Impact of multidimensional energy poverty and climate shocks on health and nutritional outcomes: Evidence from KDHS 2022

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Abstract

Access to modern sources of energy is critical to socioeconomic development. Energy poverty has therefore been associated with prevalence of some human health conditions and wellbeing. These conditions could be worsened by climate shocks. Using DHS 2022 data for Kenya, this study sought assess the impact of multidimensional energy poverty and climate shocks on child and household multidimensional health poverty. Using an instrumental variable approach, the study revealed that energy poverty has a positive and significant effect on household health poverty and an even a more pronounced effect on child health poverty. This implies that children are the major casualties of energy poverty. The study also revealed that climate shocks (specifically temperature) has a positive and significant effect on household health poverty with an even higher effect on child health poverty. However, rainfall shocks were found to have significant negative effect on both household and child health poverty with a lower effect on child health poverty. In terms of policy recommendations, the study calls for policy measures to address energy access gaps through increasing access to cleaner, reliable and affordable energy targeting poor households. It also calls for policy actions towards climate adaptation and mitigation measures to cushion the populace from effects of climate change.

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1.0 Introduction

Access to modern forms of energy is critical to socioeconomic development of a country (UNDP, 2005; WHO, 2006). Globally, approximately 2.4 billion people cook their meals everyday using traditional energy sources and about 1 billion people lack access to electricity (WWI, 2019). It is also estimated that in 2020 about 3.2 million deaths were attributed to household air pollution from burning traditional fuels of which 237,000 deaths were among under five children (WHO 2022). Studies have also shown that one of the prerequisites for satisfactory housing is access to energy and a critical factor for physical and mental health of adults (Sen et al. 2023). The standard of living is also evaluated through the various forms of energy for cooking, heating and cooling and lighting (Welsch et al. 2017), further stressing the importance of accessing modern energy.

Energy poverty has been associated with prevalence of human health conditions such as poor mental health, asthma and overweight (Sen, Karmaker, Hosan, Chapman & Saha, 2023; Oliveras et al, 2021). This may ultimately lead to health poverty, a phenomenon described by Clarke and Erreygers (2020) as deprivation of minimum health standards by a section of population. Energy poverty may therefore have an implication on health poverty in countries where most households rely on traditional biomass and unclean fuels for lighting, heating and cooking. These kinds of fuel are main contributors of especially indoor air pollution and may adversely affect health and wellbeing of young children and women who spend more time at home, (Du et al. 2021; Karmaker et al. 2022; Kakinami et ak.2017).

Lack of modern energy services to power home appliances may also affect developmental milestones of children such as lack of access to educational materials (Sen et al, 2023). Household members grow socially, physically and mentally through watching television, using mobile phones and computers. Further, access to electricity may enable households to own refrigerator for preserving food and storage of vaccines. Generally, households with access to modern energy services are more likely to register progress in socioeconomic aspects (see Shahbaz et al. 2018; Nawaz et al. 2021).

Given the cited association between household energy access and welfare, climate shocks that demand intense use of energy to overcome may affect living environment and may also affect household health outcomes (Bridge et al. 2016; Kraus 2016). Specifically, households with poor heating facilities may also suffer negative impact on human health due to cold increasing risk of morbidity and mortality from cold (Aylin et al. 2001). Energy poverty in the midst of climatic shocks may therefore impact human health and wellbeing. For instance, the recommended WHO threshold for comfortable temperatures in living rooms and common spaces is 21 and 18 degrees respectively (Ogbebor et al. 2018). This is because very low temperatures may trigger biological reactions such as hypertension and cardiovascular issues. The increasing climate change effects have spurred increased demand for energy and rising health problems hence the interest in examining the nexus between energy and health and nutritional outcomes. In this study, Energy poor households are considered to be those that do not have access to modern energy (electricity and clean cooking fuels/technologies for basic energy needs or reliance on traditional energy sources such as biomass (IEA, 2016; Parajuli 2011).

Although past studies have looked at impact of energy poverty on health and wellbeing, the young children are most at risk of in access to clean energy services which could be meliorated by ensuring all homes have adequate access to clean energy services in their homes. It is therefore important to not only looking at overall household health outcomes but also health of children under five.

2.0 Setting the context

Kenya is located in the East Africa region and located on the coast of Africa's easternmost region spanning the equator. Kenya's Latitude and longitude are within the range of 0.0263^0S and 37.9062^0 E and covers a total land area of 582,646 kilometres squared. Kenya neighbours Ethiopia to the North, Tanzania to the South, Somalia and the Indian Ocean to the east, South Sudan and Uganda to the northwest and west respectively (Figure 1). The country is 85% classified as arid and semi-arid and largely pastoral hence prone to the effects of climate change shocks and vulnerability. According to the Kenya Population and Housing Census (2019), Kenya's population was estimated at 47.5 million. About 86.6% of the population reside in rural areas while 21.3% reside in urban areas (and projected to increase to 33% and 46 % of the population by the year 2030 and 2050 respectively (KPHC 2019).

Figure 1: Map of Africa Showing location of study area

Despite being a lower middle-income country, Kenya still faces challenges of high inequality and poverty levels which has increased the country's economic and social vulnerability to shocks. In addition, although the country has expanded its climate change resilience through investments in modern sources of energy, there are still inequities in terms of access of such services.

There are significant variation in access to energy services. Overall access to electricity is about 49.6% (urban-88.6%, rural-29.9%) while proportion of population that primarily relies on clean fuels and technology was 21.2% (urban 53.4%, rural -4.9%) (KDHS 2022). This implies that about 79% of Kenya's population still rely on other sources of energy such as charcoal, fuelwood and biomass among others. This has direct and indirect effects on human health especially mental and social wellbeing of children under 5 years.

However, infant and under five mortality rates have shown a significant improvement in Kenya. Specifically, infant mortality rate improved from 61 deaths per 1000 livebirths in 1989 to 32 deaths per 1000 livebirths in 2022 (KDHS 2022). Under five mortality rates also dropped from 90 deaths per 1000 live births in 1989 to 41 deaths per 1000 live births in 2022. Stunting among under five children also dropped from 35% in 2009/9 to 18% in 2022 (male (19.6%), female 15.6%). Wasting among under five children was 4.9% while underweight/malnutrition was 8.1% (KDHS 2022). In terms of educational outcomes, proportion of children aged between 24-59 months who were developmentally on track in terms of health, learning and psychological wellbeing was 78% (KDHS 2022).

Despite the improvement in the nutritional outcomes, there is more to be done especially for children and communities in the hard-to-reach areas and achieve the SDG targets. According to UNICEF, 64,500 children still die before reaching age of five due to preventable causes. Most of these kids die before first birthday and mainly attributed to diarrhoea, pneumonia, and neonatal complications. The most affected are children living in Kenya's northern counties and urban informal settlements. The situation is further worsened by climate change effects such as droughts leading and floods leading to poor access to clean and safe water. The immunization coverage is also quite low in pastoralists counties despite national immunization coverage being 80% up from 77% in 2008. Unless the welfare of these children is looked at and region-specific interventions crafted by policy makers, their future maybe at risk as the early stages of development plays a critical role in terms of their future especially in terms of education and health which may ruin their life forever hence the vicious cycle of poverty. For instance, child stunting (impaired height for age) is a clear indictor of undernutrition that emanates from insufficient energy and nutrient intakes. It also has severe effects on future physical and mental environment of children below five years.

3.0 Problem Statement

There has been growing amount of literature on impact of energy poverty on health and well being of communities globally. However, results from studies of impact of energy poverty on the welfare of children under the age of five is still inconclusive. This paper seeks to contribute to this debate by using data from DHS 2022 for Kenya to assess the impact of energy poverty on health and nutritional outcomes among children under five years.

Although a number of studies have looked at the impact of energy poverty on physical and social wellbeing, mental and maternal health of adults (see Sen et al. 2023). Studies on impact of energy poverty on children aged under five looking at various health outcomes such as malnutrition and stunting are quite few. Despite energy poverty having evident impacts on health outcomes, there is a dearth of evidence exploring the impact of domestic energy poverty on health outcomes especially for children aged under five in Kenya. Kenya is placed in a worst position given the increased environmental degradation and use of fuel wood and other unclean sources of energy for cooking and lighting posing a significant threat to human health. Studies such as Karmaker et al (2022), also found that child development is negatively associated with the severity of energy poverty in energy poor countries. The limited empirical research on how energy poverty affects early childhood development in energy poor countries therefore motivates this study.

The study therefore seeks to fill the research gap by establishing the impact of energy poverty on various health indicators among under five. Specifically, the study seeks to address the following research questions: What is the impact of multidimensional energy poverty on household multidimensional health poverty? What is the impact of multidimensional energy poverty on child multidimensional health poverty? (ii) What is the impact of climate shock on child and household multidimensional health poverty?

We utilize cross sectional data from Kenya demographic and health survey 2022 by employing the multidimensional energy poverty index and PCA. Energy poverty is assessed at household level, focusing on access to electricity, clean cooking fuel, Access to ICT/Internet, availability of TV, availability of radio, mobile phone ownership and ownership of refrigerator as a kitchen appliance. We apply instrumental variable regression models. The findings of this study shall inform targeted policy and health interventions towards promotion of use of clean energy sources.

4.0 Literature Review

Given the significance of access to cleaner energy and its impact on health outcomes. A number of studies have evolved over the years looking at various countries both in developed and developing countries. A study by Sen et al. (2023) using multilevel logistic and probit instrumental variable regression models found that a 1 % increase in energy poverty leads to a 48 % increase in the odds of developing acute respiratory infection among young children in South Asian households. Zhang et al. (2019) also found significant negative impact of energy poverty on health using household level survey data in China. Another study by Zhang et al. (2021) also found that energy poverty reduces children’s subjective wellbeing.

Omar et al. (2021) also revealed that multidimensional energy poverty is negatively associated with the health and educational status of households. Using both subjective and objective energy poverty indicators, Churchill et al (2021) found a negative association between energy poverty and health in Australia.

Sedai et al (2021) while using panel fixed effects instrumental variable regressions to assess how additional hours of electricity in a day affects household’s consumption expenditure, income, amenities, assets, borrowing and the status of poverty found significant effects of an additional hour of electricity overall especially among poor households in rural India. Oum et al. (2019) also found that energy poverty negatively impacts household’s average school years and health status. Energy poor households have also been found to be more prone to respiratory problems thus spending more on medical care and having higher dropout rates from schools and lower earning opportunities than less energy poor households (see Phoumin et al. 2019).

Using one-way multivariate analysis of variance (MANOVA) to empirically examine the relationship between energy poverty and health problems Abbas et al. (2021), found a significant relationship of energy poverty with the sources of drinking water, access to clean water, risks of mosquito bites, obesity, sterilization, marital status, literacy, occupation and residence. Olivieras et al. (2021) also found that energy poverty impacts on health worsened during economic crisis and that women and people living in Mediterranean and Eastern European countries were at higher risks.

An overview of the literature shows that most of the studies have been focused on single dimensional fuel poverty for cooking. This study expands the literature by expanding on multidimensional energy poverty by incorporating indicators such as electricity, clean cooking fuel and household appliances. The study applies novel econometric approaches including logistic regression models and instrumental variable models to address endogeneity of energy poverty. In addition, due to heterogeneity of regions in the country, a regional specific analysis is conducted to tease out region specific effects.

5.0 Data Sources

The study used Kenya Demographic Health Survey Data 2022. The data was collected between February and July 2022. The 2022 KDHS sample was drawn from the Kenya Household Master Sample Frame (K-HMSF) based on the KPHC (2019 data in which a total of 129,067 enumeration areas (EAs) were developed (KDHS 2022). Out of the total, 10,000 EAs were selected with probability proportional to size to create the K-HMSF. The EAs were further grouped into clusters through a process of household listing and georeferencing. The 45 counties that are non-urban (excluding Nairobi and Mombasa which are fully urban) were stratified into rural and urban strata resulting into 90 strata (KDHS 2022).

The sample size was computed at 42,300 households with 25 households selected per cluster resulting into 1692 clusters (1,026 clusters in rural areas and 666 clusters in urban areas). The sample was then distributed to different sampling strata using power calculation to enable comparability of county estimates (KDHS2022). Using two stage stratified sample design 1,692 clusters were selected independently from each sampling stratum from K-HMSF using the equal Probability Selection Method (EPSEM). Twenty-five households were selected per cluster after household listing. This resulted in 42,022 households being sampled from 2022 KDHS. Interviews were then conducted in preselected households and clusters without replacement.

6.0 Methodology

6.1 Empirical Approach

To examine the impact of energy poverty and climate shock on health poverty, the study used the ordinary least square regression model where **Y** is a vector of outcome variable namely Household multidimensional health poverty index and Child multidimensional health poverty index. The model takes the form:

$$\boldsymbol{Y} = \alpha + \beta MEPI + \gamma CS + \theta X + e$$

MEPI is multidimensional energy poverty taking the value 1 if a household is energy poor and 0 otherwise. CS is a vector of climate shock variables while θ is a vector of socioeconomic and demographic variables. β and γ are coefficients to be determined representing impact of energy poverty and climate shock on health poverty.

6.2 Identification Strategy

The study posits that there could be possibility of endogeneity resulting from omitted variable bias, measurement errors, simultaneity or reverse causality. Studies have shown that energy poverty may cause health complications leading to increase expenditure on health which further reduces household's disposable income leading to increased energy poverty (Zhang et al. 2021; Awaworyi et al.2020). The study therefore adopts the use of other selection models specifically the instrumental variable approach to address endogeneity concerns. The study used access to tap/piped water as the instrument (Zhang et al. 2019; Nawaz et al.2021). The motivation for choice of instrument is that households with access to piped water are more likely to access modern energy and is unlikely to be affected by individual household health status. However, some past studies instrumented multidimensional poverty using access to sanitation services (Zhang et al. 2019, Omar et al. 2021, Zhang et al. 2021). The choice of instrument was informed by economic theory, literature reviews and test of endogeneity. The variable is captured as a binary taking the value one if a household has access to flush toilet/improved pit latrine/pit latrine with slab and 0 if household uses other traditional toilet facilities.

Further, to assess the robustness of these results, the study employed the use of Lewbel's Heteroscedasticity based instrumental variables approach (Lewbel et al. 2012). The approach uses internally generated instruments to address the endogeneity.

6.3 Multidimensional Energy Poverty

Different studies have defined energy poverty in different ways. According to UNDP (2010) energy poverty is the absence of sufficient choice in accessing adequate affordable reliable and high quality, safe and environmentally benign energy services to support economic and human development. Other studies define it as the inability of a household to afford basic energy needs (Oliveras et al. 2021; Thomson et al. 2017). In this study, we define energy poverty using the fuel poverty phenomenon (Llorca et al.2020; Santillán et al. 2020). Specifically, we define energy poverty as the inability of a household to access or afford, essential clean and modern energy sources and products to fulfil energy requirements (Nawaz et al 2021).

The measurement of energy poverty ranges from unidimensional to multidimensional approaches (Awaworyi et al. 2021; Sokolowski et al. 2020). However, the most common approach is use of multidimensional poverty (Zhang et al. 2021; Ahmed et al. 2020; Sokolowski et al. 2020). There are hardly any studies in Kenya that have attempted to define energy poverty using multidimensional approach. The study contributes to this literature by adopting a multidimensional energy poverty index factoring a range of indicators including fuel for cooking, access to electricity, mobility poverty (possession of personal vehicle), access to ICT services (internet), ownership of TV, ownership of radio; ownership of mobile phone and ownership of LPG. This study employs the Alkire and Foster (AF) method (Alkire et al. 2017; Alkire and Foster 2011). A number of studies have used this approach using household data (see Ahmed et al. 2020; Shah, 2017). Following Nawaz et al. (2021), we constructed the multidimensional energy poverty index for Kenya using data from the KDHS (2022). The index is constructed using the following indicators:

- Fuel poverty: A household is fuel poor if a household uses traditional fuel for cooking and lighting. We look at two indicators
  - Cooking fuel
  - Lighting fuel
- Mobility poverty: a household is mobility poor if a household does not own any vehicle for personal mobility. One indicator is used
  - Household ownership of personal vehicle such as a car
- ICT poverty: a household is ICT poor if a household does not have access to or cannot afford ICT related services. The study uses four indicators to measure ICT poverty
  - Access to internet
  - Access to mobile phone
  - Availability of radio
  - Availability of TV
- Appliance poverty: A household is appliances poor if it is deprived of necessary kitchen appliances. We use Ownership of LPG gas.

Table 1 presents the definition of each of the indicators used in construction of multidimensional energy poverty.

Table 1: Construction of multidimensional energy poverty index: indicators and their respective weights

Dimension	Indicator	A household is deprived of IND if..	weight
Fuel Poverty	Cooking fuel	Use traditional fuel such as wood for cooking	0.2
	Lighting fuel	Use traditional fuel for lighting (no electricity)	0.2
Mobility poverty	Personal Vehicle	Does not possess one private vehicle such as a car	0.1
ICT poverty	ICT services	Does not have access to ICT service such as internet	0.1
	Entertainment-TV	Does not have the availability of entertainment services such as TV	0.1
	Entertainment Radio	Does not have the availability of entertainment services such as Radio	0.1
	Mobile Phone	Does not have access to mobile phone	0.1
Appliance poverty	Kitchen appliance	Does not possess kitchen appliances (LPG)	0.1

The study assigns equal weights to all dimensions and equal weights to indicators in each dimension following past works of Sen et al. (2023), Alkire et al. (2011), Nawaz et al (2021); and Maduekwe et al. (2020). The study gives more weight (0.2) to use of traditional cooking fuel and lighting fuel. This is due to their significance towards energy poverty especially in developing countries. Other indicators are given weights of 0.1 so that the total weight is 1. Each household deprivation score is based on assigned weight to each indicator as per the formula:

$$c_i = \sum_{1}^{n} w_i IND_I$$

Where $IND_I = 1$ if a household deprives in an indicator i and 0 otherwise. w_i captures weight assigned to indicator i with $\sum_1^n w_i IND_I = 1$. The deprivation score is thus a continuous variable ranging between 0 and 1 where a household with a score of zero depicts a household is not deprived of energy and 1 indicates that a household is fully deprived. Since a significant proportion of households in Kenya have no access to modern energy sources, it is hard to get households with a deprivation score of 0. Alkire et al. (2011) proposed a cut off value of 0.33 while for defining multidimensional poverty (Alkire et al. 2011) given that the study used unequal weights, to compute overall deprivation score, the study used 0.4 as the cut off value (Abbas et al. 2021). Therefore, a household is considered energy poor if $c_i \geq k$. Where k=0.4 is a threshold used to identify multidimensional energy poverty. The multidimensional energy poverty index is then computed using the formula:

$$MEPI = \left[H = \frac{q}{n}\right] * [A = \frac{\sum_{i=1}^{n} c_i(k)}{q}]$$

H is headcount ratio $\left[H = \frac{q}{n}\right]$, is the ratio of the number of households with multidimensional energy poverty q is the total number of households. A capture the intensity of their deprivation and described as $[A = \frac{\sum_{i=1}^{n} c_i(k)}{q}]$. Where $c_i(k)$ is the deprivation score of household i. The multidimensional poverty index is then calculated as $EPI = (H) * (A)$. A summary statistic of the multidimensional energy poverty indicators is presented in Table 2.

Table 2: Summary statistics of the multidimensional energy poverty indicators

Variable	N	Mean	SD	Min	Max
1 if HH uses wood fuel	77381	0.690	0.462	0	1
1 If HH uses traditional fuel for lighting (not electricity)	77381	0.588	0.492	0	1
1 if HH has no personal vehicle	77381	0.938	0.242	0	1
1 if HH has no internet access	77381	0.724	0.447	0	1
1 if HH has no television	77381	0.590	0.492	0	1
1 if HH has no radio	77381	0.442	0.497	0	1
1 if HH has no mobile phone	77381	0.176	0.381	0	1
1 if HH has no LPG	77381	0.884	0.321	0	1

The summary statistics show that 69% of households use wood fuel and that 59% do not have access to electricity while about 72% have no internet access and 88% have no LPG gas. However only 18% of households had no mobile phone revealing high access to mobile phone. A description of other indicators is also highlighted in the Table 2.

6.4 Multidimensional Health Poverty

Using the same multidimensional approach in construction of energy poverty index i.e. Alkire-Foster multidimensional approach, health poverty is defined as the condition of being poor in health or a situation where a household does not have access or unable to afford basic health or health services. (Clarke et al. 2020; Iqbal et al. 2017). The individual health status is used to quantify health poverty. Specifically, the study looks at the following indicators:

- Child health: this is quantified using diarrhoea
- General health: measured using the information on any illness that occurs in the household
- Infectious disease prevalence: estimated using prevalence of malaria, hepatitis and tuberculosis

The details are presented in table 2 along with the deprivation cut-offs.

Table 2: Construction of household multidimensional health poverty index: indicators and their respective weights

Dimension	Indicator	A household is deprived of IND if…	Weight
Member health	Diarrhoea	Member had diarrhoea recently	0.1
	Tuberculosis	Household member tested for TB after diagnosis	0.3
General Health	General reported Health status	Member self-reported health status	0.1
Infectious diseases	Chest Problems	Any member suffers from chest problem	0.2
	Short Breaths	Any member suffered short breaths	0.1
	Child had Malaria	A child reported to have suffered from Malaria in the last year	0.2

Then indicators are then used to compute household multidimensional health poverty at the general household level. In addition, children are vulnerable to undernutrition due to their high dietary requirements which are worsened by energy poverty and climate shocks. The study extended assessment to child under nutrition indicators looking at three major indicators that is stunting, wasting and underweight. According to WHO (2020), children are considered stunted when a child is too short for his or her age (low height for age)) or when they have a height-for-age z-score below two standard deviations (SD) from the WHO Child Growth Standards median of same age and sex. Children are also considered underweight if they have low weight for age and defined by a weight for age z-score below -2 SD. Wasting also refers to refers to when a child is too thin for his or her height (low weight for height). Specifically, it refers to a situation where the weight for height z-score is below -2 SD suggesting acute undernutrition or rapid weight loss. The z-scores are computed using the 2006 WHO child growth standards (Clinton et al. 2016) which are then used to generate dummy variable for each of the indicators. In addition, to assess child multidimensional health poverty, the study looked at child health (diarrhoea, TB) and whether a child had at least three immunization coverage. Table 3 shows the child multidimensional health poverty indicators and their weights were computed based on the current prevalence rates of the various indicators for Kenya.

Table 3: child multidimensional health poverty indicators and their weights

Dimension	Indicator	A household is deprived of IND if…	Weight
Child health	Diarrhoea	A child had diarrhoea during the last 15 days	0.2
	Tuberculosis	A child tested TB positive post diagnosis	0.1
Immunization	Immunization	A child did not have at least three immunizations	0.3
Undernutrition	Stunting	A child is stunted	0.2
	Wasting	A child is wasted	0.1
	Underweight	A child is Underweight	0.1

The child multidimensional health poverty indicator was also computed using the same approach used to constructed multidimensional energy poverty index.

6.5 Measuring climate shocks

The study follows the works of Dell et al. 2014 and Pailler et al .(2018) that used temperature and precipitation to assess the impact of climate on wellbeing. Temperature and rainfall data were obtained from the climatic data provided by the Climatic Research Unit (CRU) at the University of East Anglia (Harris *et al.,* 2020). The climate data combines data from more than 4000 weather stations around the world and satellite data, to get high-resolution monthly estimates of temperature and rainfall over the period 1901-2020. The advantage of this database is that it is provided at fine spatial resolution (0.5x0.5 degree) grids which allows us to aggregate the data to different geographical levels. Using the county shapefile for Kenya, we extracted monthly average temperature and rainfall data between 2011 and 2020 for each of the 47 counties in Kenya. In the study, climate shocks is defined as absolute deviation from long term mean values:

$$CM_{shock} = abs[x - \bar{x}]$$

Where x is the average monthly precipitation for the year 2020 and $\bar{x}$ is the ten year monthly average rainfall. The climate shock variable is then computed to county level using the same approach for temperature variable too. Table 4 presents a summary of the various indicators used to construct household and child multidimensional health poverty indicators as well as the climate shock indicators.

Table 4: Child and household multidimensional health poverty indicators and climate shocks

Household Health Multidimensional poverty indicators (n=77381)				
Variable	**Mean**	**SD**	**Min**	**Max**
1 if HH member had diarrhea recently	0.0341	0.181	0	1
1 if HH member tested positive for TB	0.000918	0.0303	0	1
1 if HH member reported bad health	0.0346	0.183	0	1
1 if HH member suffer chest problem	0.00865	0.0926	0	1
1 if HH member suffer short breath	0.0100	0.0996	0	1
1 if child had malaria	0.00924	0.0957	0	1
Child Health Multidimensional poverty indicators (n=17847)				
1 if child had diarrhea last 15 days	0.145	0.352	0	1
1 if child put on TB treatment	0.000560	0.0237	0	1
1 if child did not take at least 3 immunization	0.211	0.408	0	1
1 if child is stunted	0.944	0.230	0	1
1 if child is wasted	0.0664	0.249	0	1
1 if child is underweight	0.108	0.310	0	1
Climate shock indicators (n =77381)				
Absolute deviation from mean temperature	0.187	0.102	0.13	0.840
Absolute deviation from mean precipitation	12.42	8.624	0.27	30.26

Table 4 shows that only 3.4%, 3.5%, 1% of household members had diarrhoea, reported bad health, and suffered short breath respectively. Other indicators such as chest problem and testing positive for TB were relatively low. However, in terms of the child health indicators, 94%, 6.6% and 11% of child experienced stunting, wasting and underweight respectively. In addition, 21% of children had not taken at least 3 immunizations. Other indicators are also presented. The table also shows that the average temperature shock was 0.187 while precipitation shock was estimated at 12.42.

To assess the robustness and sensitivity of the indices, the study explored the use of indices constructed using Principal Component Analysis method. This approach has also been used by other studies to complement multidimensional energy poverty index (see Agradi et al.2023; Pasha. 2017). The same energy related indicators were used to construct the PCA score. PCA has the advantage of not pre-assuming the weights of the indicators to measure composite scores of energy poverty whose weights are very reliant on actual data.

6.6 Measuring other explanatory variables

To ensure the robustness of the results. The study included other controls based on intuition and related literature. Table 5 presents a description of the variables used in the study and their descriptive statistics. The descriptive statistics for all the variables employed including socio-demographic variables are presented in Table 5.

Table 5: Descriptive statistics

Variable	N	Mean	SD	Min	Max
Respondent age	77381	35.72	7.696	15	49
1 if HH reside in urban areas	77381	0.309	0.462	0	1
Years of residence	77381	31.92	19.73	0	50
Number of HH members	77381	6.090	2.621	1	24
Number of children under 5	77381	1.125	1.012	0	7
1 if Household head is male	77381	0.644	0.479	0	1
Household head age	77381	43.08	11.86	16	98
1 if HH has a bank account	77381	0.233	0.423	0	1
1 if HH has internet access	77381	0.276	0.447	0	1
Number of children	77381	4.417	2.315	0	14
1 if HH member currently breast feeding	77381	0.279	0.449	0	1
1 if Respondent married	77381	0.739	0.439	0	1
Birth order of respondent	77381	2.864	1.965	1	15
1 if HH goes to bush-no toilet	77381	0.154	0.361	0	1
1 if HH has piped water	77381	0.682	0.466	0	1
1 if HH has mosquito bed nets	77381	0.711	0.453	0	1

Table 5 shows that the average age of the respondents were 36 years, 31% of the households surveyed resided in urban areas, and most of the respondents had resided in the said area for an average of 32 years. The average number of household members were 6 while average number of under five children per household was one. In addition, 64% of households were male headed and about 68% of these households had access to piped water and only 28% had access to internet. Summary statistics of other variables is also presented.

7.0 Results and discussions

7.1 Impact of multidimensional energy poverty and climate shocks on household health poverty

7.1.1 Naïve estimates-OLS regression results

The OLS model estimates show that multidimensional energy poverty has a positive and significant effect on household multidimensional health poverty.

Table 6: Impact of multidimensional energy poverty on household health multidimensional poverty-OLS model results

VARIABLES	(1) MODEL(1)	(2) MODEL(2)	(3) MODEL(3)
Energy Poverty	0.0186***	0.0186***	0.0186***
	(2.10e-06)	(2.11e-06)	(2.13e-06)
Household Head Age		1.34e-07***	1.28e-07***
		(2.90e-08)	(2.90e-08)
1 if Household head is male		-1.93e-06**	-1.81e-06**
		(7.69e-07)	(7.70e-07)
1 if Respondent married		3.50e-06***	3.04e-06***
		(8.49e-07)	(8.54e-07)
1 if HH reside in urban areas		-6.82e-06***	-7.26e-06***
		(9.28e-07)	(9.57e-07)
1 if HH head has primary education		-7.37e-07	-3.48e-07
		(1.02e-06)	(1.14e-06)
1 if HH has secondary education		2.70e-06**	3.19e-06**
		(1.27e-06)	(1.37e-06)
1 if HH head has higher education		8.76e-07	1.45e-06
		(1.65e-06)	(1.72e-06)
1 if HH poorer wealth index		-5.92e-07	-6.00e-07
		(1.07e-06)	(1.08e-06)
1 if HH is in middle wealth index		-1.53e-06	-1.34e-06
		(1.13e-06)	(1.13e-06)
1 if HH is in richer wealth index		-1.89e-06	-1.52e-06
		(1.29e-06)	(1.31e-06)
1 if HH is in richest wealth index		7.37e-06***	7.91e-06***
		(1.65e-06)	(1.68e-06)
Number of children		-5.44e-07***	-5.61e-07***
		(1.72e-07)	(1.74e-07)
1 if HH piped water		2.77e-06***	2.83e-06***
		(7.44e-07)	(7.59e-07)
1 if HH has no toilet		2.74e-06**	2.28e-06*
		(1.19e-06)	(1.21e-06)
Constant	-0.000209***	-0.000215***	-0.000210***
	(7.77e-07)	(1.89e-06)	(2.30e-06)
Regional dummies	No	No	Yes
Observations	77,381	77,381	77,381
R-squared	0.999	0.999	0.999

Robust standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

The results in Table 6 presents the impact of energy poverty (multidimensional energy poverty) on household health poverty (multidimensional health poverty). We then estimated the second model while controlling for socioeconomic variables and no regional dummies and the third model while controlling for socioeconomic variables and regional dummies to capture regional heterogeneities. The results from the second and third models still showed that energy poverty has a positive and statistically significant effect on health poverty. Specifically, a unit increase in the energy poverty index increases the health poverty index by about 0.02 even after controlling for socioeconomic characteristics and regional heterogeneity. This results lend support to the works of Nawaz et al.(2021); Kahouli, (2020); Kose, (2019); Llorca et al., (2020); Oliveras et al.,(2020); and Zhang et al., (2019). The health poverty status also increases with age of household head. This may be attributed to the fact that as one ages they do not have energy and resources to provide various energy sources and given that with age immunity is often low.

Contrary to findings by Nawaz et al (2021) and Iqbal et al. (2017), the study revealed that male headed households experience reduced health poverty compared to female headed households. This could be attributed that most often male headed households are engaged in economic activities that generate income which they can use to seek health care services. In addition, respondents who were married experienced increased health poverty while those residing in urban areas experienced reduced health poverty. This could be attributed to increased access to health services, access to information and other social amenities and utilities like electricity. Further being married means more mouths to feed which can cut down on health and energy expenses. Although unexpected, households with access to piped water and experienced increased health poverty while an increase in number of children reduced household health poverty. Richest wealth index households also experienced increased health poverty.

However, since energy poverty may be potentially endogenous to health poverty, we employed the control function approach to test for endogeneity. The approach is conducted in two stages. In the first stage, the endogenous variable which in our case is multidimensional energy poverty was regressed on the instrumental variable whether household had access to piped water or not and other explanatory variables and the predicted residuals saved. In the second stage, the outcome variable multidimensional health poverty was regressed on the endogenous variable, other explanatory variables and the residuals[3] (Wooldridge, 2010). Using this test, the null hypothesis of exogeneity is rejected with at 1% level of significance. The null hypothesis of exogeneity is also rejected when we use the Durbin-Wu-Hausman test of endogeneity at 1% significance level. In light of evidence of endogeneity of multidimensional energy poverty, we proceeded to estimate an instrumental variable regression model to address endogeneity. However, since the strengthen or credibility of exogeneity depends on the strength of instruments used, OLS and IV estimates should both be presented when exogeneity is not rejected. In addition, even if the data does not reflect endogeneity, both OLS and IV are consistent. As previously stated, we use access to piped water as an instrument to address endogeneity among energy poverty and health (Zhang et al., 2019, 2021). Table 7 presents the IV model estimates of the impact of energy poverty on health poverty. The Anderson under identification LM test and Graigg-Donald weak identification Wald test revealed that the instruments were valid and that the three models were exactly identified (see Table 7). The IV model estimates revealed that energy poverty had a significant and positive effect on health poverty even after controlling for covariates and regional heterogeneity. The results reinforce findings using OLS model.

Table 7: Impact of multidimensional energy poverty on household health multidimensional poverty-IV model results

	(1)	(2)	(3)
VARIABLES	Model1	Model2	Model3

[3] The approach is same as the 2SLS approach but the only difference is that it allows for testing for endogeneity of multidimensional energy poverty. It however hinges on assumption of exogeneity of the instrument.

MEPI	0.0180***	0.0181***	0.0182***
	(0.000259)	(0.000190)	(0.000108)
Constant	-3.57e-05	-7.68e-05	-0.000106***
	(8.24e-05)	(5.34e-05)	(3.37e-05)
Covariates	No	Yes	Yes
Regional dummies	No	No	Yes
Observations	77,381	77,381	77,381
Kelibergen-Paap LM Statistic	7.776***	13.207***	30.181***
Cragg-Donald F Statistics	7.818***	13.245***	30.328***

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

To test the robustness of the IV estimates, the study also employed Lewbel's heteroskedasticity based instrumental variable approach (Lewbel et al. (2012). The approach provides robust estimates in the absence of plausible instrument or weak instruments. The approach uses internally generated IVs to address endogeneity. Table 8 presents the results using Lewbel's heteroskedasticity based instrumental variable approach. The results show that energy poverty is one of the significant factors that increase health poverty. The results lend support to the works of Kahouli, 2020; Llorca et al. 2020; and Zhang et al. 2021).

Table 8: Impact of energy Poverty on health poverty: Lewbel Heteroskedasticity based IV

	(1)	(2)
VARIABLES	Model1	Model2
MEPI	0.0193***	0.0192***
	(9.40e-05)	(3.95e-05)
Constant	-0.000406***	-0.000410***
	(2.66e-05)	(1.26e-05)
Covariates	Yes	Yes
Regional Dummies	No	Yes
Kelibergen-Paap rk LM statistic	80.016***	413.515***
Cragg-Donald Wald F statistic	13.529***	45.392***
Hansen J Statistic	122.401***	109.261***
Observations	77,381	77,381
R-squared	0.998	0.998

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

7.1.2 Climate shocks and multidimensional health poverty

The next step of the analysis was to assess the impact of climate shocks on household health poverty. The results are presented in Table 9. Regional dummies, covariates and energy poverty are used to ensure robustness of the estimates. The results show that just like previous models the impact of energy poverty on health outcome remained consistent. In addition, without controlling for energy poverty, covariates and regional dummies, the results show that rainfall and temperature shocks have positive influence on household health poverty at 0.2% and 0.1% respectively. The positive effect remained consistent when covariates are included. However, inclusion of covariates and regional dummies found that Temperature shocks continued to increase health poverty while rainfall shocks reduced health poverty. The negative effect of rainfall shock and positive effect of temperature shock persisted on inclusion of energy poverty as a dummy. The results are consistent with works of Kahouli 2020; Fahad et al. 2020; and Nawaz et al. 2021.

Table 9: Impact of climate shocks on health poverty: OLS Model Results

VARIABLES	(1) Model1	(2) Model2	(3) Model3	(4) Model4	(5) Model5	(6) Model6
Temperature Shock	0.00147***	0.00158***	0.00122***	2.76e-05***	2.68e-05***	3.08e-05***
	(0.000128)	(0.000129)	(0.000139)	(3.34e-06)	(3.37e-06)	(3.65e-06)
Rainfall Shock	1.91e-05***	5.57e-06***	-8.77e-06***	-9.10e-08**	-1.25e-07***	-3.37e-07***
	(1.39e-06)	(1.47e-06)	(2.09e-06)	(3.68e-08)	(3.92e-08)	(5.56e-08)
MEPI				0.0186***	0.0186***	0.0186***
				(2.08e-06)	(2.09e-06)	(2.10e-06)
Constant	0.00519***	0.00468***	0.00554***	-0.000213***	-0.000219***	-0.000210***
	(3.27e-05)	(7.15e-05)	(9.07e-05)	(1.09e-06)	(1.98e-06)	(2.49e-06)
Covariates	No	Yes	Yes	No	Yes	Yes
Regional Dummies	No	No	Yes	No	No	Yes
Observations	77,381	77,381	77,381	77,381	77,381	77,381
R-squared	0.004	0.021	0.035	0.999	0.999	0.999

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

7.2 Impact of household energy poverty and climate shocks on household child health poverty

7.2.1 Naïve estimates-OLS regression results

Table 10: Impact of energy poverty on health poverty and child health poverty: OLS Results

The OLS results in Table 10 also showed that energy poverty has a positive effect on health poverty whether we control for covariates or regional dummies or not.

VARIABLES	(1) Model1	(2) Model2	(3) Model3
MEPI	0.0817***	0.0817***	0.0817***
	(1.65e-05)	(1.66e-05)	(1.67e-05)
Constant	-0.000469***	-0.000464***	-0.000462***
	(5.39e-06)	(1.45e-05)	(1.84e-05)
Covariates	No	Yes	Yes
Regional Dummies	No	No	Yes
Observations	17,847	17,847	17,847
R-squared	0.999	0.999	0.999

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

However, since energy poverty is potentially endogenous to child health poverty we test the endogeneity using control function approach. The null hypothesis of exogeneity is rejected at 5%. The same conclusion is arrived at using the Durbin Wu-Hausman test of endogeneity. We then proceeded to estimate an instrumental variable model using an instrument on access to piped water and went ahead to test the robustness of the IV model using Lewbel's heteroscedasticity based instrumental variable that uses internally generated instruments. The results are presented in Table 11 and Table 12 for IV model and Lewbel's heteroskedasticity based instrumental variable model respectively.

7.2.2 Instrumental variable regression results

Table 11: Impact of energy poverty on health poverty and child health poverty: IV Results

VARIABLES	(1) Model1	(2) Model2	(3) Model3
MEPI	0.0926***	0.0855***	0.0838***
	(0.0228)	(0.00306)	(0.00120)
Constant	-0.00390	-0.00152*	-0.00108***

	(0.00720)	(0.000835)	(0.000359)
Covariates	No	Yes	Yes
Regional Dummy	No	No	Yes
Kleibergen-Paap rk LM statistic	0.235	1.988	5.787
Cragg-Donald Wald F statistic	0.233	1.963	5.717
Observations	17,847	17,847	17,847
R-squared	0.982	0.997	0.999

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 12: Impact of energy poverty on health poverty and child health poverty: Lewbel Heteroscedasticity Based Instrumental Variable

VARIABLES	(1) Model1	(2) Model2
MEPI	0.0856***	0.0845***
	(0.00102)	(0.000324)
Constant	-0.00154***	-0.00130***
	(0.000280)	(0.000102)
Covariates	Yes	Yes
Regional Dummies	No	Yes
Kleibergen-Paap rk LM Statistic	16.546	93.813***
Cragg-Donald Wald F statistic	2.815	10.277***
Hansen J statistic	16.877*	25.339*
Observations	17,847	17,847
R-squared	0.997	0.998

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

The instrumental variables result for both models show that multidimensional energy poverty has a positive effect on child multidimensional health poverty. The effects remain consistent even after inclusion of covariates and regional dummies. The analysis was further extended to assess the impact of climate shocks on child poverty. The results are presented in Table 13.

7.1.2 Climate shocks and multidimensional health poverty

Table 13: Impact of climate shocks on child health poverty: OLS Model Results

VARIABLES	(1) Model1	(2) Model2	(3) Model3	(4) Model4	(5) Model5	(6) Model6
Temperature Shocks	0.00566***	0.00575***	0.00451***	0.000124***	0.000124***	0.000148***
	(0.00119)	(0.00120)	(0.00129)	(2.82e-05)	(2.84e-05)	(3.06e-05)
Precipitation shocks	9.34e-05***	2.69e-05**	-3.28e-05*	-3.22e-07	-5.87e-07*	-1.65e-06***
	(1.26e-05)	(1.32e-05)	(1.85e-05)	(3.00e-07)	(3.19e-07)	(4.42e-07)
MEPI				0.0817***	0.0817***	0.0817***
				(1.65e-05)	(1.66e-05)	(1.67e-05)
Constant	0.0231***	0.0207***	0.0239***	-0.000488***	-0.000481***	-0.000459***
	(0.000297)	(0.000632)	(0.000827)	(8.32e-06)	(1.55e-05)	(2.03e-05)
Covariates	No	Yes	Yes	No	Yes	Yes
Regional Dummies	No	No	Yes	No	No	Yes
Observations	17,847	17,847	17,847	17,847	17,847	17,847
R-squared	0.004	0.022	0.037	0.999	0.999	0.999

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

The results show that the impact of energy poverty on child multidimensional health poverty is consistent with the effect of energy poverty on the overall household health poverty. The results also remain consistent with inclusion of other covariates and regional dummies. Overall the results show that energy poverty is positively associated with household health poverty and child health poverty. This implies that energy poor households are more likely to experience poor health outcomes for the entire households and also poor child health outcomes but the effects are significantly higher on child health.

8.0 Discussion

The study revealed that at the household level, energy poverty is positively associated with health poverty. The results show that energy poverty increases health poverty by between 1.8% and 1.9%. on inclusion of climate shock variables, the effect remained consistent at 1.9%.

Specifically, the study revealed that energy poverty increases child health poverty by between 8.4 % and 9.2% holding all factors constant. Energy poverty was also found to increase child health poverty by about 8.1% after controlling for climate shocks. Temperature shocks also increased child health poverty by 0.01% and 0.5%. The effect is within the same range whether OLS model or IV models are used. It is therefore evident that energy poverty has positive effect on health poverty but the effect is significantly higher (about four times higher) on child health poverty meaning that children are more likely to suffer from health poverty hence serious implications for future generations.

It is also important to note that temperature shocks had positive association with household health poverty with a temperature shock increasing household health poverty by between 0.027% and 0.15%. while precipitation shock had a negative influence on household health poverty after incorporation of covariates. The effects of climate shocks were also consistent with effects on child health poverty. The negative effect of rainfall shock could be due to improved agricultural production, improved food diversity and better nutritional outcomes for household members and children. It is therefore important to note that climate shock and energy poverty are all detrimental to general household health and child health. This is also enhanced by the fact that poor households often decide to choose traditional climate dependent energy resources, such as wood, animal dung and crop residues because they are easily available. As population rises the demand for these resources increases which may further have an effect on climate change.

8.1 Conclusion and recommendations

The study sought to determine: the impact of multidimensional energy poverty on household multidimensional health poverty and multidimensional child health poverty; and the impact of climate shocks on multidimensional household health poverty and child health poverty using KDHS 2022 data. The results revealed that energy poverty has a positive and significant effect on household health poverty and child health poverty but the effect is more pronounced on child health poverty. This implies that children are the biggest casualty of energy poverty. The study also revealed that climate shock specifically temperature shocks has a positive and significant effect on household health poverty and child health poverty but the effects are higher on child health. However, rainfall shocks were found to have significant negative effect on both household and child health poverty but the effects were lower on child health poverty.

It is therefore evident that energy poverty and climate shocks has significant effect on household health poverty and child health poverty. It is therefore inherent for policy makers to come up with policy measures to address the energy gaps and come up with climate adaptation and mitigation measures to cushion the populace from effects of climate change. Specifically, there is need for policy response towards increasing access to cleaner, reliable and affordable energy targeted to poor households in order to reduce/eliminate energy poverty.

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