Environment for Development

Discussion Paper Series July 2023 ■ EfD DP 23-11

Household Electricity Consumption Inefficiency and Poverty

Evidence from Ghana

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Keywords: Households, Electricity Consumption, Efficiency, Environment, Poverty.

JEL Codes: Q01, Q42, I32

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EfD Research MS-956

May 6, 2023

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1.0 Introduction

In many Sub-Saharan African (SSA) countries, electricity demand of households has increased and is bound to increase over time. According to the International Energy Agency(IEA) (2019), SSA, with an average annual growth in electricity demand of 6.5%, is the region with the highest electricity demand growth worldwide. In Ghana, electricity demand of households increased from 1996 GWh in 2007 to about 3,932 GWh in 2016 and is estimated to grow between 6%-7% per annum (Energy Commission [EC], 2017). In comparison, the annual growth of generation averaged 5.04% between 2010 and 2017. This means without appropriate measures to reduce the mismatch there will be insufficient electricity to meet domestic demand, especially as rural electrification continues to rise. The resulting effect will be a rise in electricity prices, which will be detrimental to economic growth. Many SSA countries, including Ghana, are implementing the Sustainable Energy for All (SE4ALL) initiative and Sustainable Development Goal Seven (SDG 7) which emphasizes cost-effective means of sustainable energy supply. However, the increase in electricity supply in Ghana is mostly through thermal generation, leading to increases in greenhouse gas (GHG) emissions. In recent years, Ghana has also invested in solar energy to increase the share of renewable energy in its energy mix.

One way of meeting household energy demand and ensuring sustainability is the use of energy efficiency measures, which attempts to optimise every unit of energy input to ensure that the quantity of energy required to produce the same energy service is reduced. Efficient use of electricity reduces household electricity expenditure (Anderson, 1993) and increases electricity supply security while providing a cost-effective means of reducing GHGs (Ozturk, 2013; Filippini et al., 2014). This consequently facilitates poverty reduction and enhances economic development (Inglesi-Lotz & Pouris, 2012).

In SSA countries and many other developing countries, poverty remains the main challenge to development making it difficult for many communities to have a sustainable future. Globally, over 710 million people currently live in extreme poverty, defined as spending less than US$1.90 per day (United Nations, 2022). Despite the good prospect for economic growth in some African countries, the region continues to face high poverty levels, lack of infrastructure, lack of competitive environment, finance gaps and other human development challenges including lack of skills. (United Nations Conference on Trade and Development 2022).

In Ghana, the poverty head-count ratio declined by 7.7% between 2005/06 and 2012/13, and further by 0.8% between 2012/13 and 2016/17 (GSS 2018). The incidence of poverty in Ghana has halved between 1991/92 and 2005/06 with a decline from about 37% to 18%. (GSS 2018). The multidimensional poverty index for the country, which considers factors including deprivation in electricity, water, housing, basic household assets, sanitation, and

nutrition, amongst others, has also decreased between 2011 and 2018 (Ghana Statistical Service, 2020).

Dasgupta (1999) and Lambert et al. (2014) argue that improving energy efficiency provides an opportunity not only for supplying electricity indirectly in a cost-effective way but also for addressing poverty. However, this assertion remains largely a conjecture since there exist limited empirical studies assessing the nature and extent of electricity consumption inefficiency and how energy inefficiency affects both consumption and multidimensional poverty. The objective of this study is to investigate the impact of energy efficiency on the multidimensional and consumption poverty of households in Ghana using survey data from Ghana. The findings of this study can support the introduction of energy efficiency policies such as appliance rebates and star rating systems on the grounds that these can support poverty reduction. The study could also increase awareness of electricity consumption efficiency to support the implementation of Sustainable Development Goal 7.

2.0 Literature Review

Globally, issues relating to poverty reduction rank high on the Sustainable Development Goal agenda with both developed and developing economies agreeing to enact poverty reduction policies (Baloch et al. 2020; Maji, 2019). Originally, poverty was perceived to be an economic phenomenon with people classified as poor if they lack enough income to meet necessities, including food and shelter (Guo et al. 2022; Alkire and Fang, 2019). This motivated the measurement of poverty using income or expenditure per capita (Wagles, 2002). Measuring poverty via an income or expenditure approach usually involves setting a poverty line, which can be either absolute or relative (Mehdi, 2017). While the absolute poverty line focuses on the cost of attaining a minimum amount of resources for survival, the relative poverty line is measured as a share of the median standard of living and can be updated automatically over time for changes in living standards (Zheng, 2001; Dogan et al. 2021). Several variables have been identified to influence the poverty status of households. These include social and political forces (Rupasingha & Goetz 2007), socio-economic factors (Rupasingha & Goetz, 2007), resource endowment (Bogale, Hagedorn, & Korf, 2005), and education and energy-related variables (Oluoko-Odingo,2009).

Sen (1976), however, argues that poverty is multidimensional and must consider other factors as well as income. This view is that money-metric measurement of poverty fails to capture the multi-dimensional nature of poverty (Tsui, 2002) and oversimplifies poverty values. Multidimensional measurements of poverty consider a range of items that households are deprived of, including access to health services, education, adequate nutrition, housing and environmental resources. (Alkire and Sumner, 2013; Bossert et al., 2013; Alkire and Seth,

2015, Guo et al. 2022). Other components of the multidimensional poverty measurement include lack of opportunity (World Bank 1981) and lack of capabilities (Sen 1982; 1985)

In SSA, household consumption of energy, especially electricity, is quite significant (Romero-Jordan and Rio, 2022; Thondhlana & Kua, 2016). For example, in Ghana, residential electricity consumption constituted about 47% of the total electricity consumption in 2021 (Energy Commission, 2021). The large share of household electricity consumption in total electricity consumption and the large share of energy expenditure in total expenditure suggests that the impact of energy efficiency on poverty requires attention.

Energy efficiency is defined by Prete et al. (2017) as the ability to obtain the best out of every unit of energy input to ensure that the quantity of energy required to produce the same energy service is reduced. A good measure of energy efficiency distinguishes between technical efficiency (which focuses on the reduction in energy consumption for a given level of energy service, through the purchase of efficient technologies) and allocative efficiencies that result from technological, behavioural, operational and economic changes that reduce the amount of energy consumed per unit of energy service (Newton and Cantarello. 2014). The distinction is important because of the rebound effect in which energy savings from technical efficiency improvement could be offset by an increase in energy consumption resulting for example, from poor behavioural practices (Herring, 2000).

Several studies have been conducted to determine efficiency levels of household electricity consumption using different methodologies. Findings on average electricity consumption efficiency scores for households in different countries include Yu and Guo (2016) with scores of 93% for rural China, Filippini and Hunt (2012) (85% to 95% for the United States), Filippini et al. (2014) (83% for 27 European Union (EU) member states), Carvalho (2016) who found a mean efficiency score of about 56% for 28 transition economies and 5 OECD countries, Broadstock et al. (2016) (63% for Chinese households), Lin and Du (2014) (63.2%, for Chinese energy economy), Twerefou and Abeney (2020) (63.0% for Ghana), among others. Adjei-Mantey and Adusah-Poku (2021) also reported that socioeconomic factors including household poverty levels significantly influence the adoption of efficient household technologies.

There exists limited empirical literature on the impact of electricity consumption inefficiency on poverty. In the literature, links between energy efficiency and poverty are discussed by Dasgupta (1999), who argues that energy efficiency improvements increase disposable income, improve health outcomes due to less pollution and reduce poverty. Lambert et al. (2014) establish that energy efficiency is a key contributing factor in improved human living standards. Energy poverty together with consumption inefficiency is shown to deepen the

vicious cycle of poverty in several ways, as it deprives the poor of basic services and reduces their opportunities (Lambert, 2014; Indrawati, 2015).

Empirical studies on the impact of energy efficiency on consumption and multi-dimensional poverty are also scarce. Related studies such as Bouzarovski & Petrova (2015), Dong et al. (2022) and Li et al. (2021) focus on the relationship between energy/fuel poverty and energy efficiency. According to Bouzarovski and Petrova (2015), energy efficiency is a major driver of energy poverty which relates to situations where there is scarce access to energy supplies (Dogan et al., 2021) because of energy wastage that causes households to pay disproportionately high prices for energy.

Energy poverty, where households lack sufficient monetary resources to pay for their basic energy needs, is directly impacted by high energy costs, low household incomes and energy inefficiency (Li et al., 2021). The authors argue that consistent long-run energy poverty may decrease the welfare of households. They recommend that policymakers focus on energy efficiency and energy poverty because inefficient energy policies can increase energy poverty and make it difficult to drive investment in energy poverty mitigation.

Dong et al. (2022) conclude that improved energy efficiency can eliminate both inequality and energy poverty among Chinese households. However, the authors find significant heterogeneity and asymmetry in the impact of energy efficiency on energy poverty and inequality. They suggest technological evolution to enhance energy efficiency as an approach to overcome energy poverty and inequality among Chinese households.

Dasgupta et al (1999) emphasize a bi-directional relationship between energy efficiency and poverty. In one direction, energy inefficiency can threaten the livelihood of poor households due to their excessive expenditure on energy. On the other hand, poor households lack the funds to procure efficient appliances to enable them to save energy. Additionally, Pillai et al. (2021) indicate that improvement in energy efficiency in dwellings of low-income households may aid in breaking the cycle of poverty caused by higher energy costs. Anderson et al. (2010), Raissi and Reames (2020) and Healy and Clinch, (2004) point out that, in the wake of higher energy costs, households usually forgo expenditures on necessities like food and medicines to satisfy their energy needs. Low income has also been observed to prevent people from investing in energy efficiency improvements, which usually involve high initial costs followed by incremental savings over time (Raissi and Reanes, 2020). Simcock et al. (2017) have also established that the poor end up paying a disproportionate part of their low income for energy because of their inability to invest in energy efficiency measures due to the high upfront cost.

Lack of access to clean and affordable energy is also considered a dimension of poverty (United Nations Department of Economic and Social Affairs, 2018). Investments in energy

efficiency projects can create jobs, which could indirectly reduce the poverty incidence in a country (Ganda & Ngwakwe, 2014). The external benefits of such investments also go beyond mitigating climate change to ensure the sustainability of resource use.

Evidently, literature is lacking in studies that investigate the impact of energy efficiency on poverty in Africa and factors that link energy inefficiency and poverty in this region have not been addressed. This is a gap that this study intends to fill.

3.0 Methodology

The study uses mixed methods in addressing the key objectives. We commence by soliciting information on energy efficiency management from energy sector stakeholders through focus group discussions and semi-structured and unstructured interviews. The outcome helps us to discover the factors relating to energy inefficiency and poverty of households and consequently, enabled us to design the household survey on energy efficiency and poverty. Based on data from the survey, we estimate household electricity consumption inefficiency, consumption poverty, and multidimensional poverty. We then proceed to investigate the impact of electricity consumption inefficiency on both consumption and multidimensional poverty of households. We also acknowledge the possibility of poverty indirectly causing energy consumption inefficiency, especially for credit-constrained households. We could mitigate the challenge with an instrument, but due to data limitations and the applicability of our findings, we only present results of the impact of energy inefficiency on poverty and recommend future studies to pay close attention to the opposite relationship.

3.1 Data

The data for the analysis was obtained from a survey undertaken in three regions of Ghana: Greater Accra, Ashanti, and the Northern Region, to represent Coastal, Forest and Savannah Zones respectively. We adopt a sampling design by the Ghana Statistical Service (GSS) for the Ghana Living Standards Survey (GLSS). Based on the design, the GSS has listed rural and urban Enumeration Areas (EAs) in all the regions. We proportionally allocate EAs to the regions sampled based on rural-urban stratification. Twenty households were systematically selected from each EA following the ordered sampling frame. The final number of EAs selected were 28 urban and 3 rural areas in Greater Accra, 19 urban and 12 rural areas in Ashanti, and 8 urban and 11 rural areas in the Northern Region. Households in the EAs were located with the help of the household listing undertaken by the GSS containing the names, addresses and Global Positioning System location of all households within the EAs. We submitted all the data collection instruments and protocols for approval by the University of Ghana Ethics Committee for Humanities before going into the field.

Pretesting of the questionnaire was done in all the regions which permitted us to revise the questionnaire and check for consistencies in the logical branching after which training was organized for the interviewers to ensure a thorough understanding of the objectives of the project. The data was collected with the aid of Computer Assisted Personal Interviews (CAPI). The questionnaire was designed to collect data on a broad range of issues relating to energy consumption, dwelling characteristics, socioeconomic status, appliance ownership, electricity consumption, willingness to pay for renewable energy, personality traits, among others. Enumeration was carried out between April and May 2022.

3.2 Empirical Model and Estimation Technique.

The relationship between household electricity consumption and (in) efficiency and poverty is dicey. A household can use its disposable income for different purposes, such as savings, payment of a debt, purchase of durable goods, purchase of non-durable items. Expenditure on durable goods includes expenditure on all physical items not for immediate consumption, or whose usage spans over several periods. This includes household expenditure on electrical appliances, which is our main concern. Non-durable household expenditure involves households' expenditure on items for immediate consumption or whose usage is only for a short period (e.g., expenditure on food, medicines). Expenditures on non-durable commodities are recurrent and household consumption poverty is mostly measured through such expenditures. A household is deemed poor if its recurrent/consumption expenditure is below a given threshold (poverty line). If a household is inefficient in its electricity consumption, it will have to pay more for electricity which will reduce the amount of money available for other recurrent expenditures and consequently reduce household income.

Poverty may also indirectly influence inefficiency. For example, households that have lower income may not be able to invest in efficient technology/appliances which will contribute to technical inefficiency. However, greater technical inefficiency increases the overall inefficiency of households which ultimately leads to higher expenditure on electricity. This reduces available resources meant for other recurrent expenditures through which poverty is measured.

The study uses Ordinary Least Square (OLS) estimation to investigate the impact of energy consumption inefficiency on multidimensional poverty and a probit model to estimate energy consumption inefficiency on consumption poverty. The OLS model can be specified as:

$$PPI_i = \beta_0 + \beta_1 eff_i + \beta_2 X_i + \epsilon_i \quad (1)$$

Where PPI_i is the poverty probability index (PPI) of a household, eff_i is the efficiency score of a household and X_i is a vector that represents other factors that influence a household's

poverty probability index score. β_1 and β_2 are covariates to be estimated and ϵ_i is a normally distributed error.

The probit model can be specified as:

$$Pr\,(Y = 1/X) = \Phi(X^T\beta) \qquad (2)$$

$$Y = X_T\beta + \epsilon \qquad (3)$$

$$Pov_i = \beta_0 + \beta_1 eff_i + \beta_2 X_i + \epsilon_i \qquad (4)$$

Where Pov_i is a dummy measuring whether a household is classified as poor or not poor. The other variables were defined earlier.

Out of the 1,580 households that provided valid responses, about 1,109 respondents representing 70.2% provided information that enables us to compute the consumption and multidimensional poverty of households. This sample is therefore used for the analysis.

3.3 Dependent Variable

The study focuses on two measures of poverty: multidimensional poverty, using the Poverty Probability Index[1] (PPI) developed by Innovations for Poverty Action (IPA) and consumption poverty. Multi-dimensional poverty is a continuous variable obtained by aggregating the household scores from 10 questions in the survey that address multidimensional poverty and converting these values to an estimate of the likelihood that a household is poor. Two different multidimensional poverty measures were developed using the extreme and national poverty lines. Specifically, following the guidelines of the look-up table from IPA, we first obtain the Poverty Probability Index for each household using the aggregation of the scores from ten poverty-related questions. We then follow the look-up table under the columns of extreme poverty and national poverty (100%) to convert the PPI scores to a Poverty Likelihood (PL) measure which is used as the dependent variable. The descriptive statistics of the Poverty Likelihood variable (Table 1) indicate that the average poverty likelihood score is 7.71 for extreme poverty and 19.64 for national poverty.

Deaton and Muellbauer (1980) indicated that using per capita expenditure as a measure of poverty tends to associate larger household sizes with poverty. Thus, we use per adult equivalence expenditure following the equivalence scale recommended by Deaton and Zaidi (2002) and given as $(A + \alpha K)^{\theta}$, where A represents the number of adults above age 16 in a household, K represents the number of children below 16 years, α accounts for the household composition and indicates that the need of children is usually less than that of adults and θ reflects economies of scale in household expenditure. In this study, we set α to 0.33 based on

[1] The detailed PPI methodology for Ghana including the score cards and look-up table can be found at https://www.povertyindex.org/country/ghana

the recommendation of Deaton (2002). The value of α as set indicates that the expenditure needs of children is about a third of adults in a household.

The choice of the value for θ was based on the percentage of household expenditure that goes to food. According to GSS (2018), household expenditure on food is about 50.6% for rural households and 39.2% for urban households. Regier et al. (2019) state that food expenditure does not have an economy of scale because it is a private good. We therefore infer that approximately 50% of rural and 60% of urban households' expenditure will have some spill-over effects and consequently set θ to be 0.5 for rural households and 0.6 for urban households.

According to GSS (2018), the extreme poverty line and the upper poverty line for Ghana in 2017/2018 were Ghc 982.2 and Ghc 1760.8 per adult equivalent, respectively. We use the average inflation rate for Ghana from 2017 to 2021 of 10.844% to adjust these values to Ghc 1643.47 and 2198.7 respectively for 2022. A household is classified as experiencing extreme poverty (food poverty) if the household's per adult equivalent expenditure per year falls below the extreme poverty line. meaning that if the household devotes all its expenditure to food, it will still not be able to meet the minimum nutritional requirement (GSS, 2018). On the other hand, a household is considered poor if both its expenditure on food and non-food needs is below the upper poverty line.

We use both the extreme (lower) and upper poverty lines to develop a dummy variable for the dependent variable for consumption poverty. A household is assigned a value of 1 if its per-adult equivalent expenditure per year falls below the defined poverty threshold and zero otherwise. This means that the dependent variable measures households that are poor according to the defined threshold. We expect energy efficiency to have a negative impact on poverty. The descriptive statistics of the two dummy variables are reported in Table 1.

3.4 Independent Variables

We proceed to estimate the efficiency of household electricity consumption, which is our main independent variable, using a stochastic energy demand frontier. Specifically, to estimate the electricity consumption efficiency of households, we estimate a stochastic energy demand frontier model by Filippini and Hunt (2012) which decomposes the composite error term into a symmetric disturbance term and the inefficiency term assumed to be half-normally distributed and specified as equation 6.

$$q_i = \beta_0 + \beta_1 p_i + \beta_2 y_i + \beta_3 x_i + \upsilon_i + \mu_i \quad (5)$$

where q_i is energy demand, y_i is income, p_i is energy price, x_i includes energy-using capital, socio-economic and community variables, μ_i reflects the level of inefficiency, half-normally distributed as $\mu \sim N^+(f(z_i), \sigma^2{}_\mu)$ and υ_i is the symmetric disturbance term which assumes a normal distribution $\upsilon \sim N(0, \sigma^2{}_\upsilon)$.

Estimation of equation (5) follows a single-stage stochastic frontier estimation technique that requires the introduction of determinants of inefficiency in the estimation process such that:

$$\mu \sim N^+(f(z_i), \sigma^2{}_\mu) \qquad (6)$$

Thus, equations (5) and (6) are estimated jointly with $f(z_i)$ in equation (5) containing variables that explain the inefficiency of household electricity consumption.
Households' electricity consumption inefficiency is predicted following the conditional in-efficiency estimation technique proposed by Jondrow et al. (1982) presented as equation 7.

$$\hat{\mu}_i = E[\mu_i \mid \mu_i + v_i] \qquad \text{.......} (7)$$

and the level of efficiency as equation 8.

$$EF_i = \frac{E_i^F}{E_i} = \exp(-\hat{\mu}_i) \qquad \text{.......} (8)$$

Where the observed level of electricity consumed by the household is given by E_i and E_F is the possible minimum consumption with respect to the electricity demand frontier. An efficiency value of one indicates 100% efficiency while anything less than one indicates some level of inefficiency in the consumption of electricity. These household-specific inefficiency measures are regressed on household consumption and multidimensional poverty.

3.5 Descriptive Statistics

From the data, the average household electricity consumption efficiency is approximately 58.7%. The explanation for most demographic and socioeconomic variables such as sex, age, education, marital status, can easily be understood from Table 1. Willingness to take risks is measured on a scale of 1 to 5 (where 1 means extremely unlikely and 5 means extremely likely) and measures the extent to which a household is willing to take risks in buying a new appliance. We consider the risk-averse behaviour of a household to decrease as it moves from extremely unlikely to extremely likely.

Table 1: Descriptive Statistics

Variable	Description	Mean	Min	Max
Dependent Variables				
Multidimentional Poverty (Pov. Likelihood (National)	Continuous, following the look-up table from IPA under the national poverty category	17.156	0.500	87.1
Consumption poverty (Lower Line)	Dummy, 1 if annual expenditure per adult equivalence is less than Ghc. 1613.132, 0 otherwise.	0.104	0.000	1
Consumption Poverty (Upper Line)	Dummy, 1 if annual expenditure per adult equivalence is less than Ghc. 2198.651, 0 otherwise.	0.243	0.000	1
Independent Variables				
Efficiency scores	Continuous, measures the level of efficiency in electricity consumption and obtained from stochastic demand frontier	0.5866	0.028	0.909
Sex	Dummy, 1 if male and 0 if female	0.659	0.000	1
Age	Continuous	44.518	18.00	94
Age square	Continuous	2163.9	324	8836
Marital status	Dummy, 0 if never married, 1 if married and 2 if other forms of association.	1.095	0.000	2
Education				
No education	Dummy, 1 if no education, 0 otherwise	0.1804	0	1
Primary	Dummy, 1 if Primary level of education, 0 otherwise	0.1073	0	1
JSS/JHS/Middle	Dummy, 1 if JSS/JHS/Middle level of education, 0 otherwise	0.1974	0	1
SSS/SHS/Voc/Tech	Dummy, 1 if SSS/SHS/Voc/Technical level of education, 0 otherwise	0.3517	0	1
Tertiary	Dummy, 1 if Tertiary level of education, 0 otherwise	0.1632	0	1
Location	Dummy, 0 if rural and 1 if urban	0.748	0.000	1
Employment	Dummy, 0 if unemployed, 1 if employed	0.805	0	1
Sector of Employment	Dummy, 0 if employed in the public sector and 1 if employed in the private sector	0.82	0.000	1
Willingness to take risk		.	.	.

Extremely unlikely	Dummy, 1 if extremely unlikely to take risk, 0 otherwise	0.100	0	1
Unlikely	Dummy, 1 if unlikely to take risk, 0 otherwise	0.183	0	1
Neutral	Dummy, 1 if neutral in taking risk, 0 otherwise	0.244	0	1
Likely	Dummy, 1 if likely to take risk, 0 otherwise	0.346	0	1
Extremely likely	Dummy, 1 if extremely likely to take risk, 0 otherwise	0.127	0	1
Type of School attended	Dummy, 1 if attended/attends private school, 0 if public school	0.116	0	1

Source: Authors' estimation from household survey, 2022

4 Results and Discussion

We start the discussion by looking at the impact of energy efficiency on multi-dimensional poverty, measured by the poverty likelihood of a household as reported in Table 2.

4.1 Multidimensional Poverty

Over half of the variation in multidimensional poverty is jointly explained by the independent variables as indicated by the R-squared value of 0.53. A percentage increase in energy efficiency reduces the poverty likelihood of a household by approximately 9.4 percentage points. The empirical literature investigating the impact of energy efficiency on the poverty status of households is quite sparse. However, given that households' behaviour directly feeds into energy inefficiency and consequently multidimensional poverty, one can conclude that households that are prudent or diligent in their daily activities have higher efficiency score that reduces multidimensional poverty. This can be illustrated with the correlation results presented as Appendix 1, where energy efficiency scores positively correlate with prudent and diligent behaviours of households. Thus energy efficiency scores may capture important qualities such as prudence or diligence, that may affect the multidimensional poverty status of households.

The implication of this finding could be that the wastage behaviour of households (revealed through energy inefficiency) has negative consequences on multidimensional poverty. This suggests that the potential success of poverty intervention programmes may be predicted by the energy efficiency scores of households. However, we interpret this result with care because poverty could also indirectly cause electricity consumption inefficiency, especially for credit-constrained households. Ascertaining this fact will require the use of instrumental variables. Unfortunately, our data does not contain a good instrumental variable for this purpose. We also prefer to use the calculated energy efficiency variable rather than an instrument that may not convey the intended purpose of the study and may undermine policy implications and the external validity of our study. Further work should focus on these issues.

A further finding is that sex positively impacts the poverty likelihood of households. Specifically, male-headed households have a higher likelihood of being multidimensionally poor than female-headed households. This finding is in line with the results of Ibrahim et al. (2019) which indicate that in the Upper West region of Ghana female-headed households experience less non-monetary poverty than male-headed households. However, this goes against the findings of other studies. Nam (2019) concludes that female-headed households are more likely to experience both monetary and non-monetary poverty than male-headed households. According to Nam and Hwang (2017), following the headcount ratio, the average deprivation score and the adjusted headcount ratio based on the counting approach, male-headed households experience less multidimensional poverty than female-headed households.

Table 2: Linear regression estimates (Dependent variable - PPI using National Poverty Line)

Variable	**Coefficient**	**Standard Error**
Efficiency	-9.422***	3.448
Sex	5.35***	1.107
Age	0.404	0.286
Age square	-0.005	0.003
Marital status		.
Married	7.676***	1.435
Other	0.394	1.437
Education		
Primary	-23.668***	2.838
JSS/SHS/Middle	-33.092***	2.306
SSS/SHS/Voc/Tech	-31.732***	2.424
Tertiary	-32.391***	2.705
Location	-14.008***	1.751
Employment	-33.092**	2.306
Sector of employment	-31.732***	2.424
Willingness to take risk		
Unlikely	0.695	1.894
Neutral	3.773**	1.815
Likely	0.532	1.759
Extremely likely	-5.278***	1.877
Type of sch attended	7.037***	1.948
Constant	48.155***	7.02
Mean dependent var	17.156	
R-squared	0.529	
SD dependent var	25.208	
F-Test	46.838	
Number of obs	1109	
Prob > F	0.000	

*Note ***p<0.01, **p<0.05, *p<0.1*

Source: *Authors' estimation from household survey, 2022.*

Adeoti (2014) finds that in rural Nigeria, female-headed households are associated with higher levels of multidimensional poverty than male-headed households. Similarly, Fotros and Ghodsi (2018) conclude that the intensity and incidence of poverty among female-headed households in Iran are higher than for male-headed households. These results indicate that it is always important to be specific with the definition of poverty and especially the components/variables used to measure poverty for appropriate policy interventions. A similar conclusion was provided by Rajaram (2009) who indicate that the relationship between female-headed households and poverty depends on the choice of poverty measure, after observing that poverty measures based on housing conditions and wealth indices reflect lower levels of poverty for female-headed households than male-headed households.

In this study, the poverty probability index consists of components that include the availability of a stove and nutritional factors like food purchases. In most households, women do the cooking and will most likely procure a Liquified Petroleum Gas stove if they are the heads. Similarly, they will buy components like egg or corned beef. It is therefore not surprising that with this measure of multidimensional poverty, we observe a decreasing relation with female-headed households.

Multidimensionally poverty tends to be higher for the married compared to those who have never been married. Similar to this finding, Adepoju (2018) shows that, in rural Nigeria, married household heads are among those with the highest multidimensional poverty index scores, while household heads who have never married have the lowest multidimensional poverty scores. Education significantly reduces the likelihood of a household being multidimensionally poor. The finding is frequently supported in the literature because education is considered to have both direct and indirect impacts on the poverty status of a household. According to Gebrekidan et al. (2021), the likelihood of being multidimensionally poor reduces with the number of schooling years among rural households in Ethiopia. In Pakistan, Kiani and Kazmi (2020) identify education as an important factor in alleviating poverty and sustaining the well-being of households.

Employment is observed to reduce multidimensional poverty, and household heads employed in the private sector have a lower poverty likelihood than those employed in the public sector. This finding is similar to that of Le, Tran and Doan (2021) whose results showed that in Vietnam, a percentage increase in private sector employment reduces multidimensional poverty by 0.30%. In developing countries, public workers averagely earn about 10% wage premium compared to private sector workers, and even higher for women and low-skilled workers (Abdallah et al., 2023). However, the authors argue that this wage premium does not directly translate to a lower likelihood of being multidimensionally poor compared to people employed in the private sector.

The likelihood of being multidimensionally poor increases for households that are risk-neutral compared to those that are extremely unlikely to take a risk. However, the sign changes to a negative impact when we compare households that are extremely likely to take risks to those that are extremely unlikely to take risks. This finding could indicate that the willingness to take a risk in buying a new electrical appliance can have a positive impact on getting households out of multidimensional poverty, but risk neutrality, is not sufficient to improve the standard of living among households in Ghana.

According to Gebrekidan et al. (2021), livelihood diversification can help to mitigate the risk of poverty. Risk aversion may promote precautionary savings (Bommier and Grand 2019) which may reduce the likelihood that households will purchase the products considered in the measurement of the PPI in this study. Risk-taking people may live with the hope of a better tomorrow and thus consume more today.

Household heads that are either attending or have attended private schools have a higher poverty likelihood compared to those that have attended or are attending public schools. This result is not intuitive as one will expect private school attendance to be associated with a higher welfare effect. Further analysis of the data suggests that locational factors and household size could be key factors driving the observed results. For instance, only 11.6% of household heads have attended private schools. Out of this, about 50.4% reside in the northern region of Ghana while the figure for the Great Accra and Asante regions are 26.4% and 23.3% respectively. Conversely, respondents that have attended public school in the Northern region constitute only 15.41%, while the percentage for the Greater Accra and Asante regions are respectively 44.3% and 40.3% out of the 88.4% of the sample who have attended public schools. According to the IPA measurement of multidimensional poverty, the Northern region is associated with the highest poverty likelihood (among the three regions used in this study) as they score lower points. The higher poverty likelihood among household heads that have attended or attending private schools may be because majority of them are in the northern region where the poverty likelihood is generally high. Also, in households where the head attended private school, majority of them (59.7%) have more than four members, which increases the multidimensional poverty likelihood according to the IPA measurement. Conversely, the proportion of households where the head has attended public school and has more than four members is only about 44.9%. One can therefore conclude that the positive relationship between multidimensional poverty and the attendance of private schools may be driven by the components used in the measurement of multidimensional poverty by the IPA indicators.

4.2 Consumption Poverty

We consider two different cut-offs for the measurement of consumption poverty: the extreme poverty line (food poverty) and the upper poverty line. The results of probit regression estimates related to consumption poverty and their marginal effects are presented in Table 3. Improvement in energy efficiency reduces the probability of experiencing consumption poverty by about 10% for households below the extreme poverty line and about 14% for households above the upper poverty line. This result implies that improving energy efficiency can reduce household expenditure on electricity and by implication reduce the level of consumption poverty. This result should be interpreted with care as a reduction in poverty could also lead to energy efficiency improvement but should be established in future studies.

Table 3: Probit Regression (dependent variable consumption poverty)

Extreme Poverty Line					**Upper Poverty Line**			
Variable	**Coef.**	**St.Err.**	**Marg Eff.**	**St. Err**	**Coef**	**St. Err**	**Marg. Eff**	**St. Err**
Efficiency	-0.756**	0.323	-0.102	0.043	-0.527**	0.249	-0.143	0.067
Sex	0.169	0.149	0.023	0.020	0.204*	0.107	0.056	0.029
Age	0.047*	0.028	0.006	0.004	0.009	0.021	0.002	0.006
Age square	-0.001**	0	-0.000	0.000	0	0	-0.000	0.000
Marital Status								
Married	-0.052	.214	-0.007	0.030	-0.02	.154	-0.005	0.041
Other	-0.088	.245	-0.008	0.020	0.124	.169	0.035	0.046
Location	-0.061	.146	-0.014	0.020	-0.045	.11	-0.012	0.030
Education								
Primary	-0.788***	.198	-0.199	0.046	-0.795***	.169	-0.279	0.055
JSS/JHS/Middle	-1.819***	.245	-0.302	0.038	-1.089***	.146	-0.356	0.046
SSS/SHS/Voc/Tech	-1.131***	.169	-0.250	0.041	-0.845***	.137	-0.294	0.048
Tertiary	-1.426***	.248	-0.280	0.041	-1.271***	.177	-0.394	0.049
Employment	-0.788***	.198	-0.098	0.019	-0.432***	.11	-0.117	0.029
Sector of employment	-1.819	.245	-0.012	0.019	0.126	.122	0.034	0.033
Willingness to take risk								
Unlikely	-0.411**	.198	-0.080	0.039	-0.297*	.159	-0.089	0.048
Neutral	-0.365**	.176	-0.072	0.037	-0.076	.148	-0.024	0.047
Likely	-0.889***	.186	-0.141	0.034	-0.351**	.142	-0.103	0.043
Extremely likely	-1.102***	.284	-0.159	0.037	-0.772***	.194	-0.198	0.048
Type of school attended	-0.49**	.233	-0.066	0.031	-0.185	.156	-0.050	0.042
Constant	0.381	.685			0.614	.507		
Mean dep. Var 0.104		SD dep. var 0.305			Mean dep var. 0.243		χ^2 150.191	
Pseudo R^2 =0.271		Nº of Obs. 1109			Pseudo R^2= 0.129		SD dep. Var 0.429	
χ^2 = 170.665		Prob > χ^2 = 0.000					Nº of Obs 1109	
							Prob > χ^2 = 0.000	

*Note: ***p<.01, 00p<.05, *p<.1*

Source: Authors' estimation from household survey, 2022

Age has a quadratic effect on consumption poverty only in the case of the extreme poverty line, by first increasing with the probability to be consumption poor before later decreasing. Similar to this finding, Babatunde and Olorunsanya (2008) report that, in Nigeria, there is a positive relationship between age and poverty. Borko (2017) finds a similar relationship in Ethiopia.

We observe no significant difference between male and female-headed households in the case of extreme poverty. However, the probability of being poor increases for male-headed households when we consider the upper poverty line. Education tends to reduce the probability of being poor for both poverty lines. This is not surprising since education offers opportunities that enable households to earn higher incomes. Concerning risk, we observe that households that are willing to take risks in buying new electrical appliances reduce their probability of being poor compared to households that are extremely unlikely to take risks. We also observe that attending a private school reduces the probability of being consumption poor compared to attending a public school. This finding is in line with the results of other studies that indicate that private school students perform better academically compared to students enrolled in public schools (Romuald (2023). In Kenya, Bold et al., (2013) reported a significant premium of about one standard deviation for private schooling when considering the test scores of grade eight students. Higher academic performance may easily translate to higher labor market outcome for such students and hence escaping consumption poverty.

5 Conclusion and recommendations

Using household survey data, this study assesses the impact of household electricity consumption efficiency on multidimensional and consumption poverty in Ghana. Study results show that a percentage increase in energy efficiency reduces the likelihood of multidimensional poverty by approximately 9.4 percentage points, while the probabilities of consumption poverty reduce by approximately 10.2% using the lower (extreme) poverty line measure and 14.3% using the upper poverty line. Factors that affect poverty likelihood include sex of household head, marital status, education, employment, and attitude to risk. The study finds that male-headed households are more likely to be multidimensionally poor than female-headed households. This is possible because female-headed households may buy more of the products that are used in calculating the PPI, consequently making them better off than male-headed households.

Multidimensional poverty scores are higher for married couples than those who have never been married, while education significantly reduces the likelihood multidimensional poverty and is considered to have both direct and indirect impacts on the poverty status of a household. Employment reduces multidimensional poverty and household heads employed in the private sector are less likely to be poor than those employed in the public sector. Multidimensional poverty increases for households that are risk-neutral compared to those that are extremely unlikely to take a risk. However, households that are extremely likely to take risks reduce their likelihood of being poor compared to those that are extremely unlikely to take risks. This suggests that the willingness to take a risk may take households out of multidimensional poverty, but risk neutrality is not sufficient to improve households' standard of living.

It is recommended that government strengthens policy choices on demand-side management of electricity through efficiency improvements such as star rating and appliance rebate systems and to increase awareness among households of energy efficiency as a way of addressing poverty. Improving access to education could also improve energy efficiency which will consequently reduce poverty. Efforts should also be focused on encouraging households to take the risk of buying new electrical appliances which will reduce households' expenditure on electricity and may reduce their poverty likelihood. Further research could focus on the bidirectional impact of electricity use inefficiency and poverty.

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Appendix

Appendix 1: Correlation Table

Variables	Efficiency	Somewhat careless	Tends to be disorganised	Does things efficiently	Eakes plans and follows through with them
Efficiency	1.000				
Somewhat careless	**-0.109**	1.000			
Tends to be disorganised	**-0.165**	0.323	1.000		
Does things efficiently	**0.126**	-0.159	-0.263	1.000	
Makes plans and follows through with them	**0.093**	-0.187	-0.277	0.399	1.000