social sciences

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Energy Poverty and Health Expenditure: Empirical Evidence from Vietnam

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Abstract: Utilizing data from the 2016 Vietnam Household Living Standard Survey, we undertake an empirical investigation into the influence of energy poverty on the health expenditure of Vietnamese households. Employing a double-hurdle model, our empirical findings reveal a negative relationship between energy poverty and health expenditure. Specifically, our results indicate that for each incremental unit increase in energy poverty, there is a substantial reduction of 42.5 percentage points in the overall health expenditure of the households. Furthermore, as energy poverty deepens, we observe declines of 24.6 percentage points and 45.5 percentage points in the expenses incurred for inpatient/outpatient care and self-treatment, respectively. To validate the robustness of our results, we conduct several sensitivity analyses, including propensity score matching, double/debiased machine learning. Across all these methods, our findings consistently underscore the significant and persistent adverse impact of energy poverty on the examined outcome variables. Additionally, to examine the underlying pathways, we conduct a structural equation modeling analysis and find that the relationship between energy poverty and health expenses is mediated by household hospitalization and expenditures on essential items, such as food and daily necessities.

Keywords: energy poverty; health expenditure; multidimensional energy poverty index; VHLSS

Citation: Nguyen-Phung, Hang Thu, and Hai Le. 2024. Energy Poverty and Health Expenditure: Empirical Evidence from Vietnam. *Social Sciences* 13: 253. https://doi.org/10.3390/socsci13050253

Academic Editor: Pierre Desrochers

Received: 10 November 2023
Revised: 16 April 2024
Accepted: 19 April 2024
Published: 6 May 2024

1. Introduction

Access to modern and reliable energy services is critical for poverty alleviation, economic growth, social well-being, and sustainable development. The United Nations (2020) has placed direct emphasis on ensuring universal access to and affordability of contemporary energy sources for all individuals by 2030, as articulated within the framework of Sustainable Development Goal Seven (SDG7). It is also worth noting that the pivotal importance of SDG7 in the attainment of various other SDGs, specifically those regarding healthcare improvement, poverty alleviation, promotion of gender equality, climate mitigation, and facilitation of economic growth, enjoys widespread recognition within academic discourse, according to the International Energy Agency (IEA) (2017).

Despite progress, energy poverty, which is characterized by the shortage of modern energy facilities like electricity and clean cooking devices, remains a pressing developmental challenge, particularly in developing countries (Adusah-Poku and Takeuchi 2019; Murshed 2022; Wang et al. 2023). According to the IEA (2020), approximately 770 million people (10% of the global population) and 2.6 billion people are in need of electricity and clean fuels, respectively. The COVID-19 pandemic has worsened the situation, and the number people living in extreme poverty has increased by 71 million, as estimated by the United Nations. The IEA further anticipates that by 2030, approximately 660 million individuals are expected to experience a lack of access to electricity, while a staggering 2.4 billion people will continue to rely on traditional biomass for cooking purposes, causing pronounced detrimental health impacts (United Nations 2022). It is widely acknowledged that in addition to enduring adverse health conditions, households experiencing energy poverty also bear the burden of increased energy expenses, which in turn significantly impact health expenditure, particularly in situations of fixed disposable income (Churchill et al. 2020; Nie and Li 2023; Zhang et al. 2019). Thus, the attainment of universal health coverage—one of the key targets of the SDGs—is presented with a potential hurdle in the form of energy poverty.

Despite the growth of the literature investigating the nexus between energy poverty and health in various areas/regions, such as Australia (Prakash and Munyanyi 2021), European countries (Castaño-Rosa et al. 2020; Oliveras et al. 2021), and developing nations (Banerjee et al. 2021), there remains a scarcity of evidence regarding the specific influence of energy poverty on healthcare expenditures. Accordingly, this paper aims to explore the link between energy poverty and health expenditure in the context of Vietnamese households. Vietnam presents an intriguing context for the investigation of energy poverty dynamics. Over the past few decades, there has been a substantial surge in electricity generation, leading to near-universal access to the national electricity grid. Gencer et al. (2011) show that the percentage of the population with electricity access surged from a mere 14% in 1990 to an impressive 97% by 2010 due to substantial investments in electrification in rural areas by the Vietnamese government, along with the support of international aid donors. Nevertheless, it is essential to note that approximately one million individuals, who primarily reside in the mountainous northern part, still lack access to electricity (Feeny et al. 2021). Furthermore, the mere availability of electricity does not necessarily guarantee that households have the ability to afford its consumption. In Vietnam, a significant portion of households (25%) had insufficient electricity to meet their demands in 2010, according to Ha-Duong and Nguyen (2018). For electricity to substantially contribute to poverty alleviation, rural households must exceed the monthly subsidized electricity allocation of 50 kWh and consume electricity at higher levels (Scott and Greenhill 2014). Energy poverty encompasses not only the availability of electricity but also the nature of household energy sources. According to the WHO (2020), most Vietnamese rely on conventional fuels and technologies for their energy needs, with less than two-thirds utilizing clean fuels and advanced technologies. Nguyen et al. (2019) reveal that despite an overall transition to modern energy sources among households in Vietnam, the economically disadvantaged and the ethnic minority groups continue to rely heavily on traditional energy forms like coal and biomass.

Using data from the 2016 Vietnam Household Living Standard Survey (VHLSS), we investigated the impact of energy poverty on household health expenditure. Adhering to the framework developed by Nussbaumer et al. (2012), we calculated the multidimensional energy poverty index (MEPI), which serves as a pertinent proxy for quantifying the prevalence of energy poverty. The findings derived from the double-hurdle model reveal an inverse association between energy poverty and health expenditure. More precisely, our findings indicate that households, when exposed to energy poverty, are associated with a substantial decrease of 42.5 percentage points in the overall health expenditure of households. Furthermore, being exposed to energy poverty results in reductions of 24.6 percentage points and 45.5 percentage points in the expenses incurred for inpatient/outpatient care and self-treatment, respectively. To validate our results, we conducted various robustness checks, encompassing propensity score matching, double/debiased machine learning, and a framework to overcome omitted variable bias, as outlined by Oster (2019). The results consistently demonstrate that energy poverty has a significant and persistent detrimental effect on outcome variables. Moreover, we conducted a structural equation modeling analysis to investigate the underlying channels and found that the link between energy poverty and health expenses was mediated by household hospitalization and expenditures on essential items, such as food and daily necessities.

This study makes a valuable contribution to the growing body of scholarly work on the nexus between energy poverty and health, highlighting the importance of clean energy accessibility for the promotion of good health (Abbas et al. 2021; Karmaker et al. 2022; Twumasi et al. 2021). The previous research has consistently shown a link between indoor air pollution and negative health outcomes, such as lung cancer (Smith et al. 2013) and respiratory diseases (Po et al. 2011). Moreover, there is a correlation between indoor air pollution and adverse pregnancy outcomes, such as low birth weight (WHO 2016). Additionally, the extant research has demonstrated an inverse relationship between multi-dimensional energy poverty measures and health outcomes (Bukari et al. 2021; Oum 2019). These results are consistent with studies on the impacts of energy poverty on health in both high- and low-temperature contexts. For example, studies in developed nations with low temperatures show that energy poverty also negatively impacts health (Grey et al. 2017; Oliveras et al. 2020). Similarly, studies conducted in countries with high temperatures provide evidence supporting the detrimental association between energy poverty and health (Awaworyi Churchill et al. 2019; Thomson et al. 2019).

In addition to enhancing our understanding of the relationship between energy poverty and health, our study provides insights into the association between energy poverty and social well-being (Lin and Okyere 2021; Song et al. 2023). The study conducted by Phoumin and Kimura (2019) revealed that Cambodian households affected by energy poverty experience a significant decline in their earning capacity, with a notable 48% reduction compared to households unaffected by energy poverty. Furthermore, Chinese families with limited energy access often face food scarcity, resulting in reduced expenditure on food (Li et al. 2022; Nie and Li 2023). Another study by Porto Valente et al. (2022) supports the notion that high energy expenses have a detrimental impact on the affordability of necessities, such as clothing. These findings underscore the complex and diverse characteristics of energy poverty and its extensive effects on various aspects of health and social domains.

The remainder of this paper is structured as follows. Section 2 describes the research data and variable definitions. Section 3 outlines the identification strategies. Section 4 presents the main results, and finally, Section 5 concludes and provides policy implications.

2. Data

2.1. Data Source

The main data utilized in this study are derived from the 2016 Vietnam Household Living Standard Survey (VHLSS), which is jointly conducted by the General Statistics Office of Vietnam and the World Bank.[1] The VHLSS encompasses a wide range of data on households and individuals, including demographic background and health expenditure. A sample comprising 7551 households is employed for the analysis.

2.2. Variable Definitions

2.2.1. Measures of Energy Poverty

We evaluate the energy poverty by employing the multidimensional methodology introduced by Nussbaumer et al. (2012). The MEPI serves as a comprehensive framework for detecting households confronted with various deficiencies related to the accessibility of clean, safe, sustainable, and modern energy. The MEPI, as described by Nussbaumer et al. (2012), is a valuable tool for improving policy development by considering the occurrence and magnitude of energy poverty. Accordingly, the MEPI is fundamentally assessed based on five dimensions that indicate essential energy services. In the present study, we establish seven indicators of energy poverty, classified into five primary dimensions, by drawing upon previous research and data specific to Vietnam (Feeny et al. 2021; Que et al. 2022). These dimensions encompass cooking, electronic consumption, services, entertainment and education, and communication. Equal weights of 0.2 are assigned to all five dimensions. A comprehensive depiction of the seven indicators and five dimensions can be found in Appendix A Table A1. Each indicator is represented as a binary variable, where the values of 0 and 1 signify whether a household experiences deprivation in that specific indicator. For example, with regard to the “electronic consumption” indicator, a household is considered deprived if its per capita electricity consumption falls below 100 kW per year. Computing the MEPI involves aggregating the weighted dimensions and deriving a deprivation score. If a household's deprivation score exceeds a specified poverty threshold, its members are considered energy poor. In developing nations, a threshold value of 0.33 is commonly regarded as suitable because it facilitates a wide range of poverty outcomes, effectively accounting for those individuals facing acute poverty circumstances (Alkire and Santos 2014).

2.2.2. Measures of Health Expenditure

In this study, we incorporate three distinct measures of health expenditure: total health expenditure (THE), inpatient and outpatient health expenses (IOHE), and self-treatment expenditure (STE). The IOHE encompasses the combined costs associated with hospitalization and outpatient services. On the other hand, the STE includes household expenditures on the purchase of medicines without prescriptions, as well as the costs of acquiring medical appliances and equipment (such as blood pressure monitors, phlegm absorbers, and clinical thermometers).

2.2.3. Covariates

The selection of covariates in this study was driven by both theoretical considerations and practical significance, as established by prior research (Nie and Li 2023; Oliveras et al. 2020). To ensure comprehensive control, we incorporated two primary sets of characteristics. First, we incorporated the demographic information of the household head, including their age, gender (male), level of education, employment status, and marital status. Furthermore, we collected household-level data, including household size, a binary indicator for rural residence, an indicator for the province where the individual currently resides, medical insurance status, and the total income earned by the household.

Table 1 presents the descriptive statistics of the variables. The dataset comprises a total of 7551 valid samples. Approximately, 15.4% are identified as households experiencing energy poverty, with approximately 70% of these households located in rural areas.

Table 1. Descriptive statistics.

Variables	N	Mean	SD	Min	Max
Log of total health expenses	7551	7.605	1.591	0.693	12.216
Log of in/outpatient health expenses	7551	6.771	2.460	0	12.206
Log of self-treatment expenses	7551	5.781	1.993	0	10.968
MEPI	7551	0.192	0.194	0	1
Energy poverty	7551	0.154	0.361	0	1
Head of household's age	7551	51.884	13.902	14	104
Head of household is male	7551	0.749	0.434	0	1
Head of household's level of education	7551	1.565	1.204	0	4
Head of household's marital status	7551	0.796	0.403	0	1
Head of household's employment status	7551	0.846	0.361	0	1
Household size	7551	3.808	1.602	1	13
Medical insurance	7551	0.497	0.500	0	1
Location of rural residence	7551	0.700	0.458	0	1
Location of provincial residence	7551	49.439	28.421	1	6
Log of total household income	7551	3.300	4.910	0	13.039

Notes: SD: standard deviation, N: number of observations. Source: authors' own calculations.

3. Research Methodology

A number of households indicate zero health expenditures, thereby potentially biasing estimates obtained through ordinary least squares (OLS) regression when health expenditures are employed as the outcome variable. The Tobit model, which serves to handle the issues of censoring, truncation, and corner solutions, is deemed inappropriate due to its overly restrictive assumption that both the decision to participate and the level of consumption for a typical household are impacted by the same variables. When analyzing models that involve households and their consumption behaviors, it is recommended to consider the heterogeneity in the determinants of participation and consumption choices. Therefore, adopting the double-hurdle model is proposed as a more appropriate alternative to capture the diverse nature and varying magnitudes of these variables.

The double-hurdle model, initially introduced by Cragg (1971), postulates that households must overcome two hurdles to attain positive health expenditure. The first hurdle revolves around the household's decision regarding the allocation of financial resources towards health-related expenses, which constitutes a necessary condition commonly referred to as the participation decision. Subsequently, once the first hurdle is solved, a second hurdle, known as the sufficient condition, arises. This condition entails the household's determination of the specific level of health-related expenses. When these two conditions are fulfilled, the household reports positive health expenditure.

Given the case of Vietnam, the double-hurdle model may be a more appropriate option due to a considerable percentage of households recording zero spending for non-economic reasons. For instance, certain households may refrain from utilizing hospitals and other healthcare facilities due to religious convictions. Hence, adhering to the approach of (Bardazzi and Pazienza 2018; Bukari et al. 2021), we adopt the double-hurdle model, as indicated below:

$$H_{i1}^{*} = Z_i\alpha + \varepsilon_i \text{ participation decision} \tag{1}$$

$$H_{i2}^{*} = \Pi_i\lambda + \varsigma_i \text{ consumption decision} \tag{2}$$

$$H_i = \Pi_i\lambda + \varsigma_i \text{ if } H_{i1}^{*} > 0 \text{ and } H_{i2}^{*} > 0 \tag{3}$$

$$H_i = 0 \text{ otherwise} \tag{4}$$

where the decision to allocate resources towards health expenditure is denoted as H_{i1}^{*}, while the level of health spending is represented by H_{i2}^{*}. The actual amount expended on health is denoted as H_i, whereas the vector of the variables influencing the decision regarding health expenses is captured by Z_i. Furthermore, the vector Π_i encompasses factors that explain the magnitude of health expenditure. The terms ε_i and ς_i correspond to the stochastic error terms in the model.

4. Empirical Findings

4.1. Main Results

The findings are presented in Table 2, wherein we provide a comprehensive account of the results obtained. The empirical evidence indicates a consistent association between energy poverty and reduced levels of health expenditure. More specifically, we observe a significant decrease of 42.5 percentage points in the overall health expenditure among households experiencing energy poverty. Additionally, the households that are exposed to energy poverty exhibit a decline of 24.6 percentage points and 45.5 percentage points in the expenses incurred for inpatient/outpatient care and self-treatment, respectively.

Table 2. Impact of energy poverty on health expenditure.

Variables	THE	IOEH	STE
Energy poverty	−0.425 ***	−0.246 ***	−0.455 ***
	(0.051)	(0.067)	(0.043)
Controls	Yes	Yes	Yes
Observations	7551	7551	7551

Notes: Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. THE = total health expenditure; IOHE = inpatient and outpatient health expenses; STE = self-treatment expenditure. We report the marginal effects.

As robustness checks, we first use a threshold of 0.5 to categorize households as energy poor. Then, we employ different weights for each dimension when calculating the MEPI and assign 0.4 to the cooking dimension, 0.3 to electricity consumption, 0.1 to services, 0.1 to entertainment, and 0.1 to communications. This weight choice is substantiated by recognizing the fundamental nature of cooking as a basic human need (Feeny et al. 2021). The results are displayed in Table 3. Although the magnitude of the estimated effects is slightly larger, the findings consistently show that energy poverty significantly reduces three key outcome variables, thus corroborating our main research findings.

Table 3. Alternative measures of energy poverty.

Variables	THE	IOEH	STE
Panel A: Same weights assigned for the dimensions as the main estimate			
Energy poverty—threshold 0.5	−0.536 ***	−0.283 **	−0.504 ***
	(0.074)	(0.095)	(0.066)
Panel B: Different weights assigned for the dimensions			
Energy poverty—threshold 0.33	−0.294 ***	−0.169 ***	−0.313 ***
	(0.039)	(0.052)	(0.034)
Energy poverty—threshold 0.5	−0.497 ***	−0.319 ***	−0.493 ***
	(0.058)	(0.078)	(0.050)
Controls	Yes	Yes	Yes
Observations	7551	7551	7551

Notes: Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. THE = total health expenditure; IOHE = inpatient and outpatient health expenses; STE = self-treatment expenditure.

4.2. Robustness Checks

In order to enhance the robustness and validity of our findings, three additional methods are employed. First, we employ propensity score matching (PSM) to address the endogeneity and selection bias. Second, we use the double/debiased machine learning (DDML) approach introduced by Chernozhukov et al. (2018) to account for the potential bias emerging from the assumption of a linear association between the objective and the control variables, despite the existence of a possible nonlinear relationship. Finally, we examine the extent of bias from the unobservable variables by applying the partial identification method introduced by Oster (2019).

4.2.1. Propensity Score Matching

The utilization of PSM has been widely employed in non-experimental studies to effectively address the challenges of endogeneity and selection bias (Bukari et al. 2021; Awaworyi Churchill et al. 2019; Dehejia and Wahba 2002). By utilizing PSM, we tackle the problems of endogeneity and selection bias. Within the framework of our study, energy poverty serves as the treatment variable, which is then applied to our outcome variables (THE, IOEH, and STE). This methodological framework allows us to derive causal inferences regarding the impact of energy poverty on health expenditures. The estimated findings are reported in Table 4. The results consistently indicate that irrespective of matching techniques and regression methods (probit or logit), energy poverty significantly reduces the three main outcome variables, thus corroborating our main research findings.

Table 4. Bootstrap propensity score matching with different estimates and matching methods.

Variables	THE (ATT)	IOEH (ATT)	STE (ATT)
Panel A: Probit estimates			
Energy poverty (Kernel)	−0.655 ***	−0.794 ***	−0.814 ***
	(0. 067)	(0.115)	(0.099)
Energy poverty (Local linear regression)	−0.642 ***	−0.779 ***	−0.807 ***
	(0.059)	(0.125)	(0.096)
Energy poverty (Nearest neighbors)	−0.723 ***	−0.873 ***	−0.850 ***
	(0.103)	(0.134)	(0.112)
Energy poverty (Radius)	−0.747 ***	−0.920 ***	−0.914 ***
	(0.049)	(0.082)	(0.073)
Panel B: Logit estimates			
Energy poverty (Kernel)	−0. 656 ***	−0.794 ***	−0.813 ***

Table 4. *Cont.*

Variables	THE (ATT)	IOEH (ATT)	STE (ATT)
	(0.070)	(0.115)	(0.082)
Energy poverty (Local linear regression)	−0.643 ***	−0.779 ***	−0.807 ***
	(0.068)	(0.122)	(0.092)
Energy poverty (Nearest neighbors)	−0.658 ***	−0.843 ***	−0.788 ***
	(0.074)	(0.148)	(0.137)
Energy poverty (Radius)	−0.738 ***	−0.906 ***	−0.906 ***
	(0.079)	(0.084)	(0.076)

Notes: Bootstrap with 50 replications. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. ATT = average treatment of the treated. THE = total health expenditure; IOHE = inpatient and outpatient health expenses; STE = self-treatment expenditure.

4.2.2. Double/Debiased Machine Learning

One concern in the linear models is the potential bias stemming from the assumption of a linear association between the objective and control variables, despite the possibility of a nonlinear relationship. To address this potential bias, we employ the following semiparametric model:

$$H_i = \beta\, X_i + g(\boldsymbol{Z_i}) + e_i,\ E[e|\ X,\ \boldsymbol{Z}] = 0 \tag{5}$$

where H_i, X_i, $\boldsymbol{Z_i}$ denote the outcome variables, energy poverty, and set of control variables, respectively. β is the parameter of interest, and $g(.)$ is the unknown, potentially nonlinear function. We estimate the model using the double/debiased machine learning (DDML) introduced by Chernozhukov et al. (2018). This approach capitalizes on the Neyman orthogonality method of estimating equations and employs cross-fitting to construct the asymptotic normality of the estimators for the causal parameters. These desirable statistical properties are robustly demonstrated, even when faced with relatively mild convergence rate conditions on nonparametric estimators (Ahrens et al. 2023). Machine learning (ML) techniques are widely acknowledged for their enhanced resilience to the curse of dimensionality through the leveraging of regularization strategies, in contrast to traditional nonparametric estimators. In this robustness check, we employ four widely used machine learning methods to estimate our models—lasso, random forest, gradient boosting, and ridge. Furthermore, we provide stacking estimates, which allow us to incorporate our machine learners into one final estimate. Table 5 presents the results. The findings consistently indicate that energy poverty exerts a significant and consistent negative impact on the three primary outcome variables, regardless of the machine learners employed. These results effectively support and substantiate our research findings.

Table 5. Estimated impact of energy poverty using double/debiased machine learning.

Machine Learning Methods	THE	IOEH	STE
Energy poverty (Lasso)	−0.602 ***	−0.775 ***	−0.582 ***
	(0.063)	(0.097)	(0.077)
Energy poverty (Random forest)	−0.388 ***	−0.491 ***	−0.367 ***
	(0.065)	(0.099)	(0.080)
Energy poverty (Ridge)	−0.741 ***	−0.949 ***	−0.797 ***
	(0.062)	(0.095)	(0.077)
Energy poverty (Gradient boosting)	−0.468 ***	−0.617 ***	−0.424 ***
	(0.063)	(0.097)	(0.078)
Energy poverty (Stacking estimation)	−0.461 ***	−0.618 ***	−0.422 ***
	(0.064)	(0.098)	(0.078)
Controls	Yes	Yes	Yes
Observations	7551	7551	7551

Notes: Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. THE = total health expenditure; IOHE = inpatient and outpatient health expenses; STE = self-treatment expenditure. Stacking estimation allows the incorporation of several machine learners into a final estimate.

4.2.3. Omitted Variable Bias

Despite including a comprehensive range of control variables, the possibility of omitted variable bias remains a valid concern. For instance, energy poverty and health expenditure may be driven by social capital within a community or society, including the networks, relationships, and norms of trust and reciprocity among individuals and groups. To ensure the reliability of our findings, we conducted a robustness analysis to evaluate the potential bias arising from unobservable factors. This analysis employs the partial identification method introduced by Oster (2019), which has been widely applied in existing literature (Le and Nguyen-Phung 2024; Lyu et al. 2023). This study assesses the magnitude of selection bias on unobservable variables in relation to observable variables to account for the effect of energy poverty on health expenditure. The bias-adjusted coefficient derived by Oster (2019) is computed in the following manner:

$$\beta^* = \tilde{\beta} - \delta\,[\dot{\beta} - \tilde{\beta}]\,\frac{R_{max} - \tilde{R}}{\tilde{R} - \dot{R}} \tag{6}$$

The coefficient and R^2 value obtained from a regression analysis with energy poverty as the only independent variable are denoted as $\dot{\beta}$ and $\dot{R}$. On the other hand, the coefficients and R^2 values from a regression analysis with energy poverty as well as observed controls are denoted as $\tilde{\beta}$ and $\tilde{R}$. δ refers to the relative significance of observable variables compared to unobservable variables in causing bias, whereas R_{max} represents the R^2 derived from a hypothetical regression model that incorporates both observable and unobservable variables. In order to address the uncertainty surrounding the unknown values of δ and R_{max}, Oster (2019) suggests employing a bounding approach. This approach entails estimating the effect of energy poverty on health expense outcome within a range of values, denoted as $\tilde{\beta}$ to β^*. This estimation is made under the assumption that $\delta = 1$ and with the constraint that $R_{max} \in [\tilde{R},\ 1]$. According to Oster (2019), the recommendation for R_{max} relies on published empirical work derived from randomized control studies in reputable economics journals between 2008 and 2013. The proposed approach suggests that $R_{max} = min\{1.3\tilde{R},\ 1\}$. We adhere to this approach to calculate the maximum value of R^2 and its corresponding bounds. The robustness results can be established if the identified set $[\tilde{\beta},\ \beta^*]$ does not include zero. We also adopt the approach Oster (2019) proposed to compute the parameter δ. In this context, a value of $\delta > 1$ would suggest that the observable variables are more significant than the unobservable variables in elucidating the outcome variables, thereby confirming the presence of robust findings.

The results of the Oster (2019) analysis are shown in Table 6. We first present the estimation of δ and assess its potential value when it exceeds 1. Furthermore, we report the bounds of the coefficient. The first bound $\tilde{\beta}$ is derived from the linear estimation, including the control variables used in all the estimations. The computation of the second bound β^* is performed by utilizing Equation (6) and employing the rule of thumb suggested by Oster (2019), which involves setting $R_{max} = min\{1.3\tilde{R},\ 1\}$. The obtained findings offer a degree of assurance regarding the robustness of our main findings when excluding certain variables, as indicated when $\delta > 1$. This suggests that the unobservable variables would need to exert a more substantial influence on health expenditure than the observable variables to impact our findings significantly. Moreover, the estimated bounds derived from our analysis effectively dismiss the possibility of a null effect when the estimated bound excludes zero.

Table 6. Oster's (2019) test of omitted variable bias.

Variables	Proportionality		Identified Set	
	$\delta_{(R_{max}=min\{1.3\tilde{R},\,1\})}$	$\delta > 1$	$[\tilde{\beta},\ \beta^{*}{}_{(R_{max}=min\{1.3\tilde{R},\,1\},\ \delta=1)}]$	Excludes 0?
THE	2.054	Yes	[−0.659, −0.437]	Yes
IOHE	1.962	Yes	[−0.786, −0.495]	Yes
STE	1.831	Yes	[−0.811, −0.566]	Yes
Controls	Yes			
Observations	7551			

Notes: As the test can only be performed with a linear model, an ordinary least square model is used to estimate the health expenditure instead of a double-hurdle model. THE = total health expenditure; IOHE = inpatient and outpatient health expenses; STE = self-treatment expenditure.

4.3. Mechanisms

In our study, we employ structural equation models to examine two propositions. First, we investigate whether energy poverty influences health expenditure by adversely affecting the overall health status of households (H1). Second, we explore the possibility that energy poverty displaces expenditures on essential items such as food, leading to reduced health expenditure (H2). To measure health, we construct a variable called "hospitalization" that captures the frequency at which household members have been admitted to the hospital.[2] We assume that only severe illnesses necessitate inpatient care; thus, the frequency of hospitalization indicates the health condition within a household.

Table 7 presents the outcomes of the goodness-of-fit analysis conducted for the structural equation modeling (SEM) framework. It is worth noting that no universally standardized criterion exists for evaluating goodness-of-fit in SEM. Nevertheless, Schermelleh-Engel et al. (2003) have put forth a practical guideline indicating an acceptable level of fit. According to their recommendation, a satisfactory fit is attained when the root mean square error of approximation (RMSEA) is below 0.08, the standardized root mean square residual (SRMR) is below 0.1, and the comparative fit index (CFI) surpasses 0.95. The estimated findings of the goodness-of-fit evaluation provide empirical support for the suitability of the employed structural equation models.

Table 7. Goodness of fit of SEM incorporating control variables.

Dependent Variables	Independent Variables	RMSEA	CFI	SRMR
Total health expenditure	Energy poverty	0.040	0.995	0.009
In/outpatient health expenditure	Energy poverty	0.040	0.994	0.009
Self-treatment expenditure	Energy poverty	0.040	0.994	0.009

The SEM results, as reported in Table 8, provide empirical support for the two hypotheses under investigation and align with our initial estimates. Specifically, it is observed that energy poverty adversely influences household expenditures on food, potentially leading to a direct reduction in health expenditure. Furthermore, residing in a state of energy poverty is found to have a negative effect on household health expenses. Overall, the mediation analysis reveals that approximately 41.4% to 51.6% of the effect of energy poverty on health expenditure is mediated through food, indicating that the reduction in food expenditure serves as a significant pathway in the nexus between energy poverty and household health expenses. Therefore, this suggests that diminished food consumption is crucial in understanding the linkage between energy poverty and household health expenses.

Table 8. Path analysis of SEM incorporating control variables.

Dependent Variables	Independent Variables	Total Effect	Direct Effect	Indirect Effect
	Panel A: Total health expenditure			
Food and other necessities	Energy poverty	−0.365 ***	−0.365 ***	
Hospitalization	Energy poverty	0.101 ***	0.101 ***	
Total health expenditure	Food and other necessities	0.414 ***	0.414 ***	
	Hospitalization	0.318 ***	0.318 ***	
	Energy poverty	−0.875 ***	−0.756 ***	−0.119 ***
	Panel B: In/outpatient health expenditure			
Food and other necessities	Energy poverty	−0.365 ***	−0.365 ***	
Hospitalization	Energy poverty	0.101 ***	0.101 ***	
IOHE	Food and other necessities	0.516 ***	0.516 ***	
	Hospitalization	0.470 ***	0.470 ***	
	Energy poverty	−1.216 ***	−1.075 ***	−0.141 ***
	Panel C: Self-treatment expenditure			
Food and other necessities	Energy poverty	−0.365 ***	−0.365 ***	
Hospitalization	Energy poverty	0.101 ***	0.101 ***	
STE	Food and other necessities	0.484 ***	0.484 ***	
	Hospitalization	0.076 ***	0.076 ***	
	Energy poverty	−0.747 ***	−0.578 ***	−0.169 ***

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. IOHE = inpatient and outpatient health expenses; STE = self-treatment expenditure.

It is important to highlight that the comparative magnitude of the total effect of the second pathway in relation to the first pathway has the potential to alter the sign concerning health-related expenses. In our study, the absolute value of the total effect associated with the second pathway, characterized by a negative sign, outweighs that of the first pathway, which exhibits a positive sign. Consequently, this dominance of the second pathway leads to decreases in the three health expense outcomes. This finding accounts for the divergent sign observed in our results compared to the findings from the case study conducted in China by Nie and Li (2023).

5. Conclusions and Policy Implication

Drawing upon data from the 2016 VHLSS, this study undertakes an empirical investigation to examine the influence of energy poverty on households' health expenditures in Vietnam. To address this research question, a double-hurdle model is employed, enabling the examination of the nexus between energy poverty and health expenditure. The empirical findings reveal a significant negative association between energy poverty and health expenditure. Specifically, we find a substantial reduction of 42.5 percentage points in overall household health expenditure among households experiencing energy poverty. Moreover, being exposed to energy poverty leads to declines of 24.6 percentage points and 45.5 percentage points in expenses related to inpatient/outpatient care and self-treatment, respectively.

In order to validate the robustness of these findings, several sensitivity analyses are conducted, including propensity score matching, double/debiased machine learning, and the framework proposed by Oster (2019). Across all these analytical approaches, the results consistently underscore the significant and enduring adverse impact of energy poverty on the examined outcome variables. Furthermore, an SEM analysis was conducted to examine the underlying pathways. The results indicate that the relationship between energy poverty and health expenses is mediated by household hospitalization, which is measured by the frequency at which household members have been admitted to the hospital, and by expenditures on essential items, such as food and daily necessities.

In our findings, it is important to note that while increasing energy poverty may reduce health expenditure, this reduction might not be desirable. The decrease in health expenditure is a consequence of inadequate access to energy services and the resulting negative impact on health. Hence, our findings carry important policy implications. First, targeted interventions like subsidies for energy-efficient appliances, energy efficiency programs, renewable energy initiatives, and improved energy infrastructure can enhance access to clean, safe, sustainable, and modern energy and, thus, contribute to improved health outcomes (Barrella et al. 2023; Dobbins et al. 2019; Kyprianou et al. 2019). Furthermore, recognizing the mediating role of expenditures on essential items in the relationship between energy poverty and health expenses, it is crucial to implement comprehensive social support programs/policies. These programs/policies should encompass provisions for access to essential items such as nutritious food and financial assistance for households experiencing energy poverty. These initiatives are expected to contribute to improved health outcomes.

This study is subject to certain constraints, which principally stem from limitations related to data accessibility. While we mitigate potential omitted variable bias in our model through the utilization of Oster's framework, it is advisable for forthcoming research endeavors to encompass additional pivotal control variables such as building or dwelling age/insulation or household energy appliances/systems. This broader incorporation would enhance the comprehensiveness of the rationale underlying the association between energy poverty and health expenditure.

Author Contributions: Conceptualization, H.T.N.-P. and H.L.; methodology, H.T.N.-P. and H.L.; software, H.T.N.-P. and H.L.; formal analysis, H.T.N.-P. and H.L.; writing—original draft, H.T.N.-P. and H.L.; writing—review & editing, H.T.N.-P. and H.L.; funding acquisition, H.T.N.-P. All authors have read and agreed to the published version of the manuscript.

Funding: We acknowledge the financial support that we received from Japan Society for the Promotion of Science (JSPS) Grant-in-Aid for Research Activity Start-up (Grant No.23K18795).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The authors do not have permission to share the data.

Acknowledgments: We would like to thank the participants at the Asian and Australasian Society of Labour Economics 2023 (AASLE 2023) for their comments, as well as the two anonymous reviewers for their feedback on the early version of this manuscript.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Multidimensional energy poverty index.

Dimension	Indicator	Weight	Household Is Deprived If
Cooking	Modern cooking fuel	0.1	It uses coal/coal briquette/firewood/farm products
	Indoor pollution	0.1	It does not have gas/magnetic/electric cooker
Electricity consumption	Electricity consumption	0.2	Per capita electricity consumption is less than 100 kW
Services	Household appliance ownership	0.1	It has no fridge
	Heating or cooling	0.1	It has no water heater and electric fan and air conditioner
Entertainment	Household appliance ownership	0.2	It has no TV (either black and white or color TV)
Communication	Telecommunication means	0.2	It has no phone (either landline or mobile phone)

Notes: Dimensions have equal weight of 0.2. Source: adopted from 2016 Vietnam Household Living Standard Survey and Feeny et al. (2021).

Notes

[1] It is worth noting that the 2016 VHLSS is selected as the dataset for scrutinizing the relationship between energy poverty and health expenditure. This selection is motivated by the notable scarcity of health expenditure data in more recent surveys, such as those conducted in 2018.

[2] Unfortunately, in the context of assessing health status, our available data are limited solely to hospitalization records, with an absence of self-reported health outcomes.

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