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Can Chinese household consumption become more energy efficient? Analysis based on input–output and demand system models

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A B S T R A C T

To gain a comprehensive understanding of the role that household consumption has in the transition to a low-carbon economy, analyses of household energy use (HEU) should focus on total HEU that includes direct and indirect energy use. We examine the major factors of total HEU efficiency using input–output and Quadratic Almost Ideal Demand System models. The analyses are based on time-series non-competitive input–output tables at constant prices for 1986—2018 compiled by this study, industrial energy satellite accounts, and the data from the Chinese Household Income Project. First, the findings reveal that while total HEU is increasing rapidly, HEU intensity has declined, suggesting that household consumption has become more energy efficient. However, the primary cause is the reduction of energy intensity in production sectors rather than the household consumption structure. Second, HEU will continue to rise with advancing urbanization and expected income increasing in the future. Furthermore, changing consumption patterns may increase urban and rural HEU, with an increasing share of household facilities, transportation, and communication further driving energy use in upstream industries. Therefore, the key to improving HEU efficiency is more strongly related to technological advances on the production side than changing consumption patterns. Energy policy should primarily focus on promoting industrial technological advances and measures to advance circular economy development.

1. Introduction

Energy is a crucial constraint for China's social and economic development. In 2022, China's primary energy consumption was 157.94 exajoules, accounting for 26.4 % of total global energy consumption, which was 10.5 % higher than the second place United States (US) (Energy Institute, 2024). As the largest pollution emitter and a responsible country, at the 2020 UN General Assembly President Xi officially proposed that China would strive to reach peak carbon dioxide emissions by 2030 and carbon neutrality by 2060 (the dual carbon goal). Accordingly, China has set targets to reduce energy consumption per unit of GDP by 13.5 % by 2025 compared with 2020 and to reach a share of about 25 % of non-fossil energy consumption by 2030.

As one of the main sources of energy consumption, households have an important role in achieving these goals and have attracted wide attention. In the examination of household energy use (HEU), it is essential to consider the following two factors. First, indirect HEU should be considered in the analysis. Direct HEU refers to the energy consumed by a household in daily life, such as natural gas for cooking, petrol for driving, and other practical needs. The share of direct HEU in the total energy use was only about 18 % at the beginning of China's reform and opening-up (1978) and has decreased to about 12 % in recent years. However, the part of energy embodied in household consumption cannot be neglected, that is, indirect HEU. For example, household public transportation consumption incorporates the indirect use of energy such as oil and electricity. According to the computation in this paper, indirect HEU accounts for a much larger proportion than direct HEU. Focusing only on direct HEU largely obscures the proportion of HEU in total energy use. Second, this study contends that it is crucial to analyze the factors of HEU efficiency rather than its scale. Both direct and indirect HEU are rising, with the increase of household consumption from 0.18 trillion yuan in 1978 to 45 trillion yuan in 2022 and is expected to continue to expand with economic and income growth in the medium and long term (National Bureau of Statistics of China (NBSC),

Abbreviations: HEU, Household energy use; QUAIDS, Quadratic Almost Ideal Demand System; SDA, structural decomposition analysis; LMDI, Logarithmic mean Divisia index; EKC, Environmental Kuznets curve; LES, Linear expenditure system; AIDS, Almost Ideal Demand System; PPI, Producer price index; CPI, Consumer price index; NBSC, National Bureau of Statistics of China; CHIP, Chinese Household Income Project.

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1988–2023). Therefore, increasing HEU efficiency must be prioritized to achieve the goal of energy saving. Some measures attempt to improve HEU efficiency by influencing household consumption patterns. For example, the Chinese government has been promoting a green and low-carbon lifestyle, encouraging citizens to adopt more energy-efficient consumption patterns such as lowering the use of private cars and using fewer disposable products.

In this context, it is essential to analyze the factors affecting HEU efficiency and the contribution of household consumption patterns. For the objective, this study estimates the dynamics of both direct and indirect HEU per unit of consumption in China, analyzing the contributions of and differences between various groups and industries to identify the potential for consumption-related energy saving and highlight the areas where future efforts should be directed.

In this study, Chinese time-series non-competitive input–output tables at constant prices for 1986—2018 are compiled. Combining the data on energy use by sectors and the data from the Chinese Household Income Project, the major factors of total HEU efficiency are examined using input–output and Quadratic Almost Ideal Demand System models. The main findings are as follows. First, while total HEU is increasing rapidly, HEU intensity has reduced, suggesting that household consumption has become more energy efficient. However, the main factor in the increase of HEU efficiency is the reduction of energy intensity in production sectors, and household consumption patterns contribute little. Second, further studies show that changing consumption patterns may increase urban and rural HEU, with an increasing share of household facilities, transportation, and communication further driving energy use in upstream industries. The result reinforces the importance of energy intensity in production sectors for improving HEU efficiency. Therefore, future efforts should primarily focus on advancing industries' technology and establishing a circular economy to reduce the energy use on the production side.

The remainder of this paper is organized as follows. Section 2 reviews and summarizes previous related literature. Section 3 constructs input–output and Quadratic Almost Ideal Demand System (QUAIDS) models, with the former exploring the relationship between household consumption and energy use and the latter exploring changes in household consumption patterns. Section 4 describes the results in terms of total HEU, HEU efficiency, differences between sectors, and elasticity of consumption. Section 5 compares urban and rural HEU in China and other countries. Section 6 presents conclusions and policy implications.

2. Literature review

The literature related to this study can be divided into three main categories, a) studies exploring the role of various factors in energy use through macro-level decomposition methods, b) analyses of the correlations between household consumption and energy use patterns that combine micro data, and c) research applying demand system models to analyze household energy demand and/or energy policy effects.

2.1. Studies exploring macro-level factors that influence energy use

Although most energy is used in production chains, final demand also accounts for a certain share and indirectly affects production. Accordingly, Shui and Dowlatabadi (2005) proposed the consumer lifestyle approach, which was used to demonstrate that more than 80 % of energy use and carbon emissions in the US are caused by consumer demand and the economic activities that support it. Mi et al. (2020) determined that Chinese households contributed 34 % of the national carbon footprint in 2012, with 74 % of the national household carbon footprint derived from urban residents. These results indicate that energy use is largely related to household consumption.

Some studies have analyzed the role of HEU using decomposition methods such as structural decomposition analysis (SDA) and the logarithmic mean Divisia index (LMDI) method. SDA has predominantly been employed to decompose indirect energy use and can determine the magnitude of various factors' influence over time, generally including energy intensity, the intermediate input–output structure, consumption scale, and consumption structure. Previous studies have also included some climate and socioeconomic factors (Wang and Shi, 2012; Zhang, 2012; Zhang et al., 2016; Li et al., 2017; Jiang et al., 2021). Studies using LMDI have often separated energy use or carbon emissions into factors such as energy prices, energy structure, regional structure, and per capita income (Nie et al., 2018; Huang and Matsumoto, 2021; Wang et al., 2021). According to these studies, increased consumption and rising populations are the primary drivers of a rise in energy use (Peng and Zhang, 2013; Wang and Xia, 2017). While advances in energy intensity and production technology may decrease energy use to some extent, the slow pace of technological progress cannot compete with rapidly rising consumption.

2.2. Analyses of household consumption and energy use patterns

Previous research in this second category has applied micro data and extended input–output methods to investigate households' consumption and energy use patterns. Chitnis et al. (2012) and Zhang et al. (2020) demonstrated that more than 70 % of the increase in household carbon emissions comes from lifestyle changes in the United Kingdom and China. Among the various consumption categories, expenditures related to food, housing, transportation, and communication were found to have the greatest impact on HEU (Feng et al., 2020; Tu et al., 2021; Wei et al., 2022). Two highly significant characteristics impacting households' consumption choices and lifestyles are age and income. First, different age groups typically have different consumption needs and preferences, with some research indicating that older households have relatively lower total emissions and middle-aged households generate the highest footprint (Lim et al., 2020; Zhang et al., 2022). In contrast, other research has argued that aging reduces energy use efficiency and increases energy use (Yu et al., 2018; Long et al., 2019; Ma et al., 2021).

As for income, according to the environmental Kuznets curve (EKC) hypothesis, the relationship between energy use or carbon emissions and income per capita has an inverted U-shape. Some household-level research in China has suggested that the EKC effect is expected but the inflection point has not yet been reached (Jiang et al., 2019; Zhang et al., 2020; Chai et al., 2021). Regarding income differences, some studies have grouped different households by income level to compare energy use patterns between households in different groups (Su et al., 2017; Chen et al., 2022a; Ma et al., 2022). Mi et al. (2020) demonstrated that the top 5 % of Chinese earners contributed 17 % of the national carbon footprint, while the bottom half only accounted for 25 %. Zhang et al. (2023) demonstrated that the top 20 % of earners consume 45 % of energy, while the lowest 20 % consume only 4 %. Similarly, other studies have found that high-income households have a much higher carbon or energy footprint than low-income households (Yin et al., 2020; Lei et al., 2022).

2.3. Consumption demand system models in energy use-related research

To examine the impact of differences or changes in consumption patterns on energy use over time in more detail, studies in the third category have applied consumption demand system models such as the Environmental Input–Output Life Cycle Analysis model (Shui and Dowlatabadi, 2005), the linear expenditure system (LES) (Washizu and Nakano, 2010), and the linear approximation of the Almost Ideal Demand System (LA-AIDS) (Du et al., 2021). In recent years, the QUAIDS model has been widely used to investigate changes in energy consumption, consumption structure, and the welfare effects of energy policies (Waleed and Mirza, 2020; Bjelle et al., 2021; Díaz and Medlock, 2021; Moz-Christofoletti and Pereda, 2021; Okonkwo, 2020).

2.4. Contributions of this study

The above literature review outlines some of the mainstream directions of energy research, and this study makes three further improvements. First, previous studies have clarified the factors of total HEU, concluding that the scale of goods and services in household consumption is the dominant factor. With increased population and rising income, the scale of household consumption is bound to expand, making energy efficiency more important. The three factors that influence energy efficiency are energy intensity, technology, and household consumption patterns. This study examines consumption patterns and accounts for energy use efficiency resulting from household activities using an input–output model, building a bridge between consumption patterns and energy use. We identify the key sectors involved in the transmission from household consumption to energy use and clarify the heterogeneity between urban and rural households in a more detailed manner than previous studies.

Second, current research on the impact of income on energy use has focused on direct energy use (Hu et al., 2019; Bohlmann and Inglesi-Lotz, 2021; Liddle and Huntington, 2021). However, as noted above, direct HEU only accounts for a small share of total energy use, and current research has not established how income changes household consumption patterns. This study overcomes this limitation in two ways. The first is calculating indirect HEU employing the input–output model, and the second is using the QUAIDS model to describe the changes in Chinese households' consumption preferences. Combining these two models allows us to investigate whether consumption patterns have become more energy efficient and predict whether efficiency will advance in the future. Overall, this study analyzes the changing trends in Chinese household consumption and income and identifies key targets for promoting households' energy-saving lifestyles.

Third, we construct a unique database that includes input–output tables at constant prices and an energy satellite account, which is more appropriate for our study. We choose annual input–output tables to overcome the limitations of discontinuity. We also separate the import matrix and use a variety of price indices to deflate the input–output tables, constructing non-competitive time-series input–output tables at constant prices that exclude the effect of imported products and price changes. Compared with the existing literature, this study offer a unique dataset with advantages in terms of continuity, consistency, and integrity that supports our long-term analysis.

3. Methods and data

This study applies input–output and QUAIDS models. The input–output model is used to calculate total HEU (including direct and indirect HEU) and analyze the factors that influence variations in indirect HEU. Tthe QUAIDS model is used to calculate the price and income elasticity of household expenditures and describe changes in household consumption patterns. The combination of these two models enables us to investigate the current trends of household energy efficiency consumption related to structure and provide future predictions.

3.1. Input–output model

Employing an input–output model to analyze the efficiency of indirect HEU has several advantages. First, as a systematic methodology, this approach incorporates the production of multiple sectors and the final demand for multiple commodities produced by different sectors into one framework through input–output linkages. This framework enables us to quantify indirect energy use related to final demand. For example, an increase in the final demand for a car will raise energy use in automobile production (i.e., indirect energy use). We construct a precision input–output model to determine indirect energy use in the production processes, which is the most suitable model for the purposes of this study. Second, household consumption patterns shown by the structure of household consumption are provided clearly in the input–output dataset. Time-series input–output data enables us to analyze the effect of changes in household consumption patterns on energy use. Furthermore, the input–output dataset can be linked with household consumption micro survey data to connect the input–output model with other methods for further analysis such as the QUAIDS used in this study.

Total HEU can be divided into direct and indirect forms and expressed as follows:

$$E = E^d + E^i \tag{1}$$

where E^d and E^i denote direct and indirect HEU, respectively. The former is easily determined and directly quantifiable, and calculating the latter requires input–output methods. We calculate indirect HEU as follows:

$$E^i = eLc = e(I - A)^{-1}c \tag{2}$$

where e is the energy intensity vector, representing the amount of energy used per unit of output in each sector, L is the Leontief inverse matrix, A is the direct input–output coefficients matrix, and c is the household consumption vector. This study focuses on the impact of changes in consumption patterns (described by the consumption structure) on HEU. From Eq. (2), the following is obtained:

$$e^i = \frac{E^i}{C} = eLc\cdot(ic)^{-1} = eLs \tag{3}$$

where e^i is indirect energy use per unit of consumption, C is the household consumption scale that equals the sum of c, i is the row vector with all 1 s, and s is the proportion of various products in total consumption that represents the consumption structure. According to the Engel's Law, s will change with increased total expenditure or income. Eq. (3) quantifies indirect energy use per unit of household consumption (i.e., embodied energy use in each sector's products per 10,000 yuan of consumption), which we define as indirect HEU intensity below.

We further explore the effect of the household consumption structure on indirect energy use employing SDA. With the subscript 0 denoting the base period and 1 denoting the reporting period, the indirect HEU intensity can be decomposed according to the two polar decomposition methods commonly used in SDA (Dietzenbacher and Los, 1998) as follows:

$$\begin{aligned}
\Delta e^i &= e_1L_1s_1 - e_0L_0s_0 \\
&= e_1L_1s_1 - e_0L_1s_1 + e_0L_1s_1 - e_0L_0s_1 + e_0L_0s_1 - e_0L_0s_0 \\
&= e_1L_1s_1 - e_1L_1s_0 + e_1L_1s_0 - e_1L_0s_0 + e_1L_0s_0 - e_0L_0s_0 \\
&= \frac{1}{2}(e_1 - e_0)(L_1s_1 + L_0s_0) + \frac{1}{2}[e_0(L_1 - L_0)s_1 + e_1(L_1 - L_0)s_0] \\
&\quad + \frac{1}{2}(e_0L_0 + e_1L_1)(s_1 - s_0)
\end{aligned} \tag{4}$$

where the three righthand terms of Eq. (4) represent the effects of changes in a factor when other factors are held constant. The first term is the energy intensity effect, which represents changes in the energy used per unit of output in each sector. The second is the technology effect, which represents changes in each sector's demand for intermediate input from other sectors. The third is the consumption structure effect, which represents changes in the proportion of household consumption of various goods and services. The first two items are production side effects and the last one is a consumption side effect.

3.2. QUAIDS model

To analyze the impact of household consumption patterns on energy efficiency more comprehensively, we explore the trends in changes to the consumption structure determined by consumer behavior. To do so, we shift from the macro to the micro perspective to examine consumption behavior, constructing demand system models for the related issues. The earliest demand system model was the Working–Leser model (Working, 1943; Leser, 1963). Later, with improvement and development by Stone (1954), Lluch (1973), Deaton and Muellbauer (1980), and Banks et al. (1997), demand system models have evolved through LES, Extended LES, AIDS, and QUAIDS models. A major distinction between these models is that only the QUAIDS model is nonlinear while other models are linear.

Expenditure on goods in total expenditure can be either linear or nonlinear. When a nonlinear expenditure pattern is estimated with a linear demand system, the results are biased (Banks et al., 1997). The QUAIDS model allows for nonlinearity by including a quadratic expenditure term that varies with prices and considers households' socioeconomic characteristics to account for the difference in goods and services demand (Díaz and Medlock, 2021). This model enables us to assess the nonlinear impact of household expenditures on consumption shares (Okonkwo, 2020; Waleed and Mirza, 2020). Bjelle et al. (2021) examined 44 countries, finding that several Engel curves of the product groups are nonlinear, particularly for restaurants and hotels, clothing, tobacco and beverages, and the housing and food product sectors. Yuan et al. (2017) for China and Okonkwo (2020) also reported similar findings for South Africa. As it can be assumed that nonlinear Engel curves are widespread, the QUAIDS model has been widely applied to investigate trends in household consumption structure with changes in income and prices because of its advantage (e.g., Wu et al., 2012; Tan et al., 2014).

The QUAIDS model was first proposed by Banks et al. (1997) and is characterized by a quadratic Engel curve (w–ln$m$ relationship). Its indirect utility function is defined as follows:

$$lnV(p,m)=\left\{\left[\frac{lnm-lna(p)}{b(p)}\right]^{-1}+\lambda(p)\right\}^{-1}=\frac{lnm-lna}{b+\lambda(lnm-lna)} \tag{5}$$

According to Roy's identity, the above equation is derived for price p and expenditure m. The household consumption shares of good i (w_i) can be expressed as follows:

$$w_i=\frac{p_iq_i}{m}=\frac{p_i}{m}\left(-\frac{\partial V}{\partial p_i}\bigg/\frac{\partial V}{\partial m}\right)=\frac{\partial lna}{\partial p_i}+\frac{\partial lnb}{\partial p_i}ln\frac{m}{a}+\frac{\partial\lambda}{\partial p_i}\frac{1}{b}ln^2\frac{m}{a} \tag{6}$$

where $lna(p)=\alpha_0+\sum_{i=1}^{n}\alpha_i lnp_i+\frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}\gamma_{ij}lnp_i lnp_j$, $b(p)=\prod_{i=1}^{n}p_i^{\beta_i}$, and $\lambda(p)=\sum_{i=1}^{n}\lambda_i lnp_i$. Eq. (6) can be rewritten as follows:

$$w_i=\alpha_i+\sum_{j=1}^{n}\gamma_{ij}lnp_j+\beta_i ln\frac{m}{a}+\frac{\lambda_i}{b}ln^2\frac{m}{a} \tag{7}$$

The constraints are $\sum_{i=1}^{n}\alpha_i=1$, $\sum_{i=1}^{n}\beta_i=0$, $\sum_{j=1}^{n}\gamma_{ij}=0$, and $\sum_{i=1}^{n}\lambda_i=0$. The parameters to be estimated in Eq. (7) are α_i, β_i, γ_{ij}, and λ_i. Expenditure elasticity can be calculated as follows:

$$e_i=\frac{\partial w_i}{\partial m}\cdot\frac{m}{w_i}=\frac{1}{w_i}\frac{\partial w_i}{\partial lnm}=\frac{1}{w_i}\left(\beta_i+\frac{2\lambda_i}{b}ln\frac{m}{a}\right) \tag{8}$$

Price elasticity is

$$e_{ij}=-\delta_{ij}+\frac{\partial w_i}{\partial p_j}\cdot\frac{p_j}{w_i} \tag{9}$$

where δ_{ij} is the Kronecker function.

3.3. Data sources

The data used in this study primarily include input–output tables, energy use per sector, and Chinese households' income and expenditure. Official input–output tables in China are not published in consecutive years; therefore, this study uses the annual time-series input–output tables compiled by Zhang et al. (2021) and Zhang (2022), which provide a comparable and consistent time series in terms of sectoral classification (37 sectors; see Appendix Table A.1) and accounting caliber. Their method of compiling the annual time-series input–output tables has two advantages. First, it is consistent with the NBSC method, which guarantees better coherence and comparability with the input–output tables officially published by the NBSC. Second, it makes full use of the existing information and data provided by the NBSC and other government sectors; thus, the time-series input–output tables reflect the economic realities accurately. Zhang et al. (2021) compared the important information and parameters in their database with similar databases and the official data, including value-added rate, household consumption, capital formation structure, and import–export structure. The results confirmed that the trends in the database are much more consistent with the official NBSC data than similar databases and are more reliable.

Since the competitive table may overestimate indirect carbon emissions and energy use (Su and Ang, 2013), this study undertakes two more processes with the original tables to finally obtain the non-competitive series input–output tables with constant prices. In the first step, we split the import matrix. First, we calculate the proportion of imports of each product used for intermediate use, final consumption, and capital formation referencing the Customs micro database and Feenstra et al. (2005). Then, referencing the benchmark non-competitive input–output tables (NBSC, 2021) and the input–output tables that incorporate processing trade (Chen et al., 2020), we apply a mathematical programming method to predict the matrix of imported input coefficients for other years and separate the imported intermediate use into sectors. Finally, we use the prevailing proportionality assumption to determine service sector imports.

In the second step, we deflate the input–output tables using the appropriate price indices to eliminate the influence of price change, using different price indices for different sectors. The agricultural price index is used for the agriculture sector, the producer price index (PPI) for industrial producers is used for secondary industry sectors, the construction and installation price index is used for the construction sector, and the consumer price index (CPI) is used for the service sector. For the second quadrant, we use the CPI for consumption, the PPI for capital formation, the export price index for exports, and the import price index for imports. The agricultural price index and PPIs are obtained from China Statistical Yearbooks (NBSC, 1988–2023). CPIs are obtained from the Price Yearbook of China (NBSC, 1989–2002) and China Statistical Yearbook (NBSC, 1988–2023). Import and export price indices are obtained from China's External Trade Indices 1985–2004 (General Administration of Customs of China (GACC), 2008; GACC, School of Statistics Renmin University of China, 2006), the GACC Monthly Bulletin (GACC, 2005–2011), and the China Statistical Yearbook (NBSC, 1988–2023). The third quadrant is calculated as the difference between total input and intermediate input at constant prices. After price deflations, we optimize the third and second quadrants of the input–output tables so that their totals equal the constant price GDP from the China Statistical Yearbook. Finally, the first quadrant is adjusted using the RAS method to balance the non-competitive input–output tables at constant prices. Integrating all available data, we deflate input–output tables at constant 2000 prices for the 1986–2018 period.

We use the energy accounts produced by Ma et al. (2024), which offer three advantages. (1) The data span extensively from 1986 to 2021, making it the lengthiest among detailed sectoral energy datasets. (2) In comparison to the China Carbon Emission Accounts and Datasets (Shan et al., 2020), this database has undergone significant enhancements. It includes liquefied natural gas, and meticulously accounts for energy consumption in the coking and refining processes, following the recommended practices outlined by the United Nations Intergovernmental Panel on Climate Change (Eggleston et al., 2006). (3) The sector classification adheres to the pure product sector classification in China's input–output tables rather than the industry classification commonly used in other studies, which enhances its suitability for input–output analysis.

This study uses data from the Chinese Household Income Project (CHIP) to estimate the expenditure elasticity of each type of consumption using the QUAIDS model. The CHIP survey is conducted by Beijing Normal University and the NBSC. It was first conducted in 1988 and has now been administered six times (1988, 1995, 2002, 2007, 2013, and 2018). Because the CHIP classified rural household consumption differently in 1995, 2002, and 2007, and China had not formally established CPIs for commodities in 1988, we use data from 1995, 2002, 2007, 2013, and 2018. The vertical comparison can broadly reflect changes in household consumption patterns. Because of the different periods in which the survey was conducted, some changes occurred in the classification of household expenditures. Therefore, we integrate the expenditures and categorize them into the eight standard NBSC classifications that comprise food, tobacco, and liquor; clothing and footwear; housing; household facilities, articles, and services; transportation and communication; education, culture, and recreation; health care and medical services; and miscellaneous goods and services, matching the CPI of each province to the household consumption in each province.

4. Results

This section analyzes the factors affecting the efficiency of total HEU, revealing that production sectors' energy intensities are relatively more significant than household consumption patterns. We also investigate household consumption patterns trends to explore whether it will become more energy efficient in the future. The results indicate that changes in household consumption structure toward energy efficiency are unlikely, which reinforces the urgency of reducing production process energy intensity to improve HEU efficiency.

We first calculate direct and indirect HEU using the input–output model and the results indicate that indirect HEU accounts for a larger proportion, i.e., most energy is used in various sectors' production processes. We then decompose the factors affecting indirect HEU intensity using the SDA method, revealing that the production sectors' energy intensity is the most significant. Tracking energy use identifies the electricity, transport and communications, and heavy industry sectors as the sectors that use the most energy as their products are required by downstream sectors. We next explore the change in household structure employing the QUAIDS model to determine whether it will become more energy efficient in the future. The results show that the household consumption structure is moving toward more energy intensive as incomes rise. We calculate energy use in urban and rural households in next section, confirming that a shift in household consumption structure toward energy efficiency is unlikely. The trends and key sectors of HEU in many countries are similar to China, further confirming the importance of production side effects. The specific results are detailed below.

4.1. Basic description of household consumption and energy use: Trends and structures

From 1986 to 2018, China's economy maintained a high growth rate, and household consumption also grew continuously. Fig. 1 shows the increase in household consumption, GDP, and direct HEU. At constant prices, household consumption grew from 1346.9 billion yuan to 17,835.3 billion yuan, and GDP grew from 2766.2 billion yuan to 48,736.5 billion yuan, with average annual growth rates of 8.4 % and 9.4 %, respectively. Direct HEU also began rising gradually in 1999 and was 3.5 times higher in 2018 than in 1999, with an average annual growth rate of about 6.8 % for 1999–2018.

In terms of the consumption structure, various studies have concluded that food and clothing are less elastic and their share of expenditure gradually declines as income rises (Yuan et al., 2017; Tang et al., 2018). Accordingly, the Engel coefficient for urban residents in China has decreased from 52.4 % in 1986 to 28.8 % in 2023, and from 56.5 % to 32.4 % for rural residents. Based on the China Statistical Yearbook, Fig. 2 shows the proportions of Chinese residents' expenditures in eight categories from 1998 to 2018. The share of expenditure on food, tobacco, and liquor declined from 48.0 % to 28.4 %, representing the steepest decline among all forms of expenditure. The share of housing and transportation and communication expenditure increased significantly, and the shares of clothing and footwear, household facilities, articles, and services, and health care and medical services expenditure remained largely stable.

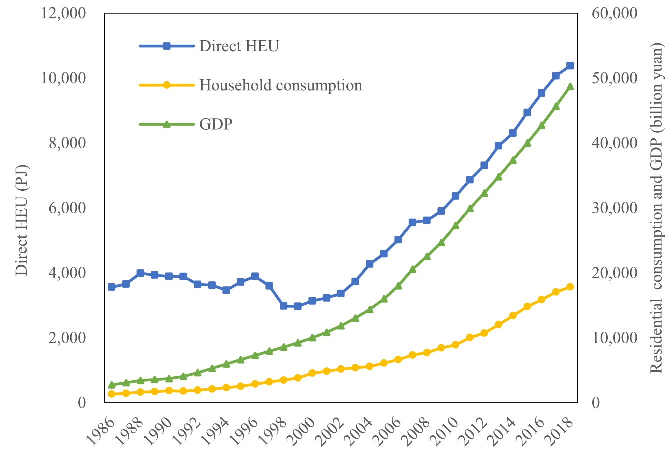

Fig. 1. Direct HEU, household consumption, and GDP at constant 2000 prices (1986–2018).

Notes: Direct HEU data is from energy accounts produced by Ma et al. (2024), and household consumption and GDP data are from the input–output tables at constant 2000 prices this study compiled.

Direct HEU has changed radically in terms of the energy products included. In the 1970s, energy availability for rural households was extremely limited. The reform and opening-up solved this problem somewhat in the 1980s. A renovation of rural grids occurred in 1998, which was accompanied by an increase in farmers' income, and rural households could afford to purchase more commercially produced energy (Wang and Feng, 2001). Urban households have more diverse energy sources that are favored as clean, efficient, and inexpensive such as natural gas and electricity. According to the China Energy Statistical Yearbook, in 1986, households consumed 158.22 million tons of coal, 1.14 million tons of liquefied petroleum gas (LPG), 700 million cubic meters (CBMs) of natural gas, and 24.8 billion kWh of electricity. By 2021, these four figures were 59.29 million tons, 27.32 million tons, 59.2 billion CBMs, and 1227.9 billion kWh, respectively.

The findings reveal that although direct HEU has changed considerably, it does not account for a significant share of total HEU. Based on Eqs. (1) and (2), this study calculates direct and indirect HEU, as shown in Fig. 3. Indirect HEU accounts for a larger proportion than direct HEU and its growth is also much larger. Total HEU increased nearly fourfold, from 11,311.9 PJ in 1986 to 43,435.3 PJ in 2018. This is attributable to the 25,307.3 PJ increase in indirect HEU, while direct HEU increased by only 6816.2 PJ. Indirect HEU in 1986 was 2.2 times greater than direct HEU, accounting for 68.5 % of total HEU; however, the gap had widened to 3.2 times by 2018, with indirect HEU accounting for 76.1 %. As for different periods, direct HEU declined at a rate of −1.4 % in 1986–1999, and indirect HEU grew slowly, with an average annual growth rate of 2.1 %. From 1999 to 2015, both entered a period of accelerated growth, with average annual growth rates of 7.1 % and 7.7 % for direct and indirect HEU, respectively. Considering that direct and indirect HEU increased in the long run, energy use efficiency deserves further attention,

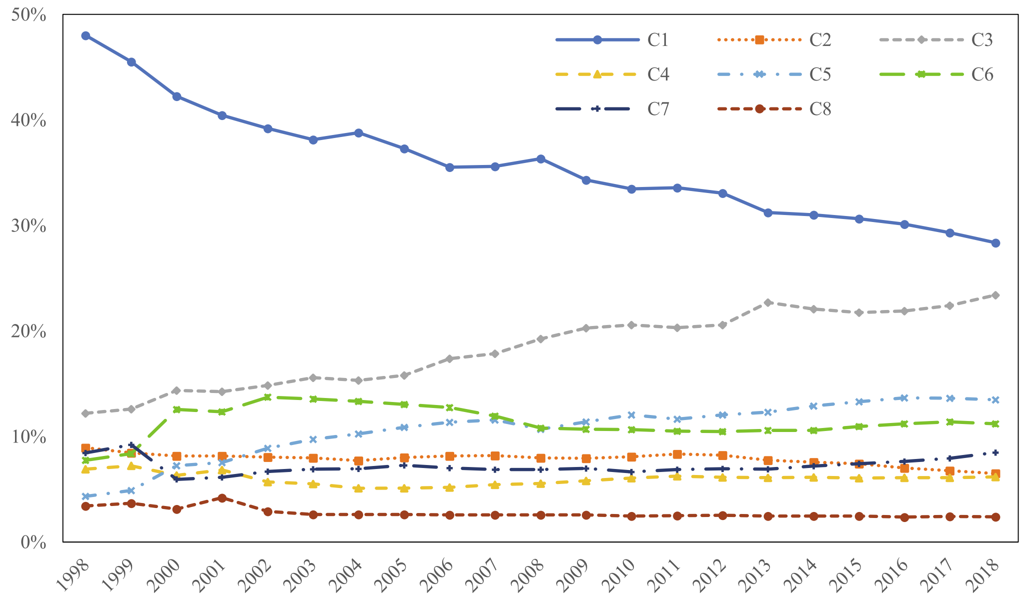

Fig. 2. Proportions of household expenditures by category (1998–2018).
Notes: Data are obtained from the China Statistical Yearbook. C1: Food, tobacco, and liquor; C2: Clothing and footwear; C3: Housing; C4: Household facilities, articles, and services; C5: Transportation and communication; C6: Education, culture, and recreation; C7: Health care and medical services; C8: Miscellaneous goods and services.

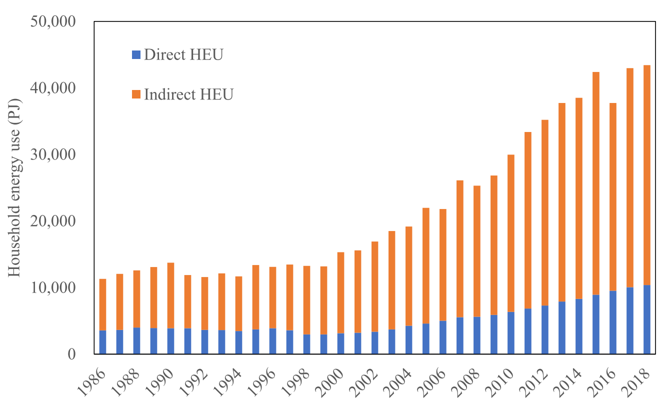

Fig. 3. Growth in direct and indirect HEU (1986–2018).
Notes: Direct HEU refers to fossil fuels and electricity used by households, and indirect HEU is fossil fuels used by sectors related to household consumption.

4.2. *Energy use efficiency related to household consumption*

4.2.1. *HEU intensity and HEU per capita*

Fig. 4 describes the energy intensity of GDP (total energy consumption per 10,000 yuan of GDP), HEU intensity, and HEU per capita. Total HEU intensity is influenced by production technology and the consumption structure. From this perspective, Chinese household consumption is moving toward becoming more energy efficient. Both direct and indirect HEU intensities continued to decline in the study period. Direct HEU intensity declined rapidly between 1986 and 1999, then remained stable. Indirect HEU intensity underwent a period of rapid decline from 57.5 GJ in 1986 to 25.5 GJ in 2001. It was more stable in the following decade and began to decline again from 24.8 GJ in 2013 to 18.5 GJ in 2018. Since households use more energy indirectly, the change in total HEU intensity was similar to that for indirect HEU, declining from 84.0 GJ to 24.4 GJ. GDP energy intensity exhibits an inverted U-shaped change between 2002 and 2008, declining steadily at other times, and is slightly higher than total HEU intensity, with similar annual average rates of decline (−3.4 % and −3.8 %, respectively). This indicates that the energy intensity of total household consumption is relatively low among the three major constituents of GDP (the other two being capital formation and net exports).

However, while total HEU intensity is decreasing, total HEU per capita has risen from 10.5 GJ to 30.9 GJ. The most important reason for this rise is increased per capita consumption, which rose from 1253 to 12,691 yuan over the study period. This result is consistent with previous findings that growth in consumption scale has far outpaced the decline in energy intensity, resulting in an overall rise in energy use (Zhang et al., 2017).

To explore the relationship between energy use and economic growth, this study combines HEU per capita with GDP per capita (Fig. 5). The findings reveal that direct HEU per capita increases very slowly as GDP per capita grows, whereas indirect HEU per capita and total HEU per capita increase rapidly. Total and indirect HEU per capita exhibit close parallel trends indicating a strong linear relationship with GDP per capita. The fitted line shows that for every 10,000-yuan increase in GDP per capita, total HEU per capita rises by about 7 GJ. Although construction of electricity grids and natural gas pipelines allows residents to directly use more energy, direct energy use grows more slowly, while indirect energy use increases rapidly indicating a huge increase in the scale of per capita consumption. Economic growth has improved infrastructure development and energy supply, and considerably increased household consumption and energy demand, which explains the strong correlation between total HEU per capita and GDP per capita.

The overall trend of HEU per capita and GDP per capita increased during the study period. An ongoing debate has ensued as to whether this trend will shift downward or whether China will follow the EKC hypothesis. At the overall economic level, Yin et al. (2015) examined the relationship between carbon emissions per capita and GDP per capita, concluding that China follows the EKC hypothesis, while Yang et al. (2015) claimed the opposite. Zhang et al. (2020) studied total carbon emissions per capita at the household consumption level (including carbon emissions from direct and indirect HEU) and per capita income, finding that the EKC curve can be demonstrated for China. This study argues that although a short-term plateau occurred in 2015–2018, no significant decline has taken place yet. Therefore, from the consumption perspective, it is difficult to determine whether the EKC holds true in

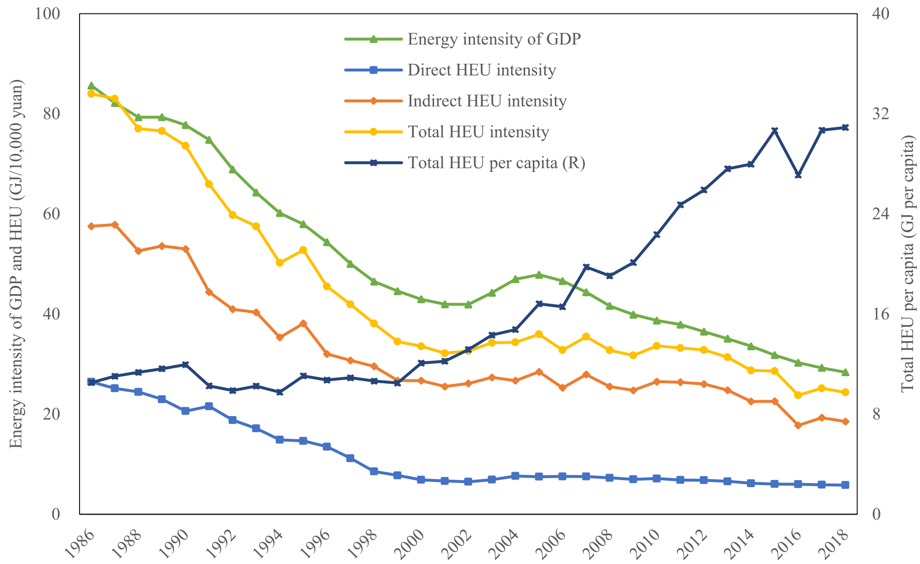

Fig. 4. Energy intensity of GDP, HEU intensity, and HEU per capita (1986–2018).
Notes: Total HEU per capita is plotted on the right axis. The GDP and population energy intensity data are obtained from the China Statistical Yearbook.

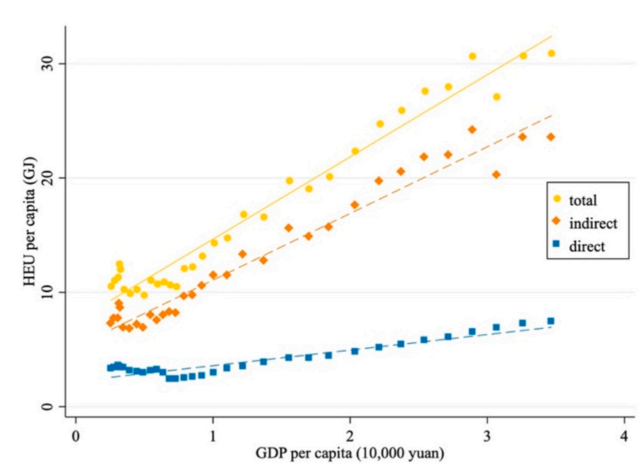

Fig. 5. HEU and GDP per capita.

China or when the inflection point will occur.

4.2.2. SDA results: factors affecting indirect HEU intensity

Total HEU increases with consumption in the long run, in aggregate and per capita terms. Considering the positive effect of household consumption, the goal is to save energy by reducing energy intensity related to household consumption rather than the consumption scale. As indirect HEU intensity is more crucial than the direct equivalent, this study uses SDA to analyze the influencing factors (Eq. (4)). Table 1 presents the results for 1986–1992, 1992–1997, 1997–2002, 2002–2007, 2007–2012, and 2012–2018.

Table 1 explains the causes of the decline in indirect and total HEU intensity in Fig. 4. First, the energy intensity effect is the most significant factor in the decrease of indirect HEU intensity in all time periods, particularly in the 1997–2012 period. Second, the technology effect is unstable but the overall effect is to increase indirect HEU intensity in the 1986–2018 period. Finally, the consumption structure makes a relatively small contribution, increasing indirect HEU intensity in most cases. Although household consumption has become more energy efficient, this change is derived from the production side rather than the consumption side. We next conduct more analysis of these two sides.

4.3. Production side analysis: key sectors of consumption-related energy use

From the production side, it is important to identify which sectors use the most energy and which are key sectors for energy efficiency. In this section, we calculate consumption-related energy use by sector over the 1986–2018 period. Appendix Fig. A.1 shows indirect energy use and Appendix Fig. A.2 shows indirect energy use intensity in the five most energy-intensive sectors: electricity and heat; petroleum refinery and processed nuclear fuel products; chemical products; metal smelting and rolling products; and transportation, storage, and postal services. It can be seen that although households consume very few energy-intensive products, these sectors' consumption-related energy use is large. Appendix Table A.2 shows in more detail the top 10 sectors in 1986, 1997, 2008, and 2018. The sectors with high indirect energy use are very

Table 1
SDA results: factors affecting indirect HEU intensity.

	Energy intensity effect		Technology effect		Consumption structure effect		Indirect HEU intensity
	Value of change	Contribution rate	Value of change	Contribution rate	Value of change	Contribution rate	Value of change
1986–1992	−19.93	120.21 %	5.85	−35.26 %	−2.50	15.05 %	−16.58
1992–1997	−2.28	22.27 %	−8.44	82.57 %	0.49	−4.84 %	−10.23
1997–2002	−9.87	215.18 %	1.68	−36.61 %	3.60	−78.57 %	−4.59
2002–2007	−11.29	−635.96 %	14.19	799.61 %	−1.13	−63.65 %	1.78
2007–2012	−3.41	179.30 %	1.39	−73.09 %	0.12	−6.22 %	−1.90
2012–2018	−5.18	69.26 %	−2.62	34.95 %	0.31	−4.21 %	−7.48
1986–2018	−57.51	147.48 %	10.71	−27.46 %	7.81	−20.02 %	−39.00

Notes: Values of change are in GJ/10,000 yuan.

stable. In conjunction with Appendix Figs. A.1 and A.2, it is worth noting the tremendous growth in the electricity sector, where more than half of overall indirect energy was used. This is followed by the transportation sector, which also had a more than twofold energy use increase.

Electricity and heat accounted for more than half of indirect energy use despite representing no more than 2 % of residents' consumption. While residents did not consume any products from the metal smelting and rolling products sector in most years, it was still one of the sectors that induced the largest indirect energy use. Therefore, energy use in these sectors was predominantly indirectly induced by other sectors' production. To more clearly demonstrate the intersectoral energy supply and demand relationship, we combine 37 sectors into 8 consumption categories (Yin et al., 2020; Zhang et al., 2022) and 10 sectors; namely, agriculture; mining; light industries; heavy industries; machinery and equipment manufacturing; electricity, heat, gas, and water; construction; business; transportation and communication; and other services (see Appendix Table A.1 for details). Energy–product flow diagrams using 1986 and 2018 as examples are presented in Fig. 6.

Taking agriculture and C1 (food, tobacco, and liquor) as an example, consumption-related energy use in 2018 was 33,013 PJ across all sectors, of which agriculture accounted for 770 PJ. However, agricultural products flowed to other sectors, and agriculture also used products

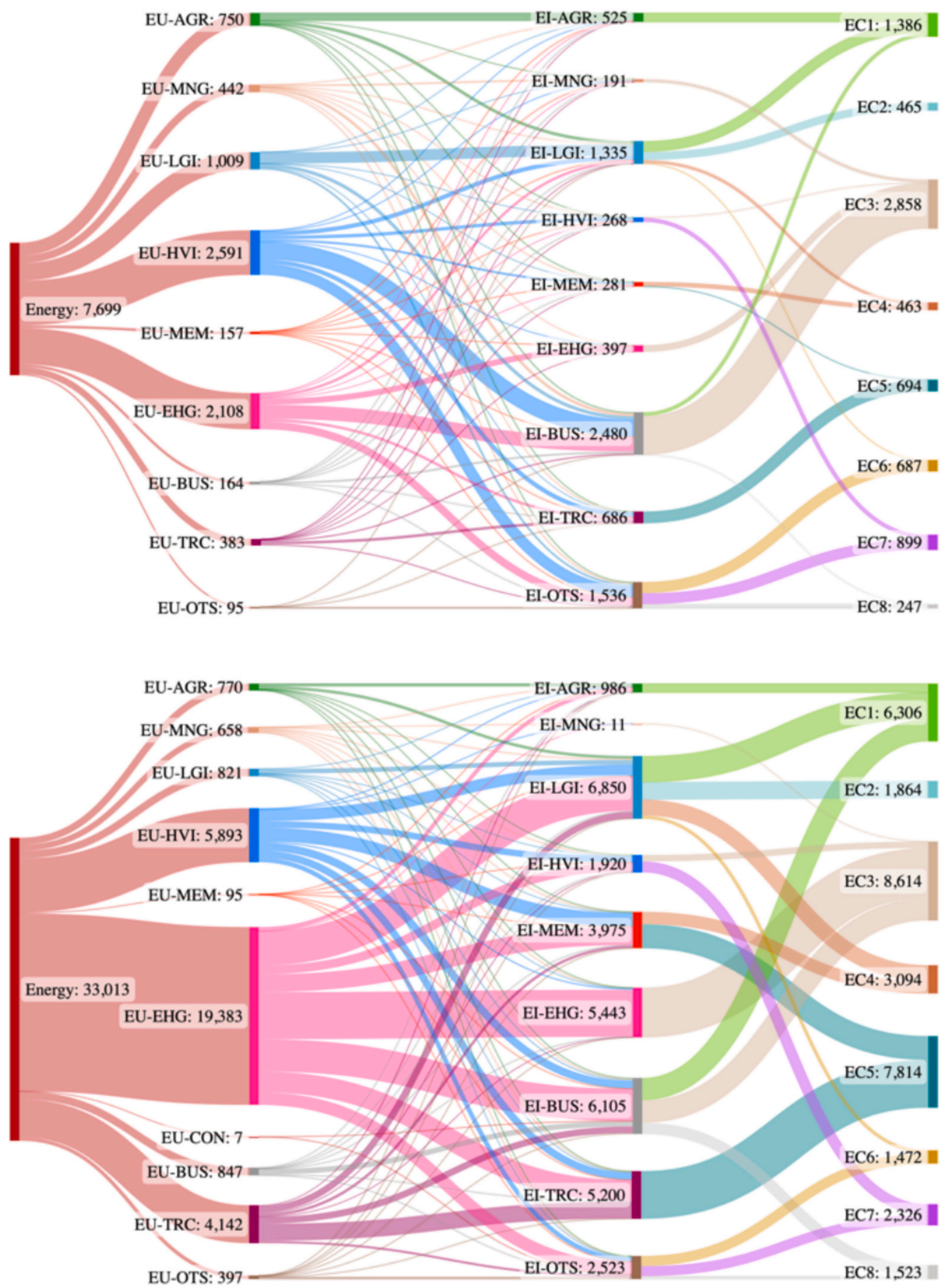

Fig. 6. Energy–product flow diagrams for household consumption (1986 and 2018).
Notes: Energy refers to overall indirect consumption-related energy use. EU = energy use, indicating the actual energy used by each sector. EI = energy input, indicating the energy embodied in the products used by each sector. EC1–EC8 are energy embodied in products consumed by categories C1–C8, in PJ. In section 4.1, we noted that the indirect HEU for 1986 and 2018 are 7749.1 PJ and 33,056.4 PJ, respectively, but the figures here differ because of rounding errors.

from other sectors that required energy. In total, 986 PJ of energy was indirectly input into agricultural production of products that were consumed by households. Meanwhile, C1 consumption includes products from other sectors. Eventually, energy use related to C1 consumption was 6306 PJ. During the study period, the average energy intensity of all sectors decreased, and electricity and metal smelting and rolling products sectors always accounted for the highest indirect energy use. This occurs for two reasons. First, they are energy-intensive sectors. Second, as upstream industries, these two sectors are increasingly used in other sectors' production processes. Residential consumption is not the most important factor here; rather, demand from other sectors indirectly stimulates their energy use. Although the electricity sector used 19,383 PJ of energy in 2018, more than 70 % went to other sectors for production. Similarly, the construction sector used 7 PJ of energy, but all of it went to other sectors as an intermediate input. In contrast, consumption shares of C6 (education, culture, and recreation) and C7 (health care and medical services) were about 15 % but corresponding sectors only accounted for less than 1 % of indirect energy use, because these sectors are downstream service sectors with low energy demand.

Figs. 2 and 6 explain the positive technology and consumption structure effects in the SDA results. From 1986 to 2018, the largest declines in the household consumption structure occurred in food and some energy-intensive industries such as coal mining products and metal products, causing a decline in indirect energy use. However, an increase in the consumption shares of some other goods and services boosted the growth of consumption in the LGI, MEM, BUS, and TRC sectors, which further drove production and energy use in the HVI and EHG sectors. The impact of these industries is larger; therefore, if their energy intensity and technology remain the same, changing consumption structures will continue to promote higher indirect energy use.

4.4. Consumption side analysis: consumption pattern elasticity measures

Focusing on the consumption side, Fig. 6 reveals that from 1986 to 2018, household consumption of C3 (housing) was consistently the most energy-intensive, but for different specific reasons, with energy primarily coming from the real estate sector in 1986 and from the electricity sector in 2018. Along with the increased consumption share, an increase occurred in energy use related to households' consumption of C5 (transportation and communication), which is only slightly lower than that of C3. Before determining whether Chinese households' consumption patterns will become more energy efficient in the future, we identify characteristics and changes in the past referencing the theory of consumer behavior.

4.4.1. Elasticity of demand for various goods and services to expenditure

The samples for the QUAIDS model include urban households in 1995 (urban 1995 hereafter), 2002, 2007, 2013, and 2018, and rural households in 2013 and 2018. The statistical description of eight consumption categories is detailed in Appendix Table A.4. Household expenditure elasticities in different years are shown in Table 2.

The measurement of expenditure elasticity first shows that the elasticities of C1 and C3 are less than 1. Consumption shares of food and housing decrease when total expenditure increases. Second, the elasticities of C6 and C5 are consistently larger than those of other categories. Residents prefer to allocate household expenditure to cars, cell phones, internet, and personal development-related consumption. Third, although C4 (household facilities, and articles) and C7 (services and medical services) are still luxury goods, their expenditure elasticities decreased close to 1. With the improvement of medical capabilities and more emphasis on health, medical services are also gradually becoming a necessity.

In summary, household expenditure elasticity varies across years and income levels, indicating changes in total household energy intensity. Low food elasticity shows that it is occupying a decreasing share of consumption and related energy use. Conversely, the high elasticity of transportation and communication raises energy use in the transportation sector, and the high elasticity of household facilities indirectly raises energy use in the electricity and metals sectors through their intertwined production relationship. This explains the phenomena in Fig. 2 and Table 1 to some extent. Based on the most recent elasticity results for 2013 and 2018, it can be predicted that if household consumption continues to increase, it will largely affect the shares of transportation and communication; household facilities; and education, culture, and recreation (rather than food and housing).

Appendix Table A.5 shows the non-compensated price elasticities in 2018 as an example. The own-price and cross-price elasticities of various goods or services vary widely, and there are no goods or services whose price has an absolute positive or negative effect on others. Residents flexibly adjust their consumption according to the price relationship between different goods or services. Thus, the main factor influencing changes in household consumption structure is income.

4.4.2. Income elasticity of consumption expenditure

The amount and structure of expenditure are related to income. A report released at the 20th National Congress of the Communist Party of China noted that China's overall development objectives for 2035 include raising per capita disposable income to new heights. To explore the extent to which income can be converted into consumption, we assume a log-quadratic relationship between expenditure and disposable income (Tan et al., 2014) as follows:

$$lnm = \mu_0 + \mu_1 lnI + \mu_2 (lnI)^2 + \delta X + f_p \tag{10}$$

Expenditure elasticity with respect to income is obtained as follows:

$$e_{m,I} = \mu_1 + 2\mu_2 lnI \tag{11}$$

where lnm and $lnI$are natural logarithms of household expenditure and disposable income per capita, respectively. X denotes control variables, and f_p is province fixed effect. The definitions and statistical description of variables are presented in Appendix Tables A.3 and A.4, respectively. Table 3 presents the coefficient estimations using CHIP 2013 and 2018 data, revealing a significant log-quadratic relationship between expenditure and income. The absolute value of coefficients obtained for rural CHIP 2013 data and rural CHIP 2018 data is slightly smaller, but the sign does not change. Thus, the results can be considered robust. Eq. (11)

Table 2
Household expenditure elasticities in different years.

	C1	C2	C3	C4	C5	C6	C7	C8
Urban 1995	0.6102	0.9224	0.5112	1.7526	1.6363	1.4535	1.2315	1.1521
Urban 2002	0.7151	0.9866	0.7986	1.4946	1.2652	1.5150	1.1807	1.2903
Urban 2007	0.7706	1.1372	1.0201	1.3541	1.0844	1.1961	1.3854	1.2497
Urban 2013	0.6510	1.1561	0.8984	1.2271	1.4363	1.5267	1.1840	1.6098
Urban 2018	0.6854	1.1026	0.8886	1.2317	1.3780	1.4300	1.1108	1.5351
Rural 2013	0.6292	1.1607	0.9757	1.2508	1.3475	1.7649	1.2290	1.3321
Rural 2018	0.6922	1.1863	0.8247	1.2247	1.2717	1.7272	1.1749	1.2474
Entire 2013	0.6900	1.2524	1.0234	1.1660	1.2283	1.5071	1.0677	1.3865
Entire 2018	0.7512	1.2235	0.9360	1.1519	1.2342	1.4074	0.9786	1.4185

Table 3
Expenditure–income relationship.

	(1) Entire 2013	(2) Rural 2013	(3) Urban 2013	(4) Entire 2018	(5) Rural 2018	(6) Urban 2018
	ln*m*	ln*m*	ln*m*	ln*m*	ln*m*	ln*m*
ln*I*	−1.4414***	−0.9279***	−1.3161***	−1.2278***	−0.7346***	−1.0074***
	(0.0523)	(0.0732)	(0.1309)	(0.0419)	(0.0573)	(0.1123)
$(\ln I)^2$	0.1100***	0.0746***	0.0983***	0.0913***	0.0551***	0.0765***
	(0.0028)	(0.0042)	(0.0066)	(0.0022)	(0.0032)	(0.0054)
years	−0.0047***	−0.0048***	−0.0032***	0.0002	0.0008***	0.0005*
	(0.0004)	(0.0005)	(0.0005)	(0.0002)	(0.0003)	(0.0003)
health	0.0436***	0.0361***	0.0483***	0.0315***	0.0446***	0.0264***
	(0.0051)	(0.0066)	(0.0072)	(0.0049)	(0.0072)	(0.0059)
minors	−0.0938***	−0.1102***	−0.0882***	−0.0720***	−0.1025***	−0.0742***
	(0.0052)	(0.0061)	(0.0092)	(0.0048)	(0.0065)	(0.0065)
elders	−0.0100*	−0.0280***	−0.0056	−0.0684***	−0.0809***	−0.0535***
	(0.0057)	(0.0072)	(0.0082)	(0.0047)	(0.0065)	(0.0061)
lndebt	−0.0041***	0.0022*				
	(0.0012)	(0.0012)				
lncar	−0.0007	0.0089***				
	(0.0013)	(0.0014)				
province fixed	Yes	Yes	Yes	Yes	Yes	Yes
Cons.	13.2362***	11.6225***	13.1063***	12.8808***	11.4754***	12.2408***
	(0.2422)	(0.3234)	(0.6531)	(0.2013)	(0.2584)	(0.5786)
N	14,532	8910	5622	18,276	8066	10,210
R^2	0.6678	0.4314	0.5832	0.5998	0.3247	0.5127

Notes: Standard errors are in parentheses. ***, **, and * represent significance at 1 %, 5 %, and 10 % levels, respectively.

shows that the higher the household income is, the greater the elasticity will be. Therefore, as disposable income rises, people will increasingly spend their income on consumption rather than savings.

This study next executes an instrumental variable test to mitigate the endogeneity problem. For rural households, the percentage of non-agriculture industry to the gross regional product of the city in which they live has been found to be a valid instrumental variable (Zhou et al., 2018). A higher percentage indicates more job opportunities other than agriculture, which will raise rural households' income. However, these data are unavailable in 2018, and since most urban households are engaged in non-agriculture industries, this instrumental variable is not valid for this cohort. Household members' average years of schooling is a more valid instrumental variable for urban households since educational attainment is positively correlated with income (Mincer, 1974). Appendix Table A.6 presents the results of the instrumental variable test, validating that the baseline results are robust.

China's economic development will lead to continuous income rises, which will increase total consumption rapidly, according to the results of expenditure–income elasticity measures. The expenditure elasticity results also indicate increased consumption shares of education, culture, and recreation and clothing will rise, and these categories do not embody much indirect energy use. However, a large increase in household consumption of transportation and communication and household facilities, articles, and services is expected to occur, which will induce high energy use, ranked as second and fourth in all the categories. Although the shares of heavy industries and electricity in household consumption are low, the energy use induced in these industries is high and will continue to rise if technological progress is not considered. More importantly, the Chinese household consumption patterns have remained quite stable and gradually changed over the past 20 years. This circumstance, which is driven by residents seeking comfortable lives, is likely to continue.

5. Additional discussion

This section makes two comparisons. The first is between urban and rural households within China and is discussed to analyze the effects of further urbanization in the future. The second is between China and multiple international regions to examine the applicability of extending the conclusions of this study.

5.1. Heterogenous analysis of urban–rural households

5.1.1. Energy use

Various differences between Chinese urban and rural areas are evident in terms of economic development and living standards. For example, in 1986, urban households used 1.3 times more raw coal than rural households, and by 2021, rural households consumed 10.8 times more raw coal, while urban households used 1.2 times more electricity and 68.5 times more natural gas. These differences are partially related to income levels. In 1986, urban residents' consumption was 218.1 billion yuan, which was less than rural residents' 311.3 billion yuan; however, in 2021, urban residents consumed 34,508.5 billion yuan, which was much higher than rural residents' 9293.1 billion yuan. Therefore, urban–rural differences relate to both direct and indirect energy use. Based on the urban–rural consumption in the input–output table and Fig. 3, we illustrate urban and rural households' energy use in Fig. 7.

From an aggregate perspective, urban HEU has been growing much faster. From 1986 to 1991, urban and rural HEU were almost equal, and rural areas sometimes used more energy. After 1991, a period of decline occurred, followed by slow growth in rural areas, while urban HEU grew at a higher rate, reaching more than three times that of rural areas. Urban HEU dominated for a long time, with indirect energy use being the most significant, accounting for 66 % of total energy use.

From a per capita perspective, Fig. 8 presents total HEU and disposable income per capita for urban and rural households. Total urban and rural HEU per capita also rose along with the increase in disposable income per capita, with the former consistently higher. Even if, over time, rural households' disposable income reaches the level of urban households' disposable income, urban households will still incur higher total energy use. This implies that urban households tend to consume a more energy-intensive mix of goods and services. While urban HEU per capita slightly decreased from 2015 to 2018, rural HEU per capita continued to increase. In the long run, total rural HEU per capita grew faster, and still has the potential to grow to the urban level.

From an intensity perspective, Fig. 9 demonstrates urban–rural differences in indirect HEU intensity. Although urban households used increasing proportions of indirect energy over rural households, urban and rural households' indirect HEU intensities are moving closer. Indirect urban HEU intensity was higher before 2013 and the two have been very similar after 2013. Indirect rural HEU intensity was even slightly

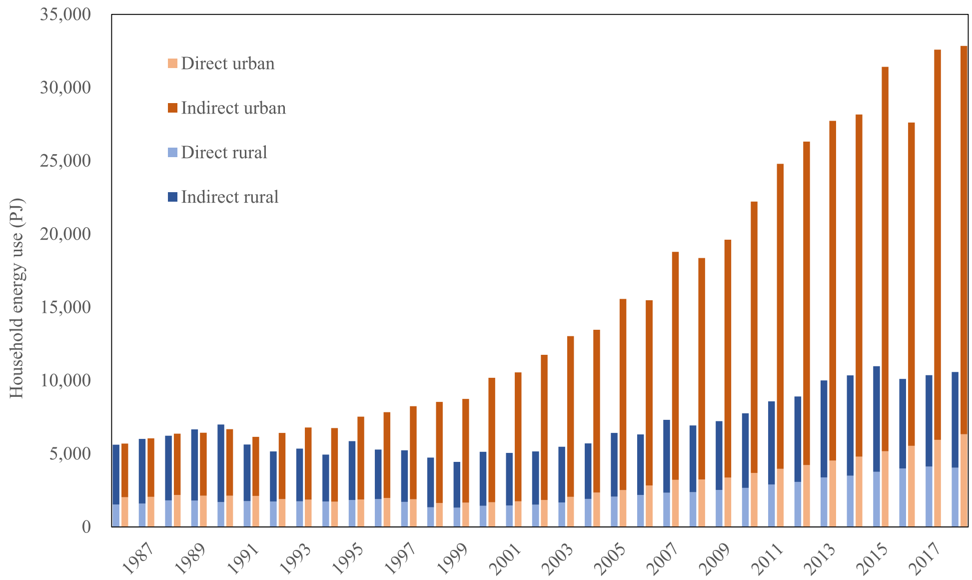

Fig. 7. Direct and indirect urban and rural HEU (1986–2018).

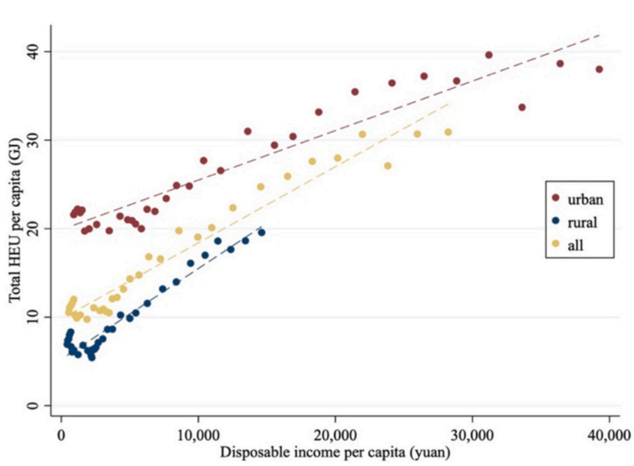

Fig. 8. Total HEU and disposable income per capita of urban and rural households (single column).

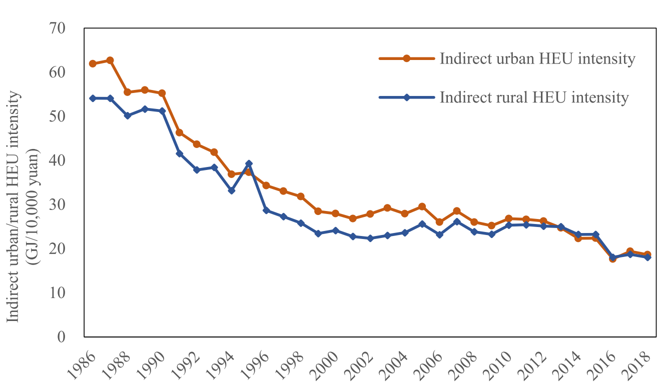

Fig. 9. Indirect urban and rural HEU intensity (1986–2018).

higher in 2013–2016.

All these phenomena are closely related to China's urbanization. First, urbanization has increased (decreased) in urban (rural) populations, and income has risen for urban and rural households, although this growth has been more rapid among urban households. Therefore, indirect urban HEU has increased more significantly (Cao et al., 2021). Second, while urbanization has turned some rural households into urban households, it has also changed rural households' lifestyles, making their consumption structure increasingly similar to that of urban households (see Appendix Fig. A.3). Indirect HEU intensities are becoming extremely close, with rural HEU per capita growing even faster than that of urban households. Chinese household consumption patterns are likely to continue to evolve toward more energy-intensive. Additional supporting evidence will be provided in the next section.

5.1.2. *Trend and effects of living standards*

This section uses data on two categories of consumer durables to demonstrate specifically how Chinese living standards have improved and examine how this improvement has directly or indirectly increased energy use. Tables 4 and 5 present the average ownership of major consumer durables per 100 households in urban and rural areas over the past 30 years, respectively. In urban areas, while growth in the ownership of washing machines, refrigerators, and color TVs has slowed, that of air conditioners has increased 480-fold in 30 years and is still on the rise. Differences are still evident in urban–rural ownership of household appliances, and air conditioner ownership is much lower in rural areas in particular.

Urban households' motorcycle ownership began to decline after 2005 as people replaced them with more comfortable cars, the number of which has grown from 0.5 to 51.4 per 100 households from 2000 to 2018. Motorcycle ownership is much higher in rural areas than in cities, where people still prefer cheaper and more convenient motorcycles. Although rural households' car ownership is only about half that of urban households, the substitution of cars for motorcycles is still apparent. The growth in the number of digital products owned was also dramatic. Before 2000, most households owned only one landline phone and no cell phones; however, by 2018, the ownership of cell phones grew from 19.5 to 254 per 100 households in urban areas. The rate of growth is even faster in rural areas, where ownership per 100 households grew from 4.3 to 266.9, with an average of more than two cell phones per household. The ownership of computers per 100 households grew from less than 10 to about 70 in urban areas, and from less than 1 to more than 20 in rural areas.

If urbanization continues in the future and rural residents' income continues to rise, the number of consumer durables such as air conditioners, cars, and computers will also continue to grow in rural areas,

Table 4
Average ownership of major consumer durables per 100 urban families.

	1990	1995	2000	2005	2010	2015	2018	2022
Washing machines	78.41	88.97	90.5	95.51	96.92	92.3	97.7	100.6
Refrigerators	42.33	66.22	80.1	90.72	96.61	94	100.9	104.4
Color TVs	59.04	89.79	116.6	134.8	137.43	122.3	121.3	120.6
Air conditioners	0.34	8.09	30.8	80.67	112.07	114.6	142.2	163.5
Cars	–	–	0.5	3.37	13.07	30	41	51.4
Motorcycles	1.94	6.29	18.8	25	22.51	22.7	19.5	17.9
Cell phones	–	–	19.5	137	188.86	223.8	243.1	254
Computers	–	–	9.7	41.52	71.16	78.5	73.1	63.4

Table 5
Average ownership of major consumer durables per 100 rural families.

	1990	1995	2000	2005	2010	2015	2018	2022
Washing machines	9.12	16.9	28.58	40.2	57.32	78.8	88.5	96.8
Refrigerators	1.22	5.15	12.31	20.1	45.19	82.6	95.9	103.9
Color TVs	4.72	16.92	48.74	84.08	111.79	116.9	116.6	116.5
Air conditioners	–	0.18	1.32	6.4	16	38.8	65.2	92.2
Cars	–	–	–	–	–	13.3	22.3	302.4
Motorcycles	–	4.91	21.94	40.7	59.02	67.5	57.4	49
Cell phones	–	–	4.32	50.24	136.54	226.1	257	266.9
Computers	–	–	0.47	2.1	10.37	25.7	26.9	25.0

Notes: Data are obtained from China Statistical Yearbooks.

and these purchases will result in electricity use. Their production processes will also increase demand in the electricity and metal smelting sector, further increasing energy use. Unlike cities in north China, which generally have central heating, residents in south China and rural areas still need alternative ways to heat their homes in winter. Air conditioners are sometimes needed to perform heating functions in winter in addition to cooling in summers. China promoted coal to electricity and coal to gas transitions in 2017. Accordingly, electricity and natural gas are used to replace coal for heating purposes. The demand for electricity and gas to supply heat for large areas in winter cannot be underestimated. Regarding transportation, cars generally consume more fuel than motorcycles. As shown above, the proportion of the petroleum refinery and processed nuclear fuel products sector in indirect energy use is already increasing and replacing motorcycles with cars will amplify this trend.

We previously demonstrated that household consumption structure has a relatively small impact on improving indirect HEU intensity. Moreover, it is unlikely that consumption patterns will change toward low-carbon and energy-efficient outcomes, and may even change in a more energy-intensive direction. While promoting green consumption is essential, we re-emphasize the overriding significance of production side effects. It is far more important to focus on energy use in the production process and improve energy efficiency in key sectors.

5.2. International comparison

Comparing the results for China with similar research for other countries reveals similarities as well as differences. Rising HEU is a general trend. HEU has risen in many countries over the past several decades, including developed countries such as the US and those in the European Union and developing countries such as Brazil (Bawaneh et al., 2024; Chudy-Laskowska and Pisula, 2023; Weiss de Abreu et al., 2021). An overall upsurge in direct energy use is evident, along with a significant increase in the energy embedded in goods and services consumed by households. Furthermore, the SDA of changes in HEU for more than 40 countries yield the same conclusion. Consumption structure has a minor role, while energy intensity and technology linkage are dominant factors (Liang et al., 2016; Ali et al., 2020; Jiang et al., 2021).

At the sectoral level, the electricity and transportation sectors are the most significant energy users. The US electricity sector uses 38 % of energy, followed by the transportation sector with 27 % (Bawaneh et al., 2024). In Japan, electricity-intensive appliances (e.g., electric water heaters, electric heaters) are some of the most significant drivers of differences in HEU and emissions (Chen et al., 2022a, 2022b). Therefore, the most important way to promote energy-efficient household consumption in developed and developing countries is to reduce the energy intensities of production sectors, with a focus on key sectors.

One difference between China and other countries is the clear division between urban and rural households in China as fewer studies have examined the urban–rural dichotomy in other countries. Chinese urban households' consumption is more similar to international trajectories, while rural households' growth potential must be emphasized in future research.

6. Conclusions

This study identifies changes in Chinese household consumption structure and household consumption-related energy use among different industries over the past three decades using input–output and QUAIDS models. The main conclusions are as follows.

First, although China's direct HEU per capita remains stable, indirect and total HEU per capita are increasing rapidly due to the rising consumption per capita. HEU intensity is decreasing, indicating that household consumption patterns are moving toward energy efficiency. This change is not primarily attributable to shifts in household consumption, but to decreased energy intensity on the production side. The share of household expenditure in transportation, storage, and postal services; electricity and heat; and metal smelting and rolling products sectors is small; however, as these sectors are energy-intensive and upstream, they account for the largest share of energy use due to production links.

Second, if disposable income continues to rise, households will be more inclined to allocate disposable income to consumption rather than savings. The QUAIDS model demonstrates that rising total expenditures can significantly increase proportions of household facilities; transportation and communication; clothing; and education, culture, and recreation, while reducing expenditure on food and housing. The consumption of clothing and education, culture, and recreation does not induce much energy use; however, consumption of housing, household facilities, and transportation and communication are noteworthy because these categories are related to the light industries, machinery and equipment manufacturing, electricity, and transportation and communication sectors, which are energy-intensive sectors or will induce energy use in upstream sectors.

Third, considering urban and rural differences, indirect urban HEU now accounts for more than 60 % of total HEU, with the scale factor playing a primary role. In addition, although urban and rural income levels still differ, the pursuit of comfort and convenience in life remains the same. With the urbanization and expected income increases in the future, both urban and rural household consumption patterns changes may increase HEU. The rise in household facilities ownership will raise consumption of electricity, transportation equipment, household facility manufacturing, and related industries, resulting in increased energy use in these industries in the future.

Based on the results, this study argues that to advance the dual carbon goal, future energy policies must specifically aim to adjust industries' technology use, establish waste recycling systems, and guide low-carbon consumption.

First, the focus of energy conservation should be on the production side, since China's secondary industries still occupy a considerable proportion of its industrial structure. In particular, electricity requires attention because it is essential for all industrial production processes. Current electricity production in China primarily depends on thermal power generation, although wind power, solar power, and other renewable energies have enormous development potential. Second, growth in household consumption is an irreversible trend, making it crucial to establish a resource recycling industrial system and develop a circular economy. Industrial production and residential life generate a considerable amount of recyclable waste, and effectively recycling and reusing this waste will decrease energy demand in the production process (Varbanov et al., 2023). Third, green consumption is an essential aspect of achieving the dual carbon goal. As living standards improve and energy pressure increases, it is crucial to control and guide residential consumption, raise residents' awareness of energy conservation, increase preferences for low-carbon commodities, and promote the shift to more energy-efficient lifestyles.

Notably, the study period ends in 2018 due to data limitations, and China has implemented some related policies in recent years, such as coal to electricity, coal to gas, and a series of industrial policies for new energy vehicles that will affect HEU. The effects of these policies are not addressed in this study and require future investigation.

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Data statement

The direct input–output coefficients matrix and household consumption matrix are compiled by authors, and they can be found in Supplementary data. Other public data are available at National Bureau of Statistics of China https://data.stats.gov.cn/english. The data from the Chinese Household Income Project are available from the website http://www.ciidbnu.org/chip/index.asp with the permission.

Declaration of generative AI and AI-assisted technologies in the writing process

The authors used no Generative AI and AI-assisted technologies in the writing process.

CRediT authorship contribution statement

Libo Wang: Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization. **Hongxia Zhang:** Writing – review & editing, Writing – original draft, Methodology, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Ming Xia:** Writing – review & editing, Methodology, Formal analysis, Data curation. **Jianhong Ma:** Formal analysis, Data curation.

Declaration of competing interest

None.

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Appendix A. Appendix

Table A.1
The bridge between consumption categories and input-output sectors.

Codes	10 Sectors	37 Sectors	Consumption category
AGR	Agriculture	(1) Agriculture, forestry, animal husbandry, and fishery	C1
		(2) Coal mining	C3
MNG	Mining	(3) Oil and gas extraction	C3
		(4) Metal mining	C3
		(5) Non-metallic minerals mining	C3
		(6) Food and tobacco	C1
		(7) Textile mill products	C2
		(8) Clothing, shoes, hats, leather, feather, and related products	C2
		(9) Sawmill products and furniture	C4
LGI	Light Industries	(10) Paper, printing and stationery, and sporting products	C6
		(15) Metal products	C4
		(20) Communication equipment, computers, and other electronic equipment	C4
		(21) Instruments and meters	C4
		(22) Other manufacturing products and scrap waste	C4
		(11) Petroleum refinery and processed nuclear fuel products	C2
HVI	Heavy Industries	(12) Chemical products	C7
		(13) Non-metallic mineral products	C2

(*continued on next page*)

Table A.1 (*continued*)

Codes	10 Sectors	37 Sectors	Consumption category
MEM	Machinery and Equipment Manufacturing	(14) Metal smelting and rolling products	C4
		(23) Metal products, machinery and equipment repair services	C2
		(16) General purpose equipment	C4
		(17) Specialized equipment	C4
		(18) Transportation equipment	C5
		(19) Electrical machinery and equipment	C4
EHG	Electricity, Heat, Gas, and Water	(24) Production and supply of electricity and heat	C2
		(25) Production and supply of gas	C2
		(26) Production and supply of water	C2
CON	Construction	(27) Construction	C2
BUS	Business	(28) Wholesale and retail traders	C1
		(30) Hotels and restaurants	C1
		(32) Financial intermediations	C8
		(33) Real estate services	C2
TRC	Transportation and Communication	(29) Transportation, storage, and postal services	C5
		(31) Information transmission, software, and information technology services	C5
OTS	Other Services	(34) Research and experimental development	C6
		(35) Culture, education, and health	C6, C7
		(36) Public administration and social organizations	C7
		(37) Other services	C8

Notes: C1: Food, tobacco, and liquor; C2: Clothing and footwear; C3: Housing; C4: Household facilities, articles, and services; C5: Transportation and communication; C6: Education, culture, and recreation; C7: Health care and medical services; C8: Miscellaneous goods and services.

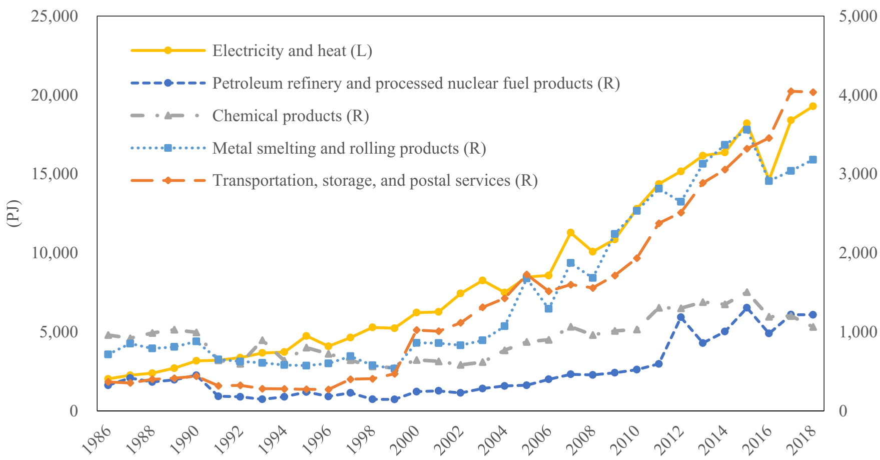

Fig. A.1. Indirect energy use in the five sectors using the most energy.

Notes: Since the energy use in electricity and heat is much more than the other sectors, it is plotted on the left axis and the other four sectors are plotted on the right axis.

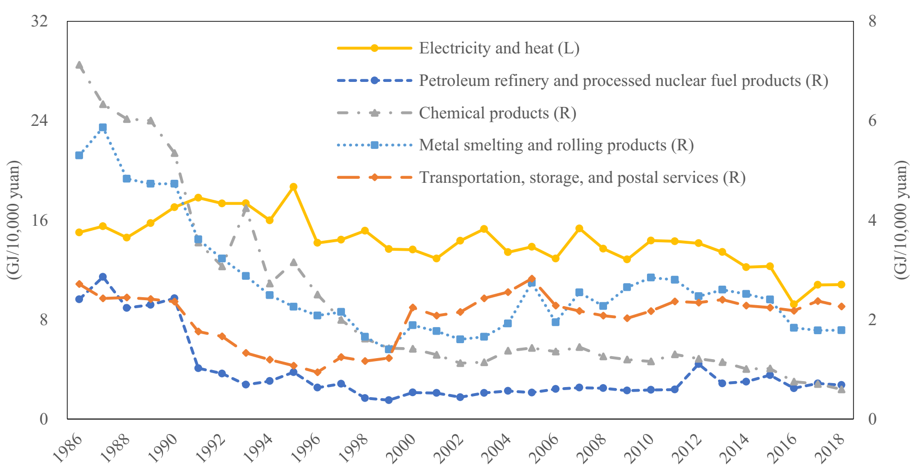

Fig. A.2. Indirect energy use intensity in the five sectors using the most energy.

Table A.2
Top 10 sectors in terms of indirect consumption-related energy use.

1986		1997	
Sectors	Shares	Sectors	Shares
Electricity and heat	26.08 %	Electricity and heat	46.93 %
Chemical products	12.39 %	Agriculture	7.35 %
Agriculture	9.70 %	Metal smelting and rolling products	7.00 %
Metal smelting and rolling products	9.21 %	Chemical products	6.49 %
Non-metallic mineral products	7.69 %	Food and tobacco	5.75 %
Food and tobacco	4.90 %	Non-metallic mineral products	4.54 %
Transportation, storage, and postal services	4.72 %	Transportation, storage, and postal services	4.05 %
Petroleum refinery and processed nuclear fuel products	4.18 %	Petroleum refinery and processed nuclear fuel products	2.30 %
Coal mining	3.88 %	Coal mining	1.69 %
Textiles	2.53 %	Information transmission, software, and information technology services	1.57 %
2008		2018	
Sectors	Shares	Sectors	Shares
Electricity and heat	53.73 %	Electricity and heat	58.33 %
Metal smelting and rolling products	8.90 %	Transportation, storage, and postal services	12.21 %
Transportation, storage, and postal services	8.15 %	Metal smelting and rolling products	9.62 %
Chemical products	4.94 %	Petroleum refinery and processed nuclear fuel products	3.68 %
Food and tobacco	4.40 %	Chemical products	3.22 %
Agriculture	3.07 %	Agriculture	2.33 %
Non-metallic mineral products	2.72 %	Food and tobacco	1.44 %
Petroleum refinery and processed nuclear fuel products	2.42 %	Non-metallic mineral products	1.32 %
Oil and gas extraction	1.39 %	Coal mining	0.94 %
Coal mining	1.20 %	Oil and gas extraction	0.81 %

Table A.3
Variables definitions.

Variables	Definitions
Dependent variable	
lnm	Logarithm of household consumption expenditure per capita
Independent variable	
lnI	Logarithm of household disposable income per capita
Control variables	
years	Average years of household members
health	Average health status of household members
minors	Number of minors in a household
elders	Number of elders in a household
lndebt	Logarithm of debt of a household
lncar	Logarithm of value of car(s) of a household
Instrumental variables	
edu	Average years of schooling of persons in a household
nonagr	Non-agriculture industry as percentage to gross regional product

Table A.4
Statistical description.

Variables	N	Mean	SD	Min	Median	Max
C1	49,841	12,574.2423	8628.0188	0	10,000.0000	104,584.0000
C2	49,841	2977.7508	3502.5515	0	1871.1000	60,342.7000
C3	49,841	7729.3718	9915.5898	0	4500.0000	145,908.6200
C4	49,841	2694.4207	3832.7613	0	1466.5000	123,254.4000
C5	49,841	3894.4303	6479.7156	0	1886.0000	145,787.9000
C6	49,841	4088.0301	6757.2858	0	1425.6000	113,369.0000
C7	49,841	2939.3433	6075.2804	0	950.2000	147,571.5100
C8	49,841	1025.0567	2200.4150	0	385.8000	62,446.5000
lnm	33,009	9.3996	0.7473	7.0353	9.3896	12.0675
lnI	32,819	9.6978	0.9259	2.7165	9.7478	13.1005
years	33,009	45.2179	18.2402	0	47	99
health	32,998	2.0095	0.7537	1	2	5
minors	33,009	0.6749	0.8053	0	0	7
elders	33,009	0.5209	0.7912	0	0	4
debt	5627	12,943.9936	42,161.3788	0	0	700,000
car	33,009	2051.2581	17,265.4591	0	0	800,000
edu	32,809	8.8160	2.9460	0	8.6667	20
nonagr	14,512	0.8904	0.0736	0.6923	0.9046	0.9996

Table A.5
Non-compensated price elasticities of all households in 2018.

Consumption Price	C1	C2	C3	C4	C5	C6	C7	C8
C1	−0.8104	1.1480	−0.5227	−0.0360	−0.0827	−1.1655	−0.2076	0.8972
C2	5.2238	−4.7966	−0.5258	0.3447	2.7395	−4.2564	1.4652	−1.4575
C3	−1.1884	−0.2069	−5.0972	0.2545	−0.8294	10.1006	−3.2534	−0.6434
C4	−0.2791	0.3665	0.5269	−4.1139	−0.8113	2.1411	−0.5167	1.5902
C5	−0.5425	2.5940	−1.7669	−0.7461	−2.2416	−0.1074	1.0056	0.6005
C6	−5.1074	−3.7652	19.0548	1.7887	−0.1535	−12.0313	2.4232	−3.8512
C7	−1.1804	1.6810	−7.9818	−0.5564	1.2282	3.1838	1.7452	0.9116
C8	11.6359	−4.0621	−3.9478	4.3077	1.7807	−12.2046	2.2399	−0.8993

Table A.6
Instrumental variables regression.

	(1) Entire 2013	(2) Rural 2013	(3) Entire 2013	(4) Urban 2013	(5) Entire 2018	(6) Urban 2018
	IV-nonagr	IV-nonagr	IV-edu	IV-edu	IV-edu	IV-edu
	ln*m*	ln*m*	ln*m*	ln*m*	ln*m*	ln*m*
ln*I*	−2.1281***	−4.7777***	−1.5531**	−6.1034***	−2.2620***	−3.0958**
	(0.6210)	(1.2429)	(0.7768)	(2.2151)	(0.5075)	(1.2289)
$(\ln I)^2$	0.1557***	0.3035***	0.1247***	0.3433***	0.1541***	0.1904***
	(0.0328)	(0.0685)	(0.0400)	(0.1087)	(0.0255)	(0.0587)
years	−0.0032***	−0.0039***	−0.0033***	−0.0033***	−0.0001	−0.0001
	(0.0004)	(0.0007)	(0.0005)	(0.0007)	(0.0002)	(0.0003)
health	0.0523***	0.0508***	0.0503***	0.0552***	0.0534***	0.0378***
	(0.0056)	(0.0085)	(0.0055)	(0.0083)	(0.0055)	(0.0069)
minors	−0.0327***	−0.0418***	−0.0344***	−0.0569***	−0.0098	−0.0016
	(0.0082)	(0.0118)	(0.0133)	(0.0203)	(0.0065)	(0.0121)
elders	−0.0046	−0.0023	−0.0035	−0.0001	−0.0423***	−0.0339***
	(0.0062)	(0.0091)	(0.0064)	(0.0096)	(0.0053)	(0.0068)
lndebt	0.0038***	0.0047***	0.0037*			
	(0.0015)	(0.0015)	(0.0021)			
lncar	0.0014	−0.0003	0.0008			
	(0.0015)	(0.0019)	(0.0015)			
province fixed	Yes	Yes	Yes	Yes	Yes	Yes
Cons.	15.3236***	27.3032***	12.7190***	36.2612***	16.6650***	21.4215***
	(2.9148)	(5.6072)	(3.7641)	(11.2648)	(2.5097)	(6.4086)
N	14,444	8845	14,445	5595	18,167	10,154
R^2	0.6337	0.2037	0.6382	0.4726	0.5450	0.4272

Notes: Standard errors are in parentheses. ***, **, and * represent significance at the 1 %, 5 %, and 10 % levels, respectively.

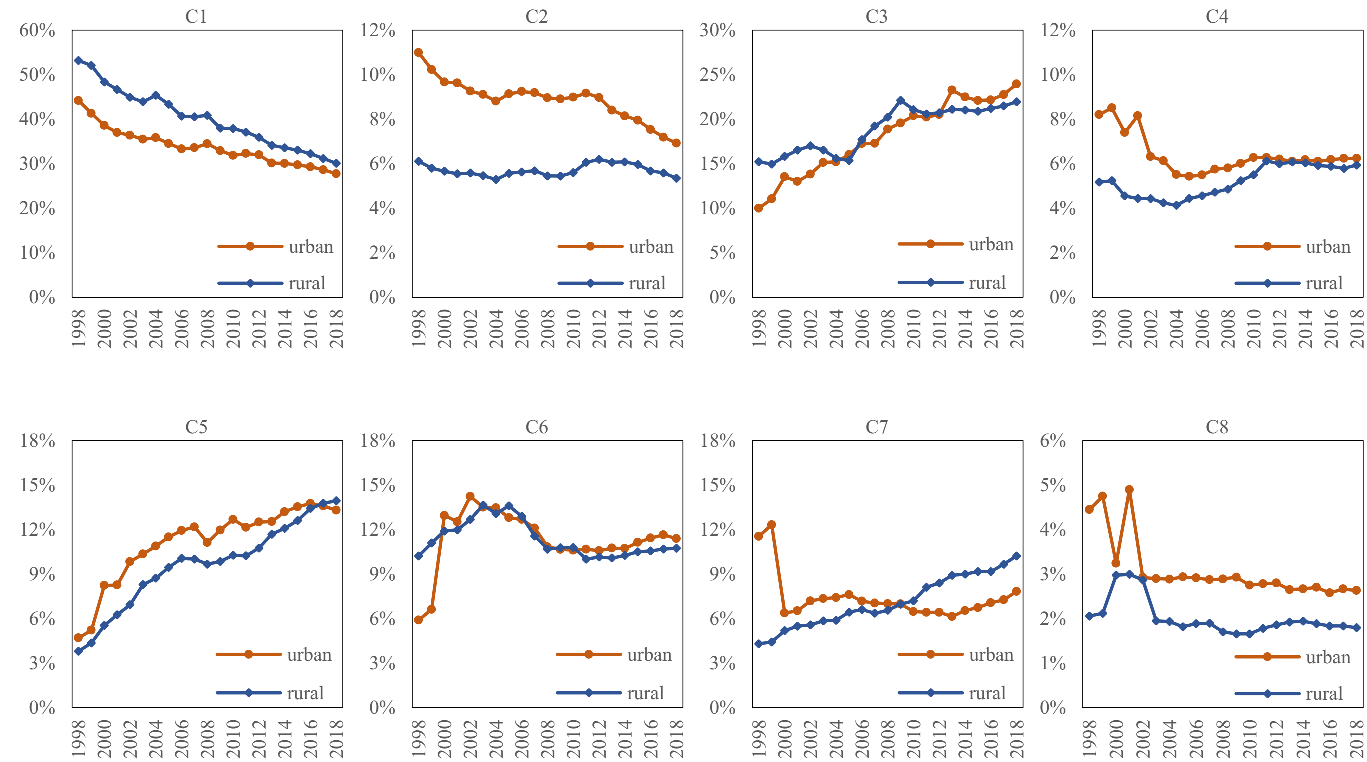

Fig. A.3. Difference in consumption shares between urban and rural households.
Notes: Data are from the China Statistical Yearbook.

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2024.108116.

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