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The Health-Energy-Water Poverty Nexus: Evidence from Togo

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The Health-Energy-Water Poverty Nexus: Evidence from Togo

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Abstract

We investigate the impact of energy and water poverty on health expenditure. Our data comes from the 2011 and 2015 waves of the nationally representative Togo Core Welfare Indicators Questionnaire survey. The analysis is motivated by recognizing that improving access to healthcare, modern energy, and clean water is critical for reducing poverty and achieving sustainable development. Our study extends beyond previous research in three crucial aspects. First, we use multidimensional measures of energy poverty and water poverty. Second, we estimate a system of structural equations to simultaneously examine the relationship between health expenditure, energy poverty, and water poverty. Third, we conduct extensive sensitivity analysis to account for a potential critique of the validity of our instruments. To our knowledge, this is the first study to examine the energy-water-health nexus within a developing country context. We find a statistically significant effect of energy poverty on health expenditure. This result is robust to alternative methods of addressing endogeneity, alternative measures of energy poverty, and other robustness checks. Our research also reveals that energy poverty significantly increases the likelihood of catastrophic health expenditure, particularly for low-income households. The policy implications stress the need for holistic, multisectoral approaches that integrate energy access improvements with health financing strategies to alleviate the burden of catastrophic health expenditure and advance progress toward sustainable development goals.

Keywords: Health expenditure, Energy poverty, Water poverty, sub-Saharan Africa

JEL codes: I10, I32, Q40, L95

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1. Introduction

The 2030 Agenda for Sustainable Development acknowledges good health, modern energy, and clean water as vital to reducing poverty and achieving sustainable development. It underscores that improving health (SDG 3), securing affordable and clean energy access (SDG 7), and guaranteeing access to safe water supplies and adequate sanitation facilities (SDG 6) are imperative in addressing not just economic deprivation but also various social issues at their roots. The agenda also emphasizes an integrated approach toward these goals and recognizes that advances made in one area could catalyze positive effects across multiple others (United Nations, 2015).

We are drawing on survey data from Togo, a low-income country in sub-Saharan Africa, to explore the impact of energy and water poverty on household health expenditure. The region's unique socioeconomic and environmental contexts present a compelling case for examining the intricate relationships among health, energy, and water – all underpinned by poverty. The chronic disease burden in sub-Saharan Africa is mainly attributable to infectious diseases, inadequate healthcare infrastructure, and limited access to quality healthcare services (WHO, 2019). Households in the region rely heavily on out-of-pocket expenditures for healthcare, which pushes them into deeper poverty. Moreover, a significant segment of the population faces affordability and reliability issues with energy sources (IEA, 2022). The critical issue of access to clean and safe water contributes significantly towards water poverty and amplifies communities' susceptibility to waterborne diseases (WHO, 2023). A cycle of poverty and compromised health outcomes persists in the region due to these complex interactions.

This paper contributes to the existing literature by providing empirical evidence on the intricate relationships and interdependencies among health expenditure, energy poverty, and water poverty. Following recent research, we consider energy poverty and water poverty from a multidimensional perspective. We adopt the approach proposed by Nussbaumer et al. (2012) to compute a multidimensional energy poverty index, and develop our own multidimensional index for safe water and sanitation. This study moves beyond previous research by estimating a system of structural equations to simultaneously examine the relationship between health expenditure, energy poverty, and water poverty. To address endogeneity concerns, we use Bartik-style instruments (Goldsmith-Pinkham et al., 2020). Furthermore, we extend our empirical analysis to estimate the incidence of catastrophic health expenditures as they relate to energy poverty and access to safe water. To ensure robust inferences, we conduct a sensitivity analysis following a method proposed by Conley et al. (2012) for models with instruments whose validity might be questionable.

We find that energy poverty has a significant effect on household health expenditure. Moreover, there is robust evidence that energy-poor households face a higher probability of incurring catastrophic health expenditures. We conclude by identifying policy implications and strategies to address the challenges associated with the health-energy poverty nexus. Our findings and policy implications can guide interventions, resource allocation, and strategies to foster sustainable development in sub-Saharan Africa.

2. Data and Variables

Our data come from the 2011 and 2015 waves of the Core Welfare Indicators Questionnaire (CWIQ) survey. This nationally representative survey is conducted by the National Institute of Statistics and Economic and Demographic Studies with technical support from the World Bank. The CWIQ survey is well suited for our analysis as it gathers information necessary to assess household poverty and wellbeing. The 2015 wave contains data on 2400 households and their members. Data were collected in six administrative health regions comprising 40 health districts. Below, we describe how we use the survey to operationalize our variables.

2.1. Health expenditure

Health can be measured in different ways, and all measures are subject to some degree of uncertainty. Studies on the relationship between energy poverty and health have used different measures of health outcomes: e.g., Awaworyi Churchill & Smyth (2021) use self-assessed health, Lin & Okyere (2020) focus on the mental health status of the household head, while Oum (2019) defines ill-health as the number of household members having temporary problems. We focus on household health expenditure as our measure, akin to the approach taken by Bukari et al. (2021). Our measure of health expenditure encompasses two categories: direct medical expenditure (e.g., doctor's fees, diagnostic tests, pharmaceuticals, herbal medicines, self-care products) and other expenses (e.g., transport and lodging costs for accompanying people). Expenditures are reported both for hospitalization and for outpatient treatment.

We also analyze the incidence of *catastrophic* health expenditure. According to the WHO definition, health expenditure is catastrophic when it is greater than 40 percent of the capacity to pay, defined as a household's *non-food* expenditure (Xu et al., 2003). In subsequent literature, researchers have used different thresholds of household non-food expenditure to estimate catastrophic health expenditure in different countries. Financial catastrophe has also been defined as arising when health expenditure exceeds a certain threshold of *total* consumption expenditure (Wagstaff & Van Doorslaer, 2003). Since there is no consensus on a specific threshold for defining catastrophic health payments, we use four different thresholds: 10% and 20% of total consumption expenditure and 20% and 40% of non-food expenditure.

2.2. Energy poverty

We measure energy poverty using the multidimensional index developed by Nussbaumer et al. (2012). The index captures both the incidence and the intensity of deprivation concerning access to modern energy services. It is constructed using five dimensions of commonly demanded household energy services: cooking, lighting, services provided through household appliances, entertainment/education, and communication. The importance of each indicator to overall energy poverty is captured by applying weights. The aggregate deprivation score for each household is generated by summing up the weighted indicators. A household is classified as energy-poor if its deprivation score exceeds the threshold of 0.33. To estimate the national energy poverty index, the headcount ratio measured as the proportion of households identified as energy poor is multiplied by the average intensity of deprivation. Nussbaumer et al. (2012) use this method to report multidimensional energy poverty indices for 29 African countries. The index has been subsequently used in studies to estimate the relationship between energy poverty and various indicators, including CO_2 emissions and health and education outcomes.

The variables used to measure the dimensions of the energy index and the weights assigned to each variable are given in Appendix Table A.1. The overall energy poverty index for Togo in 2015 was 0.63, which is much higher compared to the index for Ghana of 0.34 for the same year computed by Lin & Okyere (2020) using the same method. By comparing the estimates along the dimensions of the index, we can see that households in Togo are significantly more deprived in terms of indoor pollution, i.e., food cooked on a stove or open fire in an enclosed room without a chimney (19% in Ghana vs. 93% in Togo). On the other hand, Togolese households are relatively less deprived in terms of radio/television ownership (49% in Ghana vs. 26% in Togo).

2.3. Water poverty

The construction of water poverty indices has been the subject of several studies (e.g., Cullis & O'Regan, 2004; Garriga & Foguet (2010)). The indices aim to provide a comprehensive assessment of water poverty, encompassing multiple dimensions such as access to clean water and adequate sanitation, as well as affordability, reliability and quality of water and sanitation services. However, these indices are focused on national or regional level estimates and are thus unsuitable for capturing safe water deprivation at the household level.

To keep the calculation methods of energy and water poverty indices comparable, we propose our own multidimensional water poverty index encompassing four dimensions of commonly demanded household water and sanitation services: access to safe water, time spent on water collection, safe wastewater disposal, and clean sanitation. A key challenge in constructing any index is assigning weights, as this often involves a value judgment on the relative performance of the variables (Garriga & Foguet, 2010; Nussbaumer et al., 2012). Without a predetermined weighting scheme, we rely on the approach proposed by (Vyas & Kumaranayake, 2006) for constructing socioeconomic status indices. The approach is based on applying Principal Component Analysis (PCA), a multivariate statistical technique that creates indices or components, where each component is a linear weighted combination of the initial variables. Since the first component (PC1) explains the largest amount of variation in the original data, we use the PC1 loadings of each variable and standardize them so that the sum of the loadings is equal to one.

The variables used to measure the dimensions of the water poverty index and the weights assigned to each variable are given in Appendix Table A.2. The overall water poverty index for Togo in 2015 was 0.64. Since this is the first application of the water poverty index as defined above, we cannot directly compare our results for Togo with those for other countries. As a rough comparison, using community-level data and a different methodology, Cullis & O'Regan (2004) calculate a water poverty index ranging from 0.54 to 0.60 for South Africa, and Garriga & Foguet (2010) report an index in the range of 0.49 to 0.56 for Kenya.

2.4. Covariates

Our covariates are chosen based on theoretical relevance and practical importance, including age, gender, marital status, educational attainment, presence of illness/injury, household size, (log) household income, home ownership status, and location (rural-urban dimensions). One covariate that deserves further explanation is household income. Ideally, one would use the household permanent income since households are expected to make decisions about their expenditures based on how they perceive their permanent income. However, since permanent income is difficult to measure, it is a general practice in the literature to use household health expenditure as a proxy. Especially in a country with a low savings rate, household expenditure is a good proxy for household income (Rous & Hotchkiss, 2003). We use extensive information on different types of expenditure in our survey to calculate total household expenditure, which we use as a measure of household income.

Catastrophic health spending is usually analyzed according to socioeconomic status, i.e., income groups (Njagi et al., 2018; Sato, 2022). Thus, in our estimates of the incidence of catastrophic health expenditure, we divide households into quartiles according to their total consumption expenditure: the first quartile represents poor households, the second quartile represents lower-middle income households, the third quartile the upper-middle income households, and the fourth quartile represents rich households.

Summary statistics of the variables used in this study are presented in Table A.3 in the Appendix.

3. Method

To estimate the impact of energy and water poverty on health expenditure while addressing endogeneity concerns, we estimate the following system of equations:

$$HE_i = \alpha_0 + \alpha_1 EP_i + \alpha_2 WP_i + \sum_n \alpha_n X_{n,i} + \varepsilon_{1i} \quad (1)$$

$$EP_i = \beta_0 + \beta_1 IV_{1i} + \sum_n \beta_n X_{n,i} + \varepsilon_{2i} \quad (2)$$

$$WP_i = \gamma_0 + \gamma_1 IV_{2i} + \sum_n \gamma_n X_{n,i} + \varepsilon_{3i} \quad (3)$$

where HE is the health expenditure of household i, EP is a multidimensional measure of energy poverty, WP is a multidimensional measure of water poverty, X is a vector of control variables, and ε is the error term. The key challenge when estimating the equations above involves selecting the identifying variables, IV_1 and IV_2, which affect health expenditure solely through their impact on energy poverty and water poverty. The credibility of our results depends critically on the plausibility of these identification restrictions. Thus, we discuss in detail our instruments and perform robustness checks of our identification assumptions.

We use Bartik-style instruments, named after Bartik (1991) and recently formalized by (Goldsmith-Pinkham et al., 2020). The Bartik approach and its variants have been used across many fields of economics, including international trade (Borusyak et al., 2022), migration (Fitchett & Wesselbaum, 2022), and development (Micevska Scharf & Rahut, 2014). A Bartik instrument is typically defined as a lagged share of the endogenous variable at a certain location or region. Because the local shares are likely co-determined with the level of the outcome of interest, it might not be plausible to assume that the shares are uncorrelated with the level of the outcome. However, this assumption is not necessary for the empirical strategy to be valid. Instead, as shown by

Goldsmith-Pinkham et al. (2020), the identification strategy is valid if *changes* in the local shares are uncorrelated with the *levels* of the outcome. Hence, the empirical strategy can be valid even if the local shares are correlated with the levels of the outcome as long as we can assume that the changes in shares are uncorrelated.

To construct Bartik-style instruments, we use the 2011 and 2015 waves of the CWIQ survey and compute the changes in local shares of households with access to modern energy (IV_1) and access to safe water and sanitation (IV_2) between the two time periods. The notion here is that the identifying restrictions are correlated with energy and water poverty as they reflect the changes in the availability and affordability of local infrastructure, but they should not influence household health expenditures, at least not in the short run. As long as we control for household income, these identifying restrictions should also reduce concerns that the relation between energy and water poverty and health expenditure actually depicts the clustering of poor households in certain regions. To further alleviate endogeneity concerns, we also check for any systematic patterns of correlation among the covariates (X) and the instruments.

To estimate the system of equations (1-3), we first use the two-stage least squares (2SLS) method. With adequately defined instruments, the 2SLS produces consistent estimates. Yet, a simultaneity bias might still be present as we expect cross-correlations in the residuals of the 2SLS equations due to unobservable determinants that simultaneously impact energy and water poverty. To account for the simultaneity issues, we use a three-stage least squares (3SLS) estimator. The 3SLS estimator applies an instrumental variable procedure to produce consistent estimates and generalized least squares to account for the correlation of the error terms across equations.

To estimate the effect of energy and water poverty on the incidence of catastrophic health expenditure, we employ an instrumental variable Probit regression, applying the same identification strategy described above. This method allows us to address endogeneity and examine the relationship between energy and water poverty and the incidence of catastrophic health spending.

4. Results

4.1. Baseline results

The first two columns of Table 1 report 2SLS estimates of the effect of energy and water poverty on health expenditure. We find that a unit increase in energy poverty increases health expenditure by 5.2 percent. This result is consistent with and slightly higher than the coefficient estimated by Bukari et al. (2021) for Ghanaian households. The finding that energy-poor households spend more on healthcare is also consistent with other studies that find a positive effect of energy poverty on health service utilization (Oliveras et al., 2020; Thomson et al., 2017) or a negative effect on health outcomes (Awaworyi Churchill & Smyth, 2021; Oum, 2019; Zhang et al., 2021). The statistically insignificant coefficient on water poverty runs contrary to our expectations.

Moving to the 3SLS estimates presented in the last three columns of Table 1, we observe that male-headed, rural, and larger households are at a higher risk of water poverty, as are households with less-than-secondary education, lower income, and a reported illness or injury. The same factors are responsible for energy poverty, with the addition of widowed household heads facing a higher risk of being energy poor. The presence of a household member with illness or injury is the only factor that is positively associated with both energy/water poverty and health expenditure. All the other statistically significant factors – low education, low income, large household size, and rural residence – work in the opposite direction: they are positively related to water/energy poverty but negatively related to health expenditure.

Energy poverty has a significantly positive effect on household health expenditure. The 3SLS estimate is larger than the corresponding 2SLS estimate. This suggests that the observed relationship between health expenditure and energy poverty is not driven by unobserved characteristics related to water poverty. On the other hand, the 3SLS estimate of the impact of water poverty remains statistically insignificant.

We found the coefficient on household income to be above unity. As the estimations control for energy and water poverty – both related to income – we refrain from using this number as a measure of income elasticity. Other studies using instrumental variable methods have also found the coefficient on income to be greater than unity (Bukari et al., 2021; Rous & Hotchkiss, 2003). The progressive nature of healthcare payments may only be considered a positive indicator if the poor can access the required healthcare, especially in the context of developing countries. We explore this issue further when examining the incidence of catastrophic health expenditure.

Table 1. Effect of energy and water poverty on log health expenditure

	2SLS estimates		3SLS estimates		
	Health expenditure		Health expenditure	Energy poverty	Water poverty
Energy poverty score[a]	0.0507** (0.021)		0.145** (0.073)		
Water poverty score[a]		0.0135 (0.014)	-0.0778 (0.0254)		
Age of household head	-0.0025 (0.025)	0.0024 (0.023)	-0.0002 (0.047)	-0.0390 (0.173)	0.133 (0.208)
Age of household head squared (x100)	-0.0112 (0.026)	-0.0143 (0.024)	-0.0239 (0.049)	0.0228 (0.174)	-0.00222 (0.002)
Household head is female (ref = male)	0.147 (0.166)	0.249 (0.175)	-0.0158 (0.386)	-0.961 (1.125)	-4.051*** (1.356)
Marital status of HH head (ref = single)					
Married	0.727*** (0.210)	0.821*** (0.192)	0.849** (0.392)	0.106 (1.427)	0.904 (1.720)
Divorced	0.453 (0.292)	0.562** (0.262)	0.340 (0.547)	2.021 (1.966)	-2.244 (2.368)
Widowed	0.369 (0.378)	0.674** (0.330)	0.188 (0.718)	6.478*** (2.394)	2.598 (2.883)
Education of HH head (ref = primary school or less)					
Junior high school	0.262 (0.169)	0.0511 (0.139)	0.372** (0.164)	-5.146*** (0.872)	-4.054*** (1.050)
High school/university degree	0.693* (0.376)	0.187 (0.282)	1.006** (0.445)	-14.86*** (1.424)	-12.64*** (1.716)
Adult equivalent household size	-0.106** (0.049)	-0.0269 (0.035)	-0.179* (0.104)	1.526*** (0.239)	0.599** (0.287)
Illness/injury in the household	0.722*** (0.135)	0.827*** (0.112)	0.492** (0.242)	2.681*** (0.811)	2.947*** (0.973)
Household income (log)	1.508*** (0.245)	1.064*** (0.137)	1.166*** (0.304)	-9.957*** (0.616)	-6.081*** (0.740)
Home ownership (ref = owned house)					
Rented house	-0.256 (0.175)	-0.280 (0.173)	-0.357 (0.250)	-0.0351 (1.187)	-2.281 (1.421)
Family house	-0.383** (0.155)	-0.301* (0.158)	-0.512* (0.274)	0.732 (1.060)	-1.676 (1.271)
Rural (ref = urban)	-1.021*** (0.353)	-0.538** (0.253)	-1.271*** (0.627)	13.21*** (1.079)	13.24*** (1.300)
Instruments					
Local share of households with access to modern energy	-11.95*** (1.710)			-11.85*** (1.713)	
Local share of households with access to safe water and sanitation		-16.11*** (2.098)			-15.79*** (2.105)
Observations	1619	1639		1592	

Note: Standard errors in parentheses. All regressions include a constant.
[a] Endogenous variable. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

4.2. Catastrophic health expenditure

Catastrophic health expenditure (CHE) is typically measured in terms of incidence and intensity (Wagstaff & Van Doorslaer, 2003). Table 2 presents the incidence and intensity of CHE at four thresholds: 10% and 20% of total consumption expenditure and 20% and 40% of non-food expenditure. Incidence is measured in terms of headcount, i.e., the share of households incurring CHE. For a 10% threshold of total expenditure, our headcount measure of 33% is higher than the pooled estimate of 17% calculated for 31 sub-Saharan African countries reported by (Eze et al., 2022). On other hand, for a 40% threshold of non-food expenditure, our estimate of 7% is lower than the pooled estimate of 9% in Eze et al. To measure the intensity of CHE, we calculate the overshoot, i.e., the extent to which health payments exceed the threshold averaged over all households, and the mean positive overshoot, i.e., the extent to which health payments exceed the threshold averaged over households incurring CHE. Our mean positive overshoot measure of 19% for a 20% threshold of non-food expenditure is comparable to estimates for Ethiopia, Tanzania, and Uganda as reported by Ssewanyana & Kasirye (2020).

Table 2. Incidence and intensity of catastrophic health expenditure

	CHE/Total expenditure		CHE/Non-food expenditure	
	10% threshold	20% threshold	20% threshold	40% threshold
% Headcount	0.33	0.16	0.20	0.07
% Overshoot	0.05	0.03	0.04	0.02
% Mean positive overshoot	0.16	0.17	0.19	0.24

Table 3 presents instrumental variable probit estimates of the effect of energy and water poverty on the incidence of catastrophic health expenditures. We find robust evidence that energy poor households are more likely to face CHE. The marginal effects are higher when we measure CHE relative to non-food expenditure than relative to total consumption expenditure. This indicates that, after covering the family's subsistence needs, the energy poor face a heightened risk of impoverishment due to their health expenditures as the basic needs compete for scarce resources.

Table 3. Effect of energy poverty and water poverty on incidence of catastrophic health expenditure (CHE): estimates of IV Probit regression model

	CHE/Total expenditure		CHE/Non-food expenditure	
	10% threshold	20% threshold	20% threshold	40% threshold
	Average marginal effects			
Energy poverty[a]	0.0803***	0.0338**	0.1479***	0.0636***
	(0.0388)	(0.0019)	(0.0407)	(0.0312
	Coefficients			
Energy poverty[a]	0.0243***	0.0235**	0.0389***	0.0398***
	(0.009)	(0.012)	(0.006)	(0.008)
Water poverty[a]	-0.0096	-0.0147	-0.0213*	-0.0174
	(0.008)	(0.011)	(0.013)	(0.013)
Age of household head	-0.0129	-0.0208	-0.0158	-0.0096
	(0.014)	(0.019)	(0.013)	(0.018)
Age of household head squared (x100)	0.0183	0.0276	0.0199	0.0207
	(0.000)	(0.000)	(0.000)	(0.000)
Household head is female (ref = male)	0.150	0.279**	0.0860	0.368***
	(0.095)	(0.140)	(0.086)	(0.135)
Marital status of HH head (ref = single)				
Married	0.2922**	0.424**	0.258**	0.0864
	(0.130)	(0.202)	(0.121)	(0.199)
Divorced	0.0049	-0.155	0.144	0.0258
	(0.189)	(0.264)	(0.155)	(0.248)
Widowed	0.0457	0.0474	0.0756	-0.0887
	(0.249)	(0.333)	(0.184)	(0.270)
Education of HH head (ref = primary school or less)				
Junior high school	-0.0329	0.116	-0.0740	0.0376
	(0.075)	(0.111)	(0.066)	(0.100)
High school/university degree	0.182	0.297	0.0149	-0.0247
	(0.129)	(0.195)	(0.119)	(0.219)
Adult equivalent household size	-0.0204	-0.0388	-0.00384	-0.0131
	(0.021)	(0.032)	(0.018)	(0.028)
Illness/injury in the household	0.2526***	0.140	0.183**	0.0878
	(0.078)	(0.108)	(0.071)	(0.104)
Socioeconomic status of HH (ref = poor household)				
Lower-middle income household	0.0643	0.0433	-0.0370	0.1665
	(0.100)	(0.145)	(0.086)	(0.140)
Upper-middle income household	-0.0985	-0.0486	-0.2146**	0.1473
	(0.108)	(0.154)	(0.098)	(0.148)
Rich household	-0.2877**	-0.1220	-0.2576**	0.1001
	(0.127)	(0.154)	(0.112)	(0.172)
Home ownership (ref = owned house)				
Rented house	0.0528	-0.204	-0.107	-0.144
	(0.102)	(0.152)	(0.093)	(0.148)

Family house	0.141	-0.101	0.0794	0.0470
	(0.089)	(0.131)	(0.076)	(0.113)
Rural (ref = urban)	-0.207**	-0.410***	-0.0255	-0.212
	(0.099)	(0.155)	(0.083)	(0.132)
Tests of endogeneity				
Correlation of error terms of main equation and energy poverty equation	-0.389***	-0.163	-0.473***	-0.415**
	(0.113)	(0.186)	(0.086)	(0.139)
Correlation of error terms of main equation and water poverty equation	0.0254	0.283**	0.178**	0.262*
	(0.111)	(0.139)	(0.090)	(0.156)
Correlation of error terms of energy poverty and water poverty equations	0.414***	0.414***	0.414***	0.414***
	(0.021)	(0.021)	(0.021)	(0.021)
N = 1592				

Note: Standard errors in parentheses. All regressions include a constant.
[a] Endogenous variable. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

The progressive nature of health payments does not hold in the case of CHE. On the contrary, at lower threshold levels, households in the highest income quartile are less likely to incur CHE than those in the lowest. This is consistent with findings of studies in other sub-Saharan countries (e.g., Adisa, 2015). Other statistically significant results in Table 3 generally align with our expectations

4.3 Robustness checks

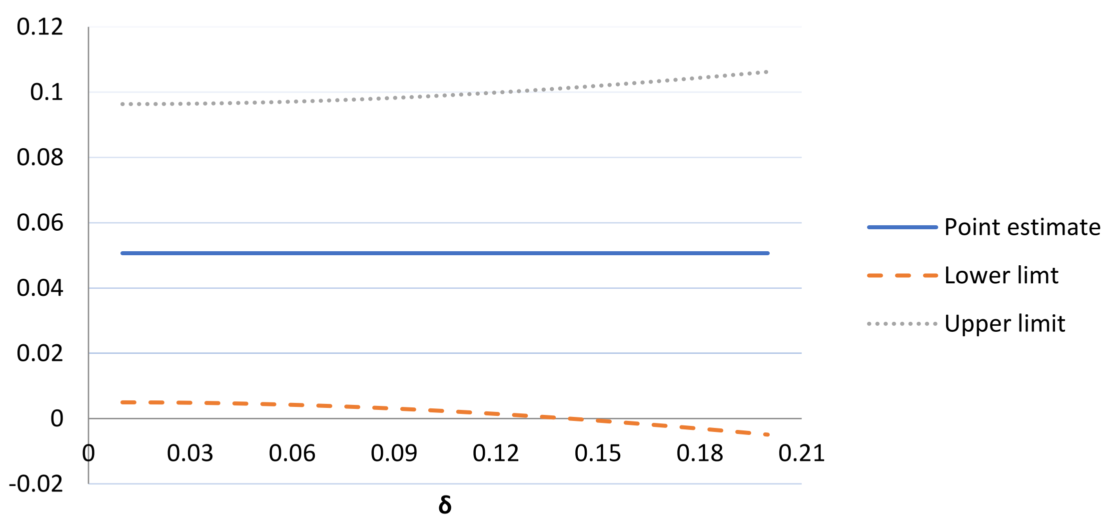
Our first robustness check addresses concerns about the validity of our identifying restrictions. We focus on the estimates for energy poverty as these coefficients are statistically significant. The first-stage estimates indicate that our instruments – changes in local shares of households with access to modern energy – are negatively related to the energy poverty index, and the first-stage F statistics exceed 10, indicating strong instruments (Stock & Yogo, 2002). However, the trade-off between instrument strength and exclusion restriction violation remains a concern (Bound et al., 1995; Conley et al., 2012). While a change in local access to modern energy is a strong instrument, the problem is that it could directly affect household health expenditure. For example, it can be argued that changes in local access to modern energy are related to (changes in) local health infrastructure, and the health infrastructure may directly affect household health expenditure. To assess this issue, we perform a sensitivity analysis using a method of drawing inference about IV models with instruments whose validity is debatable (Conley et al., 2012). The method entails a modified version of the model given in (1) and (2), and consists of estimating α_1 in the following equation:

$$HE_i = \alpha_0 + \alpha_1 EP_i + \sum_n \alpha_n X_{n,i} + \delta IV_{1i} + \varepsilon_i \quad (4)$$

where IV_1 is the instrument whose validity is debatable (in our case, the changes in the local share of households with access to modern energy) and δ is a measure of the direct impact of the instrument on the main dependent variable (household health expenditure). In the previous estimations, we assumed δ to be zero due to the strict exogeneity condition. However, one might argue that households from regions with larger changes in access to modern energy might also experience different health outcomes, in which case δ would not be equal to zero. This would result in a biased estimate of α_1.

Following Conley et al. (2012), we can estimate confidence intervals for α_1 by assuming support restrictions on δ or a prior distribution for δ. Figure 1 shows the 95% confidence interval for α_1 assuming that $\delta \in [0, \phi]$ for ϕ ranging from 0 to 0.20. The lower bound of the 95% confidence interval for α_1 crosses zero if ϕ is greater than 0.14, indicating that at this value for ϕ the confidence interval contains zero and the IV estimates are no longer significant at the $p \leq 0.05$ level. This suggests that our earlier results are robust even if changes in local access to modern energy had a direct impact on household health expenditure as large as 14%. However, we need to determine if this value for ϕ falls within a plausible range.

Fig. 1 Sensitivity analysis of instrumental variables



Since we are not aware of any direct evidence supporting a significant direct effect of changes in local access to modern energy on household health expenditure, we provide only indirect evidence. First, the correlation coefficient between local household health expenditure and changes in local access to modern energy is positive but quite low (0.049), indicating a limited direct effect. Another useful check is to look for an association between the instrument and the outcome of interest in a sample with no expected relationship (Angrist & Pischke, 2008). If changes in the local share of households with access to modern energy have a direct effect on household health expenditure, then this variable should be significant when we run a reduced-form regression for the sample of households without access to modern energy. As shown in Table 4, the coefficient of the reduced-form regression is statistically insignificant, supporting the argument that changes in local access to modern energy do not directly influence household health expenditure. Overall, this evidence increases our confidence in the identification strategy and suggests that our estimates are robust.

Table 4. Sensitivity analysis of effect of energy and water poverty

	Energy poverty	Water poverty
Reduced form estimates using samples limited to HHs without access to electricity or safe water	-0.5631	-0.0211
	(0.750)	(0.321)
IV Tobit estimates	0.0520**	0.0127
	(0.022)	(0.014)
Unidimensional measures of energy and water poverty	16.151**	-21.660
	(6.471)	(28.88)

Note: The dependent variable in all the regressions is log health expenditures. Standard errors in parentheses. All regressions include a constant and the same control variables as in Table 1.
***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

We conduct further robustness checks of our findings. First, we assess the sensitivity of our results to the use of a different estimation method. Since healthcare expenditure data are typically characterized by a large cluster of data at zero, previous research has used different sample selection and censored regression models (Bukari et al., 2021). We do not believe that this is an issue in our case since the share of households with no health expenditure is only 3.5 percent. Nevertheless, we use an IV Tobit regression model to address potential censoring issues. The results reported in Table 4 are consistent with the baseline estimates reported in Table 1. Second, we examine the robustness of our results to alternative measures of energy and water poverty. Although we argue that energy and water poverty are multidimensional in their very nature and can be properly measured by using composite indices, it is still possible that the composite indices are poorly constructed. To address this criticism, we provide estimates using unidimensional measures such as access to electricity and access to safe water. The results reported in Table 4 align with our general conclusion of a positive association between energy poverty and health expenditure, while the coefficient on water poverty remains statistically insignificant.

5. Conclusion

In this study we use an instrumental variable strategy to investigate the impact of energy and water poverty on health care expenditure. We utilize multidimensional measures of energy and water poverty and, to our knowledge, this is the first study to examine the energy-water-health nexus in a developing country context. Our findings reveal a statistically significant relationship between energy poverty and health expenditure, even after controlling for income or socioeconomic status. The effect of energy poverty is robust to alternative methods of addressing endogeneity, alternative measures of energy poverty, and other robustness checks. These results reinforce recent findings by Bukari et al. (2021). They are also consistent with the small but growing literature that examines the relationship between multidimensional energy poverty and health (Awaworyi Churchill & Smyth, 2021; Lin & Okyere, 2020; Zhang et al., 2021).

We also find that energy poverty has a substantial effect on the incidence of catastrophic health expenditure, disproportionally impacting low-income households and thus potentially exacerbating existing health inequalities. This enables us to suggest evidence-based interventions to mitigate the prevalence of catastrophic health expenditures. It has been recognized that social protection policies need to be more holistic and effective in protecting the most vulnerable from impoverishing health expenditures. However, achieving universal health coverage (SDG 3.8.1) requires public investment where resources are limited, and developing countries need to prioritize cost-effective and targeted health policies. Our study shows that the effectiveness of health financing can be enhanced through targeted protection of energy-poor households from making catastrophic health expenditures (SDG 3.8.2).

In sub-Saharan Africa, improving accessibility and affordability of energy stands as a key priority. Our research demonstrates that coordinated financing efforts in the energy sector could lead to additional benefits beyond achieving universal access to electricity (SDG 7.1.1). So far, there might have been little incentive for the health sector to contribute significantly to policies that support access to modern energy, as energy investments incur upfront costs while health benefits accrue over time. However, our study reveals the dual advantages of investing in access to modern energy, benefiting both the energy and health sectors. Consequently, comprehensive and multi-sectoral policies that simultaneously address energy and health issues are vital for achieving the desired SDG targets (Alinsato et al., 2024).

In conclusion, diverse financing mechanisms are essential for tackling energy poverty, encompassing discretionary budget authority for government ministries and support for the private sector in promoting and financing accessible and affordable modern energy. Sub-Saharan African governments need to adopt holistic approaches to address energy and health challenges hand in hand, ensuring progress toward the envisioned SDG targets.

Appendix

Table A.1. Summary of multidimensional energy poverty indicators

Dimension	Variable/deprived if… (weight)	% Deprived
Cooking	Use of fuel other than electricity or butane gas (0.2)	90.13
	Food cooked on stove or open fire (0.2)	93.45
Lighting	No access to electricity (0.2)	38.20
HH appliances	No fridge (0.13)	94.65
Entertainment/education	Neither radio nor television (0.13)	26.37
Communication	No phone (0.13)	17.91

Table A.2. Summary of multidimensional water poverty indicators

Dimension	Variable/deprived if… (weight)	% Deprived
Access to safe water	No piped water supply (0.27)	61.41
Time to collect water	Roundtrip to collect water > 30 minutes (0.21)	16.75
Safe wastewater disposal	No sewer-based sanitation facilities (0.23)	93.86
Clean sanitation	No flush toilet (0.29)	75.62

Table A.3. Summary statistics

Categorical variables	N	%	
Gender of household head	*2335*		
Female	595	25.48	
Male	1740	74.52	
Marital status of household head	*2326*		
Single	268	11.52	
Married	1626	69.91	
Divorced	174	7.48	
Widowed	258	11.09	
Education of HH head	*1683*		
Primary school or less	604	35.89	
Junior high school	878	52.17	
High school/University	201	11.94	
Home ownership	*2310*		
Owned	669	28.96	
Rented	806	34.89	
Family home	835	36.15	
Location	*2335*		
Rural	792	33.92	
Urban	1543	66.08	
Illness/injury in the household	*2335*		
No	949	40.64	
Yes	1386	59.36	
Continuous variables	**N**	**Mean**	**SD**
Total health expenditure (log)	2335	10.20	2.33
Energy poverty score (scale from 0-1)	2206	0.63	0.22
Water poverty score (scale from 0-1)	2295	0.67	0.22
Age of HH head (years)	2327	44.57	15.33
Adult equivalent HH size	2335	3.60	2.25
Household income (log)	2335	13.66	0.81

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