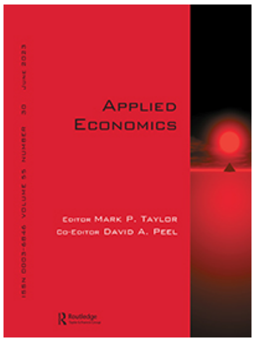

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ABSTRACT

Using the 2012–2018 waves of the China Family Panel Studies, 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/year), out-of-pocket (199 yuan/year), inpatient (230 yuan/year) and other (113 yuan/year) health care expenditures, with more pronounced impacts among females and those living in urban areas and Eastern 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 modelling 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. Combating EP is an effective way to improve people's health and reduce the burden on health care expenditures. Policymakers should also pay more attention to vulnerable groups such as women.

KEYWORDS
Energy poverty; health care expenditures; Random effects two-part model; China

JEL CLASSIFICATION
I10; I11; I32; Q40

I. 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$ in 2014 to 24.24 trillion US$ in 2040 (Global Burden of Disease Health Financing Collaborator Network 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 (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). 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 (Zhang, Li, and Han 2019) but also pay higher energy costs (Churchill, Smyth, and Farrell 2020).

Although a growing body of literature has examined the EP-health relationship in 50 developing countries (Banerjee, Mishra, and Maruta 2021) and China (Z. Zhang, Appau, and Kodom 2021), evidence on how EP affects health care expenditures in China 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 (Global Burden of Disease Health Financing Collaborator Network 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 developed countries. Furthermore, although China has achieved 100% electricity access since 2013 (World Bank 2020), an estimated 18.9% of Chinese people are energy poor (Lin and Wang

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2020), and in 2018, more than a quarter of households continued to use solid fuels (Lin and Wei 2022). EP may pose a threat to individuals' health and well-being, thereby impeding the realization of universal health coverage and the Healthy China Initiative[1]

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 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 II documents the relevant literature on measures of EP and its impacts on health and health care expenditures. Section III depicts the possible heuristic pathways of the impacts of EP on health care expenditures in China. Section IV describes the data and outlines the identification strategies. Section V presents the main results, and finally, Section VI concludes.

II. Literature review

Measures of EP

Since no consensus on the definition of EP has been reached, there is a large body of literature on how to measure EP. A commonly used method of defining EP is the proportion of income that households spend on energy. For instance, Boardman (1991) narrowly defined EP as total household energy expenditure over 10% of income, with the 10% threshold being approximately twice the median energy expenditure. Since the use of the 10% cut-off could be quite sensitive to misreporting of income and excessively sensitive to variations in energy prices (Hills 2012), another commonly used index of EP considers households to be energy poor if the proportion of their income spent on energy exceeds a certain threshold (Churchill, Smyth, and Farrell 2020). Hills (2011) proposes the 'low income, high cost' (LIHC) measure, which combines residual income below the poverty line with basic energy requirement costs above the social average. Notably, the LIHC measure handles the inclusion of high-income and high-consumption households (Nie, Li, and Sousa-Poza 2021). Nonetheless, the two measures above are unable to capture the differences between the actual energy expenditure made by households and the energy expenditure they would need to make (Churchill, Smyth, and Farrell 2020). Also popular are composite EP measures. For example, the International Energy Agency (IEA) adopts the energy development index (EDI), which consists of the share of the population with access to electricity, per capita commercial household energy consumption, per capita public sector electricity consumption, the share of commercial energy in total final energy use, and the share of productive energy in total final energy use. The EDI is particularly suitable for macro data and regional comparative assessments (Lin and Wang 2020). Nussbaumer, Bazilian, and Modi (2012) proposed the multidimensional energy poverty index focusing on deprivation of access to modern energy services (including modern cooking fuel, electricity, home appliances, entertainment, educational equipment, and communication tools) (Li et al. 2014). A summary of EP measures is shown in Table 1.

The differences between EP and fuel poverty (FP) are worth emphasizing. Lewis (1982) first defined the concept of FP as the inability to afford warmth in the home. In 2001, the UK government refined and officially adopted this concept. Hence, most FP studies focus on England, and Scotland (Li et al. 2014). FP mostly occurs in relatively

[1]This initiative gives priority to health and aims to improve national health policy and ensure the delivery of comprehensive lifecycle health services for people.

Table 1. A summary of EP measures.

Category	Indicator	Measure	Source
Single indicator	10% measure	A household spends more than 10% of its income on total household energy costs.	Boardman (1991)
	Amended 10% measure	A household spends more than 10% of its income on total household energy costs, and its income is below the third decile of the household income distribution.	Kahouli (2020)
	Twice the median percentage of full income	The household energy share is larger than twice the median percentage of energy in income.	Moore (2012)
Two-dimensional indicator	Low income, high cost (LIHC)	Residual household income is below the official poverty line, while basic energy costs for household living needs are higher than the median.	Hills (2012)
Composite indicator	Energy development index (EDI)	Five indicators: the share of the population with access to electricity, per capita commercial household energy consumption, per capita public sector electricity consumption, the share of commercial energy in total final energy use, and the share of productive energy to total final energy use.	IEA (2010)
	Multidimensional energy poverty index (MEPI)	Six equally weighted indicators: cooking fuel, lighting, entertainment, household appliances, education equipment, and communication tools.	Nussbaumer, Bazilian, and Modi (2012)

wealthy countries with cold climates, whereas EP occurs across all climates but mostly in developing countries, especially poor countries (Li et al. 2014). As stated above, EP is often defined as a lack of access to modern energy services (IEA 2002) and is strongly related to the concepts of energy markets, energy justice, energy use, energy policy, and social inequality (Primc, Dominko, and Slabe-Erker 2021). However, FP underscores the lack of sufficient income to achieve the minimum temperature threshold after gaining access to modern energy services (Li et al. 2014).[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, Oliveras et al. (2020) find that EP is associated with a higher use of health services and medication in Barcelona. Likewise, Bukari, Broermann, and Okai (2021) show that EP increases Ghana's 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 of Pakistani. Recently, Okorie and Lin (2022) show that Nigerian 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) for India.

Overall, 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, and 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 modelling (SEM) approach, we conduct a comprehensive exploration of the possible mechanisms through which EP affects health care expenditures.

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

A growing body of literature has consistently confirmed the negative impact of EP on health in developed countries (see, for instance, Churchill and Smyth 2021; Kahouli 2020). Specifically, Kahouli (2020) finds that EP leads

[2]A detailed discussion of the differences and similarities between EP and FP is available in Li et al. (2014).

to a lower likelihood of reporting good or very good SRH in France.[3] Likewise, Churchill and Smyth (2021) show that both objective and subjective indicators of EP contribute to poor SRH in Australia. Recently, several studies have also explored this topic in developing countries. For instance, Kose (2019) finds that EP is negatively associated with health in Turkey. This observation is further confirmed by Omar and Hasanujzaman (2021) for Bangladesh and by Nawaz (2021) for Pakistan. This finding is also obtained by Abbas et al. (2021) for South Asia[4]

For China, Zhang, Li, and Han (2019) show that EP decreases the likelihood of reporting good SRH. This observation is further confirmed by Z. Zhang, Appau, and Kodom (2021), who report that EP deteriorates the physical health of rural residents and impacts the mental health of their urban counterparts. More recently, Nie, Li, and Sousa-Poza (2021) find that EP leads to higher levels of depression in Chinese adults. Similarly, Li et al. (2022) also show that an increase in EP is associated with higher levels of depression in older Chinese individuals. 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 out-of-pocket (OOP) expenditures (see, e.g. Fan et al. 2020). 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 (Nord and Kantor 2006). Not only are these forced tradeoffs of basic needs stressful, but reduced food expenditure also frequently leads to decreased nutrient intake (Tuttle and Beatty 2017), especially during the high-energy demand seasons of winter and summer (Nord and Kantor 2006). Consequently, forced food expenditure reduction increases the risk of health problems such as diabetes (Fernández et al. 2018), 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, Morris, and Wilkinson (2022) confirm that high energy bills contribute to other essentials such as clothing and hygiene products being out of reach. The inability to purchase basic items probably results in depression, stress, and anxiety (Valente, Morris, and Wilkinson 2022), and individuals with higher levels of psychological problems, such as anxiety, utilize health care considerably more than those with lower levels (Eastin and 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.

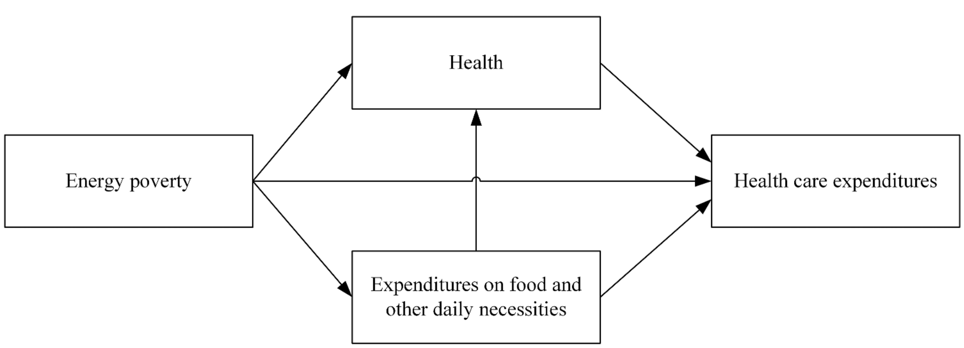

Figure 1. Underlying mechanisms through which energy poverty impacts health care expenditures.

[3]Our study is different from Kahouli (2020) because we focus on the relationship between EP and health care expenditures rather than health. In our case, we take health as one possible channel for the linkage between EP and health care expenditures.
[4]In this study, South Asia covers six countries, including Afghanistan, Pakistan, India, Bangladesh, Nepal and the Maldives..

IV. Data and methods

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. The CFPS is currently the largest and most comprehensive longitudinal survey in China (Xie and Hu 2014). It adopts multistage probability proportional to size sampling (PPS) with implicit stratification to reduce the operational cost of the survey and to better represent Chinese society. All the subsamples are obtained based on the following three stages: the primary sampling unit (PSU) is either an administrative district (in urban areas) or a county (in rural areas), the second-stage sampling unit is either a neighbourhood community (in urban areas) or an administrative village (in rural areas), and the third-stage sampling unit is the household (Xie and Hu 2014). Administrative units and measures of socioeconomic development (e.g. local GDP) are employed as the main stratification variables. The CFPS aims to track gene members who were captured in the CFPS 2010 baseline (Xie and Hu 2014). 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[5]

EP measures

Consistent with the literature (Nie, Li, and Sousa-Poza 2021), we employ multiple indices of EP. Specifically, we employ EP1 (amended 10% measure) in our main analysis, and the remaining measures (EP2-EP6) are used in the robustness checks (Nie, Li, and Sousa-Poza 2021):

- EP1 (amended 10% measure): The fraction of energy expenditure to household income is larger than 10%, with household income less than the threshold of the third decile of household income (Kahouli 2020).
- EP2 (10% measure): Household energy expenditures exceed 10% of the household's income (Boardman 1991).
- EP3 (twice the median percentage of full income): The household energy share is larger than twice the median percentage of energy in income (Moore 2012).
- EP4 (LIHC measure): Household energy expenditure is above the median level, and the household's residual income (income after energy expenditures) is below the official poverty line (i.e. 60% of the median) (Hills 2012).
- EP5 (solid fuel measure): Whether households use solid fuel as their primary fuel (1 = yes, 0 = no) (Nie, Li, and Sousa-Poza 2021).
- EP6 (energy deprivation score): A dummy constructed by the equally weighted average of EP1, EP3, EP4, and EP5, with EP2 omitted because EP1 is its derivative (1 = 0.5 or above, 0 = others) (Churchill, Smyth, and Farrell 2020).

Several reasons for selecting EP1 as our main EP measure are worth highlighting. First, although EP2 (10% measure) is the most prevalent measure of EP in existing studies, it might overestimate the prevalence of EP by including high-income households (Kahouli 2020). Thus, EP1 considers low-income households and addresses this concern. In addition, regarding LIHC, the equivalization factors for adjusting fuel costs are based on the data from 2007–2009 English Housing Survey, suggesting that the equivalization factors are specific to the domestic energy spending of English

[5]Information on energy utilization in 2010 is unavailable..

residents. However, the calculation of EP1 rests on the data of the country of interest (in our cases, CFPS data).

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. As a robustness check, we also introduce household-level health care spending, defined as household total direct health care expenditures (including those paid by or borrowed from relatives but excluding those that were reimbursed or reimbursable) in the previous year.

Control variables

Following existing studies (Bukari, Broermann, and Okai 2021), 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).

Empirical strategy

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

Modelling 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 and Norton 2018)[6] The health econometrics literature has confirmed that the two-part model (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 and Schafer 2001). To address these challenges, Olsen and Schafer (2001) 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 modelling health care expenditures (Farewell et al. 2017; Mora, Gil, and Sicras-Mainar 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[7] In the second stage, a GLM with a gamma family and log link is usually applied to address the econometric problems caused by

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

[7]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 and Ni 2020), we implement RE estimation rather than FE estimation..

skewness in health care utilization studies (Manning and Mullahy 2001). The log link is useful for correcting highly skewed data, while the gamma family may help to reduce heteroskedasticity concerns. 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 A3). Our RE-TPM estimation employs the following model:

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

$$log[E(HCE_{it}|HCE_{it} > 0, EP_{it}, X_{it})] = \beta_0 + \beta_1 EP_{it} + X_{it}^{'}\gamma + V_i \tag{2}$$

where Equation (1) estimates the first-stage RE probit model and Equation (2) 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}.

Following Jiang and Ni (2020), we employ the generalized structural equation modelling (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. Note that our latter analysis is performed at the individual level with the exception of Section 5.4.2, which assesses the impact of EP on household-level health care spending. For the individual-level analysis, we cluster standard errors at the household level.

Instrumental variable estimation

In our baseline model, the endogeneity of EP should be taken into account. The first concern is related to omitted variable bias. For instance, remittances can not only reduce household income poverty and the incidence of EP but also enable households to access health care or pay medical bills, thereby boosting household health care spending (Bukari, Broermann, and Okai 2021). In addition, living in EP can lead to household financial stress and affect an 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. Furthermore, systematic measurement error may exist, especially as households may not be able to accurately recall their energy expenditures (Churchill, Smyth, and Farrell 2020). One Australian study shows that respondents underestimated their annual energy expenditure by 13%-20% (Wilkins and Sun 2010), suggesting that measurement errors can sometimes be substantial. In our case, measurement errors due to underestimation of energy expenditure would downward bias the impact of EP on health care expenditures. Lastly, reverse causality may exist. 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 relationship.

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 (Zhang, Appau, and Kodom 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 favour thermal comfort at the expense of health expenditures (Kahouli 2020). However, 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[8]

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 and Smyth 2015). The precondition of this method is the presence of heteroskedasticity, which we confirm using the Pagan – Hall and Breusch–Pagan tests (Breusch and Pagan 1979).

V. Results

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 (Zhang, Li, and Han 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).

The distribution of health care expenditures is highly skewed, with a large mass at zero and a long right tail (Figure A1). Approximately 28%, 33%, 88% and 31% of observations have zero values in total, OOP, inpatient and other expenditures (Figure A2). 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 A3). Figure 3 and Table A2 show that respondents who live in EP are more likely to have higher health care expenditures than those who do not.

EP and health care expenditures: the RE-TPM

The RE-TPM estimation results of the impacts of EP on health care expenditures are shown in Table 2. EP is significantly associated with higher health care costs (Table 2, Columns 2, 4, 6, and 8), which is consistent with Bukari, Broermann, and Okai (2021) for Ghana, and Faizan and Thakur (2022) for India.

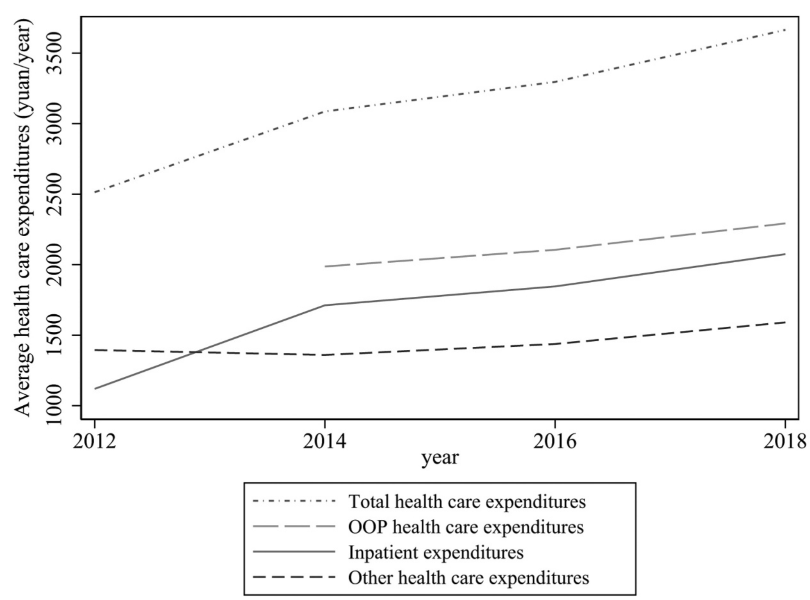

Figure 2. Average health care expenditures of adults over time: 2012–2018 CFPS.

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

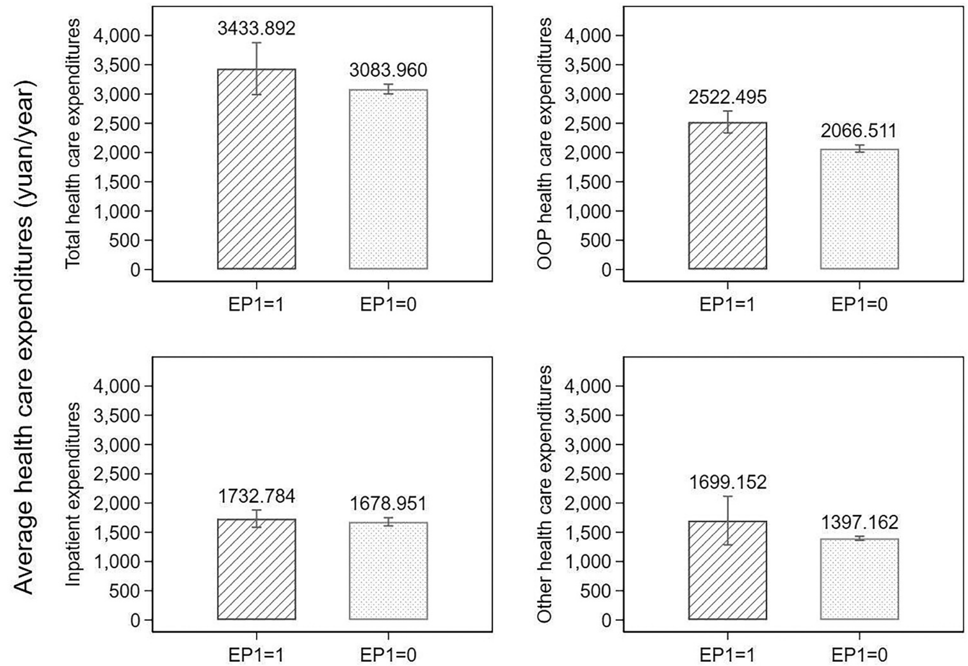

Figure 3. Average health care expenditures by household energy poverty status Notes: EP1 is a dummy variable for households' energy poverty status (1=yes, 0=no).

The marginal effects of EP on health care utilization are presented in Figure 4 and Appendix Table A4. Individuals living in EP have approximately 305 yuan/year higher total health care expenditures, 199 yuan/year higher OOP health care expenditures, 230 yuan/year higher inpatient expenditures, and 113 yuan/year higher other expenditures (see Figure 4).

Endogeneity

To address the potential endogeneity of EP, we employ Lewbel's 2SLS estimation (Lewbel 2012). The results from Table 3 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 Tables 3 and A4). This observation highlights that failure to rule out the endogeneity of EP will lead to underestimation.

Robustness checks

Alternative measures of EP

We introduce the remaining five EP measures (EP2-EP6) as our first robustness check. 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 Appendix Tables A5 and A6). 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 A6). This finding is consistent with Lima, Ferreira, and Leal (2021), who found that the use of and exposure to liquid[9] and solid fuels

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

Table 2. 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
EP1	0.020	0.095***	−0.004	0.097***	0.077***	0.047	0.014	0.077***
	(0.022)	(0.022)	(0.025)	(0.026)	(0.022)	(0.037)	(0.021)	(0.019)
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)	(0.003)	(0.003)
Gender	−0.308***	−0.173***	−0.312***	−0.198***	−0.091***	0.267***	−0.298***	−0.220***
	(0.012)	(0.016)	(0.013)	(0.017)	(0.014)	(0.024)	(0.011)	(0.013)
Primary school	−0.057***	−0.012	−0.080***	−0.034	−0.028	0.050	−0.053***	−0.021
	(0.020)	(0.023)	(0.021)	(0.024)	(0.020)	(0.033)	(0.019)	(0.020)
Middle school	−0.110***	−0.063***	−0.144***	−0.100***	−0.069***	0.079**	−0.102***	−0.077***
	(0.020)	(0.024)	(0.021)	(0.026)	(0.021)	(0.035)	(0.019)	(0.021)
High school	−0.114***	−0.068**	−0.172***	−0.125***	−0.075***	0.130***	−0.097***	−0.066***
	(0.024)	(0.029)	(0.026)	(0.031)	(0.027)	(0.043)	(0.023)	(0.025)
Vocational school	−0.059*	−0.013	−0.140***	−0.123***	−0.049	0.090	−0.049	−0.014
	(0.032)	(0.040)	(0.035)	(0.043)	(0.038)	(0.060)	(0.031)	(0.035)
University or higher	0.025	−0.042	−0.081**	−0.173***	−0.062	0.136*	0.025	−0.023
	(0.036)	(0.044)	(0.039)	(0.048)	(0.046)	(0.075)	(0.035)	(0.038)
Currently employed	−0.076***	−0.553***	−0.088***	−0.533***	−0.389***	−0.467***	0.002	−0.354***
	(0.015)	(0.019)	(0.017)	(0.021)	(0.017)	(0.026)	(0.014)	(0.015)
Married/living together	−0.009	0.211***	−0.001	0.167***	0.168***	0.136***	−0.034*	0.119***
	(0.019)	(0.023)	(0.021)	(0.024)	(0.022)	(0.034)	(0.018)	(0.020)
Urban	−0.107***	0.089***	−0.112***	0.052***	0.010	0.077***	−0.110***	0.081***
	(0.016)	(0.018)	(0.017)	(0.019)	(0.016)	(0.026)	(0.015)	(0.016)
Medical insurance	0.172***	0.078***	0.173***	−0.022	0.219***	0.001	0.142***	0.004
	(0.019)	(0.023)	(0.023)	(0.028)	(0.025)	(0.047)	(0.019)	(0.020)
Household size	−0.030***	−0.023***	−0.022***	−0.019***	−0.009**	−0.016**	−0.030***	−0.023***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.007)	(0.004)	(0.004)
Log(household income)	0.032***	0.039***	0.014	0.039***	0.016*	0.055***	0.035***	0.033***
	(0.008)	(0.008)	(0.010)	(0.010)	(0.008)	(0.014)	(0.008)	(0.007)
Constant	0.204	6.502***	−0.015	6.519***	−2.655***	8.537***	0.034	6.394***
	(0.126)	(0.146)	(0.145)	(0.164)	(0.147)	(0.271)	(0.121)	(0.130)
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

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. Household-level adjusted standard errors are in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

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, Shia, and Ma (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, Shia, and Ma 2012).

Alternative measures of health care expenditures

We also present the effects of EP on health care utilization using household-level expenditures[10]

[10]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. We control for the age and education of the household head in the regression.

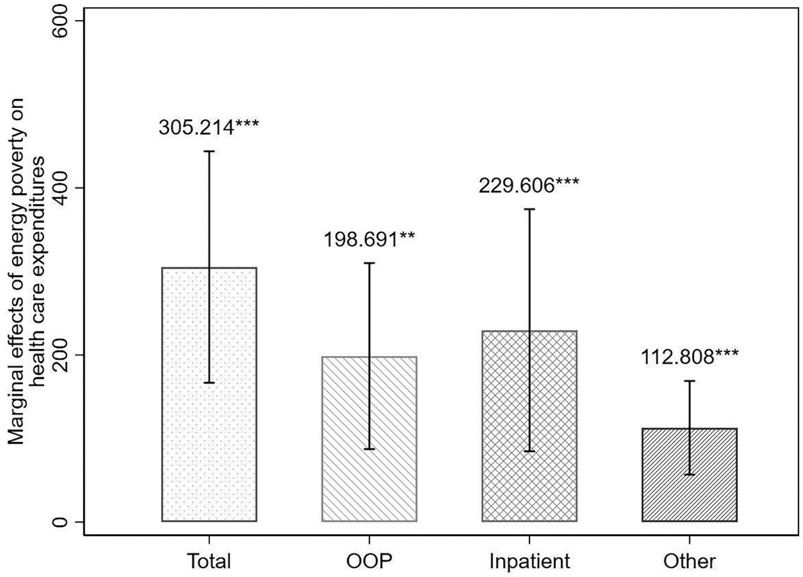

Figure 4. Marginal effects of energy poverty on health care expenditures (with 95% confidence intervals) Notes: The marginal effects of energy poverty on health care expenditures are unconditional on any amount of health care spending.

Once again, EP is significantly associated with a higher probability of having any household health care (Table A7, Column 1) and a larger expenditure if there is any (Table A7, Column 2). Moreover, energy-poor households have approximately 955 yuan/year higher health care expenditures than non-energy-poor households (Table A7, Column 3).

Alternative estimates for energy poverty and health care expenditures

As our third robustness check, we introduce three alternative models: RE, zero-inflated Poisson and zero-inflated negative binomial models. As shown in Table A8, 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 2 and A8). 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 A3). Moreover, since health care expenditures can be viewed as censored data with zero as the censored point, the Tobit model has been used in modelling health care expenditures (Lin and Wei 2022). Thus, we also use the Tobit model, and the results are similar to those of the RE-TPM (see Tables 2 and A8, Panel D).

Using sampling weights

As a final robustness check, we re-estimate the nexus between EP and health care spending adjusted by sampling weights. The impact of EP on health care utilization remains significant and positive (see Table A9). We do not use sampling weights in the main analysis mainly because our key findings are still quite robust after controlling for sampling weights.

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, OOP and other health care expenditures for females than for males (see Table 4, Panel A, Columns 1, 2 and 4). The Wald test further confirms that this gender difference is statistically significant. The results are in accordance with Oliveras et al. (2020), showing that the mean charges for primary and speciality care, diagnostic services, and annual total expenses are all significantly higher for women than for men. However,

Table 3. 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
EP1	618.371***	621.692***	352.690*	354.636*	370.092**	370.200**	275.960**	280.097**
	(233.159)	(234.186)	(198.291)	(198.167)	(177.331)	(177.273)	(132.898)	(134.616)
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	190.044	143.993	149.873	108.548	190.044	143.993	190.044	143.993
J P value	0.743	0.753	0.607	0.810	0.523	0.710	0.722	0.296
Pagan – Hall test	78.901***	91.303***	167.154***	168.485***	388.461***	388.560***	78.493***	91.068***
Breusch – Pagan test	8.6e + 05***	1.0e + 06***	4.9e + 04***	4.9e + 04***	1.0e + 05***	1.0e + 05***	2.9e + 06***	3.3e + 06***

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). The external IVs are province-level electricity prices and gas prices. Household-level clustered standard errors are in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 4. 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				
EP1	337.996***	235.194***	210.688***	128.401***
	(78.254)	(64.170)	(68.201)	(32.424)
Male				
EP1	268.865***	176.494***	251.883***	95.862***
	(62.387)	(49.174)	(80.860)	(24.502)
Controls	Yes	Yes	Yes	Yes
Observations	105484	78479	105484	105484
Wald test P-value	0.000	0.000	0.004	0.000
Panel B: By age group (18–59 versus 60+)				
Age group: 18–59				
EP1	303.384***	204.786***	241.069***	112.239***
	(70.337)	(56.513)	(77.733)	(28.466)
Age group: 60+				
EP1	307.127***	209.789***	217.127***	113.605***
	(71.225)	(57.817)	(70.231)	(28.844)
Controls	Yes	Yes	Yes	Yes
Observations	105,484	78,479	105,484	105,484
Wald test P-value	0.650	0.423	0.044	0.594
Panel C: Rural versus urban				
Rural				
EP1	294.019***	205.473***	218.886***	109.614***
	(68.468)	(56.422)	(70.805)	(27.801)
Urban				
EP1	315.332***	209.569***	238.718***	115.865***
	(73.010)	(57.742)	(76.694)	(29.393)
Controls	Yes	Yes	Yes	Yes
Observations	105484	78479	105484	105484
Wald test P-value	0.004	0.379	0.031	0.015
Panel D: By region				
East				
EP1	466.734***	253.041***	627.351**	195.142***
	(117.098)	(73.582)	(309.217)	(52.742)
Central				
EP1	270.293***	190.174***	388.675**	76.006***
	(66.104)	(54.910)	(177.969)	(20.203)
West				
EP1	230.063***	195.899***	83.669***	103.514***
	(61.339)	(58.530)	(30.963)	(29.956)
Northeast				
EP1	265.917***	171.346***	362.173**	87.697***
	(65.413)	(50.505)	(165.293)	(23.542)
Controls	Yes	Yes	Yes	Yes
Observations	105484	78479	105484	105484
Wald test P-value (East versus Central)	0.002	0.037	0.181	0.000
Wald test P-value (Central versus West)	0.426	0.879	0.072	0.185
Wald test P-value (West versus Northeast)	0.476	0.510	0.079	0.448

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). Household-level adjusted standard errors are in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

for males, EP has significantly larger marginal effects on inpatient medical costs (see Panel A of Table 4, Column 3), which is also confirmed by the Wald test. This result is possibly because different types of illness and the medical payment propensity vary by gender. For instance, Song and Bian (2014) show that there are significant differences between genders, observing a longer duration of hospitalization and higher inpatient expenditures among men. Our results suggest that this gender difference may also depend on various types of health care expenditures.

We also perform a split analysis by two age groups (those aged 18–59 and those aged 60+). We find that the marginal effects of EP on total, OOP, and other health care expenditures are higher among those aged 60+ compared to those aged 18–59 but are statistically nonsignificant (see Panel B of Table 4). Interestingly, the marginal effect of EP on inpatient spending is higher for those aged 18–59 than for those aged 60+, and a Wald test confirms that this age difference is statistically significant.

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 4, Panel C), which is confirmed by a Wald test. This finding indicates that the higher marginal effects of EP for urban residents are mainly attributable to differences in affordability and health awareness (Molla, Chi, and Mondaca 2017).

For regional differences, the marginal effects of EP on medical expenses for residents living in Eastern China are significantly higher than they are for those living in other regions of China (see Table 4, Panel D). This regional heterogeneity may be attributable to a recognized disparity in economic growth and development (Lin and Wang 2020) in which the central, western and northwestern regions are poorer than the eastern region. Their financial revenue may thus be lower, thereby leading to lower public health expenditures and reduced health care availability. As Fang, Shia, and Ma (2012) underscored, the medical cost and quality of care are often linked, and thus, households living in more economically developed regions pay higher medical costs due to the high-quality equipment and services compared to less economically developed regions.

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. The results of the goodness-of-fit test confirm the appropriateness of our four structural equation models (see Table 5).

The SEM results validate the two hypotheses (see Table 6 and Figures A4–A7). 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 5. Goodness of fit by different health care expenditures: SEM with controls.

Dependent variable	Independent variable	RMSEA	CFI	SRMR
Total health care expenditures	EP1	0.075	0.904	0.003
OOP health care expenditures	EP1	0.093	0.884	0.004
Inpatient expenditures	EP1	0.075	0.904	0.003
Other health care expenditures	EP1	0.075	0.899	0.003

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). $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 6. 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	EP1	−0.051***	−0.051***	
SRH	Food and other daily necessities	0.026***	0.026***	
	EP1	−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***	
	EP1	0.012***	0.010**	0.002***
Panel B: OOP health care expenditures				
Food and other daily necessities	EP1	−0.065***	−0.065***	
SRH	Food and other daily necessities	0.025***	0.025***	
	EP1	−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***	
	EP1	0.018***	0.014***	0.004***
Panel C: Inpatient expenditures				
Food and other daily necessities	EP1	−0.051***	−0.051***	
SRH	Food and other daily necessities	0.026***	0.026***	
	EP1	−0.022***	−0.020***	−0.001***
Inpatient expenditures	Food and other daily necessities	0.005	0.009**	−0.003***
	SRH	−0.116***	−0.116***	
	EP1	0.010**	0.008*	0.002***
Panel D: Other health care expenditures				
Food and other daily necessities	EP1	−0.051***	−0.051***	
SRH	Food and other daily necessities	0.026***	0.026***	
	EP1	−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***	
	EP1	0.008**	0.007*	0.001***

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). $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

(Table 7), suggesting that health is an important channel for the linkage between EP and health care spending.

VI. Discussion and conclusions

Evidence on how EP affects health care expenditures remains scarce, thus, 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 more developed eastern region 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. According to EP1, approximately 16.6% respondents are living in EP. The 2020 Census shows that the population aged 18 and over is 1,158.4 million[11], translating into approximately 192.29 million people who suffer from EP. Furthermore, China's additional annual medical cost of EP is 58,648 million yuan for total, 38266 million yuan for OOP, 44227 million yuan for inpatient and 21,729 million yuan for other health care spending.

[11]The information on the population aged 18 and over is available in http://www.ncjggw.gov.cn/index.php?m=content&c=index&a=show&catid=37&id=7475.

Table 7. 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

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). *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

These findings have important policy implications. China already has the world's largest ageing population and is one of the fastest ageing societies worldwide (Nie et al.2021). Such continued rapid ageing suggests a growing burden of elderly individuals, who need financial support and health care spending. 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 the energy cost burden and investing more in clean energy to improve energy accessibility, will improve people's health and reduce the burden on health care expenditures. Therefore, mitigating EP might be an effective way to curb the increasing burden on health care spending. Policymakers should pay more attention to vulnerable groups such as women. In addition, since our findings confirm that when disposable 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 the government to provide certain subsidies for the aforementioned susceptible groups to guarantee their daily necessities and to promote their use of clean energy, thereby improving their health and well-being in future.

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Data availability statement

The data that support the findings of this study are openly available in [Peking University Open Research Data] at https://opendata.pku.edu.cn/dataverse/CFPS;jsessionid=1e0dcab23e9373f51acc4489578f.

Disclosure statement

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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	3142.01	16804.35	0	3650506
OOP health care expenditures (yuan/year)[b]	78479	2131.98	8453.47	0	510000
Inpatient expenditures (yuan/year)	105484	1687.88	10512.48	0	597347
Other health care expenditures (yuan/year)	105484	1447.26	12336.18	0	3650506
Household health care expenditures (yuan/year)[c]	104875	5927.40	18348.50	0	1326696
EP measures					
EP1	105484	0.166	0.372	0	1
EP2	105484	0.222	0.416	0	1
EP3	105484	0.247	0.431	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
Urban	105484	0.477	0.499	0	1
Medical insurance	105484	0.910	0.286	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	10.65	1.19	0	16
Energy expenditure (yuan/year)[d]	105484	3026.70	3312.13	0	84970
Mediators					
Spending on food and other daily necessities[e]	105368	20374.37	23891.89	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. Descriptive statistics of Chinese adults aged 18+ by EP1: 2012–2018 CFPS.

	EP1 = 0 (Obs. = 87985)		EP1 = 1 (Obs. = 17499)		Two sample T-test
Variables	Mean/Percentage	S.D.	Mean/Percentage	S.D.	Diff.
Total health care expenditures	3083.96	12632.87	3433.89	29995.85	−349.93**
OOP health care expenditures	2066.51	8132.87	2522.50	10149.38	−455.98***
Inpatient expenditures	1678.95	10612.74	1732.78	9993.30	−53.83
Other health care expenditures	1397.16	5155.84	1699.15	27993.80	−301.99***
Household health care expenditures	5929.23	17781.86	5918.24	20968.16	10.99
Age	47.246	15.570	51.644	16.117	−4.398***
Gender	0.492	0.500	0.476	0.499	0.017***
Illiterate	0.254	0.435	0.421	0.494	−0.167***
Primary school	0.207	0.405	0.239	0.426	−0.032***
Middle school	0.283	0.451	0.232	0.422	0.052***
High school	0.149	0.356	0.086	0.281	0.062***
Vocational school	0.062	0.241	0.016	0.125	0.046***
University or higher	0.045	0.208	0.007	0.081	0.039***
Currently employed	0.747	0.435	0.689	0.463	0.058***
Married/living together	0.849	0.358	0.816	0.387	0.033***
Urban	0.498	0.500	0.367	0.482	0.131***
Medical insurance	0.913	0.282	0.899	0.302	0.014***
Household size	4.368	1.998	3.768	1.919	0.600***
Log(household income)	10.993	0.847	8.908	1.154	2.08***

Notes: EP1 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 67,211 for EP1 = 0 and 11,268 for EP1 = 1, respectively. The significance of the changes is based on independent *t*-tests. $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A3. 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**	0.0135***
	(0.002)	(0.002)	(0.0050)	(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, Norton, and Manning 2017). In modified Park test, the coefficients are all close to 2, suggesting the appropriateness of using a gamma distribution.

Table A4. 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
EP1	305.214***	198.691***	229.606***	112.808***
	(70.667)	(56.803)	(73.953)	(28.600)
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). Household-level adjusted standard errors are in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Table A5. 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: EP2				
EP2	358.354***	240.761***	248.907***	150.519***
	(59.814)	(46.847)	(63.198)	(24.053)
Controls	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes
Provincial FE	Yes	Yes	Yes	Yes
Observations	105484	78479	105484	105484
Panel B: EP3				
EP3	325.913***	231.732***	221.121***	132.071***
	(56.978)	(44.239)	(60.205)	(23.090)
Controls	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes
Provincial FE	Yes	Yes	Yes	Yes
Observations	105484	78479	105484	105484
Panel C: EP4				
EP4	317.140***	202.592***	214.914***	137.308***
	(61.175)	(47.930)	(63.139)	(24.599)
Controls	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes
Provincial FE	Yes	Yes	Yes	Yes
Observations	105484	78479	105484	105484
Panel C: EP5				
EP5	52.031	71.636*	26.580	35.979
	(54.825)	(41.763)	(56.688)	(22.008)
Controls	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes
Provincial FE	Yes	Yes	Yes	Yes
Observations	105484	78479	105484	105484
Panel D: EP6				
EP6	315.540***	224.487***	256.381***	121.786***
	(60.885)	(47.919)	(63.663)	(24.694)
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). For the second part of the GLM estimation, we use a gamma family and log links. Household-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+: 2012–2018 CFPS.

	(1) Total health care expenditures	(2)	(3) OOP health care expenditures	(4)	(5) Inpatient expenditures	(6)	(7) Other health care expenditures	(8)
	RE Probit	RE GLM	RE Probit	RE GLM	RE Probit	RE GLM	RE Probit	RE GLM
Panel A: EP2								
EP2	0.006	0.116***	−0.002	0.117***	0.069***	0.069**	0.004	0.107***
	(0.018)	(0.019)	(0.020)	(0.022)	(0.019)	(0.031)	(0.017)	(0.016)
Constant	0.240*	6.447***	−0.019	6.458***	−2.635***	8.478***	0.060	6.316***
	(0.123)	(0.143)	(0.141)	(0.160)	(0.143)	(0.268)	(0.118)	(0.128)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	105484	105484	78479	78479	105484	105484	105484	105484
Panel B: EP3								
EP3	0.012	0.104***	0.011	0.109***	0.078***	0.040	0.006	0.093***
	(0.017)	(0.018)	(0.019)	(0.020)	(0.018)	(0.030)	(0.017)	(0.016)
Constant	0.222*	6.471***	−0.054	6.469***	−2.663***	8.551***	0.054	6.345***
	(0.123)	(0.142)	(0.141)	(0.160)	(0.143)	(0.267)	(0.118)	(0.128)
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***
	(0.019)	(0.019)	(0.021)	(0.022)	(0.019)	(0.031)	(0.018)	(0.017)
Constant	0.248**	6.637***	−0.045	6.653***	−2.535***	8.611***	0.060	6.488***
	(0.116)	(0.136)	(0.134)	(0.153)	(0.137)	(0.257)	(0.112)	(0.122)
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
	(0.016)	(0.017)	(0.018)	(0.019)	(0.017)	(0.029)	(0.015)	(0.015)
Constant	0.190*	6.743***	−0.086	6.752***	−2.487***	8.667***	0.002	6.583***
	(0.115)	(0.135)	(0.132)	(0.151)	(0.137)	(0.257)	(0.111)	(0.121)
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***
	(0.019)	(0.019)	(0.021)	(0.022)	(0.019)	(0.031)	(0.018)	(0.017)
Constant	0.185	6.495***	−0.085	6.496***	−2.665***	8.502***	0.009	6.383***
	(0.123)	(0.143)	(0.142)	(0.161)	(0.144)	(0.267)	(0.119)	(0.129)
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. Household-level adjusted standard errors are in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A7. RE-TPM estimates of the impact of energy poverty on household health care expenditures among Chinese adults aged 18+: 2012–2018 CFPS.

	(1) RE Probit	(2) RE GLM	(3) Marginal effects
EP1	0.109***	0.168***	954.838***
	(0.034)	(0.026)	(141.299)
Constant	0.092	6.589***	-
	(0.204)	(0.164)	-
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. Household-level adjusted standard errors are in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Table A8. 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) Total health care expenditures	(2) OOP health care expenditures	(3) Inpatient expenditures	(4) Other health care expenditures
Panel A: RE				
EP1	446.202***	302.668***	203.042**	226.909***
	(138.411)	(114.417)	(100.101)	(78.078)
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				
EP1	463.923***	297.312***	292.496***	233.108***
	(131.802)	(104.906)	(99.889)	(71.229)
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				
EP1	565.085***	360.099***	296.855***	242.245***
	(125.329)	(100.227)	(96.005)	(52.703)
Controls	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes
Provincial FE	Yes	Yes	Yes	Yes
Observations	105484	78479	105484	105484
Panel D: Tobit				
EP1	289.604***	181.818**	285.647***	140.988**
	(93.417)	(73.552)	(77.018)	(60.119)
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). Household-level adjusted standard errors are in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Table A9. RE-TPM estimates of the impact of energy poverty on health care expenditures among Chinese adults aged 18+ using sampling weights: 2012–2018 CFPS (marginal effects).

	(1) Total health care expenditures	(2) OOP health care expenditures	(3) Inpatient expenditures	(4) Other health care expenditures
EP1	471.257**	230.590**	236.325	130.124*
	(186.167)	(111.940)	(199.712)	(75.797)
Controls	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes
Provincial FE	Yes	Yes	Yes	Yes
Observations	19819	19749	19819	19819

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). Household-level adjusted standard errors are in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

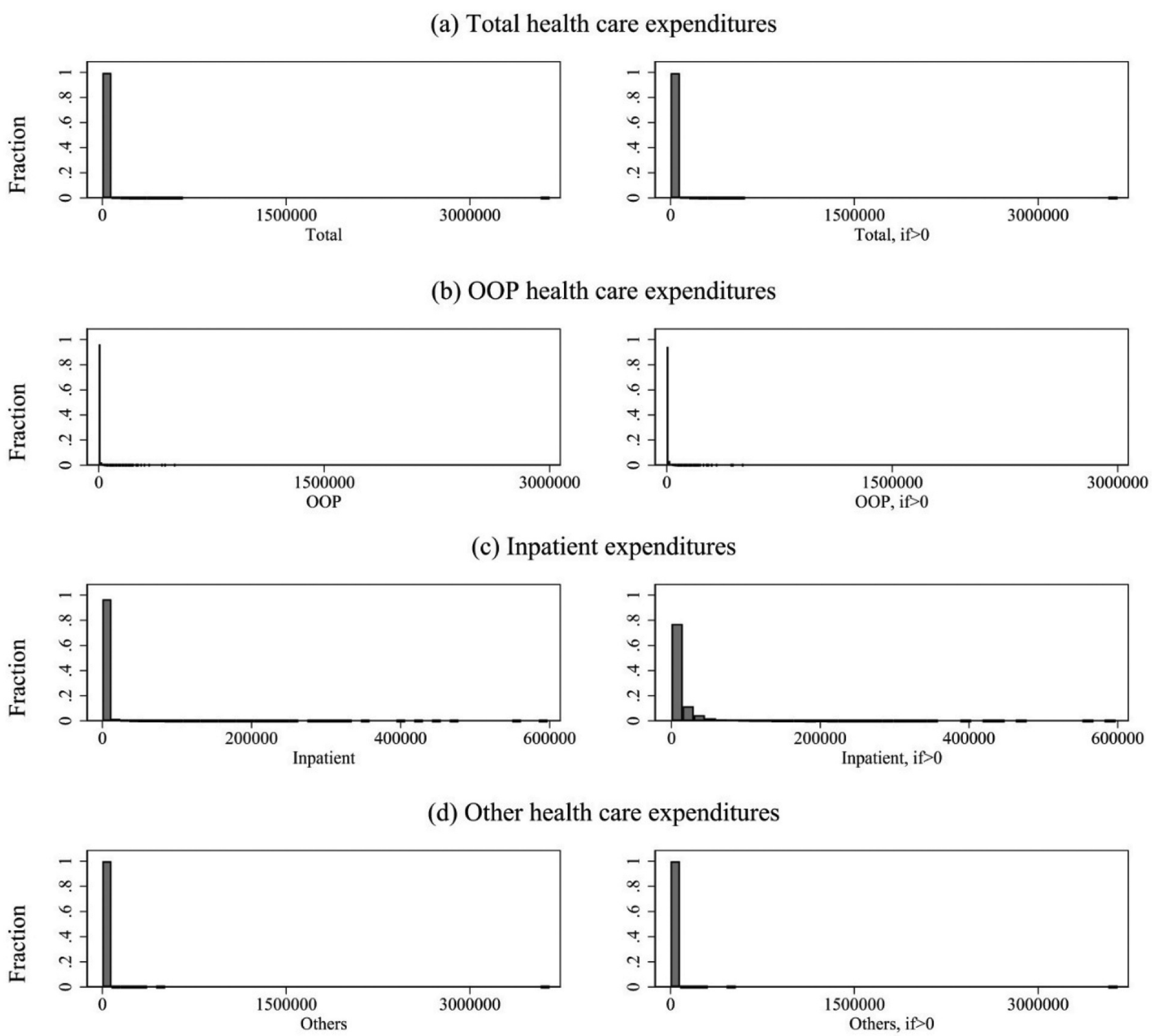

Figure A1. The distribution of four types of health care expenditures.

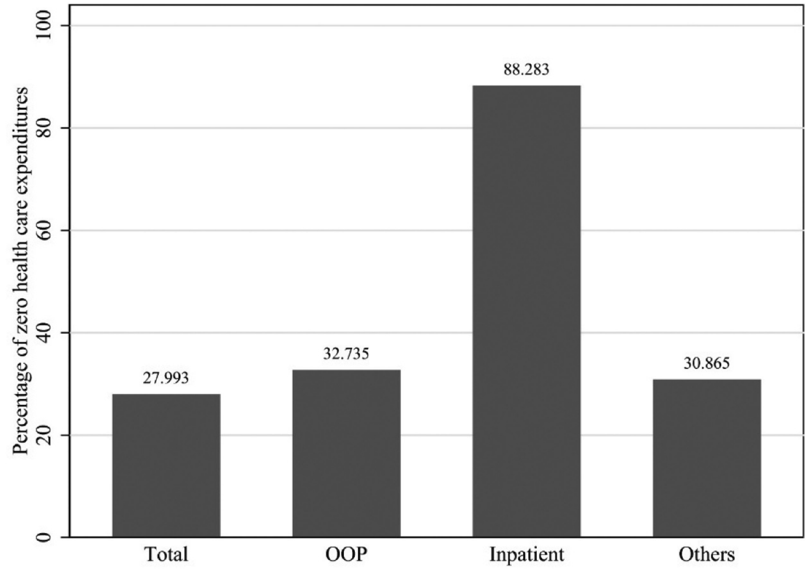

Figure A2. Percentage of zero values of health care expenditures: 2012–2018 CFPS.

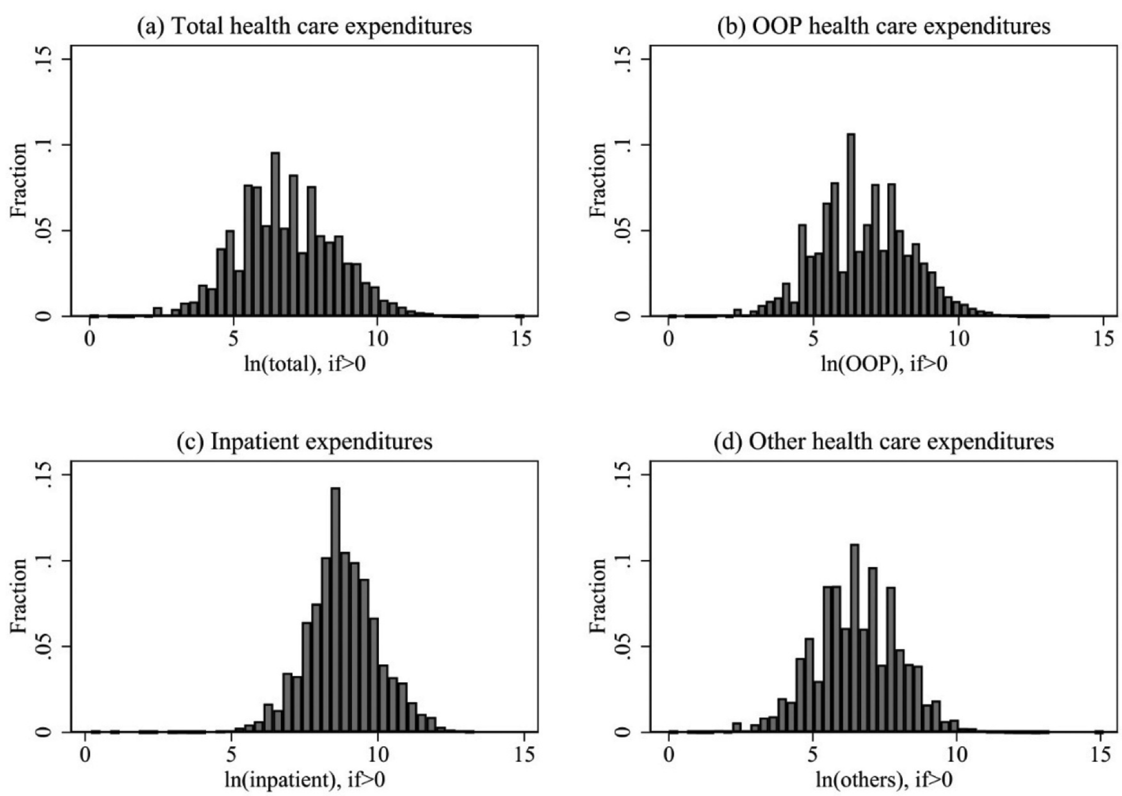

Figure A3. The distribution of four types of health care expenditures (logged form).

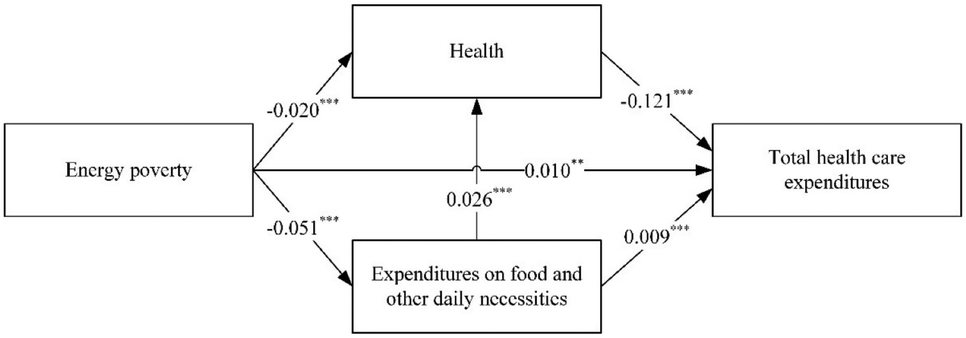

Figure A4. Underlying mechanisms through which energy poverty impacts total health care expenditures. Notes: SEM estimates with all coefficients standardized. *p < 0.1, **p < 0.05, ***p < 0.01.

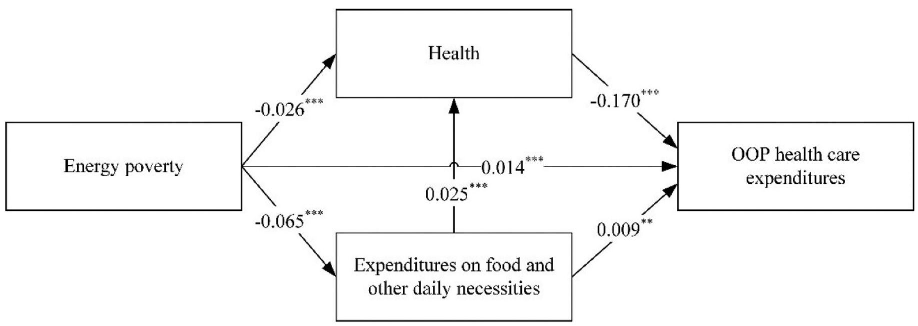

Figure A5. Underlying mechanisms through which energy poverty impacts OOP health care expenditures. Notes: SEM estimates with all coefficients standardized. *p < 0.1, **p < 0.05, ***p < 0.01.

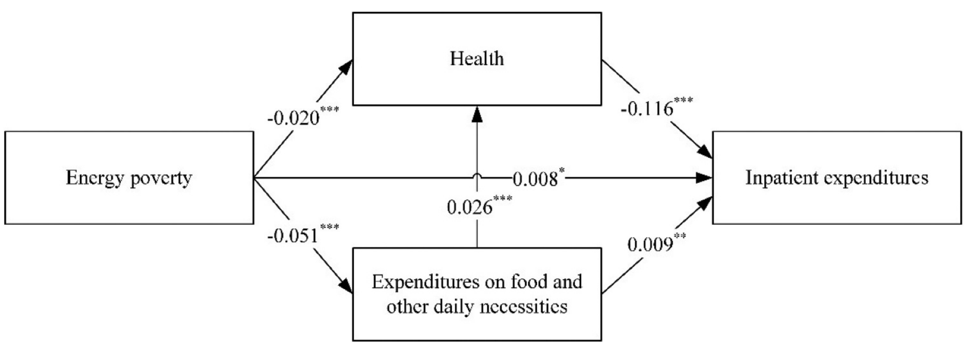

Figure A6. Underlying mechanisms through which energy poverty impacts inpatient expenditures. Notes: SEM estimates with all coefficients standardized. *p < 0.1, **p < 0.05, ***p < 0.01.

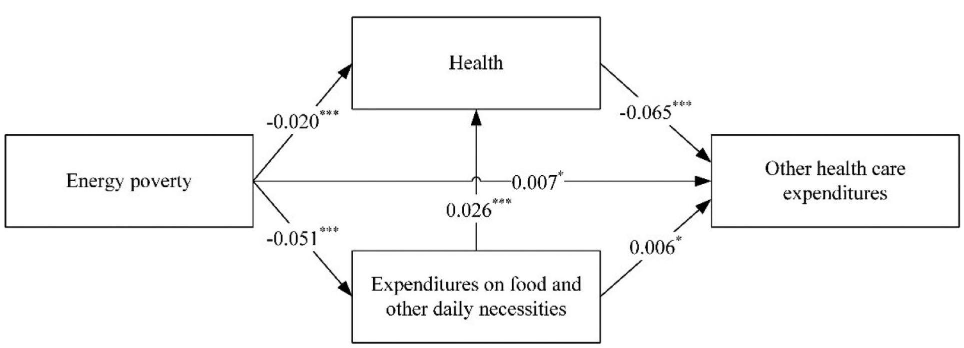

Figure A7. Underlying mechanisms through which energy poverty impacts other health care expenditures.