Energy for Sustainable Development 90 (2026) 101876

Contents lists available at ScienceDirect

Energy for Sustainable Development

journal homepage: www.journals.elsevier.com/energy-for-sustainable-development

Survey bias and the poor: How survey responses overstate electricity spending☆

Joel Mugyenyi*, Vijay Modi

Earth and Environmental Engineering, Columbia University, 500 West 120th Street, New York City, 10027 NY, USA

ARTICLE INFO

Keywords:
Sub-Saharan Africa
Survey misreporting
Utility billing data
Low-income households
Electricity affordability

ABSTRACT

Accurately estimating household electricity expenditures is essential for assessing energy poverty and informing subsidy and affordability policies. This study combines household survey data with administrative utility billing records for households in Rwanda to examine the extent and nature of misreporting in self-reported electricity spending, using a sample size of 650 households. We find systematic over-reporting among poorer households, primarily due to mismatches between survey recall periods and the irregular, prepaid nature of electricity purchases. To correct for this bias, we adjust reported expenditures using empirical distributions of monthly purchase frequency derived from utility data. Additionally, for unmatched households, we develop predictive models based on household characteristics, though these perform less reliably in data-sparse settings. Extending the analysis to Uganda, we apply both the frequency-based correction and predictive models. Across countries, adjusted estimates suggest electricity burdens for most households lie between 0.5% and 2.5% of total household expenditure across all wealth groups. These findings underscore the limitations of relying solely on household surveys to measure electricity spending in prepaid systems. They highlight the value of integrating administrative utility data with statistical correction methods to produce more accurate and policy-relevant assessments of electricity affordability.

Introduction

In many developing countries, particularly across Sub-Saharan Africa (SSA), access to electricity remains both limited and uneven (Gamette et al., 2024). However, rising household incomes and ongoing electrification efforts are rapidly increasing access and transforming energy consumption patterns (Mugyenyi et al., 2025). As new households gain access to the electricity grid, a critical policy question arises: **how does the share of household expenditure allocated to electricity evolve as household income increases?** Traditional Engel curve theory suggests that the budget share for necessities like food and energy should decline as income rises (Lewbel, 2008). Yet, empirical evidence often reveals more complex and context-specific patterns, especially in low-income and transitioning economies where affordability constraints and limited access to alternative energy sources play a significant role (Wang et al., 2024; Winkler et al., 2011).

Several studies have identified a U-shaped relationship between household income and electricity budget shares, where both the poorest and wealthiest households allocate a larger share of their budgets to electricity, with a dip among middle-income groups. For example, Hasan and Mozumder (2017) analyze data from the 2010 Bangladesh Household Income and Expenditure Survey and find that as household income rises, the share of income spent on electricity initially declines, reaching a minimum at middle-income levels, before increasing again among higher-income households. This pattern suggests that at low income levels, electricity is treated as a necessity, with consumption rising slowly as basic needs are met. However, as incomes grow further, households increase their spending on electricity, likely driven by the acquisition and use of more energy-intensive appliances and services. Similar findings by Nsabimana et al. (2022) support this view, indicating that while electricity remains essential for poorer households, consumption at higher income levels becomes more discretionary and appliance-driven.

A substantial body of research supports the classical prediction of Engel's law: as household income increases, the share of expenditure devoted to electricity tends to decline. This inverse relationship is particularly evident across Sub-Saharan Africa (SSA). Using nationally representative household surveys from 22 SSA countries conducted between 2008 and 2013, Kojima et al. (2016) find that among households with non-zero electricity expenditures, the median share of total spending allocated to electricity is approximately 3%. Despite lower absolute

☆ This document is the result of the research project funded by the Rockefeller Foundation, United States through the eGUIDE initiative.

* Corresponding author.
E-mail address: jm5352@columbia.edu (J. Mugyenyi).

https://doi.org/10.1016/j.esd.2025.101876
Received 30 June 2025; Received in revised form 21 October 2025; Accepted 21 October 2025

consumption, poorer households consistently devote a larger portion of their limited budgets to electricity, a pattern especially pronounced in urban areas; in 15 of the 22 countries studied, low-income urban households spend a higher share on electricity than wealthier ones, reflecting both affordability constraints and limited substitution options. The financial burden is particularly acute in countries such as Botswana, Mozambique, Sierra Leone, and Swaziland, where the poorest quintiles allocate between 7% and 10% of their total expenditure to electricity. By contrast, Malawi and Niger exhibit uniformly low electricity budget shares across income groups, largely due to limited grid access. On average, the poorest households in the region spend about 3.7% of their budgets on electricity, compared to 2.9% among the richest. Country-specific studies reinforce this broader pattern: in Angola, the poorest quintile allocates 4.3% of total expenditure to electricity—nearly double the share spent by the richest households (Coady et al., 2006); in Uganda, electricity budget shares decline steadily with rising income (Lee, 2013); and in Morocco, households in the lowest expenditure quintile spend an average of 4.4% of their budgets on electricity, compared to just 2% among the wealthiest (Kettani & Sanin, 2022). Similar disparities are reported in South Africa, where low-income households pay a disproportionately high share of their budgets for electricity (Kambule & Nwulu, 2021; Lesala et al., 2024).

Evidence from outside Africa also reveals similar regressive spending patterns, where poorer households bear a disproportionately high electricity cost burden relative to their income. Heltberg (2003) report this trend in Nepal, Brazil, and Guatemala, where the poorest electricity users consistently spend a higher share of their income on electricity than wealthier households. Interestingly, India stands out as an exception. Electricity expenditure shares in India remain relatively stable across income groups; about 3%–4% in urban areas and 2%–3% in rural areas. This stability is attributed to India's tiered pricing system and targeted subsidies that help low-income households manage basic electricity expenses effectively.

In Latin America and the Middle East, the regressive burden of electricity spending is also well documented. Mori and Yepez-Garcia (2020) find that in a pooled sample of 13 Latin American countries, the poorest households allocate approximately 5% of their budgets to electricity, compared to just 2.3% among the richest. In Iran, electricity remains a notable budget item for low-income households, who spend around 1.22% of their incomes on electricity, while the wealthiest spend only 0.75% (Weltbank, 2013). Similarly, Jiménez and Yepez (2021) shows that electricity burdens in Latin America are consistently higher among poorer and rural households, with wealthier groups devoting a smaller share of their budgets to electricity.

Importantly, this regressive pattern is not confined to developing economies. In high-income countries such as the United Kingdom, Advani et al. (2013) show that lower-income households allocate a larger share of their budgets to electricity. This disparity is driven by factors such as poorly insulated housing, greater reliance on electric heating, and the widespread use of costly prepayment meters among low-income households. Similar patterns are observed in the United States, where Bell-Pasht (2024) find that lower-income households spend a disproportionately large share of their budgets on electricity, underscoring the persistence of energy affordability challenges even in wealthy nations.

While much of the literature aligns with Engel's law predictions, other studies present more mixed results, highlighting the critical role of energy subsidy structures, access constraints, and location-specific factors in shaping household electricity expenditure patterns. Coady et al. (2006) demonstrates how subsidy effectiveness and electricity access influence spending patterns in countries such as Jordan, Sri Lanka, and Mali. In Jordan, the poorest households allocate 3.1% of their budgets to electricity, compared to 1.8% for the richest quintile, reflecting a higher burden on the poor despite their lower absolute consumption. This regressive burden is largely attributed to poorly targeted subsidies, which disproportionately benefit wealthier households who consume more electricity overall. In contrast, Sri Lanka exhibits the opposite trend: the poorest households spend only 0.8% of their budgets on electricity, while the richest allocate 2.1%. Although wealthier households receive the majority of subsidies due to their higher consumption levels, they also spend a larger share of their budgets on electricity, driven by widespread ownership of energy-intensive appliances and higher usage for cooling and lighting. This illustrates how even regressive subsidy structures may not always translate into higher relative burdens for the poor when absolute consumption remains low. In Mali, limited electricity access results in negligible expenditures among poorer households, with the lowest quintile spending virtually nothing on electricity, while the richest quintile allocates only 1.5%. A similar pattern is observed in Madagascar, where access constraints severely limit electricity consumption. According to Andriamihaja et al. (2008), the poorest quintile in Madagascar spends just 0.1% of their budgets on electricity, compared to 1.2% for the richest, highlighting how lack of access, not affordability, suppresses electricity spending among the poor.

Urban–rural disparities further complicate these patterns. Bacon et al. (2010) analyze household electricity spending across a diverse set of developing countries and reveal significant variation by location. In rural areas, electricity budget shares generally decline as income rises, particularly in Bangladesh, Cambodia, India, Thailand, and Uganda. However, this declining pattern is less pronounced in Vietnam and Indonesia, where electricity budget shares remain relatively stable across income groups, and is even reversed in Kenya, where higher-income rural households allocate a greater share of their budgets to electricity. In Uganda and Pakistan, electricity expenditures impose a substantial financial burden on the poorest rural households, consuming 6.9% and 4.8% of their budgets, respectively, before declining for wealthier groups. In urban areas, the relationship between income and electricity spending is less consistent. India again emerges as an exception, where urban households exhibit a clear decline in electricity budget shares as income rises. This finding contrasts with the more uniform budget shares across rural and urban India across income groups observed by Heltberg (2003), illustrating studies can report contrasting results from the same country.

Although the existing literature provide important insights, much of it is based on household survey data, which may not accurately capture electricity expenditures, particularly in contexts with prepaid electricity systems. Prepaid systems, which are common in SSA (Klug, 2021), introduce substantial challenges for expenditure measurement. Infrequent and irregular purchasing patterns can lead to substantial misreporting in surveys, as households either omit purchases or exaggerate their typical expenditures when purchases are made.

Our study addresses this critical measurement gap by directly comparing self-reported electricity expenditures from household surveys with administrative utility billing data in Rwanda, and extending these findings to Uganda using predictive modeling and frequency adjustments. To our knowledge, this is the first such study in SSA to quantify and correct for the biases introduced by prepaid electricity purchasing behaviors.

We find that in both Rwanda and Uganda, surveys consistently show higher electricity burdens for poorer households, with median budget shares exceeding 3%. However, after adjusting for the infrequent and irregular purchasing behaviors of these households, we find that the true electricity burdens are lower and more comparable to those of wealthier households, between 0.5% and 2.5%. This result challenges the conventional interpretation of survey-based expenditure data in SSA and underscores the importance of integrating utility data and adjusting for purchasing frequency to more accurately assess energy poverty.

The rest of the paper is structured as follows. "Context in Sub-Saharan Africa" section examines electricity expenditure patterns across different SSA countries. "Data" section describes the datasets used. "Methodologies" section presents descriptive and predictive analyses of discrepancies between survey-reported and utility-measured electricity use. "Findings and Discussion" section contextualizes our findings within the broader literature, and finally, the "Conclusion".

Context in Sub-Saharan Africa

This section examines the financial burden of electricity consumption across different household income groups in SSA, using the more recent nationally representative household survey data from seven countries: Benin, Ethiopia, Malawi, Tanzania, Uganda, Rwanda, and Togo.[1] The analysis focuses on how the share of household budgets allocated to electricity varies across expenditure levels, providing insights into the affordability of electricity and the degree of financial strain faced by poorer households. All monetary values are expressed in constant 2015 U.S. dollars, adjusted using purchasing power parity (PPP) conversion factors to ensure cross-country comparability.[2]

Fig. 1 illustrates this relationship through two complementary visualizations. Fig. 1(a) presents Engel curves, which plot the share of household budgets allocated to electricity against total household expenditure. These curves provide empirical evidence of how electricity spending burdens evolve across the income distribution.[3]

Several key patterns emerge. In most countries, the electricity budget share declines as household expenditure increases, consistent with Engel's law, which posits that as income rises, the proportion of spending on necessities declines. This suggests that electricity is perceived as a necessary good, but one that imposes a disproportionate financial burden on poorer households. However, important non-linearities are also observed. In Togo and Malawi, the curves exhibit a distinct U-shaped pattern: lower-income households allocate a high share of their budgets to electricity, middle-income households experience a relative decline, and higher-income households again show an increasing share. This pattern may indicate increased appliance ownership and higher consumption among wealthier households in these countries.

In contrast, Ethiopia presents a unique case. The curve initially rises before declining steadily, suggesting that even the poorest households allocate a relatively low share of their budget to electricity, likely due to highly subsidized electricity tariffs and historically low residential electricity prices (Foster & Dominguez, 2011; Moolman, 2017). This is consistent with Ethiopia's policy environment, where extensive subsidies have maintained low tariff prices, reducing the relative financial burden on low-income households.

Fig. 1(b) complements this analysis by showing the distribution of total household expenditures using kernel density estimates. These distributions help contextualize the affordability analysis. For example, Rwanda has a high concentration of households at the lower end of the expenditure spectrum, suggesting widespread vulnerability to affordability challenges. In contrast, Benin displays a broader distribution, indicating a relatively wealthier survey population.

In the following sections, we explore why households in the lowest expenditure quintiles allocate a larger share of their budgets to electricity than wealthier households. Using Rwanda as a case study, we utilize household survey data and utility billing data to compare how what households report in surveys as their electricity consumption compares to their billing data from the distribution utility.

Data

Our analysis combines two main data sources: the Fifth Integrated Household Living Conditions Survey (EICV5, 2016/17), conducted by the National Institute of Statistics of Rwanda (NISR), and administrative electricity billing data from the Rwanda Energy Group (REG), which captures prepaid electricity transactions for residential customers.[4]

Representative household survey data

EICV5 is a nationally representative household survey based on a stratified two-stage sampling design, covering all 30 districts of Rwanda. The survey includes 14,580 households and collects detailed information on housing, energy use, education, health, labor, and expenditures (NISR, 2017). For our analysis, we focus on survey modules capturing grid connectivity status, reported electricity expenditures, and total monthly household expenditures (in nominal Rwandan Francs).

Among the 3,600 households reporting grid access, we restrict the sample to 3,245 that report non-zero electricity expenditures. Households with zero reported spending, typically poorer and concentrated in the lower expenditure brackets (see Appendix Figure A6), are excluded to focus the analysis on active users. While this exclusion may introduce some bias by omitting grid-connected but non-consuming households, it allows for a clearer assessment of electricity expenditure patterns.

Utility data

The REG administrative dataset includes prepaid transaction histories for residential customers from 2013–2019, recording kilowatt-hour purchases, billed amounts, and tariff rates, along with customer identifiers, connection dates, and district-level geographic data. Because the data capture transactions rather than meter readings, there can be a mismatch between actual consumption and payment timing.

To mitigate this, we apply a smoothing algorithm following Mugyenyi et al. (2025), which distributes each payment evenly over the days between transactions to estimate daily electricity consumption. These estimates are then aggregated into monthly values to better reflect household usage patterns. A detailed analysis of electricity consumption behavior in Rwanda is provided in the companion study by Mugyenyi et al. (2025).

Matching survey to utility data

To link household survey data to utility billing records, we collaborated with NISR to obtain detailed locational identifiers for EICV5 households, including village-level administrative units, GPS coordinates, and household head names. The REG dataset includes roughly 800,000 residential accounts, of which about 430,000 contain both GPS coordinates and account holder names.

We conducted matching using a combination of spatial and name-based criteria. Names were matched using the fuzzywuzzy library (Cohen & contributors, 2011), with a similarity threshold of 80 applied to both first and last names. A match was confirmed when both name similarity exceeded the threshold and the GPS coordinates of the household and electricity meter fell within 100 m. Although REG guidelines require meters to be within 40 m of households, we expanded the threshold to 100 m to account for potential measurement errors and variations in installation practices (Rwanda Energy Group, 2022). An example of the spatial matching process is illustrated in Appendix Figure A1.

Using these criteria, we matched 790 households. When relaxing the distance constraint beyond 100 m, the match count increased to 1,151, though at the cost of increased false positive risk. To maintain consistency in electricity usage, we further restricted the sample to households that both reported electricity purchases in the survey and had corresponding utility payments in the same month. This yielded a final matched sample of 650 households.

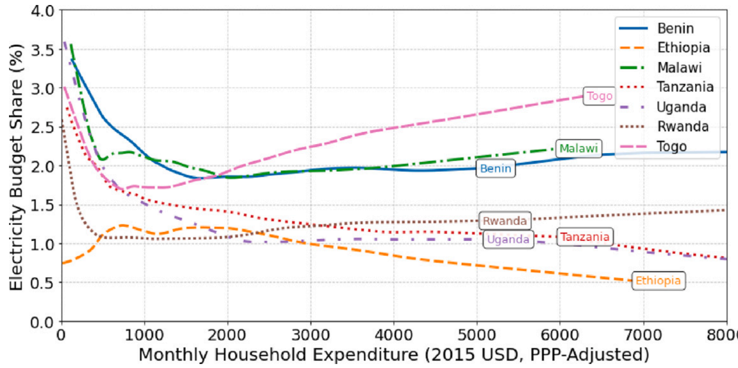
Table 1 compares descriptive statistics between the full sample and the matched subset. Matched households tend to be slightly older, live in larger households, and report higher asset ownership (e.g., mobile phones, fridges, TVs) (see Appendix). However, electricity spending levels remain comparable, suggesting that the matched sample remains

[1] Survey data sources are provided in the Appendix

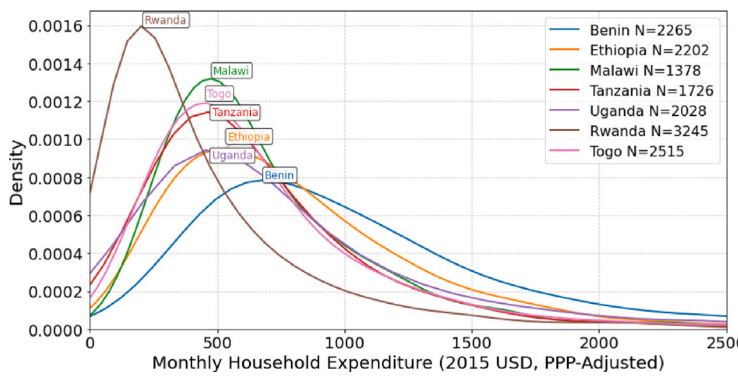
[2] Conversion factors are obtained from the World Bank (Sherouse, 2025)

[3] In this study, we use household income and total expenditure interchangeably as proxies for economic status.

[4] Access to these confidential datasets was secured through institutional partnerships with REG and NISR. The data-matching process was conducted on-site at NISR headquarters in Kigali to comply with strict confidentiality and data protection protocols.



(a) Electricity budget share (%) as a function of monthly household expenditure



(b) Kernel density estimates of household monthly expenditure.

Fig. 1. Household electricity expenditure patterns across selected Sub-Saharan African countries.

Table 1
Descriptive Statistics for Main vs. Subset Samples.

Variable	All HHs (N=3600)		Matched HHs (N=650)	
	Mean	SD	Mean	SD
Household Head Age (years)	41.21	13.83	45.92	12.73
Household Head years in school	7.87	4.29	7.53	4.11
Reported Electricity Payment(RWF)	2810.91	4594.46	3061.63	4825.53
Household Size	4.54	2.40	5.63	2.23
Number of Rooms	3.78	1.59	4.64	1.35
Total Monthly Expenses (RWF)	156,431.6	196,955.8	184,013.4	221,303.5

broadly representative of payment behavior despite demographic and economic differences.

To ensure comparability between survey and utility data, we align survey-reported four-week electricity expenditures with the smoothed monthly utility payments from REG. Specifically, we use the month and year of the household's survey report to extract the corresponding utility billing data.

Methodologies

Descriptive analysis of survey-reported and utility billing data

This section compares household electricity expenditures as reported in the EICV5 survey with administrative billing records from the utility, using a matched sample of 650 households. We proceed in four steps: (1) classify households by expenditure quintile; (2) assess rounding behavior ("heaping") in survey responses; (3) examine purchase frequency; and (4) quantify misreporting relative to utility data.

Table 2
Monthly Expenditure Quintiles (RWF; 2015 PPP USD).

Quintile	RWF range	USD Range	N (Matched HH)
Poor	6,553–48,138	21.0–154.5	130
Q2	48,139–80,377	154.5–257.9	130
Q3	80,378–129,617	257.9–415.9	130
Q4	129,618–229,850	415.9–737.5	130
Rich	229,851–3,402,860	737.5–10,919.1	130

Quintile classification

We partition monthly household expenditures into five welfare quintiles – Poor, Q2, Q3, Q4, and Rich – using 2015 PPP-adjusted USD for cross-household comparability (Table 2).

Heaping in survey data

Nearly all residential electricity customers in Rwanda use prepaid meters, paying through mobile money apps, USSD,[5] or in-person vendors. Because the smallest coin is 100 RWF and banknotes begin at 500 RWF, households often round payments to these denominations.

Fig. 2 shows evidence of digit preference: survey-reported payments cluster at 500, 1,000, and 2,000 RWF, particularly among poorer households. As shown in Fig. 2, self-reported electricity expenditures heavily reflect these denominations, exhibiting classic heaping behavior (Zinn & Würbach, 2016). Heaping introduces potential biases in analyses that rely on survey data.[6]

[5] USSD (Unstructured Supplementary Service Data) is a mobile communication protocol that works without internet access.

[6] Heaping refers to the tendency of respondents to report expenditures at preferred rounded values rather than providing precise figures.

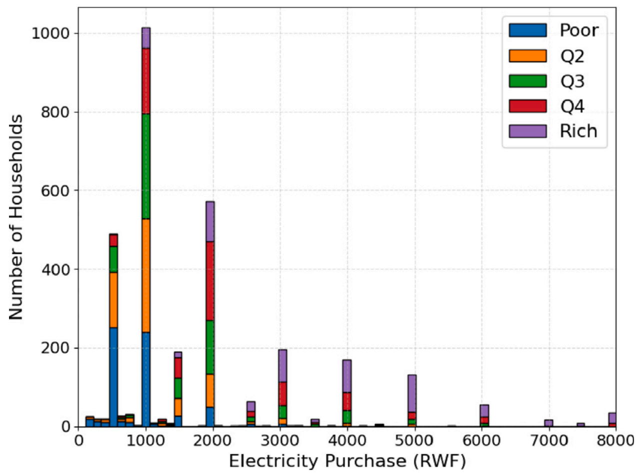


Fig. 2. Survey-reported electricity payments by expenditure quintile.

Table 3
Distribution of Reported and Utility Electricity Payments (RWF) for Matched Households.

Payment bin (RWF)	Survey (%)	Most recent utility prepaid payment(%)	Matched smoothed utility payment (%)
0–200	0.2	10.5	7.7
200–500	0.3	24.6	16.0
500	12.9	27.2	3.2
500–1000	1.8	4.4	15.8
1000	26.0	19.0	2.9
1000–2000	5.5	5.6	13.8
2000	18.5	3.3	1.5
2000–5000	18.5	2.3	19.5
5000	4.9	1.6	1.4
5000+	11.4	1.6	18.0
Aggregate	100	100	100

Table 3 compares the distribution of household electricity payments in predefined payment bins using three sources: (i) self-reported payments from household surveys, (ii) the most recent prepaid transaction recorded in utility logs near the survey date, and (iii) smoothed monthly totals calculated from matched utility billing data (see the “Data” section for details). Several key patterns emerge, highlighting systematic differences between reported and metered expenditure values. Survey data show strong heaping (e.g., 26% of reports at exactly 1,000 RWF), while utility records show many small-value top-ups (e.g., over 60% of recent payments below 1,000 RWF). This divergence reflects both recall bias and the episodic nature of prepaid purchases.

Purchase frequency

Survey-based estimates often assume regular monthly spending (Marathe & Eltrop, 2017), but utility data reveal irregular purchasing, especially among low-income households. Fig. 3 shows that poor households typically make purchases in fewer than 8 months per year, whereas richer households purchase electricity almost every month. This irregularity contributes to misreporting and suggests that surveys may overstate actual monthly spending for poorer households.

Extent of misreporting

We calculate misreporting as the percentage deviation between self-reported and utility-recorded monthly expenditure:

$$\delta_i = \frac{\text{Survey}_i - \text{Utility}_i}{\text{Utility}_i} \times 100\%.$$

Fig. 4 plots this deviation against the number of recorded transactions, revealing that poor households tend to over-report, while rich households' reports are more accurate or slightly under-reported.

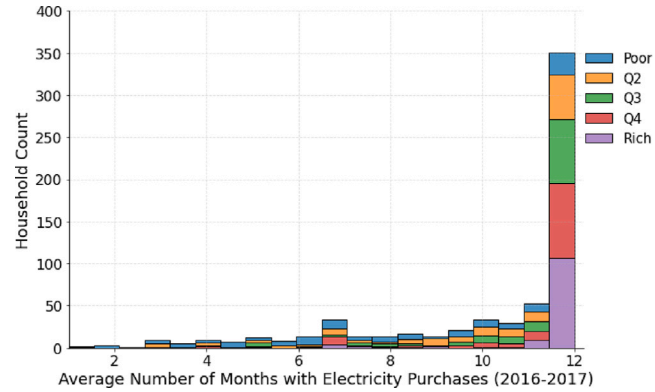


Fig. 3. Average number of months with at least one electricity purchase (2016–2017), by expenditure quintile.

Figures A3 and A2 in the Appendix provide additional detail on the distribution of misreporting across expenditure categories.

Electricity budget shares: Survey vs. Utility data

Fig. 5 compares electricity budget shares (as a percent of household expenditures) across quintiles using both survey and utility data. Among poorer households, survey-based shares are significantly higher, suggesting over-reporting. Among richer households, survey and utility estimates converge.

These results highlight the need for administrative data when assessing energy affordability, particularly for low-income households.

Accounting for intermittent purchases

Households with prepaid meters typically purchase electricity when financial resources are available. Because standard expenditure questionnaires ask for “monthly spending,” respondents may extrapolate these sporadic lump-sum purchases into a notional monthly figure, overstating what they actually spend in a typical month.

Benchmark against utility data. Fig. 5 compares survey-reported electricity budget shares with those calculated directly from utility billing records. The survey data imply a regressive pattern: the poorest quintile appears to devote the largest fraction of its budget to electricity, with wide dispersion. Utility records, however, tell a different story; median shares are lower, revealing systematic overstatement in self-reported data.

Frequency adjustment for contexts without billing records. In contexts where utility billing data are unavailable, but information on electricity purchase frequency is available, a simple correction can be applied. Specifically, the reported monthly spending can be scaled by the share of months in which the household made a purchase.[7] Fig. 6 illustrates the impact of this adjustment. After applying the frequency-based correction (orange boxplots), two effects are apparent: (1) The median electricity budget shares for the bottom two quintiles fall substantially, and interquartile ranges narrow, bringing them closer in line with the utility-derived estimates (green boxplots). (2) Despite this improvement, adjusted medians for the poorest quintiles remain slightly above the utility medians, suggesting perhaps that residual recall error and denomination-based rounding (e.g., to 500 or 1,000 RWF) still contribute to bias.

Scaling by purchase frequency offers a low-cost, intuitive method to mitigate overstatement in survey data when billing records are unavailable. However, this adjustment alone does not fully correct

[7] Formally, the adjusted monthly payment is $\tilde{E}_i = \frac{m_i}{12} E_i^{\text{survey}}$, where E_i^{survey} is the monthly reported electricity expenditure and $m_i \leq 12$ is the number of months in which any purchase was made in a year.

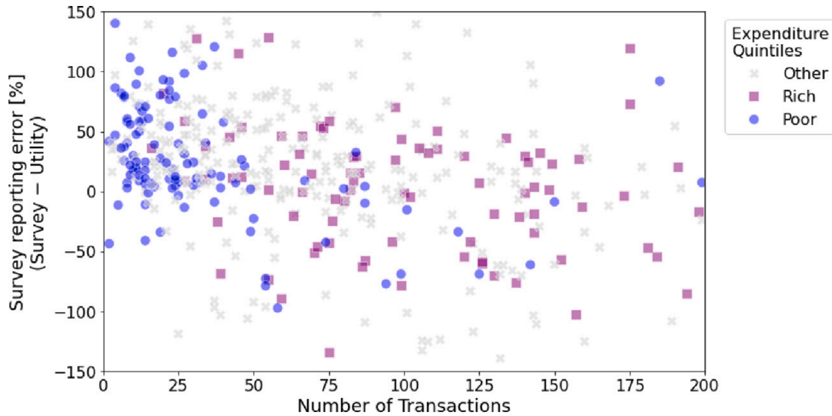


Fig. 4. Misreporting percentage deviation versus number of transactions (2016–2017), highlighting poor (blue circles) and rich (purple squares) households.

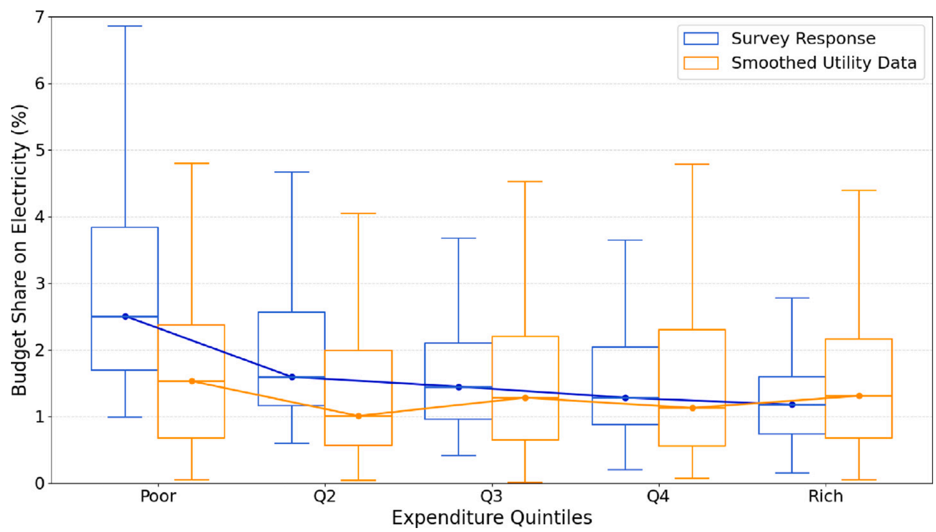


Fig. 5. Comparison of Household Electricity Budget Shares from Survey and Utility Data Across Expenditure Quintiles.

for misreporting, particularly among poorer households. Additional techniques, such as applying predictive correction models, may be required to obtain unbiased estimates of electricity affordability at the bottom of the income distribution.

Can machine learning predict expected utility-measured spending?

A key limitation of this study is the inability to match all surveyed households to corresponding utility billing records. To overcome this constraint and extend the analysis, we develop predictive models to estimate expected utility-measured spending for unmatched households. These predictions could help in more accurately estimating electricity budget shares and, by extension, informing policies that target energy affordability and access.

Feature selection and predictive relevance

We begin by identifying a set of explanatory variables from the household survey data that are both theoretically grounded and empirically associated with electricity consumption. These include income proxies, appliance ownership, housing characteristics, and education levels. A detailed summary is provided in the appendix.

We conduct a correlation analysis to gauge the strength of association between each feature and utility-measured electricity consumption (see Appendix Figure A4). As expected, electricity expenditure is positively correlated with survey-reported electricity spending (0.73) and, total household expenditure (0.69) aligning with prior studies linking income to energy use (Alberini et al., 2011; Hussain & Asad, 2012; Salari & Javid, 2017; Wallis et al., 2016).[8]

Asset ownership is also predictive: refrigerators (0.59), televisions (0.41), and mobile phones (0.36) all show meaningful correlations, on par with literature that emphasize the role of appliances as a proxy for electricity demand Genjo et al. (2005), Halvorsen and Larsen (2001), Krishnamurthy and Kriström (2015). Rural residence is negatively associated with electricity consumption (−0.36), reflecting persistent access and affordability gaps. Additional variables such as the number of rooms (0.19) and education level (0.42) further inform our modeling, drawing on prior work on housing and education as drivers of energy use (Khanna et al., 2016; Longhi, 2015; Taale & Kyeremeh, 2019).

Predictive modeling framework and methods

To estimate expected utility-measured spending, we implement a comprehensive machine learning framework. Linear regression serves as the baseline model, and we extend this with regularized linear models, including Ridge, Lasso, and ElasticNet, to address overfitting and improve generalization. Given the skewed nature of electricity consumption data and the prevalence of outliers, we also apply robust regression methods, specifically the HuberRegressor and Theil–Sen estimator, which mitigate the influence of extreme values by using robust loss functions or rank-based estimators.

[8] Correlations are shown in parentheses ()

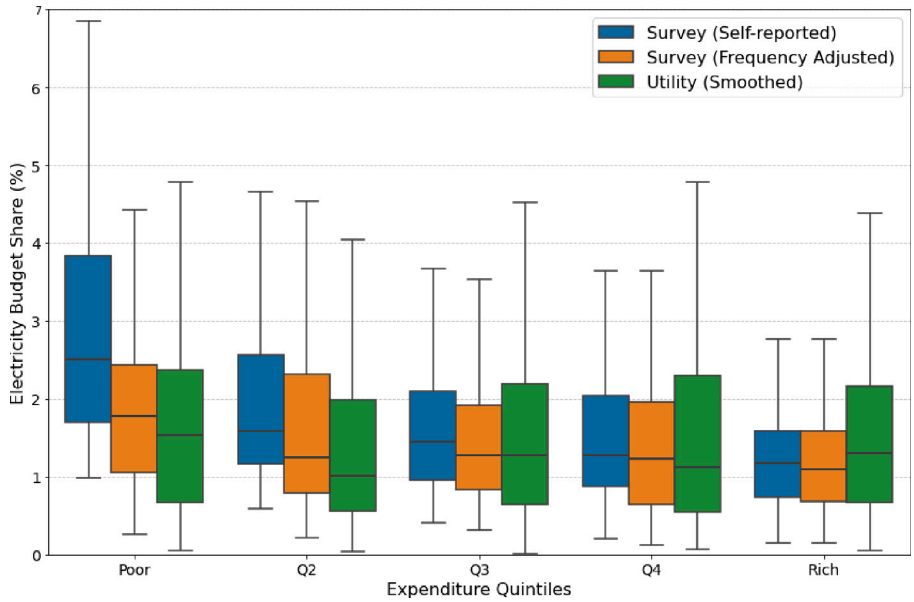


Fig. 6. Distribution of monthly electricity budget shares (%) by expenditure quintile. Boxplots compare three series: survey-reported payments (blue), utility-recorded payments (green), and survey payments re-scaled by each household's monthly payment frequency (orange). Whiskers extend to the 5th–95th percentiles; outliers are omitted.

To capture complex non-linear relationships between household characteristics and electricity consumption, we additionally employ tree-based ensemble models, including Random Forest, Gradient Boosting, Extra Trees, and XGBoost. Alternative non-parametric models such as K-Nearest Neighbors (KNN) and Support Vector Regression (SVR) are also evaluated for comparative purposes.

Model performance is assessed using 5-fold cross-validation. Mean Absolute Error (MAE) and the coefficient of determination (R^2) serve as the primary evaluation metrics. Figure A5 (see appendix) summarizes the cross-validation results. The HuberRegressor outperforms other models, achieving the lowest MAE and the highest R^2 during cross-validation.

On the test set, the HuberRegressor attains an R^2 of 0.42 and an MAE of $5.34 (2015 USD, PPP-adjusted). This moderate explanatory power most likely reflects both data limitations and unobserved household characteristics not captured in the survey.

Although tree-based models demonstrate competitive predictive accuracy, they exhibit a tendency to overfit higher consumption households, limiting their effectiveness for the primary policy interest group, low-income households. SVR and KNN models yield relatively poor predictive performance. Based on its robust performance and resistance to the influence of outlier values, the HuberRegressor is selected as the final model to predict expected utility-measured spending among unmatched households.[9]

Prediction results

Fig. 7 compares electricity budget shares derived from predicted utility consumption to those based on self-reported survey data, disaggregated by household expenditure quintile.

The model aligns closely with observed patterns among lower-income households. Predicted electricity budget shares for these groups fall within an interquartile range of 0.8%–2.2%, noticeably lower than survey-reported shares, which range from 1.8%–3.8%. This supports earlier findings (see Fig. 5) that poorer households tend to overstate electricity expenditures in surveys.

For higher-income households, model predictions exhibit less variation, likely a result of the Huber loss function's tendency to down-weight outliers. While this enhances robustness, it also limits the model's sensitivity to the greater heterogeneity in electricity use among wealthier households.

Although the HuberRegressor provides useful insights into how household characteristics relate to electricity expenditure shares, its predictive performance is constrained. The modest R^2 and sizeable mean absolute error (MAE) reflect limitations stemming from both the restricted set of predictors and the relatively small sample size.

Machine learning models can be valuable tools for estimating utility, equivalent consumption from survey data, particularly for identifying over-reporting among low-income groups, but are less reliable for capturing precise usage across the full distribution. For policy applications requiring high accuracy, especially at the upper end of the consumption spectrum, supplementary data or matched utility records remain essential.

Do similar patterns of electricity use and reporting biases hold in Uganda?

Thus far, our analysis has focused on Rwanda, where we benefit from uniquely matched household survey and utility billing data. We now extend the investigation to Uganda to examine whether similar patterns of electricity expenditure and reporting bias emerge in a comparable East African context.

Unlike in Rwanda, matched survey–utility data are unavailable in Uganda. To address this, we apply predictive models trained on Rwandan data and incorporate purchase frequency information from Ugandan utility records to interpret household survey responses. This approach enables us to approximate expected electricity expenditures and assess discrepancies in self-reported spending, contributing to a broader understanding of energy affordability and reporting behavior in Uganda.

Data sources in Uganda: Surveys and utility records

We use two primary sources. First, the Uganda National Household Survey (UNHS) 2019/2020, conducted by the Uganda Bureau of Statistics (UBOS) (UBOS, 2020), provides nationally representative data on 13,732 households, covering socioeconomic characteristics and detailed expenditure reporting. Second, administrative data

[9] Details about hyperparameter tuning can be found in the Appendix

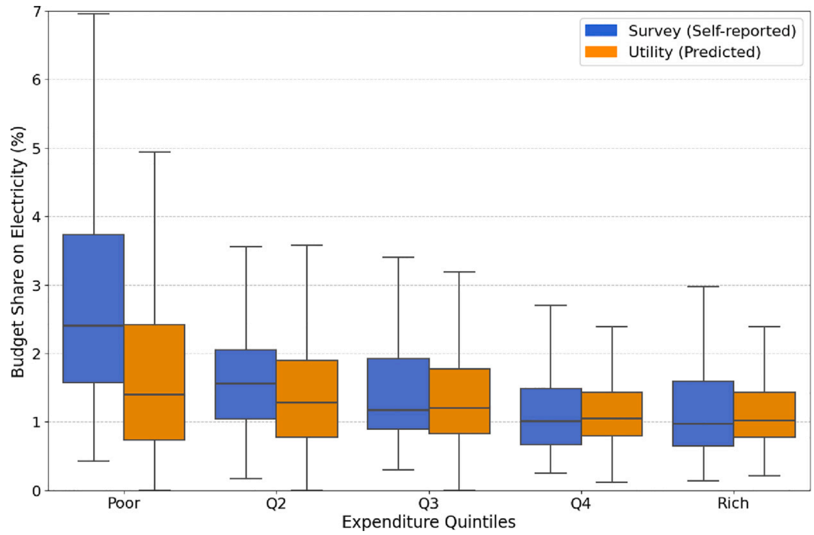


Fig. 7. Comparison of Predicted and Self-Reported Electricity Budget Shares Across Household Expenditure Quintiles.

from the Uganda Electricity Distribution Company Limited (UEDCL) include monthly billing and consumption records for 152,000 customers between 2019 and 2023. The dataset includes customer location, tariff category, connection date, and aggregated transaction records. Appendix Figure A8 shows the geographic representativeness of this dataset. Companion studies provide further insights into the state of residential electricity consumption in Uganda (Mugyenyi et al., 2024a, 2024b, 2025b).

Cross-country comparison with rwanda

Survey-reported electricity expenditures. To compare expenditures across countries, we convert all survey-reported electricity spending to 2015 PPP-adjusted USD. Fig. 8 shows Ugandan households report higher electricity spending than Rwandan households. In Rwanda, over 75% of households report monthly expenditures below $6, while in Uganda, the distribution centers around $7.50 with a longer right tail. These differences align with broader spending patterns (see Fig. 1(b)), reflecting Uganda's higher income levels.

Both countries maintain similar tariff structures. In Rwanda, the lifeline rate (up to 15 kWh/month) is $0.26/kWh, while in Uganda it is $0.18/kWh. Beyond the lifeline tier, both countries charge comparable rates (approximately $0.56–0.62/kWh).[10] Despite lower base rates in Uganda, households still report higher expenditures, consistent with greater purchasing power.

Utility-recorded purchase frequency. Without matched survey–utility data in Uganda, we proxy income by average monthly electricity consumption from utility billing data. Households are grouped into quintiles based on this metric, following established links between electricity use and income (ul Husnain et al., 2021; Pachauri & Spreng, 2004). Figure A9 in the appendix illustrates the resulting distribution.

Table 4 summarizes differences in purchasing frequency and consumption levels between countries. Ugandan households consume more electricity across all quintiles, yet those in the lower quintiles purchase less frequently, indicating lumpier usage patterns.

Broader socioeconomic difference

Table 5 compares household characteristics. Ugandan households have higher average monthly expenditures, higher electricity spending, and more years of schooling. Rwandan households, by contrast, report more rooms per dwelling. These structural differences shape electricity usage and survey reporting behaviors.

[10] Tariff data retrieved from official utility websites and adjusted to 2015 PPP USD.

Statistical tests (Appendix Tables A4–A5) confirm that differences in education, electricity spending, and expenditures are significant ($p < 0.001$), while household size is not. Appliance ownership is significantly higher in Uganda. These contrasts underscore the need to account for country-specific structures when applying predictive models across contexts.

Furthermore, it is important to acknowledge that the Rwandan EICV5 survey was conducted in 2016/2017, while Ugandan UNHS data were collected in 2019/2020. This temporal mismatch, coupled with possible differences in the timing of utility data, introduces additional sources of potential bias. Changes in tariffs, electricity access, infrastructure, or broader macroeconomic conditions over time could plausibly affect household energy consumption patterns, further complicating cross-country comparisons.

Applying rwanda insights to Uganda

Survey-reported expenditures implicitly assume consistent monthly purchases. For prepaid customers, especially in low-income households, sporadic lump-sum purchases are often misinterpreted as regular monthly spending, leading to overstated budget shares.

To correct this, we apply a frequency-adjusted correction based on Ugandan utility records. Households in both the utility and survey datasets are divided into 20 quantiles (based on monthly consumption and expenditure, respectively). For each utility quantile, we estimate the empirical distribution of active purchase months (i.e., months with at least one transaction) and assign this distribution to the corresponding survey quantile.

For each survey household i, we simulate 100 draws $M_i^{(s)}$ from the relevant purchase distribution and compute frequency-adjusted expenditures:

$$\hat{P}_i^{(s)} = P_i \cdot \frac{M_i^{(s)}}{12},$$

where P_i is the reported monthly spending. This correction scales reported values to reflect actual purchasing frequency.

Fig. 9 shows budget shares before and after adjustment. The largest corrections occur among poorer households, whose adjusted budget shares drop significantly. Among wealthier households, corrections are smaller and medians converge near 1–1.5%.

We also apply the predictive model trained in Rwanda to Ugandan households. While useful for benchmarking, its performance is limited: it underestimates electricity use for high-expenditure households and does not capture low-income irregularities (Appendix Figure A7). This underscores the challenge of cross-country generalizability.

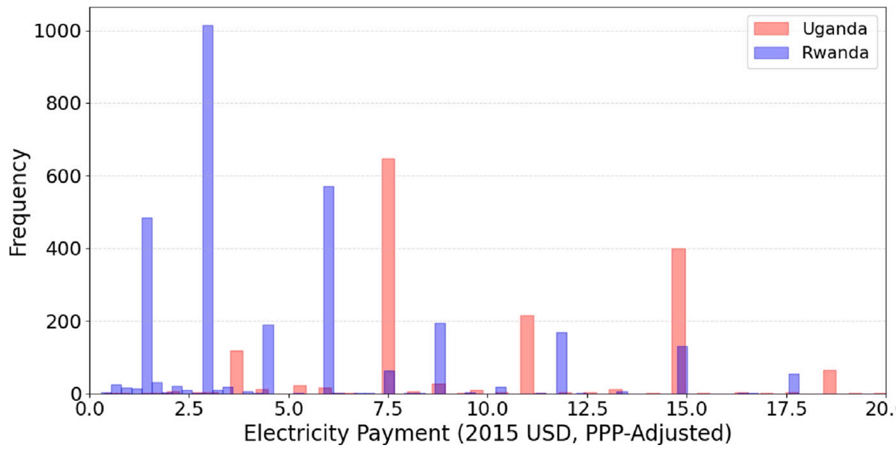


Fig. 8. Distribution of survey electricity-payment responses in Uganda (red) and Rwanda (blue), in 2015 PPP-adjusted USD.

Table 4
Average Months with Electricity Purchase and Monthly Consumption by Quintile.

Expenditure quintile	Uganda		Rwanda	
	Months	Avg. monthly consumption (kWh)	Months	Avg. monthly consumption (kWh)
Poor	5.0	4.69	8.5	3.99
Q2	8.0	10.27	10.5	5.82
Q3	10.0	17.18	11.5	10.94
Q4	11.0	28.76	12.0	17.48
Rich	12.0	59.11	12.0	35.77

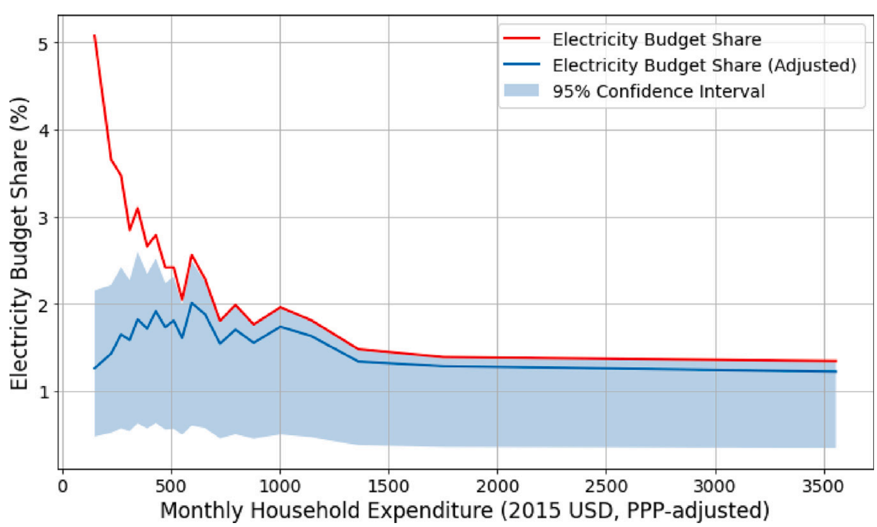


Fig. 9. Electricity budget shares vs. household expenditure (2015 USD). Red: survey-reported. Blue: frequency-adjusted. Shaded area: 95% CI.

Table 5
Descriptive Statistics for Households in Rwanda and Uganda.

Variable	Rwanda (N=3,602)		Uganda (N=1,723)	
	Mean	SD	Mean	SD
Household Head Age (years)	41.2	13.8	42.1	14.5
Years of Schooling (HH Head)	7.9	4.3	9.5	4.5
Electricity Payment (USD, PPP)	8.3	13.6	15.4	16.6
Household Size (members)	4.5	2.4	4.6	2.7
Number of Rooms	3.8	1.6	2.1	1.2
Monthly Expenditure (USD, PPP)	464.1	584.3	804.9	969.0

Cross-country comparison of budget shares

Fig. 10 displays boxplots of household electricity budget shares across expenditure quintiles for Uganda and Rwanda. The left panel illustrates self-reported (unadjusted) budget shares derived directly from household survey data, while the right panel presents budget shares adjusted for electricity purchase frequency using utility data.

Each boxplot compares countries within the same expenditure quintile, from the poorest households (“Poor”) to the richest (“Rich”). Red dashed lines at 1% and 2% indicate the range expected for household electricity spending as a share of total expenditure

In the unadjusted data (left), lower-income households have substantially higher and more variable electricity budget shares, often exceeding the 2% threshold, indicating possible over-reporting due to infrequent, lump-sum electricity purchases. After adjustment (right), median budget shares decrease, particularly among poorer households, and the distributions narrow, suggesting improved consistency and plausibility of the adjusted estimates. These results underscore the importance of correcting for prepaid usage patterns when assessing electricity affordability in survey-based studies.

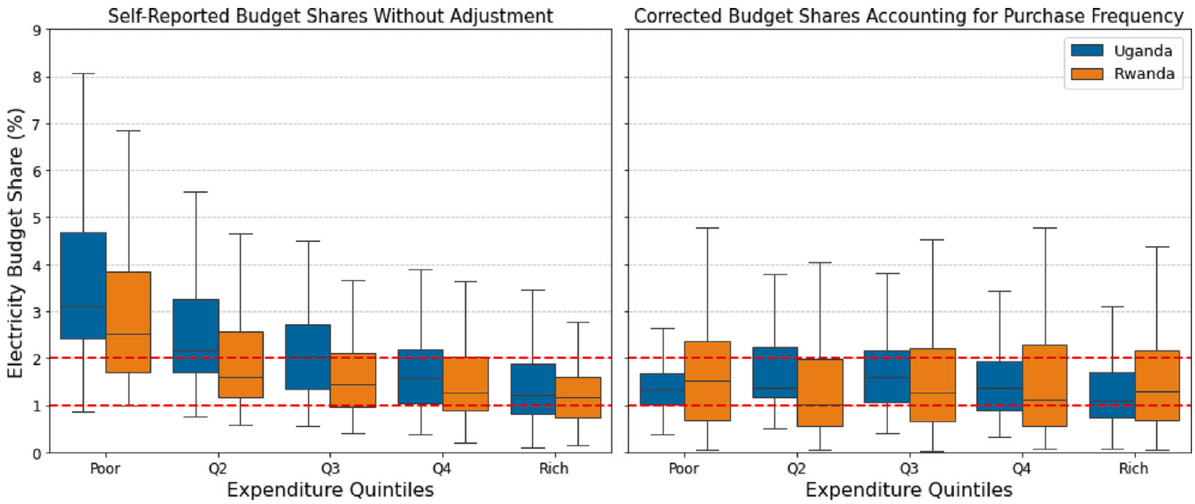


Fig. 10. Comparison of self-reported and frequency-adjusted electricity budget shares across expenditure quintiles in Uganda and Rwanda.

Findings and discussion

Our findings offer important insights into the challenges of measuring electricity expenditures in low-income, prepaid electricity contexts, common across much of Sub-Saharan Africa (SSA). In Rwanda, we find that poorer households systematically over-report their electricity spending relative to matched utility billing records. This misreporting appears to stem primarily from two sources: (1) the mismatch between survey recall periods and the irregular nature of prepaid purchases, and (2) the tendency to round expenditures to familiar denominations such as 500 or 1,000 RWF.

Interestingly, similar behaviors have been documented in high-income contexts. For example, Advani et al. (2013) show that low-income households using prepayment meters in the United Kingdom often purchase electricity infrequently due to tight budget constraints, resulting in distorted survey responses. Their study, which applies a Tobit model to correct for these biases, highlights that infrequent purchasing and lump-sum top-ups pose measurement challenges that transcend geographic settings. Our findings extend this literature by demonstrating that these same challenges are present in SSA, despite substantial differences in living standards, infrastructure, and energy policy. This suggests that the difficulty of capturing electricity expenditures in prepaid contexts is an issue wherever prepayment systems are widespread.

Our analysis also underscores the value of integrating administrative utility data to correct for misreporting. By comparing self-reported expenditures to billing records, we show that survey-based measures can systematically overstate the financial burden of electricity for low-income households. Without appropriate corrections, such overstatements may distort assessments of energy affordability and lead to poorly targeted subsidies or misinformed social protection programs. For contexts lacking matching billing records, we show that simple adjustments, such as scaling survey-reported spending by the number of months in which electricity was actually purchased, can partially reduce bias. However, even this approach does not fully correct for rounding errors or residual recall inaccuracy, especially among the poorest households. More sophisticated methods, including predictive modeling, may help further reduce error, though their performance can be limited in data-sparse settings.

Extending the analysis to Uganda reinforces the robustness of these findings. Despite Uganda's higher average living standards compared to Rwanda, poorer Ugandan households also exhibit infrequent purchasing and substantial discrepancies between reported and frequency-adjusted electricity expenditures. The consistency of these patterns across two countries with different economic profiles strengthens the generalizability of our conclusions and highlights the widespread nature of misreporting in prepaid electricity systems.

These insights are especially relevant for researchers and practitioners who rely on survey data to estimate household electricity demand in low-access or low-income settings. Several studies (Fobi et al., 2022; Marathe & Eltrop, 2017; Mugyenyi et al., 2025c; Vetter-Gindele et al., 2023) rely on self-reported electricity expenditures to project electricity usage or combine them with satellite data to model demand. Our findings suggest that such self-reports are prone to systematic bias, particularly for the poor, potentially leading to inflated demand estimates. Similarly, traditional load forecasting methods based on appliance ownership surveys often overestimate consumption due to aspirational reporting and unrealistic usage assumptions (Allee et al., 2021; Blodgett et al., 2017; Hartvigsson & Ahlgren, 2018; Pandyaswargo et al., 2020; Sandwell et al., 2016). Our results support this critique and suggest that comprehensive household expenditure surveys offer a promising alternative for inferring electricity demand. In particular, observed budget shares of electricity spending, typically around 1%–2% of total household expenditure, can provide behaviorally grounded benchmarks for modeling consumption in contexts where direct measurement is not feasible.

That said, our approach has limitations. First, survey-reported total household expenditures, used as the denominator for calculating electricity budget shares, may themselves be misreported. Errors in this measure can amplify or obscure affordability metrics, depending on whether over- or under-reporting affects the numerator and denominator asymmetrically. Second, in Uganda, the lack of household-level linkage between surveys and utility data required us to rely on a quantile-matching assumption, wherein higher household expenditures are assumed to correspond to higher electricity consumption. While supported by general patterns in the literature, this assumption may not hold uniformly across all contexts, particularly where income is informal or appliance ownership is not tightly correlated with expenditure. Future work should explore alternative strategies to better align datasets in such cases.

Despite these limitations, our study offers a practical framework for estimating household electricity demand, a critical input for infrastructure planning and energy policy. Expenditure patterns can help identify where solar home systems (SHSs) may be more appropriate (e.g., low-demand, dispersed communities) and where grid extension is likely to be cost-effective (e.g., high-income or high-expenditure clusters). This demand-side perspective complements traditional supply-side planning and can help guide more targeted and efficient electrification investments.

Finally, our findings emphasize the importance of accounting for the irregularity of prepaid electricity purchases, especially among low-income households. Conventional survey methods that assume regular monthly spending risk overstating electricity burdens and misrepresenting energy poverty. Addressing this challenge will enable more accurate demand assessments and improve the design of subsidies and infrastructure, supporting more equitable and cost-effective energy access.

Conclusion

This study highlights the challenges of accurately measuring electricity expenditures among prepaid customers in low-income contexts. By comparing survey-reported data with utility billing records in Rwanda and extending these insights to Uganda, we reveal consistent patterns of over-reporting among poorer households. These findings underscore the importance of accounting for the episodic and irregular nature of electricity purchases when analyzing survey-based energy expenditure data.

We show that simple adjustments, such as scaling reported expenditures by the actual number of purchase months, can partially mitigate these biases. However, residual rounding errors and recall biases remain, especially among the poorest households. While machine learning predictive models can help correct these biases, they face limitations in fully capturing the diverse and complex purchasing behaviors across different welfare levels. Moreover, their effectiveness depends on access to sufficiently large and high-quality matched datasets, which are often unavailable or difficult to obtain in many Sub-Saharan African contexts.

Our analysis provides valuable insights for policymakers and energy development practitioners, highlighting the need to incorporate administrative data wherever possible and to design measurement strategies that account for the nuances of prepaid electricity purchasing behavior. Such improvements are needed for developing more effective and equitable energy access policies that genuinely address the energy burdens faced by low-income households.

CRediT authorship contribution statement

Joel Mugyenyi: Data curation, Formal analysis, Investigation, Methodology, Software, Visualization, Writing – original draft. **Vijay Modi:** Conceptualization, Funding acquisition, Project administration, Supervision, Validation, Writing – review & editing.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used "Writefull" in order to improve the readability and language of the manuscript. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the published article.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

We gratefully acknowledge the valuable feedback and insightful comments provided by members of the Quadracci Sustainable Engineering Lab and the e-GUIDE Initiative. We also extend our sincere thanks to the National Institute of Statistics of Rwanda (NISR), the Rwanda Energy Group (REG), and the Uganda Electricity Distribution Company Limited (UEDCL) for generously providing access to the essential data used in this study.

Joel Mugyenyi gratefully acknowledges financial support from the Rockefeller Foundation, United States, which has been instrumental in enabling and advancing this research.

Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.esd.2025.101876.

Data availability

The authors do not have permission to share data.

References

Advani, A., Johnson, P., Leicester, A., & Stoye, G. (2013). *Household energy use in Britain: a distributional analysis*: *Technical report*, IFS Report.

Alberini, A., Gans, W., & Velez-Lopez, D. (2011). Residential consumption of gas and electricity in the US: The role of prices and income. *Energy Economics*, *33*(5), 870–881.

Allee, A., Williams, N. J., Davis, A., & Jaramillo, P. (2021). Predicting initial electricity demand in off-grid Tanzanian communities using customer survey data and machine learning models. *Energy for Sustainable Development*, *62*, 56–66.

Andriamihaja, N., Vecchi, G., et al. (2008). Evaluation of the welfare impact of higher energy prices in Madagascar. *Africa at a Turning Point*.

Bacon, R., Bhattacharya, S., & Kojima, M. (2010). Expenditure of low-income households on energy. In *Extractive industries for development series*: *vol. 16*.

Bell-Pasht, A. (2024). Low-income households spend nearly 20% of income on home energy and auto fuel costs. (Accessed: 2025-10-18).

Blodgett, C., Dauenhauer, P., Louie, H., & Kickham, L. (2017). Accuracy of energy-use surveys in predicting rural mini-grid user consumption. *Energy for Sustainable Development*, *41*, 88–105.

Coady, D. P., El Said, M., Gillingham, R., Kpodar, K., Medas, P. A., & Newhouse, D. L. (2006). Angola: Assessing the impacts of phasing out fuel and utility price subsidies, volume 1: Policy briefing. Poverty and social impact analysis. World Bank Working Paper.

Coady, D. P., El Said, M., Gillingham, R., Kpodar, K., Medas, P. A., & Newhouse, D. L. (2006). The magnitude and distribution of fuel subsidies: evidence from Bolivia, Ghana, Jordan, Mali, and Sri Lanka.

Cohen, S., & contributors (2011). fuzzywuzzy: Fuzzy string matching in python. https://github.com/seatgeek/fuzzywuzzy. (Accessed: 2024-05-14).

Fobi, S., Mugyenyi, J., Williams, N. J., Modi, V., & Taneja, J. (2022). Predicting levels of household electricity consumption in low-access settings. In *Proceedings of the IEEE/CVF winter conference on applications of computer vision* (pp. 3902–3911).

Foster, V., & Dominguez, C. (2011). Zambia's infrastructure: a continental perspective. (5599), World Bank Policy Research Working Paper.

Gamette, P., Odhiambo, N. M., & Asongu, S. A. (2024). Access to electricity and income inequality in sub-Saharan Africa: An exploratory review. *Sustainable Futures*, Article 100361.

Genjo, K., Tanabe, S.-i., Matsumoto, S.-i., Hasegawa, K.-i., & Yoshino, H. (2005). Relationship between possession of electric appliances and electricity for lighting and others in Japanese households. *Energy and Buildings*, *37*(3), 259–272.

Halvorsen, B., & Larsen, B. M. (2001). Norwegian residential electricity demand—a microeconomic assessment of the growth from 1976 to 1993. *Energy Policy*, *29*(3), 227–236.

Hartvigsson, E., & Ahlgren, E. O. (2018). Comparison of load profiles in a mini-grid: Assessment of performance metrics using measured and interview-based data. *Energy for Sustainable Development*, *43*, 186–195.

Hasan, S. A., & Mozumder, P. (2017). Income and energy use in Bangladesh: A household level analysis. *Energy Economics*, *65*, 115–126.

Heltberg, R. (2003). Household energy use in developing countries: a multicountry study. ESMAP Technical Paper, the World Bank, Washington, DC.

ul Husnain, M. I., Nasrullah, N., Khan, M. A., & Banerjee, S. (2021). Scrutiny of income related drivers of energy poverty: a global perspective. *Energy Policy*, *157*, Article 112517.

Hussain, I., & Asad, M. (2012). Determinants of residential electricity expenditure in Pakistan: urban-rural comparison. *Forman Journal of Economic Studies*, *8*, 127–141.

Jiménez, R., & Yepez, A. (2021). How do households consume energy in Latin America and the Caribbean?. (Accessed: 2025-10-18).

Kambule, N., & Nwulu, N. (2021). Prepaid electricity meters and energy poverty—Lessons from South Africa. In *The deployment of prepaid electricity meters in sub-Saharan Africa: riding the fourth industrial wave* (pp. 55–76). Springer.

Kettani, M., & Sanin, M. E. (2022). Energy consumption and energy poverty in lower income countries: driver for a solar transition. *Chair Energy*.

Khanna, N. Z., Guo, J., & Zheng, X. (2016). Effects of demand side management on Chinese household electricity consumption: Empirical findings from Chinese household survey. *Energy Policy*, *95*, 113–125.

Klug, T. (2021). Prepaid meters promise profits for African utilities but success hinges on consumer response. (Accessed: 2025-05-30).

Kojima, M., Zhou, X., Han, J., De Wit, J. F., Bacon, R., & Trimble, C. P. (2016). Who uses electricity in sub-Saharan Africa? Findings from household surveys. (7789), Findings from Household Surveys (August 9, 2016). World Bank Policy Research Working Paper.

Krishnamurthy, C. K. B., & Kriström, B. (2015). A cross-country analysis of residential electricity demand in 11 OECD-countries. *Resource and Energy Economics*, *39*, 68–88.

Lee, L. Y.-T. (2013). Household energy mix in uganda. *Energy Economics*, *39*, 252–261.

Lesala, M. E., Shambira, N., Makaka, G., & Mukumba, P. (2024). Exploring energy poverty among off-grid households in the Upper Blinkwater community, South Africa. *Sustainability*, *16*(11), 4627.

Lewbel, A. (2008). Engel curves. *The New Palgrave Dictionary of Economics*, *2*, 1–4.

Longhi, S. (2015). Residential energy expenditures and the relevance of changes in household circumstances. *Energy Economics*, *49*, 440–450.

Marathe, S., & Eltrop, L. (2017). Domestic energy consumption patterns in Kigali, Rwanda-how disparate are they in view of urbanisation? In *2017 international conference on the domestic use of energy* (pp. 120–125). IEEE.

Moolman, S. (2017). 350 Africa compared to other countries?. https://poweroptimal.com/350-increase-decade-expensive-electricity-south-africa-compared-countries/. (Accessed: 2025-05-02).

Mori, R. J., & Yepez-Garcia, A. (2020). Understanding the drivers of household energy spending: Micro evidence for Latin America. *Latin American Economic Review*, *29*, 1–33.

Mugyenyi, J., Kinhonhi, I. V., & Modi, V. (2024). Electricity outages in Uganda: Causes, trends and regional disparities. In *2024 IEEE PES/iAS powerAfrica* (pp. 1–5). IEEE.

Mugyenyi, J., Kinhonhi, I. V., & Modi, V. (2024). Natural language processing reveals core issues in Uganda's power grid: A study of outages from 2015–2022. In *2024 IEEE global humanitarian technology conference* (pp. 137–142). IEEE.

Mugyenyi, J., Muhwezi, B., Fobi, S., Massa, C., Taneja, J., Williams, N. J., & Modi, V. (2025). Post-connection electricity demand and pricing in newly electrified households: Insights from a large-scale dataset in Rwanda. *Energy Policy*, *198*, Article 114449.

Mugyenyi, J., Natuhweera, H., Tibyakinura, P., & Modi, V. (2025). *Patterns, purchases, and policy: Understanding domestic electricity use in rural and peri-urban Uganda*: *Technical report*, Columbia University, Quantitative Sustainable Economics Lab.

Mugyenyi, J., Sutil, G. G., & Modi, V. (2025). Electricity consumption: The role of grid reliability in appliance ownership and usage in Rwanda. *Energy Economics*, [ISSN: 0140-9883] *151*, Article 108907. http://dx.doi.org/10.1016/j.eneco.2025.108907.

NISR (2017). Integrated household living conditions survey. https://www.statistics.gov.rw/datasource/integrated-household-living-conditions-survey-5-eicv-5. (Accessed: 2025-05-02).

Nsabimana, A., Rukundo, B. J., Mukamugema, A., & Ngabitsinze, J. C. (2022). Residential energy demands in Rwanda: Evidence from robust models. *Energy Policy*, *160*, Article 112665.

Pachauri, S., & Spreng, D. (2004). Energy use and energy access in relation to poverty. *Economic and Political Weekly*, 271–278.

Pandyaswargo, A. H., Ruan, M., Htwe, E., Hiratsuka, M., Wibowo, A. D., Nagai, Y., & Onoda, H. (2020). Estimating the energy demand and growth in off-grid villages: Case studies from Myanmar, Indonesia, and Laos. *Energies*, *13*(20), 5313.

Rwanda Energy Group (2022). Revised new connection policy. https://www.reg.rw/fileadmin/user_upload/RevisedNewConnectionPolicy_1_-75742.pdf. (Accessed: 2024-05-14).

Salari, M., & Javid, R. J. (2017). Modeling household energy expenditure in the United States. *Renewable and Sustainable Energy Reviews*, *69*, 822–832.

Sandwell, P., Chambon, C., Saraogi, A., Chabenat, A., Mazur, M., Ekins-Daukes, N., & Nelson, J. (2016). Analysis of energy access and impact of modern energy sources in unelectrified villages in Uttar Pradesh. *Energy for Sustainable Development*, *35*, 67–79.

Sherouse, O. (2025). wbdata: A python interface to the World Bank API. https://wbdata.readthedocs.io/en/stable/. (Accessed: 2025-06-18).

Taale, F., & Kyeremeh, C. (2019). Drivers of households' electricity expenditure in Ghana. *Energy and Buildings*, *205*, Article 109546.

UBOS (2020). Uganda national household survey. https://www.ubos.org/wp-content/uploads/publications/09_2021Uganda-National-Survey-Report-2019-2020.pdf?utm_source=chatgpt.com. (Accessed: 2025-05-02).

Vetter-Gindele, J., Bachofer, F., Braun, A., Uwayezu, E., Rwanyiziri, G., & Eltrop, L. (2023). Bottom-up assessment of household electricity consumption in dynamic cities of the global south—Evidence from Kigali, Rwanda. *Frontiers in Sustainable Cities*, *5*, Article 1130758.

Wallis, H., Nachreiner, M., & Matthies, E. (2016). Adolescents and electricity consumption; investigating sociodemographic, economic, and behavioural influences on electricity consumption in households. *Energy Policy*, *94*, 224–234.

Wang, D., Fang, T., & Wang, X. (2024). Assessing the effect of income inequality on household energy poverty—empirical evidence from China. *Frontiers in Energy Research*, *11*, Article 1290904.

Weltbank (2013). *Iran-medium term framework for transition: Converting oil wealth to development*. Washington.

Winkler, H., Simões, A. F., La Rovere, E. L., Alam, M., Rahman, A., & Mwakasonda, S. (2011). Access and affordability of electricity in developing countries. *World Development*, *39*(6), 1037–1050.

Zinn, S., & Würbach, A. (2016). A statistical approach to address the problem of heaping in self-reported income data. *Journal of Applied Statistics*, *43*(4), 682–703.