





## Reducing Carbon Footprint Inequality of Household Consumption in Rural Areas

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# **Reducing Carbon Footprint Inequality of Household Consumption** in Rural Areas: Analysis from Five Representative Provinces in China

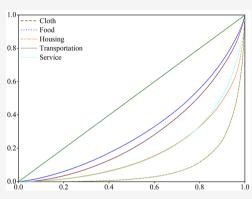
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ABSTRACT: Household consumption carbon footprint and inequality reductions are vital for a sustainable society, especially for rural areas. This study, focusing on rural China, one of the fastest growing economies with a massive population, explored the carbon footprint and inequality of household consumption using the latest micro household survey data of 2018 linked to environmental extended input-output analysis. The results show that in 2018 in rural China, the average household carbon footprint is 2.46 tons CO2-eq per capita, which is around one-third of China's average footprint, indicating the large potential for further growth. Housing (45.32%), transportation (20.45%), and food (19.62%) are the dominant contributors to the carbon footprint. Meanwhile, great inequality, with a Gini coefficient of 0.488, among rural households is observed, which is largely due to differences in type of house built or purchased (explaining 24.44% of the variation), heating (18.10%), car purchase (12.44%), and petrol consumption (12.44%). Provinces, average education, and nonfarm



income are among the important factors influencing the inequality. In the process of urbanization and rural revitalization, there is a high possibility that the household carbon footprint continues to increase, maintaining high levels of inequality. The current energy transition toward less carbon-intensive fuels in rural China is likely to dampen the growth rates of carbon footprints and potentially decrease inequality. Carbon intensity decrease could significantly reduce carbon footprints, but increase inequality. More comprehensive measures to reduce carbon footprint and inequality are needed, including transitioning to clean energy, poverty alleviation, reduction of income inequality, and better health care coverage.

KEYWORDS: household consumption, carbon footprint, inequality, EEIOA, microlevel data

#### 1. INTRODUCTION

With the increasing occurrence of natural disasters and extreme weather events, global heating is drawing increasing global attention.<sup>1,2</sup> Combating climate change is one of the core targets of the Paris agreement and the United Nations Sustainable Development Goals (SDGs). Among other countries, China vigorously put forward the target of carbon neutrality by 2060.<sup>3</sup> Mitigation of carbon emissions has become an urgent measure to tackle climate change, especially given the continuing trend of increasing carbon emissions. The carbon footprint, defined as the carbon emissions caused directly and indirectly by individuals, households, organizations, products or services, regions and countries from a life cycle perspective, is used to quantify and compare the contribution to global heating caused by human activities.<sup>4,5</sup> Individual and household carbon footprint reduction endeavors tackling climate change from the end-user and demand side perspective, so it is an indicator to inform demand-side carbon mitigation measures.

Achieving sustainable development requires the synergy of different development goals. Reducing inequality is an important SDG and is closely linked to economic development

and climate targets.<sup>6</sup> Inequality has been a major concern in academic and policy circles, and there are several approaches on how to measure inequality among different individuals and households. Income, monetary consumption, and direct energy consumption are all deployed to measure the inequality of individuals. Income is frequently employed to represent inequality of different household or individuals<sup>7</sup> and it is the most frequently used indicator for inequality analysis. However, it is hard to get income data at the household level through questionnaires<sup>8</sup> due to under-reporting in income surveys, whereas consumption data tends to be more accurate through household surveys.<sup>9</sup> Income can potentially fluctuate significantly, which may not reflect the resources and energy available for households in the long-run, whereas consumption tends to be more stable over time.<sup>10</sup> Inequality in

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consumption in monetary terms maybe be dominated by a major expenditure category, which potentially masks the diversity of basic living expenses of a household. For example, the expenses on sudden serious diseases, could substantially affect household consumption. Another important determinant for household consumption is the expense on durables/ nondurables, the value of which does not reflect the service flows they provide to households.<sup>11</sup> In comparison, direct energy consumption better reflects the gradual service change of durables/nondurables and is deemed as a good proxy for the measurement of consumption and a measure of the inequality of households.<sup>12</sup> Direct energy consumption, cannot reveal embodied or upstream environmental impacts of products consumed by individuals. From a life cycle perspective, the environmental effects of household consumptions along the entire supply chain should be taken into account when measuring the environmental inequality of households. In this study, household carbon footprints, which could be used to measure inequality among households and frequently used in the literature to measure environmental inequality, <sup>13-17</sup> was deployed to reveal the inequality of household consumption.

Household carbon footprints have been increasing substantially in the 21st century, especially in developing countries.<sup>18</sup> In addition, the gap between rural and urban areas, high and low emitters, and between people with different incomes are also significant. Globally, 36-45% of global emissions can be attributed to the top 10% emitters, whereas the bottom 50% emitters contribute 13-15% of global emissions, depending on the study.<sup>6,19</sup> In China, households in urban areas have a far higher carbon footprint than those in rural areas and carbon footprints tend to be closely related to income.<sup>20</sup> Though the inequality of household carbon footprints have been decreasing with economic development in China,<sup>5</sup> it is still one of the major issues needing attention. In addition, inequality issues in rural areas in China, where the economy, societal structure and consumption pattern are dramatically change, are getting worse in 2012 compared to the situation in 2007.<sup>20</sup> It is, therefore, essential to explore the carbon footprint inequality status in rural China. Rural China, which is one of the fastest developing areas in the process of urbanization and rural revitalization with around 560 million people, is under dramatic change in terms of household consumption, especially in the transition from "poverty alleviation" to "rural revitalization", leading to substantial change of carbon footprints and inequality.<sup>21</sup> However, there is little detailed research on carbon footprint and inequality in rural China, as well as the influencing factors. This study aims to fill this gap by exploring the household carbon footprint and related inequality by using the latest nationally representative rural household microlevel survey data in five provinces in China, which could provide solid evidence for carbon footprint and inequality reduction.

Accurate calculation of household carbon footprint and identification of the main contributors are the basis for carbon footprint reductions. The household carbon footprint is the sum of all carbon emissions during production of goods and services a household consumes (e.g., refs 22 and 23). Household consumption based carbon footprint calculation is mostly conducted based upon macro-level data provided by national statistical offices and environmental extended input—output analysis (EEIOA). Such macro-level study achieves a wide geographical coverage but lacks detailed individual differences.<sup>20,24,25</sup> However, these macro sources do not

support exploration of the variance and contributing factors of individual carbon footprints due to a limited number of consumption categories and a lack of basic socioeconomic information on individuals. $^{26,27}$  On the other hand, microlevel data could provide detailed consumption categories and socioeconomic characteristics of households, it comes at great costs and requires a rigorous sampling approach to ensure accurate representation of the overall population in a study area.<sup>28,29</sup> Stratified random sampling method was adopted in this paper to choose 1010 rural households in 25 counties in 5 provinces in China for the analysis, together with EEIOA, to reveal the patterns of household consumption based carbon footprint and inequality. At present, rural China is under the transition from solid fuels (direct combustion of coal and biomass) toward cleaner energy (electricity and natural gas) due to air pollution and health risks reasons.<sup>30</sup> We modeled how this energy transition affect carbon footprint and inequality by setting different scenarios. In addition, carbon intensity decrease, which is ongoing dramatically in China, was also simulated in different scenarios to show the change of carbon footprint as well as inequality. The study contributes to the literature in measuring the latest carbon footprint and inequality status of rural household consumption and identifying the main socioeconomic contributors to inequality, which could supplement the current macro source data based studies. The study not only lays a solid foundation for household consumption related carbon footprint reduction and equitable transition in the coming process in urbanization as well as rural revitalization in China, but provides important insights for low carbon and equitable society transition for decision makers in other areas.

### 2. METHOD AND DATA

**2.1. Direct Emissions Calculation.** The carbon footprint of household consumption could be attributed to carbon footprint of direct emissions and carbon footprint embodied in products and services (indirect emissions) (eq 1). The direct emissions mainly refer to greenhouse gases (GHGs) emissions from energy use, including petrol combustion in cars, coal, natural gas and liquid petrol gas (LPG) combustion in heating and cooking activities. The direct emissions were calculated by the absolute physical quantity of energy consumption multiplied by the carbon emission intensity of different energy categories (eq 2).

$$E_{\text{total}} = E_{\text{direct}} + E_{\text{indirect}} \tag{1}$$

Where  $E_{\text{total}}$  is the household carbon footprint,  $E_{\text{direct}}$  refers to the direct carbon emissions from energy direct combustion, and  $E_{\text{indirect}}$  refers to the carbon emissions embodied in products and services.

$$E_{\text{direct}} = \sum_{i=1}^{4} \left( Q_i \times \varepsilon_i \right) \tag{2}$$

Where  $E_{direct}$  refers to the direct carbon emissions from energy direct combustion,  $Q_i$  refers to the absolute physical quantities of the *i*<sup>th</sup> energy categories (coal, petrol, natural gas, and LPG) consumed by the households, which were derived from the questionnaire, and  $\varepsilon_i$  is the carbon emission efficiency of different energy categories, which are 1.64 kg CO<sub>2</sub>-eq/kg, 2.93 kg CO<sub>2</sub>-eq/L, 2.17 kg CO<sub>2</sub>-eq/m<sup>3</sup> and 3.13 kg CO<sub>2</sub>-eq/kg for coal, petrol, natural gas and LPG, respectively, according to the emissions factors of different energy types in China.<sup>31</sup> We adopted the Multi-Regional Input–Output (MRIO) model and rural household survey data to account for the carbon footprint of rural residents in five Chinese provinces.<sup>32</sup>

$$E_{\text{indirect}} = QLy_{i,i} \tag{3}$$

Where  $E_{\text{indirect}}$  represents the indirect carbon footprint for each consumption group i and sector j; Q is the direct industrial carbon emission intensities; L represents the MRIO Leontief inverse of the multiregional input-output model; and  $y_{ii}$  is corresponding to household consumption taken from household survey. The MRIO tables referring to CEADs (Carbon Emission Accounts and Data sets)<sup>33</sup> covers 31 provinces and 42 sectors for the year 2017. The extension of the MRIO model was filled with the carbon emissions calculated by CEADs.<sup>33</sup> The carbon emission inventories cover energy related emission of 17 fossil fuels in 47 sectors and process based emissions in cement industry. Only CO<sub>2</sub> emissions was included in carbon footprint calculation. The matrix of linkage between MRIO sectors and consumption categories could be found in SI Table S1 and the carbon intensity of different sectors in different provinces are shown in SI Table S2.

In order to analyze the inequality issues, the carbon footprint of the households is expressed in per capita form by diving the carbon footprint of the household by the household size. To eliminate the biases caused by extreme values, we delete the top 0.5% and the bottom 0.5% of carbon footprint households. Therefore, 1000 households were included in our analysis.

**2.3. Gini Coefficient Calculation.** Referring to Gini coefficient calculation in traditional economics,<sup>34</sup> the Lorenz curve and the Gini coefficient are used to measure the inequality of the households in different dimensions, including income, expenditure, direct energy use, and carbon footprint. In the Lorenz curve, the horizontal axis represents the cumulative percentage of the population and the vertical axis depicts the cumulative percentage of household consumption in different dimensions. Based on the Lorenz curve, the Gini coefficient is defined as follows:

Gini = 1 - 
$$\left| \sum_{i=1}^{N} (X_{i+1} - X_i)(Y_{i+1} + Y_i) \right|$$
 (4)

Where Gini is the Gini coefficient of different dimensions; X is the cumulative proportion of population and Y is the cumulative proportion of household consumption in different dimensions (income, monetary expenditure, direct energy use and carbon footprint). X is defined as the number of households in population group i divided by total population, with  $X_i$  indexed in nondecreasing order. Y is defined as the quantity of the household consumption in different dimensions by population group i divided by total household consumption, with  $Y_i$  arranged from lowest to the highest.

2.4. Inequality Decomposed by Different Consumption Categories. To distinguish the contribution of different consumption categories, we further decomposed the Gini coefficient of carbon footprint into Gini coefficient from food, clothing, housing, transportation and services by using Shapley approach. We further decomposed the Gini coefficient of housing, transportation and services into Gini coefficient from smaller consumption categories. The detailed decomposing

methods could be referred to previous studies<sup>12,35</sup> and are

detailed in the SI. 2.5. Factors Contributing to Carbon Footprint Inequality. As socioeconomic factors are not the components of carbon footprint, a regression based method is more suitable for investigating the contribution of socioeconomic factors to carbon footprint inequality.<sup>36,37</sup> A regression-based inequality Shapley decomposition method was adopted to separate each influencing variable's contribution. Income, nonfarm income rate, household size, rate of the elderly, rate of children, average education and province were analyzed for their relative contribution. The decomposition method is detailed in the SI.

2.6. Scenarios Setting and Analysis. Heating, which mainly refers to stove heating or heating through electrical heater, and cooking are the main drivers for direct energy consumption and their inequality greatly influenced by energy source change. Due to severe air pollution, traditional energy transiting to relatively clean energy is a key area for energy revolution in rural China. Specifically, coal and biomass substituted by electricity and natural gas, which is the mainstreams for energy transition in rural China,<sup>38</sup> was simulated and its effect on carbon footprint and inequality was calculated. In the process of decarburization, carbon intensity decrease is a trend. Its effect on carbon footprint and inequality was simulated by setting scenarios. Specifically, we modeled energy transition scenarios, carbon intensity decrease scenarios, and energy transition and carbon intensity decrease combined scenarios. We simulated the effect of energy transition scenarios on carbon footprint and its inequality, which include biomass substitute by electricity, biomass substituted by natural gas, coal substituted by electricity, coal substituted by natural gas, and biomass and coal substituted by natural gas scenarios. The substitution quantity was calculated as follows:

$$Q_1 = \frac{Q_2 \times DW_2 \times \varphi_2}{DW_1 \times \varphi_1} \tag{5}$$

Where  $Q_1$  is the physical quantity of the substituting energy type,  $Q_2$  is the physical quantity of the energy type substituted,  $DW_1$  is the lower heating value of the substituting energy type,  $DW_2$  is the lower heating value of the substituted energy type,  $\phi_1$  is the thermal efficiency of the substituting energy type, and  $\phi_2$  is the thermal efficiency of the substituted energy type. The lower heating value and thermal efficiency of different types of energy are shown in SI Table S3.<sup>39,40</sup>

Carbon intensity decrease scenarios were simulated as follows. According to the report, the carbon intensity (measured as carbon footprint per GDP) has decreased 48.1% in 2019 compared the level in 2005 with an annual 5.01% reduction rate<sup>41</sup> and China is determined to reduce its carbon intensity in 2030 to 35% of the level in 2005, which means that a 3.23% reduction rate is needed from 2019 to 2030.<sup>3</sup> We assumed that the carbon intensity would decrease at a 3.23% annual rate and simulated the carbon footprint and inequality change from 2018 to 2030.

Energy transition and carbon intensity decrease combined scenarios were set as follows. We assumed biomass and coal were substituted by natural gas by a 10% increase per year from 2019, which means that biomass and coal will be 100%

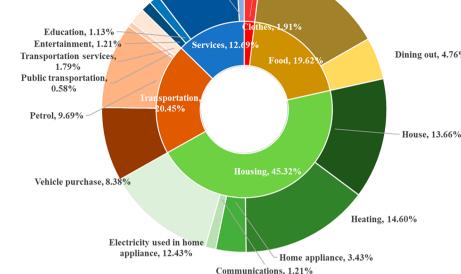


Figure 1. Contribution of detailed household consumption categories to carbon footprint in rural China.

substituted by natural gas in 2028. In 2029 and 2030, it is assumed that the energy mix is the same as that in 2028. Meanwhile, carbon intensity decreased in the same manner as it is in carbon intensity decrease scenarios from 2018 to 2030. Carbon footprint and its inequality were simulated in the above scenarios. The parameters setting for carbon intensity decrease scenarios and energy transition and carbon intensity decrease combined scenarios are detailed in SI Table S4.

**2.7. Data.** Detailed household consumption data were acquired from a national representative survey conducted in April 2019. In total 1010 rural households in 25 counties in 5 provinces were interviewed (SI Figure S1). The survey was conducted through a one-on-one in-person interviews to ensure the interviewees understood and answered the questions correctly. For household consumption, the questionnaire includes 16 consumption categories and 59 items. The detailed information on data collection process could be found in the SI. The representativeness of the sample is verified and shown in SI Tables S5 and S6, respectively (Data acquisition).

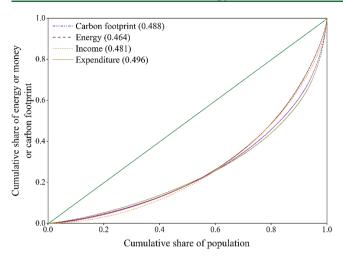
### 3. RESULTS

3.1. The Main Determinants of Household Carbon Footprints. The average per capita household consumptionbased carbon footprint in rural China is 2.46 t CO2-eq (interquartile range (IQR) = 0.90-2.74 t CO<sub>2</sub>-eq; median = 1.56 t  $CO_2$ -eq) in 2018. We further disaggregate per capita household carbon footprints into different consumption categories. As is shown in Figure 1, housing accounts for 45.32%, transportation for 20.45%, food for 19.62%, services for 12.69%, and clothes for 1.91% of the total household carbon footprint, respectively. A higher resolution of detailed consumption categories shows that food eating at home (14.87%), heating (14.60%), house built and purchase (13.66%), electricity used in home appliance (12.43%), petrol (9.69%), health expenditure (9.48%), and vehicle purchase (8.38%) are the dominating categories of the household carbon footprint.

The carbon footprint of 59 categories of consumables are detailed in SI Table S7. The dominant contributors for food are grains and pork consumption, with 0.032 and 0.025 t  $CO_2$ -eq carbon footprint, respectively. Dining out, which is an important source for both nutrients and environmental impact, accounts for 24.26% of the carbon footprint of food. Heating by coal is the largest contributor for housing, with 0.312 t  $CO_2$ -eq footprint. It is also a hotspot for the impending energy transition. In addition to vehicles purchased, petrol used in vehicles is an important source for carbon footprint. Health expenditure of households is a key contributor to services, with 0.233 kg  $CO_2$ -eq footprint.

3.2. Inequality Measurements in Different Dimensions. We measure inequality of households by using the Gini coefficient, which is a widely used index to represent inequality.<sup>12</sup> Inequality can be measured in different terms, including income, expense, direct energy use and carbon footprint.<sup>42</sup> To show the extent of inequality, we calculated the Gini coefficient on income, expense, direct energy consumption, as well as the carbon footprint in rural China. As shown in Figure 2, there are some differences among the Gini coefficients along these dimensions. Income is the most commonly used indicator to reflect the livelihood status of households, the Gini coefficient of which is 0.481, which is higher than the national average income Gini index in 2018 (0.468),<sup>43</sup> reflecting bigger gaps between household incomes in rural China. The Gini coefficient for household expenditure, that includes also home-grown food, shows the largest degree of inequality, reaching 0.496. Due to the intrinsic characteristics of monetary values, income and expense tend to have larger fluctuation and a higher Gini coefficient. Direct energy use, deemed as a better proxy than income for the measurement of consumption by some researchers,<sup>12</sup> has a Gini coefficient of 0.464. While the Gini coefficient of the carbon footprint, which measures the carbon emissions of household consumption from a life cycle perspective, is smaller

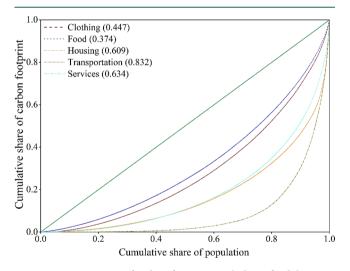
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**Figure 2.** Lorenz curve of carbon footprint, energy, and household income/expenditure. The diagonal is the line of perfect equality. The numbers presented in parentheses are the Gini coefficients.

than that of expenditure but bigger than that of energy and income, reaching 0.488. The carbon footprint Gini coefficient is a more comprehensive indicator considering life cycle carbon emissions without the problems of income based inequality measures. Therefore, we further analyze carbon footprint inequality in the following parts.

We measure the carbon footprint inequality for different consumption categories. According to Figure 3, transportation



**Figure 3.** Lorenz curve of carbon footprint in clothing, food, housing, transportation, and services. The diagonal is the line of perfect equality. The number presented in parentheses is the Gini coefficient.

has the largest inequality, with the Gini coefficient reaching 0.832, which means that there are giant differences among the households in rural China in terms of mode of transportation and associated carbon footprints. Services, including entertainment, education, health, and other services, show the next highest degree of inequality with a Gini coefficient of 0.634, followed by housing with 0.609, indicating big differences in house and heating conditions among households. In comparison and not surprisingly, the Gini coefficient for food and clothing is comparatively small, reaching 0.374 and 0.447 respectively, which reveals that the carbon footprint of basic necessities shows less variations among households.

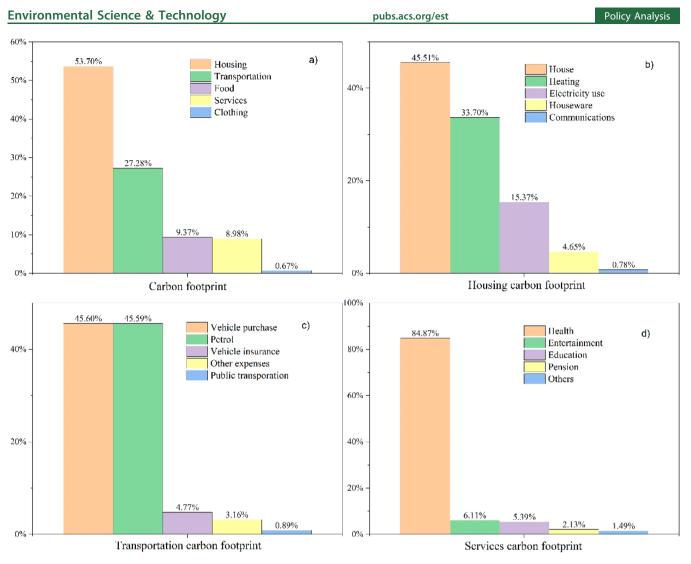
To identify the source of carbon inequality, we decomposed the carbon Gini coefficient into five aggregate categories: clothing, food, housing, transportation, and services (Figure 4a). Housing is the largest contributor to the inequality (53.70%), followed by transportation (27.28%), food (9.37%), services (8.98%), and clothing (0.67%). The priority of reducing carbon inequality includes housing, transportation, and services.

We further decomposed inequality in housing, transportation and services in more detail, shown in Figure 4b–d. Further exploration shows that house purchases, heating, and utility electricity consumption contribute 45.51%, 33.70%, and 15.37% to the carbon footprint inequality of housing. The carbon inequality in transportation is mainly attributed to carbon emissions associated with the purchase of the cars (45.60%) and petrol (45.59%), whereas the contributions of other items are relatively small. Differences in health expenditure (84.87%) is the dominant sources of inequality of carbon footprint in services. The contribution of detailed consumption categories can be found in SI Table S8.

3.3. Main Factors Contributing to Carbon Footprint Inequality. Socio-economic factors influence the consumption patterns, thus affecting household consumption-based carbon footprints (SI Tables S9 and S10). In order to quantify how socio-economic factors contribute to total carbon footprint equality, a regression-based Shapely inequality decomposition method was adopted to quantitatively analyze the relative contribution of these factors. In Table 1, the rows show the Gini coefficient of different consumption categories, and the columns demonstrate the relative contributions of those influencing factors. As there are too many variables affecting the inequality, residues, which include the contribution of all other variables, take the largest share in all dimensions. For the variables of concern, Table 1 shows that province is the most important variable contributing 27.26% to total carbon inequality, followed by household size (5.21%) and education level (4.57%). For vehicles carbon footprint inequality, total income, province, and household size are the dominant contributors, with 20.13%, 10.20%, and 8.71% contribution, respectively.

**3.4. Carbon Footprint and Inequality Change for Different Scenarios.** With economic and societal change, consumption of households in rural China is likely to increase, so is its related carbon footprint. How to effectively reduce household consumption related carbon footprint and promote equality in rural China is an important task in urbanization as well as rural revitalization, especially in the context of policy goals promoting the carbon peak in 2030 and carbon neutrality in 2060.<sup>3</sup> We modeled a set of scenarios to investigate their effects on carbon footprints and inequality associated with potential changes in domestic direct energy consumption and carbon intensity.

In the energy transition scenarios, as is shown in SI Figure S2, 100% replacing biomass by natural gas and by electricity could increase the carbon footprint by, respectively, 13.70% and 34.52%, whereas a 100% substitution of coal by natural gas and electricity could reduce the footprint by respectively 10.47% and 3.94%. Replacing biomass by natural gas would bring a lower increase of the carbon footprint than using electricity. While, replacing coal by natural gas could bring more carbon footprint reduction potential than by electricity. Therefore, changing to natural gas has lower carbon emission potential than electricity in energy transition in rural China



**Figure 4.** Decomposition of Gini coefficient of carbon footprint in different dimensions. (a) carbon footprint-based Gini coefficient decomposition by end-use activities; (b) housing carbon footprint Gini coefficient decomposition; (c) transportation carbon footprint Gini coefficient decomposition; (d) services carbon footprint Gini coefficient decomposition.

Table 1. Decomposition of	of Carbon Footpi	int Inequality (Gir	ni Coefficient)	) For Different Dimensions
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	total	house	heating	utility electricity	vehicles	petrol	health
income	2.18%	2.15%	0.86%	0.06%	20.13%	2.59%	0.02%
nonfarm rate	2.97%	5.71%	4.38%	2.61%	0.40%	10.57%	2.28%
household size	5.21%	1.01%	8.48%	8.59%	8.71%	0.38%	3.89%
age over 65	2.54%	3.74%	1.94%	0.13%	0.02%	0.57%	4.31%
average education level	4.57%	11.91%	1.14%	1.73%	1.88%	10.77%	0.70%
average living space	3.64%	10.76%	4.02%	1.73%	4.79%	1.93%	0.44%
province	27.26%	26.04%	31.07%	30.19%	10.20%	4.21%	12.34%
residues	51.64%	38.67%	48.12%	54.96%	53.86%	68.99%	76.02%
total	100%	100%	100%	100%	100%	100%	100%

without big electricity carbon footprint intensity change. When biomass and coal are all substituted by natural gas, the carbon footprint could increase to 2.54 t  $CO_2$ -eq, with a 3.23% increase. Substituting biomass by electricity and natural gas would increase the carbon footprint but would decrease the Gini coefficient. Substituting coal by electricity and natural gas would decrease the carbon footprint, though it has not obvious impact on Gini coefficient. When biomass and coal are both 100% substituted by natural gas, Gini coefficient would also be reduced to 0.440, with an 9.67% reduction (SI Figure S3). In the reduced carbon intensity scenario, the carbon footprint would be reduced to 2.08 and 1.85 t  $CO_2$ -eq in 2025 and 2030, respectively, with a 15.18% and 24.53% reduction rate compared to 2018. However, the carbon footprint Gini would increase to 0.493 and 0.495 in 2025 and 2030, respectively (Figure 5). Though carbon intensity decrease would have the potential for a significant reduction of the carbon footprint, it could cause an increase in inequality. The reduction of inequality needs more consumption-side behavior change.

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Policy Analysis

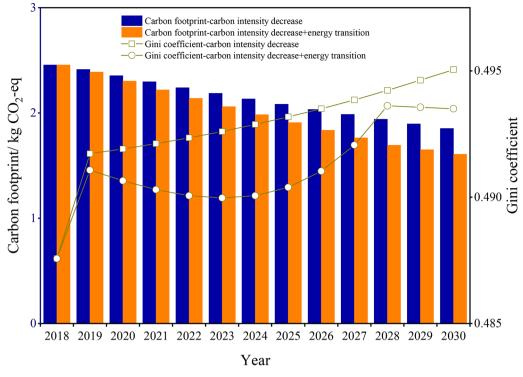


Figure 5. Carbon footprint and Gini coefficient change in carbon intensity decrease scenarios and energy transition and carbon intensity decrease combined scenarios.

Energy transition and carbon intensity decrease combined scenarios show a larger reduction potential of the carbon footprint and Gini coefficient compared to the scenario only focusing on a decline in carbon intensity (Figure 5). It is shown that the carbon footprint could be reduced to 1.61 t  $CO_2$ -eq in 2030. The Gini coefficient of carbon footprint also shows an increasing trend though there is a slight decrease from 2019 to 2023.

#### 4. DISCUSSION

4.1. Heterogeneity of Household Carbon Footprints. Compared to previous studies, our results show higher per capita household carbon footprints (SI Table S11). For instance, compared to an average 0.18-1.8 t CO2-eq household carbon footprint in rural China in 1995-2012,<sup>5,21,44</sup> our study shows a high per capita household carbon footprint in rural China (2.46 t CO<sub>2</sub>-eq) in 2018. But it is lower than per capita household carbon footprint in China  $(0.28-4.01 \text{ t CO}_2 - \text{eq} \text{ in } 1995-2015)^{45,46}$  or in cities (0.40-5.20 t CO<sub>2</sub>-eq in 1995–2015) in most previous studies, especially in recent years,<sup>21,44</sup> and it is lower than the per capita footprint of China (7.05 t  $CO_2$ -eq) in 2018.<sup>47</sup> In international comparison, it is lower than the per capita footprint in the U.S. (16.56 t CO<sub>2</sub>-eq) and Germany (9.12 t CO<sub>2</sub>-eq) in 2018, but higher than that in India (1.96 t CO<sub>2</sub>-eq) and Brazil (2.19 t  $CO_2$ -eq) in 2018.<sup>47</sup> The over 2-fold increase of the carbon footprint compared to 2012<sup>5</sup> is mainly due to an increase in consumption expenditure. According to the statistics and our survey data, consumption expenditure has increased by 2.20 times in five provinces compared to 2012. In addition, most studies on carbon footprints in rural China are based on data from statistical yearbooks, lacking detailed consumption categories, which may lead to an increase in the uncertainty of the results. In this study, we include 59 consumption items

to calculate total consumption related carbon emissions. The broader coverage of consumption items leads to a more accurate estimation of carbon footprints compared to previous studies.<sup>18</sup>

4.2. Inequality in Household Consumption Related Carbon Footprints. Though the household consumptionbased carbon footprint is on the rise, there exists significant differences between carbon footprint groups. The top 10% residents have an average per capital carbon footprint of 9.56 t CO2-eq, which is around 22 times of that of bottom 10% residents with 0.43 t CO<sub>2</sub>-eq, indicating big inequality among different emitting groups (SI Figure S4). In terms of per capita income, there are statistically significant differences between different groups (p < 0.01) as the high income groups tend to have higher carbon footprint. The highest carbon footprint group is the one with the highest income  $(3.87 \text{ t CO}_2\text{-eq})$ , whereas the lowest carbon footprint group lies in the one with income between 30%-40% (1.98 t CO<sub>2</sub>-eq) (SI Figure S5). The heterogeneity of household consumption related carbon footprint also lies in different provinces, with Hebei province having the highest value 3.15 t CO<sub>2</sub>-eq and Sichuan province having the lowest value 1.49 t  $CO_2$ -eq (SI Figure S6). The biggest difference between provinces mainly arises from differences in housing, in which heating plays the dominant role. For instance, the carbon footprint in Sichuan province is 0.03 t  $CO_2$ -eq, whereas it is 0.82 t  $CO_2$ -eq in Hebei province. The geographic location and natural conditions shape whether heating is needed or not, resulting in differences in carbon footprint from heating. In addition, heating energy sources also plays an important role, for instance, Jilin has the largest heating demand but moderate carbon footprint from heating, which can be largely attributed to biomass-based heating structure. Sichuan province, which also has considerable amount of electricity used for heating, has very low carbon

footprint for heating, mostly attributed to its low carbon intensity for electricity. The differences in other dimensions are comparatively small, with Hebei province having the largest carbon footprint in food and transportation dimensions, Jiangsu province having the largest carbon footprint in clothing dimension and Shannxi province having the largest carbon footprint in services dimension.

The Gini coefficient of carbon footprint in 2018 is 0.488, larger than that in 2012 and 2017 based on statistical data from the literature, corresponding to the trend of increasing carbon footprints in rural China.<sup>20</sup> Further exploration of the Gini coefficient of detailed consumption categories, show that necessities and items of daily consumption such as food and clothes, communications, electricity use in home appliance, personal care, and public transportation have comparatively low Gini coefficients (SI Table S12), whereas luxury items such as house purchases and vehicle purchases and associated fees such as car insurance and environmental fees have a relatively high Gini coefficient. In other words, consumption categories with low Gini coefficients tend to be necessary goods of daily life while those with a high Gini coefficient tend to be major one-time expenditures. Only a small share of households has such expenditures in a given year, and these items are significant contributors to overall inequality. Heating and health are also important contributors to the overall inequality. The difference in heating is a function of required heating days and fuel. While expenditure on serious illnesses is the main reason for inequality in health related carbon footprint.

**4.3.** Potential Carbon Footprint Changes in Rural China. As the very basic needs categories, clothing and food contribute to 1.91% and 19.62% of the carbon footprint, respectively. They are one of the fastest growing areas for environmental footprint,<sup>48</sup> especially for food,<sup>49</sup> as people are turning to more meat-oriented diets.<sup>50</sup> As eating out is becoming more widespread also in rural China, together with higher environmental impact per meal compared to eating at home,<sup>51</sup> there is high possibility that the carbon footprint from the food sector is increasing, aggravating already serious food-related environmental burdens.<sup>52</sup>

Housing is the largest component contributing to per capita carbon footprint, with newly house built, house heating, and home appliance electricity consumption taking the dominating roles. Heating is geographically diverged in China with heating in the north, whereas there is no heating in the south, though there exist some air conditioners in some places in the south. With more individual heating deployed in the south, there are possibilities that the carbon footprint of heating is increasing. The clean energy transition in rural China, is mainly driven by public health concerns, and refers to the substitution of coal and biomass with electricity and natural gas.<sup>38</sup> But this creates uncertainty to the carbon footprint. Biomass substituted by electricity or natural gas could increase the carbon footprint, whereas coal substituted by electricity or natural gas could decrease the carbon footprint (SI Figure S2). However, as China is endowed with less natural gas reserves, a 100% transition of household coal and biomass toward natural gas is challenging. As over 90% of the dwellings in the sample households are bricks and cement based, the need for new buildings in the villages is low. However, the need for apartments in the county center and city centers is increasing,<sup>53</sup> leading to possible carbon footprint increase from construction of new houses. With the ever increasing of home appliance ownership, the consumption of electricity and related carbon footprint will increase steadily, given no big change of carbon footprint intensity of electricity or efficiency of home appliances.

For transportation, car purchase and petrol are the dominant contributors. From 2007 to 2018, a yearly average increase of 26.91% of car ownership was observed, and household car ownership has increased to 31.39% in the sample households. As private cars are becoming one of the mainstream tools for transportation, the increase of car purchases and petrol consumption is about to boom, leading to car related carbon footprint increase.<sup>54</sup> The aging society might lead to more health care related expenses<sup>55</sup> and thus associated carbon footprints.

4.4. Reducing Carbon Footprint and Inequality. To reduce average carbon footprint and inequality, one of the key measures is to reduce the carbon emissions of the high carbon footprint group. When examining carbon footprint in small categories, it is found that housing and transportation explain the majority of differences between different groups (SI Figure S7). A house built or purchased and a car purchased are the dominant factors contributing to differences of carbon footprint of different groups. The reduction of new house built or purchased and car purchase could reduce the size and inequality of carbon footprint. When the carbon footprint from a new house built or purchased and a car purchase are excluded from total carbon footprint calculation, the Gini coefficient could be reduced from 0.488 to 0.404. As mentioned, though the need for new house is low, the need for a car is surging, increasing the difficulty of reducing carbon footprint size and inequality.

Province is a dominant contributor to carbon footprint inequality, which reveals big differences of household consumption related environmental impact in different provinces. The heterogeneity of carbon footprint in different provinces are detailed in SI Figure S6. The divergence of carbon intensity in those provinces contributes to the inequality of carbon footprint (SI Table S2). The decarburization of high emission sectors in certain provinces is vital to reduce carbon footprint and inequality. In addition to carbon intensity variances in different provinces, consumption structure differences contribute to the inequality. For instance, natural gas-based cooking and heating significantly increase the carbon footprint in Hebei province and increase the inequality. Homogenized cooking and heating infrastructure should be promoted to reduce the inequality of carbon footprint. The characteristics of the family also contributes the inequality, especially the household size and the average education level. Reduction of education differences contribute to reduction of carbon footprint inequality.

Technological improvement, which is characterized by carbon intensity, is a fundamental measure to reduce the carbon footprint of household consumption. Keeping the carbon intensity reduction rate, the carbon footprint could be reduced substantially given no big change of consumption behaviors. The transition toward a more carbon footprint equitable society in rural areas needs to highlight the development heterogeneity of different provinces, which is also the focal point of sustainable development in China, such as transfer payments and building a strong social net. In addition, more centralized policy change, including clean energy transition, household income increase of lower income households, and better health insurance are important to foster

a more equitable society. Consumer behavior change is important, including nudging toward eco-friendly products and energy saving. Eco-labels, which are effective tools to inform the consumer of green products, should be promoted for different products.<sup>56</sup> Public education on pro-environmental behaviors should also be promoted to foster a low carbon and equitable transition.

**4.5. Limitations of the Study.** The study employs first hand survey data and MRIO model to analyze the carbon footprint and inequality of household consumption in rural China. The uncertainty of the study lies in the following aspects. First, the survey data were based on the consumption behavior in 2018, but the latest China MRIO table is from 2017. The inconsistency of the time might bring uncertainty of the results. Second, only CO<sub>2</sub> emission was included in the study as the latest CEADs data has only CO<sub>2</sub> emission data, whereas CH<sub>4</sub> and N<sub>2</sub>O were neglected, which could underestimate the carbon footprint of household consumption. Third, as only five provinces were included in our survey, it might not reveal the true situation of rural household consumption in China generally. More provinces should be included in future studies.

#### ASSOCIATED CONTENT

#### **Supporting Information**

The Supporting Information is available free of charge at https://pubs.acs.org/doi/10.1021/acs.est.1c01374.

(PDF)

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#### Notes

The authors declare no competing financial interest.

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