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Household electric energy efficiency: A stochastic frontier analysis of Uganda's survey data

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ABSTRACT

This study examines household electric energy efficiency in Uganda by assessing how effectively households convert electricity and complementary domestic conditions into welfare-relevant services. The issue is important because electricity access and electricity consumption do not automatically translate into useful household outcomes, especially where reliability, housing quality, appliance ownership, and household resources differ. Using Uganda National Household Survey 2020/2021 data, the study constructs a household electricity-service proxy from electricity-enabled service assets and estimates household efficiency using stochastic frontier analysis, followed by fractional response models, a control-function correction, and predictive validation. The results show substantial heterogeneity in household electricity-service production. The baseline frontier estimates a mean technical efficiency of 0.604, with a median of 0.621 and a 90th percentile of 0.860, indicating that many electricity-using households operate below best-practice service performance. Efficiency is also unequal, with a Gini coefficient of 0.194 and a 90th-to-10th percentile ratio of 3.155. Electricity consumption and daily power availability are positively associated with service output, but the electricity-consumption elasticity is small, at 0.071 under the baseline specification, suggesting less than proportional service gains from additional electricity use. Efficiency is systematically associated with household assets, housing quality, literacy, household composition, electricity cost, and regional location. The evidence provides a service-oriented basis for identifying where household electricity benefits remain constrained. The study concludes that household electricity policy should move beyond connection and consumption metrics toward improving reliability, domestic service conditions, and the household capabilities that shape electricity-service performance.

1. Introduction

Electricity has become one of the most important enabling infrastructures of modern welfare, productivity, and structural transformation (Perez-Sebastian et al., 2020). At the household level, it supports lighting, refrigeration, communication, entertainment, food preservation, learning, and an expanding range of appliance-based domestic activities (Li et al., 2024). Yet the developmental significance of electricity does not arise from access alone, nor from the volume of electricity consumed in isolation (Lee et al., 2020). What ultimately matters is the extent to which households are able to convert electricity and complementary household conditions into effective services that improve daily life, raise welfare, and expand human capability (Bonan et al., 2017). This distinction is especially important in low-income settings, where access may be intermittent, housing conditions may constrain the productivity of electricity use, and households with similar electricity consumption may derive sharply different service outcomes.

This broader perspective has important implications for understanding household electricity performance. A substantial share of existing research has focused on whether households are connected to electricity, how much they spend on electricity, or whether they own particular appliances (Bayer et al., 2020; Li et al., 2024). These questions are undeniably valuable, but they do not fully address a deeper and more policy-relevant issue: whether households use electricity efficiently

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relative to the service outcomes they could feasibly attain under their observed conditions. A household may be connected but underserved. It may spend more on electricity without securing correspondingly greater service benefits. It may consume relatively modest electricity yet generate substantial household services because supply conditions, dwelling quality, and internal household organization allow more effective conversion of electricity into usable outcomes. The central analytical challenge is therefore not only to observe electricity use, but to evaluate how well households transform electricity into services (Han and Wei, 2021).

Uganda provides a relevant setting for this analysis because household electrification has expanded within a power system still marked by incomplete access, uneven uptake, and service-reliability constraints. Uganda-specific evidence shows that electricity access remains far from universal, with national access previously estimated at about 28% and rural electrification at about 9%, while more than 70% of the population continued to rely on biomass or fossil-powered lighting alternatives (Aarakit et al., 2021). Even in urban settings, access deficits persist; evidence from Kampala's informal settlements shows that proximity to the grid does not automatically translate into household connection or usable electricity service (Yaguma et al., 2022). Reliability also remains a central constraint, as recent outage analysis documents the causes, trends, and regional disparities of electricity interruptions in Uganda (Mugyenyi et al., 2024). In addition, the Yaka prepaid electricity system has made household electricity use more visible and controllable, but it also reinforces the importance of understanding how households manage limited prepaid electricity credit within constrained service environments (Nabuzale et al., 2024). This context strengthens the need to examine not only whether households use electricity, but how efficiently they transform electricity into domestic services.

Despite the growing literature on household energy and residential electricity, an important conceptual and empirical gap remains. Much of the existing work treats electricity access, electricity demand, electricity expenditure, or appliance diffusion as the main object of analysis (Han and Wei, 2021; Wang et al., 2024). Even where efficiency is considered, the evidence often remains closer to demand-side efficiency than to the efficiency with which households transform electricity and enabling household conditions into electricity services (Alberini, 2018). Consequently, three limitations persist. First, the literature often under-specifies the output of household electricity use by focusing on consumption rather than service generation (Bonan et al., 2017). Second, the empirical analysis of household electricity efficiency remains relatively limited in low-income African settings, particularly using nationally representative microdata (Jacome, 2023). Third, many studies do not integrate service production, frontier-based efficiency estimation, and determinants analysis into a single coherent empirical framework (Lee et al., 2020). These gaps matter because policies aimed at improving household energy welfare require more than expanding connections; they require understanding how effectively existing electricity is translated into meaningful household services and why that efficiency varies across households.

This study addresses these limitations by recasting household electricity use as a problem of service production and efficiency. Rather than treating electricity consumption as the final outcome of interest, the study conceptualizes household electricity services as the relevant output and evaluates the extent to which households transform electricity and enabling household conditions into those services relative to a feasible frontier. In doing so, it brings together the household production perspective and technical efficiency analysis within a unified empirical framework (Wang et al., 2024). This approach is particularly appropriate for Uganda, where the productivity of electricity use is likely to depend not only on the amount consumed but also on electricity availability, housing quality, household composition, and geographic location (Kotikot et al., 2018). By emphasizing electricity-service efficiency rather than electricity demand alone, the study advances a more conceptually coherent basis for analyzing household electric energy performance.

This study is justified by the need for a household-level measure of electricity efficiency grounded in service generation rather than raw consumption. Its significance lies in showing that electrification gains depend not only on extending access, but also on improving the reliability, quality, and productivity of household electricity use. By focusing on electricity performance, the study provides a basis for identifying where electricity-service gains are constrained and which household conditions require policy attention.

This study makes four main contributions. First, it develops a service-oriented conception of household electric energy efficiency that treats electricity services, rather than electricity consumption alone, as the relevant household output (Grabher et al., 2023). Second, it estimates the level and distribution of household electric energy efficiency using a stochastic frontier framework applied to nationally representative household survey data from Uganda (Andor et al., 2021). Third, it examines the socioeconomic, housing, and energy-access factors associated with that efficiency, thereby moving from measurement to explanation (Pakhtigian et al., 2024). Fourth, it contributes methodologically by linking service-production logic, frontier-based efficiency estimation, and bounded-outcome modeling of determinants within a single empirical design (Alberini and Filippini, 2018). In this sense, the study does not merely add another application of frontier methods; it offers a more integrated framework for understanding how households in a low-income context transform electricity into welfare-relevant services.

Guided by this motivation, this study pursued two related objectives. The first was to estimate the level and distribution of household electric energy efficiency. The second was to examine the socioeconomic, housing, and energy-access factors associated with that efficiency. In addressing these objectives, the study provides evidence that is relevant not only for Uganda but also for the wider literature on household energy transitions in low-income settings, where the expansion of electricity access must increasingly be matched by attention to the quality, equity, and productivity of household electricity use (Jeuland et al., 2021). The remainder of this paper is structured as follows. Section 2 reviews the theoretical and empirical literature. Section 3 presents the methodology. Section 4 reports the results. Section 5 discusses the findings. Section 6 presents the conclusions. Section 7 outlines the policy implications. Section 8 presents the limitations. Section 9 identifies directions for future research.

2. Literature review

Research on household electricity use and residential energy efficiency has expanded across several strands, including electricity access, household energy behavior, energy-consumption feedback, appliance use, dwelling performance, demand-side efficiency and frontier-based efficiency measurement (Firth et al., 2010; Gajdzik et al., 2023a, 2023b; Ueno et al., 2006). This distinction is central to the present study because electricity is not itself the final object of welfare (Cooper et al., 2024). Households value the services electricity enables, including lighting, refrigeration, communication, entertainment, and appliance operation (Gao et al., 2024). The review connects this evidence with the household service-production perspective used in this study.

A second issue concerns the way household electricity outcomes have been studied empirically. One strand of literature explains the factors associated with household electricity-related outcomes (Blasch et al., 2017a), while another evaluates whether households use electricity efficiently relative to what is feasible under comparable conditions (Alberini and Filippini, 2018; Weyman-Jones and Boucinha, 2024). These strands are related, but they are not identical. The first focuses on the production of electricity-enabled household services (Matar, 2015). The second focuses on the efficiency of that production process (Rowlands et al., 2015; Sotnyk et al., 2023). Since this study addresses both questions, the literature review connects the theoretical

logic of household electricity-service production with the empirical evidence on electricity services and household electricity efficiency.

2.1. Theoretical framework

The theoretical basis of this study rests primarily on household production theory and Farrell's technical efficiency theory. Household production theory provides the substantive logic of the study by treating the household as a productive unit that combines purchased inputs and household conditions to generate utility-yielding services (Becker, 1965; Stourm et al., 2020). From this perspective, electricity is not itself a final welfare outcome. Rather, households derive welfare from the services electricity makes possible (Heesen and Madlener, 2021; Pollak, 1978). This relationship can be represented as

$$U_i = U(S_i, Z_i), \tag{1}$$

where U_i denotes the utility of household i, S_i denotes electricity-derived household services, and Z_i denotes all other goods and services that enter utility. Eq. (1) captures the central theoretical idea that electricity matters because it contributes to service generation, rather than being consumed for its own sake. The corresponding household production relationship may be expressed as

$$S_i = g(E_i, A_i, H_i, N_i, L_i), \tag{2}$$

where S_i denotes household electricity services, E_i denotes electricity consumption, A_i denotes electricity availability or supply reliability, H_i denotes housing quality, N_i denotes household size, and L_i denotes locational conditions. Eq. (2) implies that household electricity services depend not only on the amount of electricity consumed but on the conditions under which electricity is converted into domestic functions. This is important because households with similar electricity consumption may still obtain significantly different service outcomes if they differ in electricity availability (Covington et al., 2023), housing quality, or internal demand pressure (Barsanti et al., 2024; Wang et al., 2024).

Farrell's technical efficiency theory (Bravo-Ureta, 1983) adds an evaluative dimension to Eq. (2). For any observed input bundle X_i, where $X_i = (E_i, A_i, H_i, N_i, L_i)$, there exists a maximum feasible service level S_i^* attainable under best-practice performance. This may be written as

$$S_i^* = \max\{S : (X_i, S) \in \mathscr{T}\}, \tag{3}$$

where $\mathscr{T}$ denotes the feasible production technology set. Eq. (3) defines the frontier service level associated with household-observed conditions. Output-oriented technical efficiency is therefore defined as

$$TE_i = \frac{S_i}{S_i^*}, 0 < TE_i \leq 1, \tag{4}$$

where TE_i denotes technical efficiency, S_i denotes observed electricity service, and S_i^* denotes frontier electricity service. If $TE_i = 1$, the household lies on the frontier; if $TE_i < 1$, the household operates below the best-practice service level. Rearranging Eq. (4) yields

$$S_i = TE_i S_i^*, \tag{5}$$

and substituting Eq. (2) into Eq. (5) gives

$$S_i = TE_i\, g(E_i, A_i, H_i, N_i, L_i). \tag{6}$$

Eq. (6) is the central theoretical expression of this study. It links the household production view of electricity service generation with Farrell's efficiency concept. The equation states that observed household electricity services reflect both productive conditions and the efficiency with which those conditions are translated into service outcomes. Household production theory identifies the relevant household output, whereas technical efficiency theory explains why households facing comparable electricity-related conditions may still differ in performance (Mityakov and Mroz, 2024). The methodology section builds directly from Eq. (6) by operationalizing household electricity service production within a stochastic frontier framework and empirically estimating household-specific efficiency.

2.2. Empirical literature

The empirical literature on household electricity outcomes is organized into two closely related strands. The first examines the factors associated with household electricity-service production. The second examines household electricity efficiency and the determinants of variation in that efficiency. These strands provide the empirical basis for this study. Table 1 summarizes the main theoretical, empirical and methodological studies that frame the review.

2.2.1. Household electricity-service production

Electricity-related household outcomes are shaped by a combination of socioeconomic resources, demographic structure, dwelling conditions, appliance ownership, and locational context (Najeeb et al., 2024). Income and wealth are frequently identified as important correlates because they influence the ability of households to pay for electricity, acquire electricity-using appliances, and improve dwelling conditions (Ali et al., 2021; Ohler et al., 2022). Education is also often associated with household electricity outcomes because it affects information, awareness, and the management of household technologies (Liang et al., 2021). Household size matters because it influences the scale and intensity of electricity demand within the home, although its effect is not always uniform (Tete et al., 2024). In some settings, larger households benefit from shared use of electricity-supported services, whereas in others experience greater demand pressure and more intensive use of available electricity (Naz and Ahmed, 2024).

Household electricity-service production is also shaped by information, behavior and the way households interact with energy-using technologies. In Japan, (Ueno et al., 2006) showed that energy-consumption feedback systems can support household energy-saving behavior by making electricity and gas use more visible to residents. In Poland, (Gajdzik et al., 2023b) found that household prosumer behavior is linked to awareness, technology use and changing expectations around household energy management. These studies show that household electricity outcomes depend not only on connection status or consumption volume, but also on the behavioral and informational conditions under which households use electricity.

Housing quality, number of rooms, tenure arrangements, and the broader appliance environment influence the extent to which electricity can generate useful services within the home (Ali et al., 2021; Tete et al., 2024). These factors shape the domestic setting in which electricity is translated into lighting, cooling, refrigeration, communication, and other functions (Barnes et al., 2022). Urban residence and regional location also appear repeatedly as important predictors because they capture differences in infrastructure, market access, electricity access conditions, and housing patterns (Liang et al., 2021). The empirical implication is that household electricity services are not generated by electricity consumption alone; they are produced within a wider material and spatial environment that conditions how effectively electricity can support domestic life (Grabher et al., 2023).

Evidence from dwelling-performance studies reinforces the importance of the domestic environment. (Tommerup et al., 2007) examined energy-efficient houses in Denmark and showed that household energy performance depends on building design, indoor conditions and actual use. (Firth et al., 2010) used sensitivity analysis for the English housing stock and showed that dwelling characteristics and uncertainty in energy-efficiency measures influence household energy outcomes. This evidence supports the inclusion of housing quality and domestic service conditions in the analysis of household electricity-service production.

Electricity availability and reliability matter as much as connection status itself (Adebayo and Prah, 2025; Obolensky et al., 2019). Grid

Table 1
Summary of literature on household electricity-service production and household electricity efficiency.

Author	Country of focus	Method	Conclusions
(Adebayo and Prah, 2025)	Nigeria	SURV	Appliance poverty creates unequal access to household energy services even where grid access exists.
(Alberini and Filippini, 2018)	United States	SFA	Residential energy efficiency contains both transient and persistent components that can be estimated using household-level data.
(Ali et al., 2021)	Malaysia	SURV; SEM	Household electricity consumption is shaped by socio-economic, dwelling and appliance-related factors in rapidly growing urban settings.
(Andor et al., 2021)	Germany	SFA	Residential electricity inefficiency is measurable at household level and is associated with household characteristics such as size and income.
(Barnes et al., 2022)	Nepal	EVAL	Quality of electricity supply matters for household development outcomes and service-level benefits.
(Blasch et al., 2017b)	Switzerland	EDF; GTRE	Energy and investment literacy are associated with electricity demand and end-use efficiency.
Boogen et al. (2021)	European residential sector	SFA; EDF	Energy-related financial literacy helps explain differences in residential electricity efficiency across households.
(Chaudhuri and Huaccha, 2023)	United Kingdom	ECON; SPAT	Local income deprivation is associated with household energy-efficiency gaps and unequal energy burdens.
(Dolšak et al., 2022)	Slovenia	SFA; IDF	Household-level energy-consumption efficiency varies across households and shows scope for energy savings.
(Ewing et al., 2025)	United States	SPAT; HED	Electric-power reliability is capitalized into housing prices, indicating the economic value of reliable electricity service.
(Firth et al., 2010)	England	CDEM; SA	Dwelling characteristics and uncertainty in household energy-efficiency measures strongly affect predicted household energy outcomes.
(Gajdzik et al., 2023a)	Poland	FC	Small-consumer energy and heat consumption trends show changing patterns in household and small-consumer energy use over time.
(Gajdzik et al., 2023b)	Poland	SURV	Household prosumer behavior is shaped by energy awareness, technology use and the changing role of households in energy management.
(Gao et al., 2024)	China	ECON	Household income has lasting effects on energy consumption, showing that household resources shape energy-use outcomes.
(Heesen and Madlener, 2021)	Germany	EXP	Applies household production theory to heat-energy consumption and shows that household conditions shape useful energy-service outcomes.
(Li et al., 2023)	China	QEX	Urban renewal affects residential energy-consumption expenditure, linking dwelling and urban conditions to electricity outcomes.
(Liang et al., 2021)	China	PANEL; HET	Residential electricity consumption differs across urban and rural households and is linked to household characteristics.
(Magnani and Vaona, 2016)	Cross-country	PANEL	Access to electricity is associated with socio-economic characteristics, supporting spatial and household-level interpretation of electricity outcomes.
(Meeks et al., 2023)	Kyrgyz Republic	RCT; IE	Electricity-quality improvements can affect household outcomes, showing that reliability is central to infrastructure benefits.
(Mityakov and Mroz, 2024)	United States	ECON	Shows that unobserved household inputs matter in household production, supporting efficiency analysis that allows households with similar observed inputs to differ in outcomes.
(Ohler et al., 2022)	United States	ECON; DEM	Appliance stock and income are important determinants of household electricity demand and elasticity.
(Otsuka, 2017)	Japan	SFA	Residential electricity-demand efficiency varies across regions and is shaped by household and regional conditions.
(Samad and Zhang, 2018)	Pakistan	IE	Electrification improves household welfare, but welfare gains depend on actual service use and household conditions.
(Sun et al., 2023)	China	SPAT; PANEL	Residential electricity consumption differs across regions and is shaped by spatially heterogeneous urban conditions.
(Tete et al., 2024)	Burkina Faso	SURV; REG	Urban residential electricity consumption is shaped by dwelling, household, socio-economic and appliance characteristics.
(Xiao et al., 2024)	China	DECOMP; SPAT	Urban residential energy consumption shows regional disparity and multiple driving forces under carbon-neutrality targets.
(Zheng et al., 2024)	China	PSFA	Household energy efficiency changes over time and is shaped by income growth and changing consumption needs.

Notes: CDEM = Community Domestic Energy Model; CF = control-function correction; DECOMP = decomposition analysis; DEM = demand modeling; ECON = econometric analysis; EDF = electricity-demand frontier; EVAL = impact evaluation; EXP = experimental or field-experimental analysis; FC = forecasting; FL = fractional logit; GTRE = generalized true random effects model; HED = hedonic analysis; HET = heterogeneity analysis; HVA = household-vulnerability analysis; IDF = input distance function; IE = impact evaluation; OPT = optimization analysis; PANEL = panel-data analysis; PSFA = panel stochastic frontier analysis; PV = predictive validation; QEX = quasi-experimental analysis; RCA = reliability-cost assessment; RCT = randomized controlled trial; REG = regression analysis; SA = sensitivity analysis; SEM =

structural equation modeling; SFA = stochastic frontier analysis; SPAT = spatial analysis; SURV = survey analysis; WEL = welfare analysis.

connection does not necessarily imply uninterrupted capacity to use electricity productively (Cooper et al., 2024; Samad and Zhang, 2018). Households facing limited supply hours, outages, unstable voltage, or weak infrastructure may be unable to translate electricity consumption into the services they expect (Meeks et al., 2023). This point is particularly important in low-income settings, where electricity systems are more uneven and where dwelling quality and local infrastructure vary sharply across locations (Ewing et al., 2025). The literature supports the view that electricity service production should be analyzed as a function not only of electricity use, but also, electricity availability, housing quality, household size, and locational conditions.

2.2.2. Household electricity efficiency and its determinants

The second empirical strand moves beyond the level of electricity use and asks whether households use electricity efficiently relative to what is feasible under their observed conditions. Residential electricity inefficiency is empirically meaningful and efficiency varies systematically across households (Andor et al., 2021). Economic capacity, dwelling quality, household composition, and electricity service environments repeatedly emerge as important correlates of electricity efficiency (Otsuka, 2017). However, the evidence is not always uniform. Higher income may improve efficiency by enabling better appliances and housing conditions; however, it may also reduce measured efficiency by increasing appliance intensity and expanding the scale of electricity use. Household size may generate economies of shared services; however, it may also produce internal congestion and greater pressure on electricity-dependent activities (Andor et al., 2021).

Frontier-based studies provide an important methodological foundation for analysing residential electricity efficiency. (Otsuka, 2017) estimated residential electricity-demand efficiency in Japan using stochastic frontier analysis and showed that efficiency varies with household and regional conditions. Andor et al. (2021) estimated the efficiency of residential electricity consumption in Germany and found measurable inefficiency in household electricity use. (Blasch et al., 2017b) showed that energy and investment literacy are associated with electricity demand and end-use efficiency in Swiss households, while (Boogen et al., 2021) linked energy-related financial literacy to residential electricity efficiency in Europe. These studies demonstrate that household electricity efficiency can be measured empirically and that efficiency differences are associated with household resources, literacy and behavioral conditions.

Dwelling conditions may raise the productivity of electricity-supported services (Jones et al., 2015). Urban residence may improve efficiency through better infrastructure, greater electricity availability, and stronger market access (Li et al., 2023). At the same time, regional disparities may generate systematic efficiency differences because households in different areas face unequal electricity conditions, housing environments, and complementary infrastructure (Sun et al., 2023; Xiao et al., 2024). These findings suggest that household electricity efficiency is not simply a technical attribute. It is embedded in broader socioeconomic, spatial, and infrastructural conditions that shape both opportunities and constraints of electricity use (Chaudhuri and Huaccha, 2023).

Recent household-level evidence also confirms that energy efficiency is shaped by broader household conditions. (Dolšak et al., 2022), using Slovenian household-level data, estimated overall energy-consumption efficiency and found substantial household-level inefficiency. (Zheng et al., 2024) applied panel stochastic frontier analysis to Chinese household energy consumption and found that household energy efficiency changes over time and is influenced by income growth and changing consumption needs. These findings broaden the empirical basis beyond electricity access studies and show that household energy efficiency is shaped by income, dwelling conditions, technology use and changing household demand.

An important methodological lesson emerges. Many studies estimate household or residential electricity efficiency; however, a considerable share of the evidence remains closer to electricity-demand efficiency than to electricity-service efficiency in the fuller household production sense (Weyman-Jones and Boucinha, 2024). This is a crucial distinction. A household may consume relatively little electricity; however, this does not necessarily imply efficient generation of electricity services. Conversely, a household may consume more electricity while still converting that input into services more effectively under its observed conditions (Alberini and Filippini, 2018). A service-oriented interpretation of electricity efficiency therefore provides a more conceptually coherent framework than one based on electricity demand alone. This is the empirical space within which the present study is located.

2.3. Positioning this study

The reviewed literature shows that household electricity outcomes and residential energy efficiency are shaped by socioeconomic conditions, demographic structure, housing quality, electricity availability, appliance environments, behavior, information and locational context (Andor et al., 2021; Gajdzik et al., 2023b; Haider et al., 2024; Jones et al., 2015; Magnani and Vaona, 2016). It also indicates that household electricity efficiency is a meaningful empirical concept, rather than a purely theoretical one. However, an important gap remains. Much of the existing work still focuses on electricity access, consumption, or appliance ownership without clearly distinguishing electricity as an input from the household services it enables (Adebayo and Prah, 2025). However, much of the frontier-based literature measures electricity-demand or energy-input efficiency, while less attention is given to electricity-service efficiency as the conversion of electricity and domestic conditions into welfare-relevant household services.

This gap is especially relevant in low-income contexts, where electricity reliability, housing disparities, appliance constraints and regional inequalities shape the household value derived from electricity use (Tesfahunegn et al., 2020; Yaguma et al., 2022). This study contributes by combining three elements within one empirical design: household electricity services as the output of electricity use, stochastic-frontier measurement of technical efficiency, and analysis of the household, housing, energy-access and spatial factors associated with that efficiency. This positioning links international evidence on residential energy efficiency with the empirical realities of household electricity-service production in Uganda.

3. Methodology

This study used microdata from the Uganda National Household Survey (UNHS) 2020/21, conducted by the Uganda Bureau of Statistics (UBOS). The UNHS is a nationally representative household-based survey that targets the non-institutional household population. The sampling frame was derived from the Uganda Population and Housing Census (UPHC) 2014 enumeration area (EA) frame, which provides a complete national listing of households by residence and region. Consistent with standard UNHS implementation, the survey applied a stratified two-stage sampling design in which EAs were selected at the first stage using probability proportional to size (PPS) (Kalton et al., 2021), followed by systematic selection of households within sampled EAs based on updated household listings. Household listing and interviewing were conducted using computer-assisted personal interviewing (CAPI) on tablet devices, with geographic coordinates recorded during field operations.

Given the stratified and clustered sampling design, survey weights were required to restore population representativeness. Following UBOS methodology, household weights were computed as the inverse of the overall probability of selection, defined as the product of the EA-level selection probability and the household-level selection probability,

with adjustment for non-response (Haziza and Beaumont, 2017). All descriptive statistics and econometric estimations in this study applied the UNHS survey weights to ensure nationally representative inferences.

The full UNHS dataset contained 197,343 household observations before analytical restrictions were imposed. Because the analysis focused on electricity-service production, the baseline stochastic frontier sample was restricted to electricity-using households with positive electricity consumption and observed service indicators, yielding 27,074 observations. The determinants, control-function and predictive-validation models used smaller complete-case samples because they required additional socioeconomic, housing, financial and literacy variables. The findings therefore refer to electricity-using households represented in these analytical samples.

The empirical strategy followed the sequence implemented in the analysis program. First, electricity consumption variables and household characteristics were constructed from the survey modules. Second, household electricity service production was estimated using stochastic frontier analysis (Andor et al., 2021; Basumatary and Devi, 2022; Otsuka, 2017). Third, determinants of technical efficiency were estimated using fractional response models with survey weights (Boogen et al., 2021). Fourth, potential endogeneity in selected explanatory variables was addressed using a control function approach. Finally, predictive performance and robustness were evaluated using cross-validated predictive validation and diagnostic procedures (Usman et al., 2024).

3.1. Analytical framework

Household electricity services were treated as the output of a stochastic production process, based on the theoretical framework. Let $i = 1, \ldots, n$ index households. The general stochastic frontier production model was specified as

$$y_i = f(x_i;\beta)\exp\,(v_i - u_i), \tag{7}$$

where y_i denotes the observed output, x_i denotes the vector of production inputs, β denotes the technology parameter vector, v_i denotes a two-sided random disturbance, and $u_i \geq 0$ denotes technical inefficiency. Taking natural logarithms yields

$$\ln y_i = \ln f(x_i;\beta) + v_i - u_i. \tag{8}$$

The composite error term is therefore

$$\varepsilon_i = v_i - u_i. \tag{9}$$

The random component captures measurement error and exogenous shocks and was assumed to follow

$$v_i \sim N(0, \sigma_v^2), \tag{10}$$

whereas the baseline inefficiency component was assumed to follow a half-normal distribution,

$$u_i \sim |N(0, \sigma_u^2)| \tag{11}$$

The variance of the composite disturbance is

$$\sigma^2 = \sigma_v^2 + \sigma_u^2, \tag{12}$$

and the relative contribution of inefficiency to total disturbance variation is summarized by

$$\lambda = \frac{\sigma_u}{\sigma_v}, \tag{13}$$

or, equivalently,

$$\gamma = \frac{\sigma_u^2}{\sigma_u^2 + \sigma_v^2}, 0 \leq \gamma \leq 1. \tag{14}$$

Technical efficiency for household i was defined as

$$TE_i = \frac{y_i}{y_i^*}, \tag{15}$$

where y_i^* denotes frontier output conditional on x_i. Under the stochastic frontier representation,

$$TE_i = \exp\,(-u_i), \tag{16}$$

so that

$$0 < TE_i \leq 1. \tag{17}$$

Eqs. (7)–(17) provide the formal link between the theoretical framework and the empirical model. The household production relationship was operationalized as a frontier technology, in which deviations from best-practice output reflect both statistical noise and household-specific inefficiency.

3.2. Household electricity service production technology

Households convert electricity consumption and enabling household conditions into electricity services within the dwelling. Let S_i denote household electricity services, E_i denote monthly electricity consumption, A_i denote electricity availability measured as daily hours of supply, H_i denote housing quality, and N_i denote household size. The core input vector was written as

$$x_i = (E_i, A_i, H_i, N_i)' \tag{18}$$

Substituting this input vector into the frontier framework yields the household electricity service production technology.

$$S_i = f(E_i, A_i, H_i, N_i)\exp\,(v_i - u_i) \tag{19}$$

Because electricity service production may systematically vary across settlement types and geographic regions, the frontier also incorporated spatial controls. Let U_i denote urban residence and let R_i denote the vector of regional controls. The empirical production technology is therefore

$$S_i = f(E_i, A_i, H_i, N_i, U_i, R_i)\exp\,(v_i - u_i). \tag{20}$$

Table 2 presents the analytical variables, symbols, descriptions and measurement rules used consistently in the service-proxy construction, stochastic frontier estimation and efficiency-determinants models.

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3.2.1. Construction of the household electricity-service proxy

The dependent variable was a household electricity-service proxy constructed to capture realized domestic services enabled by electricity rather than electricity consumption itself. Conceptually, S_i denotes household electricity services for household *i*. Empirically, the proxy was constructed from the household asset roster by identifying asset types associated with electricity-enabled domestic services and combining them with current household ownership status. These service assets captured domestic functions such as lighting, refrigeration or food preservation, communication, information access, entertainment and related appliance-based household services.

Let a_{ij} denote ownership of electricity-service asset j by household i, where $j = 1, \ldots, J$. Each component was coded as

$$a_{ij} = \begin{cases} 1, & \text{if household } i \text{ currently owned electricity} - \text{service asset } j, \\ 0, & \text{otherwise.} \end{cases} \tag{21}$$

The household electricity-service index was then constructed as an additive service-asset intensity score:

$$S_i = \sum_{j=1}^{J} a_{ij} \tag{22}$$

Table 2
Analytical variables, symbols and measurement.

Variable name	Symbol	Variable in description	Measurement / coding
asset_type	j	Type of household asset	Asset roster category identifying each reported asset type
asset_ownership_current	o_{ij}	Current household ownership of asset	Binary ownership/status field; 1 if any household member currently owns asset j, 0 otherwise
service_asset_j	a_{ij}	Electricity-service asset indicator	Binary indicator generated from asset type and current ownership; 1 if household $i$currently owns electricity-service asset j, 0 otherwise
serv_index	S_i	Household electricity-service index	Additive service-asset intensity score: $S_i = \sum_{j=1}^{J} a_{ij}$
serv_pos	S_i^+	Shifted electricity-service proxy	Strictly positive transformation: $S_i + 1$
ln_serv_pos	$\ln(S_i^+)$	Log electricity-service proxy	Natural logarithm of shifted electricity-service proxy
kwh_m	E_i	Monthly electricity consumption	Continuous; monthly household electricity use in kilowatt-hours
lnkwh	$\ln(E_i)$	Log monthly electricity consumption	Natural logarithm of positive monthly electricity consumption
hours_power	H_i	Hours with power per day	Continuous; reported average daily hours of electricity availability
hq_index	Q_i	Housing-quality index	Principal-component index from roof, wall and floor material indicators
hhsize	N_i	Household size	Number of household members
urban_d	U_i	Urban residence	Binary; 1 = urban, 0 = rural
Eastern; Northern; Western	R_i	Regional controls	Regional dummy variables; Central region omitted as reference category
asset_index	A_i	Household asset index	Composite asset index constructed from household asset-ownership indicators
te_sfa	TE_i	Technical-efficiency score	Household-specific technical efficiency predicted from the stochastic frontier

Notes: i indexes households and j indexes electricity-service asset categories. All variables are measured at household level.

where S_i captures the number of observed electricity-enabled service assets currently owned by household i. Because the index could take a value of zero, it was shifted into a strictly positive scale before logarithmic transformation:

$$S_i^+ = S_i + 1 \tag{23}$$

The dependent variable in the stochastic frontier model was therefore

$$\ln\left(S_i^+\right) \tag{24}$$

Monthly electricity consumption, measured in kilowatt-hours, entered the frontier as the principal electricity input, while average daily hours with power captured electricity availability. The household asset index entered the determinants models as a broader material-capacity measure and its coefficients are interpreted as conditional associations.

3.3. Stochastic frontier estimation

Electricity service production technology specified in Section 3.2 was estimated using stochastic frontier analysis. This framework separated random shocks from technical inefficiency and yielded household-specific efficiency estimates.

3.3.1. Cobb–Douglas stochastic frontier

The baseline empirical specification adopted a Cobb–Douglas functional form. In general form,

$$\ln S_i = \beta_0 + \sum_{k=1}^{K} \beta_k \ln X_{ki} + v_i - u_i, \tag{25}$$

where X_{ki} denotes the k-th production input. In the present application, the baseline electricity-service frontier was specified as

$$\begin{aligned}\ln S_i = {} & \beta_0 + \beta_1 \ln E_i + \beta_2 A_i + \beta_3 H_i + \beta_4 N_i + \beta_5 U_i \\ & + \delta_1 East_i + \delta_2 North_i + \delta_3 West_i + v_i - u_i,\end{aligned} \tag{26}$$

where S_i denotes household electricity services, E_i denotes monthly electricity consumption in kilowatt-hours, A_i denotes average daily electricity-supply hours, H_i denotes the housing-quality index, N_i denotes household size, and U_i denotes urban residence. The regional indicators $East_i$, $North_i$, and $West_i$ capture regional effects, with Central Uganda as the reference category.

The baseline model assumes half-normal inefficiency, as shown in Eq. (11). To assess the sensitivity to alternative distributional assumptions, an additional frontier was estimated under exponential inefficiency

$$u_i \sim \text{Exp}(\eta), \tag{27}$$

where $\eta > 0$ is the scale parameter. The half-normal specification was retained as the baseline because it provides a standard and parsimonious benchmark for non-negative household-specific inefficiency and generates the reference technical-efficiency scores used in the subsequent distributional, inequality, and determinants analyses. The exponential specification was estimated as a distributional robustness check to assess whether the main frontier patterns were sensitive to the assumed inefficiency distribution.

3.3.2. Heteroskedastic inefficiency model

The baseline frontier imposed constant inefficiency variance across households. To allow inefficiency dispersion to vary systematically with household characteristics, a one-step heteroscedastic frontier was also estimated. Let z_i denote the vector of variables explaining heterogeneity in inefficiency. The variance of the inefficiency term was parameterized as

$$\sigma_{u,i}^2 = \exp\left(z_i'\alpha\right), \tag{28}$$

which implies

$$\ln \sigma_{u,i}^2 = z_i'\alpha, \tag{29}$$

where α is the associated parameter vector. Eqs. (26), (28), and (29) were estimated jointly by maximum likelihood estimation. This specification allowed inefficiency dispersion to vary across households while preserving the same deterministic frontier structure.

3.4. Determinants of technical efficiency

Following frontier estimation, household-specific technical-efficiency scores were recovered for each observation. Because these scores are bounded on the unit interval, linear regression was inappropriate. Therefore, their determinants were estimated using a fractional logit model. Let TE_i denote the efficiency score for household i. By construction,

$$0 < TE_i \leq 1 \tag{30}$$

Let W_i denote the vector of explanatory variables. The conditional mean was specified as

$$\mathbb{E}(TE_i|W_i) = G(W_i'\delta), \tag{31}$$

where δ is a parameter vector and $G(\cdot)$ is the logistic cumulative distribution function,

$$G(t) = \frac{\exp(t)}{1+\exp(t)} \tag{32}$$

Substituting Eq. (32) into Eq. (31) yields

$$\mathbb{E}(TE_i|W_i) = \frac{\exp(W_i'\delta)}{1+\exp(W_i'\delta)}, \tag{33}$$

which guarantees fitted values in $(0|1)$. Since predicted efficiency values may lie extremely close to the boundaries, a clipped efficiency score was used in estimation:

$$\widetilde{TE}_i = \min\{\max(TE_i, \kappa), 1-\kappa\}, \tag{34}$$

where $\kappa > 0$ is a small constant. The fractional logit model was estimated by quasi-maximum likelihood estimation. To facilitate interpretation, marginal effects were computed as

$$\frac{\partial \mathbb{E}(TE_i|W_i)}{\partial W_{ji}} = G(W_i'\delta)\left[1-G(W_i'\delta)\right]\delta_j. \tag{35}$$

3.5. Control-function correction for endogeneity

Some household socioeconomic and dwelling variables may be jointly determined with electricity use behavior. In particular, asset ownership and housing quality may be correlated with unobserved factors that also influence electricity efficiency. To address this possibility, a control function approach was used. The excluded instruments were leave-one-out group-mean measures of the corresponding potentially endogenous variables. The asset-index first stage used the leave-one-out group mean of the asset index, while the housing-quality first stage used the leave-one-out group mean of the housing-quality index. The identifying logic is that these leave-one-out group means capture the broader material and dwelling environment associated with household asset ownership and housing quality, while excluding the household's own value from the instrument construction.

These instruments summarize broader group-level material and dwelling conditions while excluding the household's own asset or housing-quality value from their construction. The identifying restriction places their relationship with technical efficiency through the household-level asset and housing-quality variables after conditioning on household characteristics, electricity inputs, settlement type and region. The corresponding first-stage residuals were included in the second-stage fractional logit efficiency model, and first-stage relevance and identification diagnostics are reported in Section 4.4.1.

Let X_i^e denote a potentially endogenous regressor. Its reduced-form equation was written as

$$X_i^e = Z_i'\pi + \eta_i, \tag{36}$$

where Z_i contains instruments and exogenous covariates, π is a parameter vector, and η_i is the reduced-form disturbance. Estimation of Eq. (36) yielded the residual

$$\widehat{\eta}_i = X_i^e - \widehat{X}_i^e \tag{37}$$

This residual was then directly included in the efficiency model. The control-function fractional logit specification becomes

$$\mathbb{E}(TE_i|W_i, \widehat{\eta}_i) = G(W_i'\delta + \rho\widehat{\eta}_i), \tag{38}$$

where ρ measures the degree of endogeneity. The null hypothesis of exogeneity was

$$H_0 : \rho = 0. \tag{39}$$

Failure to reject H_0 supports exogeneity, whereas rejection indicates that the control function correction is required.

3.6. Predictive validation

Predictive validation was used to assess whether frontier-based household technical efficiency could be recovered from observed household characteristics. A least absolute shrinkage and selection operator model was estimated with the technical-efficiency score as the target variable and household, housing, financial, energy-access, and spatial variables as predictors. The penalty parameter was selected using ten-fold cross-validation. Predictive performance was assessed using the number of retained predictors, out-of-sample R^2, and cross-validation mean prediction error. The exercise served as a predictive check on the empirical structure of the frontier-based efficiency estimates.

3.7. Diagnostics and robustness analysis

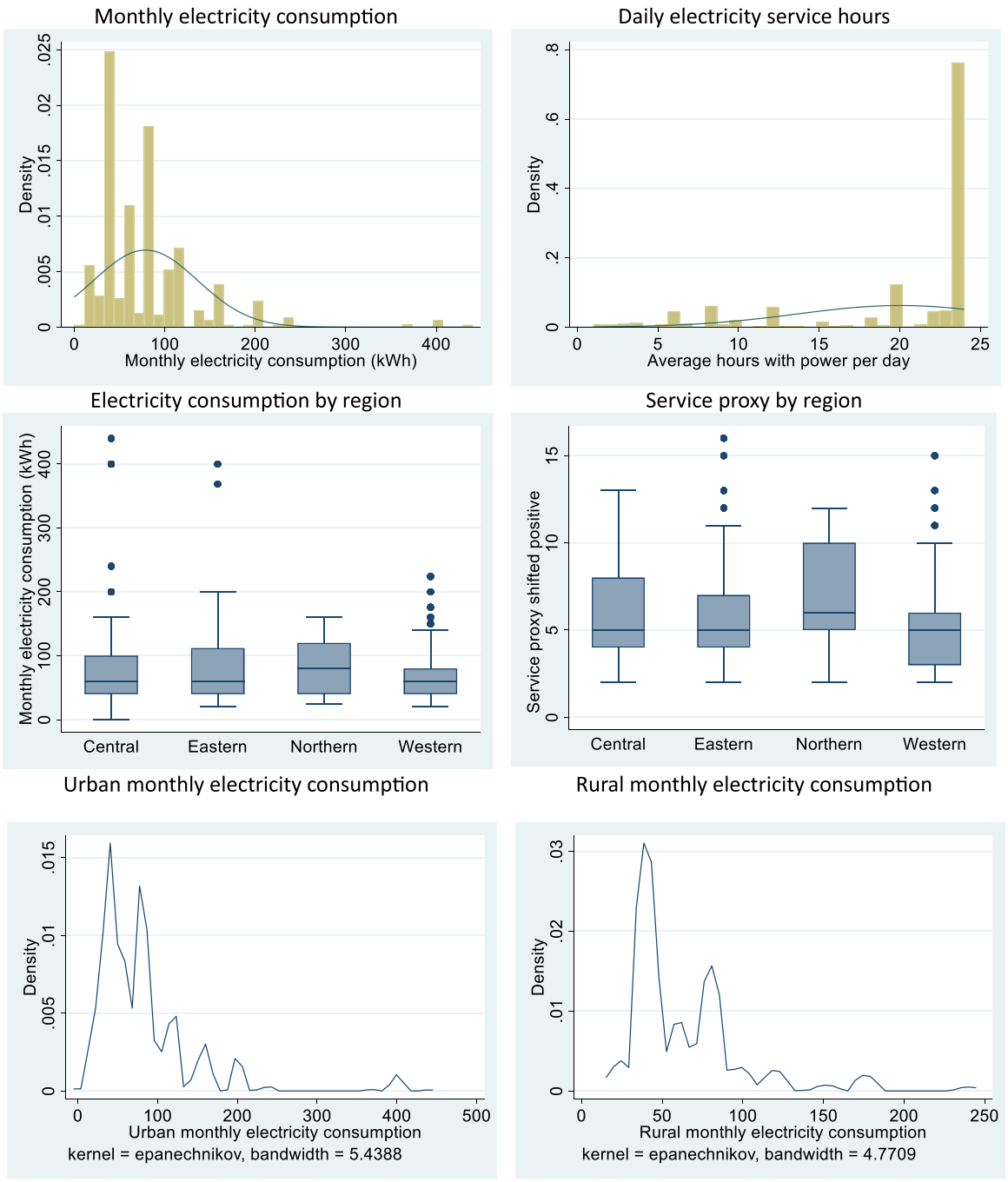
Diagnostic and robustness checks were used to assess the stability of the efficiency estimates and the adequacy of the empirical models. Bootstrap statistics were used to evaluate the sampling stability of the mean, median, and upper-tail technical-efficiency estimates. Inequality in technical efficiency was summarized using Gini, Atkinson, Generalized Entropy, and percentile-ratio measures. Agreement across frontier specifications was assessed using correlations and Bland–Altman comparison, while regression adequacy was assessed using standard specification and multicollinearity checks.

4. Results

This section presents the empirical results in a sequence that follows the analytical logic of the study. It begins with the distributional characteristics of household electricity consumption, electricity availability, and electricity-related service outcomes in order to establish the underlying heterogeneity of the household electricity environment. It then reports the baseline stochastic frontier estimates of household electricity-service production and the corresponding distribution of technical efficiency, before extending the analysis to a heteroskedastic inefficiency specification that allows efficiency variation to depend systematically on household characteristics. The section concludes by examining the determinants, predictive structure, and robustness of household technical efficiency. These results provide a coherent empirical account of how electricity is translated into household services, how efficiently that process occurs, and how the resulting efficiency profile varies across households, regions, and settlement contexts.

4.1. Household electricity consumption and service outcomes

Fig. 1 shows that household electricity conditions in the core sample are highly uneven rather than concentrated around a single common profile. At the aggregate level, mean monthly electricity consumption is about 77.6 kWh, mean daily electricity availability is about 19.8 h, and



[[parms resize(1),pos(50,50),size(200,200),bgcol(156)]]s regions and settlement types.

the mean service proxy is about 5.68. However, the distributions around these means are clearly dispersed. Monthly electricity consumption extends from values close to zero to approximately 440 kWh, with most households concentrated well below 150 kWh, indicating a strongly right-skewed distribution. Daily hours with power range from approximately 1 h to the full 24 h, but the distribution is concentrated near the upper end, showing that many households report long daily availability, even though a visible lower tail remains. The service proxy is similarly spread, ranging approximately from 2 to 16, which indicates that realized electricity-related household services vary materially across the sample.

The regional panels show that this heterogeneity is spatially structured. In the monthly kWh box plot, the Northern region appears to have the highest median consumption at approximately 80 kWh per month, compared with approximately 60 kWh in Central, Eastern, and Western Uganda. Dispersion also differs by region: Northern and Eastern Uganda show relatively wider interquartile spreads, while Central and Eastern Uganda display the most extreme upper-end outliers, reaching approximately 400–440 kWh in Central and about 370–400 kWh in Eastern Uganda. The service-proxy box plot shows a related but not identical pattern. The median service proxy is about 6 in the Northern region, compared with approximately 5 in Central, Eastern, and Western Uganda, while upper-end observations rise to about 16 in Eastern Uganda and about 15 in Western Uganda. These panels indicate that regional differences are visible not only in central levels of electricity use but also in the spread and upper-tail structure of realized service outcomes.

The rural-urban density plots further support this interpretation. Rural monthly electricity consumption is more concentrated, with most of the density appearing roughly between 30 and 90 kWh, and only a

thin upper tail extending to approximately 240 kWh. Urban consumption is more dispersed, with substantial density stretching across a broader range—roughly 30–130 kWh—and a much longer upper tail reaching beyond 400 kWh. This indicates that urban households are not only more heterogeneous in electricity consumption but also more likely to include very high-consumption observations. The panels in Fig. 1 show that electricity use, electricity availability, and electricity-related service outcomes differ materially across households, regions, and settlement types. Therefore, the descriptive result reveals structured heterogeneity in the underlying household electricity environment.

4.2. Baseline electricity service production frontier estimates

4.2.1. Baseline stochastic frontier estimates of electricity service production

Table 3 reports the baseline stochastic frontier estimates of household electricity service production under half-normal and exponential inefficiency assumptions. In both specifications, monthly electricity consumption enters positively and very strongly. The coefficient on log (kWh) is 0.0714 in the half-normal model and 0.0624 in the exponential model, with p = 0.000 in both cases. This shows that higher electricity input is associated with higher electricity service output under either distributional assumption, although the estimated elasticity remains well below one in both models. Power hours per day also remain positive and highly significant across the two specifications, with coefficients of 0.0057 and 0.0085, again with p = 0.000 in both cases. The positive relationship between electricity input, electricity availability, and service output is stable across the two baseline frontier models.

The small electricity-consumption elasticity indicates that measured service output rises only gradually as electricity consumption increases. This pattern is plausible because the service proxy is based on electricity-enabled service assets. Once households possess basic service assets, additional electricity may extend use, improve continuity, or support service quality without adding many new measured service functions. The result suggests that larger service gains require not only electricity consumption, but also complementary improvements in appliance access, reliability, housing conditions, and household capacity.

Household size was negative and highly significant in both models, with coefficients of −0.0065 in the half-normal specification and −0.0109 in the exponential specification (both p = 0.000). This pattern is consistent with internal demand pressure, whereby a given level of electricity input and availability is spread across more household members and domestic needs. Urban residence also entered negatively in both specifications, shifting from −0.0209 (p = 0.010) in the half-normal model to −0.0428 (p = 0.000) in the exponential model. Within the frontier specification, this result represents a conditional association after accounting for electricity consumption, power hours, household size, housing quality and region. The negative sign may reflect heterogeneity in urban appliance portfolios, rented or shared dwelling arrangements, and prepaid electricity-management practices that affect the conversion of electricity input into measured household services. Housing quality was less stable across specifications, remaining significant under the half-normal model but becoming statistically insignificant under the exponential model, suggesting that its role may partly operate through inefficiency heterogeneity, examined in Table 5.

The regional coefficients indicate marked spatial differentiation relative to the Central region. In the half-normal model, Eastern Uganda records a positive coefficient of 0.0355 with p = 0.006, Northern Uganda records a much larger positive coefficient of 0.1607 with p = 0.000, and Western Uganda records a negative coefficient of −0.0809 with p = 0.000. Under the exponential model, Eastern Uganda becomes effectively null at 0.0010 with p = 0.943, while the Northern and Western coefficients remain strong and highly significant at 0.1636 and −0.1039, both with p = 0.000. The Northern effect is therefore both large and stable across specifications, whereas the Eastern effect is not robust to the alternative inefficiency assumption. Western Uganda remains consistently below the Central region in both models.

The lower panel of Table 3 shows that inefficiency contributes materially to deviations from the estimated frontier. Under the half-normal model, the estimated random-noise component is sigma_v = 0.2218, while the inefficiency component is much larger at sigma_u = 0.7523. Under the exponential model, the same ordering holds, with sigma_v = 0.3139 and sigma_u = 0.4215. This is reflected in the corresponding lambda values of 3.3910 and 1.3426, both greater than one. This implies that the variation around the frontier is not primarily driven by random statistical noise; systematic inefficiency accounts for a substantial share of the unexplained variation in household electricity service production. The half-normal specification attributes a stronger relative role to inefficiency than the exponential specification, but both models point in the same direction.

4.2.2. Technical efficiency (TE) distribution and inequality metrics for baseline half-normal SFA

Table 4 shows that the distribution of technical efficiency under the baseline half-normal stochastic frontier is centered at a moderate level rather than near the frontier. The mean TE is 0.6041, while the median is slightly higher at 0.6207, indicating that the typical household operates at a little above sixty percent of frontier electricity-service performance. The fact that the median exceeds the mean indicates that the distribution

Table 3
Baseline stochastic frontier estimates of electricity service production – log(service).

	Half-normal SFA			Exponential SFA		
Covariates	**Coefficient**	**Robust Std. err.**	**p-value**	**Coefficient**	**Robust Std. err.**	**p-value**
log (kWh)	0.0714***	(0.0045)	0.000	0.0624***	(0.0061)	0.000
Power hours (per day)	0.0057***	(0.0006)	0.000	0.0085***	(0.0008)	0.000
Housing quality index (PCA)	-0.0013***	(0.0002)	0.000	0.0002	(0.0002)	0.363
Household size	-0.0065***	(0.0014)	0.000	-0.0109***	(0.0016)	0.000
Urban (=1)	-0.0209**	(0.0081)	0.010	-0.0428***	(0.0091)	0.000
Eastern	0.0355***	(0.0131)	0.006	0.0010	(0.0136)	0.943
Northern	0.1607***	(0.0113)	0.000	0.1636***	(0.0132)	0.000
Western	-0.0809***	(0.0083)	0.000	-0.1039***	(0.0087)	0.000
Constant	1.8563***	(0.0195)	0.000	1.6899***	(0.0210)	0.000
/lnsig2v	-3.0115***	(0.0459)	0.000	-2.3171***	(0.0541)	0.000
/lnsig2u	-0.5693***	(0.0204)	0.000	-1.7278***	(0.0483)	0.000
sigma_v	0.2218	(0.0051)		0.3139	(0.0085)	
sigma_u	0.7523	(0.0077)		0.4215	(0.0102)	
sigma2	0.6151	(0.0099)		0.2762	(0.0044)	
lambda	3.3910	(0.0120)		1.3426	(0.0182)	

Notes: N = 27,074. ***, ** and * represent significance at the 1%, 5% and 10% levels.
Source: Author's computation using Uganda's 2020/2021 National Household Survey data

Table 4
Technical efficiency (TE) distribution and inequality metrics for baseline half-normal SFA.

Statistic (Technical Efficiency)	Bootstrap mean	Std. deviation	5th percentile	95th percentile
Mean TE	0.6041	(0.0013)	0.6021	0.6063
Median TE (p50)	0.6207	(0.0014)	0.6200	0.6248
90th percentile TE (p90)	0.8597	(0.0016)	0.8586	0.8647
Atkinson indices A (e)	A(0.5) = 0.0327	A(1) = 0.0686	A(2) = 0.1472	Gini = 0.1938
Generalized Entropy indices GE (a)	GE(-1) = 0.0863	GE(0) = 0.0711	GE(1) = 0.0622	GE(2) = 0.0573
Percentile ratios	p90/p10 = 3.1550	p90/p50 = 1.3710	p10/p50 = 0.4350	p75/p25 = 1.7540

Notes: Technical efficiency (TE) is predicted from the baseline stochastic frontier model estimated on the core analytical sample N = 27,074. $e > 0$ is the inequality aversion parameter for $A(e)$, a is the income difference sensitivity parameter for $GE(a)$.

is pulled downward by a lower-efficiency segment. At the upper end, the 90th percentile reaches 0.8597, showing that households near the top of the distribution operate much closer to the frontier than the average household. These values indicate a clear spread between the center of the efficiency distribution and its upper tail.

The bootstrap statistics show that these distributional estimates are highly stable. The bootstrap standard deviation of mean TE is 0.0013, with a narrow 5th to 95th percentile range of 0.6021–0.6063. The median TE is similarly tightly concentrated, with a bootstrap standard deviation of 0.0014 and a corresponding interval of 0.6200–0.6248. The 90th percentile TE also exhibits very limited variation, with a bootstrap standard deviation of 0.0016 and a 5th to 95th percentile range of 0.8586–0.8647. These narrow bootstrap bands indicate that the central features of the estimated efficiency distribution are not being driven by unstable resampling variation.

The inequality metrics indicate that technical efficiency is not uniformly distributed across households. The Gini coefficient is 0.1938, which indicates moderate dispersion in efficiency levels. The Atkinson indices increase from 0.0327 at A(0.5) to 0.0686 at A(1) and 0.1472 at A(2), indicating that measured inequality becomes more pronounced when more weight is placed on lower-efficiency households. The Generalized Entropy indices are all positive, ranging from 0.0863 at GE(-1) to 0.0573 at GE(2), confirming dispersion across the efficiency distribution. The percentile ratios reinforce this pattern: p90/p10 = 3.1550 shows that households near the top of the distribution achieve more than three times the efficiency level of households near the bottom, while p90/p50 = 1.3710 and p10/p50 = 0.4350 indicate that upper-end households lie well above the median and lower-end households lie far below it. Overall, Table 4 indicates that the estimated technical-efficiency distribution is not only moderate in central tendency but also meaningfully unequal across households.

4.2.3. *Distribution and diagnostic assessment of SFA technical efficiency estimates*

Fig. 2 indicates that the baseline half-normal SFA produces a technical-efficiency distribution concentrated in the middle-to-upper part of the unit interval rather than near full efficiency. The histogram

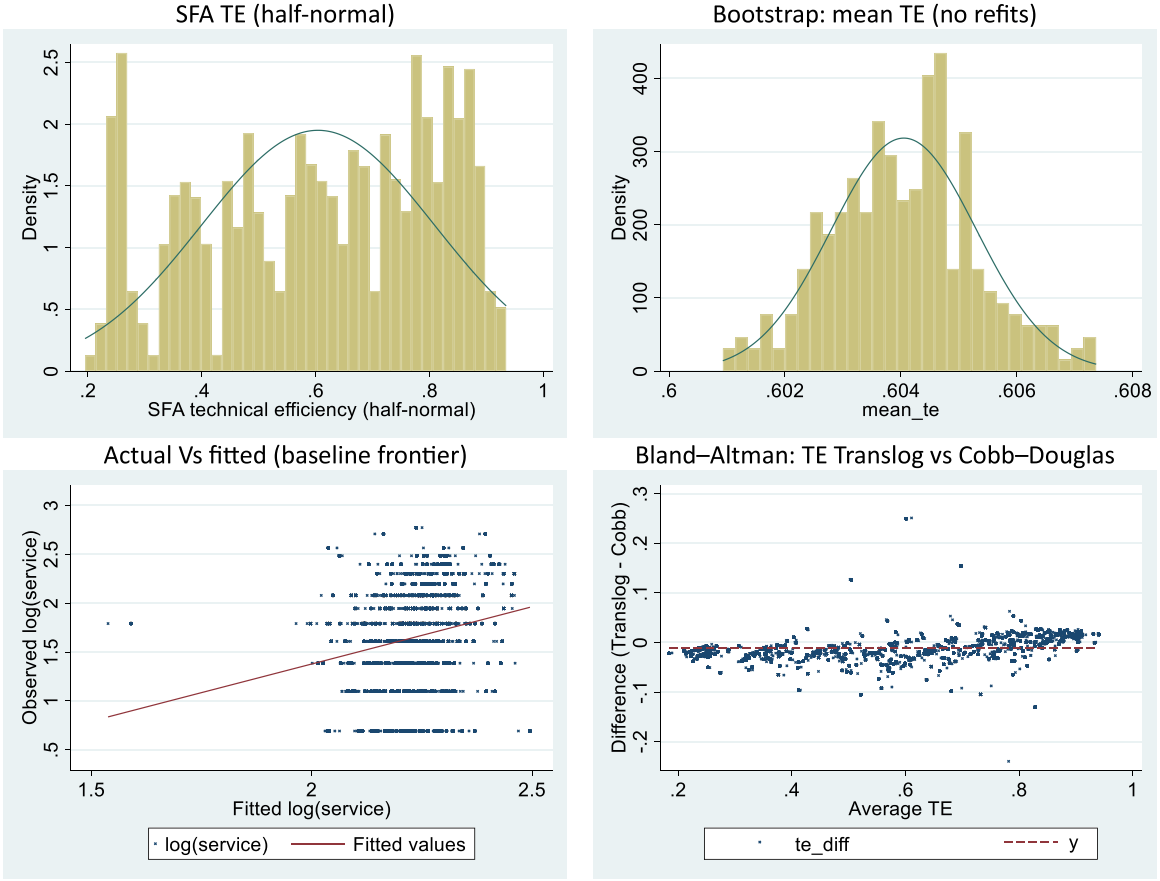


Fig. 2. Distribution and Diagnostic Assessment of SFA Technical Efficiency Estimates.

shows that most households lie roughly between 0.4 and 0.9, with relatively few observations at the lower extreme, and this visual pattern is consistent with the summary statistics in Table 4, where the mean TE is 0.6041, the median is 0.6207, and the 90th percentile is 0.8597. The adjacent bootstrap distribution of the mean TE is tightly centered around the sample mean, with very little dispersion, and this is consistent with the reported bootstrap standard deviation of only 0.0013 and the narrow 5th–95th percentile interval of 0.6021–0.6063. The first two panels show that the estimated efficiency is moderate on average and that the central level of efficiency is highly stable under resampling.

The diagnostic panels show a stable relationship between observed and fitted service outcomes. The actual-versus-fitted panel shows a clear positive association between observed and fitted values from the baseline frontier, indicating that the fitted component closely tracks the observed service outcomes over most of the sample range. The Bland–Altman panel comparing the Translog and Cobb–Douglas efficiency estimates shows that the pairwise differences are centered close to zero and remain relatively narrow over the range of average TE values, which indicates strong agreement between the two specifications. This visual conclusion is consistent with the very high reported correlations between the two-efficiency series, namely, 0.9917 in the Pearson correlation and 0.9909 in the Spearman rank correlation. Overall, Fig. 2 indicates that the baseline half-normal efficiency estimates are stable under resampling and consistent with the alternative frontier specification used for diagnostic comparison.

4.3. *Electricity service production frontier with heteroskedastic inefficiency*

Table 5 reports the one-step stochastic frontier estimates, in which the variance of inefficiency is allowed to vary systematically across households. In the production frontier, the coefficient on log monthly electricity consumption remains positive and highly significant at 0.0679 ($p = 0.000$), indicating that higher electricity input continues to be associated with higher electricity-service output, even after allowing inefficiency to be heteroscedastic. Daily hours with power also remain positive and statistically significant, with a coefficient of 0.0023 ($p = 0.000$), showing that longer electricity availability is still associated with higher service production, although the magnitude is smaller than in the baseline model. Household size remains negative and highly significant at −0.0054 ($p = 0.000$), while the housing-quality index is also negative and highly significant at −0.0025 ($p = 0.000$). The core production inputs continue to show a stable and statistically strong relationship with household electricity-service output in the heteroscedastic specification.

The spatial coefficients in Table 5 differ from the baseline frontier in some important respects. Urban residence becomes positive and highly significant, with a coefficient of 0.1053 ($p = 0.000$), indicating higher frontier-adjusted service output for urban households once heterogeneity in inefficiency is modeled directly. Relative to the Central region, both Eastern Uganda and Northern Uganda record positive and highly significant coefficients of 0.0966 and 0.0911, respectively (both $p = 0.000$). By contrast, the coefficient for Western Uganda is −0.0089 ($p = 0.196$), indicating no statistically significant difference from the Central region in this specification. The frontier component of Table 5 shows that electricity service production remains strongly differentiated across settlement type and region, but the estimated spatial profile changes once the inefficiency variance is allowed to depend on household characteristics.

The lower part of Table 5 reports the heteroscedastic inefficiency equation, where the coefficients refer to the variance of inefficiency rather than directly to efficiency itself. Age of household head enters negatively and significantly at −0.0027 ($p = 0.000$), indicating a lower inefficiency variance at higher age. Female headship is very close to zero at −0.0017 and statistically insignificant ($p = 0.880$), implying no detectable difference in inefficiency variance by headship gender. The asset index has a large negative coefficient of −1.0601 ($p = 0.000$), showing a strong reduction in inefficiency variance as asset ownership increases. Literacy categories are positive and significant relative to those who cannot read or write, with coefficients of 0.5267 ($p = 0.005$) for those who can read only and 0.1337 ($p = 0.000$) for those who can read and write, while highest grade completed is negative and

Table 5
One-Step SFA estimates of electricity service production with heteroskedastic inefficiency.

Covariates	Coefficient	Robust std. err.	z-value	p-value	[95% conf.	interval]
log(service)						
log (kWh)	0.0679***	(0.0051)	13.230	0.000	0.0579	0.0780
Power hours (per day)	0.0023***	(0.0005)	4.820	0.000	0.0014	0.0032
Housing quality index (PCA)	-0.0025***	(0.0002)	-12.270	0.000	-0.0029	-0.0021
Household size	-0.0054***	(0.0013)	-4.070	0.000	-0.0079	-0.0028
Urban (=1)	0.1053***	(0.0085)	12.340	0.000	0.0886	0.1221
Central (=0)						
Eastern	0.0966***	(0.0126)	7.690	0.000	0.0720	0.1213
Northern	0.0911***	(0.0105)	8.670	0.000	0.0705	0.1118
Western	-0.0089	(0.0069)	-1.290	0.196	-0.0225	0.0046
Constant	1.6711***	(0.0249)	67.060	0.000	1.6223	1.7200
lnsig2v						
Constant	-3.4979***	(0.0337)	-103.860	0.000	-3.5639	-3.4318
lnsig2u						
Age household head	-0.0027***	(0.0004)	-7.380	0.000	-0.0034	-0.0020
Female head (=1)	-0.0017	(0.0116)	-0.150	0.880	-0.0245	0.0210
Asset index	-1.0601***	(0.0108)	-98.530	0.000	-1.0812	-1.0390
Cannot read or write (=0)						
Can read only	0.5267***	(0.1868)	2.820	0.005	0.1606	0.8928
Can read and write	0.1337***	(0.0233)	5.740	0.000	0.0881	0.1793
Highest grade	-0.0020***	(0.0005)	-4.140	0.000	-0.0029	-0.0010
Mobile money saving (=1)	0.0768***	(0.0159)	4.830	0.000	0.0456	0.1080
Bank saving (=1)	0.1229***	(0.0129)	9.530	0.000	0.0976	0.1481
Electricity cost (UGX)	0.0000***	(0.0000)	18.520	0.000	0.0000	0.0000
Constant	1.7724***	(0.0371)	47.710	0.000	1.6996	1.8452
sigma_v	0.1740	(0.0029)			0.1683	0.1798

Notes: N = 12,006. ***, ** and * represent significance at the 1%, 5% and 10% levels.
Source: Author's computation using Uganda's 2020/2021 National Household Survey data.

significant at −0.0020 (p = 0.000). These estimates indicate that the dispersion of inefficiency is not constant across households but systematically varies with human-capital and asset-related characteristics.

The financial and cost variables in the inefficiency-variance equation are also statistically significant. Mobile money savings enter positively at 0.0768 (p = 0.000), and bank savings are likewise positive at 0.1229 (p = 0.000), indicating greater inefficiency variance among households with these characteristics. Electricity cost is positive and highly significant, with a coefficient of 0.0000164 (p = 0.000), showing that higher electricity expenditures are associated with greater dispersion in inefficiency. The estimated noise component is sigma_v = 0.1740, which is smaller than the corresponding estimate in the baseline half-normal model, indicating a tighter random-error component in the heteroscedastic specification. Table 5 shows that once inefficiency is allowed to vary systematically across households, both the production frontier and the variance of inefficiency exhibit clear and statistically structured patterns rather than remaining homogeneous across the sample.

4.4. Determinants of household electricity technical efficiency

4.4.1. Fractional logit and control-function frontier determinants of technical efficiency

Before presenting the second-stage fractional logit estimates, the first-stage diagnostics for the control-function correction are reported to clarify instrument relevance and identification. Table 6 reports the excluded instruments, first-stage relevance statistics, and overidentification-test status for the asset-index and housing-quality first-stage equations.

The excluded instruments were generated as leave-one-out group-mean measures of the corresponding potentially endogenous variables. The first-stage results indicate that both instruments are relevant predictors of their respective endogenous regressors. The implied instrument F-statistic is calculated as the square of the robust t-statistic because each equation contains one excluded instrument for one potentially endogenous regressor. Since each first-stage equation is exactly identified, overidentification tests are not applicable. The second-stage fractional logit and control-function estimates are reported in Table 7.

In Table 7, Age of household head remains negative and highly significant in both models, shifting only slightly from −0.0010 to −0.0008, with the marginal effect staying at −0.0002. This indicates only a very small decline in expected technical efficiency as head age increases. The more revealing contrast concerns female headship and urban residence.

Table 6
First-stage diagnostics for the control-function correction of endogeneity.

Diagnostic item	Asset-index first stage	Housing-quality first stage
Potentially endogenous variable	Asset index	Housing-quality index
Excluded instrument	Leave-one-out group mean of asset index	Leave-one-out group mean of housing-quality index
N	12,006	12,006
Overall first-stage F	193.3500	6.5200
Prob > F	0.0000	0.0000
R^2	0.2228	0.1038
Root MSE	2.3324	3.7603
Instrument coefficient	0.7894***	3.0019***
Robust SE	0.0245	0.3107
t-statistic	32.2800	9.6600
p-value	0.0000	0.0000
Implied instrument F	1042.0000	93.3200
Overidentification test	Not applicable; exactly identified	Not applicable; exactly identified

Notes: N = 12,006. First-stage regressions used probability weights and included the exogenous controls used in the efficiency-determinants model. *** represents significance at the 1% level.
Source: Author's computation using Uganda's 2020/2021 National Household Survey data.

Table 7
Fractional logit and control-function stochastic frontier estimates.

	Fractional logit (FL) TE model		Control-function FL-TE model	
Covariates	**Coefficient**	**dy/dx**	**Coefficient**	**dy/dx**
Age household head	-0.0010***	-0.0002***	-0.0008***	-0.0002***
Female head (=1)	-0.0141***	-0.0029***	0.0186***	0.0038***
Urban (=1)	0.0084**	0.0017**	-0.0122***	-0.0025***
Central (=0)				
Eastern	-0.0362***	-0.0074***	-0.0400***	-0.0082***
Northern	-0.3304***	-0.0683***	-0.3277***	-0.0678***
Western	0.1477***	0.0298***	0.1786***	0.0360***
Household size	-0.0005	-0.0001	0.0039***	0.0008***
Housing quality (HQ) index (PCA)	0.0071***	0.0014***	0.0402***	0.0082***
Power hours (per day)	-0.0113***	-0.0023***	-0.0141***	-0.0029***
Electricity cost (UGX)	-5.1e-6***	-1.0e-6***	-4.5e-6***	-9.1e-7***
Asset index (PCA)	0.3715***	0.0756***	0.3886***	0.0791***
Cannot read or write (=0)				
Can read only	0.1621***	0.0331***	0.2024***	0.0410***
Can read and write	0.1011***	0.0207***	0.0665***	0.0136***
Highest grade	-0.0020***	-0.0004***	-0.0001***	-0.0001***
Mobile money saving (=1)	-0.0150***	-0.0031***	-0.0531***	-0.0108***
Bank saving (=1)	0.0324***	0.0066***	0.0406***	0.0083***
Constant	-0.9339***		-0.9867***	
CF residual (Asset Index)			-0.0193***	-0.0039***
CF residual (HQ Index)			-0.0342***	-0.0070***

Notes: N = 12,006. ***, ** and * represent significance at the 1%, 5% and 10% levels.
Source: Author's computation using Uganda's 2020/2021 National Household Survey data.

In the baseline model, female headship enters negatively at −0.0141 with a marginal effect of −0.0029, while urban residence enters positively at 0.0084 with 0.0017. Once the control-function correction is introduced, female headship becomes positive at 0.0186 with 0.0038, whereas urban residence becomes negative at −0.0122 with −0.0025. The corrected model indicates higher expected technical efficiency for female-headed households, but lower expected technical efficiency for urban households, conditional on the included covariates.

The regional pattern is much more stable and remains one of the clearest features of Table 7. Relative to the Central region, Eastern Uganda records lower expected technical efficiency in both models, with coefficients of −0.0362 and −0.0400, while Northern Uganda shows by far the strongest negative gradient, at −0.3304 and −0.3277, with marginal effects of roughly −0.068 in both cases. Western Uganda, by contrast, remains positive throughout, rising from 0.1477 to 0.1786, with marginal effects increasing from 0.0298 to 0.0360. Household size also changes once endogeneity is addressed: it is essentially zero in the baseline model at −0.0005, but becomes positive and significant in the corrected model at 0.0039 with a marginal effect of 0.0008. Housing quality is positive and highly significant in both models, but its role becomes much stronger in the control-function specification, increasing from 0.0071 to 0.0402, with the marginal effect rising from 0.0014 to 0.0082. Table 7 indicates that the regional ordering of efficiency is robust, while the corrected model also points to a stronger positive gradient in favor of better housing conditions.

Among the remaining covariates, the asset index was the strongest positive predictor of expected technical efficiency in both models. Its coefficient increased slightly from 0.3715 to 0.3886, and its marginal effect remained large at 0.0756 and 0.0791. This makes asset ownership

one of the most influential positive correlates in the table. By contrast, both power hours and electricity costs remained negative in the two specifications. Power hours moved from −0.0113 to −0.0141, with marginal effects of −0.0023 and −0.0029, while electricity costs remained negative but numerically very small, at −5.1e-6 and −4.5e-6. Literacy variables remained positive in both models, indicating higher expected technical efficiency relative to the omitted literacy category, although the magnitude was larger for the lower literacy category than for the higher one in the corrected specification. Highest grade completed remained negative, but the coefficient was small in absolute terms. The two saving variables continued to move in opposite directions: mobile-money savings remained negative, becoming more strongly negative in the corrected model, while bank savings remained positive in both specifications. The table therefore points to a clear pattern in which assets, housing quality, literacy, and formal financial savings load positively, while electricity costs, longer reported power hours, and mobile-based savings load negatively.

Results in Table 7 further show that, the control-function residual terms are both negative and highly significant. The residual linked to the asset index enters at −0.0193 with a marginal effect of −0.0039, while the residual linked to housing quality enters at −0.0342 with −0.0070. The significance of these residuals indicates correlation between the potentially endogenous household conditions and unobserved efficiency-related factors. In the corrected specification, expected technical efficiency varies systematically by region, asset position, housing quality, electricity conditions, financial behavior and demographic characteristics. Table 7 indicates that expected household technical efficiency is not evenly distributed across the sample. It systematically varies by region, asset position, housing conditions, literacy, selected financial behavior, and some demographic characteristics, and several of these gradients become sharper once endogeneity is explicitly accounted for.

4.4.2. Model validation and predictive performance of technical efficiency estimates

Fig. 3 shows that predicted household technical efficiency varies more clearly across regions than across settlement types. In the regional margins panel, the conditional mean of predicted technical efficiency is highest in the Western region, at approximately 0.66, followed by the Central region at approximately 0.62–0.63 and the Eastern region at approximately 0.61–0.62, while the Northern region records the lowest predicted level at approximately 0.54–0.55. The vertical confidence bars are relatively tight, indicating that the regional ordering is visually well defined, especially the gap between the Northern region and the rest of the country. By contrast, the urban-rural margins panel shows only a very small difference in predicted technical efficiency at the means. Rural households are predicted at approximately 0.625, while urban households are predicted at approximately 0.627, and the confidence intervals overlap substantially. The figure indicates that predicted technical efficiency is much more strongly differentiated by region than by settlement type when evaluated at average covariate values.

The lower two panels of Fig. 3 indicate that the predicted efficiency values closely track the observed SFA technical efficiency scores. In both the LASSO prediction and linear approximation plots, the cloud of observations lies along a clear upward-sloping relationship, showing that higher predicted values correspond closely to higher observed technical efficiency. The alignment is particularly tight through the central part of the distribution, where most observations are concentrated. However, at the upper end, the fitted line continues to rise while the observed efficiency values flatten below one; thus, the highest predictions are

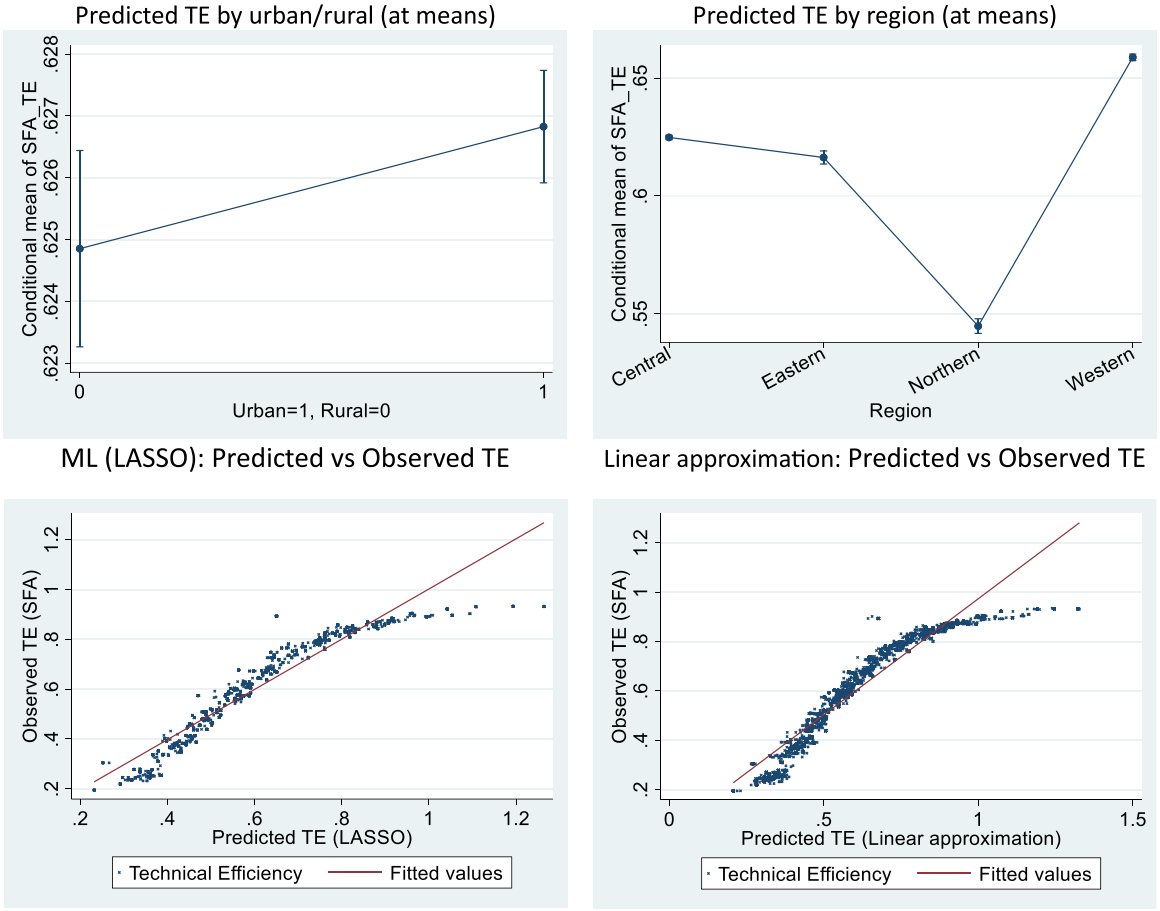


Fig. 3. Predicted and Observed Household Electricity Technical Efficiency.

associated with some compression in actual TE. Nevertheless, the overall visual pattern remains strongly monotonic and compact, with only a limited number of more dispersed observations away from the main cluster. Fig. 3 shows that the predictive models recover the broad ranking and level of household technical efficiency quite closely, and that the correspondence between predicted and observed efficiency remains strong across most of the sample range.

Table 8 shows that the predictive performance of the LASSO model improves dramatically as the penalty parameter is relaxed from the most restrictive specification to the cross-validated solution. At the first lambda value of 0.1845, the model retains 0 nonzero coefficients, yields an out-of-sample R^2 of 0.0011, and records a cross-validation mean prediction error of 0.0390, indicating essentially no useful predictive content under heavy penalization. By contrast, at the selected lambda of 0.0003, the model retains 15 nonzero coefficients, the out-of-sample R^2 rises to 0.9040, and the cross-validation mean prediction error falls sharply to 0.0038. The lambda before specification at 0.0004 produces the same 15 retained coefficients, the same R^2 of 0.9040, and the same prediction error of 0.0038, showing that predictive performance is highly stable around the selected tuning parameter rather than driven by an isolated optimum. Table 8 indicates that household technical efficiency is strongly predictable from the retained covariates, and that this predictive structure is both compact and stable over the final part of the cross-validation path.

5. Discussion

5.1. Household electricity-service production is heterogeneous and spatially structured

The distributional evidence in Fig. 1 indicates that household electricity service production in Uganda is embedded in an uneven domestic electricity environment. The wide spread in electricity consumption, daily power availability, and the service proxy suggests that households do not enter the service-production process from similar starting points. This matters because the generation of household electricity services depends not only on whether electricity is present, but on the level, regularity, and usable intensity of electricity available within the home (Hermanus and Rose Cirolia, 2024; Hirmer et al., 2025). The strongly right-skewed consumption profile further indicates that the household electricity landscape is shaped less by broadly shared high use than by a concentration of households at modest consumption levels, alongside a much smaller upper tail. Household electricity service production therefore emerges from unequal input conditions rather than from a common baseline of electricity use (Ajinjeru et al., 2017; Munro and Bartlett, 2019).

The regional and rural-urban patterns indicate that this heterogeneity is spatially structured rather than randomly distributed. Northern Uganda's relatively stronger central position in electricity use and realized service outcomes is best understood as a pattern within the electricity-using analytical sample. Since the analysis is restricted to households with positive electricity consumption and observed service indicators, the regional medians reflect households already participating in electricity-service production. In a historically uneven infrastructure setting, these users may be concentrated in better-served towns, trading centers, public-service locations, or households with stronger complementary service assets. Central and Eastern Uganda, by contrast, display more pronounced upper-tail observations, pointing to sharper internal differentiation within those regional distributions (Muchunku and Heinemann, 2022). The rural-urban contrast reinforces the same pattern: rural electricity use is more compressed within a lower-to-middle range, whereas urban use is more dispersed and extends further into the upper tail. Household electricity-service production is therefore shaped by localized service concentration as well as broader spatial inequality.

Table 8
Cross-validation for LASSO prediction of technical efficiency.

ID	Description	lambda	No. of nonzero coefficients	Out-of-sample R squared	CV mean Prediction error
1	first lambda	0.1845	0	0.0011	0.0390
68	lambda before	0.0004	15	0.9040	0.0038
*69	selected lambda	0.0003	15	0.9040	0.0038

Notes: N = 9542. * lambda selected by cross-validation. lambda selected based on stop() stopping criterion.
Source: Author's computation using Uganda's 2020/2021 National Household Survey data.

5.2. Household electricity efficiency is moderate but unequally distributed

The baseline frontier results show that household electricity-service production in Uganda is shaped by both electricity inputs and the efficiency with which those inputs are converted into domestic services. The prominence of the inefficiency component relative to random noise points to a substantive performance gap in the household production process. The central issue is the degree to which available electricity is transformed into lighting, refrigeration, communication, entertainment and other welfare-enhancing services under observed household conditions.

The estimated efficiency distribution places most households in an intermediate range. With mean technical efficiency of about 0.60 and median technical efficiency of about 0.62, typical households realize only part of the service potential embedded in their electricity conditions. The frontier represents service-conversion levels observed among better-performing households within the same national setting, making the efficiency gap empirically meaningful. The inequality measures show that household electricity efficiency is unevenly distributed. The spread between lower- and higher-performing households indicates that electricity does not generate service benefits at a common rate across households. The bootstrap and specification-comparison diagnostics support the stability of this pattern. Overall, household electricity efficiency appears moderate, unequal and strongly differentiated across households.

5.3. Structural drivers and robustness of household electricity efficiency

The heteroscedastic frontier results show that household electricity efficiency is shaped by a structured combination of productive conditions and household characteristics rather than by a common inefficiency process applying equally to all households (Andor et al., 2021; Otsuka, 2017). The persistence of positive electricity-input and electricity-availability gradients in the production frontier confirms that service generation still depends fundamentally on the quantity of electricity used and the continuity of supply (Alberini and Filippini, 2018). At the same time, the continued negative role of household size indicates that the conversion of electricity into household services becomes more demanding as internal household pressure increases. What emerges from this specification is a more differentiated view of electricity efficiency: households are not separated only by how much electricity they consume, but also by how their social and domestic conditions affect the productivity of that consumption (Burnett and Madariaga, 2018; Liang et al., 2021). Household electricity efficiency is embedded in a wider service-production environment shaped by electricity use, supply continuity, household composition and domestic conditions.

The spatial pattern reinforces this point by showing that household electricity efficiency is closely tied to place (Adkins et al., 2017; Afrianto et al., 2025). Once inefficiency is allowed to vary systematically across households, urban residence shifts into a positive frontier position, while Eastern and Northern Uganda also record stronger frontier performance

relative to the reference region. This change matters because it suggests that part of what initially appeared as a direct production difference was in fact bound up with differences in the distribution of inefficiency across space (Xia et al., 2025). Regional and settlement effects capture the broader infrastructural and household environments within which electricity is translated into services. The heteroscedastic specification links spatial disparities to systematic variation in household electricity performance.

The lower part of Table 5 clearly shows that household electricity efficiency is socially differentiated. The large negative role of the asset index in the inefficiency-variance equation indicates that asset endowments not only accompany better performance but stabilize household electricity use in a way that narrows inefficiency dispersion (Haider et al., 2024; Liang et al., 2021). The negative contribution of age and schooling works in a similar direction, suggesting that electricity efficiency is more ordered in households with stronger human and material resources (Kamana-Williams et al., 2025; Otsuka, 2017). By contrast, the positive gradients on literacy categories, saving variables, and electricity cost in the variance equation indicate that some household characteristics widen the spread of inefficiency rather than compress it, pointing to greater internal differentiation in how electricity is converted into services (Alberini and Filippini, 2018). Household electricity efficiency is shaped by the interaction of assets, education, costs and locational conditions. It functions as a socially and spatially conditioned form of performance within the broader domestic economy of electricity use.

The results indicate that household electricity efficiency is a patterned household outcome shaped by social, spatial and material conditions (Liang et al., 2021). The strongest gradients point to the importance of assets, housing quality, literacy and regional location, suggesting that electricity efficiency is closely tied to domestic capabilities that enable electricity to be converted into useful services (Haider et al., 2024). Households with stronger material endowments and better dwelling conditions are therefore better positioned to convert electricity into service outcomes (Liang et al., 2021). This pattern is consistent with the broader view that household electricity efficiency depends on complementary conditions within the home and not on electricity input alone (Han and Wei, 2021; Sotnyk et al., 2023).

The regional and corrected-model results reinforce this interpretation. The regional structure remains visible across the baseline and corrected specifications, indicating that spatial differences are part of the empirical organization of household electricity efficiency. The changes observed for female headship, urban residence, household size and housing quality after the control-function correction also show that some household gradients are sensitive to potential endogeneity in domestic conditions (Borozan, 2018; Nyangon and Byrne, 2021). The predictive results provide additional support by showing that technical efficiency can be recovered from observed household characteristics with stable cross-validation performance. Overall, the robustness and predictive evidence link household electricity efficiency to structured differences in household resources, dwelling conditions and spatial context.

6. Conclusions

This study reframed household electricity use in Uganda as a problem of electricity service production and technical efficiency rather than electricity consumption alone. By treating electricity services as the relevant household output, it showed that household electricity performance is shaped not only by whether electricity is accessed or consumed, but by how effectively it is converted into useful domestic services. The findings therefore moved the analysis beyond conventional indicators of connection, expenditure, and use, and established household electric energy efficiency as a distinct and policy-relevant dimension of household energy performance.

The results showed that household electricity service production in Uganda was highly heterogeneous and spatially differentiated. Electricity consumption, electricity availability, and realized service outcomes were unevenly distributed across households, regions, and settlement types, indicating that households did not operate under a common electricity-use environment. This heterogeneity carried through to the frontier estimates, which revealed that household electric energy efficiency was moderate on average, rather than close to best-practice performance. The evidence indicated that a substantial share of the service potential embedded in existing household electricity conditions remained unrealized for much of the sample.

The study further showed that household electric energy efficiency was not evenly distributed across households. The efficiency distribution displayed clear dispersion, with meaningful differences between lower- and higher-performing households, indicating that the welfare gains associated with electricity were realized at unequal rates. In addition, the determinants analysis demonstrated that efficiency was systematically patterned by household and spatial characteristics, including assets, housing quality, literacy, household composition, electricity cost, and regional location. These findings established that household electricity efficiency was neither random nor purely technical; it was embedded in wider social, material, and locational conditions that shaped the productivity of electricity use within the home.

The study showed that a service-oriented efficiency framework provided a more coherent basis for understanding household electricity performance in a low-income setting such as Uganda. By integrating service-production logic, stochastic frontier estimation, and determinants analysis within a single empirical design, the study demonstrated that the central issue was not only whether households used electricity, but how well they transformed it into welfare-enhancing services. Household electric energy efficiency therefore emerged as a crucial lens through which the quality, inequality, and developmental value of household electricity use can be more accurately understood.

Policy implications

The findings indicate that household electricity policy in Uganda should move beyond a narrow focus on connection expansion and place greater weight on the quality and productivity of household electricity use. Because household electricity service production depends not only on access but also on the reliability of supply and the ability to convert electricity into useful domestic services, electrification policy should be complemented by measures that improve service continuity, reduce supply interruptions, and strengthen the usability of electricity within the home. Policies that treat electricity access as an endpoint are likely to overstate the welfare gains of electrification when households remain unable to translate electricity into meaningful service outcomes.

The results also imply that household electricity interventions should be more explicitly targeted. The moderate and unequally distributed efficiency profile shows that the realized benefits of electricity are not shared uniformly across households, whereas the persistent regional gradients indicate that spatial disparities are deeply embedded in household electricity performance. This calls for a more differentiated policy architecture in which regions and household groups facing systematically weaker electricity service outcomes receive tailored support. A uniform national approach is unlikely to be sufficient where household electricity efficiency is shaped by uneven domestic, infrastructural, and locational conditions.

Finally, the evidence suggests that electricity policy should be linked more closely to broader household capability conditions. The importance of assets, housing quality, literacy, and selected financial characteristics shows that household electricity efficiency is partly constrained by the wider domestic environment in which electricity is used. Policies aimed at improving household electricity performance should therefore be integrated with measures that strengthen housing conditions, expand household asset access, improve energy-related information and literacy, and ease financial constraints that limit productive electricity use. In this sense, improving household electric energy efficiency requires

not only better electricity systems but also stronger household conditions for transforming electricity into welfare-enhancing services.

Limitations

The analysis is bounded by the scope of the data and measurement design. The analysis used cross-sectional UNHS 2020/21 household survey data, so the results capture household electricity-service efficiency at one point in time. They do not show how efficiency changes across seasons, tariff cycles, outages, appliance acquisition, housing improvements, or changes in household income and composition. Longitudinal panel data would be better suited to examining persistence, adjustment, and transition in household electricity-service efficiency over time. In addition, the efficiency measure is household-level rather than appliance-specific, and the analysis is restricted to electricity-using households with positive electricity consumption and observed service indicators. These limitations define the scope of inference: the study estimates household electricity-service efficiency under observed survey conditions, not engineering efficiency for individual appliances or dynamic efficiency trajectories.

Future research

Future research should extend this analysis using panel or repeated-survey data to examine how household electricity-service efficiency changes as electricity reliability, tariffs, appliance ownership, housing quality, and household resources evolve. Further work could compare electricity-service efficiency across countries, examine appliance-specific service outcomes, and combine survey data with metered electricity-use data where available. Such evidence would strengthen understanding of the dynamic pathways through which households convert electricity into welfare-relevant services.

CRediT authorship contribution statement

Geoffrey Mubiinzi: Writing – review & editing, Writing – original draft, Software, Methodology, Formal analysis, Conceptualization. **Livingstone Senyonga:** Writing – review & editing, Validation, Supervision, Methodology, Conceptualization. **Twaha Kigongo Kaawaase:** Writing – review & editing, Validation, Supervision, Project administration, Methodology, Conceptualization. **Francis Wasswa:** Writing – review & editing, Supervision, Resources, Methodology, Formal analysis, Conceptualization. **Muyiwa S. Adaramola:** Writing – review & editing, Visualization, Validation, Supervision, Resources, Formal analysis, Conceptualization. **Maria Nantongo:** Writing – review & editing, Visualization, Validation, Supervision, Methodology, Investigation, Conceptualization.

Ethical approval

This study used secondary anonymized household survey data and did not involve direct interaction with human participants.

Consent to publish

Not applicable.

Consent to participate

Not applicable.

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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.

Data availability

Data will be made available on request.

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