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Impact of internal migration on household energy poverty: Empirical evidence from rural China

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HIGHLIGHTS

- This study investigated the impact of internal migration on household energy poverty.
- The instrumental variable method was employed.
- Internal migration significantly reduced the possibility of family energy poverty.
- This effect was larger for families in central and western regions and villages near counties.
- This effect mainly works by increasing family income and changing family structure.

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ABSTRACT

Reducing energy poverty has been recognized as an effective way to eliminate overall poverty and achieve sustainable development for individuals, which are two major global challenges. This study investigated how migration affected household energy poverty in rural China. Drawing on data from the China Family Panel Studies, we adopted the instrumental variable method to examine the causal relationship between internal migration and energy poverty and probe its mechanisms. We found that internal migration significantly reduced the likelihood of family energy poverty. Specifically, the probability of energy poverty in a family with labor migration was 13.1% lower than in a family without labor migration, and the probability of energy poverty decreased by 6.4% when each additional laborer in the family migrated. Furthermore, a heterogeneity analysis revealed that labor migration had a particularly significant impact on families in central and western regions and villages near counties. Migration also plays amore important role for low-income households with less-educatedmale heads. The mechanism analysis revealed that labor migration could reduce the probability of family energy poverty by increasing family income, which outweighed the negative effects of the increased share of elderly and children left behind by migration. These findings offer important policy insights for countries undergoing development and transformation.

1. Introduction

Reducing poverty and achieving sustainable development are two major global challenges. The International Energy Agency [1] indicated that there is a "poverty trap" between economic and energy poverty, whereby a family's economic poverty leads to energy poverty, which in turn exacerbates economic poverty. Families experiencing higher levels of economic poverty have more difficulty obtaining and using clean energy, and are more dependent on solid fuel. However, energy poverty significantly impacts the welfare of families by increasing overall poverty levels [2]. Item 7 of the Sustainable Development Goals calls for "ensuring the access to affordable, reliable, sustainable and modern

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energy for everyone by 2030." Thus, reducing energy poverty constitutes an important basis for achieving sustainable development [3].

The term "energy poverty" refers to a lack of energy availability, accessibility, and affordability [4]. The main characteristics of energy-poor populations is that they are unable to obtain electricity or other modern clean-energy services, and, therefore, they rely on traditional biomass energy or other solid fuels for cooking and heating [5]. According to the IEA [6], by 2030, 2.52 billion people worldwide will be facing energy poverty and relying on traditional biomass energy because they will have no access to clean energy. Although the global situation has improved over time, energy poverty levels still differ widely between countries [7–9]. While relative energy poverty is an issue for developed countries, it is more prevalent in rural, poverty-stricken, and ethnic minority areas of underdeveloped countries [8,9].

With that in mind, this study focuses on energy poverty in rural China, the world's largest developing country, with a large share of its population living in rural areas. The Chinese government has implemented a series of policies aimed at alleviating energy poverty, focusing on the use of clean energy such as electricity and natural gas [10]. By 2015, all rural areas in China were covered by the power grid [11]. By the end of 2020, China accounted for about 42.2% of the total installed capacity of renewable energy power, totaling 930 million kilowatts [12]. Utilization of clean energy has significantly increased in China, and infrastructure related to energy usage has been comprehensively upgraded [13]. Although energy poverty in China is showing a downward trend overall, its characteristics differ across regions. Energy consumption in some areas is still dominated by solid fuels, and many families continue to face energy poverty [14]. Lin and Wang [15] conducted a study using Chinese General Social Survey (CGSS) data and found that the proportion of people facing energy poverty in China in 2014 was 18.91%. Wang et al. [16] used China Family Panel Studies (CFPS) data to find that the energy poverty intensity in China decreased to 53.59% in 2018. Despite this decrease, there is still a significant gap in energy poverty levels between urban and rural areas, with rural areas facing more serious problems. The *International Energy Agency (IEA): World Energy Outlook 2022* indicated that "new targets continue to spur the massive build-out of clean energy in China, meaning that its coal and oil consumption both peak before the end of this decade." Thus, exploring energy poverty in China is theoretically and practically important.

Drawing on three waves of data (2014, 2016, and 2018) from the CFPS, this study adopts a combination of the fixed effects model and instrumental variable strategy to examine the impact of family labor migration on energy poverty in China's rural areas. The Instrumental Variable (IV)-Fixed effects model can effectively address the endogeneity issue stemming from reverse causality and omitted variables. The results using this model indicate that labor migration significantly alleviates energy poverty in rural China. Specifically, having at least one migrant in the family reduced the probability of energy poverty among families by 13.1%, and each additional laborer reduced the probability of energy poverty by 6.4%. These findings are robust to adopting alternative IVs, using alternative energy poverty measures, and changing model specifications. A heterogeneity analysis reveals that labor migration has a particularly significant impact on families in central and western regions and villages close to counties in China. Migration also plays a more important role for low-income households with less-educated male heads. The mechanism analysis reveals that labor migration can reduce the probability of family energy poverty by increasing family incomes, which outweighs the increased probability of energy poverty caused by the higher share of elderly and children left behind.

This study contributes to the literature in three important ways. First, this study enriches the growing literature on the relationship between off-farm employment and energy poverty. Several studies have indicated that non-agricultural employment activities influence energy poverty among families [17,18]. However, to the best of our knowledge, no study has attempted to explain this issue from the perspective of the spatial allocation of labor or investigate whether the spatial migration of labor also alleviates energy poverty. The spatial migration of workers is closely related to non-agricultural employment. On the one hand, many rural workers migrate to engage in non-agricultural employment to obtain higher income. On the other hand, there are significant differences between the spatial migration of labor and non-agricultural employment, as is reflected in the fact that the former will significantly change the family structure. Focusing on migration, this study further contributes to the literature by discussing the overlap between migration and non-agricultural employment and by comparing effects on energy poverty between local job changes and urban migration. Given the importance of endogeneity issues [19–22], this study uses the IV method to overcome the endogeneity problems caused by reverse causality and missing variables. We also compare the validity of the IV by comparing it to three alternative IVs.

Second, this paper contributes to the literature on the causes of energy poverty. Studies on China's energy poverty highlight the relatively high proportion of energy consumption expenditure caused by insufficient income [16,21]. Some studies have confirmed that labor migration in China has created a large left-behind population [23], which has impacted the welfare of elderly individuals and children who are left behind after migrants leave [24]. Labor migration can reduce the energy poverty of families by increasing family income. This has been suggested by the conclusions of previous studies (e.g., [25,26]); however, no study has explained how labor migration can affect energy poverty among families by changing their permanent population structures (i.e., increasing the share of the elderly and children left behind). We fill this research gap by examining how an increase in income and a change in family structure act as mechanisms through which migration affects energy poverty.

Third, this study complements research on how energy poverty differs along several dimensions. The literature has shown that the use of energy is generally affected by the educational level [27–29], age [30,31], and gender of family members, as well as the structure [32,33], social network [34], and other characteristics of families. Combining these findings, we provide additional evidence about whether these important factors, as well as others not discussed in the literature (e.g., village-level characteristics), influence how migration impacts energy poverty. The results of this study's heterogeneity and mechanism analyses can be used as a reference for alleviating energy poverty in China and other developing countries.

The remainder of this paper is structured as follows. Section 2 presents the theoretical framework concerning how labor migration affects energy poverty. Section 3 introduces the study's model and variables. Section 4 discusses the results of the benchmark regression, heterogeneity analysis, robustness test, and mechanism analysis. Finally, Section 5 presents conclusions and suggestions for further research.

2. Theoretical framework

This section provides a theoretical framework showing how migration is likely to affect household energy poverty (see Fig. 1). We highlight two main channels that play a role in opposite ways, improvements in economic status and changes in family structure, which correspond to the migrants and those left behind.

The first important channel is improvement in economic status. As shown in many studies, family income is the most important and direct factor affecting energy poverty [35,36]. When a family's income increases, the family's energy consumption will gradually change, its consumption structure will become diversified, and its understanding of the importance of clean energy as opposed to biomass energy will increase [32]. Several studies show that non-agricultural activities can improve the economic conditions of rural families and increase their income to alleviate their energy poverty. For instance, based on 2018 CFPS data, Lin and Zhao (2021) [37] studied the relationship between

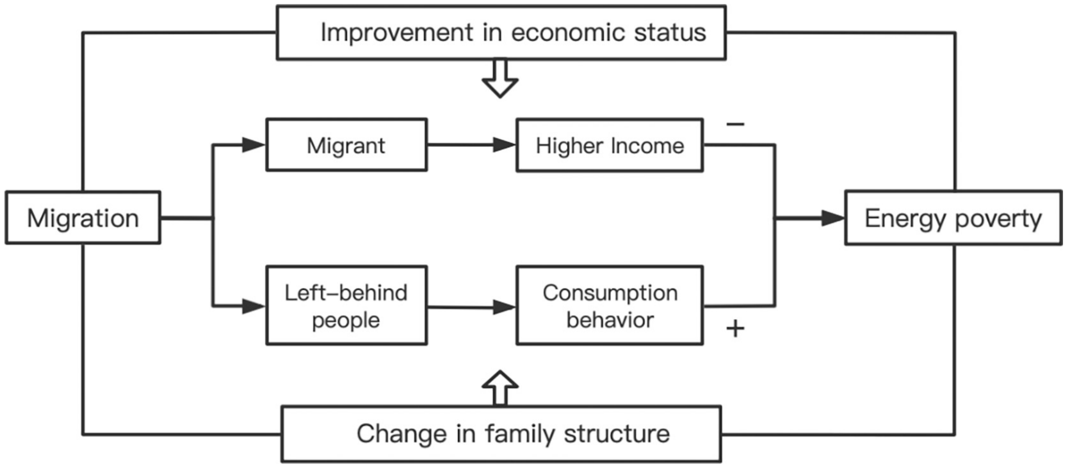

Fig. 1. Theoretical Framework of How Migration Affects Energy Poverty.

energy poverty and non-agricultural employment among rural families in China from the aspects of affordability and accessibility, finding that non-agricultural employment can alleviate the energy poverty of rural families by increasing their total income. Studying rural families in the Gansu, Henan, and Shandong Provinces in China, Ma et al. (2019) [18] found that non-agricultural employment income can promote energy transformation in rural areas of China and increase clean energy consumption and reduce families' solid fuel expenditure; moreover, the energy transformation effect, arising from non-agricultural employment income, was more significant in areas with a more developed economy. Based on CGSS data from 2015, Zou and Luo (2019) [17] found that families who engaged in non-agricultural work changed their energy consumption characteristics and obtained liquefied petroleum gas, which increased their electricity consumption.

These studies provide a theoretical basis for understanding why an increase in income is the key linkage between migration and energy poverty in China. Labor migration may play a similar role in reducing energy poverty by increasing income because labor migration is an important part of finding non-agricultural employment for rural people.

According to the *Migrant Investigation Report 2021*,[1] the total scale of migrant workers in China has recently expanded. By 2021, the total number of migrant workers in China reached 292.51 million, of which 58.7% accounted for outgoing migrant workers. In terms of industrial distribution, 99.5% of migrant workers worked in secondary and tertiary industries. Many studies have also confirmed that labor migration plays an important role in reducing poverty, increasing family income, and strengthening the consumption capacity of rural families in China [38,39]. Labor migration can significantly increase family income, especially for low- and middle-income families [40]. Alternatively, a family's income directly affects its energy consumption, as well as its choice and use of clean energy. A lower income will make it difficult for families to afford clean energy, which is more expensive [41,42]. Therefore, families with higher poverty levels are more likely to use solid fuels instead of clean energy [43]. In a study based on data from fixed observation points for Chinese families, Li et al. (2021) [28] found that rural families who changed their energy from traditional fuel to natural gas saw their fuel consumption expenditures increase by at least 80% and experienced aggravated energy poverty, which is one of the main reasons why low-income families are reluctant to choose clean energy as fuel. In addition, the price of energy is the main factor leading to energy poverty. The rise in energy prices also leads to an increase in the energy consumption expenditure of families, which aggravates their energy poverty [44–46], Migrant workers' remittances account for a large proportion of total family income, which is crucial for meeting the living needs of other family members [47–49], and has a significant impact on the expenditure of left-behind family members in rural areas of China, especially their increased expenditures on household consumer goods, thus mitigating the poverty of the left-behind population [50,51].

The second potential channel is changes in family structure, which may lead to a higher probability of energy poverty. Although both migration and off-farm employment affect energy poverty by increasing household income, few studies have discussed this overlap. Moreover, the difference between labor migration and off-farm employment has also been overlooked: Migrants often change their jobs far away from their village rather than locally. The outflow of the rural family labor force will change the family structure of the rural left-behind population. Labor migration has resulted in a large number of left-behind people, which has significantly changed the structure of families in rural China [23].

In addition, most workers are young and middle-aged adults, whereas those left behind are elderly and children. Many studies show that elderly people rarely purchase cleaner energy, and may even purchase more appliances, which may not alleviate energy poverty [52]. The adoption of traditional (rather than clean) energy is likely to worsen the health status of the elderly population [53,54]. Thus, the impact of migration on energy poverty may work through two potentially opposite channels: increases in income and changes in family structure, which are positively and negatively associated with energy poverty, respectively.

Although many studies have investigated the factors that influence energy poverty, few studies have discussed family energy poverty in China from the perspective of labor migration. Labor migration has become a very common social phenomenon in China, and the increase in income and change in family structure it causes have had a profound impact on the lifestyles of China's families. It is thus important to examine which channel is dominant.

3. Data and empirical strategy

3.1. Data and variables

The data used in this study were obtained from the CFPS, which was carried out in 2010 by the Institute of Social Science Survey of Peking University. It reflects changes in China's society, economy, population, education, and health by tracking and collecting data at three levels: the individual, family, and community. The CFPS is a nationwide social tracking survey project that collects comprehensive samples covering 25 provinces (and autonomous regions) in China. The data have been published once every two years, and five waves of data from 2010 to

[1] See http://www.stats.gov.cn/tjsj/zxfb./202204/t20220429_1830126.html.

2018 are available. The content-rich questionnaires fall into four types: community, family, adult, and children. The survey's data have been used in many studies to examine energy poverty issues in China. For example, Zhang et al. [55] conducted an empirical study based on data from the 2014–2018 CFPS that used the instrumental variable method and mediator effect model, and found that family energy poverty reduced the subjective well-being of children by affecting their academic performance. Zhang et al. [56] used 2010 CFPS data to prove that energy poverty had a negative impact on health. Using data from 2012 to 2018, Nie et al. [57] found that energy poverty significantly reduced the subjective well-being of adults in China. This study used data from 2014 to 2018, based on data availability and continuity, with approximately 12,500 family samples retained after data cleaning and merging.

3.1.1. Energy poverty

This study focused on the impact of out-migration on the energy poverty of rural families. Energy poverty was the main dependent variable of interest. As social and economic development advances, the definition of energy poverty is changing. As indicated by Andadari et al. [58], its definition includes the income used in energy consumption, energy structure quality, and difficulty in obtaining energy. From the perspective of capacity, Day et al. [59] argued that energy poverty should be defined as the inability of families to obtain sufficient, affordable, and high-quality energy to meet their survival and development needs. Khanna et al. [4] provided a definition by outlining three factors: (1) People are unable to obtain the energy they need for life due to an energy shortage, which occurs mostly in developing countries (e.g., in Africa); (2) people are unable to obtain modern forms of energy due to a lack of infrastructure investment and other conditions; and (3) families cannot afford energy due to its price or their economic condition. However, the nature of energy poverty differs between developed and developing countries. In developed countries, most studies have focused on the affordability of energy, specifically clean modern energy; in developing countries, most studies have focused on the availability and accessibility of energy, in a context in which many families do not use modern energy [16].

There are many ways to measure energy poverty [55,57]. The 10% indicator method, proposed by Boardman [60], expresses energy poverty as the percentage of energy consumption expenditure out of total net income in a specific household. If the ratio is higher than 10%, the household is considered to be living in energy poverty. The method of constructing the 10% indicator is shown in Eq. (1). Following Wang and Lin [61], energy consumption is defined as the total energy bill by adding up household electricity consumption per year (CNY), household fuel consumption (including gas, liquefied gas, coal, firewood, charcoal, etc) per year (CNY) and household heating bill per year (CNY). If the 10% indicator >10%, the household is facing energy poverty:

$$10\%\text{indicator} = \frac{\text{Equivalized fuel costs}}{\text{Equivalized disposable income}} \tag{1}$$

However, the 10% indicator has limitations, the most significant of which is that it includes high-income households, which may lead to a higher measurement of energy poverty levels among the population [62]. Considering data availability and the characteristics of Chinese families, we mainly follow the Hills [63] method and use the low-income/high-costs (LIHC) indicator to measure energy poverty. The advantage of this measurement method is that it can more objectively depict the energy poverty situation of a household, which has led it to be widely used. We construct this indicator as shown in Eqs. (2), (3), and (4):

$$\text{Equivalized net income} \leq 60\%\text{Equivalized median net income} \tag{2}$$

$$\text{Equivalized fuel costs} \geq \text{Required provincial median fuel costs} \tag{3}$$

where the equivalized net income is calculated as :

$$\text{Equivalized net income} = \frac{\text{Income} - \text{Household fuel costs}}{\text{Family size}} \tag{4}$$

If the per capita energy cost of a family is higher than the provincial median and its household surplus income is lower than 60% of the provincial median per capita household income, the household is considered to be facing energy poverty. Since energy construction in China differs significantly across provinces, we follow Cheng et al. [64] and replace the national reference with the median of per capita household energy cost and household income in each province. To avoid measurement error, we also select the 10% indicator and indicator for clean energy use as proxies of energy poverty for robustness checks. The former reflects energy poverty at the affordability level, whereas the latter reflects whether the household can access clean energy. These three variables are dummy variables equal to 1 if households face energy poverty and 0 otherwise.

3.1.2. Labor mobility

The core explanatory variable in this study was labor migration in a family. The dummy variable and continuous variable are assessed according to the presence of labor migration in the family and the number of migrant laborers. The study used the answers to the questions "In the past 12 months, has anyone in your family gone out for work (such as in the city) to earn money?" and "In the past 12 months, who in your family went out for work (such as in the city) to earn money?" in the CFPS questionnaire to construct proxy variables of labor migration and the number of migrant laborers, respectively.

3.1.3. Controls variables

The control variables selected in this study include the characteristic variables at the level of family head (age, age squared, gender, marital status, educational level, and self-reported health status of family head) and characteristic variables at the family level (family size, number of children aged below 15 years, and number of elderly aged above 60 years). For the gender of the family head, 1 was used to denote male and 0 to denote female. For the marital status of the family head, 1 denoted married and 0 denoted other statuses. For the educational level of family head, 0 denoted illiteracy, 1 denoted primary school, 2 denoted junior middle school, 3 denoted senior high school, and 4 denoted university and above. Self-reported health status ranged from 1 (very poor) to 5 (excellent). Family size was measured as the number of family members counted in the CFPS. Appendix Table A1 shows the explanatory and descriptive statistical results for all of the variables.

3.2. Descriptive statistics

As shown in Appendix Table A1, the average value of family energy poverty calculated by the LIHC indicator method was 0.187, which is lower than the 10% indicator (0.243). This is very close to the measurement in the literature. For instance, using CFPS data from 2012 to 2018, Nie et al. [57] calculated that the 10% indicator was 0.225, and the LIHC indicator method calculated it as 0.132. We adopted the LIHC indicator for the main analysis and used the 10% indicator in robustness checks for comparative purposes. In addition, 51.9% of the rural population cannot access clean energy; this was also used as a proxy for energy poverty in the robustness checks. From 2014 to 2018, the proportion of rural families with labor migration reached 50.8%, and the number of migrant laborers per family was 0.81. The average household size of Chinese families is about four, with an average of 0.81 elderly persons over the age of 60, and 0.95 children under 15 years old in each family. In terms of individual characteristics, the average age of the family head is approximately 51. The proportion of male family heads among the households was 55.6%, the proportion of married family heads was 89.3%, and their educational level was generally not high.

Table 1 compares the main variables between households with and without labor mobility. The samples were grouped according to whether

Table 1
Comparison between households with and without labor mobility.

	Labor Mobility	No Labor Mobility	Mean Difference
LIHC	0.099	0.281	−0.181***
10% Indicator	0.142	0.350	−0.208***
Clean energy	0.518	0.521	−0.003
Family size	4.862	3.702	1.160***
Gender	0.522	0.593	−0.071***
Marital status	0.918	0.868	0.050***
Educational level	1.256	1.249	−0.007
Health	2.835	2.793	0.042*
Age	48.681	53.178	−4.498***
Number of elderly	0.666	0.964	−0.298***
Number of children	1.116	0.780	0.335***

Note: ***, **, and * indicate that the coefficients are statistically significant at the 1%, 5%, and 10% levels, respectively.

there was labor migration in the family. A comparative analysis revealed that the ratio of energy poverty was significantly lower for households with migrants (9.9% and 14.2% proxied by LIHC and the 10% indicator, respectively) than for households without migrants (28.1% and 35% proxied by LIHC and the 10% indicator, respectively). This suggests that energy poverty is likely negatively associated with migration. In addition, significant differences in other control variables were observed between families with and without labor migration, indicating that the simple use of the OLS method may cause a deviation in the empirical results. Therefore, this study further adopted the IV method.

3.3. Empirical strategy

The following panel fixed effect model was used to explore the impact of labor migration on the energy poverty of families:

$$EP_{ijt} = \beta_0 + \beta_1 \text{migration}_{ijt} + \beta_2 X_{ijt} + \delta_i + \varepsilon_t + \mu_{ijt} \tag{5}$$

where EP_{ijt} represents the energy poverty of household *i* in province *j* during year *t*; migration_{ijt} represents the labor migration of household *i* in province *j* during year *t*, which is used to examine whether there is labor migration in the family and calculate the number of migrant laborers; and X_{ijt} is a series of control variables, including family-level and individual-level characteristics. The characteristic variables at the household level include the number of family members, elderly aged above 60, and children aged below 15. The characteristic variables at the individual level includes age, gender, marital status, health status, and the educational level of the family head. δ_i is the household-fixed effect, ε_t is the time-fixed effect, and μ_{ijt} is the error term.

Although the fixed-effects model above can address the issues stemming from time-invariant factors, it may still suffer from reverse causality and missing variables. The higher probability of energy poverty in a family indicates that the proportion of energy consumption expenditure in the family's total income is higher and the family's income is lower, and the family members are more likely to migrate to increase their family income. In addition, there may be unobservable factors that may affect energy poverty and labor migration simultaneously. Therefore, to solve the endogeneity problem caused by reverse causality and missing variables in the model, we employed the instrumental variable method. Following Rozelle et al. [65] and Huang and Sun [66], migration network—the proportion of labor migrants (excluding the family itself) in the village—was selected as the instrumental variable of family labor migration. This is a reasonable choice because the migration proportion of labor as an important social capital in the same region can play a role in transmitting information about off-farm employment opportunities. Thus, for any family, the proportion of labor outflow of other families in the same region is related to the household labor migration, but it is exogenous for the energy poverty of such families and is irrelevant to the unobservable items affecting their energy poverty.

The main specification of the first stage of the IV estimation is shown below:

$$\text{migration}_{ijt} = \pi IVM_{mk_i} + \varphi X_{ijt} + \delta_i + \varepsilon_t + \mu_{ijt} \tag{6}$$

where IVM_{mk_i} represents migration network in the village. After showing that this instrument meets the exclusion restrictions, we also use other instruments for comparative purposes. First, we use the average number (rather than the ratio) of migrants in the village as an instrument. Second, we also adopt the lagged proportion of labor migration in the village as an instrument. Third, we follow Bartik [67] and construct a Bartik IV, multiplying the ratio of out-migration in the village by its first difference.

4. Results and discussion

4.1. Bassline results

Table 2 shows the regression results for the impact of labor migration on the energy poverty of rural families. Columns (1) to (4) present the OLS regression results, and Columns (5) and (6) further control for time and household fixed effects. In Columns (1), (3), and (5), whether the family experienced labor migration was used as the core explanatory variable. In Columns (2), (4), and (6), the number of migrant laborers in a family was used as the core explanatory variable. The results show that, regardless of the control variables added, labor migration has a negative impact on the energy poverty of families at a 1% significance level. Without controlling for the control variables at the family head and family characteristics levels, the result in Column (1) reveals a significantly negative relationship between labor migration and energy poverty, and the regression coefficient for whether there is labor migration in a family is −0.174. After the control variables are added, the regression result in Column (3) shows that the regression coefficient for whether there is labor migration in a family is −0.146. The regression result in Column (2) shows that the number of migrant laborers in a family negatively affects their energy poverty at the 1% level, with a regression coefficient of −0.085. In Column (4), the regression coefficient of the number of migrant laborers in a family is −0.072.

After time and individual fixed effects are added, the result in Column (5) shows that the coefficient for whether there is labor migration in a family is −0.131. This indicates that, after the migration of labor in a family, their energy poverty is reduced by 13.1%. The result in Column (6) shows that the coefficient of the number of migrant laborers in a family is −0.064, indicating that every additional migrant labor in a family reduces energy poverty by 6.4%. Thus, the regression results show that labor migration significantly reduces the energy poverty of families, and a larger scale of labor migration in a family is more conducive to reducing energy poverty. Our findings align with those of studies on the relationship between off-farm employment and energy poverty. For instance, Lin and Zhao [37] constructed a comprehensive household energy poverty index to measure household energy poverty and found that household non-farm employment can significantly reduce it; the likelihood of facing energy poverty was reduced by 16.6% for households with non-farm employment. Zheng [68] used 2014 and 2016 data from the China Labor-force Dynamics Survey (CLDS) and found that the probability of clean energy use increased by 14.7% when there was non-farm employment in a household.

4.2. Endogeneity issues

The results shown above use the fixed effect method to demonstrate a potential negative correlation between labor migration and family energy poverty. However, a further causality analysis may cause issues such as reverse causality and missing variables. Therefore, the instrumental variable method was used to address the endogeneity issue. As mentioned, the proportion of labor migration in other families

Table 2
Baseline results.

	Dependent Variable: LIHC					
	(1)	(2)	(3)	(4)	(5)	(6)
Labor_dum	−0.174***		−0.146***		−0.131***	
	(−23.65)		(−18.99)		(−12.89)	
Labor_num		−0.085***		−0.072***		−0.064***
		(−26.88)		(−20.21)		(−13.45)
Controls	No	No	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	Yes	Yes
Household FE	No	No	No	No	Yes	Yes
Constant	0.277***	0.256***	0.484***	0.432***	0.444***	0.396***
	(42.69)	(45.23)	(9.91)	(8.87)	(5.85)	(5.23)
Observation	12,507	12,558	12,228	12,278	12,228	12,278
R^2	0.028	0.025	0.025	0.021	0.039	0.035

Note: This table shows the results obtained using ordinary least squares regression. For all regressions, the dependent variable is the LIHC. In Columns (1), (3), and (5), whether the family experienced labor migration is the core explanatory variable. In Columns (2), (4), and (6), the number of migrant laborers in a family is the core explanatory variable. Columns (1) and (2) show the regression results without any control variables added, Columns (3) and (4) show the results with control variables added and without controlling for time and individual variables, and Columns (5) and (6) show the results with control variables added and time and household fixed effects controlled for. Control variables include family size, gender, marital status, educational level, health level, age, age squared, number of the elderly, and number of children. ***, **, and * indicate that the coefficients are statistically significant at the 1%, 5%, and 10% levels, respectively.

(excluding the family itself) in the village was selected as the instrumental variable for labor migration. The results of the instrumental variable in the first stage are shown in Appendix Table A2. The results indicate that the labor migration network has a significantly positive impact on the labor migration of families, where in an increased number of laborers going out of the village makes it more likely that a family has labor(s) going out for work. In addition, the F value estimated at the first stage is greater than the critical value, indicating that there is no problem with the weak instrumental variables.

The results of the instrumental variable in the second stage are shown in Table 3. Columns (1) and (2) show the IV-FE results without the control variables added. Columns (3) and (4) show the IV-FE results with the control variables added. Keeping the endogeneity issue in mind, the results in Columns (3) and (4) using the IV-Fixed effects model further prove that the labor outflow of a family significantly reduces the probability of energy poverty in rural families. When there is labor migration in a family, energy poverty will be reduced by 10.7%. For each additional migrant laborer in a family, energy poverty will be reduced by 5%.

Table 3
Estimation results using IV: Second stage.

	Dependent variable: LIHC			
	(1)	(2)	(3)	(4)
labor_dum	−0.130***		−0.107***	
	(−4.49)		(−3.49)	
labor_num		−0.060***		−0.050***
		(−4.45)		(−3.48)
Controls	NO	NO	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes
Constant	0.289***	0.270***	0.441***	0.399***
	(18.74)	(22.26)	(5.75)	(5.25)
Observation	12,507	12,558	12,228	12,278
R^2	0.035	0.031	0.038	0.034
Cragg-Donald Wald F statistic	982.875	1224.479	903.503	1170.645

Note: This table shows the results obtained using the IV regression. For all regressions, the dependent variable is LIHC and the IV is the ratio of migrants in other households (excluding the household itself) to total labor in the village. Columns (1) and (3) show LIHC regression results for whether there is labor migration in the family, and Columns (2) and (4) show the LIHC regression results for the number of migrant laborers in the family. Columns (3) and (4) include control variables while Columns (1) and (2) are the baseline results without other control variables. All regressions control for year fixed and family fixed effects. Control variables include family size, gender, marital status, educational level, health, age, age squared, number of elderly, and number of children; ***, **, and * indicate that the coefficients are statistically significant at the 1%, 5%, and 10% levels, respectively.

The coefficients of IV results are slightly smaller than those of fixed effects model. Jiang [69] discusses different types of endogeneity and shows that, although IV estimates are larger than their corresponding uninstrumented estimates in most cases, an OLS estimate overestimates the population average treatment effect in the case of affirmative endogeneity. One example is related to the impact of years of education on earnings. In our case, the slightly smaller coefficient of IV results could be explained in two ways. First, there is the unobserved factor of "ability" which would affect migration and energy poverty in the same direction. Second, households with a lower probability of energy poverty are less financially constrained to migrate to cities. Both the missing variables and the reverse causality may lead to a larger OLS estimate compared to the IV estimate. Similar cases are identified in Shi [70] who examine the impact of migration on individual health status.

We use migration network (the share of migration in the village) as the IV because migration is an important form of social capital that can influence the household migration decision, as people from the same village can transmit off-farm employment information. This provides evidence on the validity of the IV. In addition, the selection of instrumental variables needs to meet the exclusion restriction, by which the migration proportion of labor in other families in the same village will affect the energy poverty of a family only by affecting the migration of laborers from a particular family. However, we are concerned that migration share could affect other dimensions of social capital that are likely associated with energy poverty [71]. The migration proportion of labor in other families in the village can be regarded as an important social network. China's society is dominated by the acquaintance relationship, and the social network is an important source of material support for families. For example, families with strong social networks may be more likely to receive gifts from relatives and friends, thus reducing their energy poverty risk.

To verify the rationality of the instrumental variable, we examined whether it would affect energy poverty through channels (e.g., by receiving more financial support from relatives) other than household labor migration. We utilized information about the receipt of gifts from relatives and friends drawn from the following question in the CFPS questionnaire: "How much cash or real economic assistance has your family received from relatives living in different places in the past 12 months, including children, parents, parents in law and other relatives?" In Table A3, the regression is conducted with gifts from relatives and friends used as the dependent variable and the labor migration network used as the independent variable. The lack of a strong correlation between the two variables would verify that the instrumental variable meets the exclusion hypothesis. The results in Table A3 are consistent with expectations: The labor migration network has no direct impact on gifts from relatives and friends. Therefore, the energy poverty of a family cannot be affected through this channel. It is worth noting that we cannot completely rule out the possible interference caused by the channels on each other, but gifts from relatives and friends are the most obvious channels with potential impacts. This finding largely proves the rationality of the instrumental variable.

4.3. Heterogenous effects

This study has discussed the overall impact of labor migration on energy poverty. Through various methods, it has proven that the labor migration of a family has a significantly negative impact on their energy poverty. Next, this study explores the heterogeneous impact of labor migration on energy poverty along several dimensions.

First, the study examines regional differences in the impacts of labor migration on families' energy poverty. The samples are divided into an eastern region group and central and western regions group according to differences in regional economic development levels. The economically developed provinces are in the eastern region in China, whereas the central and western regions are economically underdeveloped. Lin and Wang [15] indicated that there were significant differences in energy poverty between the eastern region and central and western regions in China and that energy poverty was more serious in the central and western regions. Therefore, we expect that the impact of labor migration on energy poverty is relatively small in the eastern region and relatively large in the central and western regions. The results are shown in Appendix Table A4, where Columns (1) and (2) show results for the eastern region and Columns (3) and (4) show results for the central and western regions, respectively. The results indicate that, as for both labor migration proxies, moving out of agriculture leads to a higher probability of eliminating energy poverty in the central and western regions. The results of the empirical test are consistent with Lin and Wang [15], as out-migration may play a more important role in eliminating energy poverty in regions where energy poverty rates are high.

Second, focusing on access to the local market, we examined whether and how the main effects differ depending on the distance from the urban center (the nearest county). We divided the population into people from villages close to the county[2] and those from villages far away from the county.[3] The heterogeneous effects in Appendix Table A5 show that out-migration is likely to have a larger negative impact on energy poverty for households located near the county. This suggests that living close to the county may provide more off-farm opportunities for rural people.

Third, the study conducted an analysis from the perspective of microeconomic characteristics. The samples were divided into high-income and low-income class groups according to the 0.75 quantile of family income. The regression results are shown in Appendix Table A6. Columns (1) and (2) show the regression results for low-income families, and Columns (3) and (4) show the regression results for high-income families. Column (1) indicates that the coefficient of labor migration in a family on the energy poverty of low-income families is -0.132 (significant). Column (2) shows that the coefficient of the number of migrant laborers in a family on the energy poverty of low-income families is -0.073 (significant). However, the results in Columns (3) and (4) are not significant. These results suggest that labor migration has a significant impact on low-income families but has no impact on high-income families. This result may occur because low-income families have fewer ways to increase income than high-income families have. Income growth brought about by labor migration is an important source of increased family income and reduced energy poverty for low-income families, making this impact more significant. This is also consistent with the conclusion of Xu and Chen [42], who found that energy poverty had a greater impact on low-income families.

Fourth, we examined whether individual-level characteristics help eliminate energy poverty. We focused on two dimensions, gender and educational attainment.[4] The results are shown in Appendix Tables A7 and A8. Regarding gender, out-migration in households with male heads was found to have a larger impact on energy poverty reduction. This is consistent with the fact that male migrants considerably outnumber female migrants in China. For instance, in 2021, the share of male migrants was 64.1%, whereas that of female migrants was only 35.9%.[5] Regarding the education dimension, we found that the coefficients on migration were larger for illiterate people. This maybe because low-level human capital might be associated with low household income, which would make out-migration an important factor in addressing energy poverty. Our research findings are consistent with Crentsil et al. [52], who found that male-headed households and households with higher levels of education were less likely to face energy poverty and that energy poverty faced by male-headed households was 3.42% lower than that faced by female-headed households. Moreover, households with incomplete secondary education will have a 13.7% lower likelihood of multidimensional energy poverty than households without formal education. However, migration may be self-selected based on education level. This issue is beyond the scope of this study, and we thus interpret the results with caution.

Finally, we also discuss the overlap between migration and non-agricultural employment by opening the "black box" of migration. Specifically, we compared the effects of inter-town (relatively long-distance) migration and intra-town (relatively short-distance) off-farm employment, which may give a more nuanced view of what migration accomplishes. The results are shown in Table 4, where the independent variables reflect whether there is intra-town labor migration in the family, the number of intra-town migrant laborers in the family (shown in Columns [1] and [2]), whether there is inter-town labor migration in the family, and the number of inter-town migrant laborers in the family (shown in Columns [3] and [4]). The results show that inter-town migration eliminated rural households' energy poverty while the impact of intra-town off-farm employment on energy poverty was insignificant (although negative). This suggests that relatively long-distance migration has a stronger effect than changing jobs locally. This maybe because those who migrate relatively longer distances are more likely to have higher earnings [70]. In the mechanism analysis below, we show that the income channel matters and that the change in family structure also plays a pivotal role.

An interesting result is obtained through the above heterogeneity analysis, in which labor migration has a significant impact on the energy poverty of families in the central and western regions and villages close to the county. The impact is also larger for low-income households with less-educated male heads. These findings provide a reference by which developing countries can address energy poverty in rural areas.

4.4. Robustness checks

We conduct a series of sensitivity analyses in this section to check the robustness of the estimation results.

The first concern is that our main results may change with other poverty measures. Thus, a robustness check was conducted by replacing

[2] The distance is below the median value.

[3] The distance is above the median value.

[4] We used the gender and educational attainment of the household head because migration is likely to be a household decision significantly influenced by the head.

[5] Data are taken from the Migrant Investigation Report 2021. For more information, please refer to http://www.stats.gov.cn/tjsj/zxfb./202204/t20220429_1830126.html.

Table 4
Comparison between inter-town migration and intra-town off-farm employment.

	Dependent Variable: LIHC			
	Inter-town migration	Inter-town migration	Intra-town off-farm employment	Intra-town off-farm employment
	(1)	(2)	(3)	(4)
labor_dum	−0.072*		−0.021	
	(−1.91)		(−0.86)	
labor_num		−0.038**		−0.009
		(−2.18)		(−0.84)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes
Constant	0.645	0.614	0.332	0.274
	(1.36)	(1.38)	(1.06)	(0.95)
Observation	1023	1047	1677	1686
R^2	0.055	0.056	0.024	0.023

Note: This table shows the results obtained using fixed effects models. The dependent variable is the LIHC. The independent variables reflect whether there is intra-town labor migration in the family and the number of intra-town migrant laborers in the family (Columns [1] and [2]), whether there is inter-town labor migration in the family, and the number of inter-town migrant laborers in the family (Columns [3] and [4]). All regressions control for year fixed and family fixed effects. Control variables include family size, gender, marital status, educational level, health, age, age squared, number of elderly, and number of children; ***, **, and * indicate that the coefficients are statistically significant at the 1%, 5%, and 10% levels, respectively.

the definition of energy poverty. Considering the economic development in China, this study used two alternative methods to calculate energy poverty, as mentioned. In descriptive analyses, different methods of calculating energy poverty lead to different results. Therefore, to check the robustness of the regression results, we used the 10% indicator to measure energy poverty and examined the impact of the labor force on family energy poverty. The IV-FE estimation results are presented in Appendix Table A9. The regression results for the family and the number of migrant laborers in the family are significant at the 1% level, indicating that the main results are robust. We also used an indicator reflecting whether rural households use clean energy to measure energy poverty and examined the heterogeneous effects by region. The results are shown in Appendix Table A10. They indicate that the impact of labor migration on energy poverty is significant only for the central and western regions, which is consistent with the results shown in Appendix Table A4.

Second, we are also concerned about the validity of the empirical strategy. Because the main dependent variable in this study was a binary variable, the robustness of the results was further checked by replacing the model. The LIHC is a binary variable, so the probit model was used for the robustness check. Appendix Table A11 shows the regression results based on the probit model. The results show that the coefficient of whether there is labor migration in the family on energy poverty is −0.671, which is significant at the 1% level. Column (2) shows that the coefficient of the number of migrant laborers in the family on energy poverty is −0.388, which is significant at the 1% level. The regression results of the probit model are consistent with the main study results, further indicating that they are robust. In addition, the random effects model (rather than the fixed effects model used in this study) maybe more appropriate for the analysis. To rule out this possibility, we conducted a Hausman test; the results are shown in Table A12. The value of the Hausman test was 86.54, larger than the critical value, suggesting that the fixed effects model is reasonable in our case.[6] Following Oster [72], we also ran an Oster test. The results, shown in Table A13, suggest that unobservable variables are not a significant issue for our main identification since they are unlikely to compound the main results.

In addition to the poverty measures and model specification, the validity of the IV is an issue. Although we have shown that the IV we used to be moderately reasonable, we cannot fully rule out all the channels (other than social network) through which the proportion of migration in the village can affect household energy poverty, which may violate the exclusion restriction. With this in mind, we used other IVs for comparative purposes. We first used the average number of migrants in families within the village as the instrumental variable. The IV-FE results are presented in Appendix Table A14. Columns (1) and (2) show that the main results barely changed. We also used the lagged term of the previous IV (migration ratio in the village) as a new IV to address the endogeneity of migration. The results are shown in Columns (3) and (4) of Table A14, with the coefficients on labor migration being negative and identical to those in Table A3. In addition, as stated in Section 3, we also constructed a Bartik IV to replace the previous IV and re-estimated the IV-fixed effects model. We still observed a negative impact of labor migration on energy poverty, as shown in Table A15.

4.5. *Underlying mechanisms*

In this section, we further explore the mechanisms through which migration might affect household energy poverty. Based on the theoretical framework enumerated in Section 2, income increase and changes in family structure are the two main channels that may play opposite roles in mitigating energy poverty. Therefore, we focused on these two channels. However, we present the results with caution since we cannot rule out other channels.

First, we explored whether labor migration can further reduce energy poverty within families by increasing family income, with some preliminary evidence having been shown in the heterogeneity analysis. We directly regressed the mechanism variables on the explanatory variable (migration). The results are presented in Table 5, showing the

Table 5
Channel of income.

	Income (log)	
	(1)	(2)
labor_dum	0.539***	
	(7.59)	
labor_num		0.255***
		(7.60)
Controls	Yes	Yes
Year FE	Yes	Yes
Household FE	Yes	Yes
Constant	8.875***	9.007***
	(49.54)	(50.34)
Observation	12,013	12,013
R^2	0.189	0.190

Note: This table shows the results obtained using the IV regression. The dependent variable is the logarithm of family income. The independent variable is an indicator reflecting whether the family experienced labor migration (Column 1) and the number of migrant laborers in a family (Column 2). Control variables include family size, gender, marital status, educational level, health, age, age squared, number of elderly, number of children, the regression control for year fixed effects, and family fixed effects; ***, **, and * indicate that the coefficients are statistically significant at the 1%, 5%, and 10% levels, respectively.

[6] Using the random effects model produces a result similar to that produced using the fixed effects model.

relationship between labor migration and family income. Column 1 shows that the coefficient on the migration dummy is 0.539, indicating that labor migration increases family income by 53.9%. Column 2 shows that an additional migrant increases family income by 25.5%.

We also provide additional evidence about the income channel by showing the heterogeneous effects based on migrant income (see Appendix Table A16). We found that out-migration plays a more important role in families with higher migrant income. This provides supplementary evidence about how the income channel influences migration's role in energy poverty reduction.

We now turn to the second channel. Labor migration may change a family's left-behind population structure; this has an important impact on consumption expenditures and energy use, and is directly related to energy poverty. For example, when a large number of young laborers leave, most of the people who stay behind are elderly individuals or children. This study explored whether labor migration has an impact on energy poverty by changing the left-behind population structure; the results are shown in Table 6. The change in the left-behind population structure was measured as the change in the share of elderly individuals over 60 years old and children younger than 15 years old in the family due to labor migration. We calculated the difference in the share of elderly and children before and after labor migration.

Table 6 shows that labor migration changed the population structure of families by increasing the share of left-behind children and elderly individuals, suggesting that most of the laborers going out of the village for work are young people. As shown in many studies, left-behind people (especially the elderly) are less likely to adopt clean energy, and they also spend less on energy such as electricity [68]. This suggests that migration may have two opposite effects on energy poverty, through changes in family structure and income.

We provide additional evidence on this issue. We divided the sample into two groups according to the median of the number of elderly in the family to examine whether the effects of migration on energy poverty differ depending on the share of elderly in a family. The regression results are shown in Appendix Table A17. The results in Columns (1) and (2) are insignificant, suggesting that the impact of migration on energy poverty is limited for households with a large number of elderly individuals left behind. However, the results in Columns (3) and (4) suggest that labor migration has a significant impact on energy poverty for households with a small number of elderly people. Our results are consistent with those of Zhou et al. [73], who found that the greater the number of elderly people in a household, the less the household's energy poverty was reduced.

Our results are also consistent with those of He et al. [74], who indicated that an increase in the number of elderly individuals and children left behind in rural areas was not conducive to reducing a family's energy poverty in China because the elderly tend to use traditional stoves, which are low-cost, low-efficiency, and highly polluting. In addition, some advanced appliances require high levels of knowledge, and elderly individuals and children left behind in rural areas lack the expertise to use and maintain them. Combined with the baseline results in Section 4.1, we conclude that, although changes in family structure can increase the probability of energy poverty, the energy poverty-reducing channel of higher income stemming from migration outweighs that risk, resulting in a negative overall impact of migration on energy poverty.

Another related issue is whether the effect of migration is greater in provinces that are more electrified. Based on the China Electrification Annual Development Report 2021, we classified the families into three categories: those from highly electrified, moderately electrified, and low-electrified provinces. We expected that migrants raise the incomes of left-behind families and bring new knowledge about better and more efficient appliances. This could be verified through the previous results in Appendix Table A10, which show that migration leads to a higher probability of clean energy use among the left-behind people in the central and western regions. If this is true, the impact on those living in highly electrified provinces is likely to be larger because they are more likely to adopt better appliances with their increased income. The results in Appendix Table A18 support this conclusion, showing that the magnitude of the coefficient on migration is largest for those from highly electrified provinces, followed by those from moderately electrified provinces. By contrast, the impact of migration is insignificant on those from low-electrified provinces.

5. Conclusions and recommendations

This study used data from the 2014–2018 CFPS to empirically examine the impact of labor migration on the energy poverty of rural families. The results indicate that labor migration significantly alleviates energy poverty in rural China. Specifically, the probability of energy poverty is reduced by 13.1% for families with labor outflow compared to families without, and each additional laborer going out of the village for work reduces the probability of energy poverty by 6.4%. The findings of the negative impact of migration on household energy poverty are robust to adopting an IV strategy using four alternative IVs, using alternative energy poverty measures, and changing the model specifications. A further heterogeneity analysis reveals that labor migration has a more significant impact on families in central and western regions and villages close to counties. Migration also plays a more important role for low-income households with less-educated male heads. The

Table 6
Channel of family structure.

	Share of left-behind	Share of left-behind	Share of left-behind children	Share of left-behind children	Share of left-behind elderly	Share of left-behind elderly
	(1)	(2)	(3)	(4)	(5)	(6)
labor_dum	0.284***		0.186***		0.099***	
	(28.28)		(23.99)		(15.37)	
labor_num		0.135***		0.088***		0.047***
		(37.32)		(30.03)		(16.25)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.046*	0.104***	0.023	0.060***	0.023	0.044***
	(1.81)	(5.46)	(1.17)	(3.88)	(1.44)	(2.89)
Observation	12,228	12,278	12,228	12,278	12,228	12,278
R^2	0.216	0.541	0.099	0.416	0.182	0.248

Note: This table shows the results obtained using the IV regression. Columns (1) and (2) show the impact of migration on the share of left-behind people (including the elderly and children) in household size. Columns (3) and (4) show the impact of migration on the share of left-behind children in household size. Columns (5) and (6) list the impact of migration on the share of left-behind elderly in household size. Control variables include family size, gender, marital status, educational level, health, age, age squared, number of elderly, number of children, the regression control for year fixed effects, and family fixed effects; ***, **, and * indicate that the coefficients are statistically significant at the 1%, 5%, and 10% levels, respectively.

mechanism analysis reveals that labor migration can reduce the probability of family energy poverty by increasing family income, which outweighs the negative effects of the increased share of elderly and children left behind after migration occurs.

These findings can help China and other developing countries eliminate energy poverty and improve the well-being of their populations. Based on its conclusions, this study offers the following policy suggestions. First, to foster rural revitalization in China, the government should pay more attention to energy poverty in rural areas. The No. 1 Central Document for 2023 outlined nine tasks, of which bolstering high-quality rural industries, increasing farmers' incomes, and developing a beautiful countryside are closely aligned with the main findings of this study. The government should formulate policies for initiatives such as strengthening infrastructure construction and developing local industries to help rural people transition smoothly from agriculture to off-farm sector. This will increase rural incomes and thus reduce energy poverty among rural households. Second, as China's "green development" philosophy is contributing to global sustainable growth, the widespread usage of clean energy could provide a sound model for developing countries. It may be helpful to strengthen training in the use of advanced clean energy appliances for left-behind elderly individuals and children in order to popularize and promote the use of clean energy. Third, to revitalize the countryside, the government must guarantee that there will be no large-scale return to poverty. This could be done via clean energy subsidies for economically underdeveloped areas, low-income groups, and households with relatively low human capital. The government should ensure the benefits of migrants in cities, such as by improving their social security level, raising their bargaining power in the labor market, and eliminating market discrimination. This could help to increase their willingness to pay for clean energy.

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CRediT authorship contribution statement

Xinjie Shi: Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Funding acquisition, Conceptualization. **Liu Cui:** Writing – review & editing, Writing – original draft, Software, Methodology, Data curation. **Zuhui Huang:** Supervision, Investigation, Funding acquisition. **Pei Zeng:** Project administration, Investigation. **Tongwei Qiu:** Supervision, Project administration. **Linlin Fu:** Project administration, Funding acquisition. **Qiang Jiang:** Project administration.

Declaration of Competing Interest

The authors declare no conflict of interest.

Data availability

The data are available upon request at http://www.isss.pku.edu.cn/cfps/sjzx/gksj/index.htm.

Appendix A. Appendix

Table A1
Variable definitions.

Variable	Definition	Mean	Std. Dev.	Min	Max
LIHC		0.187	0.390	0	1
10% Indicator	>10% = 1	0.243	0.429	0	1
Clean energy	Using Clean energy = 0	0.519	0.499	0	1
Labor_dum	Labor mobility = 1	0.508	0.499	0	1
Labor_num	Number of household labor mobility	0.810	0.983	0	6
Family size	Number of persons in household	4.286	1.897	1	16
Age	Age (in years)	50.839	13.023	4	94
Gender	Male = 1	0.556	0.496	0	1
Marital status	Married = 1	0.893	0.308	0	1
Educational level	Level of education	1.254	1.108	0	4
Health	Self-reported health status	2.815	1.271	1	5
Number of elderly	Number of people aged >60 in the family	0.811	0.863	0	4
Number of children	Number of children aged <15 in the family	0.949	1.058	0	8

Note: The LIHC and 10% indicator are dependent variables; Labor_dum and Labor_num are independent variables; controls include family size, gender (male = 1, female = 0), marital status (married = 1, otherwise = 0), educational level (illiterate = 0, primary school = 1, middle school = 2, high school = 3, university school or higher = 4), Health level (Excellent = 5, Good = 4, Average = 3, Poor = 2, Very Poor = 1), age, age squared, number of elderly (number of people aged over 60 in the family), and number of children (number of children under 15 in the family).

Table A2
Estimation results at the first stage of the IV regression.

	labor_dum	labor_num	labor_dum	labor_num
	(1)	(2)	(3)	(4)
proportion	1.916***	4.073***	1.836***	3.869***
	(31.35)	(34.99)	(30.06)	(34.21)
Cragg–Donald Wald F statistic	982.875	1224.479	903.503	1170.645
Year FE	Yes	Yes	Yes	Yes

(continued on next page)

Table A2 (*continued*)

	labor_dum	labor_num	labor_dum	labor_num
	(1)	(2)	(3)	(4)
Household FE	Yes	Yes	Yes	Yes
Controls	No	No	Yes	Yes
Observation	12,507	12,558	12,201	12,257

Note: This table shows the results obtained using the IV regression; for all regressions, the independent variable is IV; Columns (1) and (2) show the results of the IV regression for labor migration in the family and the number of migrant laborers, respectively, without adding the control variables; Columns (3) and (4) show the results of the IV regression for labor migration in the family and the number of migrant laborers, respectively, with the control variables added; all regressions control for year fixed effects and family fixed effects; control variables include family size, gender, marital status, educational level, age, age squared, number of elderly, and number of children; ***, **, and * indicate that the coefficients are statistically significant at the 1%, 5%, and 10% levels, respectively.

Table A3
IV exclusion restriction.

	Dependent Variable: Income from Relatives
Social network	−397.869
	(−0.41)
Controls	Yes
Year FE	Yes
Household FE	Yes
Observation	12,261
R^2	0.002

Notes: This table shows the results obtained using ordinary least squares regression, where the dependent variable is income from relatives, and the independent variable is migration network in the village (IV). The control variables include family size, gender, marital status, educational level, health, age, age squared, number of elderly, and number of children, and all regressions control for year fixed effects and family fixed effects. ***, **, and * indicate that the coefficients are statistically significant at the 1%, 5%, and 10% levels, respectively.

Table A4
Heterogeneous impacts by region.

	Dependent Variable: LIHC			
	Eastern	Eastern	Midwest	Midwest
	(1)	(2)	(3)	(4)
labor_dum	−0.099*		−0.105***	
	(−1.72)		(−2.91)	
labor_num		−0.045*		−0.050***
		(−1.66)		(−2.95)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes
Constant	0.508***	0.473***	0.425***	0.380***
	(3.57)	(3.33)	(4.63)	(4.18)
Observation	4187	4200	8041	8078
R^2	0.026	0.025	0.048	0.042

Note: This table shows the results obtained using the IV-FE regression; the dependent variable is LIHC; Columns (1) and (2) are LIHC regression results for labor migration in the family and the number of migrant laborers in the family in the eastern region, whereas Columns (3) and (4) show LIHC regression results for labor migration in the family and the number of migrant laborers in the family in the central and western regions; control variables include family size, gender, marital status, educational level, health, age, age squared, number of elderly, number of children; all regressions control for year fixed effects and family fixed effects; ***, **, and * indicate that the coefficients are statistically significant at the 1%, 5%, and 10% levels, respectively.

Table A5
Heterogeneous impacts by distance from village to county.

	Dependent Variable: LIHC			
	Close-distance	Close-distance	Long-distance	Long-distance
	(1)	(2)	(3)	(4)
labor_dum	−0.272***		−0.123***	
	(−3.12)		(−3.47)	
labor_num		−0.109***		−0.059***

(*continued on next page*)

Table A5 (*continued*)

	Dependent Variable: LIHC			
	Close-distance	Close-distance	Long-distance	Long-distance
	(1)	(2)	(3)	(4)
		(−3.17)		(−3.41)
Controls	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Constant	0.635***	0.527***	0.427***	0.382***
	(4.12)	(3.56)	(6.09)	(5.51)
Observation	1940	1961	10,286	10,315
R^2	0.122	0.122	0.108	0.100

Note: This table shows the results obtained using the IV-FE regression; since village information is available only for 2014, the data used for this table are from the 2014 survey; the dependent variable is LIHC; Columns (1) and (2) show the LIHC regression results for labor migration in the family and the number of migrant laborers in the family in the village close to the county, and Columns (3) and (4) show the LIHC for whether there is labor migration in the family and the number of migrant laborers in the family in the village far from the county; control variables include family size, gender, marital status, educational level, health, age, age squared, number of elderly, number of children; all regressions control for year fixed effects and county fixed effects; ***, **, and * indicate that the coefficients are statistically significant at the 1%, 5%, and 10% levels, respectively.

Table A6
Heterogeneous impacts by income group.

	Dependent Variable: LIHC			
	Low Income Group	Low Income Group	High Income Group	High Income Group
	(1)	(2)	(3)	(4)
labor_dum	−0.132***		−0.005	
	(−2.86)		(−0.54)	
labor_num		−0.073***		−0.002
		(−2.86)		(−0.54)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes
Constant	0.602***	0.582***	−0.008	−0.010
	(5.15)	(4.97)	(−0.37)	(−0.49)
Observation	9052	9052	3176	3226
R^2	0.047	0.044	0.003	0.000

Note: This table shows the results obtained using the IV-FE regression; the dependent variable is LIHC; Columns (1) and (2) show the LIHC regression results for labor migration in the family and the number of migrant laborers in the family in the low family income group, and Columns (3) and (4) show the LIHC for whether there is labor migration in the family and the number of migrant laborers in the family in the high family income group; control variables include family size, gender, marital status, educational level, health, age, age squared, number of elderly, and number of children; all regressions control for year fixed effects and family fixed effects; ***, **, and * indicate that the coefficients are statistically significant at the 1%, 5%, and 10% levels, respectively.

Table A7
Heterogeneous impacts by gender.

	Dependent Variable: LIHC			
	Men	Men	Women	Women
	(1)	(2)	(3)	(4)
labor_dum	−0.160***		−0.086*	
	(−3.27)		(−1.67)	
labor_num		−0.078***		−0.037
		(−3.26)		(−1.61)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes
Constant	0.727***	0.663***	0.439***	0.431***
	(5.49)	(5.05)	(2.92)	(2.88)
Observation	6817	6849	5411	5429
R^2	0.041	0.038	0.034	0.033

Note: This table shows the results obtained using the IV-FE regression; the dependent variable is LIHC; Columns (1) and (2) show the LIHC regression results for labor migration in the family and the number of migrant laborers in families with a male head, and Columns (3) and (4) show the LIHC for whether there is labor migration in the family and the number of migrant laborers in families with a female head; control variables include family size, marital status, educational level, health, age, age squared, number of elderly, and number of children; all regressions control for year fixed effects and family fixed effects; ***, **, and * indicate that the coefficients are statistically significant at the 1%, 5%, and 10% levels, respectively.

Table A8
Heterogeneous impacts by education.

	Dependent Variable: LIHC			
	Non-illiterate	Non-illiterate	Illiterate	Illiterate
	(1)	(2)	(3)	(4)
labor_dum	−0.101***		−0.151*	
	(−2.98)		(−1.82)	
labor_num		−0.050***		−0.065*
		(−3.03)		(−1.73)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes
Constant	0.386***	0.335***	0.935***	0.907***
	(4.27)	(3.74)	(3.09)	(3.04)
Observation	8369	8409	3859	3869
R^2	0.038	0.036	0.052	0.045

Note: This table shows the results obtained using the IV-FE regression; the dependent variable is LIHC; Columns (1) and (2) show the LIHC regression results for labor migration in the family and the number of migrant laborers in families where the head of the household is educated, and Columns (3) and (4) show the LIHC for whether there is labor migration in the family and the number of migrant laborers in families where the head of the household is uneducated; control variables include family size, gender, marital status, health, age, age squared, number of elderly, and number of children; all regressions control for year fixed effects and family fixed effects; ***, **, and * indicate that the coefficients are statistically significant at the 1%, 5%, and 10% levels, respectively.

Table A9
Alternative measure of energy poverty.

	Dependent Variable: 10% Indicator	
	(1)	(2)
labor_dum	−0.098***	
	(−2.89)	
labor_num		−0.046***
		(−2.88)
Controls	Yes	Yes
Year FE	Yes	Yes
Household FE	Yes	Yes
Constant	0.569***	0.544***
	(6.68)	(6.38)
Observation	11,933	11,933
R^2	0.053	0.049

Note: This table shows the results obtained using the IV-FE regression; the dependent variable is the 10% indicator; the independent variable in Column (1) reflects labor migration in the family, and the independent variable in Column (2) reflects the number of migrant labors in the family; control variables include family size, gender, marital status, educational level, health, age, age squared, number of elderly, and number of children; the regression controls for province fixed effects; ***, **, and * indicate that the coefficients are statistically significant at 1%, 5%, and 10% levels, respectively.

Table A10
Alternative measure of energy poverty.

	Dependent Variable: Whether using clean energy			
	Eastern	Eastern	Midwest	Midwest
	(1)	(2)	(3)	(4)
labor_dum	0.033		−0.060*	
	(0.60)		(−1.73)	
labor_num		0.016		−0.028*
		(0.60)		(−1.73)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes
Constant	0.062	0.071	0.558***	0.544***
	(0.46)	(0.52)	(6.33)	(6.21)
Observation	4179	4179	8015	8015
R^2	0.035	0.036	0.043	0.047

Note: This table shows the results obtained using the IV-FE regression; the dependent variable is an indicator for whether a family uses clean energy, equal to 1 if the household does not use clean energy (suggesting that the family members live in energy poverty); control variables include family size, gender, marital status, educational level, health, age, age squared, number of elderly, and number of children; all regressions control for year fixed effects and family fixed effects; ***, **, and * indicate that the coefficients are statistically significant at the 1%, 5%, and 10% levels, respectively.

Table A11
Alternative model.

	Dependent Variable: LIHC	
	(1)	(2)
labor_dum	−0.671***	
	(−5.83)	
labor_num		−0.388***
		(−6.84)
Controls	Yes	Yes
Year FE	Yes	Yes
County FE	Yes	Yes
Constant	−0.131*	−0.845***
	(−1.71)	(−5.95)
lnsig2u	−0.863***	−0.241***
	(−134.48)	(−37.69)
Observation	12,144	12,188

Note: This table shows the results obtained using the xtivprobit regression model; the dependent variable is the LIHC; the independent variable is a dummy for labor migration in the family in Column (1) and the number of migrants in Column (2); control variables include family size, gender, marital status, educational level, health, age, age squared, number of elderly, and number of children; the regression controls for year fixed effects and county fixed effects; ***, **, and * indicate that the coefficients are statistically significant at the 1%, 5%, and 10% levels, respectively.

Table A12
HausmanTest.

	LIHC	
	(1)	(2)
	FE	RE
labor_dum	−0.131***	−0.146***
	(−13.47)	(−19.42)
Controls	Yes	Yes
Constant	0.444***	0.484***
	(5.81)	(10.24)
Observation	12,228	12,228
R^2	−0.462	0.025
Hausman	86.54	
p-value	(0.00)	

Note: This table shows the result of the Hausman test; Column (1) shows the result of the fixed-effects model and column (2) shows the result of the random effects model.

Table A13
Oster test

Parameter Assumptions	
$1.3R^2$; $\delta = 1$	Estimated β from Eq. (2) = 0
(1)"True" β Bound	(2) δ
[−0.14865, −0.11293]	2.027

Notes: This table shows the main results of the Oster test.

Table A14
Alternative measure of IV.

	Dependent Variable: LIHC			
	IV: Average number of migrants in the village		IV: lagged proportion of migrants in the village	
	(1)	(2)	(3)	(4)
labor_dum	−0.171***		−0.259**	
	(−2.89)		(−2.47)	
labor_num		−0.082***		−0.129**
		(−2.88)		(−2.48)

(continued on next page)

Table A14 (*continued*)

	Dependent Variable: LIHC			
	IV: Average number of migrants in the village		IV: lagged proportion of migrants in the village	
	(1)	(2)	(3)	(4)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes
Constant	0.453***	0.404***	0.379***	0.329***
	(5.81)	(5.23)	(3.44)	(2.98)
Observation	12,017	12,060	8147	8147
R^2	0.038	0.034	0.068	0.059

Note: This table shows the results obtained using the IV-FE regression; the dependent variable is LIHC; the independent variables are a dummy for labor migration in the family in columns (1) and (3) and the number of migrant laborers in the family in columns (2) and (4); Columns (1) and (2) adopt the average number of migrants in other families in the village as an IV, and Columns (3) and (4) adopt the lagged proportion of migrants in the village as an IV; control variables include family size, gender, marital status, educational level age, age squared, number of elderly, and number of children; we also control for year fixed effects and family fixed effects; ***, **, and * indicate that the coefficients are statistically significant at the 1%, 5%, and 10% levels, respectively.

Table A15
Estimation results using Bartik IV.

	Dependent variable: LIHC			
	(1)	(2)	(3)	(4)
labor_dum	−0.210*		−0.208*	
	(−1.84)		(−1.75)	
labor_num		−0.088*		−0.087
		(−1.65)		(−1.56)
Controls	NO	NO	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes
Constant	0.330***	0.293***	0.455***	0.392***
	(5.73)	(6.73)	(5.81)	(5.10)
Observation	12,506	12,557	12,227	12,277
R^2	0.029	0.031	0.031	0.033

Note: This table shows the results obtained using the IV-FE regressions; for all regressions, the dependent variable is LIHC, and the independent variables are labor migration instrumented by Bartik IV; Columns (1) and (2) show LIHC regression results for whether there is labor migration in the family and the number of migrant laborers in the family without adding the control variables, respectively; Columns (3) and (4) show the LIHC regression results for whether there is labor migration in the family and the number of migrant laborers in the family with control variables added, respectively; all regressions control for year fixed and family fixed effects; control variables include family size, gender, marital status, educational level, health, age, age squared, number of elderly, and number of children; ***, **, and * indicate that the coefficients are statistically significant at the 1%, 5%, and 10% levels, respectively.

Table A16
Heterogeneous impacts by migrant income.

	Dependent Variable: LIHC			
	Low migrant Income	Low migrant Income	High migrant Income	High migrant Income
	(1)	(2)	(3)	(4)
labor_dum	−0.182***		0.164	
	(−4.57)		(0.57)	
labor_num		−0.081***		0.027
		(−4.53)		(0.46)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes
Constant	0.427***	0.371***	0.064	0.218
	(4.64)	(4.05)	(0.16)	(0.86)
Observation	9154	9195	3074	3083
R^2	0.053	0.041	0.002	0.002

Note: This table shows the results obtained using the IV-FE regression; the dependent variable is LIHC; Columns (1) and (2) show the LIHC regression results for labor migration in the family and the number of migrant laborers in the family in the low migrant income group, and Columns (3) and (4) show the LIHC for whether there is labor migration in the family and the number of migrant laborers in the family in the high migrant income group; control variables include family size, gender, marital status, educational level, health, age, age squared, number of elderly, and number of children; all regressions control for year fixed effects and family fixed effects; ***, **, and * indicate that the coefficients are statistically significant at the 1%, 5%, and 10% levels, respectively.

Table A17
Heterogeneous impacts by number of elderly in the family.

	Dependent Variable: LIHC			
	large number of elderly	large number of elderly	small number of elderly	small number of elderly
	(1)	(2)	(3)	(4)
labor_dum	−0.091		−0.136***	
	(−1.53)		(−3.67)	
labor_num		−0.042		−0.066***
		(−1.50)		(−3.67)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes
Constant	0.595***	0.561***	0.378**	0.325**
	(4.51)	(4.25)	(2.46)	(2.14)
Observation	6090	6104	6138	6174
R^2	0.033	0.029	0.043	0.039

Note: This table shows the results obtained using the IV-FE regression; the dependent variable is LIHC; Columns (1) and (2) show the LIHC regression results for labor migration in the family and the number of migrant laborers in the family with a large number of elderly, and Columns (3) and (4) show the LIHC for whether there is labor migration in the family with a small number of elderly people; control variables include family size, gender, marital status, educational level, health, age, age squared, number of elderly, and number of children; all regressions control for year fixed effects and family fixed effects; ***, **, and * indicate that the coefficients are statistically significant at the 1%, 5%, and 10% levels, respectively.

Table A18
Heterogeneous impacts by electrification.

	Dependent Variable: LIHC					
	Highly electrified	Highly electrified	Moderately electrified	Moderately electrified	Low electrified	Low electrified
	(1)	(2)	(3)	(4)	(5)	(6)
labor_dum	−0.220***		−0.110***		−0.006	
	(−3.17)		(−2.87)		(−0.09)	
labor_num		−0.100***		−0.051***		−0.004
		(−3.09)		(−2.87)		(−0.10)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.541***	0.439**	0.488***	0.434***	0.222	0.224
	(3.05)	(2.47)	(5.04)	(4.51)	(1.22)	(1.24)
Observation	2115	2124	6914	6948	3199	3206
R^2	0.022	0.026	0.052	0.046	0.011	0.011

Note: This table shows the results obtained using the IV-FE regression; the dependent variable is LIHC; Columns (1) and (2) show LIHC regression results for labor migration in the family and the number of migrant laborers in the family in highly electrified provinces; Columns (3) and (4) show the results for moderately electrified provinces, and Columns (5) and (6) show the results for low-electrified provinces; control variables include family size, gender, marital status, educational level, health, age, age squared, number of elderly, and number of children; all regressions control for year fixed effects and family fixed effects; ***, **, and * indicate that the coefficients are statistically significant at the 1%, 5%, and 10% levels, respectively.

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