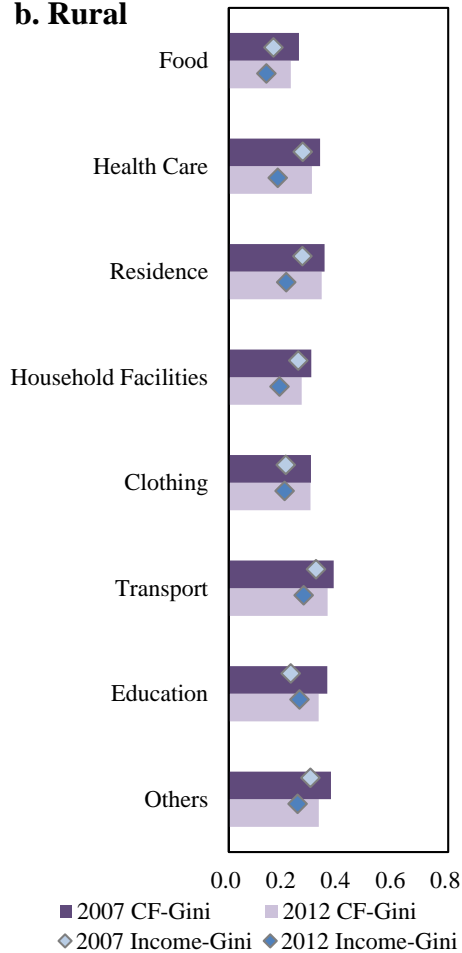


- Rural, poor
- Rural, lower-middle
- Rural, middle
- Rural, upper-middle
- Rural, rich
- Urban, very poor
- Urban, poor
- Urban, lower-middle
- Urban, middle
- Urban, upper-middle
- Urban, rich
- Urban, very rich
- Provincial Gini coefficient
- National Gini coefficient

### a. China



### b. Rural



### c. Urban

