

# Unclean but affordable solid fuels effectively sustained household energy equity

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Extensive use of traditional solid fuels necessitates a clean transition to modern energy, yet rising costs hinder equitable progress, presenting a challenge that remains underexplored. Here we quantify household energy inequities in China and evaluate shifts during the cooking and heating transition by compiling data from nationwide questionnaire surveys and statistic datasets. We find that by meeting 42.6% of household energy needs at low costs, solid fuels sustain equitable energy consumption across different income groups, being measured by the Concentration Index (CI). However, energy burden inequity remains substantially with the CI value increases by up to 43% during the transition, particularly when moving away from biomass for cooking. Switching to electric heating with natural gas cooking would limit such increases by only 15.5%. The study underscores the negative equity impacts of solid fuel cessation, advocating for phased transitions and targeted subsidies to ensure a just clean energy transition.

Solid fuels such as coal and biomass play a pivotal role as a residential energy source across many low-income and middle-income countries (LMICs, see Supplementary Note 1), with their usage widespread among ~2.8 billion individuals globally<sup>1,2</sup>. Notably, the inefficient combustion of solid fuels is associated with high emissions of harmful air pollutants, leading to significant indoor and outdoor air pollution, contributing to millions of premature deaths annually<sup>1,3,4</sup>. The adverse health implications linked to the household solid fuel usage are particularly pronounced in China, as evidenced by their 7.5% contribution to total energy consumption yet accounting for 68% of fine particulate matter (PM<sub>2.5</sub>) exposure<sup>5</sup>.

Transitioning from solid fuels to clean energy is a crucial step for human health preservation and aligns with many Sustainable Development Goals (SDGs)<sup>6,7</sup>. However, the suspension of solid fuels could escalate energy expenditures and deepen the household burden, especially for rural low-income population as they are highly relying on these dirty fuels<sup>8,9</sup>. The disparities in energy access may reduce household welfare for certain populations during the clean energy transition, hindering their ability to heat homes, cook safely, and perform daily tasks<sup>10,11</sup>. Determining the embodied energy inequity

changes is critical to sustain the household welfare and social equity with the realm of policy formulation for clean energy transition, realizing the synergistic benefits of various SDGs, including but not limited to affordable clean energy, no poverty, reduced inequalities, human health, and climate action<sup>12,13</sup>.

However, due to insufficient household energy survey, particularly the lack of information on non-commodity biomass consumption, the current extent of energy inequity remains unclear. The role of solid fuels in fulfilling residential energy demands, and their contributions in energy inequity issues are also insufficiently explored. The complex energy structure, along with pervasive phenomenon of mixed use of multiple energy, leads to substantial challenges in elucidating changes in energy inequity throughout the energy transition process<sup>14,15</sup>. These cognitive gaps obstruct a nuanced understanding of household energy equity, potentially impeding an affordable and equitable energy transition, thereby undermining efforts towards sustainable development.

In this study, we elucidate the extent and causes of current energy inequity from multiple perspectives, and subsequently quantitatively assess the changes in energy inequity within the clean energy

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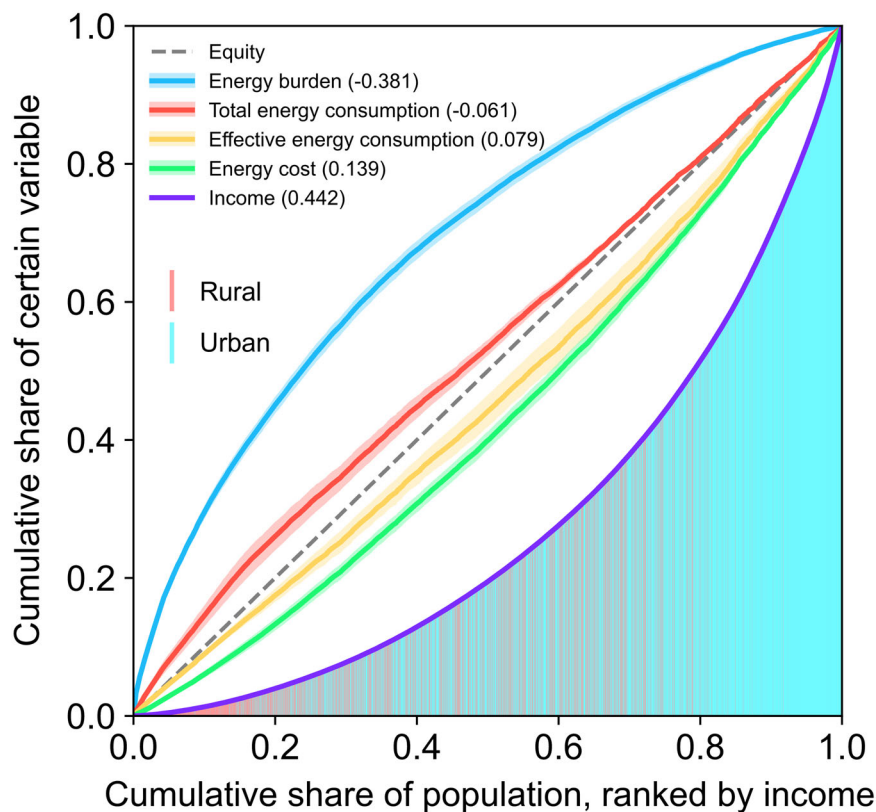
transition pathways by developing a comprehensive dataset encompassing detailed energy and socioeconomic information in China. This dataset is derived from available national and provincial statistics yearbooks, and more importantly, a nationwide energy survey and fuel-weighting measurement campaign that covered 31 provinces in China (excluding Hong Kong, Macao, and Taiwan province) to contain information on both commercial and free fuel consumption for different activities. The inequities in total and effective household energy consumption, energy cost, and energy burden, indicating their disparities across different income groups, are quantitatively evaluated utilizing the Concentration Index (CI) (see Methods). Through decomposition methods, we delineate the contributions of specific energy types and activities to income-related inequity and examine the role of income in the broader context of energy inequality across the entire population. This study highlights the escalating energy burden inequity in the suspension of solid fuel by conceptualizing transition scenarios, providing valuable insights for energy transition strategies in China and potentially other LMICs.

## Results

### Slight inequity in household energy consumption but significant in energy burden

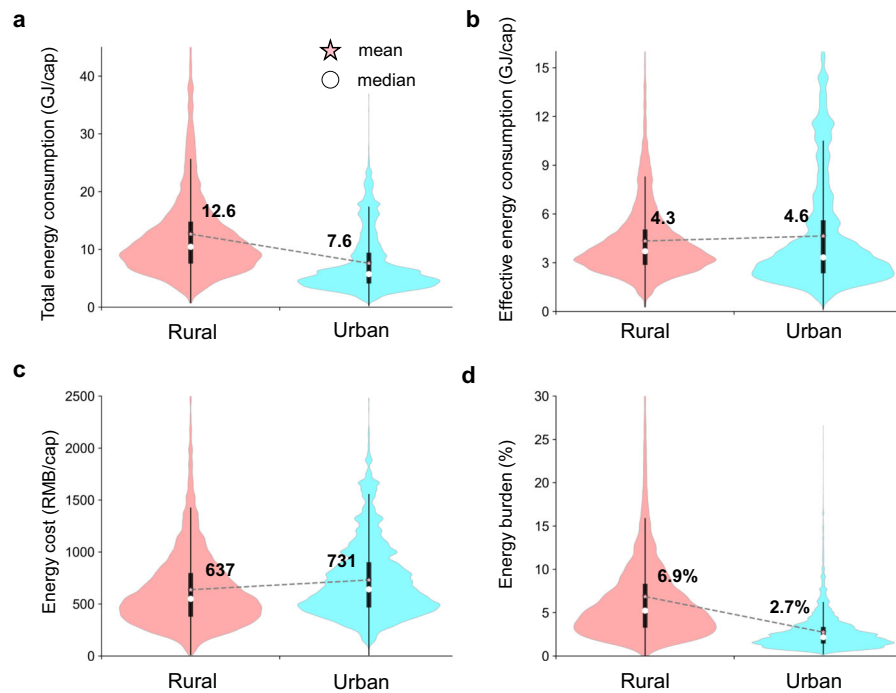
The inequities in household disposable income and different energy indicators in China were examined through Concentration curves and CI values. Apart from (total) energy consumption that refers to the entire amount of energy consumed by a household, effective energy consumption denotes the useful portion of energy derived from the total consumption, excluding losses and waste. Energy cost is the

expenditure on purchasing energy, while energy burden represents the proportion of this expenditure relative to disposable income. The CI value of income inequity, equal to the Gini coefficient, was 0.442 (Fig. 1), indicating the income disparity among populations even after getting rid of poverty in the country. This value was close to some other estimates within a reasonable variation range from different datasets<sup>16–18</sup>, for example, ref.<sup>19</sup> reported a Gini coefficient of 0.418 by using the provincial macro data from national statistical yearbooks. The CI values of the total energy amount and effective energy consumed were  $-0.061$  [ $-0.081$ ,  $-0.040$  as 95% confidence interval] and  $0.079$  [ $0.047$ ,  $0.109$ ], respectively, suggesting relatively slight disparities in the amount of energy consumed among different income groups. The former negative value further indicated that the people with lower income levels (Supplementary Note 2) tended to consume relatively larger quantity of household energy, however, the energy utilization efficiency among the low-income population was less compared to the high-income population (Supplementary Note 2) as the later CI value was positive nearly equity. Different from the energy consumption amount, the inequity in the energy cost was larger, with the CI value of  $0.139$  [ $0.121$ ,  $0.158$ ]. One recent study based on the sampled household survey data estimated that the CI value of household energy cost in China was  $0.114$ , that was close to our estimate here<sup>8</sup>. The positive value indicated that the high-income population spent more on their household energy. More notably, the CI value of household energy burden was as high as  $-0.381$  [ $-0.399$ ,  $-0.362$ ], indicating that the low-income population endured seriously disproportionate burdens to meet their daily energy demands.



**Fig. 1 | Concentration curve and Concentration Index of various indicators related to income and household energy utilization in China in 2017.** The x-axis represents the cumulative share of the population arranged by disposable income, ranging from the lowest income groups on the left to the highest income groups on the right. The y-axis signifies the cumulative share of the respective indicators corresponding to the ordered population. The best estimates of the Concentration

Index are represented by solid lines, derived as the median of 1000 Monte Carlo simulations, with the values provided in parentheses, while the error bands depict the uncertainty as the 95% confidence interval from these simulations. Data for Hong Kong, Macao and Taiwan province are not included. Source data are provided as a Source Data file.



**Fig. 2 | Comparison of per capita household.** **a** Total and **(b)** effective energy consumption (GJ/cap,  $10^9$  J per capita), **(c)** energy cost (RMB/cap, 1 RMB  $\approx$  US\$ 0.15 in 2017) and **(d)** energy burden (%) between rural and urban areas in China in 2017. In the violin plots, thick bars represent the interquartile range (IQR), the range

between the first and third quartiles, while thin bars extend to 1.5 times the IQR. The data reflect the distribution of energy indicators across the entire rural and urban populations in China. Data for Hong Kong, Macao and Taiwan province are not included. Source data are provided as a Source Data file.

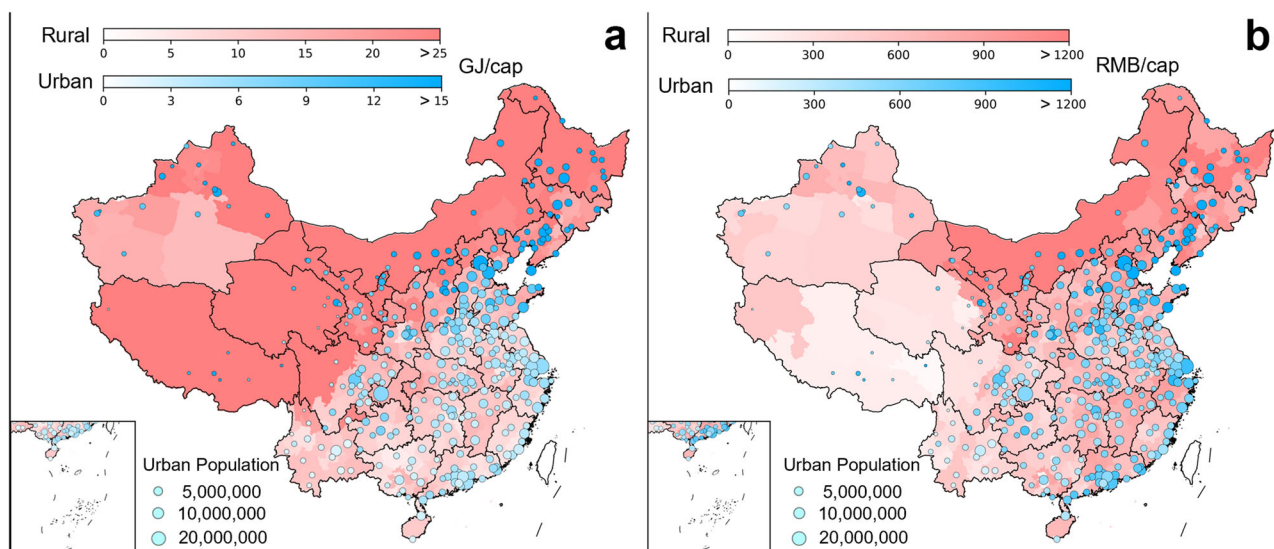
In China, the urban-rural dual structure has significantly affected many aspects of socioeconomical development, including household income, energy mix and costs<sup>20</sup>. The average household total energy consumption for the rural population was  $12.6 \pm 8.3$  (as 1 standard deviation) GJ/cap ( $10^9$  J per capita), markedly surpassing that in the urban population ( $7.6 \pm 5.2$  GJ/cap) (Fig. 2a). But in the effective energy consumed, the amounts were  $4.3 \pm 2.4$  and  $4.6 \pm 3.4$  GJ/cap for the rural and urban population (Fig. 2b), respectively, showing a much smaller difference between rural and urban people. The value for rural effective energy was close to another estimate of 4.2 GJ/cap<sup>21</sup>. It was observed that both rural and urban populations have nearly equal demands in effective energy, though rural individuals consumed more inefficient fuels to meet these daily demands. Urban residents expectedly have high costs on household energy use, but less energy burden (Fig. 2c, d). The energy burden was  $2.7 \pm 2.1\%$  on average for the urban resident, but as high as  $6.9 \pm 6.2\%$  for the rural. Besides the significant disparities between the urban and rural groups, the inequalities in both energy cost and energy burden within groups were also substantial, and even larger among the rural population than the urban group (Supplementary Table 1). Household energy structure was different among the rural populations, showing high degrees of distinct mixes. Stacked use of multiple traditional and/or modern energies were pervasive in rural areas<sup>4</sup>. Low-cost or nearly free traditional solid fuels including biomass fuels and raw coal chunks were still frequently utilized in many rural homes; meanwhile, clean energy transition has been strongly advocated but increased residential energy costs and burdens<sup>8,15</sup>.

Energy demands and consumption patterns vary by region and are influenced by access to natural resources, climatic conditions, and behaviors. Household energy consumption was high in northern and western regions (Fig. 3a), mainly attributed to strong heating demands. Notably, for most rural residents the consumption exceeded 25 GJ/cap, and was as high as 44 [39, 48] GJ/cap *e.g.*, in the Tibetan Plateau, which was more than sixfold of the consumption in the southeast region

(Supplementary Table 2 and Supplementary Fig. 1). The spatial distribution of effective energy mirrored a similar pattern with relatively smaller regional disparities compared to that in the total energy consumption. However, it is interesting to note that the spatial distribution of household energy cost diverged from that of energy consumption amount (Fig. 3b). Rural residents located in the Tibetan Plateau had lower expenditures on daily household energy, being around ~410 RMB/cap (1 RMB  $\approx$  US\$ 0.15 in 2017), while the national average was 637 [577, 694] RMB/cap for the rural residents. Meanwhile, in the northeast and northwest regions, where energy consumption was also high due to longer heating demands, the associated energy cost, as well as the energy burden, was high, reaching 1015 [924, 1100] (11.9% [10.9%, 13.0%]) and 835 [761, 906] (15.0% [13.7%, 16.4%]) RMB/cap, respectively. Heating energy structure was different between the cold Tibetan Plateau and the north China region, though both have strong energy demand<sup>22</sup>. In the Tibetan Plateau, residents commonly utilize free dung cake or firewood to meet their heating needs<sup>23</sup>, substantially alleviating their energy costs and burdens. Conversely, rural residents from the northern China use commercial coal for a substantial portion of their heating energy supply<sup>24</sup>, contributing to the inequity of energy cost and burden across different regions. For the urban population, the spatial distributions in energy consumption and energy cost were generally much homogeneous, giving their similar energy mix structure and high adoption of modern clean energies.

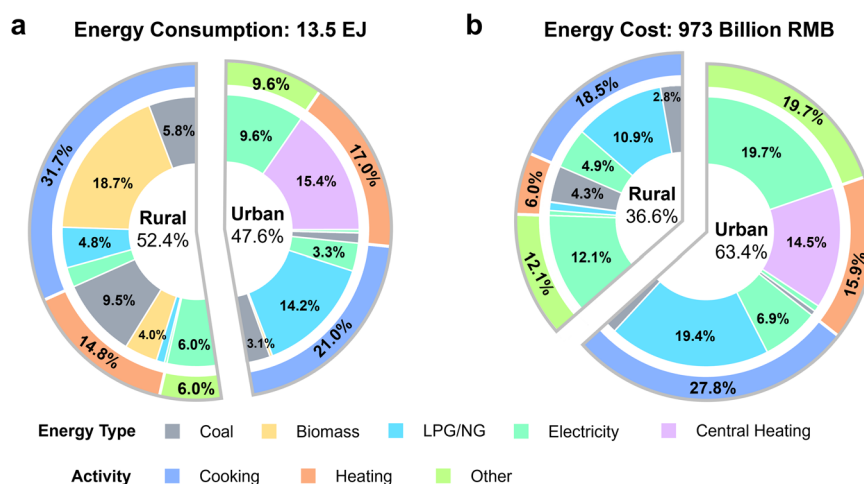
### Free biomass fuels are still important in meeting energy demands

The total household energy consumption was 13.5 [12.8, 14.2] EJ ( $10^{18}$  J), accounting for ~16% of total national final energy consumption<sup>25</sup>, with the rural and urban residents' consumption share of 52.4% [50.0%, 55.1%] and 47.6% [44.9%, 50.0%], respectively (Fig. 4a). Despite a substantial clean energy transition in the past decade<sup>26–28</sup>, traditional solid fuels remained the predominant sources of rural residential energy



**Fig. 3 | The spatial per capita household.** **a** Total energy consumption (GJ/cap,  $10^9$  J per capita) and **(b)** energy cost (RMB/cap, 1 RMB  $\approx$  US\$ 0.15 in 2017) in China in 2017. The data are presented in the form of municipal-level information in the graph, where the color intensity represents the value of the data, with red area

indicating rural data and blue circle indicating urban data. The location and size of the blue circle respectively represent the location of the major city and the urban population size. Data for Hong Kong, Macao and Taiwan province are not available. Source data are provided as a Source Data file.



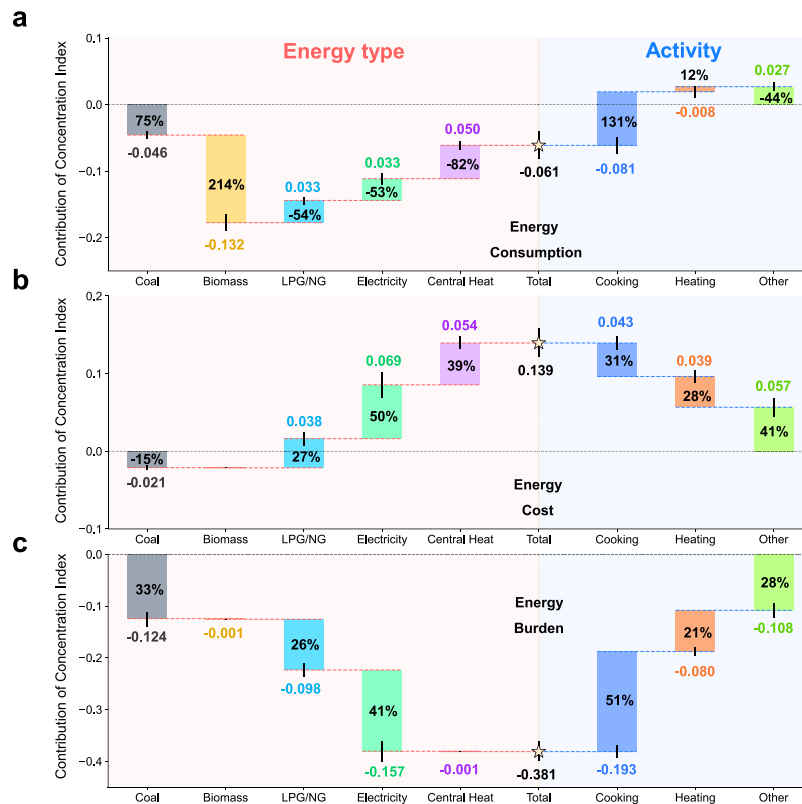
**Fig. 4 | The contribution of different energy types and activities to household.** **a** total energy consumption ( $1\text{ EJ} = 10^{18}$  J) and **(b)** cost (1 RMB  $\approx$  US\$ 0.15 in 2017) in China in 2017. The ring diagram distinguishes between rural and urban contributions. For both categories, the outer rings depict the proportions of different activities, including cooking, heating, and other. Within each activity, the inner

rings illustrate the proportions of different energy types, including coal, biomass, liquefied petroleum gas and natural gas (LPG/NG), electricity, and thermal energy in central heating. All proportion values are based on national totals. Data for Hong Kong, Macao and Taiwan province are not included. Source data are provided as a Source Data file.

carriers, with the fractions of coal and biomass fuels at 29.2% [26.3%, 32.4%] and 43.2% [39.8%, 46.7%], respectively. Therefore, of the 973 [906, 1036] billion RMB energy expense, only 36.6% [33.7%, 39.6%] (356 [322, 388] billion RMB) occurred in the rural area (Fig. 4b), of which 80.5% [77.7%, 82.9%] were paid for the use of modern clean energies including gas and electricity, with the others for coals and very few commercial biomasses. Including urban usage, solid fuels contribute to 42.6% [40.3%, 45.3%] of the national energy consumption, yet they account for only 9.3% [8.4%, 10.4%] of the cost. LPG/NG (liquefied petroleum gas and natural gas) and electricity consumption in the urban area were 1.9 [1.7, 2.2] and 1.8 [1.5, 2.1] EJ, respectively, being 2.5 times and 1.5 times the consumption in rural homes. Thermal energy being supplied by central heating plays a pivotal role in urban energy system, accounting for 32.3% [28.5%, 36.5%] and 22.9% [19.7%, 26.6%] of its total consumption and cost, respectively. Owing to a

larger coverage of population and higher efficiencies, the cost of thermal energy was comparatively lower than that of other clean energy utilization approaches.

The discrepancy of energy demand, energy carrier type, utilization efficiency and price could lead to distinct energy consumption amount and costs for different daily activities, including cooking, heating, lighting, and others. On average, cooking accounted for over 50% of the national total household energy consumption; the fractions were 60.4% [58.6%, 62.2%] and 44.0% [40.7%, 47.5%] in the rural and urban areas, respectively. While biomass fuels prevail as an important energy source for cooking in the rural area, urban residents largely used LPG/NG. The energy cost of cooking energy in the urban population was 1.5 times that of the rural population, a figure closely aligning with the population ratio<sup>17</sup>. This means that despite more use of free biomass fuels, the per capita cost of cooking energy in the rural



**Fig. 5 | Decomposition analysis in Concentration Indexes of household.** **(a)** Total energy consumption, **(b)** energy cost and **(c)** energy burden. The left part illustrates the contribution of different energy types, including coal, biomass, liquefied petroleum gas and natural gas (LPG/NG), electricity, and thermal energy in central heating, with a dashed line drawn to the right below the bar indicating a decrease in Concentration Index, and above it indicating an increase. The right part represents the contribution of different activities, including cooking, heating and other, with a

dashed line drawn to the left signifying the same meanings regarding Concentration Index changes. Data are presented as median values (bars) and 95% confidence intervals (error bars) from 1000 Monte Carlo simulations, indicating the best estimates and the associated uncertainty of the Concentration Index. Data for Hong Kong, Macao and Taiwan provinces are not included. Source data are provided as a Source Data file.

population was not necessarily lower than that in the urban area. This was partly explained by the fact that a significant portion of urban residents switched to piped natural gas thereby significantly replacing expensive LPG. The cost of LPG was still high in some rural areas, especially those mountain villages and regions with less gas resources<sup>29</sup>. Heating activities consumed 28.2% [26.6%, 29.9%] and 35.7% [32.0%, 39.8%] of the energy consumed in the rural and urban areas, respectively. A majority of urban heating energy was supplied through central heating systems, whereas in the extensive rural areas of the northern regions, solid fuels, especially commercial coal, remained the main heating energy source. Other activities, such as cooling, lighting and entertainment, etc., are exclusively powered by electricity. These activities collectively contributed to 15.6% [14.0%, 17.2%] of the total energy consumption, but accounted for 31.8% [29.4%, 34.1%] of the total cost. The urban consumption was 1.6 times that of the rural, reflecting the greater prevalence of electrical devices and consumption in urban homes<sup>30</sup>.

### Cooking energy difference contributes largely to the inequity

To quantitatively elucidate factors contributing to the inequity, the CIs of total and effective energy consumption, energy cost, and energy burden were decomposed to different energy types and activities, as described in the Methods. The total consumption of clean energy exhibited significant inequity, with a 0.116 [0.105, 0.127] contribution to the CI (Fig. 5a), highlighting a substantial disparity in clean energy access among populations across different income levels. However, this inequity was entirely offset by the CI contribution of biomass fuel (−0.132 [−0.144, −0.120]), indicating that the use

of biomass helps maintain equitable access to sufficient household energy for low-income population. Taking the price factor into account, the impact of solid fuel utilization to the CI of cost was only −0.021 [−0.024, −0.018] (Fig. 5b), since the contribution of the non-commercial biomass fuels to the overall cost was nearly negligible. For clean energy, encompassing both gaseous fuels and electricity, contributed to varying degrees of increase in the CIs of energy consumption and cost. Specifically, the inequity in electricity cost notably exhibited a significant impact, resulting in a 50% contribution (0.061 [0.053, 0.085]) to the CI of energy cost, since wealthier families had a greater number of household appliances and a higher willingness to meet their energy demands by using electricity devices.

Different activities, being comprised of distinct energy mix, also differently contributed to disaggregated energy inequity among individuals with different income levels. The impact of cooking activity to the CI of total energy consumption was particularly notable, at −0.081 [−0.093, −0.068], indicating that the low-income population used more energies for cooking, which was explained by their low utilization efficiency. All activities exhibited positive CI values in the equity analysis of energy cost, which means that they all increased the inequity of energy cost, being manifested as high-income population expend more money on household energy for that activity. Notably that low-income population consumed more cooking energy but expended less money because most free biomass fuels were utilized for cooking in rural areas. Heating energy consumption was previously found to be positively correlated with the income level<sup>14</sup>, consequently the CI values of energy cost in the heating activity (0.039 [0.032, 0.048])

aligned consistently with the positive CI of effective energy consumption (Supplementary Fig. 2).

To clarify the role of income disparity in overall energy inequality, we attributed the discrepancy of energy usage among different individuals (as seen from the Gini coefficient) to various natural and socioeconomic factors, while the CI value more specifically indicates the discrepancy being explained by the income difference. The climatic condition, being characterized by heating degree days (HDD) and cooling degree days (CDD), explained 51% of the Gini coefficient in household total energy consumption (Supplementary Fig. 3a). Factors including household income, the fraction of clean energy use ( $F_c$ ), and HDD each contributed equally to the Gini coefficient of energy cost, collectively accounting for 70.3% of the total (Supplementary Fig. 3b). This underscores their substantial roles in explaining household energy cost, wherein the income and HDD primarily account for different energy demand, while the  $F_c$  represents the quality of energy utilized.

Reasonably, income difference was one primary factor influencing energy burden inequality, contributing 53.3% to its Gini coefficient, while another 24.2% could be attributed to the climatic conditions (Supplementary Fig. 3c). Low-income population experiencing high heating demands were more likely to encounter a severe energy burden, surpassing 50% on the household scale<sup>8</sup>. Considering the inequity of different income groups in the energy burden, all energy types and activities yielded to the negative CIs of energy burden, resulting the total CI at  $-0.381$  (Fig. 5c). This implies that all forms of energy usage, regardless of type or activity, disproportionately burdened the low-income population, albeit with varying degrees of inequity. In the context of solid fuels, coal contributed 33% [29%, 36%] to the CI of the energy burden, while biomass fuels had limited impacts on the energy burden inequity. LPG/NG and electricity contributed to 26% [22%, 29%] and 41% [37%, 46%] of the CI of energy burden, respectively. Despite that the central heat was only available for the urban population, it had minimal changes in the CI of energy burden. This is mainly attributable to the offsetting influence of two factors on inequity: less burden for the rural resident under the rural-urban gap, and increased burden for the urban low-income population among the entire urban population. Given its universal necessity, cooking activity contributed most significantly to energy burden inequity, comprising 51% [48%, 53%] of its CI. Since there were lower heating burden for those located in the south, the contribution of heating to CI of total energy burden was considerably less, at only 21% [19%, 23%]. The remaining 28% [25%, 32%] of the CI of energy burden was contributed by the utilization of electricity in other activities.

### Suspension of solid fuels would deepen energy burden inequity

Non-commercial biomass fuels contribute significantly to the energy supply of rural residents while incurring minimal costs, thereby substantially alleviating the energy burden on low-income population. However, it has been also widely documented that burning of biomass fuels, as well as low-quality coal, pose adverse impacts to human health by producing large amounts of hazardous air pollutants, from which there are strong calls on clean household energy transition from solid fuels to modern household energies. Therefore, it is reasonable to speculate that energy burden would significantly escalate with the substitution of biomass fuels during the clean energy transition, which implies a likely increasing trend in the inequity of energy burden<sup>8</sup>. To elucidate the role of solid fuels in mitigating energy burden inequity and to assess the impact of energy transition to gas or electricity, this study further designed a series of clean energy transition scenarios based on the ideal assumptions (see Methods and Supplementary Table 3) to reveal potential changes in energy inequity. The clean energy chosen to replace solid fuels varies based on the fuel types (coal and biomass) and activities (cooking and heating) across different scenarios.

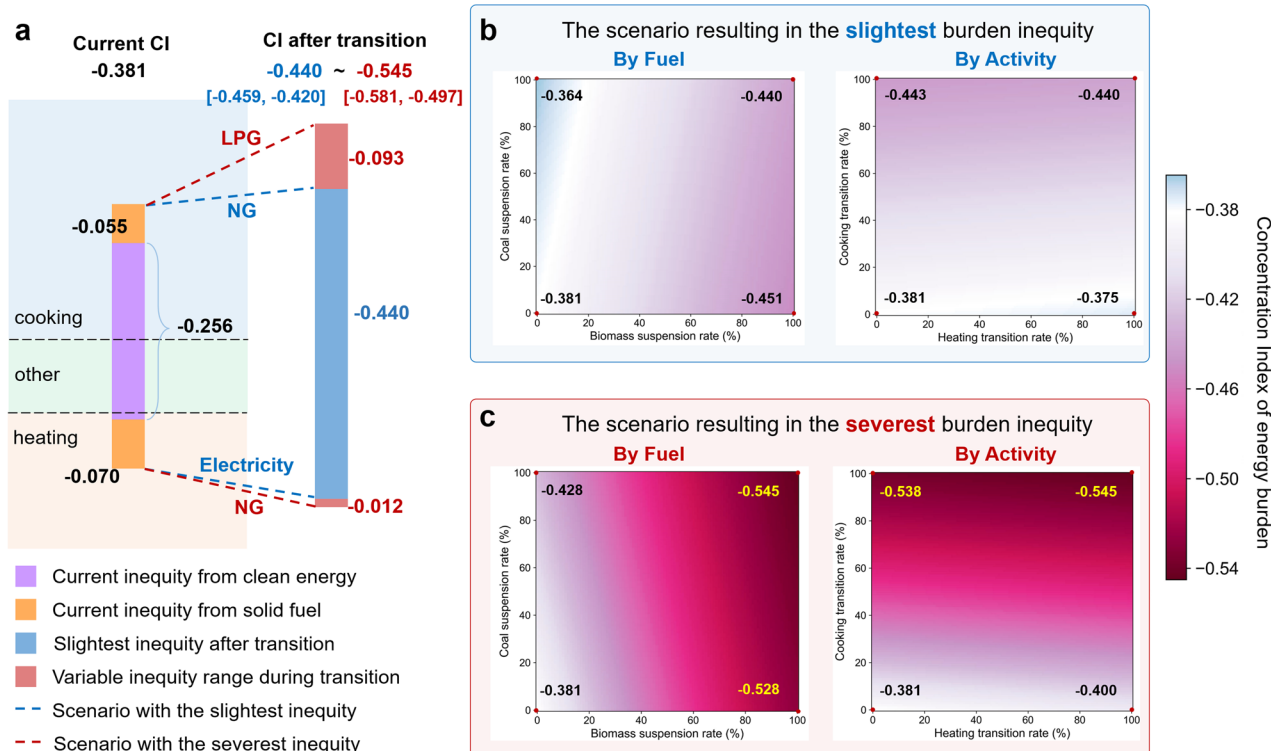
The entire elimination of solid fuels will deepen the energy burden inequity in any case, while the CI decreases from the current value ( $-0.381$ ) to a range of  $-0.440$  [ $-0.459$ ,  $-0.420$ ] to  $-0.545$  [ $-0.581$ ,  $-0.497$ ] varying in different replacement scenarios (Fig. 6a). This implies that the utilization of solid fuels helps mitigate the potential significant increase in the inequity of household energy burden in China. The proportion of this mitigation ranged from 15.5% to 43.0%, as represented by the CI value. Without solid fuels, a significant portion of rural households with lower income levels would bear an unsustainable energy burden, potentially exceeding 80%, or they might face energy shortages in crucial activities like cooking or heating, leading to a decline in overall living quality. It also needs to note that, despite the increasing inequity of energy burden, the clean energy transition contrarily reduces the inequity of energy cost (Supplementary Fig. 4), narrowing the energy cost gap between different income groups.

Owing to their prices, the type of clean energy selected determines the final inequity change after the entire suspension of solid fuels. Cooking transition to natural gas aligned with heating transition to electricity is regarded as the optimal scenario to relieve the burden inequity. Since the higher thermal efficiency ratio of electrical heating equipment, primarily air source heat pump, which has been recommended as important alternative equipment for the clean heating project in northern China<sup>31,32</sup>, electricity demonstrates more apparent price advantages than natural gas in terms of heating energy. Despite having the advantage of not relying on pipeline facilities, LPG is much more expensive than other energy sources for cooking. It leads to the most significant increase in the energy burden inequity when transitioning to natural gas for heating at the same time. The wide CI range between the scenario resulting in the slightest inequity (CI =  $-0.440$ ) and severest inequity (CI =  $-0.545$ ) announces the significance of appropriate and affordable energy choice for clean transition.

The extent of inequity changes during the clean energy transition also depends on the type of solid fuel suspended and household activity. Compared to coal, the suspension of biomass significantly exacerbates of energy burden inequity, reducing the CI value to a range of  $-0.451$  [ $-0.467$ ,  $-0.434$ ] to  $-0.528$  [ $-0.562$ ,  $-0.494$ ] (Fig. 6b, c). Due to the dominant energy consumption and extensive application of biomass, the energy transition in cooking activity would also dominate the changes in burden inequity. In contrast, the transition from coal and in heating activity do not induce substantial CI changes, and may even slightly alleviate the burden inequity in the scenario of slightest inequity (Fig. 6b). Nevertheless, it is important to note that this evaluation solely considers energy prices, while some factors such as accessibility will also influence the transition choices, and intervention subsidies and fuel usage habits. For instance, laying natural gas pipelines in rural areas may incur intensive costs, indicating that LPG remains widely used in rural cooking. Government subsidies for clean energy transition in rural areas are necessary to avoid unbearable residential energy burdens and excessive energy burden inequity.

### Implication on the inequity of climate and health

Household clean energy transition is tightly linked with other significant environment-related SDGs, particularly good health (SDG 3) and climate action (SDG 11). Aligned with energy inequity, climate, and health inequity would also be affected by the suspension of solid fuels. The inequity of CO<sub>2</sub> emissions among different income groups exhibits slight changes during the energy transition, with the CI shifting from a current value of 0.074 [0.056, 0.090] to a range of 0.035 [0.012, 0.063] to 0.081 [0.064, 0.096] (Supplementary Fig. 5a). This phenomenon could be attributed to the opposite inequity impacts of suspending biomass versus coal. Owing to its carbon neutrality, the suspension of biomass narrows the gap in CO<sub>2</sub> emissions between different income groups<sup>33</sup>, while the transition away from inefficient coal conversely reduces carbon emissions among low-income population.



**Fig. 6 | Changes in Concentration Index (CI) of household energy burden under the clean energy transition scenarios.** **a** The overall trend of Concentration Index values during the transition to clean energy. The dashed lines represent the two transition scenarios resulting in the slightest and severest inequity, when the upper and lower sections depict transitions for cooking and heating, respectively, with the types of clean energy replacing solid fuels noted alongside the dashed lines,

including liquefied petroleum gas (LPG), natural gas (NG), and electricity. Heat maps illustrate the changes in Concentration Index relative to the degree of energy and activity transition in scenarios resulting in **(b)** the slightest inequity and **(c)** the severest inequity. Data for Hong Kong, Macao and Taiwan province are not included. Source data are provided as a Source Data file.

Under climate policy, CO<sub>2</sub> emissions increase the cost and burden on residents, whether through direct household carbon taxes or subsequent energy price hikes<sup>34</sup>. Given the constant cost per unit CO<sub>2</sub> emissions for all energy types, the inequity of the extra cost due to CO<sub>2</sub> emissions (CO<sub>2</sub> cost) should mirror the inequity of emissions. However, the burden inequity due to CO<sub>2</sub> emissions is significantly different. The current CI value for the burden due to CO<sub>2</sub> cost is  $-0.480$   $[-0.498, -0.463]$  (Supplementary Fig. 5b), even exceeding the inequity of energy burden. The suspension of biomass could further exacerbate the burden inequity of CO<sub>2</sub> costs, potentially decreasing the CI value to  $-0.550$   $[-0.569, -0.539]$ . This indicates that energy and climate policies must be implemented with extreme caution, especially regarding biomass suspension, as they are likely to exacerbate resident burden inequities in multiple ways.

Mitigating air pollution and protecting residents' health are the primary drivers of clean energy transition. Combustion of solid fuels induces severe household air pollution, which is a major health exposure pathway for the population. A previous study has reported an inverse relationship in the inequity of ambient and indoor PM<sub>2.5</sub> exposure<sup>35</sup>: affluent urban residents experience higher ambient PM<sub>2.5</sub> exposure, while populations with lower income face greater overall PM<sub>2.5</sub> exposure due to more severe indoor pollution. The clean energy transition will undoubtedly reduce health exposure inequities by improving both indoor and ambient air quality in rural areas, though urban residents will also benefit from reduced pollution transmission<sup>36</sup>. The indoor pollution model is essential for effectively evaluating the health exposure due to household air pollution, thereby providing more quantitative insights into the contribution of energy transition to health equity<sup>37</sup>. Furthermore, despite the potentially greater monetary value of health benefits from the perspective of

value of statistical life compared to the costs of energy transition<sup>32</sup>, more comprehensive evaluations of the impacts on household welfare, in terms of energy, economic burden, and health, are necessary to uncover the potential inequity and develop more effective, targeted and feasible clean energy strategies.

## Discussion

The intricate residential energy structure in China, particularly in rural areas, conceals the current and future condition of energy inequity. This study, by constructing a comprehensive socioeconomic and energy dataset, evaluates energy inequity from multiple aspects and highlights the potential impact of suspending traditional solid fuels on this inequity. We find that the inequity of energy consumption among different income levels is not pronounced, as the use of solid fuels, particularly biomass, offsets the inequity of energy consumption induced by clean energy. However, there still exists substantial inequity in energy burden, as indicated by the CI value of  $-0.381$ , with cooking and electricity usage being the primary contributors, accounting for 51% and 41%, respectively. Nevertheless, solid fuels, which are extensively used in the low-income population, cover 42.6% of household energy needs at only 9.3% of the energy costs, effectively sustaining the energy equity in both consumption and burden. The entire suspension of solid fuels could exacerbate the energy burden inequity by up to 43.0%, resulting in a CI value of  $-0.545$ , in which the transition away from biomass and in cooking activity are the primary drivers of inequity rise. Transitioning to natural gas for cooking and to electricity for heating could effectively mitigate the exacerbation in burden inequity, reducing the CI rise to as low as 15.5%. Our findings pose a serious challenge to achieving SDGs, including no poverty (SDG1), affordable and clean energy (SDG7), and reduced inequalities

(SDG10), providing valuable insights for clean energy strategies and policies aimed at sustain the energy welfare and equity among populations.

Universal access and utilization of clean modern energy will be a prolonged process, as unclean traditional solid fuels continue to constitute a significant portion of energy consumption in China, especially rural areas. Our findings suggest that prioritizing the transition away from coal, particularly for heating, could slow down the rise in the burden inequity during this process. This is, in fact, consistent with the priorities of the clean energy campaign in the North China Plain (2017–2021), and also important in reducing carbon emission in the country to meet the dual-carbon target. In contrast, the cessation of biomass fuel usage presents greater challenges and will take longer to address burden inequity. Inefficient biomass burning not only increases total energy requirements, exacerbating the time and economic burden on impoverished populations to collect fuels but also emits higher levels of air pollutants, thereby heightening health risks<sup>38</sup>. Therefore, the development and promotion of high-efficiency biomass stoves are crucial for alleviating both burden and health inequities as an interim measure during the lengthy energy transition process. This study also provides the optimal energy transition route to the minimal inequity, which needs more governmental efforts on the improvement of energy infrastructure including power grid and gas pipeline. The policies aimed at promoting rural merging, urban-rural integration and urbanization are appreciated to reduce the disparities in energy access and lead to a relative just energy transition.

Our study demonstrates the income is the primary factor contributing to current energy burden inequality, with the principal obstacle to clean energy transition being the exacerbated burden on low-income population in rural areas. Although the potential health benefits of the energy transition may be substantial and could exceed the associated costs<sup>32</sup>, achieving such a transition spontaneously is challenging without economic improvement, as it does not significantly alleviate the burden on residents. This fact underscores the essential role of subsidy policies in facilitating these transitions and mitigating burden inequity. Such subsidy should not only target energy prices but also encompass clean energy equipment, infrastructure, and associated costs. Despite the significant improvements in regional air quality achieved by the clean heating campaign<sup>31</sup>, there remains a notable absence of equivalent policies for clean cooking, which is of broader necessity. While cooking energy has undergone considerable transitions<sup>26</sup>, and some argue that this will naturally progress with rising incomes<sup>39,40</sup>, substantial solid fuel usage persists in rural cooking, predominantly from dirty but free biomass sources. Our findings indicate that cooking is currently the primary contributor to energy burden inequity. Therefore, subsidies for clean cooking and support for the rural low-income reliant on biomass are especially crucial for the acceleration of energy transition.

As a leading example among LMICs, China's actions to clean energy transition are mirrored in regions like South Asia and Tropical Africa<sup>41,42</sup>. Notably, these tropical regions exhibit negligible demand for heating energy. However, their reliance on solid biomass fuels for cooking is pronounced, leading to severe indoor pollution and significant health risks<sup>43</sup>. These areas are currently experiencing rapid population growth, which in turn escalates the demand for residential energy. The transition to clean energy sources in these regions necessitates a multifaceted approach, which requires not only considering the availability of energy resources but also addressing the potential burdens and inequalities that may arise post-transition for residents. In this context, the availability of lower-cost clean energy technologies and international financial assistance are imperative for reducing the disparities in residential energy burdens between nations.

There are several limitations in this study. First, the estimation of effective energy consumption, as well as the allocation and

replacement of energy types in this study, heavily depended on the measures of energy efficiency. However, the granularity of energy efficiency categorization used in our analysis is somewhat coarse, distinguishing only among different types of energy. A more nuanced approach, offering finer differentiation, would likely yield a more accurate assessment of residential energy demands and actual energy well-being, considering regional variations, different activities, and types of stoves used. Secondly, the transition scenarios in our study primarily consider energy prices, while additional costs, such as those for devices, infrastructure, and maintenance, could disproportionately heighten the financial burden on low-income population, resulting in a larger inequity. Moreover, due to the insufficient information available to accurately describe future energy technologies, prices, and household incomes, the ideal scenarios could only suggest the potential inequity changes during the energy transition under current socioeconomic conditions. Therefore, developing more comprehensive pathways with temporal characteristics is essential to provide nuanced insights, more accurate projections for the impact of clean energy transitions, and to inform effective energy strategies and policies over time. Nevertheless, these limitations will not detract from the main conclusions and insights of this study. Also note that the study primarily employs the CI to quantitatively assess energy inequity related to income levels. It is crucial to promote and discuss more comprehensive and well-defined concepts about energy inequality, to promoting a justice in terms of actual energy welfare.

## Methods

### Data Summary

This study developed a comprehensive county-level dataset for 2017, encompassing 2337 counties across 31 provinces in China, with the exclusion of Hong Kong, Macao, and Taiwan province. Data were collected separately for rural and urban areas within each county, and the population was categorized into five distinct income groups based on disposable income.

The dataset is extensive, incorporating socioeconomic data, environmental indicators and energy metrics. It provides detailed insights into energy distribution, disaggregated by county, rural/urban areas, energy type, activity, and income level. This dataset addresses the limitations of previous macro-level energy data in terms of scale<sup>44</sup>, offering a broader and more comprehensive characterization of national and regional energy mixing, consumption patterns, and cost attributes compared to typical household survey data. Crucial for advancing our understanding of energy dynamics, this dataset aids in analyzing energy structures, building comprehensive emission inventories, and evaluating the inequities associated with energy use and emissions.

### Socioeconomic and environment data

Socioeconomic data, including population, disposable income and gross domestic product, was primarily sourced from the County Statistical Yearbooks. Environment data, specifically HDD and CDD were calculated using of 5 °C for HDD and 25 °C for CDD<sup>45</sup>, as shown in Eqs. (1) and (2).

$$HDD = \sum_{d=1, t < 5^{\circ}\text{C}}^{365} (5 - t) \quad (1)$$

$$CDD = \sum_{d=1, t > 25^{\circ}\text{C}}^{365} (t - 25) \quad (2)$$

where  $d$  and  $t$  represent the day and the temperature, respectively. Specifically,  $d, t < 5^{\circ}\text{C}$  (or  $t > 25^{\circ}\text{C}$ ) indicates a day when the temperature falls below 5 °C (or rises above 25 °C).



### Household energy consumption

The dataset for fuel energy consumption in both rural and urban areas was derived from the PKU-FUEL inventory database (accessible at <https://inventory.pku.edu.cn/>). For rural areas, energy data were meticulously collected through a national-scale survey conducted in 2017. This survey, which followed the first national survey conducted in 2012, was designed to comprehensively assess rural residents' energy carriers and pollutant emissions. It covered all 31 provinces in China, yielding 56,556 valid household questionnaires. These questionnaires provided detailed insights into the energy mix within rural households. The survey methodology, including sampling, interviewing, and fuel-weighting techniques, has been extensively documented in previous studies<sup>22,26</sup>.

The questionnaires focused on time-sharing data for each type of energy usage, which enhances accuracy and flexibility in energy stacking surveys. Household activities were categorized into two primary sections: cooking and heating. Additionally, the sampling spanned both the heating and non-heating seasons. For cooking activities, different behaviors were assigned specific time fractions: staple food cooking (15%), subsidiary food preparation (80%), and water boiling (5%).

County-level energy consumption data were calculated based on the average results from the fuel-weighting and time-sharing data collected during the survey, stratified by both fuel types and activities. The fuel types considered in this study include four varieties of coal (peat, lump coal, anthracite, and honeycomb coal), eight types of biomasses (fuelwood, brushwood, straw, grass, corncobs, animal dung, charcoal, processed biomass, and biogas), LPG, natural gas (NG), and electricity. Overall electricity consumption data were directly obtained from the survey questionnaires.

A proportional relationship was assumed between electricity and fuel in terms of effective energy consumption and time allocation. Therefore, the electricity usage for cooking and heating activities was estimated as Eq. (3):

$$EE_{elec,act}^{rural,c} = EE_{fuel,act}^{rural,c} \times \frac{T_{elec,act}^{rural,c}}{T_{fuel,act}^{rural,c}}, act \in \{cooking, heating\} \quad (3)$$

where  $c$  denotes the specific county,  $T$  represents the time allocation for energy use,  $elec$  refers to the electricity used, and  $fuel$  is the aggregate of all fuel types consumed.  $EE$  stands for the effective energy consumption, which indicates the thermal output available for different uses. The  $EE$  of all fuel consumption was calculated as Eq. (4):

$$EE_{fuel,act}^{rural,c} = \sum_f E_{f,act}^{rural,c} \times \eta_f \quad (4)$$

where  $E_{f,act}$  stands for the energy consumption associated with each fuel type ( $f$ ) and activity ( $act$ ). The parameter  $\eta_f$  denotes the thermal efficiency of the respective fuel. Note that due to data limitations, this study primarily focused on the efficiency differences among various energy types. The efficiency data utilized in this analysis were sourced from the survey conducted by ref. 21. Consequently, electricity consumption specifically for cooking and heating activities could be directly calculated using Eq. (5):

$$E_{elec,act}^{rural,c} = \frac{EE_{elec,act}^{rural,c}}{\eta_{elec}} \quad (5)$$

when the portion of electricity consumption not allocated to cooking and heating activities was categorized under "other activities" for the purposes of this study.

For urban areas, household energy consumption data were primarily sourced from the China City Statistical Yearbook<sup>46</sup> and the

China Energy Statistical Yearbook<sup>47</sup>. These datasets were then down-scaled to county-level using regression models related with socio-economic and climate indicators<sup>28</sup>.

In addition to conventional energy sources, the energy consumption attributed to central heating in each county  $c$  was calculated separately, following the methodology introduced by ref. 28, as shown in Eq. (6):

$$E_{cent\ heat}^{urban,c} = \sum_{d \in HD_c} \Delta t_{d,c} \times A_c \times e \quad (6)$$

where  $HD_c$  represents the total number of days allocated for urban central heating, primarily obtained from official government notice;  $\Delta t_{d,c}$  represents the difference between the outdoor temperature and the standard indoor heating temperature (20 °C<sup>48</sup>) on day  $d$ ;  $A_c$  refers to the area covered by central heating, with data sourced from China City Statistical Yearbook. The parameter  $e$  is the rate of heat consumption per unit degree day according to the design standard, set as 0.11 MJ/(°C·d·m<sup>2</sup>) in this study<sup>49</sup>.

Urban residents typically relied on a limited quantity of solid fuels, primarily due to improved energy accessibility and stringent pollution control policies. The allocation of these solid fuels for cooking and heating purposes was estimated based on the fuel usage patterns observed in corresponding rural areas for similar activities. Additionally, given the widespread availability of centralized heating system and reliable electricity supply, natural gas was rarely used for heating in urban households and has thus been excluded from this analysis. Assuming that urban residents meet their effective energy demands with electricity in a manner similar to their rural counterparts, electricity consumption was allocated to various activities using Eqs. (7) and (8):

$$\frac{EE_{fuel,cook}^{rural,c} + EE_{elec,cook}^{rural,c}}{pop_{rural,c}} = \frac{EE_{fuel,cook}^{urban,c} + EE_{elec,cook}^{urban,c}}{pop_{urban,c}} \quad (7)$$

$$\frac{EE_{fuel,heat}^{rural,c} + EE_{elec,heat}^{rural,c}}{pop_{rural,c}} = \frac{EE_{fuel,heat}^{urban,c} + EE_{elec,heat}^{urban,c}}{(1 - \alpha_c) \times pop_{urban,c}} \quad (8)$$

where  $pop$  denotes the population and  $\alpha_c$  represents the proportion of urban population covered by the central heating system, which could be calculated as Eq. (9):

$$\alpha_c = \frac{A_c}{RS_c} \quad (9)$$

where  $A_c$  represents the area covered by central heating, and  $RS_c$  denotes the total urban residential area. Similarly, electricity consumption in urban areas that is not allocated to cooking and heating activities is categorized under "other activities".

Overall, the household energy consumption data in this study encompass both rural and urban areas across all 2337 counties, enabling a detailed categorization of energy usage by activities (cooking, heating, and other activities) and fuel types (coal, biomass, LPG, NG, electricity, and central heating thermal energy).

### Household energy cost

The calculation of household energy costs in this study was primarily determined by two factors: energy consumption and energy price. Due to data limitations, a uniform energy price was applied across both rural and urban areas within the same county. Prices for LPG and commercial solid fuels, including coal, charcoal, and processed biomass, were obtained from the survey questionnaires. Meanwhile, provincial prices for natural gas and electricity were sourced from the Price Monitoring Center of the National Development and Reform

Commission<sup>50</sup>. For a comprehensive analysis, all prices were standardized to a common unit (RMB/GJ), allowing for the calculation of total household energy costs, as shown in Eq. (10):

$$Cost_{ene,act}^{r,c} = E_{ene,act}^{r,c} \times P_{ene}^c \quad (10)$$

where  $r$  represents rural or urban areas,  $c$  denotes the county;  $ene$  refers to the specific energy type (excluding central heating);  $P$  is the energy price.

The cost associated with central heating was determined by three key factors: the area covered by central heating, the duration of heating, and the cost of heating per unit area. The price data for central heating ( $P_{cent,heat}^c$  in RMB/m<sup>2</sup>/d) were meticulously collected from local government notices, which detail the cost per unit of heating area over a specified period. The total cost of central heating in each county  $c$  was then calculated using Eq. (11):

$$Cost_{centheat}^{urban,c} = HD_c \times A_c \times P_{centheat}^c \quad (11)$$

### Distribution to different income level

Within the same county, significant variations in energy consumption patterns and energy structures were observed among residents across different income levels. In official government statistics, both urban and rural households were categorized into five quintiles (each representing 20% of the households) based on income levels. These quintiles were classified as poor, lower middle, middle, upper middle, and rich. Detailed data on average household size, per capita disposable income, and residential expenditure for each income group are provided in the national and provincial statistical yearbooks<sup>51</sup>.

For this study, the initial data were organized by households, with the five income-level groups equally divided. However, for analytical purposes, it was necessary to restructure this data to reflect divisions based on population rather than households. By utilizing household size information from the initial dataset, income and expenditure were recalculated to represent these redefined population groups. In the county-level analysis, income distribution within these groups was then assessed based on their average income and proportional representation at the provincial level.

To accurately apportion energy consumption across various income groups within each county, a systematic approach was employed. In rural areas, the fraction of clean energy ( $F_c$ ) was first used as a key indicator for allocating clean energy sources such as LPG, NG, and electricity. This approach was informed by regression models from previous studies, which linked  $F_c$  to factors such as income and HDD, specifically in the context of cooking and heating<sup>22,26</sup>. Subsequently, the total energy cost was apportioned among different income groups in line with their respective household expenditures. For each group, the difference between the cost of clean energy and their total energy cost was calculated, serving as a proxy for allocating the cost of commercial solid fuels. Finally, the total effective energy consumption was equally divided into fifths, representing the energy demand for each income quintile. The discrepancy between the effective energy consumption from commercial sources and the total energy demand within each group was then used as a proxy for allocating the consumption of free biomass fuels.

In urban areas, the substantial influence of rental costs leads a non-proportional relationship between household expenditures and energy costs. Consequently, the random forest regression (RFR) model was extensively employed for energy allocations. The independent variables in these models include urban residents' income, HDD, and CDD across the 2337 counties. Initially, a RFR model was developed to estimate the fraction of solid fuels ( $F_s = 1 - F_c$ ) used in cooking and heating activities. This fraction was then calculated for different

income groups and applied to allocate solid fuel consumption. Additionally, separate RFR models were constructed to estimate the per capita cost of clean energy for each specific activity (cooking, heating, and other activities). These models facilitated the allocation of clean energy consumption across the five income groups in urban areas. To ensure model robustness and avoid overfitting, all RFR models underwent a rigorous tenfold cross-validation process. The average results from these iterations were adopted as the final outcomes. Performance metrics and further details of these models are provided in the Supplementary Fig. 6.

### Inequity measure

The energy indicators examined in this study included total and effective energy consumption, energy cost, and energy burden. Specifically, the energy burden was defined as the ratio of energy cost to income. Energy inequity, the central focus of this study, was characterized by disparities in these indicators across different income groups. Both energy consumption and cost were calculated on a per capita basis for discussion. The indicators for each population group were calculated by Eqs. (12)–(14):

$$Epc_{r,c,l} = \frac{\sum_{ene,act} E_{ene,act,l}^{r,c}}{pop_{r,c,l}} \quad (12)$$

$$Cpc_{r,c,l} = \frac{\sum_{ene,act} Cost_{ene,act,l}^{r,c}}{pop_{r,c,l}} \quad (13)$$

$$Bud_{r,c,l} = \frac{Cpc_{r,c,l}}{income_{r,c,l}} \quad (14)$$

where  $Epc$  and  $Cpc$  represent per capita energy consumption and per capita energy cost, respectively;  $Bud$  denotes the energy burden;  $r$  represents rural or urban areas;  $c$  refers to the specific county;  $l$  refers to the income level group;  $ene$  and  $act$  correspond to specific types of energy and activity, respectively.

Two indices were employed in this study to quantify disparity: the Gini coefficient and the Concentration Index (CI). These indices were derived from the Lorenz curve and the Concentration curve, respectively, each providing distinct insights into the nature of disparity. The Lorenz curve is graphically depicted as the cumulative percentage of the population, ranked by a specific indicator (e.g., per capita energy consumption), on the horizontal axis, contrasted with the cumulative percentage of the corresponding indicator (in this case, energy consumption) on the vertical axis. The Concentration Curve is conceptually similar to the Lorenz curve but with the horizontal axis fixed as the cumulative percentage of the population sorted by income, while the vertical axis represents the cumulative percentage of a specific indicator (e.g., energy consumption) corresponding to the population on the horizontal axis. The formulas for calculating both the Gini coefficient and the CI were also similar as shown in Eqs. (15) and (16).

$$Gini = \frac{2}{N\mu} \times \sum_{i=1}^N \frac{i}{N} J_i - \frac{N+1}{N} \quad (15)$$

$$CI = \frac{2}{N\mu} \times \sum_{i=1}^N \frac{i}{N} K_i - \frac{N+1}{N} \quad (16)$$

where  $N$  represents the total population under study;  $J_i$  represents the magnitude of a specific indicator  $J$  (e.g., per capita energy consumption) exhibited by the  $i$ th individual, with individuals ranked according to the value of  $J$ ;  $K_i$  represents the magnitude of the same or another

indicator  $K$ , with the key distinction that individuals are ranked based on their income levels;  $\mu$  stands for the average value of the indicator (either  $J$  or  $K$ ) across the entire population.

The Gini coefficient quantifies the overall disparity of a specific indicator within a population (referred to as “inequality” in this study), with its value ranging from 0 to 1. A Gini coefficient of 0 signifies complete equality (e.g.,  $J_1 = J_2 = \dots = J_n$ ), while a value of 1 indicates total inequality (e.g.,  $J_1 = \dots = J_{n-1} = 0, J_n = 1, N \rightarrow +\infty$ ). The CI varying from  $-1$  to 1, measures the disparity of a specific indicator in relation to income levels (referred to as “inequity” in this paper). A CI value of 0 denotes the absence of significant inequity across different income groups. When positive, a CI value approaching 1 suggests that the indicator is predominantly concentrated among wealthier segments of the population, whereas a negative CI value nearing  $-1$  indicates a concentration among less affluent groups.

Originally introduced to assess health exposure inequity among socioeconomic groups<sup>52</sup>, the CI was primarily employed in this study to examine the inequity of energy distribution across different income groups. The CI more effectively illuminated energy disparities linked to income levels compared to the Gini coefficient, offering a clearer representation of energy variations in household welfare or burden driven by socioeconomic factors<sup>35,53</sup>. Additionally, this study also analyzed the overall inequality using the Gini coefficient to better understand the role of income in the context of energy disparity.

### Contribution decomposition

The CI value in this study was attributed to different types of energy and activities. This attribution process illuminated the disparities in energy indicators that arise from specific energy types and activities among various income groups. For each individual, the overall energy indicator was calculated as the linear sum of contributions from these different types and activities using Eq. (17):

$$K_i = \sum_{ene} K_{i,ene} = \sum_{act} K_{i,act} \quad (17)$$

Given the fixed rank of the population by income, the contribution of each energy type or activity to the CI could be directly attributed by Eq. (18):

$$CI_h = \frac{2}{N\mu} \times \sum_{i=1}^N \frac{i}{N} K_{i,h} - \frac{\mu_h}{\mu} \times \frac{N+1}{N} \quad (18)$$

where  $h$  represents a specific energy type or activity, and  $\mu_h$  is the average value of  $K_{i,h}$  across the entire population.

To ascertain the factors contributing to overall inequality, RFR models were first established for the energy indicator  $J$  in relation to various factors as shown in Eq. (19):

$$J \sim model(Income, HDD, CDD, F_c, Rural/Urban) \quad (19)$$

where  $J$  represents the energy consumption, energy cost or energy burden of an individual;  $F_c$  denotes the fraction of clean energy use; *Rural/Urban* is a categorical variable, assigned a value of 0 for rural individuals and 1 for urban individuals. Following previous studies<sup>54</sup>, the Shapely approach was applied to decompose the Gini coefficient of the indicator  $J$  with respect to the factor  $x_i$  as shown in Eq. (20).

$$Gini_{x_i}(J) = \sum_{S \subseteq \{x_1, x_2, \dots, x_n\} \setminus \{x_i\}} \frac{|S|!(n - |S| - 1)!}{n!} \times mv(S, x_i) \quad (20)$$

where  $S$  represents the traversal of all subsets of the set  $\{x_1, x_2, \dots, x_n\} \setminus \{x_i\}$ ;  $|S|$  is the number of elements within a particular subset  $S$ ;  $n$  is the total number of factors ( $n = 5$ );  $mv(S, x_i)$  refers to the marginal contribution of factor  $x_i$ , which could be calculated using the

RFR models using Eq. (21):

$$mv(S, x_i) = Gini(model(S \cup \{x_i\})) - Gini(model(S)) \quad (21)$$

where  $model(S)$  signifies the simulation of the distribution of the energy indicator  $J$  among the population. This simulation was conducted by setting all variables within the subset  $S$  to a certain value across the population, typically the average value for all individuals, while keeping the other variables unchanged.  $Gini(model(S))$  refers to the Gini coefficient calculated from this simulated distribution. The process for the expanded set  $S \cup \{x_i\}$  was conducted in a manner similar.

### Solid fuel suspension scenarios

This study established a series of ideal scenarios to evaluate the potential impact of transitioning to clean energy on energy inequity. For each activity and solid fuel, different types of clean energy were considered as replacements. Energy inequities were evaluated under varying extents of transition, ranging from 0% to 100%, for each fuel and activity. Notably, LPG was exclusively used for cooking activities. The specific energy choice and the resulting inequity in different scenarios are presented in Supplementary Table 3.

Under the assumption of constant income levels and energy efficiency, the guiding principle for substitution was to maintain the original total effective energy consumption for each activity within each income group. It is important to highlight that the most efficient electric heating technology currently available was the air source heat pump<sup>55,56</sup>, which offered substantially higher efficiency compared to traditional electric heaters. Therefore, the replacement of solid fuel heating with electricity was assumed to benefit from this increased efficiency. Throughout the energy transition, the CI for energy cost and burden, resulting from the replacement of solid fuels, were computed to integrally evaluating the effects of the clean energy transition on energy inequity.

### Climate inequity evaluation

Current and post-transition per capita CO<sub>2</sub> emissions were calculated based on energy consumption and emission factors (EFs). The EFs for CO<sub>2</sub> from fossil fuel combustion were sourced from the emission factor database in the PKU-FUEL inventory (<https://inventory.pku.edu.cn/>). CO<sub>2</sub> emissions resulting from electricity and thermal consumption were converted based on the current fuel mixed in power generation and the corresponding EFs. Given a constant price per unit of CO<sub>2</sub> emissions, the inequity in extra cost due to CO<sub>2</sub> emissions could be calculated to mirror the inequity in CO<sub>2</sub> emissions, as indicated by the CI value. The CO<sub>2</sub> burden was defined as the ratio of extra cost due to CO<sub>2</sub> emissions to disposable income. The inequity of CO<sub>2</sub> burden was calculated under a specific CO<sub>2</sub> price (100 RMB/ton), given that the CI value of the burden remains constant regardless of the CO<sub>2</sub> price.

### Uncertainty analysis

A 1000-time Monte Carlo simulation was conducted to evaluate the uncertainty of energy inequities. Energy consumption data were selected from a uniform distribution with a coefficient of variation (CV) of 20% for biomass fuel and CVs of 15% for other commercial energies, as introduced in the previous study<sup>28</sup>. Energy efficiencies were sampled from a uniform distribution, with the CVs matching those of the ensemble of energy efficiency data reported in literature<sup>21</sup>. Energy prices in county level were sampled from a normal distribution, where the mean is the energy survey price of the specific county, and the standard deviation is the standard deviation of energy prices across all counties within the same province. Emission factors of CO<sub>2</sub> were sampled from a lognormal distribution database built in PKU-FUEL inventory. In the results of 1000 simulations, the 2.5th and 97.5th

percentiles are presented to indicate uncertainty, corresponding to a 95% confidence interval.

### Reporting summary

Further information on research design is available in the Nature Portfolio Reporting Summary linked to this article.

### Data availability

Basic energy information and CO<sub>2</sub> emission data are accessible at <https://inventory.pku.edu.cn/>. Environmental variables, including Heating Degree Days (HDD) and Cooling Degree Days (CDD), were derived from temperature datasets available at <https://cds.climate.copernicus.eu/cdsapp#!?search?type=dataset>. The compiled environmental data (HDD and CDD), along with socioeconomic data covering population figures, five income levels, as well as energy consumption and cost metrics utilized in this study, can be accessed at <https://doi.org/10.5281/zenodo.13897588>. Source data are provided with this paper.

### Code availability

The codes utilized to conduct this study are publicly available at <https://doi.org/10.5281/zenodo.13897588>.

### References

- World Health Organization (WHO). *Household Air Pollution*. Accessed 19 January 2024. <https://www.who.int/news-room/fact-sheets/detail/household-air-pollution-and-health> (2023).
- Stoner, O. et al. Household cooking fuel estimates at global and country level for 1990 to 2030. *Nat. Commun.* **12**, 5793 (2021).
- Wang, Q. et al. Impacts of residential energy consumption on the health burden of household air pollution: Evidence from 135 countries. *Energy Policy* **128**, 284–295 (2019).
- Wu, D. et al. Toxic potency-adjusted control of air pollution for solid fuel combustion. *Nat. Energy* **7**, 194–202 (2022).
- Yun, X. et al. Residential solid fuel emissions contribute significantly to air pollution and associated health impacts in China. *Sci. Adv.* **6**, eaba7621 (2020).
- The Sustainable Development Goals Report 2023: Special Edition. Accessed 19 January 2024. <https://unstats.un.org/sdgs/report/2023/> (2023).
- Rosenthal, J., Quinn, A., Grieshop, A. P., Pillarisetti, A. & Glass, R. I. Clean cooking and the SDGs: integrated analytical approaches to guide energy interventions for health and environment goals. *Energy Sustain. Dev.* **42**, 152–159 (2018).
- Wang, Q. et al. Examining energy inequality under the rapid residential energy transition in China through household surveys. *Nat. Energy* **8**, 251–263 (2023).
- Chapman, A., Fujii, H. & Managi, S. Multinational life satisfaction, perceived inequality and energy affordability. *Nat. Sustain.* **2**, 508–514 (2019).
- Sambodo, M. T. & Novandra, R. The state of energy poverty in Indonesia and its impact on welfare. *Energy Policy* **132**, 113–121 (2019).
- Nguyen, T. T., Nguyen, T.-T., Hoang, V.-N., Wilson, C. & Managi, S. Energy transition, poverty and inequality in Vietnam. *Energy Policy* **132**, 536–548 (2019).
- Mainali, B., Luukkanen, J., Silveira, S. & Kaivo-oja, J. Evaluating synergies and trade-offs among sustainable development goals (SDGs): explorative analyses of development paths in South Asia and Sub-Saharan Africa. *Sustainability* **10**, 815 (2018).
- Das, D., Ahmad, S. & Kirshner, J. Opportunities and challenges associated with the uptake of residential clean fuel usage. *Curr. Env. Hlth. Rep.* **11**, 204–209 (2024).
- Zhu, X. et al. Stacked use and transition trends of rural household energy in mainland China. *Environ. Sci. Technol.* **53**, 521–529 (2019).
- Carter, E. et al. Household transitions to clean energy in a multi-provincial cohort study in China. *Nat. Sustain.* **3**, 42–50 (2020).
- Xie, Y. & Zhou, X. Income inequality in today's China. *Proc. Natl Acad. Sci.* **111**, 6928–6933 (2014).
- National Bureau of Statistics. *China Statistical Yearbook 2018*. (China Statistical Press, 2018).
- Liu, J., Huo, C. & Chen, L. A study of household income inequality in China: perspective of educational homogeneity marriage. *Econ. Res-Ekon. Istraz.* **36**, 2463–2483 (2023).
- Zhao, H. et al. Inequality of household consumption and air pollution-related deaths in China. *Nat. Commun.* **10**, 4337 (2019).
- Ludwig, J., Marufu, L. T., Huber, B., Andreae, M. O. & Helas, G. Domestic combustion of biomass fuels in developing countries: a major source of atmospheric pollutants. *J. Atmos. Chem.* **44**, 23–37 (2003).
- Niu, S. et al. Measurement of effective energy consumption in China's rural household sector and policy implication. *Energy Policy* **128**, 553–564 (2019).
- Shen, G. et al. Substantial transition to clean household energy mix in rural households in China. *Natl. Sci. Rev.* nwac050 <https://doi.org/10.1093/nsr/nwac050> (2022).
- Zhang, X., Xu, J., Zhai, L. & Zhao, W. Characterization of aerosol properties on the burning emissions of typical residential fuels on the Tibetan plateau. *Environ. Sci. Technol.* **56**, 14296–14305 (2022).
- Yun, X. et al. Coal is dirty, but where it is burned especially matters. *Environ. Sci. Technol.* **55**, 7316–7326 (2021).
- IEA. *Key World Energy Statistics 2021*. Accessed 19 November 2023. <https://www.iea.org/reports/key-world-energy-statistics-2021> (2021).
- Tao, S. et al. Quantifying the rural residential energy transition in China from 1992 to 2012 through a representative national survey. *Nat. Energy* **3**, 567–573 (2018).
- Meng, W. et al. Energy and air pollution benefits of household fuel policies in northern China. *Proc. Natl Acad. Sci.* **116**, 16773–16780 (2019).
- Zhang, W. X. et al. Urban residential energy switching in China between 1980 and 2014 prevents 2.2 million premature deaths. *One Earth* **4**, 1602–1613 (2021).
- Li, H., Ai, X., Wang, L. & Zhang, R. Substitution strategies for cooking energy: To use gas or electricity? *J. Environ. Manag.* **303**, 114135 (2022).
- Lin, B. & Zhu, P. Measurement of the direct rebound effect of residential electricity consumption: an empirical study based on the China family panel studies. *Appl. Energy* **301**, 117409 (2021).
- Meng, W. et al. Significant but inequitable cost-effective benefits of a clean heating campaign in Northern China. *Environ. Sci. Technol.* **57**, 8467–8475 (2023).
- Ma, T. et al. Costs and health benefits of the rural energy transition to carbon neutrality in China. *Nat. Commun.* **14**, 6101 (2023).
- Yao, C., Chen, C. & Li, M. Analysis of rural residential energy consumption and corresponding carbon emissions in China. *Energy Policy* **41**, 445–450 (2012).
- Venjakob, M., Wagner, O. & Schnurr, B. Can a CO<sub>2</sub> tax be socially just? Analysis of the social distribution effects of the German CO<sub>2</sub> taxation. *Energies* **16**, 6232 (2023).
- Luo, Z. et al. Reduced inequality in ambient and household PM<sub>2.5</sub> exposure in China. *Environ. Int.* **170**, 107599 (2022).
- Shen, G. et al. Impacts of air pollutants from rural Chinese households under the rapid residential energy transition. *Nat. Commun.* **10**, 3405 (2019).
- Tao, S., Shen, G., Cheng, H. & Ma, J. Toward clean residential energy: challenges and priorities in research. *Environ. Sci. Technol.* **55**, 13602–13613 (2021).
- Jiang, K. et al. Pollutant emissions from biomass burning: a review on emission characteristics, environmental impacts, and research perspectives. *Particuology* **85**, 296–309 (2024).

39. Ward, D. S. & Mahowald, N. M. Contributions of developed and developing countries to global climate forcing and surface temperature change. *Environ. Res. Lett.* **9**, 074008 (2014).
  40. Ma, W., Zhou, X. & Renwick, A. Impact of off-farm income on household energy expenditures in China: implications for rural energy transition. *Energy Policy* **127**, 248–258 (2019).
  41. Quadrelli, R. & Peterson, S. The energy-climate challenge: recent trends in CO<sub>2</sub> emissions from fuel combustion. *Energy Policy* **35**, 5938–5952 (2007).
  42. Acheampong, A. Governance, credit access and clean cooking technologies in Sub-Saharan Africa: implications for energy transition. *J. Policy Model.* **45**, 445–468 (2023).
  43. Rao, N. D., Kiesewetter, G., Min, J., Pachauri, S. & Wagner, F. Household contributions to and impacts from air pollution in India. *Nat. Sustain.* **4**, 859–867 (2021).
  44. Wang, N., Fu, X. & Wang, S. Spatial-temporal variation and coupling analysis of residential energy consumption and economic growth in China. *Appl. Energy* **309**, 118504 (2022).
  45. Zhu, D. et al. Temporal and spatial trends of residential energy consumption and air pollutant emissions in China. *Appl. Energy* **106**, 17–24 (2013).
  46. National Bureau of Statistics. *China City Statistical Yearbook 2018*. (China Statistical Press, 2018).
  47. National Bureau of Statistics. *China Energy Statistical Yearbook 2018*. (China Statistical Press, 2018).
  48. GB/T 18883-2022. Standards for indoor air quality. (2022).
  49. DB/11T 1150-2019. The norm of energy consumption of heating system operation (2019).
  50. Wang, Q. Energy Data 2020. Accessed 15 October 2023. <https://www.efchina.org/Reports-zh/report-lceg-20210430-3-zh> (2021).
  51. National Bureau of Statistics. *China Provincial (Beijing, Tianjin, Hebei, Shanxi, Inner Mongolia, Liaoning, Jilin, Heilongjiang, Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Shandong, Henan, Hubei, Hunan, Guangdong, Guangxi, Hainan, Chongqing, Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang) Statistical Yearbook 2018*. (China Statistical Press, 2018).
  52. O'Donnell, O., van Doorslaer, E., Wagstaff, A. & Lindelow, M. *Analyzing Health Equity Using Household Survey Data: A Guide to Techniques and Their Implementation* (The World Bank, Washington, DC, 2008).
  53. Tabiri, K. G., Adusah-Poku, F. & Novignon, J. Economic inequalities and rural-urban disparities in clean cooking fuel use in Ghana. *Energy Sustain. Dev.* **68**, 480–489 (2022).
  54. Wu, S., Zheng, X. & Wei, C. Measurement of inequality using household energy consumption data in rural China. *Nat. Energy* **2**, 795–803 (2017).
  55. Zhang, Q., Zhang, L., Nie, J. & Li, Y. Techno-economic analysis of air source heat pump applied for space heating in northern China. *Appl. Energy* **207**, 533–542 (2017).
  56. Wu, W. & Skye, H. M. Residential net-zero energy buildings: Review and perspective. *Renew. Sust. Energy Rev.* **142**, 110859 (2021).
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### Author contributions

G.F.S. conceived and designed the analysis, K.J., R.X., J.H.W., W.X.Z., Y.Q.Z., and S.T. contributed data and analysis tools, K.J. performed the analysis, K.J., R.X., Z.H.L., Y.J.L, Y.T.M., and G.F.S. analyzed results and visualization, K.J and G.F.S draft the manuscript, K.J., R.X., Z.H.L., Y.J.L, J.H.W., W.X.Z., Y.Q.Z., Y.T.M., G.F.S., and S.T. read and approved the paper.

### Competing interests

The authors declare no competing interests.

### Additional information

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