

Measurement of inequality using household energy consumption data in rural China

Shimei Wu, Xinye Zheng and Chu Wei *

Measuring inequality can be challenging due to the limitations of using household income or expenditure data. Because actual energy consumption can be measured more easily and accurately and is relatively more stable, it may be a better measure of inequality. Here we use data on energy consumption for specific devices from a large nation-wide household survey ($n = 3,404$ rural households from 12 provinces) to assess inequality in rural China. We find that the overall inequality of energy consumption and expenditure varies greatly in terms of energy type, end-use demand, regions and climatic zones. Biomass, space heating and cooking, intraregional differences, and climatic zones characterized as cold or hot summer/cold winter contribute the most to total inequality for each indicator, respectively. The results suggest that the expansion of infrastructure does not accompany alleviation of energy inequality, and that energy affordability should be improved through income growth and targeted safety-net programmes instead of energy subsidies.

China's income inequality has surpassed that of the United States and ranks among the highest in the world¹. The richest 1% of Chinese citizens control about a third of the nation's wealth². The growing inequality has increased the risk of instability and is ranked as the nation's top social challenge, above corruption and unemployment³.

Numerous studies have attempted to explore the underlying sources of China's income and consumption inequality^{4–6}. However, the use of income data for measuring inequality remains a limitation and consumption data may be more appropriate and precise⁷. For example, the collection of income data through household surveys suffers greatly from under-reporting, while measuring consumption data is much easier and more accurate⁵. In addition, income is usually subject to short-term fluctuations and may not fully reflect the resources available to households in the long term, while consumption remains relatively steady because households are generally able to smooth consumption over time⁸.

Despite these advantages, the use of consumption inequality data, measured as aggregated monetary expenditures, has its drawbacks. First, aggregated consumption expenditure may mask basic living demands and leave out disaggregated information on consumption of specific goods and services. For example, unintended and undesirable expenditure shocks, such as out-of-pocket expenses for serious diseases, will squeeze out consumption for basic needs and impoverish rural households⁹, biasing the inequality measure downward. Second, monetary expenditure is an approximation of durable/non-durable goods consumption, but the value itself does not capture qualitative changes in the nature of durable goods and consumption. For example, the conspicuous consumption phenomenon^{10,11} suggests that measuring inequality in terms of expenditures does not necessarily reflect consumption status and may overestimate the willingness to pay for certain durable/non-durable goods. More importantly, monetary expenditure does not tell us how much service flow the consumer received by utilizing such goods.

The flow of services from ownership of durable goods is a complementary measure. Some researchers have attempted to measure 'actual' consumption by converting the consumption of durable goods to the value of their service flows over time^{7,12}. However, this

method of measuring service flows for each year in the lifecycle is derived from a pre-defined function, which does not account for the replacement rate of new durable goods, changes in consumers' preferences and lifestyle changes. One exception is the research that uses the US Residential Energy Consumption Survey (RECS) to assess ownership inequality in durable goods⁸. However, the exclusion of usage information for each durable good limits their ability to assess consumption inequality in service flows from durable goods.

To address these shortcomings, we take advantage of the Chinese Residential Energy Consumption Survey (CRECS) to assess consumption inequality in the service flows of durable goods. This data set provides detailed information on energy usage and consumption behaviour at the device level (for example, space heater or cooking device), including power capacity, usage frequency and usage duration. Because the energy consumption for a specific device captures the consumer's utility, we argue that service flow is a useful measure of consumption inequality, with advantages over income or expenditure data, and that measuring energy consumption is a good proxy for service flows from durable goods. The literature has widely accepted that usage of modern energy, such as electricity, is a good proxy for economic activities^{13–15}. Especially at the household level, access to modern energy has greatly improved living standards and can serve as a key indicator of socioeconomic development^{16–19}. The measurement of inequality in energy flows can supplement existing measures of inequality. Moreover, we compare energy-based inequality with monetary-based inequality, explore inequality in different dimensions, and disaggregate the sources of inequality. The results provide in-depth insights into the multi-dimensional inequality distribution in rural China, and indicate that the inequality of energy consumption and energy expenditure varies greatly in terms of fuels, end-uses, regions and climatic zones.

Survey design and measurement of energy inequality

We used data from CRECS 2013, which aims to monitor the overall pattern of Chinese household energy consumption in the context of the dynamic socioeconomic background with a focus on rural households. We surveyed 3,404 rural households in 65 villages in 12 provinces. See Supplementary Fig. 1 for geographical

Department of Energy Economics, School of Economics, Renmin University of China, No 59, Zhongguancun Street, Haidian district, Beijing 100872, China.
*e-mail: xiaochu@ruc.edu.cn

distribution of sample units and Methods for survey details, including sampling, implementation, data quality control and representativeness checks. The survey asked which energy-consuming devices a household owns and what energy sources they use. We use this data to calculate the use of eight fuel types (coal, natural gas, LPG, solar power, biomass, electricity, district heat and other) to provide energy for five end-use activities (cooking, powering home appliances, water heating, space heating and space cooling). See Methods for details.

Our estimation shows that the average energy consumption for a representative Chinese rural household in 2013 was 1293 kgce, at a cost of 1,324 yuan. Among eight energy sources, biomass dominates rural households' energy supply, accounting for 53% of total energy needs, followed by electricity (22.8%), coal (11.4%) and LPG (6.1%). Solar power, used only for water heating, accounts for 1.4% of total energy supply. Natural gas and district heat are not accessible in most rural areas. As for end-use activities, energy demand for cooking is the largest energy use, accounting for 41.6% of total energy consumption. Biomass dominates as a cooking fuel, followed by LPG and electricity. Around 39.1% of total energy is used for space heating, which mainly relies on biomass and coal. Home appliances and water heating account for 12.6% and 6.1% of total consumption, respectively. The demand for space cooling is negligible, at 0.6% of total energy consumption.

We use the Lorenz curve and Gini coefficient to visualize inequality in energy consumption flows across households. This approach is data-driven and easy to understand, and allows inter-country and intra-country comparisons²⁰. Moreover, we use the Lorenz asymmetry coefficient (LAC) to capture the most pertinent asymmetries in distribution. The LAC quantifies the visual impression and can be a useful supplement to the Gini coefficient. See Methods for a detailed introduction of the Lorenz curve, Gini coefficient and LAC.

Energy inequality and income/expenditure inequality

We are interested in the difference between energy-based inequality and monetary-based inequality. Figure 1 displays the Lorenz curve for electricity consumption, aggregated energy consumption, energy expenditure, household income and household expenditure.

We observe that the distribution curve of electricity consumption closely tracks the household income curve from the third to the top quintile. The inequality measure in terms of total energy consumption yields a Gini coefficient of 0.407. The distribution of energy expenditure is skewed toward the 'perfect inequality' line and shows the greatest inequality. The energy expenditure curve is lower than and converging with household expenditure between the bottom and fourth quintile. The Gini coefficients for energy expenditure and household expenditure reach the shockingly high levels of 0.552 and 0.522, respectively. Both numbers are consistent with Xie and Zhou¹, who suggest that China's latest Gini coefficient is in the range of 0.53–0.55. Moreover, we found that $LAC < 1$ for all five variables, which means that the inequality of these variables primarily comes from the many small users.

We see a similar pattern in Fig. 1 among the five measures but also notice that the Gini coefficient is different. First, income inequality (0.471) is notably lower than the inequality measures using household expenditure (0.522) and energy expenditure data (0.552). This observation is consistent with previous findings that respondents tend to under-report their income³, which reduces the variation in income data and leads to a smaller inequality score. Second, the inequality of electricity consumption (0.451) was relatively low and uniform across China, mainly thanks to the wide coverage of grid infrastructure²¹. As for aggregated energy consumption, it shows the lowest inequality index (0.407), which may be attributable to the substitution capacity among diverse energy sources in rural areas. Furthermore, the expenditure-based inequality

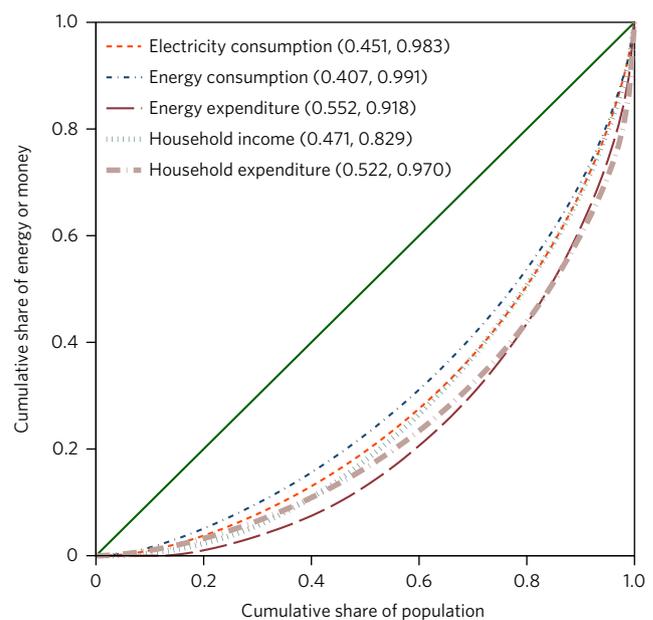


Fig. 1 | Lorenz curve of energy and household income/expenditure. The diagonal is the line of perfect equality. The first and second numbers presented in parentheses are the Gini coefficient and LAC, respectively.

measurement reveals greater disparity than does a measurement of inequality based on physical quantity. This is because rural households can obtain energy services through the use of traditional biomass instead of commercial energy, at little or no monetary cost.

It is not clear whether these energy-based Lorenz curves are systematically different from the monetary-based inequality. Figure 2 shows the differences and associated confidence intervals for different Lorenz curves. We find the gaps range from 0.02 to 0.14, and are all significant ($p < 0.01$). It suggests that the measurement of inequality depends on the indicator selected and they are not good proxies for each other. Compared with the household income or expenditure data, the energy consumption was a more direct measure of inequality since it captured directly the service flows.

Aside from the energy consumption distribution among the population, we are also interested in the nexus between income distribution and energy consumption (see Supplementary Note 1 for energy inequality by income subgroups). Figure 3 depicts the distribution of the cumulative percentage of household income on the horizontal axis versus the cumulative percentage of energy consumption/expenditure distributed along the vertical axis. The Gini coefficients of electricity consumption and energy expenditure corresponding to the Lorenz curve, shown in Fig. 3, are 0.372 and 0.438; these are lower than those using population–electricity pairs (0.451) and population–energy expenditure pairs (0.552) in Fig. 1. We also observe that the energy consumption Gini coefficient in terms of the income criterion is 0.417, slightly higher than the population–energy pairs (0.407). This implies that the distribution of electricity consumption and energy expenditure is more equal by income groups than by population, but not for the case of aggregated energy. $LAC < 1$ for three income–energy pairs, indicating that the energy inequality is primarily due to the many small users.

In short, energy-based inequality is systematically different from inequality measurement using household income/expenditure data. Because energy data have the additional advantage of reflecting the service flows from durable goods, they can serve as a complementary or even better measure of consumption inequality.

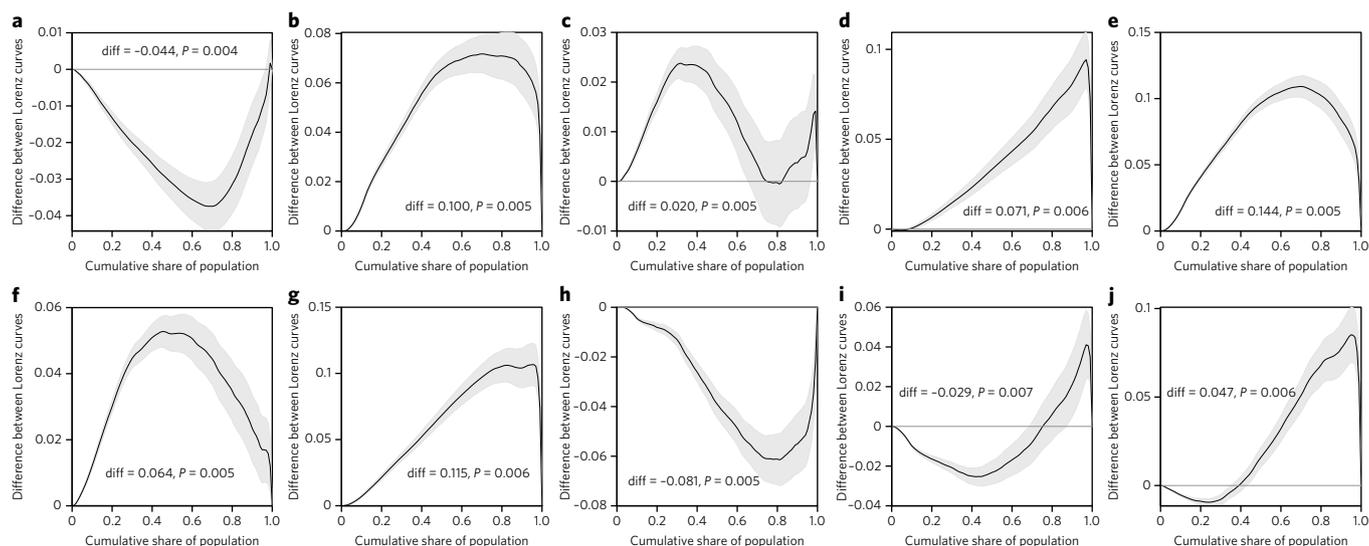


Fig. 2 | Difference between Lorenz curves. The solid line is the difference between two Lorenz curves and the grey area is the 95% confidence interval. **a**, Electricity versus energy consumption. **b**, Electricity versus energy expenditure. **c**, Electricity versus household income. **d**, Electricity versus household expenditure. **e**, Energy consumption versus energy expenditure. **f**, Energy consumption versus household income. **g**, Energy consumption versus household expenditure. **h**, Energy expenditure versus household income. **i**, Energy expenditure versus household expenditure. **j**, Household income versus household expenditure.

Energy inequality by fuel type and end use

To gain insights into potential causes of energy inequality and identify its major sources from both supply and demand dimensions, we examine the energy inequality by fuel type and end-use. Figure 4a shows the energy Lorenz curves of energy consumption of electricity, coal, LPG and biomass. It reveals great differences among various energy types. For example, inequalities in LPG use are the starkest, with a Gini coefficient of 0.870, as more than 75% of households consume none. It is followed by coal, half of which is consumed by about 10% of the households; its Gini coefficient is 0.8. As for biomass, its Gini coefficient is 0.688, implying that the top 10% of the surveyed rural households account for more than 40% of biomass consumption. By comparison, the distribution of electricity is more equal, with a Gini coefficient of 0.451. This inequality of electricity is worse than in developed countries but better than in some developing nations (see Supplementary Note 2). The top 10% account for 34% of total electricity consumption. $LAC < 1$ for four energy types, indicating that the large number of small users contribute most to the energy inequality.

Figure 4b shows the Lorenz curve of energy consumption by end-use activities. The distribution of energy used for home appliances closely mirrors the distribution of electricity in Fig. 4a, because most appliances, electronics and lighting are powered by electricity. It shows the smallest Gini coefficient (0.394). Cooking energy is unevenly distributed, with a Gini coefficient of 0.519. Moreover, more than 40% of interviewed households have no energy consumption for space heating, which registers a higher Gini coefficient, at 0.708. The distribution of energy used for space cooling and water heating is farther away from the ‘perfect equality’ line. Among the five energy demands, water heating has the highest Gini coefficient, at 0.907, followed by space cooling (0.892). These values are close to the perfect inequality score 1, thus indicating severe disparity. Among five end-use demands, the LAC for appliances is greater than 1, indicating that the inequality is mainly attributed to the few top classes. For other end-use activities whose $LAC < 1$, the bottom classes contribute most to the energy inequality.

To identify the inequality source, we use the Shapley approach to decompose Gini coefficients into various components (see Methods). Figure 5a shows that, among energy types, biomass

is prominent, contributing 61.4% to the overall energy inequality, followed by electricity (12.1%), coal (10%), LPG (6.5%) and district heat (5.1%). The remaining types, including solar power, natural gas and others, together contribute 4.8% of energy inequality. Regarding the five end-use activities, as shown in Fig. 5b, space heating and cooking are the major contributors to total energy inequality, accounting for 49% and 36.4%, respectively. Water heating and appliances account for 8.2% and 5.9% of energy inequality, respectively. Space cooling contributes only 0.5% to overall energy inequality.

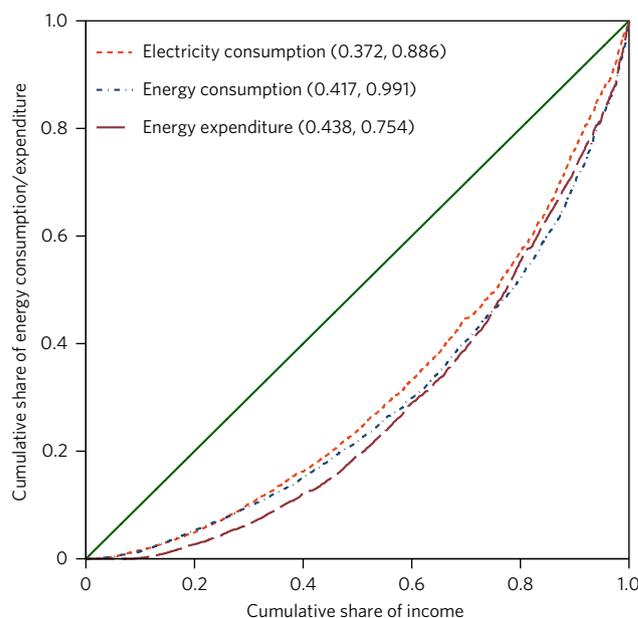


Fig. 3 | Lorenz curve of energy with income on X axis. The diagonal is the line of perfect equality. The first and second numbers presented in parentheses are the Gini coefficient and LAC, respectively.

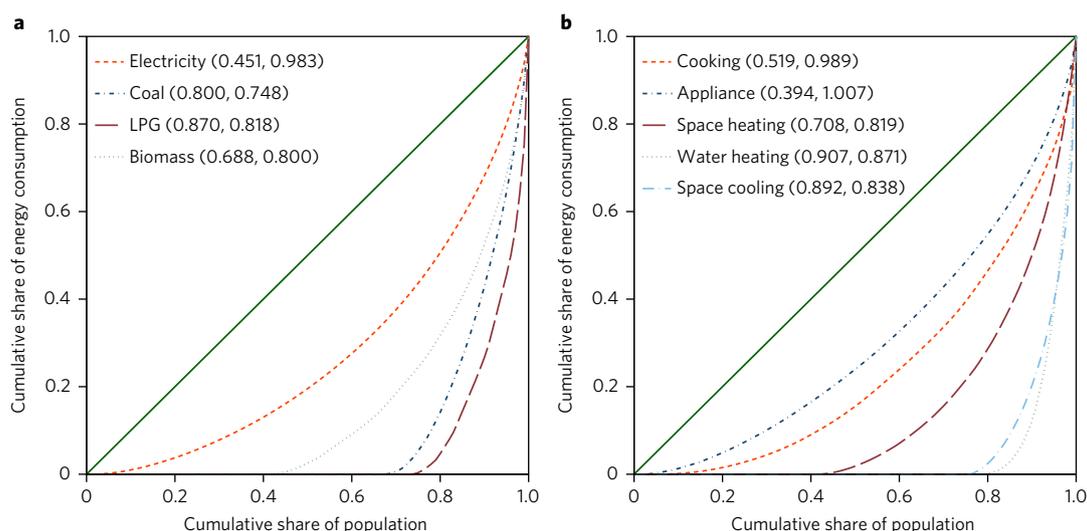


Fig. 4 | Lorenz curve of energy consumption by energy type and end uses. a, Lorenz curve of energy consumption by energy types. **b**, Lorenz curve of energy consumption by end-use activities. The diagonal is the line of perfect equality. The first and second numbers presented in parentheses are the Gini coefficient and LAC, respectively.

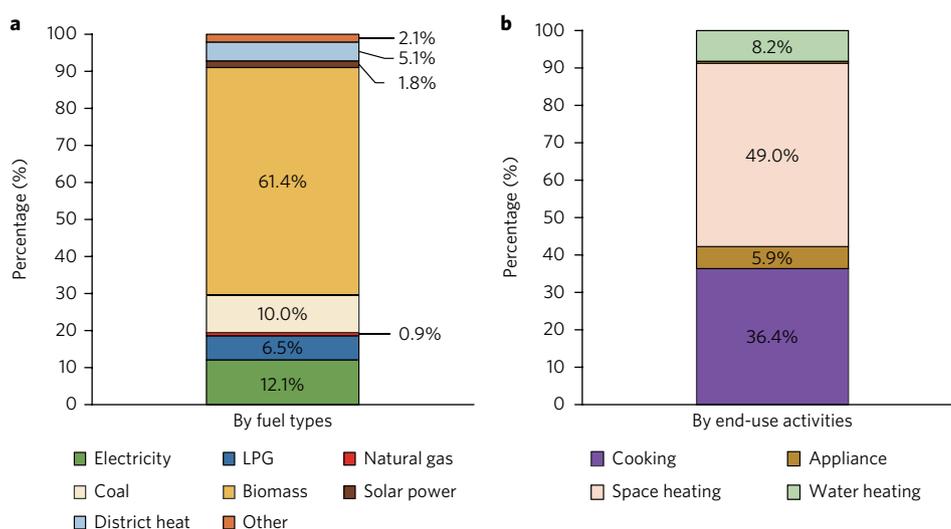


Fig. 5 | Decomposition of energy consumption-based Gini coefficient by energy sources and end-use activities. a, Decomposition of energy inequality by energy types. **b**, Decomposition of energy inequality by end-use activities. Because the contribution of space cooling accounted for only 0.5%, it is not displayed in **b**.

Regional disparity of energy inequality

Regional inequality, especially coastal–inland inequality, accompanied China's reforms in the past three decades^{4,22}. To examine whether energy inequality shows regional disparity, we classify our sample into East, Middle and West on the basis of geography and development stage (see Supplementary Fig. 2). The Lorenz curve for East, Middle and West in Fig. 6a shows a tiny difference of inequality in electricity consumption. The West has the highest Gini coefficient, at 0.457, followed by the Middle (0.447) and East (0.430). The LAC for the Middle is greater than 1, indicating that electricity inequality in the Middle is mainly due to the few top households. Compared with Fig. 6a, the distribution of energy consumption in Fig. 6b reflects a larger regional disparity. The East is closer than its counterparts to the 45 degree diagonal line. Its Gini coefficient is 0.360, much lower than that of the Middle (0.409) and West (0.413).

The regional divergence is further amplified in Fig. 6c. The Middle has the largest Gini coefficient in terms of energy expenditure. Its score is strikingly high, at 0.583, followed by the West (0.563) and East (0.485). The LAC in Fig. 6b,c is less than 1 for all regions, indicating that many small users are responsible for the inequality. In brief, the East is relatively less unequal among the three regions; inequality of energy expenditure is extensive among regions and is more severe than the inequality of electricity/energy consumption.

The climatic differences are expected to affect energy consumption patterns and inequality measures through space heating and cooling demand²³. To examine this, we classify the mainland into five climatic zones (Supplementary Fig. 3). Figure 6d shows a similar pattern for five zones in terms of electricity consumption. The temperate area (Zone V) has the largest Gini coefficient (0.490); the cold area (Zone II) registers the lowest inequality (0.431). The LAC

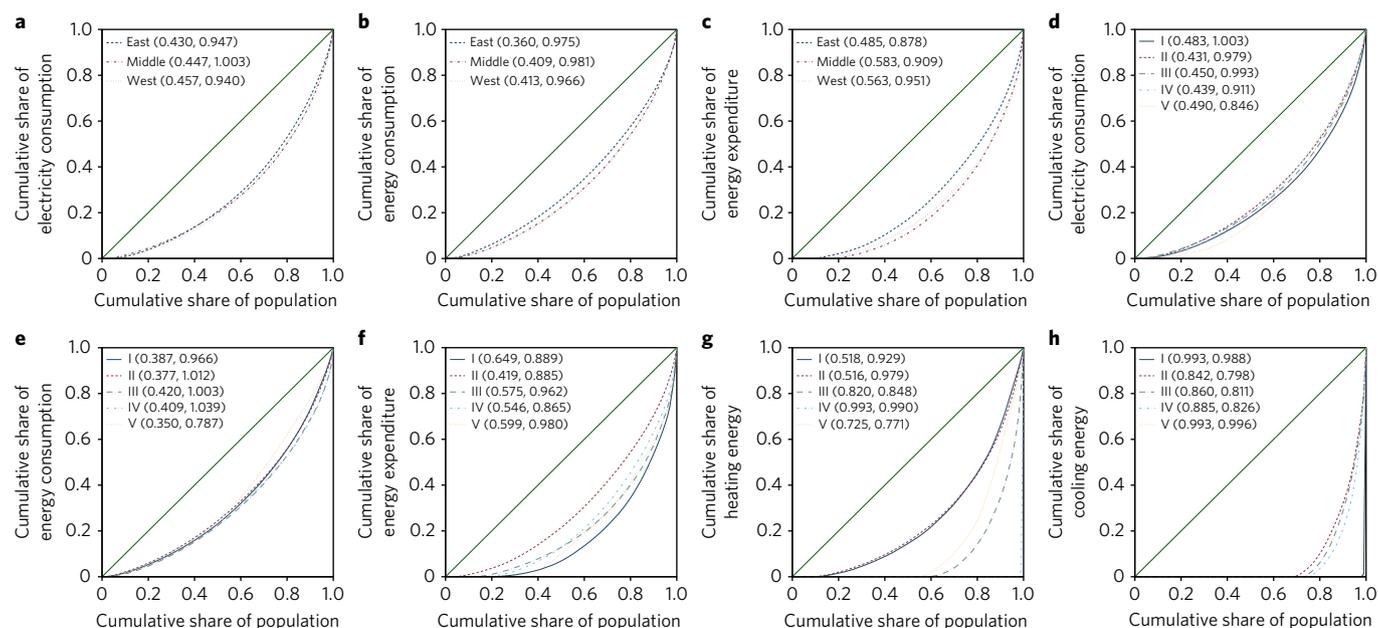


Fig. 6 | Lorenz curve by region and climatic zones. **a**, Lorenz curve of electricity by region. **b**, Lorenz curve of energy consumption by region. **c**, Lorenz curve of energy expenditure by region. **d**, Lorenz curve of electricity by climate zones. **e**, Lorenz curve of energy consumption by climate zones. **f**, Lorenz curve of energy expenditure by climate zones. **g**, Lorenz curve of space heating energy consumption by climate zones. **h**, Lorenz curve of space cooling energy consumption by climate zones. The diagonal is the line of perfect equality. The first and second numbers presented in parentheses are the Gini coefficient and LAC, respectively.

of the severely cold area (Zone I) is greater than 1, indicating that the electricity inequality is mainly attributable to the few top users. With respect to the inequality of aggregated energy consumption, as shown in Fig. 6e, Zone III (hot summer and cold winter) and Zone IV (hot summer and warm winter) have high Gini coefficients of 0.420 and 0.409, respectively. Zone V is relatively equal in terms of energy consumption and has the lowest inequality score (0.35). The LAC score > 1 indicates that energy inequality in Zones II, III and IV is mainly due to the few upper users. Figure 6f exhibits a big divergence. Zone I (0.649) is more unequal than Zone II (0.419) in terms of energy expenditure. The other three climatic zones also have high Gini coefficients, greater than 0.5. However, LAC < 1 in all five climate zones, implying that many small users contribute most to inequality. Figure 6g shows that space heating varies greatly among climate conditions. Zone III, IV and V, mostly located in the south, heavily skew to the ‘perfect inequality’ line and have relatively high inequality scores. By contrast, inequality of space heating energy is quite similar in cold areas (Zones I and II). In addition, Fig. 6h shows an extremely skewed distribution with respect to space cooling energy. The residents in the cold area (Zone I) and temperate area (Zone V) have little need for space cooling, leading to a nearly vertical curve, with Gini coefficients as high as 0.993. For remaining zones, the energy consumption for space cooling is highly unequally distributed, with Gini coefficients of 0.842–0.885. In short, energy expenditure inequality is greater than electricity/energy consumption inequality. The demand for heating in winter is more equally distributed in cold areas than in warm areas, while the demand for cooling in summer is more equally distributed in hot areas than in cold or temperate areas.

To identify the sources of inequality, Fig. 7a presents overall Gini coefficients and their components by regions. The first bar shows that the inequality within the three regions accounts for one-third of the electricity inequality index, in which the East contributes the largest share (14.1%), followed by the Middle (9.7%) and West (9.1%). The regional disparity constitutes approximately 18.4% of the overall inequality. As for inequality in terms of energy consumption,

it indicates that inequality in the West contributes a sizeable share (14.5%), followed by the East (10.0%) and Middle (8.0%). The inequality result from the East–Middle–West gap accounts for 23.8% of overall energy inequality. The remaining 43.8% comes from the residual overlap effect. The third bar presents the sources of energy expenditure inequality. It shows that the inequality within the East, Middle and West areas contributes approximately 32.6% of aggregate inequality. Specifically, the East dominates as a source of inequality, with a large share of 15.8%, followed by the West (8.5%) and Middle (8.3%). Moreover, the between-group effect and overlap effect constitute 23.9% and 43.5%, respectively, of total inequality.

Figure 7b shows a similar pattern in terms of within-group effect. The inequality within the five climatic zones explains 26–29% of the overall energy inequality. Specifically, Zones II and III are two major sources of inequality, together contributing approximately 25% of electricity inequality, 25% of the energy consumption Gini coefficient and 22% of the energy expenditure inequality index. The contribution from the remaining climatic zones is minimal: Zone I (1.5–1.8%), Zone IV (1.2–2.3%) and Zone V (less than 1%). The overall energy inequality in rural China also partly results from the regional difference. The between-group effect constitutes 9.5% of electricity inequality, while accounting for a larger proportion of energy consumption inequality (20.6%) and energy expenditure inequality (27.9%). The overlap effect constitutes around 46–62% of total inequality.

In short, Fig. 7 suggests that intra-regional inequality constitutes around one-third of the total inequality index, while the coastal-inland disparities are relatively small⁴, accounting for 18–24% of inequality. Among five climatic zones, Zones II and III dominate the within-group effect and account for approximately one-quarter of overall Gini coefficient, while the inter-regional gap contributes 10–28% of energy inequality.

Conclusion and policy implications

Since the 1980s, inequality has increased substantially in China. Although numerous studies have investigated this inequality, there are

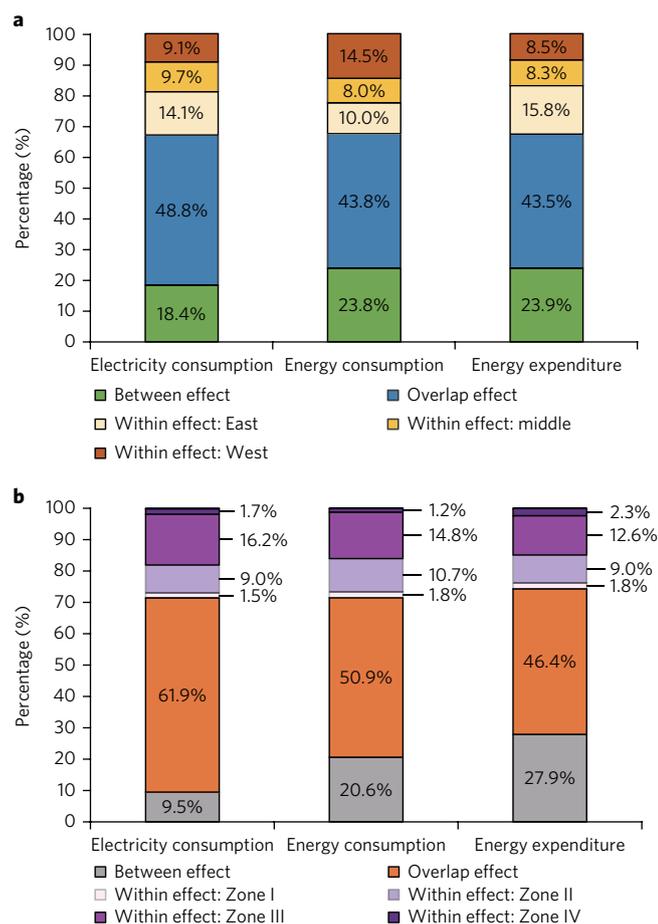


Fig. 7 | Decomposition of Gini coefficient by region and climatic zones.

a, Decomposition of electricity inequality, energy consumption inequality and energy expenditure inequality by regions. **b**, Decomposition of electricity inequality, energy consumption inequality and energy expenditure inequality by climate zones. Because the contribution of Zone V accounted for only 0.2%, 0.1% and 0.1% for electricity, energy consumption and energy expenditure inequality, respectively, it is not displayed in **b**.

drawbacks to using income and monetary expenditure in measuring inequality. On the basis of a large, detailed survey data set, the CRECS 2013, we employ the Lorenz curve, Gini coefficient and LAC to examine the many dimensions of inequality distribution and identify its sources in rural China. We offer a new interpretation of inequality by proposing the importance of energy consumption in measuring service flow. Because household energy consumption captures service flows from consumption of durable goods, it is a complementary and more direct measure to visualize consumption inequality.

The results also indicate that the inequality of energy consumption and expenditure among rural households varies greatly. Among all energy types, LPG is the most unevenly distributed, with the highest Gini coefficient (0.870), followed by coal (0.800) and biomass (0.688). Electricity is the most equally distributed, with the lowest Gini coefficient, at 0.451. Among end-use activities, water heating is the most unevenly distributed energy demand, with a Gini coefficient of 0.907. It is followed by space cooling (0.892), space heating (0.708), cooking (0.519) and home appliances (0.394). A decomposition analysis shows that, among all energy types, biomass contributes the most (61%) to total energy inequality. Space heating and cooking demand account for 49% and 36%, respectively, of overall energy inequality.

We also observe a great regional disparity in energy inequality. The most affluent area, the East, has less inequality than the Middle and West. In winter, cold areas are more equal in terms of energy demand for space heating. However, hot areas have the least inequality in terms of energy consumption for space cooling. A formal decomposition analysis indicates that the intra-regional inequality and East–Middle–West gap constitute around 32–33% and 18–24%, respectively, of total inequality. Climatic Zones II and III are two major sources of inequality, together accounting for 22% of energy expenditure inequality and 25% of the electricity/energy consumption Gini coefficient, respectively. The within effect and inter-regional differences contribute 26–28% and 10–28%, respectively, of energy inequality.

Our examination of the components of inequality have important implications for public policy. For example, although rural residents now have better energy infrastructure to access commercial energy, biomass still dominates both energy use and inequality, indicating that the energy transition has a long way to go. Moreover, energy affordability emerges as a new issue. Among all energy types, only electricity inequality is moderate in comparison with other fuels, but is still as high as 0.451. Energy expenditure inequality is also more severe than electricity/energy inequality. This suggests that energy affordability is another important barrier to alleviating energy inequality, even though there is complete energy infrastructure.

One task of a policymaker is to lessen inequality. The improvement of energy accessibility through expanding infrastructure is on the priority list for reducing inequality. For example, given the largest Gini coefficient of LPG and the greatest inequality contribution from biomass, special attention should be paid to reducing inequality in energy consumption by promoting a transition from biomass to LPG or other modern energy. New-build LPG storage and distribution stations near to towns and villages with a dense population will improve the access to LPG and substitute the consumption of biomass. Regarding end-use demand, the adoption of solar water heaters is expected to alleviate inequality in water heating²⁴.

As for affordability, one common policy option is to subsidize energy. However, there is substantial evidence that energy subsidies are a highly inefficient way to make energy affordable to the poor^{25–28} and that subsidies mainly benefit the wealthiest households^{29,30}. Our findings call for removal of existing energy subsidies and for targeted safety-net programmes as better instruments than ad hoc subsidies. First, as our results suggest, the negative correlation between energy price and inequality supports the recommendation not to emphasize direct energy subsidies. Second, population-based energy inequality is more uneven compared with income-based energy inequality. This suggests that energy subsidies aiming to alleviate energy inequality may fail, mainly because most energy subsidy benefits are distributed to the non-targeted rich group. Moreover, the moderate income-based energy inequality indicates that growth of income, rather than energy subsidies, will be a more effective way to reduce energy inequality. A progressive policy of income security, supported by resources diverted from energy subsidies, could be more helpful for equality³¹. From the cost-efficiency perspective, targeted safety-net programmes provide a more consistent delivery of more benefits per expenditure, while the history of energy subsidy programmes is filled with examples of unintended consequences and runaway costs³².

Although this study provides important contributions, it is not without limitations. In particular, it relies on a cross-section household survey; thus, it does not track dynamic changes in energy inequality. In addition, the income/expenditure and energy measures inevitably suffer from the common challenge of subjective measurement error in collecting microdata, especially in rural regions of developing countries³³. These limitations highlight important directions for future research.

Methods

Survey design, sampling and implementation. The data source we use is the CRECS, which allows us to assess consumption inequality in energy flows from durable goods. This survey was launched in 2012 by the Department of Energy Economics at Renmin University of China. The CRECS aims to monitor the overall pattern of household energy consumption in the context of the dynamic socioeconomic background. The CRECS has been conducted through a face-to-face interview with a structured questionnaire survey. The questionnaire includes six modules: household demographics; dwelling characteristics; kitchen and home appliances; space heating and cooling; private and public transportation; and energy billing, metering and pricing options. The questionnaire structure of the CRECS follows the U.S. EIA's RECS. However, the main difference is that the CRECS also collects detailed information on the device parameters (such as the power, vintage and energy efficiency label) and the consumption behaviour (such as the usage frequency and duration, as well as maintenance) for each individual piece of equipment. This enables us to derive the device-based energy consumption.

The first pilot survey (CRECS 2012) was conducted during December 2012–February 2013 and covers 1,450 urban and rural households³⁴. The CRECS 2013 focused on rural household energy consumption. It was jointly implemented by three institutions at Renmin University of China during June–September 2014. The Department of Energy Economics designed the questionnaire, trained the interviewers, contacted the respondents by telephone and managed the data quality. The Youth League recruited the interviewers and implemented and managed the survey. The National Survey Research Center (NSRC), an interdisciplinary scientific research institute at Renmin University of China, was responsible for sample selection. The NSRC has undertaken many large-scale projects, for example, the first national and continuous social survey, called the Chinese General Social Survey (CGSS)³⁵. The questionnaire of CRECS has been reviewed and approved by the ethics committee of NSRC to ensure the privacy of all participants is protected.

The ideal case is to cover all provinces; the greater the coverage, the better the representation. However, one needs to balance the survey's completeness against time and cost. Given the great disparity and diversity of rural energy in China, the NSRC and the Department of Energy Economics invited experts from different disciplines covering energy economics, field surveys, agricultural economics, statistical analysis and sociology to discuss the sample selection strategy in April 2014. These experts came from Renmin University of China (School of Agricultural Economics and Rural Development, School of Sociology and Population Studies, and the Institute of Statistics and Big Data), Peking University (National School of Development) and the Chinese Academy of Social Sciences (Rural Development Institute). The meeting reached a consensus and identified 12 representative provinces that vary substantially in terms of energy types, spatial location, climatic conditions and socioeconomic indicators. The 12 provinces are: Hebei, Heilongjiang, Jiangsu and Zhejiang, Fujian, Hubei, Hunan, Guangdong, Sichuan, Yunnan, Shaanxi and Gansu.

On the basis of the sixth National Population Census of 2010, the NSRC first excludes counties in which the agricultural proportion of the population is less than 5%. The county-level units are treated as the primary sampling units (PSU). PSUs are county-level units, which refers to counties (*xian*), county-level cities (*xian ji shi*) and city districts (*qu*) in cities, which are administered by prefectures or higher levels of government. All PSUs are ranked according to the percentage of the non-agricultural population. There remain 65 PSUs, which were selected with a one-sixteenth sampling fraction. The secondary sampling units (SSU) in each selected PSU are villages, selected in accordance with the number of villages within each county. There are 65 villages, which were selected as the SSUs following a simple random sampling procedure. For each selected SSU, 60 households were randomly selected from the village using Kish random numbers. The householder or his/her spouse (or person older than 18) from each sampled household was eligible to serve as the survey respondent. This sampling procedure yielded 3,900 rural households in 65 counties (villages) across 12 provinces. NSRC uses a sampling procedure similar to the CGSS. One difference is that the CRECS 2013 covers counties and villages, while the CGSS uses a three-level sampling structure covering counties, townships and villages. Another difference is that the latest CGSS began using a street-mapping strategy to select a representative sample of households³⁵.

The Youth League of Renmin University has established an online system to list all sampled counties to facilitate the registration process and management for interviewers. Any registered undergraduate and graduate students from Renmin University are eligible to become interviewers. To avoid language barriers, the applicants are encouraged to choose their hometown or neighbouring area as their survey destination. The university staff is also encouraged to participate in this programme to guide the students.

In May 2014, around 390 students from over 800 applicants were selected on the basis of their previous survey experience, language skill, age and participation in civic activities. The selected students and staff formed 65 teams for the sampled villages, with 6 team members on average. All interviewers attended a two-day training lecture in June 2014. The Youth League explained general information about the field survey method, travel safety and disease prevention. Moreover,

they received intensive training by the Department of Energy Economics. The interviewers attending these training course were expected to grasp the following knowledge and skills. First, they had to be able to properly use smartphones or GPS devices that we provided to locate the households' geographical coordinates. Second, they were taught to distinguish various energy measurement units in local slang and convert them into standard units. However, to ensure the data's quality, they were required to record both the original units and the standard units using different colours. Third, they learned how to read the power capacity and energy efficiency labels for home appliances, which are key parameters to estimate device-based energy consumption. Most importantly, they were instructed to estimate the quantity of biomass, which has become the biggest challenge for rural energy surveys. For example, one can use band tape to measure the length, width and height of a firewood pile, or the diameter and height of a dung heap. All of these instructions and background information are included in a well-drafted manual for each interviewer.

The CRECS 2013 was implemented during the 2014 summer holiday (July and August), when students were available to work. Each team was expected to interview around 60 selected rural households. The teams who were involved in CRECS 2013 were expected to take 60–90 minutes to finish a questionnaire. All questionnaires were returned to the Department of Energy Economics in September.

Data quality control. There are four important measures to ensure the quality of the survey. First, the competitive selection procedures and pre-defined incentive mechanisms ensure that most interviewers have strong motivation. To create the incentives, the summer survey programme is treated as a social practice project and associated with the students' performance evaluation. Each member can obtain one course credit once he or she finishes the survey. In addition, the university reimburses actual travel expenses and provides allowances for all verified activities. Moreover, for the participants in CRECS, the Department of Energy Economics provides an additional monetary subsidy (30 yuan) for each verified questionnaire. However, one cannot gain credit or travel reimbursement in the case of invalid data.

Second, the investigators have adequate knowledge and skills to conduct the survey. As mentioned before, less than half of the applicants are selected. Most interviewers have prior experience with field surveys and are familiar with the local language, plus they take an intensive professional training course. These capacities ease their conversations with the surveyed rural households, most of whom are elderly people who do not speak Mandarin. Moreover, the sampled villages have been traced since 2012. This enables the interviewers to utilize the previously documented information to better understand the villages. In addition, the respondents in these villages know about the summer survey, which eliminates the respondents' doubts and smooths the interviews.

Third, the whole survey process is under the control of an efficient hierarchical management system. There are three management levels that are responsible for the process. The core team includes the teachers and experts who participate in the survey design and have proven survey experience. It serves as the national steering team and is responsible for sample replacement and other ongoing issues. The second level is the regional supervisor, who collects daily feedback and directs the team's work for each province. Most of these supervisors are graduate students who have experience in large-scale field surveys. The third level is the team leader and guiding teacher (if assigned), who sets up the schedule, manages the daily affairs and reports daily progress to the regional supervisor.

Fourth, a strict post-survey quality control procedure is applied to clean up invalid parts of the sample. We have developed a strategy to identify 'good interview–good respondent' pairs. In September 2014, around 3,560 questionnaires were recovered, with a high response rate of 91%. For each team, 10% of surveyed households were randomly selected for telephone revisits on the basis of some key variables (for example, the householder's age, the TV brand, and so on). The team leader was contacted for further confirmation once mismatched questionnaires were found. After excluding some suspect and invalid samples, there remain 3,404 verified samples covering 65 villages across 12 provinces. The sample distribution is presented in Supplementary Fig. 1.

Representativeness. Supplementary Table 1 provides a comparison of household characteristics for CRECS 2013 with the official statistics. The average rural household size is 3.58 members, with 52.5% male and an average age of 40.6 years for all members. These demographic variables are consistent with the official numbers, in which the average household size is 3.3 people, 51.3% of family members are male, and the average age is 37 years. The number of labour force members per household in CRECS 2013 is 2.19 people, slightly higher than the official data (2.1 people). The dwelling area in our sample is 143.62 m², which is very close to the National Bureau of Statistics value (143.95 m² in 2012).

The household income/expenditure data and their composition also show great similarity to the official statistics. For example, the average per capita disposable income and per capita expenditure in CRECS 2013 is 10,837.5 yuan and 6,528.9 yuan, which is not significantly different from the official number (9,429.6 yuan and 7,485.1 yuan, respectively). As for the income/expenditure composition, except for the higher clothing expenditure in our sample, the CRECS is also consistent with the NBS's number.

In addition, the ownership of major home appliances and transportation vehicles shows that the CRECS is nationally representative. For example, the penetration rate of cars, refrigerators, washing machines, televisions, computers and air conditioners for 100 rural households in CRECS and official statistics is 10.05 versus 9.9, 75.4 versus 72.9, 69.7 versus 71.2, 98.6 versus 112.9, 20.7 versus 20, and 22.9 versus 29.8, respectively. The CRECS yields a remarkably lower rate of television ownership because the questionnaire allows reporting only of up to two TVs.

As shown in Supplementary Table 2, the households chosen in CRECS also reflect different income classes. The sample we surveyed spans from the poorest (less than 2,000 yuan per person) to the richest group (greater than 50,000 yuan per person) in rural China.

Measuring energy consumption. We use a bottom-up device-based accounting approach to estimate energy consumption. The strategy is as follows: we set up eight fuel types (coal, natural gas, LPG, solar power, biomass, electricity, district heat and other) and five end-use activities (cooking, powering home appliances, water heating, space heating and space cooling)³⁴. Energy consumption for transportation is not included in order to make our results comparable with other relevant studies. We first estimate the daily energy consumption for each device (appliance) based on its output power (or consumption rate for stoves), usage frequency and duration, and energy efficiency grade. Then, the daily energy consumption for each device is adjusted into annual data based on the respondent's duration of residence at the surveyed dwelling in year 2013. Finally, the total household energy consumption in standard coal equivalent unit (kgce) is aggregated on the basis of the device-based energy usage in physical units and the conversion coefficient for each energy.

This bottom-up device-based accounting approach has several merits. First, it allows us to aggregate household energy consumption by fuel type or end use. Second, it can accommodate estimation and aggregation of non-meterable energy, such as biomass. Third, the commonly used 'recall-based approach' in household surveys asks the respondent to report a quantity/expenditure for a specific good over a long period. In comparison, our estimation procedure is based on the devices' physical parameters and routine daily consumption behaviour, which is expected to be relatively reliable and less prone to subjective bias. It should be noted that this bottom-up device-based accounting approach is much more precise than the self-reported approach, but less accurate than device-based meter measurement. Moreover, it inevitably suffers from the common challenge of subjective measurement error in collecting microdata, especially in rural regions of developing countries.

Measuring inequality. The Lorenz curve and the Gini coefficient are the most widely used analytical tools in economics literature to measure inequality. There have been several attempts to measure inequality in the areas of climate change and environmental economics^{36,37}. However, very few studies in the energy literature have analysed inequality in energy consumption. Jacmart, et al.³⁸ were the first to apply the Lorenz curve to examine the inequality trend in terms of per capita energy consumption over the period 1950–1975. Their results suggest a slow decrease of energy inequality. Saboohi³¹ estimates the Gini coefficient of urban and rural areas in Iran, finding that the total Gini coefficients for final energy consumption and energy subsidies are 0.21 and 0.23, respectively. Energy subsidies may create greater inequality. Jacobson, et al.²³ formally present the energy Lorenz curve and corresponding energy Gini coefficient. They compare the distribution of electricity consumption in five countries. They conclude that the shape of the energy Lorenz curve depends on the nation's wealth, income distribution, infrastructure, climatic conditions, and energy efficiency measures, as well as the size and geographic distribution of the rural population. Using the same data as Jacobson, et al.²³, Kammen and Kirubi²⁰ adopt the Gini–Lorenz method to assess energy poverty. Moreover, Druckman and Jackson³⁹ generalize this idea and extend this framework to measure resource inequality. They find that different levels of inequality are associated with different commodities.

The traditional Lorenz curve is a coordinate graph representing inequality of the income distribution. In the context of energy consumption, the energy Lorenz curve is a ranked distribution of the cumulative percentage of the population on the horizontal axis versus the cumulative percentage of energy consumption distributed along the vertical axis. In normal cases, a point on the energy Lorenz curve shows that $y\%$ of the overall energy resource is consumed by $x\%$ of the people.

Based on the energy Lorenz curve, the energy Gini coefficient is a numerical tool for analysing the level of inequality. Mathematically, the energy Gini coefficient can be defined as

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

where X is the cumulative proportion of the population and Y is the cumulative proportion of energy consumption. X is measured as the number of energy users in population group i divided by total population, with X_i indexed in non-decreasing order. Y is measured as the quantity of energy used by population group i divided by total energy use, with Y_i ordered from lowest to highest energy consumption.

The Gini coefficient is a unit-free measure and ranges from 0 to 1. It provides a well-understood quantitative measure of inequality. The larger the Gini value, the greater the inequality in energy consumption. A zero value of the Gini coefficient indicates perfect equality, with all households receiving an equal share. Conversely, a Gini coefficient of 1 suggests complete inequality, where one unit uses all of the energy.

In our case, a significant portion of the study population simply does not use certain fuels or certain end uses. Of the portion of the population that does use them, it is unclear by visual inspection of the Lorenz curve how unequal the distribution is. The LAC can supplement the Gini coefficient to assess the amount of asymmetry of the Lorenz curve and reveal which classes contribute most to the inequality⁴⁰. The coefficient (S) can be calculated as:

$$S = F(\bar{\mu}) + L(\bar{\mu}) = \frac{m + \delta}{n} + \frac{L_m + \delta\mu'_{m+1}}{L_n} \quad (2)$$

$$\delta = \frac{\bar{\mu} - \mu'_m}{\mu'_{m+1} - \mu'_m}$$

where $\bar{\mu}$ is the mean of energy consumption, m is the number of individuals with energy consumption less than $\bar{\mu}$, L_m is the cumulative energy consumption of individuals with energy consumption less than $\bar{\mu}$ and L_n is the cumulative energy consumption of all individuals. If the point where the Lorenz curve is parallel to the line of equality lies below the axis of symmetry, $S < 1$, which indicates that the poor individuals contribute most to the inequality. Correspondingly, if $S > 1$, the inequality is mainly due to the few wealthiest individuals. When $S = 1$, the Lorenz curve of the assemblage is symmetric.

Gini coefficient by energy sources and end-use activities. Following Shorrocks⁴¹, we also use a Shapley approach to decompose Gini coefficients into a sum of the contributions generated by separate components, by energy types and end-use activities. There is set N of n players. Players can form coalitions S that are subsets of N . We denote s as the number of players in subset S , and $v(S)$ is known as the coalition force or the worth of the coalitions. The Shapley value is designed as a fair way to divide the surplus to player k , denoted by e_k . It is defined as:

$$e_k = \sum_{\substack{S \subseteq N \\ s \in \{0, n-1\}}} \frac{s!(n-s-1)!}{n!} mv(S, k) \quad (3)$$

$$mv(S, k) = (v(S \cup \{k\}) - v(S))$$

where $mv(S, k)$ is the marginal contribution of player k after he joins coalition S . To decompose inequality using the Shapley approach, the Gini coefficient for a subset of components is estimated by suppressing the inequality generated by the complementary subset of components. For this, we generate a counterfactual vector of the variable that equals the sum of the components of the subset (factors of the coalition) plus the average of the complementary subset.

This approach is used to decompose the Gini coefficient by energy source (electricity, coal, LPG and biomass) and end-use activity (cooking, appliance, space heating, water heating and cooling).

Gini coefficient by regions and climatic zone subgroups. The Gini coefficient can be decomposed into the following components, following a strategy similar to that suggested by Yang⁴²:

$$G = G_{\text{within}} + G_{\text{between}} + G_{\text{overlap}} \quad (4)$$

$$G_{\text{within}} = \sum_i \frac{n_i}{n} w_i G_i$$

$$G_{\text{between}} = 1 - \sum_i \frac{n_i}{n} \left(2 \sum_{k=1}^i w_k - w_i \right)$$

where n_i/n measures the proportion of group i in the total population. w_i is the i th group's proportion of the variable of interest (that is, electricity consumption, energy consumption or energy expenditure). G_i is i th group's Gini coefficient. The term G_{within} measures the inequality within group i and the term G_{between} measures the disparity across groups. The term G_{overlap} is a residual that depends on the frequency and magnitude of overlaps between energy consumption in different groups. It yields a zero value if the ranges of household energy consumption do not overlap. For example, comparing the top electricity consumption in Hubei province with the bottom electricity consumption in Hebei province, this difference may have an important influence on overall inequality. Further, if the highest electricity consumption in the low-electricity group is lower than the lowest electricity consumption in the high-electricity group, then the overlap-group effect equals zero.

This approach is used to decompose the Gini coefficient by three regions (East, Middle and West), five climatic zones (Zones I, II, III, IV and IV) and five income subgroups.

Data availability. The aggregated data and Stata code files that support the Tables and Figures within this paper are available on Figshare (doi: <https://doi.org/10.6084/m9.figshare.5172496.v1>)⁴³. The CRECS data set is managed by the National Survey Research Center at Renmin University of China (NSRC). Access to individual raw data is protected as private information and subject to a four-year embargo policy. Because the data set we used in the present study (CRECS 2013) was collected in 2014, the anonymized transcripts will be available from the corresponding author upon reasonable request after September 2018.

Received: 18 July 2016; Accepted: 31 July 2017;
Published online: 25 September 2017

References

- Xie, Y. & Zhou, X. Income inequality in today's China. *Proc. Natl Acad. Sci. USA* **111**, 6928–6933 (2014).
- Kaiman, J. China gets richer but more unequal. *The Guardian* (28 July 2014).
- Woellert, L. & Chen, S. China's Income Inequality Surpasses US, Posing Risk for Xi. *Bloomberg* (28 March 2014).
- Kanbur, R. & Zhang, X. Which regional inequality? The evolution of rural–urban and inland–coastal inequality in China from 1983 to 1995. *J. Compar. Econ.* **27**, 686–701 (1999).
- Cai, H., Chen, Y. & Zhou, L.-A. Income and consumption inequality in urban China: 1992–2003. *Econ. Devel. Cult. Change* **58**, 385–413 (2010).
- Benjamin, D., Brandt, L. & Giles, J. The evolution of income inequality in rural China. *Econ. Devel. Cult. Change* **53**, 769–824 (2005).
- Cutler, D. M. & Katz, L. F. Rising inequality? Changes in the distribution of income and consumption in the 1980's. *Amer. Econ. Rev.* **82**, 546–551 (1992).
- Hassett, K. A. & Mathur, A. A new measure of consumption inequality. *AEI Econ. Stud.* **2**, (2012) http://www.aei.org/wp-content/uploads/2012/06/-a-new-measure-of-consumption-inequality_142931647663.pdf.
- Reform and Innovation for Better Rural Health Services in China* (The World Bank, Washington DC, 2015); <http://www.worldbank.org/en/results/2015/04/02/reform-innovation-for-better-rural-health-services-in-china>.
- Li, J. J. & Su, C. How face influences consumption. *Int. J. Market Res.* **49**, 237–256 (2007).
- Corneo, G. & Jeanne, O. Conspicuous consumption, snobism and conformism. *J. Public Econ.* **66**, 55–71 (1997).
- Krueger, D. & Perri, F. Does income inequality lead to consumption inequality? Evidence and theory. *Rev. Econ. Stud.* **73**, 163–193 (2006).
- Chen, X. & Nordhaus, W. D. Using luminosity data as a proxy for economic statistics. *Proc. Natl Acad. Sci. USA* **108**, 8589–8594 (2011).
- Arora, V. & Lieskovsky, J. *Electricity Use as an Indicator of US Economic Activity* EIA Working Paper Series (EIA, Washington DC, 2014).
- Henderson, J. V., Storeygard, A. & Weil, D. N. Measuring economic growth from outer space. *Amer. Econ. Rev.* **102**, 994–1028 (2012).
- Joyeux, R. & Ripple, R. D. Household energy consumption versus income and relative standard of living: A panel approach. *Energy Policy* **35**, 50–60 (2007).
- Aklin, M., Cheng, C.-Y., Urpelainen, J., Ganesan, K. & Jain, A. Factors affecting household satisfaction with electricity supply in rural India. *Nat. Energy* **1**, 16170 (2016).
- Jorgenson, A. K., Alekseyko, A. & Giedraitis, V. Energy consumption, human well-being and economic development in central and eastern European nations: A cautionary tale of sustainability. *Energy Policy* **66**, 419–427 (2014).
- Anderson, D. in *World Energy Assessment: Energy and the Challenge of Sustainability* (eds. United Nations Development Programme) (UNDP, New York, 2000).
- Kammen, D. M. & Kirubi, C. Poverty, energy, and resource use in developing countries. *Ann. NY Acad. Sci.* **1136**, 348–357 (2008).
- China to realize nationwide electricity coverage. *State Council* (4 August 2015); http://english.gov.cn/state_council/ministries/2015/08/04/content_281475160764026.htm
- Fleisher, B., Li, H. & Zhao, M. Q. Human capital, economic growth, and regional inequality in China. *J. Dev. Econ.* **92**, 215–231 (2010).
- Jacobson, A., Milman, A. D. & Kammen, D. M. Letting the (energy) Gini out of the bottle: Lorenz curves of cumulative electricity consumption and Gini coefficients as metrics of energy distribution and equity. *Energy Policy* **33**, 1825–1832 (2005).
- Han, J., Mol, A. P. & Lu, Y. Solar water heaters in China: a new day dawning. *Energy Policy* **38**, 383–391 (2010).
- Dube, I. Impact of energy subsidies on energy consumption and supply in Zimbabwe. Do the urban poor really benefit? *Energy Policy* **31**, 1635–1645 (2003).
- Kebede, B. Energy subsidies and costs in urban Ethiopia: The cases of kerosene and electricity. *Renew. Energy* **31**, 2140–2151 (2006).
- Pitt, M. M. Equity, externalities and energy subsidies The case of kerosine in Indonesia. *J. Dev. Econ.* **17**, 201–217 (1985).
- Alam, M., Sathaye, J. & Barnes, D. Urban household energy use in India: efficiency and policy implications. *Energy Policy* **26**, 885–891 (1998).
- Soile, I. & Mu, X. Who benefit most from fuel subsidies? Evidence from Nigeria. *Energy Policy* **87**, 314–324 (2015).
- Coady, D., Parry, I. W. H., Sears, L. & Shang, B. *How Large Are Global Energy Subsidies?* International Monetary Fund Working Paper No. 15/105 42 (IMF, Washington DC, 2015).
- Saboohi, Y. An evaluation of the impact of reducing energy subsidies on living expenses of households. *Energy Policy* **29**, 245–252 (2001).
- Larson, D. F., Lampietti, J., Gouel, C. & Cafiero, C. Food security and storage in the Middle East and North Africa. *World Bank Econ. Rev.* **28**, 48–73 (2014).
- Meyer, B. D., Mok, W. K. C. & Sullivan, J. X. Household surveys in crisis. *J. Econ. Perspect.* **29**, 199–226 (2015).
- Zheng, X. et al. Characteristics of residential energy consumption in China: Findings from a household survey. *Energy Policy* **75**, 126–135 (2014).
- Bian, Y. & Li, L. The Chinese general social survey (2003–8). *Chinese Sociol. Rev.* **45**, 70–97 (2012).
- Tol, R. S., Downing, T. E., Kuik, O. J. & Smith, J. B. Distributional aspects of climate change impacts. *Glob. Environ. Change* **14**, 259–272 (2004).
- Groot, L. Carbon Lorenz curves. *Resour. Energy Econ.* **32**, 45–64 (2010).
- Jacmart, M. C., Arditi, M. & Arditi, I. The world distribution of commercial energy consumption. *Energy Policy* **7**, 199–207 (1979).
- Druckman, A. & Jackson, T. Measuring resource inequalities: The concepts and methodology for an area-based Gini coefficient. *Ecol. Econ.* **65**, 242–252 (2008).
- Damgaard, C. & Weiner, J. Describing inequality in plant size or fecundity. *Ecology* **81**, 1139–1142 (2000).
- Shorrocks, A. F. Decomposition procedures for distributional analysis: a unified framework based on the Shapley value. *J. Econ. Inequal.* **11**, 99–126 (2013).
- Yang, D. T. Urban-biased policies and rising income inequality in China. *Amer. Econ. Rev.* **89**, 306–310 (1999).
- Wei, C., Wu, S. & Zheng, X. Figshare Digital Repository (2017); <https://doi.org/10.6084/m9.figshare.5172496.v1>

Acknowledgements

We thank J. Guo, Z.T. Huang, J.Q. Hu and J.S. Fu for their input in survey design and implementation and data collection. We are grateful to J. Tang and W.D. Wang for their technical guidance and Y.C. Liu, R.L. Yang and Y. Zhang for their support to CRECS. Funding for this work was provided by the National Science Foundation of China (Grant no. 71622014, 41771564, 71774165), Ministry of Education of China (Grant nos 14JJD790033, 16YJA790049) and Beijing Natural Science Foundation (Grant no. 9152011).

Author contributions

All authors contributed to survey design and data collection. S.M.W. conducted the data analysis. X.Y.Z. secured project funding. C.W. drafted the manuscript. S.M.W. and C.W. edited the manuscript.

Competing interests

The authors declare no competing financial interests.

Additional information

Supplementary information is available for this paper at doi:10.1038/s41560-017-0003-1.

Reprints and permissions information is available at www.nature.com/reprints.

Correspondence and requests for materials should be addressed to C.W.

Publisher's note: Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.