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ABSTRACT

Energy Poverty and Health Care Expenditures: Evidence from the China Family Panel Studies

Using the 2012-2018 waves of the China Family Panel Studies (CFPS), we investigate the impact of energy poverty (EP) on health care expenditures among Chinese adults aged 18+. Employing a methodology combining a random effects two-part model and instrumental variable estimations, we show that EP leads to higher levels of total (305 yuan), out-of-pocket (199 yuan), inpatient (230 yuan) and other (113 yuan) health care expenditures, with more pronounced impacts among females and those living in urban areas and Central and Western China. These results are robust not only to alternative EP and health care expenditure measures but also to a series of estimation approaches that control for endogeneity. An additional structural equation modeling analysis of the underlying pathways further reveals that this EP-health care expenditure relationship is mediated by individual self-reported health as well as expenditures on food and other daily necessities.

JEL Classification: I10, I11, I32, Q40, R21

Keywords: energy poverty, health care expenditures, China

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1. Introduction

Achieving universal health coverage, such as access to quality essential health care services and access to safe, effective, quality and affordable essential medicines and vaccines for all, is one of main targets of the Sustainable Development Goals (SDGs) (United Nations, 2015). It has been projected that global spending on health will increase from 9.21 trillion US$ (61.7 trillion yuan) in 2014 to 24.24 trillion US$ (162.4 trillion yuan) in 2040 (Dieleman et al., 2017). To achieve universal health coverage, however, energy poverty (EP), that is, a lack of access to modern energy services such as electricity and clean cooking facilities (International Energy Agency (IEA), 2010), poses a potential challenge. Although the global electricity access rate has grown from 83% in 2010 to 90% in 2019, 759 million people were still without access in 2019, and 660 million people will still be without electricity in 2030 (United Nations, 2022). Meanwhile, 57% of the global population was using clean cooking fuels and technologies in 2010, increasing to 66% in 2019 (United Nations, 2022). At the current rate of progress, however, one-third of the world's population will still be without clean cooking fuels and technologies in 2030, resulting in significant adverse health effects (United Nations, 2022). Households with EP not only suffer from poor health (Churchill & Smyth, 2021; Kahouli, 2020; Zhang et al., 2019) but also pay higher energy costs, thereby affecting health care expenditures, especially when disposable income is certain.

Although a growing body of literature has examined the EP-health relationship in Australia (Churchill & Smyth, 2021; Prakash & Munyanyi, 2021), France (Kahouli, 2020), Spain (Oliveras, Artazcoz, et al., 2020), 27 European countries (Oliveras, Peralta, et al., 2020), 50 developing countries (Banerjee et al., 2021), and China (Zhang et al., 2019; Z. Zhang et al., 2021), evidence on how EP affects health care expenditures remains scarce. China is a particularly apt case for this topic because during the 2014-2040 period, the annualized rate of growth in health spending in China will be the highest (7.7%) among 184 countries (Dieleman et al., 2017). Additionally, health care expenditures in China are still very unequal across different subpopulations, possibly due to different benefit packages and various financing schemes (Wang et al., 2018), and the rapid expansion of social health insurance has not reached the universal level of generosity seen in other developed countries. Despite an unprecedented increase in per capita GDP from 385 yuan in 1978 to 72,000 yuan in 2020 (National Bureau of Statistics, 2021), this rapid economic growth was not accompanied by equally substantial improvements in health (Baeten et al., 2013; Nie et al., 2022). Furthermore, although China has achieved 100% electricity access since 2013 (World Bank, 2020) and per capita electricity consumption has surpassed the average in upper-middle-income countries (Nie, Li, & Sousa-Poza, 2021), an estimated 18.9% of Chinese people are energy poor (Lin & Wang, 2020), and in 2018, more than a quarter of households continued to use solid fuels (Lin & Wei, 2022). Due to the unsustainable energy consumption and high energy expenditures in China, EP may pose a threat to individuals' health and well-being, thereby impeding the realization of universal health coverage and the Healthy China Initiative.

Using data from the 2012-2018 waves of the China Family Panel Studies (CFPS), this study aims to investigate how EP affects health care expenditures among Chinese adults aged 18+. This study thus extends the literature on the EP-health/health care expenditure nexus in three ways. Using rich longitudinal data from China, ours is the first study to examine the relationship between EP and various types of health care expenditures (including total, inpatient, out-of-pocket (OOP) and other) in China, thereby painting a differentiated picture of the impact of EP on health care expenditures. Furthermore, by including self-reported health (SRH) as well as expenditures on food and other daily necessities, we provide a comprehensive analysis of the underlying mechanisms through which the impact of EP is manifested. In doing so, this study provides useful insights into the relationship between EP and health care costs in developing economies. Finally, we explore the heterogeneous impacts of EP across different sociodemographic characteristics, which will provide useful guidance for policies or interventions to alleviate EP and the burden of health care costs.

The rest of this paper is organized as follows. Section 2 documents the relevant literature on the impacts of EP on health and health care expenditures. Section 3 depicts the possible heuristic pathways of the impacts of EP on health care expenditures in China. Section 4 describes the data and outlines the identification strategies. Section 5 presents the main results, and finally, Section 6 concludes.

2. Literature review

2.1 Impacts of EP on health

A growing body of literature has investigated the EP-health nexus in developed economies (see, for instance, Churchill & Smyth, 2021; Kahouli, 2020; Lacroix & Chaton, 2015; Llorca et al., 2020; Oliveras, Peralta, et al., 2020; Prakash & Munyanyi, 2021). Specifically, Lacroix and Chaton (2015) show that being energy poor (proxied by self-reported perceptions of thermal discomfort) increases the probability of reporting poor health in France. Similarly, Kahouli (2020) finds that both objective EP and subjective EP[1] lead to a lower likelihood of reporting good or very good SRH in France. Likewise, Oliveras, Peralta, et al. (2020) confirm that EP is positively correlated with poor SRH in 27 European countries. This finding is further reinforced by Churchill and Smyth (2021), who show that both objective and subjective indicators of EP contribute to poor SRH in Australia. In the same country, Prakash and Munyanyi (2021) find that EP leads to an increased likelihood of being obese.

Recently, several studies have also explored this topic in developing countries (Abbas et al., 2021; Kose, 2019; Nawaz, 2021; Omar & Hasanujzaman, 2021; Pan et al., 2021; Zhang et al., 2019; Z. Zhang et al., 2021). For instance, Kose (2019) finds that EP is negatively associated with both subjective and objective health in Turkey. This observation is further confirmed by Omar and Hasanujzaman (2021) for Bangladesh and by Nawaz (2021) for Pakistan. Similarly, Banerjee et al. (2021) confirm that lower EP is associated with higher life expectancy in 50 developing countries. This finding is also obtained by Abbas et al. (2021) for South Asia[2] and by Pan et al. (2021) for 175 countries (including countries in Central and North Africa and Sub-Saharan Africa)[3]. For China, Zhang et al. (2019) show that EP decreases the likelihood of reporting good SRH. This observation is further confirmed by Z. Zhang et al. (2021), who report that EP deteriorates the physical health of rural residents and impacts the mental health of their urban counterparts.

2.2 Impacts of EP on health care expenditures

Only a handful of studies have examined the relationship between EP and health care expenditures. For instance, drawing on the cross-sectional data of the 2016 Barcelona Health Survey, Oliveras, Artazcoz, et al. (2020) find that EP is associated with a higher use of health services and medication. Likewise, using data from the 2016-2017 Ghana Living Standard Survey, Bukari et al. (2021) show that EP increases household expenditures on health, medical products, and outpatient and hospitalization services. This observation is further confirmed by Nawaz (2021), who finds that EP leads to higher per capita health expenditures based on the 2018-19 Pakistan Household Integrated Economic Survey. Recently, using data from the Nigerian 2019 General Household Survey, Okorie and Lin (2022) show that energy-poor households have higher odds of experiencing catastrophic health expenditures than non-energy-poor households. This result is also found by Faizan and Thakur (2022) based on data

[1] The 10% indicator is used as the objective EP measure, and the difficulty that a household encounters in heating its dwelling because of financial constraints or dwelling characteristics is used as the subjective EP measure.
[2] In this study, South Asia covers six countries, including Afghanistan, Pakistan, India, Bangladesh, Nepal and the Maldives.
[3] These 175 countries include five regions, namely, East Asia and the Pacific, Europe and Central Africa, Latin America and the Caribbean, the Middle East and North Africa and Sub-Saharan African.

from the National Sample Survey 68th quinquennial round of Household Consumer Expenditure in India. Their study indicates that the per capita expenditure on health-related problems is high in energy-poor households compared to non-energy-poor households.

Overall, although a number of contributions have assessed the impacts of EP on health outcomes in both developed and developing countries, very few studies have examined the EP-health care expenditure relationship, and virtually no such research exists for China. Moreover, almost all such studies suffer from a major drawback. That is, their cross-sectional design precludes any causal analysis, but the research overall pays little attention to the underlying pathways through which EP may affect health care expenditures. To address these shortcomings, we perform a longitudinal analysis of 2012-2018 CFPS data to identify the effect of EP on different types of health care expenditures among Chinese adults aged 18+. In doing so, we first use a random effects two-part model (RE-TPM) to investigate the impacts of EP on health care expenditures. We then employ an instrumental variable (IV) technique to shed more light on the causal relationships between these two variables. Finally, using a structural equation modeling (SEM) approach, we conduct a comprehensive exploration of the possible mechanisms through which EP affects health care expenditures.

3. Underlying pathways of the impact of EP on health care expenditures

As stated above, the literature on the EP-health relationship has consistently confirmed that EP contributes to the deterioration of health in both developed countries and developing countries such as China (Zhang et al., 2019; Z. Zhang et al., 2021). In addition, the evidence on the determinants of health care expenditures in China suggests that poor health increases health care expenditures such as total, inpatient, outpatient and OOP expenditures (see, e.g. Fan et al., 2020; Wang et al., 2018; A. Zhang et al., 2017; Zhang et al., 2018). Based on all of the above observations, we formulate the following hypothesis:

Hypothesis 1: *EP increases health care expenditures by deteriorating individuals' health*.

The inability of poor households to access or afford both adequate nutrition and energy services leads to the "heat or eat" dilemma, which forces these households to make tradeoffs (Anderson et al., 2012; Nord & Kantor, 2006). Among poor households in the UK, for instance, a temperature just two or more standard deviations (SD) colder than expected contributes to a significant reduction in food spending (Beatty et al., 2014). Not only are these forced tradeoffs of basic needs stressful, but reduced food expenditure also frequently leads to decreased nutrient intake (Lee & Frongillo Jr, 2001; Park & Eicher-Miller, 2014; Tuttle & Beatty, 2017), especially during the high-energy demand seasons of winter and summer (Nord & Kantor, 2006). Consequently, forced food expenditure reduction increases the risk of diabetes (Berkowitz et al., 2015; Fernández et al., 2018), hyperlipidemia (Seligman et al., 2010), hypertension (Stuff et al., 2004), and heart disease (Vozoris & Tarasuk, 2003), thereby leading to increased household health care expenditures. At the same time, EP may also affect the consumption of essentials in addition to food. For example, Valente et al. (2022) confirm that high energy bills contribute to other essentials such as clothing and hygiene products being out of reach. Non-energy-poor households are found to spend more on food (16.2%) and nonfood (24.3%) items than energy-poor households (Sambodo & Novandra, 2019). The inability to purchase basic items probably results in depression, stress, and anxiety (Valente et al., 2022), and individuals with higher levels of psychological problems, such as anxiety, utilize health care considerably more than those with lower levels (Eastin & Guinsler, 2006). In addition to diagraming the above factors as a simple heuristic of possible channels for the impact of EP on health care expenditures in China (see Figure 1), we formalize the relationship between EP and expenditures on food and other daily necessities as our second hypothesis:

Hypothesis 2*: EP increases health care expenditures by crowding out expenditures on food and other daily necessities.*

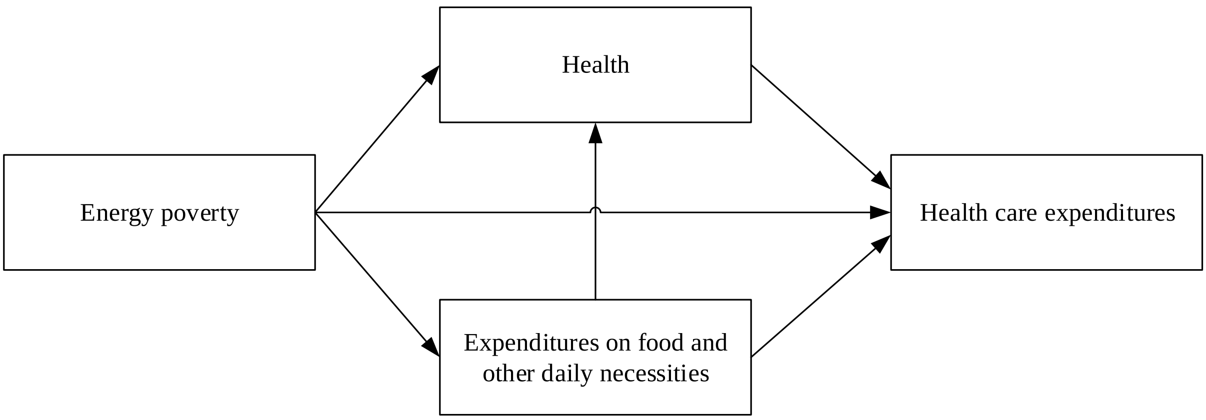

Figure 1 Underlying mechanisms through which energy poverty impacts health care expenditures

Notably, due to data availability, we focus on only these two underlying pathways. Nonetheless, it is highly possible that there are other channels through which EP affects health care expenditures. For example, Bukari et al. (2021) confirm that the negative impact of EP on health outcomes is weakened in the presence of remittances and health insurance in Ghana, suggesting that remittances and health insurance are potential mediators linking EP to health care expenditures.

4. Data and methods

4.1 Study design and population

Our dataset is taken from the CFPS administered by Peking University's Institute of Social Science Survey. It currently encompasses five waves: 2010, 2012, 2014, 2016, and 2018. The survey constitutes a nationally representative sample that captures both the socioeconomic development and the economic and noneconomic well-being of Chinese households (Xie, 2012), as it covers 25 provinces, municipalities, or autonomous regions representing 95% of the Chinese population. Productive use of rich CFPS data in prior research confirms its ability to shed light on health care utilization and health expenditures in China (Tang et al., 2021; Yip et al., 2019). Our study sample is adults aged 18 or older for whom there is detailed information on household income, household energy expenditures, individual health care expenditures, and individual and household demographic and socioeconomic characteristics. We exclude individuals who do not live at home. Additionally, to identify households' EP status, we exclude those with zero household income. Our analysis sample is an unbalanced panel of 40,991 adults and 105,484 observations from 2012 to 2018[4].

4.2 EP measures

To evaluate EP, we employ six measures (Nie, Li, & Sousa-Poza, 2021). EP3 is used in our main analysis, and the remaining measures are used in the robustness checks:

- EP 1: twice the median percentage of full income (EP1, Moore, 2012). Households whose energy[5] share is larger than twice the median percentage of energy to income are defined as EP1.
- EP 2: the 10% measure (EP2, Boardman, 1991). Households that have energy expenditures over 10% of their income are defined as EP2.
- EP 3: the amended 10% measure (EP3, Kahouli, 2020). Since Boardman's original 10% measure might overestimate EP prevalence by including high-income households (Kahouli, 2020), we employ an amended 10% measure that only considers low-income households, those with an income below the third decile of the household income distribution (Kahouli, 2020).
- EP 4: the low income-high cost (LIHC) measure. Household EP status identification

[4] Information on energy utilization in 2010 is unavailable.
[5] Household energy expenses include water, electricity, fuel and heating costs.

using the LIHC measure has two requirements: (1) equivalized energy expenditure[6] that exceeds the median level of the equivalized energy expenditure for the reference population; and (2) households' residual income (equivalized income[7] after equivalized energy expenditure) that must be below the income poverty line of 60% of the median equivalized income after housing costs.

- EP 5: the solid fuel measure. Given the high prevalence of biomass use in China (see, e.g., Tang and Liao, 2014), we include an indicator for whether households use solid fuel as their primary fuel (1 = yes, 0 = no).
- EP 6: the energy deprivation score. Following Churchill et al. (2020), we define this composite measure as follows:

$$EDS = W_1 EP_1 + W_3 EP_3 + W_4 EP_4 + W_5 EP_5 \quad (1)$$

where *EDS* denotes the energy deprivation score, $W_1 = W_3 = W_4 = W_5 = 0.25$, with EP2 omitted because EP3 is its derivative. We then generate EP6 as a dummy equal to one if the household energy deprivation score is 0.5 or above.

4.3 Health care expenditure measures

In this paper, we introduce four types of health care expenditures, namely, total health care expenditures, inpatient health care expenditures, OOP expenditures and other. Specifically, total health care expenditures include inpatient expenditures and other health care costs. In particular, inpatient expenditures are the amount of the cost (including the amount reimbursed or to be reimbursed) of hospitalization, including medicine, treatment, and inpatient services as well as the costs of living, food, nursing care, and "red envelope" bribes. Other is the amount of the cost (including the amount reimbursed or to be reimbursed) of medical care, excluding expenditures on hospitalization. OOP expenditures are the amount that has been paid directly by the family in the past year, excluding the amount reimbursed or to be reimbursed. This information, however, is available only in the 2014, 2016, and 2018 waves.

All four types of health care expenditures are measured in yuan/year and are deflated using the consumer price index for health care spending retrieved from the China Statistical Yearbook.

4.4 Control variables

[6] Equivalization factors that we use for energy costs in different household structures: 0.82=one person, 1=two people, 1.07=three people, 1.21=four people, and 1.32=five or more people (DBEIS, 2020).

[7] Equivalization factors that we use for household income is the OECD-modified equivalence scale: 1 for the first adult, 0.5 for an additional adult, 0.5 for a child aged 14 and over, and 0.3 for a child aged 0-13 (Churchill et al., 2020; Hagenaars et al., 1994)

Following existing studies (Bukari et al., 2021; Jiang & Ni, 2020), we control for individual demographic and socioeconomic characteristics, including age, age squared, gender (1 = male, 0 = female), educational level (illiterate, primary school, middle school, high school, vocational school, and university or higher, with illiterate as the reference), employment status (1 = currently employed, 0 = otherwise), marital status (1 = married/living together, 0 = otherwise), location type (1 = urban, 0 = rural), and medical insurance (1=yes, 0=no). We also control for household characteristics, including household size and logged household income. Lastly, we add a provincial dummy (Beijing as the reference group) to capture possible geographic heterogeneity together with a wave dummy (2012 as the reference year).

4.5 Empirical strategy

4.5.1 Random-effects two-part model (RE-TPM)

Modeling health care expenditures has always been a challenge since the distributions of these semi-continuous outcome variables display substantial skewness and their distributions have a substantial point mass at zero (Deb & Norton, 2018)[8]. Duan et al. (1983) proposed a two-part model (TPM) to fit data on expenditures for medical care. The health econometrics literature has confirmed that TPM is the best way to estimate a dependent variable with a substantial point mass at zero and many positive values (Belotti et al., 2015). Specifically, in the context of a TPM, we first estimate the probability that a respondent has any health care spending with a logit or probit model using the full sample. Then, we estimate a generalized linear model (GLM) for respondents who have any health care expenditures. These two processes, however, may be related, and a high level of utilization on one occasion may affect the probability of utilization on another occasion with repeated measures or longitudinal data (Olsen & Schafer, 2001). To address these challenges, Olsen and Schafer (2001) and Tooze et al. (2002) developed the RE-TPM to account for the correlation between the two equations by introducing random effects (RE) into both equations and allowing them to be correlated with each other. This approach has been widely used in modeling health care expenditures (Farewell et al., 2017; Liu et al., 2010; Mora et al., 2015).

In this paper, we estimate the extensive margins (probit model, if any health care expenditures) and intensive margins (GLM, amount of health care expenditures if any) separately using a RE-TPM[9]. In the second stage, a GLM with a gamma family and log link is

[8] In our dataset, of the four types of health care expenditures, zero health care expenditures account nearly 45% of our sample on average, and the distribution is highly skewed.

[9] Since fixed effects (FE) estimates are biased in nonlinear models with small group sizes (with a few exceptions where conditional maximum likelihood estimators exist) (Jiang & Ni, 2020), we implement RE estimation rather than FE estimation.

usually applied to address the econometric problems caused by skewness in health care utilization studies (Manning et al., 2005; Manning & Mullahy, 2001). The log link is useful for correcting highly skewed data, while the gamma family may help to reduce heteroskedasticity concerns[10]. The Box–Cox test and modified Park test on four types of health care expenditures confirm the appropriateness of our choices of gamma family and log link (see Appendix Table A2). Our RE-TPM estimation employs the following model:

$$\Phi^{-1}[P(HCE_{it} > 0|EP_{it}, X_{it})] = \alpha_0 + \alpha_1 EP_{it} + X_{it}'\theta + U_i \quad (2)$$

$$log[E(HCE_{it}|HCE_{it} > 0, EP_{it}, X_{it})] = \beta_0 + \beta_1 EP_{it} + X_{it}'\gamma + V_i \quad (3)$$

where equation (2) estimates the first-stage RE probit model and equation (3) estimates the second-stage RE GLM; HCE_{it} represents the health care expenditures of individual i at wave t; EP_{it} denotes individual i's household energy poverty status at wave t; X_{it} is a vector of the control variables, including sociodemographic covariates, provincial dummies and wave dummies; and U_i and V_i are random intercepts in the two equations for individual i and are assumed to be uncorrelated with X_{it}.

Since the approaches to estimating a RE-TPM require setting up the likelihood function manually (Liu et al., 2010; Olsen & Schafer, 2001; Tooze et al., 2002) and there are no routines in any package to estimate a RE-TPM, following Jiang and Ni (2020), we employ the generalized structural equation modeling (GSEM) approach to perform RE-TPM estimation. Specifically, GSEM has three key features that are suitable for our estimation: (i) Equations in GSEM can take nonlinear forms, such as probit. (ii) Equations in GSEM can use different samples, such as the full sample and subsamples for the first and second equations, respectively. (iii) Individual-level RE can be specified as latent variables in GSEM.

4.5.2 Instrumental variable estimation

In our baseline model, there are possibilities for potential endogeneity in EP, including omitted variable bias, measurement error, and simultaneity bias. One of the most obvious endogeneity concerns arises from omitted variable bias. First, some factors may simultaneously affect EP and health care spending. For instance, some unobservable variables, such as individual expectations regarding income or job loss, may impact not only EP but also health care spending. This phenomenon might render the estimated coefficient of EP to be biased upward. In addition, living in EP can lead to household financial stress and affect an

[10] GLMs can model heteroskedasticity because they allow the variance of the outcome to be a function of its predicted value through the choice of an appropriate distribution family (Deb & Norton, 2018).

individual’s propensity to pay for health care services, which may lead to a delay in seeking health care or forgoing health care altogether to reduce costs (Bodenmann et al., 2014). This phenomenon may cause our results to be downward biased. The second potential endogeneity concern comes from the systematic measurement error in estimating EP. For example, households may not be able to accurately recall their energy expenditures (Churchill et al., 2020). Notably, measurement errors can sometimes be substantial. One study showed that Australian respondents underestimated their annual energy expenditure by 13%-20% (Wilkins & Sun, 2010). Our results may also be affected by simultaneity bias. For example, individuals with poorer health tend to spend more on health care services. Additionally, the use of medical equipment and the energy consumed to maintain a thermally comfortable home for recovery may increase energy costs. However, having a large amount of health care expenditure might also lead to a reduction in energy expenditures. Thus, it is rather difficult to decide the true direction of this bias.

Following Nie, Li and Sousa-Poza (2021), we introduce provincial energy prices as IVs (including provincial average electricity and natural gas prices) for two-stage least squares (2SLS) estimation. We do so because higher energy prices increase the likelihood of EP (Churchill et al., 2020; Q. Zhang et al., 2021), which consequently affects individuals’ health care expenditures. One threat to the exogeneity of our IVs is that higher energy prices may cause households to tradeoff between energy and health expenditures. Households may decide to maintain health expenditures but reduce residential energy expenditures or favor thermal comfort at the expense of health expenditures (Kahouli, 2020). However, as Nie, Li and Sousa-Poza (2021) pointed out, Chinese residents have a relatively small share of energy expenditures and are unlikely to face large changes in allocating household budgets to energy and health due to fluctuations in energy prices[11].

Thus, we adopt the Lewbel (2012) 2SLS approach, which first employs only an internally constructed IV and then combines it with an external IV (provincial energy prices). This method has been widely used in the absence of an external or valid IV (Mishra & Smyth, 2015; Nie, Li, & Sousa-Poza, 2021). The precondition of this method is the presence of heteroskedasticity, which we confirm using the Pagan–Hall and Breusch–Pagan tests (Breusch & Pagan, 1979).

[11] Energy expenditures are unlikely to account for a large share of household budgets and are thus unlikely to significantly affect other expenditures (Churchill & Smyth, 2021). In China, the average share of energy expenditures in household income is approximately 7%-8% (Cheng et al., 2021).

4.5.3 Coarsened exact matching (CEM)

Since some pre-existing differences might lead to self-selection, we apply a coarsened exact matching (CEM) approach to address such endogeneity. This matching method has been widely used (Aaskoven et al., 2022; Aneja & Xu, 2022; Lyons & Zhang, 2017) and been shown to produce less bias than propensity score matching (PSM) (King et al., 2011).

CEM improves the comparability between the treatment and control groups and keeps the covariate distributions of the two groups as balanced as possible (Iacus et al., 2012). Specifically, CEM temporarily coarsens each individual variable and then runs the exact match. Then, the following analysis can be performed on the uncoarsened matched data. The multivariate imbalance measure (L1, ranging from 0 to 1, with a larger value indicating a higher imbalance between the matched and control groups (Blackwell et al., 2009)) represents the degree of imbalance of the two groups.

As a matching method of the monotonic imbalance bounding (MIB) class, CEM shows advantages over other matching methods, such as PSM and exact matching (EM). CEM allows the choice of balance between the treated and control groups ex ante rather than having to discover it ex post. Additionally, adjusting the imbalance in one variable has no effect on the maximum imbalance in any other. In contrast, PSM requires setting the size of the matching solution ex ante and then checking the balance after matching. CEM matches the sample based on the coarsened data, while EM simply matches the treated unit to all the control units with the same covariate values, which may produce very few matches. In this paper, we incorporate a broad array of covariates in CEM, including age, gender (1 = male, 0 = female), educational level (illiterate, primary school, middle school, high school, vocational school, and university or higher, with illiterate as the reference), employment status (1 = currently employed, 0 = otherwise), marital status (1 = married/living together, 0 = otherwise), household size, location type (1 = urban, 0 = rural), medical insurance (1=yes, 0=no) and logged household income. Then, we apply the RE-TPM based on the weights to address the possible bias due to self-selection.

5. Results

5.1 Descriptive statistics

As shown in Table A1, the percentage of respondents living in EP ranges from 14% to 35%, which is similar to other EP studies in China (Nie, Li, & Sousa-Poza, 2021; Zhang et al., 2019). The average per capita total, OOP, inpatient and other health care expenditures are approximately 3142, 2132, 1688, and 1447 yuan annually, respectively (Table A1), and the average health care expenditures all trend upward over the 2012-2018 period (Figure 2).

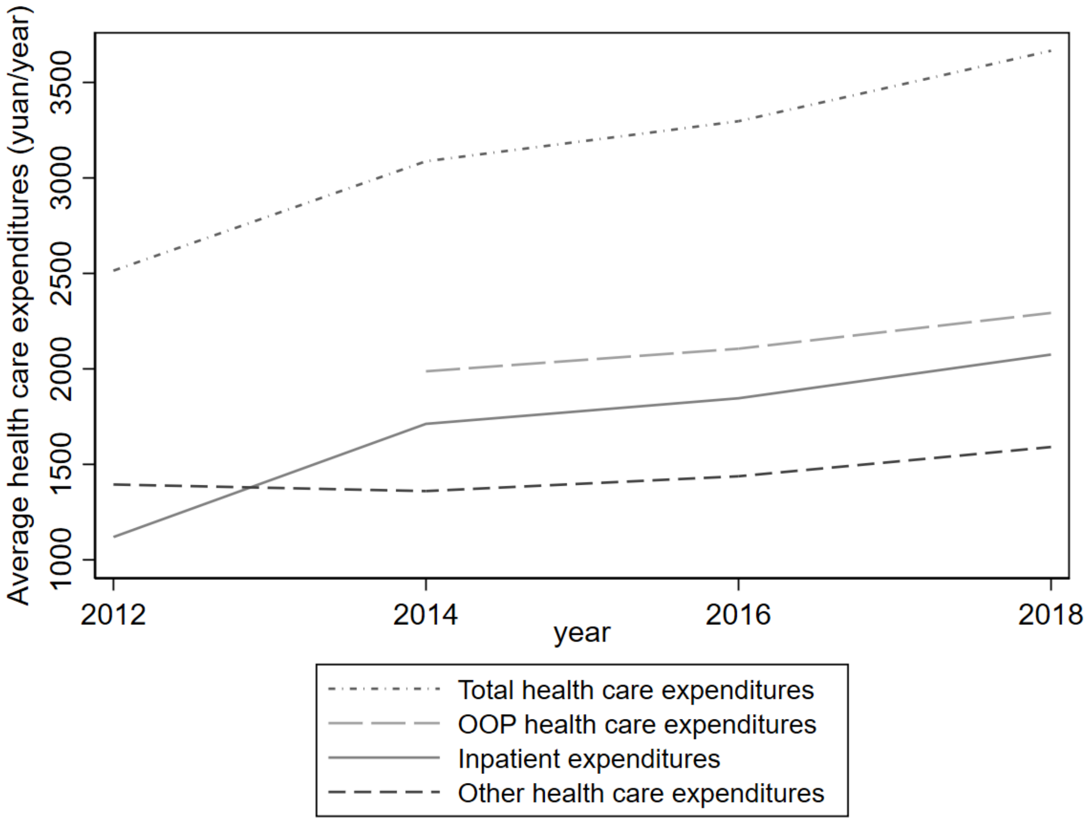

Figure 2 Average health care expenditures of adults over time: 2012-2018 CFPS

The distribution of health care expenditures is highly skewed, with a large mass at zero and a long right tail (Figure 3). Approximately 28%, 33%, 88% and 31% of observations have zero values in total, OOP, inpatient and other expenditures (Figure A1). Moreover, the distributions of logged health care expenditures confirm the appropriateness of our use of the log link in the second stage of RE-TPM estimation (Figure 4). Figure 5 and Table A7 show that respondents who live in EP are more likely to have higher health care expenditures than those who do not.

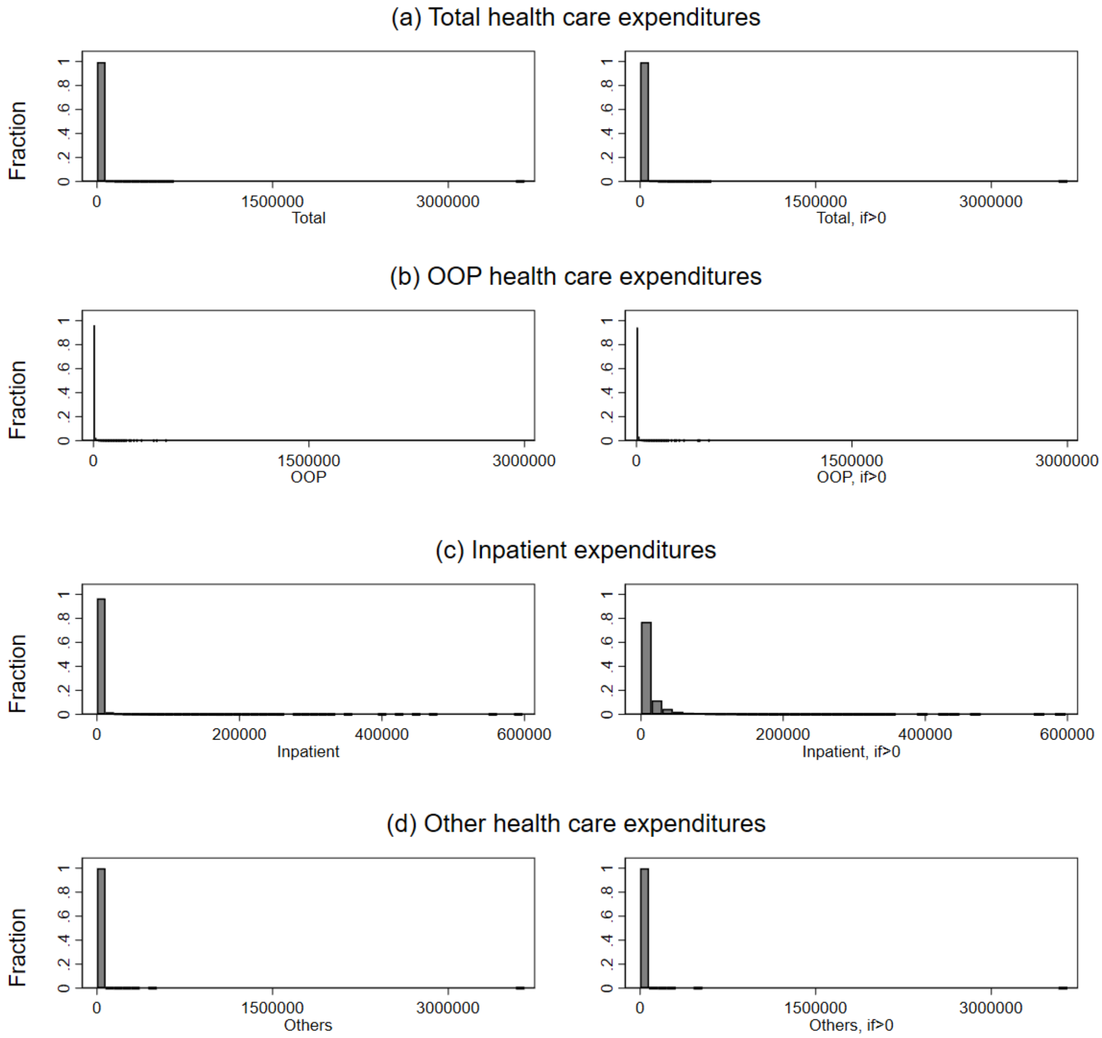

Figure 3 The distribution of four types of health care expenditures

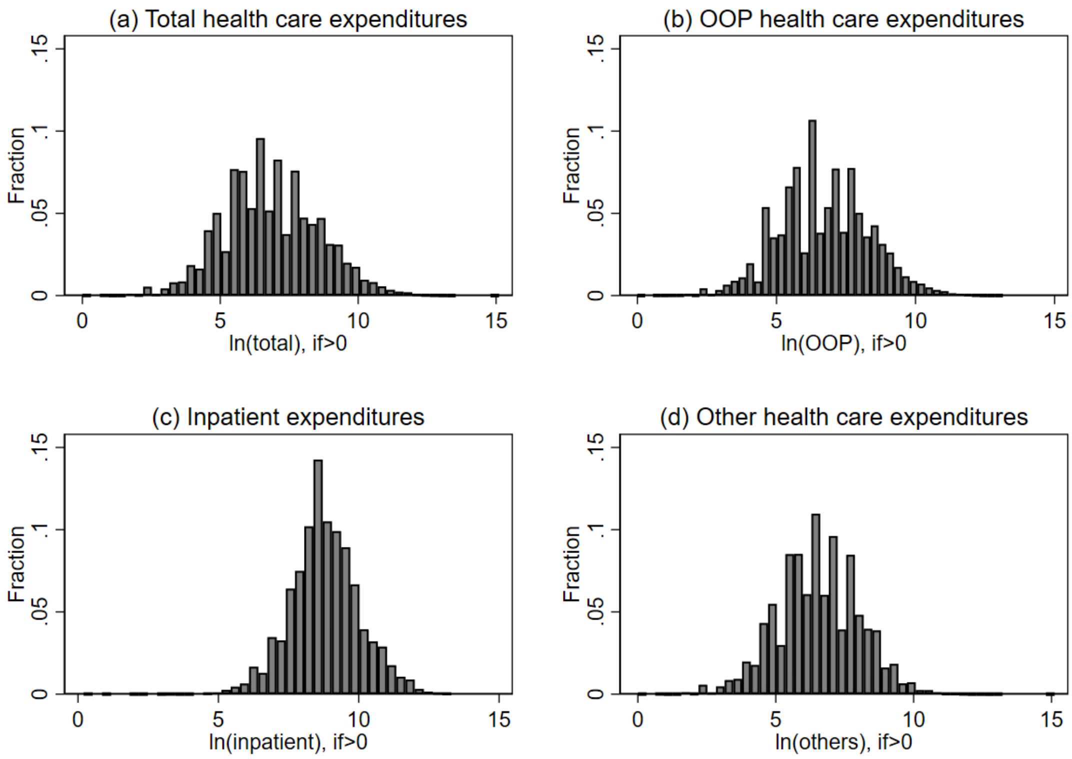

Figure 4 The distribution of four types of health care expenditures (logged form)

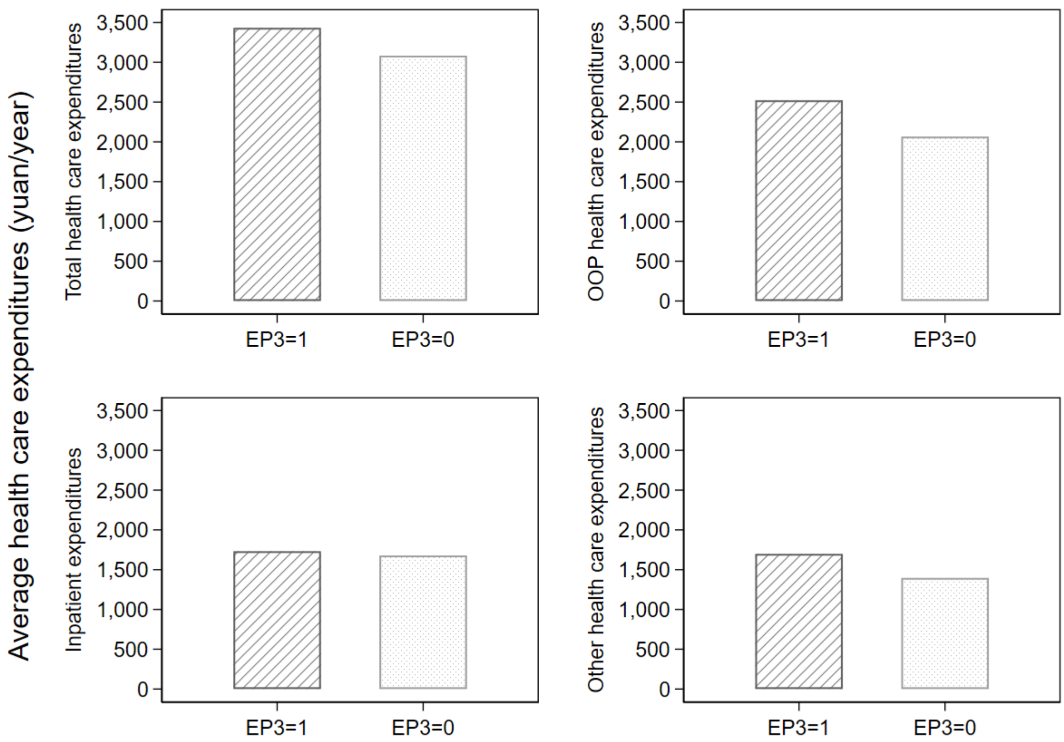

Figure 5 Average health care expenditures by household energy poverty status
Notes: EP3 is a dummy variable for households' energy poverty status (1=yes, 0=no).

5.2 EP and health care expenditures: The RE-TPM

The RE-TPM estimation results of the impacts of EP on four types of health care expenditures are shown in Table 1. EP is significantly associated with higher health care costs, regardless of whether the expenditures are total, inpatient, OOP or other expenditures (Table 1, Columns 2, 4, 6, and 8), which is consistent with Oliveras, Artazcoz, et al. (2020) for Spain, Bukari et al. (2021) for Ghana, and Faizan and Thakur (2022) for India.

The marginal effects of EP on health care utilization are presented in Figure 6 and Appendix Table A3. Individuals living in EP have approximately 305 yuan higher total health care expenditures (10% of the average value of total health care expenditures), 199 yuan higher OOP health care expenditures (9% of the average value of OOP expenditures), 230 yuan higher inpatient expenditures (14% of the average value of inpatient expenditures), and 113 yuan higher other expenditures (8% of the average value of other expenditures) (see Figure 6).

Turning to demographic and socioeconomic characteristics, males use health care services less often than females, which is confirmed by, for instance, Wang et al. (2018) for China, Schlichthorst et al. (2016) for Australia and van den Bussche et al. (2011) for Germany. Gender differences in the severity of illness and in health behavior patterns might explain this discrepancy (Wang et al., 2018). In addition, we show that individuals with medical insurance are more likely to have health care services than those without medical insurance, which is in accordance with Tan et al. (2019) and Wang et al. (2018) for China.

Table 1 RE-TPM estimates of the impact of energy poverty on health care expenditures among Chinese adults aged 18+: 2012-2018 CFPS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Total health care expenditures		OOP health care expenditures		Inpatient expenditures		Other health care expenditures	
	RE Probit	RE GLM	RE Probit	RE GLM	RE Probit	RE GLM	RE Probit	RE GLM
EP3	0.020	0.095^{***}	-0.004	0.097^{***}	0.077^{***}	0.047	0.014	0.077^{***}
	(0.019)	(0.022)	(0.022)	(0.025)	(0.021)	(0.037)	(0.018)	(0.018)
Age	0.011^{***}	0.023^{***}	0.014^{***}	0.027^{***}	0.000	0.031^{***}	0.016^{***}	0.030^{***}
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)	(0.002)	(0.003)
Age squared/100	0.008^{***}	0.002	0.003	-0.007^{*}	0.016^{***}	-0.027^{***}	0.000	-0.009^{***}
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.002)	(0.003)
Gender	-0.308^{***}	-0.173^{***}	-0.312^{***}	-0.198^{***}	-0.091^{***}	0.267^{***}	-0.298^{***}	-0.220^{***}
	(0.013)	(0.016)	(0.014)	(0.017)	(0.015)	(0.025)	(0.012)	(0.014)
Primary school	-0.057^{***}	-0.012	-0.080^{***}	-0.034	-0.028	0.050	-0.053^{***}	-0.021
	(0.019)	(0.023)	(0.021)	(0.024)	(0.020)	(0.033)	(0.018)	(0.020)
Middle school	-0.110^{***}	-0.063^{***}	-0.144^{***}	-0.100^{***}	-0.069^{***}	0.079^{**}	-0.102^{***}	-0.077^{***}
	(0.019)	(0.024)	(0.021)	(0.025)	(0.021)	(0.034)	(0.018)	(0.020)
High school	-0.114^{***}	-0.068^{**}	-0.172^{***}	-0.125^{***}	-0.075^{***}	0.130^{***}	-0.097^{***}	-0.066^{***}
	(0.023)	(0.029)	(0.025)	(0.031)	(0.026)	(0.043)	(0.022)	(0.025)
Vocational school	-0.059^{*}	-0.013	-0.140^{***}	-0.123^{***}	-0.049	0.090	-0.049^{*}	-0.014

	(0.031)	(0.040)	(0.033)	(0.043)	(0.038)	(0.061)	(0.030)	(0.034)
University or higher	0.025	-0.042	-0.081**	-0.173***	-0.062	0.136*	0.025	-0.023
	(0.035)	(0.043)	(0.038)	(0.047)	(0.045)	(0.075)	(0.034)	(0.037)
Currently employed	-0.076***	-0.553***	-0.088***	-0.533***	-0.389***	-0.467***	0.002	-0.354***
	(0.015)	(0.019)	(0.016)	(0.020)	(0.016)	(0.027)	(0.014)	(0.015)
Married/living together	-0.009	0.211***	-0.001	0.167***	0.168***	0.136***	-0.034**	0.119***
	(0.018)	(0.022)	(0.020)	(0.024)	(0.022)	(0.034)	(0.017)	(0.019)
Urban	-0.107***	0.089***	-0.112***	0.052***	0.010	0.077***	-0.110***	0.081***
	(0.013)	(0.017)	(0.015)	(0.018)	(0.016)	(0.026)	(0.013)	(0.014)
Medical insurance	0.172***	0.078***	0.173***	-0.022	0.219***	0.001	0.142***	0.004
	(0.018)	(0.023)	(0.022)	(0.028)	(0.025)	(0.046)	(0.018)	(0.020)
Household size	-0.030***	-0.023***	-0.022***	-0.019***	-0.009**	-0.016**	-0.030***	-0.023***
	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.006)	(0.003)	(0.003)
Log(household income)	0.032***	0.039***	0.014*	0.039***	0.016**	0.055***	0.035***	0.033***
	(0.007)	(0.008)	(0.008)	(0.010)	(0.008)	(0.013)	(0.007)	(0.007)
Constant	0.204*	6.502***	-0.015	6.519***	-2.655***	8.537***	0.034	6.394***
	(0.115)	(0.144)	(0.133)	(0.161)	(0.144)	(0.269)	(0.111)	(0.125)
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Provincial FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	105484	105484	78479	78479	105484	105484	105484	105484

Notes: The dependent variables are total health care expenditures, OOP health care expenditures, inpatient expenditures, and other health care expenditures. The controls include age, age squared, gender (1 = male, 0 = female), educational level (illiterate, primary school, middle school, high school, vocational school, and university or higher, with illiterate as the reference), employment status (1 = currently employed, 0 = otherwise), marital status (1 = married/living together, 0 = otherwise), location type (1 = urban, 0 = rural), medical insurance (1=yes, 0=no), household size, logged household income, wave dummies (with 2012 as the reference) and provincial dummies (with Beijing as the reference). For the second part of the GLM estimation, we use a gamma family and log links. Individual-level adjusted standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

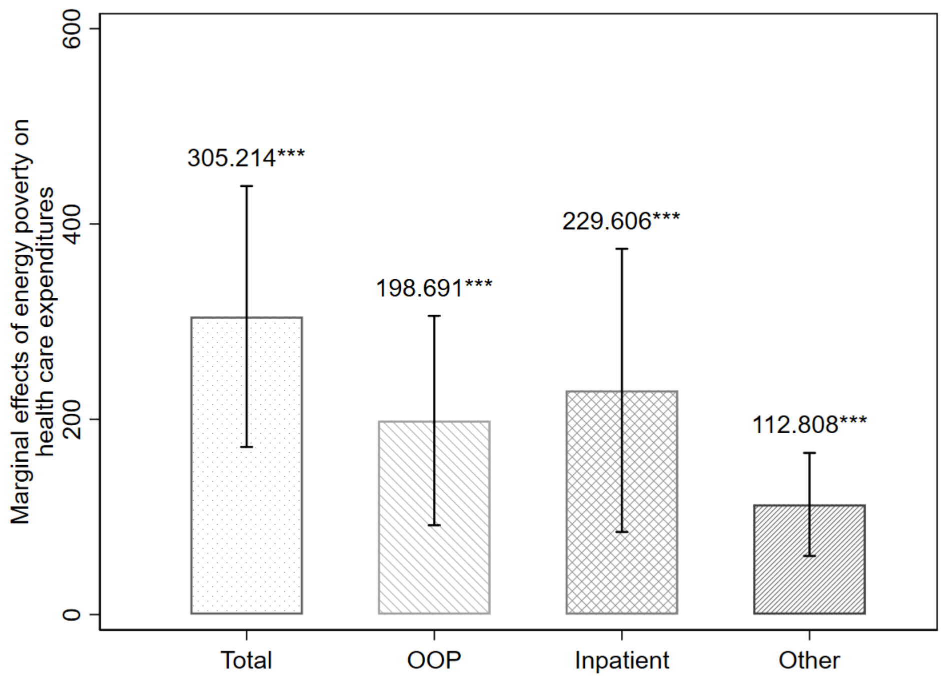

Figure 6 Marginal effects of energy poverty on health care expenditures (with 95% confidence intervals)

5.3 Endogeneity

To address the potential endogeneity of EP, we employ Lewbel's 2SLS estimation (Lewbel, 2012)[12]. The results from Table 2 also confirm that EP significantly increases one's health care spending, regardless of whether the expenditures are total, OOP, inpatient, or other expenditures. The Pagan–Hall and Breusch–Pagan tests affirm the presence of heteroskedasticity, which is the premise of Lewbel's 2SLS method. Additionally, the first-stage F-statistics, which exceed 10, indicate that there is no weakness in the IV, and the Hanson J tests confirm the exogeneity of the IV.

In addition, compared with the marginal effects of RE-TPM estimation, we find that the magnitude in 2SLS estimation is somewhat larger. The marginal effects of EP in the 2SLS estimates are approximately 1.6-2.5 times larger than those of the RE-TPM (see Table 2 and Table A3). This observation highlights that failure to rule out the endogeneity of EP will lead to underestimation.

Table 2 Lewbel's 2SLS estimates of the impact of energy poverty on health care expenditures among Chinese adults aged 18+: 2012-2018 CFPS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Total health care expenditures		OOP health care expenditures		Inpatient expenditures		Other health care expenditures	
	Internal IV	Internal & external IV	Internal IV	Internal & external IV	Internal IV	Internal & external IV	Internal IV	Internal & external IV
EP3	618.371***	624.433***	352.690*	355.921*	370.092**	370.477**	275.960**	282.959**
	(232.358)	(234.037)	(197.979)	(197.906)	(176.632)	(176.533)	(131.104)	(133.978)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Provincial FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	105484	105484	78479	78479	105484	105484	105484	105484
First stage F-statistic	397.90	303.72	313.32	230.32	397.90	303.72	397.90	303.72
J P value	0.7397	0.7313	0.5907	0.7817	0.5217	0.7198	0.7161	0.2146
Pagan–Hall test	78.901***	88.142***	167.154***	169.059***	388.461***	388.485***	78.493***	87.788***
Breusch–Pagan test	8.6e+05***	9.7e+05***	4.9e+04***	4.9e+04***	1.0e+05***	1.0e+05***	2.9e+06***	3.2e+06***

Notes: The dependent variables are total health care expenditures, OOP health care expenditures, inpatient expenditures, and other health care expenditures. The controls include age, age squared, gender (1 = male, 0 = female), educational level (illiterate, primary school, middle school, high school, vocational school, and university or higher, with illiterate as the reference), employment status (1 = currently employed, 0 = otherwise), marital status (1 = married/living together, 0 = otherwise), location

[12] We also employ CEM-based RE-TPM estimation. The matching results show that the imbalance between the treatment and control groups of each covariate is improved for both means and quartiles (minimum, 25 quartile, 50 quartile, 75 quartile, maximum) (see Table A8). The multivariate L1 distance is decreased as well, suggesting that CEM makes the two groups more comparable. We run a CEM-based RE-TPM using weights derived from CEM. The estimated marginal effects are comparable to those of 2SLS estimation (see Tables A9 and A10).

type (1 = urban, 0 = rural), medical insurance (1=yes, 0=no), household size, logged household income, wave dummies (with 2012 as the reference) and provincial dummies (with Beijing as the reference). The external IVs are province-level electricity prices and gas prices. Individual-level adjusted standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5.4 Robustness checks

5.4.1 Alternative measures of EP

As there is currently no consensus on the definition of EP, we introduce the remaining five EP measures as our first robustness check: twice the median percentage of full income (EP1, Moore, 2012), the 10% measure (EP2, Boardman, 1991), the LIHC measure (EP4, Hills, 2011), biomass use (EP5, Zhang et al., 2019) and the energy deprivation score (EP6, Churchill et al., 2020). We find that both estimated coefficients and the marginal effects of the alternative EP measures are quite similar to those of our baseline estimates, with the exception of EP5 (see Table 3 and Table A4). Different from other EP measures, households in EP5 (meaning those using biomass as their main energy source) are significantly associated with a higher probability of having total, OOP and other health care expenditures but not with health care cost burden conditional on having any expenditures (Table A4). This finding is consistent with Lima et al. (2021), who found that the use of and exposure to liquid[13] and solid fuels contribute to a higher probability of incurring health care expenditures.

These distinct results for EP5 possibly stem from the fact that these families tend to live in areas where medical resources are scarce or difficult to access. Households living in these deprived areas often pay extremely low medical costs due to low-quality equipment and services and financial constraints. As noted by Fang et al. (2012), although there is no one-to-one correspondence between the cost and quality of care, they tend to be correlated. The lower OOP costs paid by rural residents than urban residents might be explained by the lower quality of care in rural areas (Fang et al., 2012).

Table 3 RE-TPM estimates of the impact of energy poverty on health care expenditures among Chinese adults aged 18+: 2012-2018 CFPS (marginal effects)

	(1) Total health care expenditures	(2) OOP health care expenditures	(3) Inpatient expenditures	(4) Other health care expenditures
Panel A: EP1				
EP1	325.913***	231.732***	221.121***	132.071***
	(55.067)	(42.653)	(60.144)	(21.680)
Controls	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes
Provincial FE	Yes	Yes	Yes	Yes
Observations	105,484	78,479	105,484	105,484

[13] Liquid fuels include domestic heating and lighting oil; such fuels are carbon-intensive energy alternatives similar to solid fuels (Lima et al., 2021).

Panel B: EP2				
EP2	358.354***	240.761***	248.907***	150.519***
	(57.535)	(44.922)	(62.557)	(22.628)
Controls	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes
Provincial FE	Yes	Yes	Yes	Yes
Observations	105,484	78,479	105,484	105,484
Panel C: EP4				
EP4	317.140***	202.592***	214.914***	137.308***
	(58.864)	(46.056)	(63.088)	(23.152)
Controls	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes
Provincial FE	Yes	Yes	Yes	Yes
Observations	105,484	78,479	105,484	105,484
Panel C: EP5				
EP5	52.031	71.636*	26.580	35.979*
	(52.399)	(39.794)	(56.021)	(20.353)
Controls	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes
Provincial FE	Yes	Yes	Yes	Yes
Observations	105,484	78,479	105,484	105,484
Panel D: EP6				
EP6	315.540***	224.487***	256.381***	121.786***
	(58.565)	(45.932)	(63.638)	(23.149)
Controls	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes
Provincial FE	Yes	Yes	Yes	Yes
Observations	105,484	78,479	105,484	105,484

Notes: The dependent variables are total health care expenditures, OOP health care expenditures, inpatient expenditures, and other health care expenditures. The controls include age, age squared, gender (1 = male, 0 = female), educational level (illiterate, primary school, middle school, high school, vocational school, and university or higher, with illiterate as the reference), employment status (1 = currently employed, 0 = otherwise), marital status (1 = married/living together, 0 = otherwise), location type (1 = urban, 0 = rural), medical insurance (1=yes, 0=no), household size, logged household income, wave dummies (with 2012 as the reference) and provincial dummies (with Beijing as the reference). For the second part of the GLM estimation, we use a gamma family and log links. Individual-level adjusted standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5.4.2 Alternative measures of health care expenditures

We also present the effects of EP on health care utilization using household-level expenditures[14]. Once again, EP is significantly associated with a higher probability of having any household health care (Table 4, Column 1) and a larger expenditure if there is any (Table 4, Column 2). Moreover, energy-poor households have approximately 955 yuan higher health care expenditures (16% of the average value of household health care expenditures) than non-energy-poor households (Table 4, Column 3).

Table 4 RE-TPM estimates of the impact of energy poverty on household health care expenditures among Chinese adults aged 18+: 2012-2018 CFPS

	(1)	(2)	(3)
	RE Probit	RE GLM	Marginal effects

[14] Household health care expenditures are household total direct health care expenditures (excluding that was reimbursed or reimbursable but including that was paid by or borrowed from relatives) in the previous year.

EP3	0.109***	0.168***	954.838***
	(0.034)	(0.026)	(141.301)
Constant	0.092	6.589***	-
	(0.202)	(0.162)	-
Controls	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes
Provincial FE	Yes	Yes	Yes
Observations	45970	45970	45970

Notes: The dependent variable is household health care expenditures. The controls include age, age squared, gender (1 = male, 0 = female), educational level (illiterate, primary school, middle school, high school, vocational school, and university or higher, with illiterate as the reference), employment status (1 = currently employed, 0 = otherwise), marital status (1 = married/living together, 0 = otherwise), location type (1 = urban, 0 = rural), medical insurance (1=yes, 0=no), household size, logged household income, wave dummies (with 2012 as the reference) and provincial dummies (with Beijing as the reference). For the second part of the GLM estimation, we use a gamma family and log link. Individual-level adjusted standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5.4.3 Energy poverty and health care expenditures: RE, zero-inflated Poisson, zero-inflated negative binomial and Tobit estimates

As our third robustness check, we introduce three alternative models: RE, zero-inflated Poisson and zero-inflated negative binomial models. The zero-inflated Poisson model assumes that positive outcomes come from a Poisson model, while the zero-inflated negative binomial model assumes that they are from a negative binomial model. Although these two models are usually applied for count data, they can also be used for semi-continuous variables. As shown in Table 5, once again, EP has a consistently positive and significant effect on health care expenditures. The marginal effects, however, based on RE, zero-inflated Poisson, and zero-inflated negative binomial models are considerably larger than those of the RE-TPM estimates (see Tables 1 and 5). This finding is primarily due to the differences in the assumed distribution of the second stage: zero-inflated Poisson assumes a Poisson distribution, but zero-inflated negative binomial assumes a negative binomial distribution, and our RE-TPM applies a gamma distribution. We use a modified Park test to confirm the appropriateness of the gamma family in our case (see Appendix Table A2). Moreover, since health care expenditures can be viewed as censored data with zero as the censored point, the Tobit model has been used in modeling health care expenditures[15] (Azorliade et al., 2022; Lin & Wei, 2022). Thus, we also use the Tobit model, and the results are similar to those of the RE-TPM (see Tables 1 and 5, Panel D).

Table 5 RE, zero-inflated Poisson, zero-inflated negative binomial and Tobit model estimates of the impact of energy poverty on health care expenditures among Chinese adults aged 18+ by sociodemographic characteristics: 2012-2018 CFPS (marginal effects)

	(1)	(2)	(3)	(4)

[15] As the Tobit model is sensitive to the normality and heteroskedasticity assumptions (Gregori et al., 2011), the most frequently used model in analyzing health care expenditures is the TPM. Thus, we apply only the RE-TPM in our baseline estimation.

	Total health care expenditures	OOP health care expenditures	Inpatient expenditures	Other health care expenditures
Panel A: RE				
EP3	446.202***	302.668***	203.042**	226.909***
	(137.699)	(113.773)	(100.529)	(76.860)
Controls	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes
Provincial FE	Yes	Yes	Yes	Yes
Observations	105484	78479	105484	105484
Panel B: Zero-inflated Poisson				
EP3	463.923***	297.312***	292.496***	233.108***
	(130.566)	(103.878)	(100.220)	(69.998)
Controls	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes
Provincial FE	Yes	Yes	Yes	Yes
Observations	105484	78479	105484	105484
Panel C: Zero-inflated negative binomial				
EP3	565.085***	360.099***	296.558***	242.245***
	(124.809)	(99.629)	(96.567)	(51.306)
Controls	Yes	Yes	Yes	Yes
Observations	105484	78479	105484	105484
Panel D: Tobit				
EP3	289.604***	181.818**	285.647***	140.988**
	(89.570)	(71.353)	(74.710)	(56.383)
Controls	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes
Provincial FE	Yes	Yes	Yes	Yes
Observations	105484	78479	105484	105484

Notes: The dependent variables are total health care expenditures, OOP health care expenditures, inpatient expenditures, and other health care expenditures. The controls include age, age squared, gender (1 = male, 0 = female), educational level (illiterate, primary school, middle school, high school, vocational school, and university or higher, with illiterate as the reference), employment status (1 = currently employed, 0 = otherwise), marital status (1 = married/living together, 0 = otherwise), location type (1 = urban, 0 = rural), medical insurance (1=yes, 0=no), household size, logged household income, wave dummies (with 2012 as the reference) and provincial dummies (with Beijing as the reference). Individual-level adjusted standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5.5 Heterogeneity analysis

To identify the most vulnerable group and deepen our understanding of the impact of EP on health care expenditures, we investigate the relationship by different sociodemographic characteristics.

Regarding gender, EP has larger marginal effects on total and other health care expenditures for females than for males (see Table 6, Panel A, Columns 1 and 4). The results are in accordance with Bertakis et al. (2000) and Oliveras, Artazcoz, et al. (2020), showing that the mean charges for primary and specialty care, diagnostic services, and annual total expenses are all significantly higher for women than for men (Bertakis et al., 2000). Additionally, females have a higher use of medications, such as psychotropic drugs and painkillers (Oliveras, Artazcoz, et al., 2020). Moreover, Oliveras, Artazcoz, et al. (2020) argue that EP increases the health inequalities between genders: women without EP generally have worse health outcomes than men without EP, and this situation is worsened for people living in EP. However, for males, EP has larger marginal effects on OOP and inpatient medical costs (see Panel A of Table 6, Columns 2 and 3). This result is possibly because different types of illness and the medical payment propensity vary by gender. For instance, Song and Bian (2014) investigate the gender differenced in inpatient health care use in China and show that there are significant differences between genders, observing a longer duration of hospitalization and higher inpatient expenditures among men. Although prior studies have confirmed higher health care service utilization for women than for men (Schlichthorst et al., 2016; van den Bussche et al., 2011; Wang et al., 2018), our results suggest that this gender difference may also depend on various types of health care expenditures.

Regarding urban–rural heterogeneity, the results show that the impact of EP on urban residents' medical expenses is significantly higher than that on rural residents' medical expenses (see Table 6, Panel B). Our results show that in China, living in EP significantly increases the probability of having any medical expenditure for rural residents but not for urban residents (see Appendix Table A6). Nonetheless, compared to rural residents, the positive effects of EP on the amount of medical expenses are much larger for urban residents (see Appendix Table A6). This finding indicates that the higher marginal effects of EP for urban residents are mainly attributable to differences in affordability and health awareness (Molla et al., 2017).

For regional differences, the marginal effects of EP on medical expenses for residents living in Central and Western China are significantly higher than they for those living in Eastern and Northeast China (see Table 6, Panel C). This regional heterogeneity may be attributable to a recognized disparity in economic growth and development (Lin & Wang, 2020) in which the central and western regions are poorer than the eastern and northwestern regions. Their financial revenue may thus be lower, thereby leading to lower public health expenditures and reduced health care availability. Prior studies have shown that the density of health facilities, health workers and hospital beds is much lower in Western and Central China than in Eastern China (Pan & Shallcross, 2016; T. Zhang et al., 2017). This is also the case for the average health status (Sun et al., 2011), which may lead to a higher likelihood of health care utilization (see Table A6, Panel C, Columns 1, 3, 5, 7). The higher medical expenses in the central and western regions stem from the fact that delivering health care in less economically developed areas is costly (see Table A6, Panel C, Columns 2, 4, 6, 8).

Table 6 RE-TPM estimates of the impact of energy poverty on health care expenditures among Chinese adults aged 18+ by sociodemographic characteristics: 2012-2018 CFPS (marginal effects)

	(1) Total health care expenditures	(2) OOP health care expenditures	(3) Inpatient expenditures	(4) Other health care expenditures
Panel A: By gender				
Female				
EP3	313.289***	139.622*	194.587**	136.415***
	(88.157)	(75.238)	(89.016)	(39.089)
Controls	Yes	Yes	Yes	Yes
Observations	53833	39937	53833	53833
Male				
EP3	288.678	251.221***	281.189**	87.789
	(9.24e+09)	(79.400)	(125.987)	(1,418.537)
Controls	Yes	Yes	Yes	Yes
Observations	51651	38542	51651	51651
Panel B: Rural versus urban				
Rural				
EP3	279.167***	179.813***	253.223	102.531*
	(73.401)	(65.287)	(11266.472)	(54.434)
Controls	Yes	Yes	Yes	Yes
Observations	55205	40510	55205	55205
Urban				
EP3	325.001**	247.508***	114.242	137.230***
	(130.582)	(95.670)	(134.824)	(49.533)
Controls	Yes	Yes	Yes	Yes
Observations	50279	37969	50279	50279
Panel C: By region				
East				
EP3	7.388	-28.656	7.636	41.985
	(145.999)	(109.579)	(170.697)	(57.827)
Controls	Yes	Yes	Yes	Yes
Observations	34112	25238	34112	34112
Central				
EP3	558.959***	455.142***	436.646***	159.193***
	(138.742)	(119.197)	(154.026)	(48.808)
Controls	Yes	Yes	Yes	Yes
Observations	26427	19650	26427	26427
West				
EP3	336.403***	262.248***	259.235**	127.486***
	(99.196)	(83.559)	(101.805)	(42.474)
Controls	Yes	Yes	Yes	Yes
Observations	29953	22517	29953	29953
Northeast				
EP3	166.772	-30.529	17.647	50.847
	(185.133)	(154.061)	(179.073)	(73.538)
Controls	Yes	Yes	Yes	Yes
Observations	14992	11074	14992	14992

Notes: The dependent variables are total health care expenditures, OOP health care expenditures, inpatient expenditures, and other health care expenditures. The controls include age, age squared, gender (1 = male, 0 = female), educational level (illiterate, primary school, middle school, high school, vocational school, and university or higher, with illiterate as the reference), employment status (1 = currently employed, 0 = otherwise), marital status (1 = married/living together, 0 = otherwise), location type (1 = urban, 0 = rural), medical insurance (1=yes, 0=no), household size, logged household income, wave dummies (with 2012 as the reference) and provincial dummies (with Beijing as the reference). Individual-level adjusted standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5.6 Underlying mechanisms

We adopt four structural equation models to test our two hypotheses that EP increases health care expenditures by deteriorating individuals' health (H1) and by crowding out expenditures on food and other daily necessities (H2). To obtain a fully ranked fitted model and test the goodness of fit, we rescale health care expenditures as well as food and other daily necessities by dividing by 1,000. Although there is no uniform goodness-of-fit criterion for SEM, Schermelleh-Engel et al. (2003) recommended the following rule of thumb for an acceptable fit: root mean square error of approximation (RMSEA) < 0.08, standardized root mean square residual (SRMR) < 0.1, and comparative fit index (CFI) > 0.95. The results of the goodness-of-fit test confirm the appropriateness of our four structural equation models (see Table 7)[16].

The SEM results validate the two hypotheses and accord with our baseline estimates, confirming that living in EP results in higher health care expenses, irrespective of the type of health care cost (see Table 8 and Figures 7-10). Specifically, EP decreases the amount of households' expenditures on food and other daily necessities, which in turn may directly decrease health care spending or indirectly increase it by deteriorating SRH. Additionally, living in EP worsens respondents' SRH, thereby inducing higher health care expenses. Overall, approximately 4%-6% of the effect of EP on health care expenditures is mediated by expenditures on food and other daily necessities, and approximately 16%-24% is mediated by health (Table 9), suggesting that health is an important channel for the linkage between EP and health care spending[17].

Table 7 Goodness of fit by different health care expenditures: SEM with controls

Dependent variable	Independent variable	RMSEA	CFI	SRMR
Total health care expenditures	EP3	0.075	0.904	0.003
OOP health care expenditures	EP3	0.093	0.884	0.004
Inpatient expenditures	EP3	0.075	0.904	0.003
Other health care expenditures	EP3	0.075	0.899	0.003

Notes: The dependent variables are total health care expenditures, OOP health care expenditures, inpatient expenditures, and other health care expenditures. OOP health care expenditures are available only in 2014, 2016, and 2018. The controls include age, age squared, gender (1 = male, 0 = female), educational level (illiterate, primary school, middle school, high school, vocational school, and university or higher, with illiterate as the reference), employment status (1 = currently employed, 0 = otherwise), marital status (1 = married/living together, 0 = otherwise), household size, location type (1 = urban, 0 = rural), medical insurance (1=Yes, 0=No), logged household income, wave dummies (with 2012 as the reference) and provincial

[16] The CFI values in Table 7 are approximately 0.9, which is acceptable for SEM.

[17] As a robustness check, we redefine individuals' health status using interviewer-rated health status (ranging from 1=very poor to 7=very good). We rerun the SEM estimates, and the results are similar to those in Table 8, with approximately 3%-5% of the effect of EP on health care expenditures being mediated by spending on food and other daily necessities and approximately 16%-30% being mediated by health. The detailed results are available from the authors upon request.

dummies (with Beijing as the reference). Individual-level adjusted standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

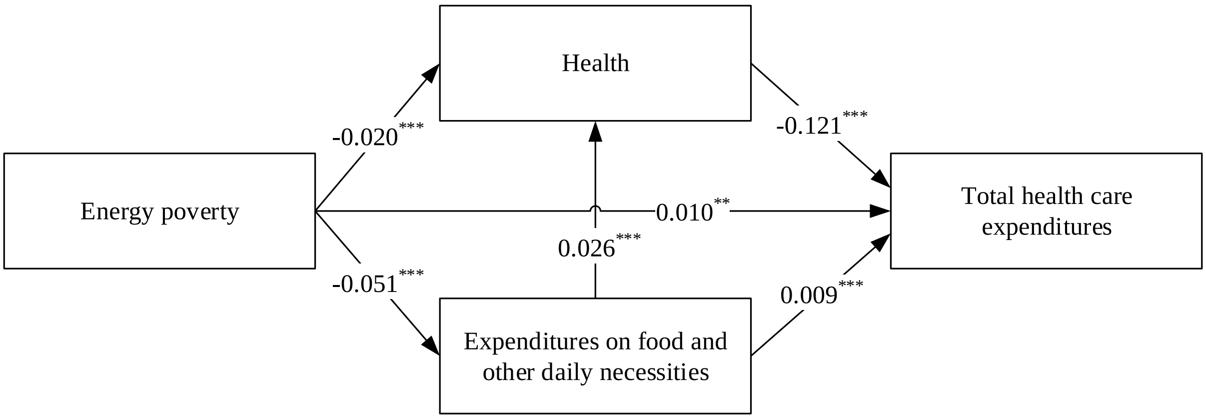

Figure 7 Underlying mechanisms through which energy poverty impacts total health care expenditures

Notes: SEM estimates with all coefficients standardized. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

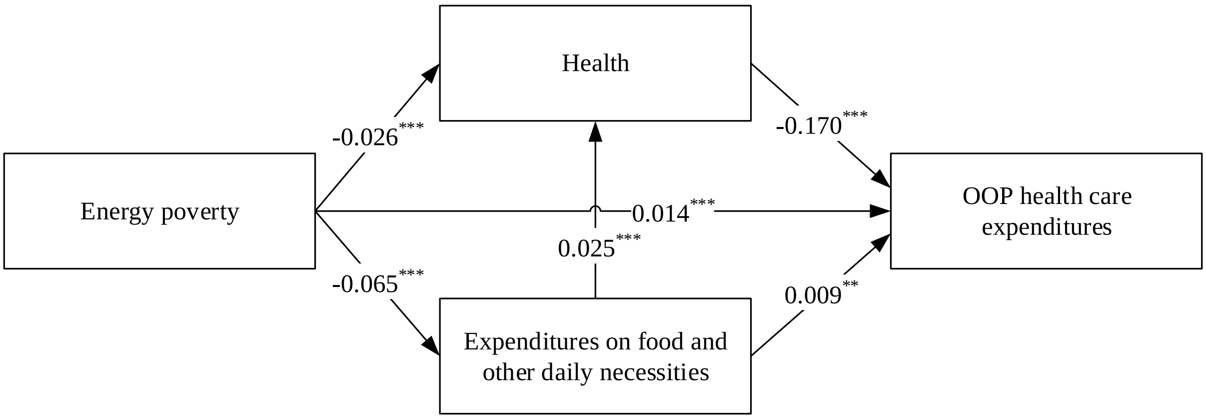

Figure 8 Underlying mechanisms through which energy poverty impacts OOP health care expenditures

Notes: SEM estimates with all coefficients standardized. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

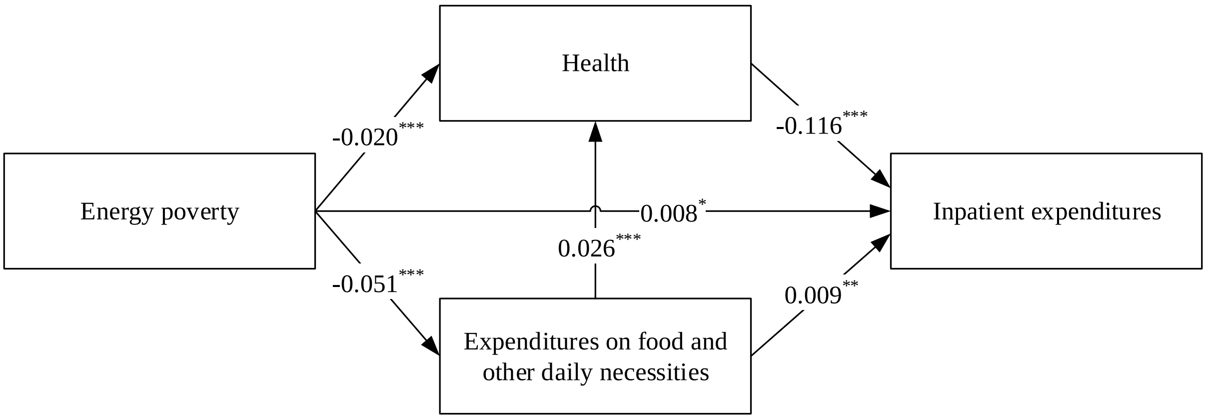

Figure 9 Underlying mechanisms through which energy poverty impacts inpatient expenditures

Notes: SEM estimates with all coefficients standardized. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

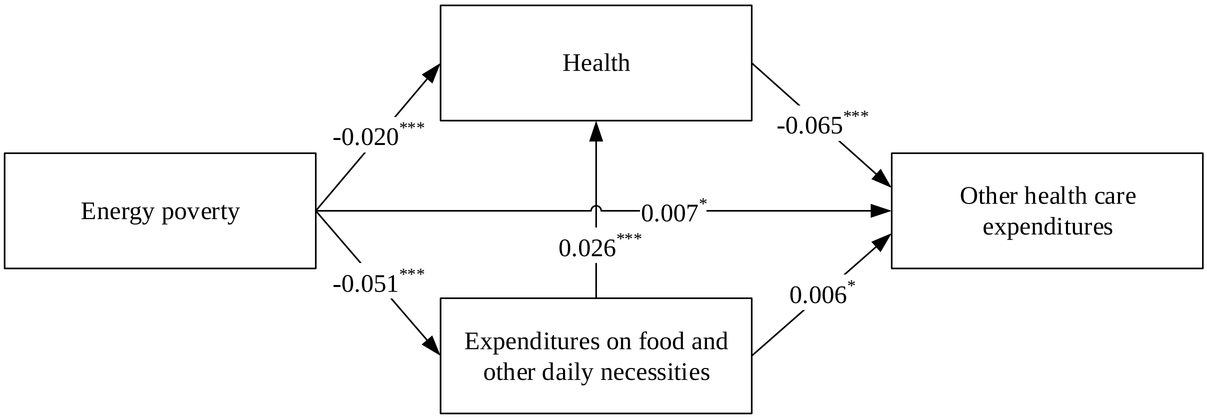

Figure 10 Underlying mechanisms through which energy poverty impacts other health care expenditures

Notes: SEM estimates with all coefficients standardized. * p < 0.1, ** p < 0.05, *** p < 0.01.

Table 8 Path analysis by different health care expenditures: SEM with controls

Dependent variable	Independent variable	Total effect	Direct effect	Indirect effect
Panel A: Total health care expenditures				
Food and other daily necessities	EP3	-0.051***	-0.051***	
SRH	Food and other daily necessities	0.026***	0.026***	
	EP3	-0.022***	-0.020***	-0.001***
Total health care expenditures	Food and other daily necessities	0.006*	0.009***	-0.003***
	SRH	-0.121***	-0.121***	
	EP3	0.012***	0.010**	0.002***
Panel B: OOP health care expenditures				
Food and other daily necessities	EP3	-0.065***	-0.065***	
SRH	Food and other daily necessities	0.025***	0.025***	
	EP3	-0.028***	-0.026***	-0.002***
OOP health care expenditures	Food and other daily necessities	0.004	0.009**	-0.004***
	SRH	-0.170***	-0.170***	
	EP3	0.018***	0.014***	0.004***
Panel C: Inpatient expenditures				
Food and other daily necessities	EP3	-0.051***	-0.051***	
SRH	Food and other daily necessities	0.026***	0.026***	
	EP3	-0.022***	-0.020***	-0.001***
Inpatient expenditures	Food and other daily necessities	0.005	0.009**	-0.003***
	SRH	-0.116***	-0.116***	
	EP3	0.010**	0.008*	0.002***
Panel D: Other health care expenditures				
Food and other daily necessities	EP3	-0.051***	-0.051***	
SRH	Food and other daily necessities	0.026***	0.026***	
	EP3	-0.022***	-0.020***	-0.001***
Other health care expenditures	Food and other daily necessities	0.004	0.006*	-0.002***
	SRH	-0.065***	-0.065***	
	EP3	0.008**	0.007*	0.001***

Notes: The dependent variables are total health care expenditures, OOP health care expenditures, inpatient expenditures, and other health care expenditures. OOP health care expenditures are available only in 2014, 2016, and 2018. The controls include age, age squared, gender (1 = male, 0 = female), educational level (illiterate, primary school, middle school, high school, vocational school, and university or higher, with illiterate as the reference), employment status (1 = currently employed, 0 = otherwise), marital status (1 = married/living together, 0 = otherwise), household size, location type (1 = urban, 0 = rural), medical insurance (1=yes, 0=no), logged household income, wave dummies (with 2012 as the reference) and provincial dummies (with Beijing as the reference). Individual-level adjusted standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 9 Indirect effects of energy poverty on health care expenditures and their proportion to the total effect: SEM with controls

Mediators	Indirect effect	Standard error	Z value	Indirect effect/total effect
Panel A: Total health care expenditures				
Food and other daily necessities	-0.000***	0.000	-2.766	0.050
SRH	0.002***	0.000	6.678	0.193
Panel B: OOP health care expenditures				
Food and other daily necessities	-0.001**	0.000	-2.135	0.042
SRH	0.004***	0.001	7.337	0.239
Panel C: Inpatient expenditures				
Food and other daily necessities	-0.000**	0.000	-2.497	0.059
SRH	0.002***	0.000	6.668	0.230
Panel D: Other health care expenditures				
Food and other daily necessities	-0.000*	0.000	-1.650	0.043
SRH	0.001***	0.000	6.416	0.159

Notes: The dependent variables are total health care expenditures, OOP health care expenditures, inpatient expenditures, and other health care expenditures. OOP health care expenditures are available only in 2014, 2016, and 2018. The controls include age, age squared, gender (1 = male, 0 = female), educational level (illiterate, primary school, middle school, high school, vocational school, and university or higher, with illiterate as the reference), employment status (1 = currently employed, 0 = otherwise), marital status (1 = married/living together, 0 = otherwise), household size, location type (1 = urban, 0 = rural), medical insurance (1=yes, 0=no), logged household income, wave dummies (with 2012 as the reference) and provincial dummies (with Beijing as the reference). Individual-level adjusted standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

6. Conclusions

Although a large body of literature has examined the EP-health relationship in various countries (Banerjee et al., 2021; Churchill & Smyth, 2021; Kahouli, 2020; Z. Zhang et al., 2021), evidence on how EP affects health care expenditures remains scarce. Our study not only extends the literature on EP-health/health care expenditures but also investigates the underlying mechanisms and heterogeneity across different sociodemographic characteristics.

Our findings confirm that EP leads to higher levels of total, OOP, inpatient and other health care expenditures. Our heterogeneity analysis further demonstrates that the positive impact of EP on health care spending is much stronger for females, those living in urban areas, and those living in the less developed central and western regions of China. Lastly, our mechanism analysis shows that approximately 4%-6% of the effect of EP on health care expenditures is mediated by spending on food and other daily necessities and that approximately 16%-24% is mediated by health.

These findings have important policy implications. China already has the world's largest aging population and is one of the fastest aging societies worldwide (Nie, Li, Zhang, et al., 2021). Additionally, the number of adults aged 60 and over in China is projected to reach 491.5 million (36.5% of the total population) by 2050 (United Nations, 2020). Such continued rapid aging suggests a growing burden of elderly individuals, who need financial support and health care spending. To contain the rising burden on medical expenditures, in 2015, the Chinese government proposed "Three Medical Linkages" (codevelopment of the medical insurance, hospital and drug industries). The reform is promoted from the medical supply side, which aims to control physicians' demand-inducing behavior through improvements in medical payment practices. At the same year, the Chinese government proposed "Several Opinions on Controlling Unreasonable Growth of Medical Costs in Public Hospitals". This policy requires the determination and quantification of medical cost growth in each region, regular public disclosure of key medical cost monitoring indicators. Current tools for curbing health care spending in China are mainly focused on the supply side. However, our findings provide a way of mitigating the excessive increase in medical costs from the demand side. Combating EP, including alleviating energy cost burden and investing more in clean energy (e.g. constructing clean energy infrastructure) to improve energy accessibility, will improve people's health and reduce their burden on health care expenditures. As such mitigating EP might be an effective way to curb the increasing burden on health care spending. Policy makers should pay more heed for vulnerable groups, such as women and those residing in less economically developed regions. In addition, since our findings confirm that, when disposal income is certain, EP has a crowding-out impact on expenditures on food and other daily essentials and then induces health care expenditures, it is vitally important for government to provide certain subsidies for aforementioned susceptible groups to guarantee their daily necessities (e.g. food and clothing) and promote their use of clean energy, thereby improving their health and well-being in future.

Conflicts of interest

None.

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Appendix:

Table A1 Descriptive statistics of Chinese adults aged 18+: 2012–2018 CFPS

Variables	Obs.	Mean/ percentage	S.D.	Min	Max
Dependent variables					
Total health care expenditures (yuan/year) [a]	105484	3142.011	16804.349	0	3650506
OOP health care expenditures (yuan/year) [b]	78479	2131.981	8453.468	0	510000
Inpatient expenditures (yuan/year)	105484	1687.881	10512.477	0	597347
Other health care expenditures (yuan/year)	105484	1447.260	12336.176	0	3650506
Household health care expenditures (yuan/year) [c]	104875	5927.403	18348.498	0	1326696
EP measures					
EP1	105484	0.247	0.431	0	1
EP2	105484	0.222	0.416	0	1
EP3	105484	0.166	0.372	0	1
EP4	105484	0.138	0.345	0	1
EP5	105484	0.349	0.477	0	1
EP6	105484	0.218	0.413	0	1
Individual characteristics					
Age	105484	47.976	15.747	18	90
Gender	105484	0.490	0.500	0	1
Educational level					
Illiterate	105484	0.281	0.450	0	1
Primary school	105484	0.212	0.409	0	1
Middle school	105484	0.275	0.446	0	1
High school	105484	0.138	0.345	0	1
Vocational school	105484	0.054	0.227	0	1
University or higher	105484	0.039	0.193	0	1
Currently employed	105484	0.737	0.440	0	1
Married/living together	105484	0.844	0.363	0	1
Medical insurance	105484	0.910	0.286	0	1
Urban	105484	0.477	0.499	0	1
Regions					
East	105484	0.323	0.468	0	1
Middle	105484	0.251	0.433	0	1
West	105484	0.284	0.451	0	1
Northeast	105484	0.142	0.349	0	1
Household characteristics					
Household size	105484	4.269	1.998	1	21
Log(Household income)	105484	10.647	1.192	0	16
Energy expenditure (yuan/year) [d]	105484	3026.700	3312.125	0	84970
Mediators					
Spending on food and other daily necessities [e]	105368	20374.365	23891.892	0	873814
Self-reported health (SRH)					

Poor	105484	0.174	0.379	0	1
Fair	105484	0.168	0.374	0	1
Good	105484	0.366	0.482	0	1
Very good	105484	0.173	0.378	0	1
Excellent	105484	0.119	0.324	0	1

Source: 2012-2018 CFPS.

[a] Total health care expenditures include inpatient expenditures and other health care expenditures.

[b] OOP health care expenditures are the out-of-pocket expenditures of total health care costs last year, excluding reimbursed or will be reimbursed cost from total health care expenditures. The information on OOP health care expenditures is only available in year of 2014, 2016, and 2018.

[c] Household health care expenditures are household total direct health care expenditures (excluding that was reimbursed or reimbursable but including that was paid by or borrowed from relatives) in the previous year.

[d] Household energy expenditures include water, electricity, fuel and heating costs.

[e] Expenditures on food and other daily necessities include food expenditure (food, snacks, beverage, cigarettes and alcohol, including having meals at home and eating out), and daily used commodities and necessities expenditure (e.g., detergent, soap, toothpaste, toothbrush, etc.).

Table A2 Box-Cox test and modified Park test for RE-TPM

	(1) Total health care expenditures	(2) OOP health care expenditures	(3) Inpatient expenditures	(4) Other health care expenditures
Box-Cox test	-0.026***	-0.016***	0.010**	0.014***
	(0.002)	(0.002)	(0.005)	(0.002)
Modified Park test	1.951***	1.914***	2.250***	1.905***
	(0.011)	(0.018)	(0.043)	(0.014)
Controls	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes
Provincial FE	Yes	Yes	Yes	Yes
Observations	75956	52789	12360	72926

Notes: The dependent variables are total health care expenditures, OOP health care expenditures, inpatient expenditures, and other health care expenditures only for positive observations. The controls include age, age squared, gender (1 = male, 0 = female), educational level (illiterate, primary school, middle school, high school, vocational school, and university or higher, with illiterate as the reference), employment status (1 = currently employed, 0 = otherwise), marital status (1 = married/living together, 0 = otherwise), household size, location type (1 = urban, 0 = rural), medical insurance (1=yes, 0=no), logged household income, wave dummies (with 2012 as the reference) and provincial dummies (with Beijing as the reference). Standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Although significant from 0, all the parameters in Box-Cox test are close to 0, which justifies the use of the log model as the best approximation (Deb et al., 2017). In modified Park test, the coefficients are all close to 2, suggesting the appropriateness of using a gamma distribution.

Table A3 RE-TPM estimates of the impact of energy poverty on health care expenditures among Chinese adults aged 18+: 2012-2018 CFPS (marginal effects)

	(1) Total health care expenditures	(2) OOP health care expenditures	(3) Inpatient expenditures	(4) Other health care expenditures
EP3	305.214***	198.691***	229.606***	112.808***
	(68.157)	(54.698)	(73.959)	(26.907)
Controls	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes
Provincial FE	Yes	Yes	Yes	Yes
Observations	105484	78479	105484	105484

Notes: The dependent variables are total health care expenditures, OOP health care expenditures, inpatient expenditures, and other health care expenditures. The controls include age, age squared, gender (1 = male, 20 = female), educational level (illiterate, primary school, middle school, high school, vocational school, and university or higher, with illiterate as the reference), employment status (1 = currently employed, 0 = otherwise), marital status (1 = married/living together, 0 = otherwise), household size, location type (1 = urban, 0 = rural), medical insurance (1=yes, 0=no), logged household income, wave dummies (with 2012 as the reference) and provincial dummies (with Beijing as the reference). Individual-level adjusted standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A4 RE-TPM estimates of the impact of energy poverty on health care expenditures among Chinese adults aged 18+: 2012-2018 CFPS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Total health care expenditures		OOP health care expenditures		Inpatient expenditures		Other health care expenditures	
	RE Probit	RE GLM	RE Probit	RE GLM	RE Probit	RE GLM	RE Probit	RE GLM
Panel A: EP1								
EP1	0.012	0.104***	0.011	0.109***	0.078***	0.040	0.006	0.093***
	(0.015)	(0.017)	(0.017)	(0.020)	(0.017)	(0.030)	(0.014)	(0.015)
Constant	0.222**	6.471***	-0.054	6.469***	-2.663***	8.551***	0.054	6.345***
	(0.113)	(0.141)	(0.129)	(0.157)	(0.141)	(0.265)	(0.109)	(0.123)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	105484	105484	78479	78479	105484	105484	105484	105484
Panel B: EP2								
EP2	0.006	0.116***	-0.002	0.117***	0.069***	0.069**	0.004	0.107***
	(0.016)	(0.018)	(0.018)	(0.021)	(0.018)	(0.031)	(0.015)	(0.015)
Constant	0.240**	6.447***	-0.019	6.458***	-2.635***	8.478***	0.060	6.316***
	(0.113)	(0.141)	(0.129)	(0.157)	(0.141)	(0.265)	(0.109)	(0.123)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	105484	105484	78479	78479	105484	105484	105484	105484
Panel C: EP4								
EP4	0.005	0.103***	0.017	0.093***	0.072***	0.044	0.009	0.096***
	(0.016)	(0.019)	(0.019)	(0.021)	(0.019)	(0.031)	(0.015)	(0.016)
Constant	0.248**	6.637***	-0.045	6.653***	-2.535***	8.611***	0.060	6.488***
	(0.107)	(0.135)	(0.123)	(0.150)	(0.135)	(0.255)	(0.104)	(0.118)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	105484	105484	78479	78479	105484	105484	105484	105484
Panel D: EP5								
EP5	0.062***	0.003	0.058***	0.020	0.021	-0.009	0.066***	0.007
	(0.014)	(0.017)	(0.016)	(0.018)	(0.016)	(0.028)	(0.013)	(0.014)
Constant	0.190*	6.743***	-0.086	6.752***	-2.487***	8.667***	0.002	6.583***
	(0.107)	(0.135)	(0.122)	(0.149)	(0.135)	(0.255)	(0.103)	(0.117)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	105484	105484	78479	78479	105484	105484	105484	105484
Panel E: EP6								
EP6	0.027*	0.097***	0.023	0.102***	0.080***	0.059*	0.024	0.081***
	(0.016)	(0.018)	(0.019)	(0.021)	(0.018)	(0.031)	(0.016)	(0.016)
Constant	0.185	6.495***	-0.085	6.496***	-2.665***	8.502***	0.009	6.383***
	(0.113)	(0.142)	(0.130)	(0.158)	(0.142)	(0.265)	(0.110)	(0.124)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	105484	105484	78479	78479	105484	105484	105484	105484

Notes: The dependent variables are total health care expenditures, OOP health care expenditures, inpatient expenditures, and other health care expenditures. The controls include age, age squared, gender (1 = male, 0 = female), educational level (illiterate, primary school, middle school, high school, vocational school, and university or higher, with illiterate as the reference), employment status (1 = currently employed, 0 = otherwise), marital status (1 = married/living together, 0 = otherwise), household size, location type (1 = urban, 0 = rural), medical insurance (1=Yes, 0=No), logged household income, wave dummies (with 2012 as the reference) and provincial dummies (with Beijing as the reference). For the second part of the GLM estimation, we use a gamma family and log link. Individual-level adjusted standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A5 RE, Zero-inflated Poisson, zero-inflated negative binomial and Tobit model estimates of the impact of energy poverty on health care expenditures among Chinese adults aged 18+ by sociodemographic characteristics: 2012-2018 CFPS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Total health care expenditures		OOP health care expenditures		Inpatient expenditures		Other health care expenditures	
	Probit	**GLM**	**Probit**	**GLM**	**Probit**	**GLM**	**Probit**	**GLM**
Panel A: RE								
EP3	-	446.202***	-	302.668***	-	203.042**	-	226.909***
	-	(137.699)	-	(113.773)	-	(100.529)	-	(76.860)
Constant	-	4774.249***	-	1886.744***	-	762.517	-	3891.357***
	-	(1689.360)	-	(720.048)	-	(1143.967)	-	(1050.299)
Controls	-	Yes	-	Yes	-	Yes	-	Yes
Wave FE	-	Yes	-	Yes	-	Yes	-	Yes
Provincial FE	-	Yes	-	Yes	-	Yes	-	Yes
Observations	-	105484	-	78479	-	105484	-	105484
Panel B: Zero-inflated Poisson								
EP3	-0.021	0.139***	-0.001	0.139***	-0.071***	0.064	-0.015	0.154***
	(0.016)	(0.040)	(0.018)	(0.048)	(0.018)	(0.052)	(0.015)	(0.045)
Constant	-0.149	7.257***	0.022	7.318***	2.329***	9.001***	-0.044	7.720***
	(0.096)	(0.353)	(0.107)	(0.319)	(0.121)	(0.346)	(0.094)	(0.482)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Provincial FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	105484	105484	78479	78479	105484	105484	105484	105484
Panel C: Zero-inflated negative binomial								
EP3	-0.016	0.174***	0.002	0.170***	-0.071***	0.067	-0.013	0.162***
	(0.017)	(0.039)	(0.019)	(0.046)	(0.018)	(0.050)	(0.016)	(0.034)
Constant	-0.236**	7.175***	-0.020	7.362***	2.329***	8.974***	-0.066	7.370***
	(0.102)	(0.255)	(0.111)	(0.266)	(0.121)	(0.323)	(0.096)	(0.259)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Provincial FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	105484	105484	78479	78479	105484	105484	105484	105484
Panel D: Tobit								

EP3	-	620.291***	-	387.800**	-	2646.206***	-	328.086**
	-	(199.526)	-	(152.596)	-	(692.526)	-	(139.087)
Constant	-	-4336.551**	-	-3901.959***	-	-8.76e+04***	-	-3183.640
	-	(2096.314)	-	(953.213)	-	(5838.058)	-	(2259.989)
Controls	-	Yes	-	Yes	-	Yes	-	Yes
Wave FE	-	Yes	-	Yes	-	Yes	-	Yes
Provincial FE	-	Yes	-	Yes	-	Yes	-	Yes
Observations	-	105484	-	78479	-	105484	-	105484

Notes: The dependent variables are total health care expenditures, OOP health care expenditures, inpatient expenditures, and other health care expenditures. The controls include age, age squared, gender (1 = male, 0 = female), educational level (illiterate, primary school, middle school, high school, vocational school, and university or higher, with illiterate as the reference), employment status (1 = currently employed, 0 = otherwise), marital status (1 = married/living together, 0 = otherwise), household size, location type (1 = urban, 0 = rural), medical insurance (1=yes, 0=no), logged household income, wave dummies (with 2012 as the reference) and provincial dummies (with Beijing as the reference). Individual-level adjusted standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A6 RE-TPM estimates of the impact of energy poverty on health care expenditures among Chinese adults aged 18+ by sociodemographic characteristics: 2012-2018 CFPS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Total health care expenditures		OOP health care expenditures		Inpatient expenditures		Other health care expenditures	
	RE Probit	RE GLM	RE Probit	RE GLM	RE Probit	RE GLM	RE Probit	RE GLM
Panel A: By gender								
Female								
EP3	0.014	0.099***	-0.021	0.069**	0.076***	0.036	0.012	0.086***
	(0.027)	(0.028)	(0.032)	(0.033)	(0.029)	(0.047)	(0.026)	(0.024)
Constant	0.054	6.688***	-0.139	6.823***	-2.243***	8.355***	-0.162	6.310***
	(0.169)	(0.191)	(0.192)	(0.213)	(0.188)	(0.331)	(0.161)	(0.166)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	53833	53833	39937	39937	53833	53833	53833	53833
Male								
EP3	0.025	0.090***	0.012	0.128***	0.081**	0.059	0.017	0.066**
	(0.026)	(0.034)	(0.031)	(0.040)	(0.032)	(0.058)	(0.025)	(0.028)
Constant	0.094	6.065***	-0.104	5.961***	-3.448***	9.299***	-0.007	6.252***
	(0.160)	(0.218)	(0.186)	(0.245)	(0.223)	(0.459)	(0.156)	(0.191)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	51651	51651	38542	38542	51651	51651	51651	51651
Panel B: Rural versus urban								
Rural								
EP3	0.059**	0.095***	0.010	0.089***	0.091***	0.071	0.049**	0.070***
	(0.025)	(0.027)	(0.029)	(0.032)	(0.028)	(0.049)	(0.024)	(0.023)
Constant	-0.509**	5.591***	-0.776***	6.007***	-8.528	4.916***	-0.645***	5.757***
	(0.253)	(0.319)	(0.270)	(0.339)	(.)	(0.275)	(0.248)	(0.322)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	55205	55205	40510	40510	55205	55205	55205	55205
Urban								
EP3	-0.028	0.098***	-0.014	0.119***	0.047	0.004	-0.027	0.096***
	(0.029)	(0.036)	(0.035)	(0.042)	(0.035)	(0.057)	(0.028)	(0.030)
Constant	0.696***	6.627***	0.532***	6.662***	-2.435***	8.634***	0.507***	6.407***
	(0.155)	(0.193)	(0.181)	(0.222)	(0.193)	(0.321)	(0.149)	(0.167)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	50279	50279	37969	37969	50279	50279	50279	50279
Panel C: By region								
East								
EP3	-0.091**	0.023	-0.083*	0.009	-0.009	0.016	-0.071**	0.046
	(0.036)	(0.042)	(0.043)	(0.051)	(0.042)	(0.076)	(0.035)	(0.034)
Constant	0.875***	6.597***	0.657***	6.860***	-1.933***	8.224***	0.554***	6.213***
	(0.177)	(0.218)	(0.211)	(0.270)	(0.218)	(0.399)	(0.171)	(0.185)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	34112	34112	25238	25238	34112	34112	34112	34112
Middle								
EP3	0.063*	0.178***	0.067	0.200***	0.083*	0.173**	0.037	0.123***
	(0.038)	(0.046)	(0.045)	(0.054)	(0.045)	(0.077)	(0.036)	(0.039)
Constant	0.326*	5.139***	-0.104	5.111***	-2.633***	6.201***	0.239	5.299***
	(0.175)	(0.216)	(0.209)	(0.253)	(0.214)	(0.353)	(0.165)	(0.185)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	26427	26427	19650	19650	26427	26427	26427	26427
West								
EP3	0.094***	0.109***	0.026	0.129***	0.137***	0.027	0.069**	0.084***
	(0.035)	(0.036)	(0.040)	(0.041)	(0.037)	(0.059)	(0.033)	(0.032)
Constant	0.142	7.001***	0.065	7.488***	-2.549***	7.484***	-0.191	7.057***
	(0.438)	(0.426)	(0.441)	(0.440)	(0.515)	(0.421)	(0.412)	(0.431)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	29953	29953	22517	22517	29953	29953	29953	29953

Northeast								
EP3	-0.017	0.055	-0.064	0.006	0.073	-0.077	-0.012	0.038
	(0.045)	(0.055)	(0.052)	(0.066)	(0.055)	(0.087)	(0.043)	(0.047)
Constant	0.625**	5.623***	0.197	5.744***	-2.531***	8.037***	0.417*	5.401***
	(0.245)	(0.313)	(0.299)	(0.388)	(0.319)	(0.492)	(0.234)	(0.273)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14992	14992	11074	11074	14992	14992	14992	14992

Notes: The dependent variables are total health care expenditures, OOP health care expenditures, inpatient expenditures, and other health care expenditures. The controls include age, age squared, gender (1 = male, 0 = female), educational level (illiterate, primary school, middle school, high school, vocational school, and university or higher, with illiterate as the reference), employment status (1 = currently employed, 0 = otherwise), marital status (1 = married/living together, 0 = otherwise), household size, location type (1 = urban, 0 = rural), medical insurance (1=Yes, 0=No), logged household income, wave dummies (with 2012 as the reference) and provincial dummies (with Beijing as the reference). For the second part of the GLM estimation, we use a gamma family and log link. Individual-level adjusted standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A7 Descriptive statistics of Chinese adults aged18+ by EP3: 2012-2018 CFPS

Variables	EP3=0 (Obs.= 87985)		EP3=1 (Obs.= 17499)		Two sample T-test
	Mean/ Percentage	S.D.	Mean/ Percentage	S.D.	t
Total health care expenditures	3083.960	12632.869	3433.892	29995.846	-2.516**
OOP health care expenditures	2066.511	8132.866	2522.495	10149.384	-5.300***
Inpatient expenditures	1678.951	10612.738	1732.784	9993.300	-0.619
Other health care expenditures	1397.162	5155.838	1699.152	27993.795	-2.958***
Age	47.246	15.570	51.644	16.117	-33.922***
Gender	0.492	0.500	0.476	0.499	4.016***
Primary school	0.207	0.405	0.239	0.426	-9.410***
Middle school	0.283	0.451	0.232	0.422	13.973***
High school	0.149	0.356	0.086	0.281	21.879***
Vocational school	0.062	0.241	0.016	0.125	24.673***
University or higher	0.045	0.208	0.007	0.081	24.240***
Currently employed	0.747	0.435	0.689	0.463	15.856***
Married/living together	0.849	0.358	0.816	0.387	10.835***
Urban	0.498	0.500	0.367	0.482	31.870***
Medical insurance	0.913	0.282	0.899	0.302	5.989***
Household size	4.368	1.998	3.768	1.919	36.515***
Log(household income)	10.993	0.847	8.908	1.154	278.257***

Notes: EP3 is defined as a total household energy expenditure over 10% of income, and an income below the third decile of the household income distribution. The observations of OOP health care expenditures are 67211 for EP3=0 and 11268 for EP3=1, respectively. The significance of the changes is based on independent *t*-tests. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A8 Univariate imbalance and multivariate L1 distance before and after CEM

Univariate imbalance: before CEM							
Variables	L1 before CEM	mean	min	25%	50%	75%	max
Age	0.131	4.398	0	6	5	5	0
Gender	0.017	-0.017	0	0	0	0	0
Primary school	0.032	0.032	0	0	0	0	0
Middle school	0.052	-0.052	0	0	0	-1	0
High school	0.062	-0.062	0	0	0	0	0
Vocational school	0.046	-0.046	0	0	0	0	0
University or higher	0.039	-0.039	0	0	0	0	0
Currently employed	0.058	-0.058	0	0	0	0	0
Married/living together	0.033	-0.033	0	0	0	0	0
Urban	0.131	-0.131	0	0	0	0	0
Medical insurance	0.014	-0.014	0	0	0	0	0
Household size	0.155	-0.600	0	-1	-1	-1	-6
Log(household income)	0.829	-2.085	-4.905	-2.202	-1.810	-1.700	-5.974
Multivariate L1 distance: 0.975							
Univariate imbalance: after CEM							
Variables	L1	mean	min	25%	50%	75%	max
Age	0.033	-0.007	0	0	0	0	0
Gender	1.50E-14	1.70E-14	0	0	0	0	0
Primary school	8.70E-15	6.00E-15	0	0	0	0	0
Middle school	1.10E-14	5.80E-15	0	0	0	0	0
High school	6.70E-15	2.30E-15	0	0	0	0	0
Vocational school	1.50E-15	2.40E-16	0	0	0	0	0
University or higher	6.50E-16	8.70E-17	0	0	0	0	0
Currently employed	1.20E-14	1.40E-14	0	0	0	0	0
Married/living together	8.10E-15	1.20E-14	0	0	0	0	0
Urban	1.30E-14	1.00E-14	0	0	0	0	0
Medical insurance	2.60E-15	3.80E-15	0	0	0	0	0
Household size	0.003	0.003	0	0	0	0	0
Log(household income)	0.313	-0.172	0.323	-0.121	-0.044	-0.359	-0.252
Multivariate L1 distance: 0.872							

Table A9 CEM based RE-TPM estimates of the impact of energy poverty on health care expenditures among Chinese adults aged 18+: 2012-2018 CFPS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Total health care expenditures		OOP health care expenditures		Inpatient expenditures		Other health care expenditures	
	RE Probit	RE GLM	RE Probit	RE GLM	RE Probit	RE GLM	RE Probit	RE GLM
EP3	0.043	0.197***	0.042	0.170***	0.136***	0.140***	0.026	0.149***
	(0.032)	(0.031)	(0.038)	(0.036)	(0.035)	(0.051)	(0.031)	(0.027)
Age	0.030***	0.038***	0.044***	0.041***	0.004	0.032***	0.035***	0.046***
	(0.007)	(0.006)	(0.008)	(0.007)	(0.008)	(0.010)	(0.007)	(0.006)
Age squared/100	-0.007	-0.017***	-0.024***	-0.025***	0.013*	-0.030***	-0.013**	-0.028***
	(0.007)	(0.006)	(0.008)	(0.007)	(0.008)	(0.010)	(0.007)	(0.005)
Gender	-0.419***	-0.191***	-0.411***	-0.183***	-0.105***	0.229***	-0.415***	-0.229***
	(0.032)	(0.029)	(0.035)	(0.033)	(0.035)	(0.046)	(0.030)	(0.025)
Primary school	-0.068*	-0.036	-0.075*	-0.010	-0.058	0.117*	-0.032	-0.044
	(0.041)	(0.037)	(0.045)	(0.041)	(0.043)	(0.060)	(0.039)	(0.032)
Middle school	-0.146***	-0.181***	-0.204***	-0.188***	-0.147***	0.013	-0.104**	-0.172***
	(0.042)	(0.039)	(0.047)	(0.045)	(0.048)	(0.062)	(0.040)	(0.035)
High school	-0.209***	-0.203***	-0.186***	-0.211***	-0.150**	0.148	-0.168***	-0.189***
	(0.061)	(0.062)	(0.071)	(0.070)	(0.072)	(0.100)	(0.059)	(0.054)
Vocational school	-0.080	0.021	-0.060	-0.025	-0.190	0.335	-0.015	0.018
	(0.148)	(0.145)	(0.172)	(0.176)	(0.196)	(0.273)	(0.144)	(0.129)
University or higher	-0.382	-0.454	-0.706**	-0.604	-0.283	1.028	-0.390*	-0.524**
	(0.236)	(0.285)	(0.299)	(0.436)	(0.354)	(0.690)	(0.232)	(0.232)
Currently employed	-0.107**	-0.515***	-0.087*	-0.569***	-0.430***	-0.430***	0.006	-0.377***
	(0.043)	(0.041)	(0.049)	(0.045)	(0.046)	(0.058)	(0.040)	(0.034)
Married/living together	-0.114**	0.191***	-0.117**	0.139***	0.223***	0.080	-0.160***	0.079*
	(0.053)	(0.049)	(0.059)	(0.051)	(0.060)	(0.070)	(0.050)	(0.042)
Urban	-0.107***	-0.059*	-0.133***	-0.078**	-0.043	-0.008	-0.099***	-0.044
	(0.035)	(0.033)	(0.039)	(0.038)	(0.039)	(0.051)	(0.033)	(0.029)
Medical insurance	0.202***	0.275***	0.144*	0.200***	0.433***	0.324***	0.160**	0.086
	(0.070)	(0.065)	(0.082)	(0.073)	(0.090)	(0.118)	(0.068)	(0.060)
Household size	-0.073***	-0.057***	-0.058***	-0.041***	-0.027**	-0.030*	-0.069***	-0.052***
	(0.011)	(0.010)	(0.012)	(0.011)	(0.012)	(0.016)	(0.010)	(0.009)
Log(household income)	0.059**	0.265***	0.053*	0.264***	0.114***	0.179***	0.069***	0.209***
	(0.027)	(0.025)	(0.032)	(0.029)	(0.028)	(0.040)	(0.026)	(0.022)
Constant	-0.430	3.448***	-0.493	3.826***	-4.666***	6.817***	-0.722	4.119***
	(0.439)	(0.435)	(0.538)	(0.479)	(0.610)	(0.544)	(0.442)	(0.405)
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Provincial FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28012	28012	19318	19318	28008	28008	28012	28012

Notes: The dependent variables are total health care expenditures, OOP health care expenditures, inpatient expenditures, and other health care expenditures. The controls include age, age squared, gender (1 = male, 0 = female), educational level (illiterate, primary school, middle school, high school, vocational school, and university or higher, with illiterate as the reference), employment status (1 = currently employed, 0 = otherwise), marital status (1 = married/living together, 0 = otherwise), household size, location type (1 = urban, 0 = rural), medical insurance (1=yes, 0=no), logged household income, wave dummies (with 2012 as the reference) and provincial dummies (with Beijing as the reference). For the second part of the GLM estimation, we use a gamma family and log link. Individual-level adjusted standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A10 CEM based RE-TPM estimates of the impact of energy poverty on health care expenditures among Chinese adults aged 18+: 2012-2018 CFPS (marginal effects)

	(1) Total health care expenditures	(2) OOP health care expenditures	(3) Inpatient expenditures	(4) Other health care expenditures
EP3	590.065	393.008**	417.141***	212.045***
	(25,176.707)	(163.148)	(89.231)	(76.558)
Controls	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes
Provincial FE	Yes	Yes	Yes	Yes
Observations	18400	9245	18398	18400

Notes: The dependent variables are total health care expenditures, OOP health care expenditures, inpatient expenditures, and other health care expenditures. The controls include age, age squared, gender (1 = male, 0 = female), educational level (illiterate, primary school, middle school, high school, vocational school, and university or higher, with illiterate as the reference), employment status (1 = currently employed, 0 = otherwise), marital status (1 = married/living together, 0 = otherwise), household size, location type (1 = urban, 0 = rural), medical insurance (1=yes, 0=no), logged household income, wave dummies (with 2012 as the reference) and provincial dummies (with Beijing as the reference). Individual-level adjusted standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

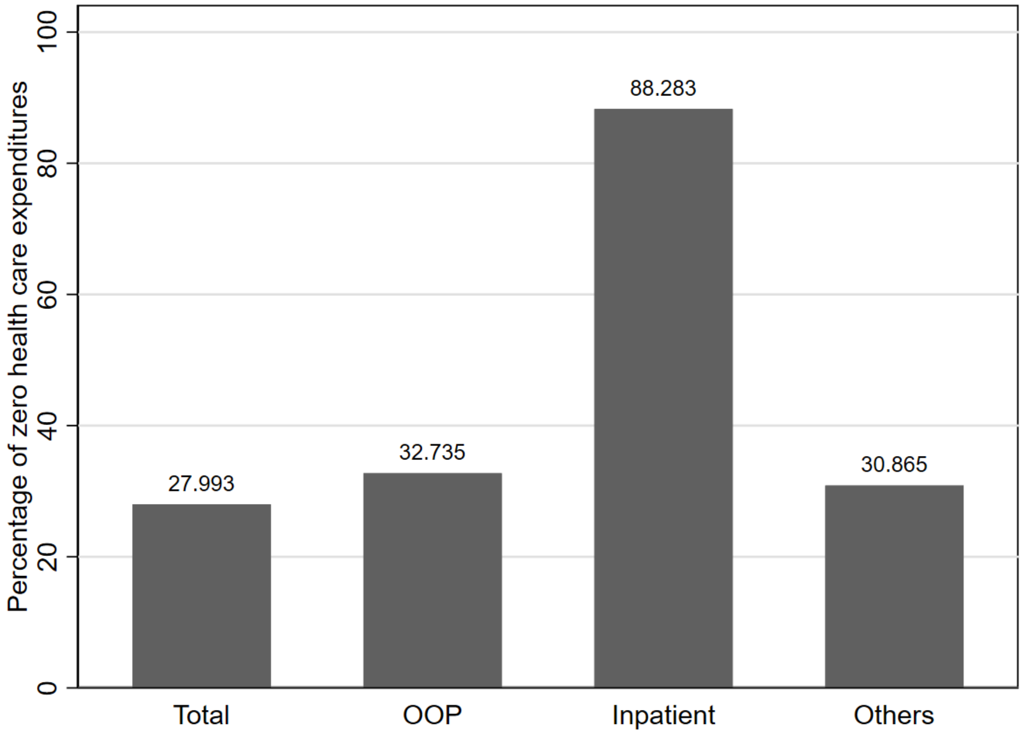

Figure A1 Percentage of positive (or 0) values of health care expenditures: 2012-2018 CFPS