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Financial inclusion, natural disasters and energy poverty: Evidence from China

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ABSTRACT

Using China Family Panel Studies data, this paper examines how financial inclusion affects energy poverty in China. We find substantial evidence that financial inclusion has a significant impact on reducing all three measures of energy poverty. In particular, the positive role of financial inclusion on energy poverty reduction can be also found in the presence of natural disasters. Results are further substantiated by a set of robustness checks as well as an instrumental variable strategy and propensity score matching strategy to address for the potential self-selection bias. In the end, heterogeneous effects and the underlying mechanism are explored.

1. Introduction

China has long been facing severe energy poverty problem that needs to be seriously treated and urgently solved.[1] According to the China Family Panel Studies (CFPS) data, in 2014, there were 33.2% of Chinese residents utilizing bio-fuel to cook, with a high of 49.83% for rural areas and a low of 13.44% for the urban. This number has seen a decline but still maintained at 23.9% in 2018. From the perspective of expenditure, in 2018, 12.4% of Chinese household income was used on energy; and the proportion of households who spend >10% of their income on energy was as high as 36%. Meanwhile, there has been existing substantial urban-rural disparity in energy poverty, with more serious energy poverty issue in rural than in urban areas.[2]

Energy poverty could result in a variety of negative influences on individual and household welfare, including education (Apergis et al., 2022; Takada et al., 2007), physical and mental health (Pan et al., 2021; Thomson et al., 2017), medical expenditure (Bukari et al., 2021) and subjective well-being (Nie et al., 2021; Zhang et al., 2021). Apart from those effects at the individual level, energy poverty also has a negative impact on economic development in both the short-term and the long-term (Amin et al., 2020; Narayan and Smyth, 2008; Le and Nguyen, 2019; Iyke et al., 2021; and Lee et al., 2022).

In view of the adverse significance of energy poverty, identifying the factors that contribute to it is of great importance. One potential reason for energy poverty is liquidity constraints, given the core of energy poverty is the energy consumption burden due to the expensive nature of modern and clean fuels.

The recently rapid development of financial inclusion might take a role in addressing the energy poverty issue through its effect of reducing households' liquidity constraints (Chidozie, 2022; Lahcen and Gomis-Porqueras, 2021). Financial inclusion refers to individuals' accessibility and effective usage of a variety of financial services including making deposits, obtaining loans, owning insurance, and utilizing digital payments (Sarma, 2008; Park and Mercado, 2018). In fact, there has been evidence suggesting the beneficial impact of financial inclusion on poverty reduction (Park and Mercado, 2018; Honohan, 2008; Anand and Chhikara, 2013; Jeanneney and Kpodar, 2011), although its effect on energy poverty at the household level has rarely been studied.

The goal of this paper is to investigate whether and how financial inclusion affects households' energy poverty status. We find a significant effect of financial inclusion on reducing all three measures of energy poverty. Specifically, our baseline model shows that a standard

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[1] The International Energy Agency's (IEA) defined energy poverty as a lack of access to modern energy services, such energy services as household access to electricity and commercial energy (IEA, 2002), and as household access to electricity and clean cooking facilities (IEA, 2010).

[2] Table 4 provides the comparison on energy poverty between urban and rural areas across the years 2014, 2016, and 2018. We can find that for all three years and all three different measurements of energy poverty, rural areas have more severe energy poverty issues than urban areas. For example, in 2014, 13.4% of urban residents use biofuel to cook. By contrast, this number has achieved 49.8% in rural areas.

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deviation increase in financial inclusion decreases the probability of burning biofuel to cook, the percentage of household income spent on energy, and the probability of falling into the category of energy poor households identified by the 10% cut-off on energy expenditure-income ratio by 0.09, 0.02, 0.003 standard deviation, respectively. Our result is robust to a set of alternative measures for both the dependent variable and the key explanatory variable we are interested in.

One difficulty in our study is to identify the causal relationship between financial inclusion and energy poverty in the presence of potential self-selection issue. That is, the status of financial inclusion is not exogenous—there might exist systematic difference between the households who are in good state of financial inclusion and those who are not. We employ three identification strategies to address this potential endogeneity issue. First, we include household fixed effects to avoid the possible biased estimation resulting from the unobserved time-invariant household characteristics. Second, we apply an instrumental variable (IV) strategy, in which the average status of financial inclusion across all other households in the same community in the same year is used as the instrument. The rationale of choosing this instrument is that the household's status of financial inclusion is likely to be affected by the other households in the same community due to the neighborhood effect and the catching-up effect while others' financial inclusion status is irrelevant to the household's energy usage. Third, we adopt a propensity score matching method (PSM) to address the potential self-selection bias in the baseline results. We define the households whose financial status is above the median as the treatment group and estimate a logistic model for each year based on a set of household characteristics to generate the propensity scores. We then use the estimated propensity scores to perform kernel-weighted matching in which the quadratic kernel function is applied as the weighting scheme. Results estimated based on the matched sample still indicate that financial inclusion helps reduce energy poverty.

Furthermore, we examine the effect of financial inclusion on household energy poverty in the presence of natural disasters. We construct an interaction term between financial inclusion and a dummy indicating whether or not a household suffered any natural disasters. Results show that given the severity of natural disasters, households who are in a better status of financial inclusion experience significantly lower energy poverty.

Heterogeneous effects across different household characteristics are also studied in this paper. We find a larger effect of financial inclusion for rural households, households whose income level is below the median, households whose head's education level is primary school or below, and those whose head is unemployed.

In the end, we explore the plausible mechanism through which financial inclusion affects energy poverty. Our empirical results show that financial inclusion has a more prominent effect on energy poverty reduction for households who have liquidity constraints, suggesting that at least one mechanism is that financial inclusion works on liquidity, making modern energy more accessible and affordable.

This paper contributes to the literature in the following three aspects. First, our paper enriches the research on how the financial inclusion affects household welfare. Some studies have examined the impact of financial inclusion on education (Bukari and Koomson, 2020), health (Gyasi et al., 2019; Njiru and Letema, 2018), and household business (Stein and Yannelis, 2020). Others focus on the relation between finance and energy poverty. Lakatos and Arsenopoulos (2019) propose the potential of financial instruments to tackle energy poverty. Qu and Hao (2022) explore the impact of digital economy and financial development on China's energy poverty at the provincial level. They find that the digital economy has a significant mitigation effect on energy poverty, while the effect of financial development is only significant in the eastern region. Dong et al. (2022) finds that financial inclusion is helpful to reduce energy poverty by using the province-level data of China. Nguyen et al. (2021) confirms the role of financial development on energy poverty alleviation by using a global sample of 65 economies, consisting of 36 low- and lower-middle-income economies and 29 upper-middle-income economies for the period from 2002 to 2015. Moreover, they find this effect is particularly significant to low-and middle-income economies. At the household level, Dogan et al. (2021) and Koomson and Danquah (2021) both find the positive effect of financial inclusion on relieving household energy poverty. Endogeneity in both papers is addressed by applying the distance to the nearest bank as an instrumental variable. In addition, Dogan et al. (2021) show that health and income serve as channels through which financial inclusion influences energy poverty. Our paper contributes to this vein of literature by investigating the relation between financial inclusion and energy poverty at the household level in the context of China. In particular, different from Dogan et al. (2021) in which they show that health and income work as the mechanism variables, our results suggest that liquidity constraints is another channel through which financial inclusion takes a role in reducing energy poverty.

Second, our paper belongs to the large empirical literature in studying the determinants of energy poverty. It has been found that government spending (Nguyen and Su, 2022), housing conditions (Chen and Feng, 2022), the development of education and training (Apergis et al., 2022), working in non-agriculture sector (Lin and Zhao, 2021), financial literacy (Ye and Yue, 2023), income inequality (Nguyen and Nasir, 2021), and environmental regulations (Ma et al., 2022) have explanatory power for energy poverty. In particular, Zhou et al. (2022) investigates the relation between financial markets and energy consumption. Results show that a more developed financial market helps to reduce energy poverty to a greater extent by expanding the channels to access to credits. Similar results could be also found in Canh et al. (2020) and Le et al. (2020). Our paper thus enriches the literature on factors influencing energy poverty by examining the effect of financial inclusion.

In the end, findings in this paper also have important policy implications. Tackling with relative poverty has been put in priority since 2020 when the absolute poverty was eliminated in China. As a result, alleviating energy poverty has received great attention due to its effect on improving relative poverty.[3] Our findings that promoting financial inclusion is a way of alleviating energy poverty thus offer a guide for policymakers who seek alternative policy interventions to accelerate the transition process to modern and clean energy.

The remainder of the paper proceeds as follows. Section 2 illustrates the data and empirical strategy. Section 3 presents the baseline results and a set of robustness checks. The potential endogeneity issue, heterogeneous effects, as well as discussions on mechanisms through which financial inclusion helps reduce energy poverty are also presented in this section. The final section concludes.

2. Data and empirical strategy

2.1. The survey data

The data utilized for analysis in this paper is from 2014, 2016, and 2018 wave of China Family Panel Studies (CFPS). Conducted by Institute of Social Science Survey of Peking University, the CFPS provides a high-quality dataset, covering three modules including individuals, households, and communities, to depict the transition of China's economy, society, population, education, and health. The module we mainly use in

[3] A sequence of policies related to energy poverty has been proposed in recent years. For example , "Decision of the CPC Central Committee and the State Council on Winning the Fight against Poverty" issued in 2015 by the State Council has proposed to improve the overall service level of electricity in poor areas. "Notice on the Action Plan to Further Support Energy Development in Poverty stricken Areas and Boost Poverty Alleviation" issued in 2018 by National Energy Administration proposed that the energy service level in poverty stricken areas needs to get significant improvement by 2020.

this paper is the household module that includes detailed information on the household's and household head's demographic characteristics, economic and financial conditions, and all the information needed to construct the financial inclusion index and the status of energy poverty.

Since its launch in 2010, the CFPS surveys a representative sample of Chinese households every two years. We restrict our analysis to data from 2014 to 2018, since 2014 is the first wave in which the definitions of key variables utilized in this paper are consistent with those in the subsequent years and 2018 is the latest data we are able to access to. We then process our data in the following four steps. First, we drop the household sample whose household head age is beyond 16–80 years old. Second, we drop those with missing information used to define the key explanatory variables (e.g., information on household deposits or loans) or for any utilized variable in regressions to make various specifications comparable. Third, we winsorize 1% of observations at both tails for all continuous variables to eliminate the adverse effect of extreme values. In the end, we keep only the households that are observed for at least two waves which allows for the application of fixed household effect model. The finalized sample consists of 33,684 observations from 12,837 households, spanning 967 communities of 25 provinces. Among these observations, 31.0% are from the 2014 wave. The proportions from 2016 and 2018 wave are, respectively, 35.5% and 33.4%. By urban-rural status, the numbers of urban household observations in 2014, 2016, and 2018 wave are 4637, 5698, and 5535, with a total for the three waves of 15,870. The total number of rural households is 17,408, respectively, with 5661 for the 2014 wave, 6079 for the 2016 wave, and 5668 for the 2018 wave.

2.2. Energy poverty

Three measures of energy poverty, which are, respectively, whether to use biofuel to cook[4] (IEA, 2002, 2010; Li et al., 2014; Nie et al., 2021; Vijay et al., 2005), the percentage of household income that is spent on energy (Boardman, 2013; Churchill and Smyth, 2020), and whether or not a household is categorized as energy poor household based on a 10% cut-off rule (Boardman, 1991; Bouzarovski and Petrova, 2015), are utilized in our baseline analysis. Specifically, for bio-fuel usage and the 10% cut-off definition, energy poverty is an indicator variable that equals to one if a household uses bio-fuel to cook and if >10% of household income is spent on energy and fuel, respectively, and zero otherwise. As for the percentage of household income spent on energy, the higher the proportion is, the severe the poverty of energy will be.

The data shows that China still suffers a serious energy poverty problem. In the finalized sample, 28.2% reported biofuel usage when cooking, the average ratio of energy expenditure to household income is as high as 17.4%, and the percentage of households who spend >10% of household income on energy and fuel is even higher which has achieved 38.9%.

Alternative measures for energy poverty are further constructed for robustness purpose. Oxford Poverty and Human Development Initiative (OPHI), inspired by the concepts of deprivation, proposes a multidimensional measure for energy poverty. Specifically, the multidimensional energy poverty index (MEPI) is generated by a weighted sum of deprivations involving six indicators in five dimensions, which are cooking, lighting, household appliances, entertainment/education and communication (See Table 1 for details in the indicators used to generate the energy deprivation scores). Household i's MEPI thus could be written as follows:

$$d_i = \sum_{i=1}^{5} w_i I_i \tag{1}$$

Where d_i is the total weighted household energy deprivation score. $I_i = 1$ if a household is deprived in indicator i and $I_i = 0$ otherwise. w_i is the weight assigned to indicator i with $\sum_{i=1}^{5} w_i = 1$. On this basis, MEPI ranges from 0 to 1. Weights could be determined following an equivalence rule by giving a weight of 0.2 to each of the five dimensions. Alternatively, higher weights could be offered to fundamental necessaries of people's livelihood such as cooking and lighting (Adusah-Poku and Takeuchi, 2019; Koomson and Danquah, 2021; Nussbaumer et al., 2013). We therefore construct two MEPIs by varying weights w_i, where one is based on the equivalence rule and the other is assigning 0.205 for each of the two indicators in cooking, 0.20 for lighting, and 0.13 for each of the rest three dimensions (Koomson and Danquah, 2021). We then use a cut-off 0.33 to determine whether or not a household is in energy poverty. The average MEPI constructed by treating all dimensions equivalently and giving higher weights on cooking and lighting are 0.19 and 0.31, respectively.

2.3. Financial inclusion

We define financial inclusion based on financial accessibility, financial permeation, and financial utilization (Sarma, 2008; Park and Mercado, 2018). Specifically, following Yin and Zhang (2020), four dimensions of financial services, including the ownership of savings account, the ownership of insurance, the accessibility to credits, and the utilization of digital payments, are used to construct the financial inclusion index by applying the iterated principal factor method. Factor loadings are generated using the iterated principal factor method to capture the extent to which each variable contributes to the shared variation among the four-dimensional measures. We then obtain a composite index of financial inclusion derived by the Bartlett method and is normalized to sum to unity. The average status of financial inclusion is 0.34 with a standard deviation at 0.29. Financial inclusion in the urban area is much better than that in the rural. Moreover, it has seen an increasing trending over the period from 2014 to 2018 (Table 4).

2.4. Summary statistics

Table 3 presents the summary statistics of variables utilized in our empirical analyses. The average age is 50.5 years old, 85.3% are in marriage, the average level of education is above primary school but below middle school, and 39.1% of household heads work in the non-agriculture sector. 47.6% of the sample are female and 51.7% are in rural regions. The average household size is 4.1. 17.8% of household heads rated themselves as very unhealthy. Finally, the proportion of the elderly and children in the household, respectively, are 14.8% and 15.0%.

2.5. Econometric model

We estimate the following econometric model to study the impact of financial inclusion on household energy poverty:

$$Energy\ Poverty_{it} = \alpha + \beta Financial\ Inclusion_{it} + \gamma X_{it} + T_t + u_{it} \tag{2}$$

Where, *Energy Poverty*$_{it}$ is the energy poverty status for household i at time t.

Financial Inclusion$_{it}$ represents for the financial inclusion status for household i at time t. X_{it} is a set of household characteristics including the household head's age, gender, education, marriage status, health status, household size, whether rural area, the proportion of the elderly in the household, the proportion of children in the household, and whether the household head works in non-agriculture sector. T_t is the year fixed effect. The key interest is the coefficient of

[4] Biofuel is widely used in cooking nationwide in China, particularly in rural area. According to 2010 Census data, 4.9 hundred million rural residents and 1.7 hundred million urban residents in China were using biofuel to cook. >75% of Chinese rural households rely on solid fuel to meet their cooking needs. This number has seen a decline in cities and towns, which are 8% and 36%, respectively (Tang and Liao, 2014).

Table 1
Dimensions, Indicators and Weights for Multi-dimensional Energy Poverty Index.

Dimension	Indicator	Variables	Deprivation cut-off (energy poor if …)	Weights for MEPI1	Weights for MEPI2
Cooking	Modern cooking fuel	Use biofuel to cook	True	0.2	0.205
	Indoor pollution	Use biofuel/coal to cook	True	0	0.205
Lighting	Electricity access	Household electricity expenditure is greater than zero	False	0.2	0.2
Household appliances	The ownership of household appliances	Household appliance are worth more than zero	False	0.2	0.13
Entertainment/ education	The ownership of entertainment/ education appliances	Have a TV/computer	False	0.2	0.13
Communication	Telecommunication means	Have a cell phone	False	0.2	0.13

Financial Inclusion$_{it}$, β, which indicates whether and to what extent the household's energy poverty responds to the status of financial inclusion.

3. Results

3.1. Baseline results

Table 5 presents the baseline results. The columns (1) ~ (3) of Table 5, using the three measures of energy poverty defined in section 2.2, respectively, report the results estimated by OLS regressing households' energy poverty on financial inclusion with province and year fixed effects included. We control for the province fixed effects to do the within-province estimation since there are large variations in economic conditions across provinces in China. Take column (1) of Table 5 as an example in which energy poverty is proxied by whether to use biofuel to cook. We find the estimated coefficient of financial inclusion is −0.136 and statistically significant at the 1% level. According to the point estimate, one standard deviation increase in financial inclusion leads to 0.1 standard deviation decrease in energy poverty. This implies that the probability of using biofuel to cook will be reduced by 4.5% for each standard deviation increase in financial inclusion. Different specifications by using the other two measures of energy poverty do not invalidate our conclusion. As shown in columns (2) and (3), the coefficients of financial inclusion are still significantly negative.

In columns (4) ~ (6) of Table 5, we re-estimate eq. (2) by employing OLS model with fixed effects to obtain within-estimators. However, rather than including province fixed effects as we did in columns (1) ~ (3), we control for the household fixed effect to exclude the time-invariant household characteristics that might affect both the status of energy poverty and financial inclusion. We find the effect of financial inclusion on energy poverty is still negative and statistically significant. In sum, a better status of financial inclusion helps to reduce energy poverty in China.

It is worth to point out that our results are consistent with Lakatos and Arsenopoulos (2019), Nguyen et al. (2021), Koomson and Danquah (2021), and Dogan et al. (2021) which also find the positive financial impact on relieving energy poverty. We thus further substantiate these findings by providing evidence from China households.

3.2. Endogeneity

3.2.1. Instrumental variable results

One issue is that the status of financial inclusion is not exogenous, that is, there exists systematic difference between the households who are in good state and those who are not, resulting in a self-selection bias estimation. Following Yin and Zhang (2020), we instrument the financial inclusion status of a certain household with the average status of financial inclusion across all other households in the same community. We consider that the household's status of financial inclusion to be highly positively correlated with other households in the same community because of the neighborhood effect and the catching-up effect. Furthermore, a household's energy poverty status is less likely correlated with other households' status of financial inclusion. The average status of other households' financial inclusion thus is a good instrument variable in our empirical settings.

We estimate Eq. (2) using the two-stage least square (2SLS) method. The results are reported in Table 6. For each panel, we examine the impact of financial inclusion on the three different measures of energy poverty as we did in the baseline analysis, where Panel A includes the province fixed effects while Panel B includes the time-invariant household fixed effects. The first stage results suggest that the instruments are strong. Specifically, we find that for all specifications, the instruments are significant at the 1% level with F-statistics larger than the critical value of the weak instrument test (Staiger and Stock, 1997). We therefore reject the null hypothesis that the instruments are weak. The second stage results show that the coefficients of the financial inclusion are significantly negative for all specifications. Take column (1) of Table 6 as an example in which energy poverty is proxied by whether to use biofuel to cook. According to the point estimate, one standard deviation increase in financial inclusion leads to 0.56 standard deviation decrease in energy poverty. Thus, addressing endogeneity concerns does not weaken the results obtained from the baseline model.

3.2.2. Propensity score matching (PSM) results

We further apply the propensity score matching approach to address the potential self-selection bias in the baseline result. Our sample is divided into two groups based on whether the household's status of financial inclusion is above the median, in which households whose status of financial inclusion is above the median are categorized as the treatment group. Control group will be constructed from those whose financial inclusion status is below the median.

We then obtain comparable household pairs with similar characteristics by applying the kernel-weighted matching method. The idea of kernel-weighted matching is to compare household i in the treatment group to the entire control group and weigh the households in the control group based on their similarity to household i. Thus, the advantages of applying kernel matching lie in the fact that it yields lower variance and a higher similarity in household fundamentals between the treated and the control group since all observations in the control group are used to construct one matched household for each treated household. A logistic regression model is conducted to generate the propensity score, which is the probability of a household to be categorized into the high status of financial inclusion. The general form of the effect of financial inclusion estimated by PSM is:

$$\frac{1}{N}\sum_{i\in\{FI_i=1\}}\left(Energy\ Poverty_i-\sum_{j\in\{FI_j=0\}}\omega(p_i,p_j)Energy\ Poverty_j\right) \tag{3}$$

Where, $\omega(\cdot)$ are the weights assigned for households j in the control group to construct a counterfactual firm for firm i in the treatment group. We employ the Quadratic kernel function as the weighing scheme.

Appendix A presents the standardized bias results on the univariate comparison of the variables used to determine the status of financial inclusion between the treatment and the control group. We find that the standardized bias for all the variables except for the gender variable has been substantially large before matching, suggesting the significant difference between the treatment and the control group, but has sharply reduced after matching. Take age as an example. Before matching, its standardized bias between the treatment and the control group is as large as >80%. However, among the matching sample, the standardized bias between the two groups has been greatly reduced to <5%.

PSM analysis results are presented in Table 7, where column (1) and (2) are, respectively, report the results estimated by the OLS model and the 2SLS model. We include the household fixed effects to obtain within-estimators for both specifications. Results show that the coefficients of financial inclusion are negative and statistically significant, suggesting that the baseline results still hold when taking the potential self-selection bias into consideration.

3.3. Robustness analysis by using alternative measures

To check the robustness of our results, we first apply alternative measures of the dependent variable. In the baseline model, energy poverty is measured by whether or not using biofuel to cook, the proportion of household income spent on energy and whether a household is defined as energy poor household based on the 10% cut-off rule. In this subsection, we apply a more comprehensive index proposed by OPHI, i.e., multidimensional energy poverty index (MEPI), to reflect a multi-dimensional energy poverty covering cooking, lighting, household appliances, entertainment/education and communication. As illustrated in section 2.2, we construct two MEPIs by varying the weights assigned to each of the five dimensions.

Table 8 presents the results on the estimated effect of financial inclusion on a household's energy poverty measured by MEPI, where MEPI1 denotes the MEPI that treats the five dimensions without distinction while MEPI2 denotes the one that puts more weights on cooking and lighting which are the two essentials in people's livelihood. The results reported in Panel A and B are estimated from an OLS model and the 2SLS model, respectively, with both including household fixed effects. As shown in Table 8, the results are not sensitive to the choice of weights. We find that all the estimates for the coefficients on financial inclusion are still significantly negative. Take column (1) of Table 8 as an example. The coefficient of financial inclusion is -0.330 which is statistically significant at the 1% level. That is, one standard deviation increase in financial inclusion leads to 0.24 standard deviation decrease in energy poverty. Our findings are robust to a variety of measures of dependent variables.

Next, we re-estimate Eq. (2) using alternative measures of financial inclusion. In addition to the composite index obtained from applying factor analysis, Yin et al. (2021) proposes an alternative index of financial inclusion by adding up the indicators for the four dimensions of financial services. By its construction, the larger the value is, the better the status of financial inclusion is. In particular, a value of zero indicates that the household cannot access to or utilize any of the four financial services shown in Table 2 while a value of four indicates that she is able to make use of the all. Table 9 presents the results estimated using the index of financial inclusion calculated following Yin et al. (2021), where column (1) and (2) are estimated by the OLS model and the 2SLS model, respectively. We find the coefficients of the newly-defined financial inclusion index in both specifications are still significantly negative, demonstrating the robustness of our results. Specifically, as shown in column (1) of Table 9, according to the point estimate, one standard deviation increase in the status of financial inclusion would decrease energy poverty by 0.02 standard deviation.

3.4. Further analysis: financial inclusion, natural disasters, and energy poverty

So far, we have found that a better status of financial inclusion is associated with a less severity of household energy poverty. The results are robust to a variety of alternative measures of the dependent variable, energy poverty, and the key explanatory variable of our interest, financial inclusion. Furthermore, the findings still hold when the potential self-selection issue is addressed by instrumental variable strategy and propensity score matching method.

In this subsection, we further investigate the effect of financial inclusion on household energy poverty in the presence of natural disasters. Narayan (2003) confirms the negative impact of natural disasters on a set of important macroeconomic indicators such as GDP, income, consumption, and trade. Other studies have explored the relation between natural disasters and energy consumption. Lee et al. (2021) finds that natural disasters impose detrimental effects on energy consumption by using data covering 123 countries over the period from 1990 to 2015. Moreover, this impact is particularly stronger for low-income countries and those in the Africa regions. Similar findings could be also found in Loayza et al. (2012), Rakshit (2021), and Yin et al. (2022). Huang et al. (2022) and Churchill et al. (2022) both find that the extreme weather would significantly increase the consumption on energy.

Despite the rich evidence shown above that the natural disaster has a negative impact on energy consumption, whether and how financial inclusion would play a role on reducing energy poverty in the presence of natural disasters is still unclear. On one hand, financial inclusion might help reduce energy poverty in the presence of natural disasters. Acheampong (2018) accounts for the negative impact of natural disasters on energy consumption by the post-disaster incapability of reconstruction resulting from the substantial economic loss made by the disaster. Given the nature of financial inclusion is to provide accessibility to and more efficient use of a variety of financial services, financial inclusion has the potential to alleviate liquidity constraint problems. In this sense, financial inclusion might reduce energy poverty if it could provide more liquidity in the presence of natural disasters. On the other hand, financial inclusion might not have a significant effect on energy poverty reduction in the presence of natural disasters. Collier and Babich (2019) find that due to the decreased expected returns after disasters, financial institutions choose to greatly reduce the amount of loans, resulting in more severe post-disaster energy poverty. If it is the case, promoting financial inclusion might only have moderate effect on resolving liquidity constraint problems and thus has no significant effect on energy poverty.

Table 2
Dimensions and Indicators for Financial Inclusion Index.

Dimension	Details
Banking account	Household has a banking account, including savings, current, fixed deposit or microfinance account
Loan/Credit	Household has access to loan/credit from banks, microfinance institutions or other formal financial institutions
Insurance	Household owns commercial insurance
Digital payment	Household has on-line business activities or digital payment.

Table 3
Summary statistics.

Variable	Description	Obs.	Mean	SD	Min	Max
Energy Poverty1 (EP1)	Use biofuel for cooking	33,684	0.2823	0.4501	0	1
Energy Poverty2 (EP2)	Energy expenditure/Household income	33,684	0.1743	0.4618	0	6
Energy Poverty3 (EP3)	Energy expenditure/Household income>0.1	33,684	0.3891	0.4876	0	1
MEPI1	Multidimensional energy poverty index (Equivalent weights)	33,684	0.1887	0.3913	0	1
MEPI2	Multidimensional energy poverty index (Inequivalent weights)	33,684	0.3061	0.4609	0	1
Financial Inclusion (FI)	Financial inclusion index	33,684	0.3373	0.2855	0	1
Age	The age of the head of households	33,684	50.5049	13.6690	16	80
Gender	Dummy variable equals 1 if the head of the household is male	33,684	0.5238	0.4994	0	1
Education	the education level of the household head is divided into eight categories: illiterate, primary school, middle school, high school, vocational school, junior college, and university or higher	33,684	2.6165	1.3342	1	8
Married	Dummy variable takes the value of 1 if the head of the household get married	33,684	0.8526	0.3545	0	1
Rural	Dummy variable equals 1 if household live in the countryside	33,684	0.5168	0.4997	0	1
Poor health	Dummy variable takes the value of 1 if the head of the household is unhealthy	33,684	0.1782	0.3827	0	1
Household size	Number of people within a household	33,684	4.0971	1.9740	1	21
Kid ratio	The proportion of children who are younger than or equal to 16	33,684	0.1497	0.1692	0	0.857
Elderly ratio	The proportion of elderly people who are older than or equal to 65	33,684	0.1476	0.2700	0	1
Job	Dummy variable equals 1 if the household head has a non-agriculture job	33,684	0.3908	0.4879	0	1
Natural Disasters1	Natural disasters (community level)	28,478	0.5314	0.4990	0	1
Natural Disasters2	Population affected by earthquake disaster (province level)	33,684	39.1069	360.582	0	3587
Natural Disasters3	Number of earthquake disasters (province level)	33,684	0.3332	1.0421	0	8
Natural Disasters4	Economic losses from earthquake disasters (province level)	33,684	38,406	284,270	0	2,779,840
Natural Disasters5	Crop damage area (province level)	33,684	928.667	729.581	0	4223.7
Natural Disasters6	Population affected by natural disasters (province level)	33,684	808.732	545.673	0	2491
Natural Disasters7	Economic losses from natural disasters (province level)	33,684	140.104	132.976	0	837.7
Mechanism variables						
Credit constraint	Loan application was rejected	33,684	0.0444	0.2060	0	1
Liquidity constraint1	Non-housing assets are less than annual income	33,684	0.4344	0.4957	0	1
Liquidity constraint2	monthly expenditure is greater than the total labor income in three months	33,684	0.2763	0.4472	0	1
Liquidity constraint3	The average monthly expenditure is greater than the average monthly income	33,684	0.4143	0.4926	0	1

Table 4
Descriptive statistics of the key variables by year and regions.

Variable	2014			2016			2018		
	Full sample	Urban	Rural	Full sample	Urban	Rural	Full sample	Urban	Rural
EP1	0.3315	0.1344	0.4983	0.2795	0.1080	0.4455	0.2397	0.0859	0.3917
EP2	0.2850	0.2283	0.3330	0.1252	0.1083	0.1416	0.1238	0.0987	0.1487
EP3	0.4446	0.4152	0.4695	0.3652	0.3209	0.4081	0.3631	0.2900	0.4353
FI	0.2525	0.3227	0.1932	0.3402	0.4034	0.2789	0.4127	0.4711	0.3551

We therefore construct an interaction term between financial inclusion and a dummy indicating whether or not a household suffered any natural disasters and estimate the following econometric model to test for the impact of financial inclusion on energy poverty in the presence of natural disasters.

The key interest is on the coefficient of the interaction term, θ:

$$\begin{aligned} Energy\ Poverty_{it} = & \alpha + \beta_1 Financial\ Inclusion_{it} + \beta_2 Natural\ Disaster_{it} \\ & + \theta Financial\ Inclusion_{it} * Natural\ Disaster_{it} + \gamma X_{it} \\ & + T_t + \delta_i + u_{it} \end{aligned} \tag{4}$$

Where, $Natural\ Disaster_{it}$ is an indicator variable which takes the value of one if the community in which household i is located had ever suffered any of the natural disasters including drought, flood, forest fire, typhoon, frost damage, hail damage, landslide, mud-rock flow, plant disease and insect pest in agriculture and forestry, earthquake, and infectious disease during the period from 2010 to 2013; and takes a value of zero otherwise. All the other variables are defined same as in eq. (2).

Table 10 presents the estimation results of Eq. (4), where Panel A reports the results estimated using only the 2014 data while Panel B applies data from all the three waves.[5] For each panel, the first column

[5] The CFPS only contains the information on natural disasters at the community level during the period from 2010 to 2013. Panel A reports the result estimated using only the 2014 data on the rationale that natural disasters took place during 2010 to 2013 only have their impact in 2014. The estimated results using the data from 2014 to 2018 are also provided in Panel B of Table 10 in the case that we believe these impacts can last until the end of our analysis period.

Table 5
Baseline results.

	OLS			FE		
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	EP1	EP2	EP3	EP1	EP2	EP3
FI	−0.1356***	−0.0304***	−0.0059	−0.0239**	−0.0312**	−0.0291*
	(0.0086)	(0.0095)	(0.0110)	(0.0101)	(0.0154)	(0.0158)
Age	−0.0013***	−0.0015***	−0.0023***	0.0002	0.0001	−0.0015***
	(0.0002)	(0.0003)	(0.0003)	(0.0004)	(0.0007)	(0.0006)
Gender	0.0633***	−0.0017	0.0135**	0.0229***	−0.0288***	0.0054
	(0.0043)	(0.0052)	(0.0054)	(0.0059)	(0.0099)	(0.0089)
Education	−0.0393***	−0.0171***	−0.0272***	−0.0068*	0.0075	−0.0031
	(0.0018)	(0.0021)	(0.0023)	(0.0041)	(0.0067)	(0.0060)
Married	−0.0015	−0.0302***	−0.0184**	0.0049	−0.0159	−0.0012
	(0.0062)	(0.0077)	(0.0076)	(0.0101)	(0.0163)	(0.0146)
Rural	0.2135***	0.0119**	0.0298***	0.0825***	−0.0064	0.0047
	(0.0050)	(0.0056)	(0.0060)	(0.0143)	(0.0211)	(0.0184)
Poor health	0.0494***	0.0018	0.0300***	0.0079	−0.0016	0.0135
	(0.0062)	(0.0067)	(0.0070)	(0.0068)	(0.0100)	(0.0096)
Household size	0.0138***	−0.0075***	−0.0102***	0.0041	−0.0133***	−0.0179***
	(0.0014)	(0.0016)	(0.0016)	(0.0031)	(0.0042)	(0.0046)
Kid ratio	−0.0724***	0.0970***	0.1621***	−0.0258	0.0339	0.1069***
	(0.0149)	(0.0196)	(0.0186)	(0.0247)	(0.0412)	(0.0388)
Elderly ratio	0.0003	0.0496***	0.0937***	0.0235	0.0450	0.0382
	(0.0100)	(0.0108)	(0.0115)	(0.0185)	(0.0277)	(0.0267)
Job	−0.1267***	−0.0492***	−0.0384***	−0.0259***	−0.0365***	−0.0404***
	(0.0051)	(0.0056)	(0.0064)	(0.0064)	(0.0098)	(0.0099)
Constant	0.3091***	0.4134***	0.5673***	0.2721***	0.3560***	0.5916***
	(0.0173)	(0.0220)	(0.0333)	(0.0304)	(0.0503)	(0.0435)
Province Fixed Effects	YES	YES	YES	–	–	–
Year Fixed Effects	YES	YES	YES	YES	YES	YES
Household Fixed Effects	–	–	–	YES	YES	YES
Observations	33,684	33,684	33,684	33,684	33,684	33,684
R-squared	0.261	0.049	0.067	0.026	0.026	0.017

Notes: Results are estimated using 2014, 2016 and 2018 CFPS data. The dependent variables are, respectively, EP1 (whether use biofuel for cooking), EP2 (energy expenditure/household income), and EP3 (whether energy expenditure/household income is >0.1). The key interested variable is financial inclusion index (FI). Other controls include age, gender, education, marriage status, whether the household is located in the rural area, whether the household head is in poor health, household size, kid ratio, elderly ratio, and whether the household head currently works in the non-agriculture sector. All regressions control for the year fixed effect. Provincial fixed effects and household fixed effects are further controlled in columns (1) ~ (3) and columns (4) ~ (6), respectively. Robust standard errors clustered at the household level are reported in parentheses. Significance levels: *** 1%, ** 5% and * 10%.

Table 6
Addressing endogeneity: instrumental variable strategy.

	2SLS			FE-IV		
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	EP1	EP2	EP3	EP1	EP2	EP3
Second Stage						
FI	−0.8185***	−0.2891***	−0.2185***	−0.3227***	−0.6571***	−0.4701***
	(0.0462)	(0.0446)	(0.0530)	(0.0766)	(0.1224)	(0.1181)
Control variables	YES	YES	YES	YES	YES	YES
Province fixed effects	YES	YES	YES	–	–	–
Year fixed effects	YES	YES	YES	YES	YES	YES
Family fixed effects	–	–	–	YES	YES	YES
Observations	29,011	29,011	29,011	29,011	29,011	29,011
R-squared	0.137	0.033	0.057	0.122	0.013	0.010
First Stage						
IV	0.4840***			0.3960***		
	(0.0130)			(0.0210)		
F-Statistic of first regression	1408.20			354.76		
t value	37.53***			18.63***		
Cragg-Donald Wald F statistic	1507.42			405.97		

Notes: Results are estimated using 2014, 2016 and 2018 CFPS data. The dependent variables are, respectively, EP1 (whether use biofuel for cooking), EP2 (energy expenditure/household income), and EP3 (whether energy expenditure/household income is >0.1). The key interested variable is financial inclusion index (FI). Other controls include age, gender, education, marriage status, whether the household is located in the rural area, whether the household head is in poor health, household size, kid ratio, elderly ratio, and whether the household head currently works in the non-agriculture sector. All regressions control for the year fixed effect. Provincial fixed effects and household fixed effects are further controlled in columns (1) ~ (3) and columns (4) ~ (6), respectively. The instrument variable is the mean value of the financial inclusion at the community level. Robust standard errors clustered at the household level are reported in parentheses. Significance levels: *** 1%, ** 5% and * 10%.

Table 7
Addressing endogeneity: propensity score matching strategy.

	(1)	(2)
Dependent variable	EP1	EP1
FI	−0.0240**	−0.3269***
	(0.0101)	(0.0770)
Control variables	YES	YES
Year fix effects	YES	YES
Family fix effects	YES	YES
Observations	33,465	28,833
R-squared	0.027	0.121
First Stage		
IV		0.3958***
		(0.0214)
F-Statistic of first regression		349.72
t value		18.70***
Cragg-Donald Wald F statistic		399.56

Notes: Results are estimated using 2014, 2016 and 2018 CFPS data. The dependent variable is EP1, i.e., whether to use biofuel for cooking. The key interested variable is financial inclusion index (FI). Other controls include age, gender, education, marriage status, whether the household is located in the rural area, whether the household head is in poor health, household size, kid ratio, elderly ratio, and whether the household head currently works in the non-agriculture sector. All regressions control for the year fixed effect and the household fixed effect. The instrument variable is the mean value of the financial inclusion at the community level. Robust standard errors clustered at the household level are reported in parentheses. Significance levels: *** 1%, ** 5% and * 10%.

Table 8
Robustness check: alternative measures of energy poverty.

	FE		FE-IV	
	(1)	(2)	(3)	(4)
Dependent variable	MEPI1	MEPI2	MEPI1	MEPI2
FI	−0.3298***	−0.0661***	−0.8988***	−0.4409***
	(0.0157)	(0.0147)	(0.1358)	(0.1222)
Control variables	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
Family fixed effects	YES	YES	YES	YES
Observations	23,233	23,233	19,581	19,581
R-squared	0.071	0.029	0.173	0.161
First Stage				
IV			0.3630***	
			(0.0298)	
F-Statistic of first regression			148.00	
t value			12.17***	
Cragg-Donald Wald F statistic			167.30	

Notes: Results are estimated using only 2016 and 2018 CFPS data, since a unified standard of defining MEPI cannot be applied to the 2014 data due to its different questionnaire design. The dependent variable is multidimensional energy poverty index, and the key interested independent variable is financial inclusion index. Other controls include age, gender, education, marriage status, whether the household is located in the rural area, whether the household head is in poor health, household size, kid ratio, elderly ratio, and whether the household head currently works in the non-agriculture sector. All regressions control for the year fixed effect and the household fixed effect. The instrument variable is the mean value of the financial inclusion at the community level. Robust standard errors clustered at the household level are reported in parentheses. Significance levels: *** 1%, ** 5% and * 10%.

reports the OLS results and the second column reports the 2SLS results. We find that in all specifications, the coefficient of the interaction term is significantly negative, suggesting the capability of financial inclusion in relieving energy poverty in the face of natural disasters. Take column (2) of Panel A as an example. Given the presence of natural disasters, an increase in financial inclusion by one standard deviation results in a decrease in household energy poverty by 0.317 standard deviation.

Table 9
Robustness check: alternative measures of financial inclusion.

	(1)	(2)
	FE	FE-IV
Dependent variable	EP1	EP1
FI_new	−0.0075***	−0.0648***
	(0.0027)	(0.0143)
Control variables	YES	YES
Year fixed effects	YES	YES
Family fixed effects	YES	YES
Observations	33,684	29,001
R-squared	0.027	0.135
First Stage		
IV		0.5048***
		(0.0187)
F-Statistic of first regression		741.59
t value		27.23***
Cragg-Donald Wald F statistic		827.17

Notes: Results are estimated using 2014, 2016 and 2018 CFPS data. The dependent variable is EP1, i.e., whether to use biofuel for cooking. The key interested variable is the newly-measured financial inclusion index (FI_new), constructed by adding up the indicators for the four dimensions of financial services. Other controls include age, gender, education, marriage status, whether the household is located in the rural area, whether the household head is in poor health, household size, kid ratio, elderly ratio, and whether the household head currently works in the non-agriculture sector. All regressions control for the year fixed effect and the household fixed effect. The instrument variable is the mean value of the newly-defined financial inclusion at the community level. Robust standard errors clustered at the household level are reported in parentheses. Significance levels: *** 1%, ** 5% and * 10%.

Table 10
Financial inclusion, natural disasters, and energy poverty (community level).

	Dependent variable: EP1			
	Panel A. Using only 2014 data		Panel B. Using 2014–2018 data	
	(1)	(2)	(3)	(4)
	OLS	2SLS	OLS	2SLS
FI	−0.0371**	−0.7031***	−0.0418***	−0.4842***
	(0.0157)	(0.0842)	(0.0108)	(0.0509)
FI* Natural Disasters1	−0.2863***	−0.7868***	−0.1935***	−0.4218***
	(0.0282)	(0.1198)	(0.0171)	(0.0546)
Natural Disasters1	0.2223***	0.3203***	0.1911***	0.2462***
	(0.0130)	(0.0306)	(0.0090)	(0.0186)
Control variables	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
Province fix effects	YES	YES	YES	YES
Observations	11,360	10,128	25,427	23,308
R-squared	0.306	0.110	0.274	0.188
First Stage				
IV		0.4858***		0.5838***
		(0.0299)		(0.0173)
F-Statistic of first regression		245.03		641.10
t value		16.23***		25.84***
Cragg-Donald Wald F statistic		265.52		646.15

Notes: The dependent variable is EP1, i.e., whether to use biofuel for cooking. The key interested variable is the interaction term between financial inclusion index and natural disasters at the community-level. Other controls include age, gender, education, marriage status, whether the household is located in the rural area, whether the household head is in poor health, household size, kid ratio, elderly ratio, and whether the household head currently works in the non-agriculture sector. All regressions control for the year fixed effect and the province fixed effect. The instrument variable is the mean value of the financial inclusion at the community level. Robust standard errors clustered at the household level are reported in parentheses. Significance levels: *** 1%, ** 5% and * 10%.

Table 11
Financial inclusion, natural disasters, and energy poverty (province level).

	Dependent variable: EP1					
	(1)	(2)	(3)	(4)	(5)	(6)
FI	−0.0177*	−0.0176*	−0.0185*	0.0995***	0.0865***	0.0755***
	(0.0104)	(0.0102)	(0.0105)	(0.0284)	(0.0271)	(0.0236)
FI* Natural Disasters2	−0.0359*					
	(0.0202)					
Natural Disasters2	0.0083					
	(0.0104)					
FI *Natural Disasters3		−0.0181**				
		(0.0073)				
Natural Disasters3		0.0074**				
		(0.0033)				
FI* Natural Disasters4			−0.0035			
			(0.0023)			
Natural Disasters4			0.0012			
			(0.0012)			
FI* Natural Disasters5				−0.0193***		
				(0.0044)		
Natural Disasters5				0.0153***		
				(0.0034)		
FI* Natural Disasters6					−0.0175***	
					(0.0043)	
Natural Disasters6					0.0161***	
					(0.0029)	
FI* Natural Disasters7						−0.0223***
						(0.0052)
Natural Disasters7						0.0101***
						(0.0035)
Control variables	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES
Family fixed effects	YES	YES	YES	YES	YES	YES
Observations	33,684	33,684	33,684	33,684	33,684	33,684
R-squared	0.027	0.027	0.027	0.027	0.027	0.028

Notes: Results are estimated using 2014, 2016 and 2018 CFPS data. The dependent variable is EP1, i.e., whether to use biofuel for cooking. The key interested variables are the interaction terms between financial inclusion and the number of population affected by the earthquake disaster, the number of earthquake disasters, economic losses from earthquake disasters, crop damage area, the number of population affected by natural disasters, and economic losses from natural disasters, respectively. Other controls include age, gender, education, marriage status, whether the household is located in the rural area, whether the household head is in poor health, household size, kid ratio, elderly ratio, and whether the household head currently works in the non-agriculture sector. All regressions control for the year fixed effect and province fixed effect. The instrument variable is the mean value of financial inclusion at the community level. Robust standard errors clustered at the household level are reported in parentheses. Significance levels: *** 1%, ** 5% and * 10%.

In view of the unavailability of data on natural disasters at the community level during our study period, we further collect the provincial-level natural disaster data from the National Bureau of Statistics of China. Specifically, six measures of provincial-level natural disaster conditions are collected, including disaster-affected area of crops, the number of people affected by natural disasters, the direct economic losses from natural disasters, the number of earthquake disaster experienced, and the direct economic losses of earthquake disaster.

Natural Disaster$_{it}$ in Eq. (4) refers to each of the six measures of natural disasters in year t in the province where household i is located. The regression shown in Eq. (4) thus will be repeated six times.

Results estimated from the OLS model with household fixed effect included are reported in Table 11 where from column (1) to (6), we individually re-examine whether and how financial inclusion affects energy poverty in presence of natural disasters under each of the six measures of natural disasters. The key interest is still on the coefficients of the interaction term between natural disaster and financial inclusion. Similar to what we have obtained in Table 10, we find a significantly relieving effect of financial inclusion on energy poverty in the presence of natural disasters. Specifically, given the severity of natural disasters, households who are in better status of financial inclusion are associated with a lower level of energy poverty for all six measures of natural disasters.

3.5. Heterogeneous effects

Our sample covers households with different education levels, employment statuses, and income levels. In addition, there are large variations in economic development between the rural and urban area in China. We therefore examine the heterogeneous effects of financial inclusion on energy poverty across different types of households. The model used to estimate is as follows:

$$Energy\ Poverty_{it} = \alpha + \beta_1 Financial\ Inclusion_{it} + \beta_2 Z_{it} + \theta Financial\ Inclusion_{it} {}^{*} Z_{it} + \gamma X_{it} + T_t + \delta_i + u_{it} \tag{5}$$

Where, Z_{it} denotes the category that household i in year t belongs to. Existing studies have found the following portraits, including education and training (Apergis et al., 2022), working in non-agriculture sector (Koomson and Danquah, 2021; Lin and Zhao, 2021), and income level (Jeanneney and Kpodar, 2011; Karpinska and Śmiech, 2020; Nguyen et al., 2021), are closely related to the severity of energy poverty. Based on the previous literature, each household in our sample would be classified based on whether it is a rural household, household income level, household head's education level, and household head's employment status, respectively.

The regression shown in eq. (5) thus will be repeated four times. For income level, we divide our sample into two categories according to whether or not the household income is above the median , For education, households are categorized into two groups based on whether the education level of the household head is higher than primary school.

Table 12
Heterogeneous effects.

	Dependent variable: EP1			
	(1)	(2)	(3)	(4)
FI	0.0083	−0.0015	0.0078	0.0019
	(0.0108)	(0.0110)	(0.0112)	(0.0119)
FI*rural	−0.0622***			
	(0.0178)			
rural	0.1035***			
	(0.0158)			
FI*below median income		−0.0414**		
		(0.0167)		
below median income		0.0367***		
		(0.0081)		
FI*low education			−0.0724***	
			(0.0184)	
low education			0.0249*	
			(0.0142)	
FI* unemployment				−0.0456***
				(0.0160)
unemployment				0.0428***
				(0.0094)
Control variables	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
Family fixed effects	YES	YES	YES	YES
Observations	33,684	33,684	33,684	33,684
R-squared	0.027	0.028	0.027	0.027

Notes: Results are estimated using 2014, 2016 and 2018 CFPS data. The dependent variable is EP1, i.e., whether to use biofuel for cooking. The key interested variable is financial inclusion index. Other controls include age, gender, education, marriage status, whether the household is located in the rural area, whether the household head is in poor health, household size, kid ratio, elderly ratio, and whether the household head currently works in the non-agriculture sector. All regressions control for the year fixed effect and province fixed effect. The instrument variable is the mean value of financial inclusion at the community level. Robust standard errors clustered at the household level are reported in parentheses. Significance levels: *** 1%, ** 5% and * 10%.

All the other variables are defined same as in eq. (2). The coefficient of the interaction term is our interest, since it illustrates how the effect of financial inclusion on energy poverty differs across different groups.

We then apply the OLS model with household fixed effects included. The heterogeneous effect results by whether it is a rural household, household income level, household head's education level, and household head's employment status are, respectively, presented in columns (1) ~ (4) of Table 12.

We find the effect of financial inclusion on reducing energy poverty is much larger for rural households, households whose income level is below the median, households whose head's education level is primary school or below, and those whose head is unemployed. Take column (1) of Table 12 as an example. The coefficient on the interaction term is −0.06 and statistically significant at 1%. According to the point estimate, one standard deviation increase in financial inclusion reduces the probability of a rural household to suffer energy poverty by 0.04 standard deviation. This finding is consistent with Chen and Feng (2022). One potential explanation that accounts for the differential effects is that households who are rural, less educated, and unemployed are more likely to be the low-income population, having a higher probability of suffering energy poverty, on one hand, and being in a worse state of financial inclusion, on the other. A better status of financial inclusion has the potential to promote their income or alleviate liquidity constraints by increasing their probability of accessing to credits, which both would help reduce energy poverty to a greater extent compared to the relatively high-income population.

Our findings in Table 12 have important policy implications. Given promoting financial inclusion helps to alleviate energy poverty as illustrated in this paper, identifying which groups are more sensitive is important since the expedition of financial inclusion can be more effective by applying policies that target to these groups.

Table 13
Mechanisms: liquidity constraints.

	Dependent variable: EP1			
	(1)	(2)	(3)	(4)
FI	−0.0207**	−0.0028	−0.0208*	−0.0223**
	(0.0102)	(0.0116)	(0.0106)	(0.0113)
FI* Credit constraint	−0.0598*			
	(0.0355)			
Credit constraint	0.0269			
	(0.0192)			
FI* Liquidity constraint1		−0.0377**		
		(0.0154)		
Liquidity constraint1		0.0223***		
		(0.0075)		
FI* Liquidity constraint2			−0.0073	
			(0.0084)	
Liquidity constraint2			0.0000	
			(0.0058)	
FI* Liquidity constraint3				−0.0037
				(0.0136)
Liquidity constraint3				−0.0022
				(0.0071)
Control variables	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
Family fixed effects	YES	YES	YES	YES
Observations	33,684	33,684	33,684	33,684
R-squared	0.027	0.027	0.027	0.027

Notes: Results are estimated using 2014, 2016 and 2018 CFPS data. The dependent variable is EP1, i.e., whether to use biofuel for cooking. The key interested variable is the interaction term between financial inclusion and liquidity constraints. Other controls include age, gender, education, marriage status, whether the household is located in the rural area, whether the household head is in poor health, household size, kid ratio, elderly ratio, and whether the household head currently works in the non-agriculture sector. All regressions control for the year fixed effect and province fixed effect. The instrument variable is the mean value of financial inclusion at the community level. Robust standard errors clustered at the household level are reported in parentheses. Significance levels: *** 1%, ** 5% and * 10%.

3.6. *Discussion on mechanisms*

In this section, we investigate the plausible channel through which financial inclusion imposes an impact on a household's energy poverty. Theoretical models of liquidity constraints propose two ways relating liquidity constraints to consumption. First, liquidity constraints impose an indirect impact on consumption by affecting poor agents' capacity in taking advantage of business opportunities, resultantly detriment to their income (Black and Lynch, 1996). Second, liquidity constraints have a direct effect on consumption due to the unaffordability resulting from both limited internal funds and the inaccessibility to external financing (Carroll, 2001; Crossley and Low, 2014; Gross and Souleles, 2002; Hall and Mishkin, 1982; Leth-Petersen, 2010; Zeldes, 1989).

Financial inclusion, given its core refers to whether individuals are able to access to and how effectively they use a variety of financial services, has the potential to promote the consumption on clean energy and thus alleviate energy poverty by reducing households' liquidity constraints (Chidozie, 2022; Lahcen and Gomis-Porqueras, 2021). For example, owning a bank account does not directly improve economic situations, though, it is a necessary condition to access to bank loans. To test for this channel, we construct four variables by using the information on household credit situation, consumption, income and financial assets in CFPS to reflect the household's liquidity constraints.

The first one is whether a household has any credit constraints. We consider a household is liquidity constrained if it has credit constraints (Jappelli, 1990; Benvenuti et al., 2022). Specifically, if a household reports that "I applied for a loan but was rejected" or "I never apply for a loan since I believe it will not be approved", it will be defined as a constrained household; otherwise it will be treated as an unconstrained one. Next, Zeldes (1989) argues that a household could be determined as a liquidity-constrained one if its non-housing assets are less than annual income. We therefore base on this criterion to define liquidity constraints in our context. Third, a household will be recognized as the one with liquidity constraints if its average monthly expenditure is greater than three times its monthly income (Nirei, 2006). In the end, we consider a household is liquidity-constrained if the household's monthly expenditure is greater than monthly income. Columns (1) ~ (4) of Table 13 present the results on the impact of financial inclusion on energy poverty by the above illustrated four measures of liquidity constraints. In all four specifications, we include an interaction term between the corresponding measure of liquidity constraints and financial inclusion. We expect to obtain a negative sign of the coefficients of these interaction terms if financial inclusion helps to alleviate energy poverty through relaxing households' liquidity constraint.

As shown, the interaction terms are all negative although the coefficients for the last two measures of liquidity constraints are not statistically significant, suggesting that financial inclusion has a greater impact on liquidity-constrained households' energy poverty. We therefore conjecture that the liquidity constraint is a potential channel through which financial inclusion imposes an effect on energy poverty.

4. Conclusion

This paper highlights the important role of financial inclusion on household energy poverty in China. To illustrate, we construct a financial inclusion index by applying the factor analysis method and test its effect on the severity of household energy poverty. Results demonstrate that financial inclusion has a significant impact on reducing all three measures of energy poverty. Besides, the positive role of financial inclusion is also confirmed in the presence of natural disasters. Our results are robust to a variety of alternative measures, regression specifications and strategies.

Further analysis suggests that the impact of financial inclusion is more prominent for rural households, households whose income level is below the median, households whose head's education level is primary school or below, and those whose head is unemployed. From the policy perspective, these findings suggest potentially effective ways to reduce energy poverty through financial inclusion by targeting certain groups of population. In the end, results verify that liquidity constraints serve as an underlying channel through which financial inclusion imposes an effect on alleviating energy poverty.

CRediT authorship contribution statement

Zhichao Yin: Conceptualization, Supervision, Methodology, Funding acquisition. **Rui Wang:** Software, Formal analysis, Visualization. **Xi Wu:** Writing – original draft, Writing – review & editing, Funding acquisition.

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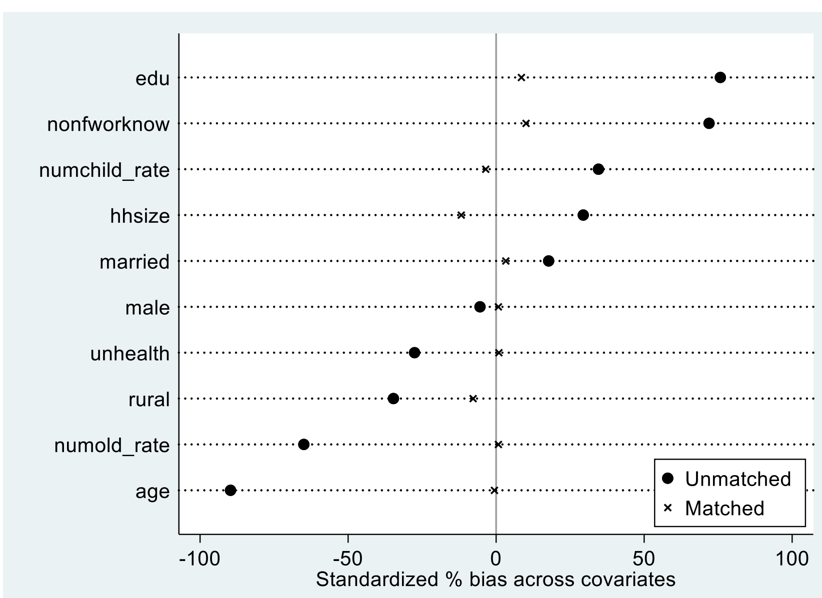
Appendix A. The standardized bias before and after matching



Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2023.106986.

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