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Solar Use Dynamics in Uganda: Household Characteristics and Energy Choice Factors

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ABSTRACT

This study analyzes household solar photovoltaic (PV) adoption in Uganda using data from the 2018 to 2019 National Panel Survey and a multivariate probit modeling approach, jointly examining how financial, demographic, and contextual factors shape energy source choices. By explicitly distinguishing between grid-connected and off-grid households, the analysis captures heterogeneity in access constraints, enabling more refined insights into energy transitions. Empirical results reveal that household income, savings, and education significantly predict solar PV uptake among non-grid-connected communities, with rural households likely to adopt, especially when these attributes are present. In contrast, grid access and urban residence decrease the likelihood of solar adoption, emphasizing a substitution effect between grid electricity and solar solutions; additionally, gender and savings play more pronounced roles in rural areas, where male-headed households and those maintaining savings show higher adoption rates. The findings recommend targeted interventions—such as microfinance expansion, rural savings initiatives, and enhanced information campaigns—to lower upfront barriers and accelerate solar PV adoption, while emphasizing the need for integrated, equitable strategies that blend centralized and decentralized energy pathways for sustainable development in Uganda.

Keywords: Sustainable Energy Transitions, Rural Electrification, Off-Grid Solutions
JEL Classifications: Q42, Q40, C35, D12

1. INTRODUCTION

Access to reliable electricity remains essential for sustainable development and improved household welfare, promoting critical activities such as education, healthcare, agricultural processing, and local enterprise—all of which drive economic transformation (World Bank, 2025; Asghar, et al. 2022; Matimbwa 2024; Perez-Sebastian et al., 2020; Sinalda, 2025). Despite progress towards Sustainable Development Goal 7, Uganda still faces a substantial energy access gap: in 2023, only about 51% of households had access to electricity, with urban access much higher (76%) than rural (%) (SE4ALL Africa, 2025). This gap reflects not just slow grid expansion but underlying infrastructure and affordability challenges, making decentralized and off-grid renewables increasingly relevant as policy alternatives. Solar photovoltaic (PV) systems, in particular, stand out for their technological flexibility and falling costs. Uganda's abundant sunlight supports year-round generation, allowing rural households to bypass grid limitations and shifting domestic energy choices toward solar (Goyal and Blimpo, 2021; Legesi, 2025; ACME Uganda, 2024; EasyPower Uganda, 2025; Blimpo and Cosgrove-Davies, 2023). Recent surveys suggest that about one-third of households now use solar for lighting (Uganda Bureau of Statistics, 2020), indicating steady growth in adoption. Nevertheless, substantial barriers persist—primarily initial capital costs, limited consumer awareness, and weak after-sales service—which slow broader uptake.

Earlier household-level studies, like Alinaitwe (2023), used Living Standards Measurement Survey (LSMS) data to identify predictors of solar adoption—such as income, savings, and education—yet mainly treated grid access as a preference, and energy choice independently for each household. The present paper extends this literature by dividing households according to actual grid access, thereby distinguishing between those with and without grid connectivity. This key step addresses heterogeneity: It recognizes that lack of electricity access/adoption is frequently not a matter of preference or choice for many Ugandan households. By employing a multivariate probit framework that accommodates interdependence across energy sources (solar, grid electricity, kerosene) and integrating pricing and supply reliability indicators, the study provides uniquely granular insights into substitution and complementarity among lighting options.

Empirically, this approach clarifies the socioeconomic and infrastructural factors shaping Ugandan households' energy decisions—especially when grid connectivity is unavailable—and offers practical guidance for policies to accelerate rural electrification via decentralized technologies and targeted support for off-grid solar.

The rest of the paper is structured as follows: Section 2 reviews relevant literature, Section 3 presents the empirical framework and data, Section 5 reports the main findings, and Section 6 concludes with policy implications.

2. LITERATURE REVIEW

Adoption of renewable household technologies has been widely examined across developing regions. Empirical evidence (Hassan and Lucchino, 2016; Blimpo and Cosgrove-Davies 2019; Alinaitwe, 2023) emphasizes economic capacity, affordability, education, and institutional support as the most consistent predictors of solar photovoltaic (PV) uptake. Access to credit and installment financing schemes markedly increase adoption likelihood (Etongo and Naidu, 2022), whereas high up-front costs and limited technical knowledge act as primary obstacles. Studies in Asia and Africa, for example (Wijayatunga and Attalage, 2005; Urmee and Harries, 2011; Buragohain, 2012; Ondraczek, 2013; Aarakit et al., 2021), find that income stability, education of the household head, and reliable market products strongly influence the decision to invest in solar systems.

Analyses across Sub-Saharan Africa report heterogeneity by geography and energy context. In Ethiopia and Tanzania, for instance, household size and education raise the probability of solar adoption, while environmental awareness further strengthens participation (Rahut et al., 2018). Comparable results from Uganda reveal that income, savings, and education enhance adoption, whereas grid connectivity and urban residence exert negative influence (Alinaitwe, 2023). The negative relationship with grid access emphasizes solar's main role as an off-grid energy substitute rather than a complement to utility power.

A key contribution of the current study is its methodological approach of dividing the sample into households with and without access to grid electricity. This distinction recognizes that not adopting grid electricity is not always a matter of household choice but often reflects infrastructural constraints and access limitations. By accounting for this heterogeneity, the analysis clarifies that many Ugandan households transition to solar photovoltaics due to lack of grid access rather than preference, providing a more refined understanding of energy adoption behaviours.

Recent literature also highlights new dimensions affecting adoption. The decline in international prices for photovoltaic (PV) modules has improved affordability (Aarakit et al., 2021), but challenges in quality control and limited service infrastructure still constrain market confidence. Additionally, gender, perceived reliability, and policy incentives—such as tax rebates or donor-financed programs—account for variability between regions. Consistent with global assessments, Ugandan households appear sensitive to supply reliability and cost ratios between grid and solar power (Aarakit et al., 2021).

This study further contributes to the empirical discussion by employing a multivariate probit model, which jointly estimates correlated household energy decisions—solar PV, grid electricity, kerosene, and others. This multivariate approach isolates how common household attributes simultaneously influence multiple energy choices, extending prior single-equation analyses and contextualizing solar PV adoption within Uganda's evolving energy transition landscape (Alinaitwe, 2023).

3. METHODS AND DATA

3.1. Econometric Model

Consider a choice situation where n individuals can choose from m alternatives where at least one alternative must be chosen. Let $y_{ij} \in \{0, 1\}$ be the binary response for individual $i = 1, \ldots, n$ for alternative $j = 1, \ldots, m$ where $y_{ij} = 1$ means that the alternative was chosen and $y_{ij} = 0$ means that the alternative was not chosen. For each alternative, there is a latent variable, denoted $y*_{ij}$, which is specified as:

$$y*_{ij} = xij\beta j + \varepsilon iji = 1.,n \tag{1}$$

where x_{ij} is a k vector of covariates which may differ between alternatives and individuals, and βj is a vector of k parameters (Cameron and Trivedi, 2005). The observed variable y_{ij} is related to the latent variable as:

$$y_{ij} = \begin{cases} 1 if\ y^*_{ij} > 0 \\ 0\,0therwise \end{cases} \tag{2}$$

A household can choose one or several alternatives. If the errors ε_{ij} in equation (1) are independent between alternatives and ε_{ij} has a standard normal distribution, we have alternative specific binary probit models that can be estimated separately for each alternative j. If the errors are normally distributed but correlated across alternatives, the model is a multivariate probit model (Ashford and Sowden 1970). Let $y_i = (y_{i1}, \ldots, y_{im})$ be the responses to all the alternatives for the individual i, and let $x_i = (x_{i1}, \ldots, x_{im})$ be the vector of covariates for individual i. Following the notation in Chib and Greenberg (1998), the probability of observing y_i is:

$$\Pr\left(y_i|x_i,\beta,\Sigma\right)=\int_{A_{im}}^{z}---\int_{A_{i1}}^{z}\phi\mathrm{m}(\mathrm{t}\,|\,0,\Sigma)\mathrm{dt} \quad (3)$$

where $\phi_m(t|0, \Sigma)$ is the probability density for an m dimensional multivariate normal distribution with mean 0 and correlation matrix Σ and where the intervals A_{ij} are given by:

$$A_{ij}=\begin{cases}(-\infty,x\beta_j) & if\ \mathrm{yij}=1\\ (x_{ij}\beta_{j,\infty}) & \mathrm{if\ yij}=0\end{cases} \quad (4)$$

The matrix Σ is in correlation form with m (m − 1)/2 free parameters denoted $\sigma = (\sigma_1, \ldots, \sigma m(m-1))$, and $\beta = (\beta 1, \ldots, \beta m)$ are the parameters for the m alternative specific models.

Estimation of the model in equation (3) with maximum likelihood methods involves highly nonlinear integrals and is a computational challenge when there are more than two or three alternatives (McFadden, 1989). A direct approach to estimation is to use simulated maximum likelihood methods (McFadden, 1989) with efficient simulation of the multivariate normal distribution (Börsch-Supan and Hajivassiliou 1993; Hajivassiliou and Ruud 1994; Cappellari and Jenkins 2003). The computational time required for simulated maximum likelihood is approximately proportional to m^2, rendering the method impractical for large m due to the computational burden. A less computationally intensive approach is based on approximating the multivariate distribution with a sequence of bivariate probit models to obtain parameter estimates for the overall multivariate probit model (Mullahy, 2016).

The choices analyzed in this paper have at most three alternatives. Thus, we use a simulated maximum likelihood estimator.

The estimated parameters in the multivariate probit model are difficult to interpret, and we will rather report the marginal effects on the probability of choosing an alternative from a change in a covariate (Cameron and Trivedi, 2005; Mullahy, 2017). The probability of observing y_{ij} as given in equation (3) can be written as $p_{ij}(\mathrm{x}_i)$ where the parameters β and Σ have been suppressed to emphasize the dependence on the covariates x_i. Let h index one of the covariates in the model. If x_h is a continuous variable, the marginal effect on the probability of observing y_{ij} of a change in covariate x_h is:

$$\frac{\partial p_{ij}\left(\mathbf{x}_i\right)}{\partial x_h} \quad (5)$$

If x_h is a dummy variable, the marginal effect is based on the difference in probability resulting from the two different values for the dummy variable (Wooldridge 2010).

The average marginal effects of a change in covariate h on the probability of alternative j, denoted μ_{jh}, is defined as:

$$\mathrm{\mu jh}=n^{-1}\sum_{i=1}^{n}\frac{\partial P_{ij}(x_i)}{\partial(x_h)} \quad (6)$$

The standard errors for the average marginal effects can be estimated with the delta method (Wooldridge, 2010).

3.2. Data

3.2.1. Data description

The analysis utilizes household-level data from the 2018 to 2019 Uganda Living Standards Measurement Survey (LSMS), also known as the Uganda National Panel Survey (UNPS), implemented by the Uganda Bureau of Statistics (UBOS) in collaboration with the World Bank (Uganda Bureau of Statistics, 2019). The dataset provides a nationally representative sample of more than 3,200 households, stratified by region, district, and rural–urban location. After data cleaning procedures to remove incomplete observations on energy use or socioeconomic characteristics, a total of 2,803 households remained for econometric estimation. The survey captures detailed information on household demographics, income, economic activities, and energy consumption behavior. Key variables used in the analysis include household income, savings behavior, years of education, age, and gender of the household head, household size, grid access, and electricity reliability. The price per kilowatt-hour is derived from the Electricity Regulatory Authority (ERA). Dummy variables are defined for residence type (urban = 1) and formal savings ownership (1 = household maintains a savings account).

Relative to the 2023 dataset used in (Alinaitwe, 2023), this study retains the same LSMS wave but reclassifies households by grid connectivity to explore heterogeneity in non-grid contexts. It also introduces electricity reliability (average hours of supply per day) as a new explanatory variable, providing a more comprehensive representation of energy security factors influencing adoption.

3.2.2. Variables

Several socioeconomic and demographic factors influence the decision to adopt and utilize solar photovoltaic (PV) systems. Drawing from empirical evidence in the solar adoption literature (Section 2), Table 1 summarizes the key variables used in the empirical analysis of solar photovoltaic (PV) adoption among Ugandan households. The table presents the definition of each variable, the expected direction of influence (hypothesis), the measurement approach, and relevant literature references.

4. RESULTS AND DISCUSSION

4.1. Descriptive Statistics

Table 2 presents the summary statistics of the variables used in this study. In terms of household demographics, the average age of the household head was 48 years (with considerable variation between 18 and 98 years). The typical household had about six members. 67% of the households were male-headed. The average educational attainment was approximately 6 years of completed schooling. Most Ugandans live in rural communities, as reflected in our sample. Only 24% of the households surveyed were in

Table 1: Variables influencing solar PV adoption

Variable	Description and measurement	Expected effect	Reference
Annual household income	Total household income earned over the previous year, measured as continuous variable in Ugandan Shillings (UGX).	Positive; higher income increases adoption likelihood.	Smith and Urpelainen (2014), Guta (2018)
Savings	Dummy variable indicating whether the household has savings in a financial institution (1=Savings, 0=None).	Positive; savings increase the ability to invest.	Guta (2018)
Education	Number of years of schooling completed by the household head.	Positive; higher education increases adoption.	Guta (2018)
Gender of household head	Dummy variable (1=Male, 0=Female). Women may be more motivated by energy scarcity, but men may have higher income.	Ambiguous; motivation versus financial capacity trade-off.	SDG Action (2024), Joint Research Centre (2024), Guta (2018)
Age of household head	Age of household head in years, continuous variable. Younger may be more innovative; older may have greater wealth.	Positive or negative; depends on wealth versus innovation effect.	Guta (2018)
Urban location	Dummy (1=Urban, 0=Rural). Urban households have better access to markets and infrastructure.	Positive; urban location increases adoption likelihood.	Lewis and Pattanayak (2012)
Household size	Number of household members, continuous. Large size spreads fixed costs but may increase expenditures.	Ambiguous; positive or negative effect	Guta (2018)
Electricity price	Price per kWh of grid electricity (UGX/kWh), continuous variable. Higher prices encourage solar as a substitute.	Positive; higher prices increase solar adoption	Ondraczek (2013)
Reliability of grid electricity	Average grid electricity hours per day, used as a reliability proxy. A more reliable grid reduces solar demand.	Negative; higher reliability decreases solar adoption.	Ondraczek (2013)
Grid access	Dummy (1=Access, 0=No access). Used for stratification, as grid-connected households may see solar as redundant.	Negative; grid access lowers solar uptake	Guta (2018)

Table 2: Descriptive statistics of variables used in the analysis, n=2803

Variable	Units	Mean	Standard deviation	Minimum	Maximum
Energy variables Solar use (1=Solar use)	Dummy	0.365	0.481	0	1
Grid (1=Grid access)	Dummy	0.369	0.483	0	1
Electricity use (1=Use electricity)	Dummy	0.126	0.332	0	1
Electricity hours per day	Hours	2.818	7.381	0	24
Electricity price per kWh	UGX	689.373	78.867	572.4	771.1
Kerosene use (1=Kerosene use)	Dummy	0.258	0.437	0	1
Household demographics and characteristics					
Age of household head	Years	47.800	15.728	18	98
Household size	Count	5.759	2.999	1	22
Gender (1=Male household head)	Dummy	0.666	0.471	0	1
Education level	Years	5.912	4.467	0	16
Income (millions)	UGX	10.908	352.500	−430.0	18720
Savings (1=Savings in the bank)	Dummy	0.845	0.362	0	1
Urban (1=Urban)	Dummy	0.241	0.428	0	1

urban areas. The economic status of the households surveyed is reflected in their average annual income of UGX 11 million (USD 3,725). Interestingly, 85% reported that they had savings in the bank.

The use of solar PV and access to grid electricity are relatively low, with only 36% of households using solar PV and 37% having access to grid electricity. About a quarter of households use kerosene. Surprisingly, only 13% of households use grid electricity.

Looking at the entire sample, electricity was available for only 2.8 h a day. However, electricity was available on average 19.5 h/day for those connected to the grid, reflecting common electricity supply reliability issues caused in part by weak and faulty grids and widespread theft of both electricity and cables (Wabukala et al., 2023).

Table 3 presents the frequency distribution of households and their responses regarding energy use from various energy sources across availability of grid electricity and a rural/urban split. The data show that 1,016 households used solar photovoltaic (PV) systems, with a significant majority (875) located in rural areas. A total of 355 respondents reported using grid electricity, with a predominant proportion (269) living in urban settings. It is noteworthy that some households are utilizing multiple energy sources. Specifically, 17 households use a combination of solar PV and grid electricity, while 90 households use both solar PV and kerosene. Furthermore, 23 households reported using a combination of grid electricity and kerosene. Interestingly, no households in the sample have adopted all three energy sources simultaneously. Finally, 234 respondents had access to grid electricity but chose to use only solar PV.

We show the raw correlations between the variables in Table 4. The correlation coefficients measure the strength and direction of the relationship between variables. As expected, the correlation coefficient between solar use and access to grid electricity is

Table 3: Distribution of households by energy source, grid availability and location

Energy Sources			Grid is available			Grid not available			Total
Solar	Grid	Kerosene	Rural	Urban	Total	Rural	Urban	Total	
0	0	0	147	116	203	595	65	660	923
0	0	1	111	68	179	352	29	381	560
0	1	0	71	244	315				315
0	1	1	9	14	23				23
1	0	0	156	78	234	628	47	675	909
1	0	1	13	3	16	72	2	74	90
1	1	0	6	11	17				17
1	1	1							
Sum			513	534	1047	1647	143	1790	2837

Table 4: Correlation matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) Solar use (1=Solar use)	1.000											
(2) Grid (1=Grid access)	−0.172	1.000										
(3) Electricity use (1=Uses grid electricity)	−0.249	0.496	1.000									
(4) Electricity hours per day	−0.254	0.500	0.863	1.000								
(5) Electricity price per kWh	−0.040	0.150	0.177	0.190	1.000							
(6) Kerosene use (1=Kerosene use)	−0.269	−0.008	−0.094	−0.077	0.049	1.000						
(7) Age of household head	0.013	−0.029	−0.038	−0.044	0.030	0.048	1.000					
(8) Household size	0.155	−0.080	−0.044	−0.053	0.064	−0.030	0.049	1.000				
(9) Gender (1=Male)	0.119	−0.035	−0.018	−0.014	−0.014	−0.041	−0.152	0.159	1.000			
(10) Education level	0.055	0.241	0.284	0.289	0.094	−0.045	−0.245	0.039	−0.274	1.000		
(11) Income	0.028	−0.010	−0.002	−0.003	0.008	−0.013	−0.006	0.027	0.024	0.043	1.000	
(12) Savings (1=Savings in the bank)	0.100	0.057	0.053	0.044	−0.036	−0.003	−0.103	0.041	−0.054	0.135	0.011	1.000
(13) Urban (1=Urban)	−0.179	0.490	0.464	0.477	0.104	−0.044	−0.031	−0.072	0.005	0.248	0.037	0.053

Grid is a dummy variable taking on 1 for access to grid-electricity and 0 for no access, electricity_price is electricity prices per kWh, Household size is the size of the household, electricity hours is average hours grid electricity is available per day, and education level are the years of completed schooling of the household head, Urban is a dummy variable taking on 1 if a household is located in the urban and 0 otherwise, gender is a dummy variable taking on 1 for male and 0 for female and Saving is a dummy variable taking on 1 for if household has savings in the bank and 0 otherwise

negative (−0.17), suggesting that these two energy sources are substitutes. The use of solar PV is also negatively (−0.251) correlated with the use of grid electricity.

In addition, urban, electricity prices and electricity hours are negatively associated with the use of solar photovoltaic. We would expect a positive correlation between electricity prices and the use of solar energy, but this is not the case. This pattern could be due to the lock-in effect as a result of the high initial solar cost. Moreover, grid electricity has a higher voltage compared to solar energy, which is why it is viewed as a better and more versatile form of electricity.

Income, age, household size, savings, having a male household head, and education are positively correlated with the use of solar PV.

4.1.1. Negative incomes

The negative total income for some households, as reported in Table 2, is puzzling and also challenging because in the econometric analysis we want to use the logarithm of income. To examine the characteristics of households with negative income, we categorize the data into five groups as shown in Table 5. Households with positive income are divided into four quantiles for comparison with households with negative income. We observed that households with negative income align closely with the third income quantile in terms of connection to the grid, solar use, savings, household size, and education level. This suggests that households with negative income may not necessarily be poor households. The reason for a negative income for the 124 households in our sample may be under-reporting (or even deliberately hiding) of some income sources. It might also reflect an economic reality where some households that are self-employed or involved in businesses may, for certain years, have such high investment costs that their income is negative.

4.2. A Multivariate Probit Model of Solar PV Adoption and use

We examine the determinants of solar PV use by applying the multivariate probit model. Regarding the income variable, we take the logarithm, which reduces the sensitivity of the results to some very high-income households. Negative or zero incomes are set to 1 (that is, the logarithmic income variable gets the value of 0), and we add a dummy variable to the model indicating negative or zero income.

Not every household has access to grid electricity; therefore, the data is divided into two separate groups. One group with access to grid electricity, and the other without access. In the multivariate regression models, the group with access to grid electricity has four choice alternatives: solar PV, grid electricity, kerosene, and none of these. The group with no electricity grid access has three choice alternatives: solar PV, kerosene and none of these. The alternative with no use of any of these three energy sources for lighting serves as the baseline in the multivariate probit model. We present all regression results as average marginal effects for easier interpretation.[1]

4.2.1. Households with access to grid electricity

The results of the multivariate probit regression analysis for households with access to the electricity grid are presented in Table 6. In addition to the average marginal effects for the covariates, the table includes the estimated correlation matrix for the error terms in the multivariate probit model. The estimated correlation coefficients are all negative and highly statistically significant. The fact that they are statistically significant justifies the use of the multivariate probit model in lieu of separate probit models for each of the light sources.

The multivariate probit regression analysis, presented in Table 6, yields several significant insights into the determinants of solar PV uptake and use. Model 1 reveals that the reliability of the grid's electricity, measured by hours of availability per day, exhibits a negative correlation with the use of solar PV power. Specifically, a one-hour increase in the reliability of the grid corresponds to a 7% decrease in the probability of solar PV use ($P < 0.01$). This finding is consistent with previous research by Aarakit et al. (2021), which noted increased solar PV uptake in response to grid outages.

Interestingly, electricity prices do not appear to significantly influence solar PV use decisions. This may be attributed to the limited variation in electricity prices, the predominance of other factors, such as reliability, or a combination of both.

The characteristics of households play a crucial role in the use of solar PV. For example, each additional household member increases the likelihood of solar use by 6% ($P < 0.01$). This positive correlation, consistent with the findings of Giri and Goswami (2017) and Guta (2018), may be due to the distribution of fixed costs among more members or the need for lighting for the children's homework.

A positive relationship exists between income and solar PV use (coefficient = 0.14, $P < 0.01$). A 1% increase in income corresponds to a 0.14 percentage point increase in the probability of solar PV use. This finding supports solar PV as a normal good. We also find that the negative income dummy is positive and statistically significant. Households with negative income are not necessarily

1 All estimation is conducted using Stata version 18, and the mvprobit program by Cappellari and Jenkins (2003) with 50 random draws used in the simulated maximum likelihood estimator. The average partial effects are calculated using Stata's margins command.

Table 5: Descriptive statistics across different quantiles and income groups

Categories	Quantile 1	Quantile 2	Quantile 3	Quantile 4	Non-positive income
Observations (n)	670	670	670	669	124
Solar use (1=Solar use)	0.249	0.333	0.451	0.438	0.313
Grid (1=Grid access)	0.224	0.296	0.388	0.578	0.333
Electricity use (1=Uses grid electricity)	0.038	0.054	0.116	0.297	0.124
Electricity hours per day	0.846	1.324	2.684	6.391	2.973
Kerosene use (1=Kerosene use)	0.245	0.336	0.258	0.202	0.211
Age of household head	48.846	48.748	47.130	47.170	44.639
Household size	5.028	5.431	5.982	6.631	5.605
Gender (1=Male)	0.396	0.390	0.337	0.232	0.252
Education level	4.124	4.909	6.218	8.420	5.830
Income (Millions)	0.241	1.000	2.813	43.662	−7.471
Savings (1=Savings in the bank)	0.751	0.824	0.870	0.931	0.864
Urban (1=Urban)	0.134	0.158	0.257	0.416	0.238

Table 6: Multivariate probit regression results as average marginal effects, for households with grid access

Variable	Dependent variable		
	Solar PV	Grid electricity	Kerosene
	(1)	(2)	(3)
Electricity price per kWh (UGX)	−0.442 (0.613)	0.340 (0.888)	1.051 (0.633)
Electricity hours	−0.072*** (0.007)	0.119*** (0.006)	−0.036*** (0.006)
Age of household head	0.005 (0.003)	0.002 (0.004)	0.002 (0.003)
Household size	0.057*** (0.016)	0.001 (0.021)	−0.005 (0.016)
Gender (1=Male)	0.070 (0.103)	−0.179 (0.130)	−0.004 (0.100)
Education level	0.027* (0.013)	0.025 (0.017)	−0.011 (0.013)
Negative income (1=Yes)	2.123*** (0.561)	2.271** (0.750)	−1.035* (0.520)
Total income (ln)	0.140*** (0.035)	0.158*** (0.047)	−0.086** (0.033)
Savings (1=Yes)	0.151 (0.145)	0.047 (0.198)	−0.127 (0.132)
Urban (1=Yes)	−0.268** (0.100)	0.156 (0.134)	−0.038 (0.099)
Correlation matrix Grid electricity	−0.292*** (0.089)		
Kerosene	−0.648*** (0.049)	−0.208** (0.094)	
Observations			1047
Log likelihood			−1179.25

Standard errors in parentheses. *P<0.1; **P<0.05; ***P<0.01

poor households, as we have already argued on the basis of Table 5. Given that analysis, a positive coefficient is reasonable. Having a negative income increases the probability of adopting solar PV.

Taking into account education, each additional year of education for the household head is associated with an increase 3% in the probability of solar PV use ($P < 0.1$).

Urban households are 27% less likely to use solar PV compared to rural households, ceteris paribus. This finding contradicts previous research by Lewis and Pattanayak (2012), who found a positive association between urban areas and the adoption of cleaner energy sources like solar PV. The data do not suggest why urban residency, after controlling for electricity hours and other factors, has a negative impact on uptake.

Considering model 2 and model 3, the analysis of grid electricity use reveals a positive correlation with grid reliability, income, and negative income. In contrast, kerosene use is negatively affected by the reliability of the grid, income, and the negative income dummy.

These findings collectively suggest that increases in income and grid reliability tend to favor the use of cleaner energy sources (solar PV and grid electricity) while reducing reliance on kerosene.

This comprehensive analysis provides valuable information on the complex interplay of factors that influence household energy choices in the context studied. More research may be necessary to explain some of the unexpected findings, such as the negative impact of urban residency on the use of solar PV.

4.2.2. Households without grid electricity accessibility

The results of the multivariate probit regression analysis for households without access to the electricity grid are presented in Table 7. The correlation coefficient between the error terms in the multivariate model is negative and highly statistically significant, which justifies the use of the multivariate probit model and not the binary probit model.

In this subsample, the use of solar PV is influenced by gender, education, income, negative income, savings, and location, as seen in Table 7.

The analysis indicates that male-headed households have a 24% higher likelihood of using solar PV ($P < 0.01$) than female-headed households. This finding contrasts with Guta's (2018) research in Ethiopia, which reported lower adoption rates for solar PV in male-headed households. It also differs from Wassie and Adaramola (2021), who found that gender is insignificant in solar PV uptake decisions. In particular, our results do not support the hypothesis presented in Section 4.0.1.

The educational attainment of the household head shows a positive correlation with the use of solar PV. Each additional year of education is associated with a 3% increase in the probability of using solar PV ($P < 0.05$). This finding explains the role of education in promoting the uptake of renewable energy.

Income shows a significant positive relationship with solar PV use. A 1% increase in income corresponds to a 0.21 percentage point increase in the probability of solar PV use ($P < 0.01$). Interestingly, the dummy variable for negative income still shows a positive and statistically significant effect in this subsample, with households reporting negative income being 2.58% more likely to adopt solar PV ($P < 0.01$).

Savings emerge as a crucial factor in the uptake and use of solar PV. Households with savings show a 31% higher probability of using solar PV compared to those without savings. This suggests that the ability to manage initial investment costs plays an important role in the decision to adopt and use solar technology. Consistent with the findings in Table 5, urban residency is associated with a reduced likelihood of using solar PV. Urban households are 28% less likely to use solar PV compared to their rural counterparts, ceteris paribus.

4.3. Robustness Check: Rural versus Urban Households

The results of the multivariate probit model when households with access to the electricity grid are divided into urban and rural areas are reported in Table 8. A log likelihood test for differences between the above results and the results for the combined sample in Table 6 has a test statistic of 50.96, which, with a χ^2-distribution with eight degrees of freedom, has a $P < 0.01$. Thus, there are statistically significant differences between these two groups of households.

The stratification of the sample into urban and rural subgroups reveals important differences in the determinants of solar PV adoption, highlighting the importance of location-specific factors in energy transition strategies. This classification will help us assess the sensitivity of the findings presented in Tables 6 and 7. The results of households with access to the grid, subdivided into urban and rural, are reported in Table 8. The negative and statistically significant coefficient for electricity availability hours in both urban and rural subsamples suggests that grid reliability consistently influences solar PV use across locations. The similarity in magnitude of these coefficients indicates that

Table 7: Multivariate regression results for households without grid access

Variable	Dependent variable	
	Solar PV	Kerosene
	(1)	(2)
Age of household head	0.003 (0.002)	0.006** (0.002)
Household size	0.015 (0.011)	−0.004 (0.011)
Gender (1=Male)	0.238*** (0.072)	−0.127 (0.074)
Education level	0.029** (0.010)	0.016 (0.010)
Negative income (1=Yes)	2.593*** (0.342)	−0.532 (0.348)
Total income (ln)	0.206*** (0.022)	−0.011 (0.023)
Savings (1=Yes)	0.313*** (0.087)	0.043 (0.088)
Urban (1=Yes)	−0.284** (0.119)	−0.122 (0.122)
Correlation matrix		
Kerosene	−0.556*** (0.033)	
Observations	1790	
Log likelihood	−2019.26	

Standard errors in parentheses. *P<0.1; **P<0.05; ***P<0.01

improvements in grid reliability have comparable effects on reducing solar PV uptake in both urban and rural areas.

Although household size is positively correlated with solar PV use in both sub-samples, the strength of this relationship varies. That is, in urban areas it is significant at 5% level while in rural areas it is significant at 10% level. This difference suggests that household size may be a more robust predictor of solar PV uptake and use in urban settings compared to rural areas.

A striking disparity emerges in the influence of income. In the rural subsample, both the income and the dummy for negative income are statistically significant, while in the urban subsample, neither variable shows statistical significance. Thus, income plays a more crucial role in solar PV use decisions for rural households compared to their urban counterparts. Therefore, income-targeted policies or financial incentives for solar PV uptake may be more effective in rural areas.

The results of the multivariate probit model when households without access to the electricity grid are divided into urban and rural areas are reported in Table 9. A log likelihood test for differences between the above results and the results for the combined sample in Table 7 has a test statistics of 11.70 which with a χ^2-distribution with six degrees of freedom has a $P = 0.069$. Thus, the formal test of statistical significance fails to reject the null hypothesis of no differences between these two groups of households. However, there may be some specific differences in the parameter estimates between the two groups.

A consistent finding across both urban and rural subsamples is the significant positive impact of income-related variables on solar PV use. Both income and the dummy variable for negative income have a positive and significant effect on solar PV use in both subsamples. This consistency suggests that financial capacity is a universal driver of solar PV use among non-grid connected households, regardless of urban or rural setting.

A disparity emerges in the influence of the gender of the head of the household. In the rural subsample, male-headed households show a relatively higher likelihood of using solar PV (coefficient 0.23, P = 0.05). However, in the urban sub-sample, there is no significant effect of this variable. Therefore, gender dynamics in energy decision-making may be more pronounced in rural areas, possibly due to traditional social structures or differing gender roles.

The impact of education on solar PV use also differs between the subsamples. Education has a positive and significant effect

Table 8: Multivariate probit regression results as average marginal effects, for urban and rural households with grid access

Variable	Solar PV	Urban Electricity	Kerosene	Solar PV	Rural Electricity	Kerosene
Electricity price	0.087 (1.023)	0.672 (1.165)	0.656 (1.070)	−0.660 (0.778)	−1.266 (1.678)	1.107 (0.802)
Electricity hours	−0.076*** (0.010)	0.101*** (0.007)	−0.039*** (0.007)	−0.066*** (0.010)	0.170*** (0.014)	−0.030** (0.009)
Age of household head	0.008 (0.005)	0.006 (0.005)	0.001 (0.005)	0.004 (0.004)	−0.007 (0.009)	0.002 (0.004)
Household size	0.052* (0.025)	−0.025 (0.026)	0.009 (0.024)	0.059** (0.021)	0.050 (0.039)	−0.018 (0.021)
Gender (1=Male)	−0.021 (0.165)	−0.276 (0.157)	−0.107 (0.150)	0.094 (0.134)	0.044 (0.274)	0.043 (0.137)
Education level	0.025 (0.019)	0.025 (0.020)	−0.012 (0.020)	0.030 (0.018)	0.037 (0.037)	−0.012 (0.019)
Negative income (1=Yes)	1.129 (0.823)	3.171*** (0.953)	−1.031 (0.798)	2.863*** (0.769)	0.626 (1.441)	−0.962 (0.692)
Total income (ln)	0.060 (0.052)	0.212*** (0.060)	−0.091 (0.050)	0.195*** (0.049)	0.080 (0.089)	−0.071 (0.044)
Savings (1=Yes)	0.521 (0.274)	0.104 (0.250)	−0.310 (0.207)	−0.011 (0.176)	−0.075 (0.365)	0.016 (0.172)
Correlation matrix Grid electricity	−0.284** (0.120)			−0.512*** (0.158)		
Kerosene	−0.659*** (0.078)	−0.285** (0.133)		−0.649*** (0.060)	−0.152 (0.157)	
Observations			534			513
Log likelihood			−562.87			−590.90

Standard errors in parentheses*P < 0.1; **P<0.05; ***P<0.01

Table 9: Multivariate probit regression results as average marginal effects, for urban and rural households without grid access

Variable	Urban (N=143)		Rural (N=1647)	
	Solar	Kerosene	Solar	Kerosene
Age of household head	0.001 (0.008)	0.011 (0.008)	0.003 (0.002)	0.005* (0.002)
Household size	0.009 (0.046)	−0.050 (0.046)	0.017 (0.011)	−0.002 (0.012)
Gender (1=male)	0.346 (0.279)	−0.125 (0.268)	0.226** (0.075)	−0.137 (0.077)
Education level	−0.006 (0.035)	0.031 (0.035)	0.033** (0.010)	0.016 (0.011)
Student (1=yes)	−4.827 (245.284)	−4.231 (371.241)	0.165 (0.221)	0.033 (0.231)
Negative income (1=yes)	5.175*** (1.450)	−0.022 (1.199)	2.425*** (0.355)	−0.548 (0.366)
Total income (ln)	0.353*** (0.094)	−0.018 (0.076)	0.196*** (0.024)	−0.009 (0.024)
Savings (1=yes)	0.610 (0.382)	−0.065 (0.323)	0.293** (0.090)	0.044 (0.091)
Correlation matrix				
Kerosene	−0.649*** (0.129)	−0.553*** (0.034)		
Observations	143	1647		
Log likelihood	−139.65	−1873.76		

Standard errors in parentheses. *P<0.1; **P<0.05; ***P<0.01

(coefficient: 0.27) in the rural sub-sample but not in the urban sub-sample. This suggests that education plays a crucial role in raising awareness of renewable energy options in rural areas. The lack of significance in urban areas could be attributed to generally higher levels of awareness or preference for grid electricity when education increases.

The role of savings in solar PV uptake also shows a marked difference between subsamples. Savings have a positive (0.29) and significant ($P < 0.05$) effect in the rural sub-sample but not in the urban one. This indicates that having financial reserves is particularly important for rural households in adopting solar PV, possibly due to limited access to other financing options or the need to manage higher upfront costs in rural areas.

5. CONCLUSION

Results from the multivariate probit estimation highlight the complex and interrelated nature of household lighting choices. The negative and statistically significant correlation between solar and grid electricity outcomes confirms a substitution effect: improvements in grid reliability reduce solar uptake. For grid-connected households, each additional hour of reliable supply decreases the probability of solar use by roughly 7 percent, validating similar trends reported in Alinaitwe (2023). Income and education remain strong positive predictors, indicating that wealthier and better-educated households are more willing or able to invest in solar systems.

In off-grid communities, gender, savings, and education exert even stronger effects. Male-headed households and those maintaining bank savings display higher adoption probabilities, reflecting both resource control and liquidity constraints. Education enhances awareness of system benefits and technical trust, further increasing adoption likelihood. The influence of savings highlights the importance of accessible micro-finance or installment programs to overcome high initial costs.

Interestingly, urban residency continues to suppress solar uptake even among non-grid households. Urban residents often expect grid connections or possess alternative energy coping strategies less reliant on stand-alone solar. Consequently, solar technology remains predominantly a rural solution embedded within off-grid energy strategies.

Overall, the evidence points to three major policy implications.

Financial accessibility remains the cornerstone of solar expansion; credit schemes and rural savings cooperatives should be strengthened to reduce entry costs.

Efforts to expand the grid should balance with decentralized renewable options to prevent renewed inequalities when grid reliability rises.

Education and information campaigns can accelerate household confidence in solar systems' durability and payback benefits.

6. DATA AVAILABILITY STATEMENT

This study uses secondary data from the Uganda National Panel Survey (UNPS, 2018-2019), administered by the Uganda Bureau of Statistics (UBOS) in collaboration with the World Bank. The household survey data was obtained freely from the World Bank Microdata Library at https://microdata.worldbank. org/index.php/catalog/3795. The prices of electricity used in the analysis were obtained from the Electricity Regulatory Authority (ERA) website at https://www.era.go.ug/. Both datasets are publicly accessible, and the authors had no special access privileges others would not have.

7. CONFLICTS OF INTEREST

The authors declare that they have no conflict of interest.

8. DECLARATION – OF GENERATIVE AI AND AI – ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

During the preparation of this work, the author(s) used perplexity. ai in order to correct and improve grammar. After using this tool/service, the authors re-viewed and edited the content as needed and take full responsibility for the publication's content.

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