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Determinants of electricity consumption from decentralized solar PV mini-grids in rural East Africa: An econometric analysis

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ABSTRACT

The use of decentralized solar photovoltaic (PV) mini-grids for rural electrification is increasing in developing countries, but little is known about the determinants of electricity consumption of communities electrified through these technologies. This paper examines the factors influencing the electricity consumption of rural households and small businesses electrified by off-grid PV mini-grids based on actual metered load data and a survey of 218 customers in two isolated small towns (Omorate and Tum) in Ethiopia. Empirical analyses were performed using Censored Tobit models. Results showed that the load curves of the two towns have different characteristics and patterns. While the load curve at Omorate is regularly interrupted for 13 h a day due to load-shedding, the mini-grid at Tum generates enough electricity to meet demand. Empirical results showed that electricity consumption of households is significantly associated with household size, income, dwelling type, number of rooms, cooling fans, cooking with electricity and load-shedding. In contrast, the electricity consumption of businesses is strongly linked with income, electricity price, number of rooms, number of cooling fans, refrigerators, number of other (productive use) appliances, and load-shedding/location. The findings suggest three key points. First, electricity demand of rural households and businesses is influenced by separate but interconnected sets of factors. Second, supply-side factors, appliance factors, type of end-use of electricity and location -specific factors influence demand more than income and price factors. Third, mini-grid policy making and dimensioning in rural East Africa must take into account the differing electricity demands and determinants across customer groups and locations.

1. Introduction

Over the last two decades, rural electrification has made significant progress in many developing countries [1]. Central to this expansion of rural electricity access are distributed energy systems such as mini-grids [2,3]. Reports show that 47 million people in 134 countries were connected to mini-grids in 2019, the majority of them living in rural areas of developing countries [2]. Most of these mini-grids are powered by solar, hydro and diesel. Recent studies [4] indicate that many countries in sub-Saharan Africa (SSA) are also increasingly using solar photovoltaic (PV) mini-grids with battery storage and backup diesel generators (DGs) as an essential part of the solution for increasing rural electricity access. Despite improved access to electricity through mini-grids however, evidence from emerging studies suggests that per capita electricity consumption in rural communities connected to mini-grids has remained low [5]. For example, in a comprehensive field assessment of 24 operational community-owned PV mini-grids in India conducted by Katre et al. [6], it was found that rural households' electricity consumption from mini-grids was generally low, with 73% of the households studied falling into the customer category of 'less than 30% reduction in monthly kerosene usage.' Similarly, Peters et al. [7] noted that insufficient electricity demand was one of the main issues facing the commercial viability of village-level mini-grids in East Africa. In contrast, in their study of electricity purchased by households and businesses in an off-grid village in Tanzania from a community-based micro-hydro-electric plant, Hartvigsson et al. [8] found that electricity purchased by households and small businesses grew significantly by 56% and 37%, respectively, over a period of 30 months.

These seemingly divergent findings suggest the need for more knowledge on rural electrification through distributed mini-grids and specifically on the factors influencing the electricity usage behaviors of rural households (HHs), and small and medium enterprises (SMEs). Understanding the determinants and patterns of electricity consumption allows for proper sizing of techno-economically viable PV mini-grids and efficient usage of the electricity generated. A thorough analysis

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Abbreviations

AfDB	African Development Bank
DG	Diesel Generator
DSM	Demand Side Management
EEU	Ethiopian Electric Utility(Electricity Provider)
ETB	Ethiopian Birr(Ethiopian Currency)
GNI	Gross National Income
HHs	Households
LED	Light-emitting Diode
m.a.s.l.	Meters above sea level
MG	Mini-grid
MLE	Maximum Likelihood Estimation Method
MLR	Multiple Linear Regression
MoWE	Ministry of Water and Energy of Ethiopia
OLS	Ordinary Least Square Regression
PV	Photovoltaic
SE	Standard Error
SMEs	Small and Medium Enterprises
SSA	Sub-Saharan Africa
UEAP	Universal Electricity Access Program

and comprehensive understanding of what drives and constrains the electricity usage of households and businesses is also essential for informed policy making, energy planning and identifying appropriate demand side management (DSM) strategies. Yet, there is little research and empirical data on the major determinants of electricity consumption of rural households and businesses electrified through off-grid mini-grids. The literature on rural electrification in the developing world has typically focused on grid extension, feasibility of decentralized mini-grids, forecasts of energy demand of rural households and the socio-economic benefits of access to electricity [9,10]. A few studies that were carried out to examine rural electricity demand and its determinants in developing countries (see Table 1) indicate that household electricity consumption is influenced by various economic and non-economic factors including education level, socio-demographics, dwelling factors, income, electricity price, appliance ownership, local economic development, weather conditions, among factors [6,11–18].

However, the empirical evidence from these (Table 1) and other recent studies may not reflect the situation in the rather unique context of mini-grid-electrified communities in remote off-grid villages. One of the many reasons for this is that households in off-grid areas face additional barriers to their usage of electricity from limited access to commercial electricity and appliance markets. Secondly, nearly none of the previous works have explicitly addressed electricity usage from renewable mini-grids in off-grid areas based on metered data. Thirdly, most previous works on rural electricity usage were based on aggregated national survey data rather than micro-level metered data. Moreover, the literature to date on the determinants of rural household electricity consumption primarily deals with consumers powered by conventional grids [14,15,17,18], but distributed renewable energy systems are fundamentally different from conventional power grids in terms of their energy sources, operation, energy management and energy storage. As a result, the electricity consumptions of households and businesses electrified through decentralized mini-grids and the variables that govern them remain poorly understood. This gap in knowledge and empirical evidence could lead to policy measures and mini-grid dimensioning that is misaligned with the actual demand. Against this backdrop, this paper aims to examine the determinants of electricity consumption of rural households and businesses electrified by stand-alone PV mini-grids using a metered dataset together with surveys from two isolated rural towns in Ethiopia.

This research is novel in many ways. First, it introduces predictor

Table 1
Summary of the recent previous work on rural electricity consumption and its determinants in developing countries.

Ref	Country	Main focus of the study	Major findings (Pros)	Cons
[6]	India	Energy consumption of rural households and businesses from community-owned mini-grids.	Energy consumption of rural households and businesses remained low and below expectations.	Falls short of analyzing the driving factors for the low energy consumption.
[11]	South Africa	Study on the determinants of household electricity demand.	Household income and electricity price are major determinants of demand.	Users were supplied by grid, not by a mini-grid.
[12]	Bangladesh	Investigation of factors affecting households' choice of electricity consumption and expenditure levels from off-grid mini-grids.	Higher education level, gender (females), and appliance ownership leads to choice of higher tier clean electricity.	Survey data were generated for a proposed MG service, not from actual operating electricity services.
[13]	Honduras	Forecasting energy demand in isolated rural communities.	Stochastic demand prediction, in contrast to deterministic methods, gives more realistic results for the designing of MGs.	Mainly focused on demand projection, rather than on determinants of demand.
[14]	China	Analysis of rural household energy consumption based on survey data.	Provides comprehensive analysis of the factors affecting rural household energy consumption.	The electricity is supplied by a conventional power grid, not from a mini-grid.
[15]	India	Rural household Electricity consumption determinants.	Demand for electricity is not necessarily elastic to income and other socioeconomic variables in rural regions.	Electricity was supplied by conventional grid, not by a mini-grid.
[16]	DR Congo	Investigation of factors affecting electricity consumption in DR Congo from 2000 to 2018.	Economic growth, access to electricity, population; and labor force have positive effects on consumption.	National level aggregated data. Does not specifically address rural communities.
[17]	Ethiopia	Analysis of determinants of household energy choices of rural households.	Wealthier and more educated households with larger family size, and better road access consume more electricity than poorer households in remote areas.	The survey households were powered by grid, not by renewable mini-grids.
[18]	Cameroon	Assessment of the drivers of electricity consumption based on household surveys.	Appliances, household income, housing structure and weather conditions have greatest impact on energy consumption.	The electricity is supplied by conventional grid, not by renewable mini-grids.

(explanatory) variables, rarely considered before, such as load-shedding, ownership of private solar home systems (SHSs) and DGs, productive use appliances, and cooking with electricity to explain variations in electricity consumption among rural users. Second, it is perhaps the first study that attempted to analyze the factors determining electricity consumption of rural households and businesses powered by off-grid renewable mini-grids (intermittent energy source) in a developing country context. Third, unlike most previous studies which rely on national level aggregate data or simulation, this study uses micro-level metered hourly load and monthly consumption data together with data gathered through door-to-door surveys; and hence allows for a more thorough empirical analysis. A major strength of this paper is thus the depth, quality, and reliability of both the power and survey data, which were collected from a proportionally large sample size compared to the total mini-grid electrified population in the two towns. The research makes four important contributions.

- It contributes to scientific progress in the field of rural household energy demand theory in sub-Saharan Africa context and beyond.
- It provides a knowledge base for strategic planning of mini-grid-based rural electrification projects and the formulation of informed energy policies.
- It offers useful practical knowledge to support the design and dimensioning of techno-economically viable solar PV mini-grids.
- It gives mini-grid operators useful evidence base to identify a more appropriate technical, operational and management options.

2. Methodology

2.1. Research design

An interdisciplinary case study approach combining quantitative and qualitative research methods was used in this study. An interdisciplinary approach allows for a comprehensive understanding of the interactions and influences of various factors on rural electricity consumption. The case study method, on the other hand, enables us to conduct an in-depth investigation and analysis of the relationships between the main determinants and the electricity consumption of households and SMEs within a defined setting, using actual data drawn from multiple sources and methods. Consequently, the case study was conducted following six iterative processes, as suggested by Yin [19] and Crowe et al. [20]. Fig. 1 presents the flow chart of these iterative processes and steps that were followed when conducting this interdisciplinary case study.

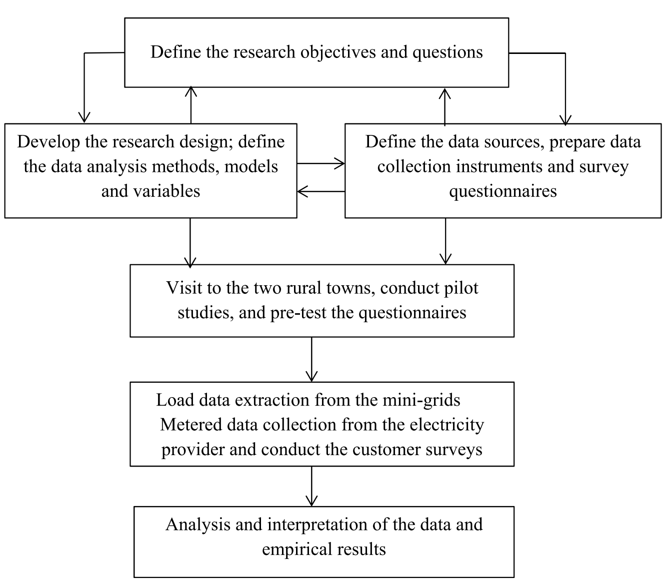


Fig. 1. A flow chart of the processes and steps followed when conducting the case study.

2.2. Description of the case study sites

This case study was carried out in two remote rural towns, named Omorate and Tum, in southern Ethiopia (Fig. 2). Both towns are powered only by stand-alone PV mini-grids (hereafter MGs). The two towns were purposively chosen due to similar installation design and age of their MGs, expected similarities in electricity demand, similar number of MG customers, and the fact that they were among the first 12 rural towns to be electrified with PV MG in Ethiopia.

The geographic location of the mini-grids was chosen owing to their comparable[1] distance from the national grid, differing microclimatic conditions, and the availability of metered energy data. Omorate is located between 4°80′16″ N Latitude and 36°3′29″ E Longitude with an average elevation of 368 m above sea level (m.a.s.l.) whereas Tum is situated between 6°15′16″ N Latitude and 35°31′18″ E Longitude with an average elevation of 1439 m. a.s.l. The mean annual temperature in Omorate is 28.2 °C while in Tum it is 21.6 °C. In 2021, Omorate had a population of 3,852, with approx. 770 households, while Tum had a population of 4,856, with approx. 950 households. The MG in Omorate has a total installed capacity of 375 kWp and is equipped with a 600 kWh storage battery. The MG in Tum, on the other hand, has an installed capacity of 550 kWp and is equipped with a 750 kWh battery. Both MGs began operating around the same time, May 01, 2021. As of June 2021, the total number of MG customers was 97 in Omorate and 137 in Tum. By December 2021, the number of customers in Omorate had grown to 443 (a growth of over 350%); of which 301 (68%) were[2] ordinary households, 112 (25%) were[3] SMEs, typically household-based businesses, and 30 (7%) were[4] institutions. In a similar pattern, the number of consumers in Tum had increased to 450 by December 2021; (an increase by 228%) with 384 (85%) households, 40 (9%) SMEs and 26 (6%) were institutions.

2.3. Sampling and data collection

This study uses real-time hourly load data directly retrieved from the energy management system of each MG and customers' monthly electricity consumption data metered over an eight-month period (May 1–December 31, 2021) in combination with data collected through surveys and field visits. Hourly load data at each MG over the 245 days (8-month period) were extracted on daily basis directly from the MGs. Metered monthly consumption data for all customers were collected from local EEU offices. The EEU dataset contains detailed information

[1] Ethiopian Electric Utility (EEU) is a state-owned utility company that manages power distribution and sales from all power plants in Ethiopia including off-grid mini-grids; while its sister company Ethiopian Electric Power (EEP)manages power generation and transmission. In 2016, the Ethiopian Ministry of Water and Energy (MoWE) and the EEU identified 250 rural towns/villages that are isolated from the national grid and need to be electrified using PV-Diesel hybrid mini-grid systems through the Universal Electricity Access program (UEAP). The Omorate and Tum MGs are among the first 12 MGs installed in the country out of the 250 planned. The construction of these MGs was financed by the Ethiopian Government and the World Bank. In February 2021, a contract between SinoSoar and EEU was signed for the construction of another 25 mini-grids, backed by the African Development Bank (AfDB).

[2] Throughout this paper, ordinary rural households are those customers that use electricity primarily for household/domestic purposes; and are thus 'non-productive' users.

[3] SMEs refers to those customers that use electricity primarily for productive uses (business activities) but could also simultaneously use it for domestic purposes.

[4] Institutions refer to government offices, ministries, public schools, health centers, churches and mosques etc.

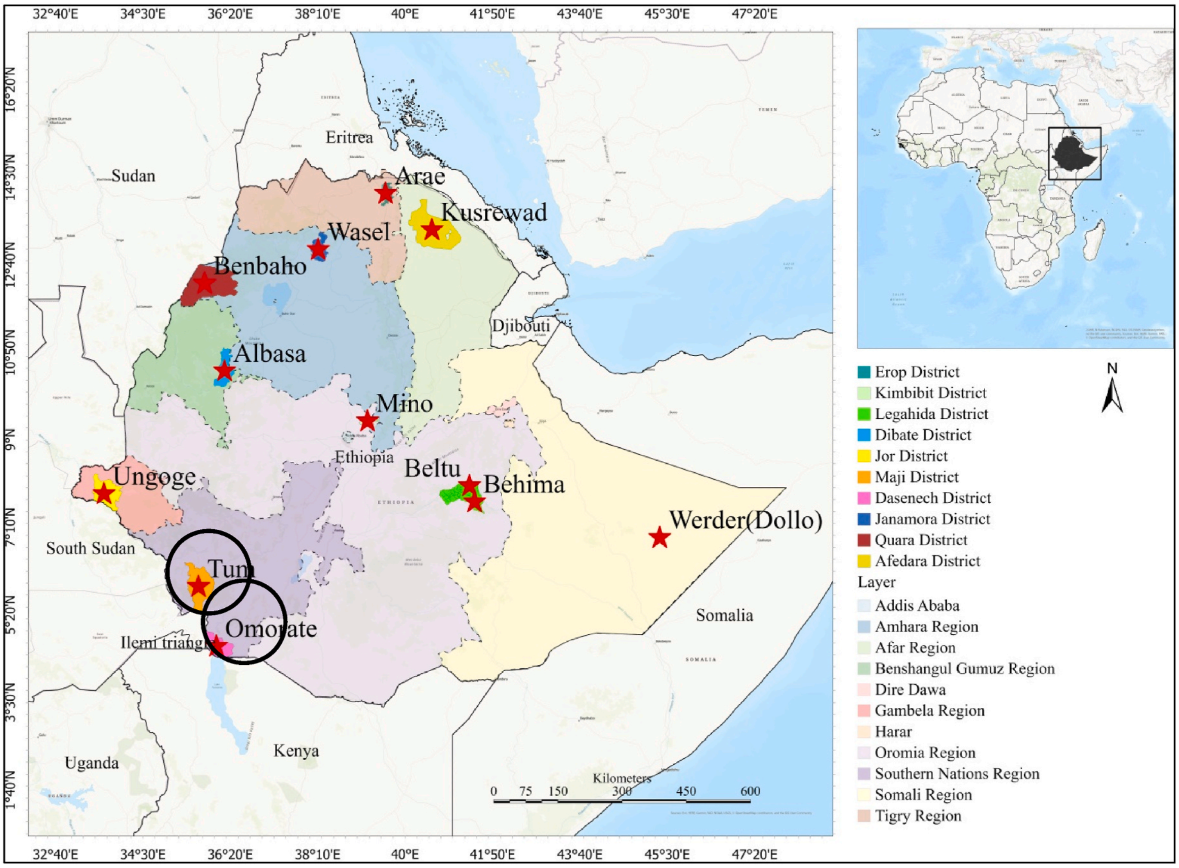


Fig. 2. Location map of Omorate and Tum towns in Ethiopia along with 10 other rural towns where stand-alone solar PV mini-grids have been installed for rural electrification (Source Ethiopian Electric Utility - EEU, 2021).

about the customer's name, address, customer type (domestic, SMEs/ productive, or institution). Throughout the paper, a clear distinction is thus made between the different customer/user groups. The EEU dataset also provides information about the billing month, amount of electricity consumed, consumption charge, tariff category and a monthly service charge. After obtaining the EEU dataset, detailed surveys were conducted at both locations using purposive random sampling. First, all customers registered in the EEU billing list were identified and grouped into three categories (HHs, SMEs, and institutions) as per EEU's classification. A random sampling of 20% was then applied to select sample HHs in each location. For SMEs, however, a snowball sampling method was used and data was collected from as many samples as possible until the data was saturated. This was done to ensure that the survey data captures most of the heterogeneity in electricity consumption across consumers and that robust empirical analysis is performed. Finally, the survey was carried out through face-to-face interviews from November 22, 2021 to January 16, 2022 using a semi-structured questionnaire that was carefully designed, pre-tested and revised after pilot studies and following Yin's [19] guidelines.

For each sample household and SME, the data collected from the EEU were compared with the bill presented by the respondent and the kWh meter readings as illustrated in Appendix I. The data collected through surveys included demographic and socioeconomic information, dwelling type, number of rooms, monthly consumptions and charges, ownership and stock of electrical appliances, productive use of electricity, frequency and duration of power interruptions per day and week, major cooking fuels, and a range of qualitative information. During the same period, in-depth interviews and discussions were held with more than 15 key informants in each town including MG operators, EEU staff, local political administrators, community leaders and SMEs and women groups' representatives. The final dataset used in this study is thus collected from 128 households, 90 SMEs, and 10 public or state institutions (Table 2).

2.4. Econometric model specification

Several studies have analyzed the determinants of household energy consumption using ordinary least square (OLS) regression and Multiple Linear Regression (MLR) models [21,22]. Standard OLS models can provide unbiased and consistent estimates when the dependent variable y is unrestricted. However, in the context of distributed PV MGs, the power supplied by the PV plant (and therefore the customer's electricity consumption) is subject to various exogenous variables including the PV's generation capacity, frequency and duration of power outages, and capacity of the storage batteries, among others. As a result, the metered maximum electricity consumption value (y) may not represent the true (latent) energy requirement (y^*) for some of the customers. In fact, the exact value of the maximum electricity consumption of these customers is unknown; then y is said to be right-censored. Electricity consumption values are also non-negative (the minimum value is zero), meaning that

Table 2
Distribution of sampled households, SMEs and institutions in each town.

Consumer group	Omorate		Tum		Total samples
	Total number (N)	Sample size (n)	Total number (N)	Sample size (n)	
Households	301	68	384	60	128
SMEs	112	50	40	40	90
Institutions	30	5	26	5	10
Total	443	123	450	105	228

y is also left-censored. This makes the dependent variable both right and left-censored. Using standard OLS models with a restricted or limited dependent variable results in biased and inconsistent β estimates since the distribution of y, and hence the error term, is likely to be non-normal and heteroskedastic [23,24].

Let X denote the independent variables that explain household electricity consumption, the latent regression equation for potential electricity consumption of household i, y_i* is given by

$$y_i * = X_i \beta + \varepsilon_i \tag{1}$$

where $\varepsilon_i \sim$ iid $N(0, \sigma^2)$ and i = 1,2,3 … n, β are the marginal effects of X_i's on the y_i*.

When the electricity consumption values (y_i) are subject to a certain threshold level (τ) due to load-shedding or generation capacity shortages, the observed y_i will be defined as:

$$y_i = \begin{cases} y_i^* & if \;\; y_i^* \leq \tau \\ \tau_y & if \; y_i^* > \tau \end{cases} \tag{2}$$

Note that the observed consumption value y_i is the same as the latent (true) consumption y_i* for observations less than or equal to the threshold τ; however, y_i is unobservable and is restricted to be equal to the threshold τ_y when the consumption value is greater than τ. In such circumstances, where the dependent variable y_i is constrained and the conditions for OLS regression are not met, the Tobit regression delivers unbiased and consistent estimates of the linear relationship between y_i and exogenous predictor variables X using the Maximum Likelihood Estimation (MLE) method [23,24]. Combining the structural Tob it equation (1)with the observed measurement equation (2), the censored Tobit model used in this study is defined as:

$$y_i = \begin{cases} y_i^* = X_i\beta + \varepsilon_i & if \; y_i^* \leq \tau \\ \tau_y \quad if \;\; y_i^* > \tau \end{cases} \tag{3}$$

2.5. Variables used for the empirical analyses

The dependent variable y_i in this empirical analysis is the mean monthly electricity consumption (kWh) of households and SMEs. Since customers were connected to the MGs at different times, the mean monthly electricity consumption of each customer is calculated based on when they were connected using equation (4). Based on past research and information from the pilot studies, relevant explanatory variables expected to influence the dependent variable were identified. Summary statistics of these independent variables is presented in Table 3. The mean values for dummy variables represent the share of customers with the given characteristics. A scatterplot matrix of bivariate relationships between some of the key variables is shown in Appendix II.

$$Y_{i,m} = \frac{\sum_{n=1}^{N} E_i}{N} \tag{4}$$

Y_i is the mean monthly electricity consumption of household i, E_i is the household's electricity consumption in month n, and N is the total number of months the household has been connected.

2.6. Characteristics of sample households and businesses

According to the survey data, 76% of the sampled customers were

Table 3
Summary statistics of the variables (N = 218).

Variable/statistic	Data type	Variable definition/description	Mean	St. Dev	Min	Max
Y_i	Censored	Average monthly electricity consumption of the customer in kWh	65.36	86.40	3.14	800
[a]Gender	Categorical	Dummy: 1 = Female, 0 = otherwise	0.34	0.47	0	1
[a]Age	Continuous	Age of the household head in years	40.55	12.30	20	77
Educational level	Continuous	Total number of years of schooling of the household head	9.37	4.31	0	16
Household size	Continuous	Total number of family members	5.27	2.31	1	16
Monthly income	Continuous	Average monthly income of the customer in Ethiopian Birr (ETB)	10,890	14,035	1050	152,176
[b]Monthly electricity expenditure	Continuous	Average monthly electricity expenditure of the customer in ETB	124.23	244.57	20.86	2275
Price of electricity (tariff rate)	Continuous	Electric tariff rate applied to the customer (ETB/kWh/month)	0.70	0.59	0.27	2.5
Kerosene/diesel consumption	Continuous	Average weekly kerosene + diesel consumption (L)	0.71	2.61	0	20
[c]Price of diesel/kerosene	Continuous	Price of diesel/kerosene in local market (ETB/L)	37.82	30.14	35	50
Firewood consumption	Continuous	Average firewood consumption in bundles/week	2.42	1.59	0.50	12
[c]Price of firewood	Continuous	Cost of firewood in local market in ETB/bundle	85.83	31.76	35	200
Charcoal consumption	Continuous	Average charcoal consumption in bags/week	0.79	0.64	0	2.5
Price of charcoal	Continuous	Cost of charcoal in local market in ETB/bag	222.05	87.68	100	350
Load-shedding/power outage	Categorical	Dummy: 1 = if the customer is subject to load-shedding, 0 = otherwise	0.54	0.35	0	1
[a]Ownership of TV	Categorical	Dummy: 1 = if the customer owns TV, 0 = otherwise	0.63	0.48	0	1
No of refrigerators	Continuous	Total no of refrigerators the customer owns and uses	0.61	0.78	0	4
No of space cooling fans	Continuous	Total no of space cooling fans the customer owns & uses	0.30	0.51	0	3
No of electric cooking stoves	Continuous	Total no of electric cookstoves the customer owns and uses	0.35	0.50	0	2
No of other electrical appliances	Continuous	No of other (productive use) appliances the customer owns and uses	0.49	0.64	0	5
[c]Total no of appliances	Continuous	Total no of appliances and equipment the customer owns and uses	3.58	1.51	0	7
Private PV/DG Ownership	Continuous	Total no of private Solar Home Systems (SHS) and Diesel Generators (DG) the customer owns and uses	0.17	0.38	0	1
[c]Access to appliance markets	Continuous	Distance to the nearest main road or high way in km	161.54	28.28	152	192
[c]Price of electric cooking stove	Continuous	Cost of a typical electric cooking stove in local market	1406	1735	1050	2600
[c]Price of refrigerators	Continuous	Cost of a 300 L typical fridge in local market	28,907	56,808	24,000	32,000
[c]Price of cooling fans	Continuous	Cost of a standard space cooling fan in local market	6265	1453	3580	7950
Dwelling type	Categorical	Dummy: 1 = if the house is made of brick/concrete, 0 = otherwise.	0.64	0.55	0	1
Number of rooms	Continuous	Total number of rooms in the building/house	3.94	1.74	1	12
[c]Location/site	Categorical	Dummy: 1 = if the customer is located in Omorate, 0 = otherwise	0.46	0.49	0	1

[a] Variables omitted from the regression analyses due to very weak relationship with the dependent variable.
[b] Variables omitted from the regression analyses due to endogeneity with the dependent variable.
[c] Variables omitted from the regression analyses due to multicollinearity with other explanatory variables.

male-headed, while 24% were female-headed. In terms of education level, 58% of the respondents have completed secondary education. The average household size is 5.27 persons and the average gross monthly household income is Ethiopian Birr ETB 10890 (US$ 218 in 2021). This equates to a monthly per capita income of US$ 41, while the monthly gross national income (GNI) per capita in Ethiopia in 2021 was US$ 74. Around 17% of all customers are productive users of electricity. The mean monthly electricity tariff for households is ETB 0.38/kWh and ETB1.7/kWh for SMEs. Correspondingly, the mean monthly electricity expenditure per household was ETB 46 and ETB 250 for SMEs. About 17% of all customers own private Solar Home Systems (SHS)/DGs and/or rechargeable Light-emitting Diode (LED) torches in addition to the MG service. Most of these customers are in Omorate, where power outages are pervasive. A significant percentage (67%) of the customers own and use at least one household electrical[5] appliance besides basic devices such as mobile phones and radios; and 28% own at least two[6] other electrical appliances and equipment. Most of the latter are SMEs. The various types of SMEs operating in the two sites are listed in Appendix III. More than 95% of these enterprises are household-owned and self-managed, and about 46% of them were created after the launch of the MGs. The survey data also showed that 23.4% of the customers, mostly households, use MG electricity for cooking purposes for 2–5 days a week. In terms of location both Omorate and Tum are geographically located in remote areas, 152 km and 192 km away from the nearest major road or highway (see Fig. 2).

2.7. Empirical model diagnostic tests and model respecification

A series of diagnostic tests were performed to determine the most suitable estimation method that fits the data well. As depicted by the Kernel density function plots in Fig. 3, the sample data for electricity consumption of both ordinary households (3a) and businesses (3b) is skewed to the right and not normally distributed. In addition, the density plots for the mean monthly electricity consumptions of households and SMEs do not overlap as can be seen from the large difference between the two sample means (dashed lines). This suggests that the electricity consumption behavior of households is notably different from that of SMEs, and therefore separate empirical analyses are needed for the two customer groups. On the other hand, Fig. 4a and b shows that Y_i has near-normal distribution for both customer groups when the variable is log transformed (log-normal distribution).

The Breusch-Pagan test for homoscedasticity of residuals showed heteroskedastic residuals. To address the heteroskedasticity problem we applied robust standard errors instead of conventional standard errors (SEs) following Cameron and Miller [25]. Another technique that we employed, particularly relevant to our dataset are clustered SEs [26]. Considering the potential variation in the electricity consumption between the customers in the two locations, town-level clustering of SEs was applied to generate a more consistent coefficient estimates. Therefore, in this paper, two separate Tobit regression analyses with robust SEs that are adjusted for two clusters by location were used to examine the determinants of electricity consumption of ordinary households and small-businesses from decentralized PV mini-grids in rural remote Ethiopia.

To measure the reliability of the survey data, Cronbach's alpha (α) test was performed, using 28 test-items and all observations ($n = 218$) except institutions. The test yielded a Cronbach's α value of 0.84 for the test scale based on all the 28 items, suggesting that the test items included in the survey questionnaire were internally consistent and that the data has a good degree of reliability [27]. Of the 28 explanatory variables initially considered for the Tobit analyses, 15 were included in the final models; others are removed due to multicollinearity, a weak relationship with the outcome variable or endogeneity. Since the[7] price of electricity is determined by the quantity consumed by the customer per month, it was suspected that price is an[8] endogenous explanatory variable (x_j); i.e. higher consumption leads to higher tariff rates. To test the endogeneity of price, we performed two separate Hausman tests for the two customer groups (households and SMEs) following Davidson and MacKinnon [28]. The test for coefficient of residuals of price resulted in $F(1,111) = 3.17$; $Prob > F = 0.077$ for the households, and $F(1, 76) = 8.36$; $Prob > F = 0.005$ for SMEs. The results indicate that electricity price is indeed endogenously related to the dependent variable in both models, and therefore, the original Tobit equations may not provide consistent estimates. Following Terza [29], we applied the Control Function (two stage residual inclusion - 2SRI) method to address the endogeneity problem of electricity price in both Tobit models. The reason for choosing the control function over Instrument Variable (IV) regression to address the endogeneity problem is due to lack of a valid exogenous instrument variable (Z) that is strongly correlated with 'price' but independent of the error term ε in the equations.

3. Results and analysis

3.1. Load curves and demand analysis

Based on the daily load reports that were retrieved from the energy management system of each MG, the load curves and[9] electricity demand at each town were analyzed. The results, shown in Fig. 5, depict that the load curves of the two towns have a distinctly different characteristics and distribution patterns. Fig. 5 shows that the load curve at Omorate is interrupted and close to zero kW for more than half of the day i.e. between 17:00 and 19:00 and again between 22:00 and 08:00. The main reason for this is that following the rapid increase in the number of MG customers and consumption per consumer, the MG at Omorate was no longer able to meet the demand. As a result, a complete load-shedding of up to 13 h each day, in two time slots (see Fig. 5), has been in effect since August 2021 to save energy during low demand hours and supply it during the evening peak hours. By January 2022, the load in Omorate was routinely shed off for 13 h each day. In contrast, the MG at Tum produces enough power to fulfill the demand and customers have 24 h of electricity service with no load-shedding so far. At Omorate, the demand spikes to 90 kW within an hour of connection to the power feeder, and remains above 90 kW for most of the day time until it is shed off at 17:00. At Tum, in contrast, the demand is relatively low, stable and remains around 30 kW for most of the day time.

At both locations, the maximum demand (peak load) occurs in the late evening hours. The reason is that at this time of the day almost all lighting units are switched on and most of the[10] businesses are open. Nonetheless, the peak load at Omorate (128 kW) is more than two and a

[5] **Household appliances** includes electrical cookers, cooking stoves, juice makers, coffee makers, irons, space cooling fans, refrigerators, deep freezers, water heaters, rechargeable LEDs, TVs etc.

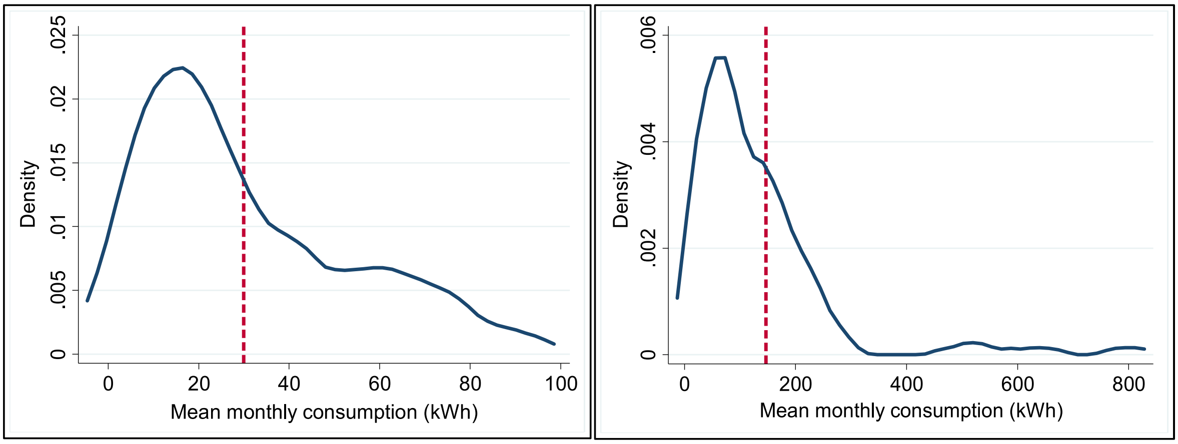
[6] **Other appliances and equipment** refers to power intensive devices usually used by SMEs such as light electric drills, compressors, dough mixers, welding machines, hair dryers, straighteners, small machines.

[7] The Ethiopian Electric Utility (EEU) uses the same progressive seven-tier tariff structure for household and SME-level electricity services from all power sources, including MGs across the country, based on the amount of electricity consumed per user; from ETB 0.273/kWh for monthly consumption of up to 50 kWh to ETB 2.00/kWh for monthly consumption of up to 300 kWh and ETB 2.481/kWh for monthly consumption exceeding 500 kWh.

[8] An endogenous independent variable is a variable that is correlated with, or has non-zero covariance with, the random error term ε_i in the equation [40].

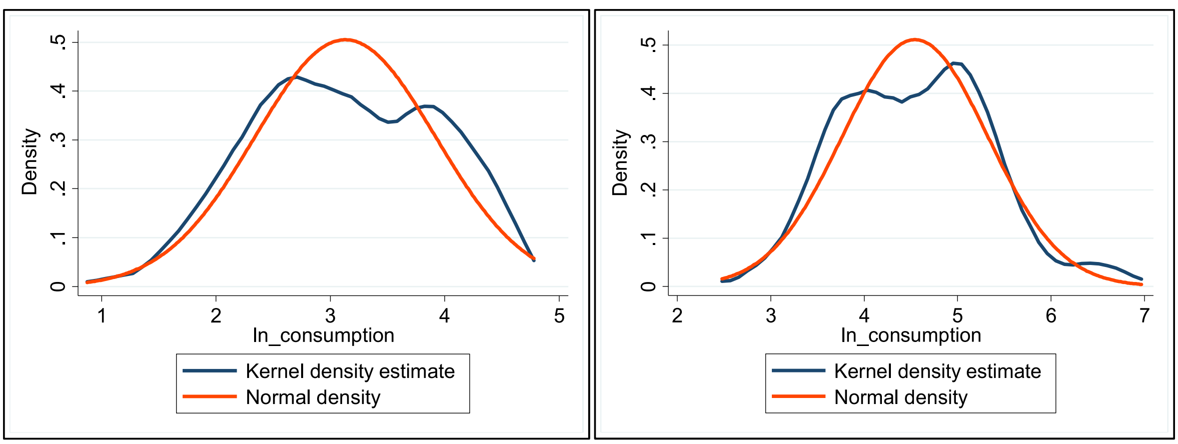
[9] In this paper consumption refers to the total amount of electrical energy (kWh) used by the consumer per day, per month or per year, while demand (load) is the rate of that consumption, typically per hour (kW).

[10] Because of the hot tropical climate that prevails throughout the Omo Valley, locals typically begin to stroll around, mingle, and drink beer in the late afternoon and into the evening.



a b

Fig. 3. Kernel density plot for monthly electricity consumption of households (a) and SMEs (b).



a b

Fig. 4. Kernel density plot for the log-transformed mean monthly electricity consumption of ordinary households (a) and SMEs (b) against the normal density plot.

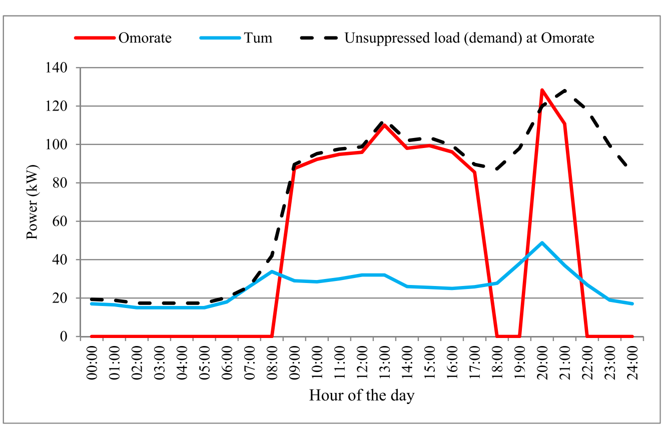


Fig. 5. Comparison of the average daily load curves of the two towns (based on data directly retrieved from the energy management systems of each MG over the course of 8 months of operation).

half times that of the peak load at Tum (49 kW). As will be discussed further later in this paper, the high energy demand at Omorate throughout the day, compared to Tum, is related to the substantial productive use of power by SMEs, the hotter climatic conditions and considerable power demand for space cooling and refrigeration, especially in the afternoon; the higher income level of customers and therefore higher ownership of electrical appliances, and better access to appliances. During the field visits and door-to-door surveys, we learned that the peak loads at both sites, both during the day and at night, were primarily driven by productive use customers. The minimum demand at Tum is 15 kW and occurs early in the morning at 05:00. The minimum demand at Omorate, nevertheless, is unknown since the load curve does not show the complete unsuppressed demand distribution. Based on the same dataset, the average daily total electricity consumption was calculated to be 1030 kWh for Omorate and 575 kWh for Tum. To calculate the impact of load-shedding on the power demand at Omorate, we used a Multiple Imputation (MI) method of predicting missing load data [30, p. 119–120] based on the current (December 2021) incomplete load dataset and the load curve in May 2021 when the supply was fully meeting the demand. Subsequently, a new complete unsuppressed load curve, shown by the broken lines in Fig. 5, was constructed. According to the new complete load curve, the total daily unsuppressed energy requirement at Omorate is 1808 kWh, indicating that about 708 kWh of this daily requirement is unmet due to load-shedding (generation capacity shortage). This is the sum of the area between the current incomplete load curve and the broken line (unsuppressed) load curve, which amounts to an average unmet power demand of 54 kW per hour of load-shedding.

3.2. Monthly electricity consumption patterns by sector

The average monthly electricity consumption by customer type over the eight-month period was calculated using the metered dataset to understand the share of each sector in the total electricity consumption at each location. The overall mean monthly electricity consumption per customer (N = 837) was calculated at 72 kWh. However, ordinary households typically consume 30 kWh per month, while SMEs consume 137 kWh per month. In terms of per capita, the mean monthly per capita consumption was 6.4 kWh among households and 27.5 kWh among productive users. Table 4 presents summary statistics of monthly electricity consumption by sector at both sites.

The mean monthly consumption of SMEs is more than three times that of households at both sites. In Omorate, productive users/SMEs consume over half of the electricity supplied by the mini-grid (54%) per month, while representing only 25.3% of the total number of customers. In Tum, they account for 28% of the total monthly electricity consumption although they make up only 9% of the total customers. Overall, productive users/SMEs accounted for 45% of the monthly electricity consumption, despite representing only 17% of the total consumers. Similar results were reported by Sharma et al. [5] for rural India and Hartvigsson et al. [8] for Tanzania.

The average monthly consumption of households in Omorate (53 kWh) is more than twice of their counterparts in Tum (22 kWh). Likewise, SMEs in Omorate consume more electricity each month (159 kWh) than SMEs in Tum (90 kWh). The fact that the median values in Table 4 are below the mean for all customer groups suggests that the distribution of the data is skewed to the right (positively skewed), and that the monthly energy consumption of most of the customers in each group are clustered around the left tail of the distribution. This is consistent with our survey findings where nearly 60% of the households in Omorate consume less than 50 kWh per month and about 70% of the households in Tum consume less than 20 kWh per month; while SMEs users in Omorate consume as much as 800 kWh per month. In accord with our findings, Agrawal et al. [31] found that surveyed rural households in India on average consumed 39 kWh per month. In contrast a study on a small community-based MG in Tanzania [8] showed the average monthly electricity consumption of households to be 7 kWh and productive users to be 20 kWh. Another study in the same country by Scott and Coley [32] found the average monthly electricity consumption of households electrified by MGs to range from 2.4 to 3.12 kWh.

3.3. Empirical results

The Censored Tobit models for the electricity consumption of households (1) and productive use customers/SMEs (2) both showed satisfactory goodness-of-fit (Pseudo R^2 = 0.703 and R^2 = 0.699 respectively). Some of the significant variables are common to both models. Yet, a few variables such as price and number of refrigerators influence the SMEs-model more significantly than the households-model. In general, many of our findings corroborate previos researches, while a few others are novel and unique to this study. The parameters estimated by model (1) reveal that household electricity consumption is significantly associated with monthly income, household size, dwelling type, number of rooms, number of cooling fans, cooking with electricity and load-shedding/location. On the other hand, the parameters estimated by model (2) indicate that the electricity consumption of productive users is strongly correlated with income, price (tariff rate), number of refrigerators, number of cooling fans, number of 'other (productive use) appliances', number of rooms, and load-shedding/location.

The average marginal effects of the estimated parameters explaining the electricity consumption of households and productive users are presented in Tables 5 and 6, respectively. Another way to determine the relative influence of the estimated parameters on the electricity demand is to compute their 'marginal elasticity (ey/ex)'. This method is similar to the marginal effect except that instead of estimating the influence of a "one unit" change in the predictor variable X on the dependent variable yi*, it measures the effect of a 1% change in X on the dependent variable. The marginal elasticities (ey/ex) of the estimated parameters influencing electricity consumption of households and SMEs are shown in Tables 7 and 8, respectively.

3.3.1. Demographic and dwelling factors

The parameter estimates of the *household model (1)* in Table 5 show that the uncensored mean monthly electricity consumption of

Table 5
Average marginal effects of the factors influencing electricity consumption of HHs.

Tobit regression				Number of obs = 128		
				F(16,112) = 44.27		
				Prob > F = 0.000		
Log pseudolikelihood = - 62.85				Pseudo R^2 = 0.703		
.margins, dy/dx (*)						
ln_consumption	Delta-method					
	dy/dx	Robust Std. Err.	z	P> |z|	[95% Conf. Interval]	
Household size	0.027*	0.015	1.81	0.070	−0.002	0.057
Education level	0.013	0.009	1.37	0.172	−0.005	0.031
[a]Dwelling type	0.161**	0.080	2.00	0.046	0.003	0.319
No of rooms	0.167**	0.082	2.03	0.045	0.004	0.328
ln_income	0.012**	0.006	2.05	0.043	0.003	0.024
Price/tariff rate	0.180	0.342	0.07	0.191	−0.644	0.295
No of refrigerators	0.025	0.088	0.28	0.777	−0.148	0.198
No of space cooling fans	0.199***	0.032	6.12	0.000	0.135	0.263
No of other appliances	0.063	0.051	1.23	0.217	−0.037	0.164
[b]Private PV ownership	−0.039	0.095	−0.42	0.674	−0.226	0.146
[c]Cooking with electricity	0.182***	0.053	3.42	0.001	0.078	0.287
[d]TV ownership	0.014	0.113	0.12	0.902	−0.208	0.236
Fuelwood use per wk	−0.026	0.018	−1.38	0.167	−0.063	0.010
Charcoal use per wk	0.031	0.087	0.36	0.720	−0.140	0.202
[e]Load-shedding/ location	0.408***	0.129	3.02	0.003	0.133	0.641

Table 4
Summary statistics of monthly electricity consumption by sector at the two towns.

Sector	Location	Min	Max	Median	Mean	St. Dev.	% Demand
Households	Omorate	3.14	200.5	41.4	52.7	22.8	44.5
	Tum	2.5	61.5	13.6	22.2	14.9	56.3
Productive users/SMEs	Omorate	12.0	800.1	110.9	158.5	170.8	53.6
	Tum	5.3	192.5	55.86	88.9	55.7	28.1
State/public institutions	Omorate	7.7	434.1	85.0	98.1	100.8	9.5
	Tum	6.2	398.3	76.6	90.4	80.1	15.6

Table 6
Average marginal effects of the factors influencing electricity consumption of SMEs.

Tobit regression			Number of obs = 128			
Log pseudolikelihood = - 63.687			F(16,74) = 51.31			
			Prob > F = 0.000			
			Pseudo R^2 = 0.699			
.margins, dy/dx (*) predict (e(0,.))						
ln_consumption	Delta-method					
	dy/dx	Robust Std. Err.	z	P> | z|	[95% Conf. Interval]	
Household size	0.000	0.009	0.08	0.936	−0.018	0.019
Education level	0.005	0.005	1.11	0.268	−0.004	0.016
[a]Dwelling type	0.013	0.023	0.58	0.560	−0.031	0.058
No of rooms	0.120***	0.021	5.58	0.000	0.078	0.163
ln_income	0.087*	0.270	1.74	0.082	0.056	0.101
Price/tariff rate	0.385***	0.127	3.02	0.003	0.132	0.639
No of refrigerators	0.067**	0.032	2.10	0.036	0.004	0.130
No of space cooling fans	0.109*	0.058	1.87	0.061	−0.005	0.223
No of other appliances	0.227**	0.114	1.99	0.046	0.003	0.451
[b]Private PV ownership	0.049	0.049	1.00	0.318	−0.047	0.146
[c]Cooking with electricity	0.139	0.100	1.39	0.164	−0.057	0.337
[d]TV ownership	0.000	0.019	0.00	0.999	−.0384	0.038
Fuelwood use per wk	−0.030	0.037	−0.80	0.421	−0.104	0.043
Charcoal use per wk	0.074	0.045	1.62	0.104	−0.015	0.163
[e]Load-shedding/ location	0.401***	0.085	4.70	0.000	0.234	0.569

Table 7
Marginal elasticities of the factors influencing electricity consumption of households.

.margins, ey/ex (*)						
Average marginal elasticities						
Model VCE: Robust, Clustered						
ln_consumption	Delta-method					
	ey/ex	Robust Std. Err.	z	P> | z|	[95% Conf. Interval]	
Household size	0.048*	0.026	1.81	0.070	−0.004	0.100
Education level	0.039	0.028	1.36	0.174	−0.017	0.095
Dwelling type	0.110**	0.055	2.00	0.045	0.002	0.219
No of rooms	0.232***	0.037	6.17	0.000	0.158	0.306
ln_income	0.013**	0.001	5.43	0.002	0.010	0.016
Price/tariff rate	0.002	0.039	0.07	0.941	−0.074	0.080
No of refrigerators	0.002	0.007	0.28	0.777	−0.013	0.017
No of space cooling fans	0.170***	0.050	3.31	0.001	0.070	0.280
No of other appliances	0.010	0.008	1.24	0.217	−0.006	0.026
Private PV ownership	−0.001	0.003	−0.42	0.674	−0.007	0.005
Cooking with electricity	0.018***	0.005	3.45	0.001	0.007	0.028
TV ownership	0.001	0.013	0.12	0.902	−0.024	0.027
Fuelwood use per wk	−0.021	0.015	−1.38	0.168	−0.051	0.008
Charcoal use per wk	0.004	0.011	0.36	0.720	−0.018	0.026
Load-shedding/ location	0.525**	0.150	2.69	0.021	0.400	0.640

Table 8
Average marginal elasticities of the factors influencing electricity consumption of productive users. Robust SEs are clustered by town/location.

.margins, ey/ex (*)						
Average marginal elasticities						
Model VCE: Robust, Clustered						
ln_consumption	Delta-method					
	ey/ex	Robust Std. Err.	z	P> | z|	[95% Conf. Interval]	
Household size	0.000	0.010	0.08	0.936	−0.020	0.022
Education level	0.012	0.011	1.10	0.270	−0.009	0.035
Dwelling type	0.007	0.012	0.58	0.559	−0.017	0.032
No of rooms	0.109***	0.019	5.62	0.000	0.071	0.147
ln_income	0.103*	0.059	1.74	0.082	−0.013	0.220
Price/tariff rate	0.252***	0.012	10.42	0.000	0.106	0.155
No of refrigerators	0.011**	0.005	2.11	0.035	0.000	0.022
No of space cooling fans	0.007*	0.003	1.89	0.059	−0.000	0.014
No of other appliances	0.013**	0.006	2.00	0.046	0.000	0.027
Private PV ownership	0.002	0.002	1.01	0.314	−0.001	0.005
Cooking with electricity	0.015	0.010	1.39	0.165	−0.006	0.036
TV ownership	0.000	0.008	0.00	0.999	−0.017	0.017
Fuelwood use per wk	−0.003	0004	−0.80	0.423	−0.012	0.005
Charcoal use per wk	0.0204	0.012	1.63	0.103	−0.004	0.045
Load-shedding/ location	0.340***	0.070	4.61	0.000	0.200	0.490

households is positively and significantly associated with the household size ($p < 0.1$); such that the average monthly consumption of a household increases by 2.82% for every additional member of the household, holding other variables constant. The result, which is in line with previous studies [14,17,22], illustrates that electricity consumption increases with family size. Conversely, household size is not strongly correlated with electricity consumption of SMEs *(model 2)*. Similarly, both models showed no evidence that the education level of the household head is strongly correlated with electricity consumption. The coefficient estimates for the variable dwelling type, however, shows that households who live in 'modern' brick/concrete houses consume approx. 15% more electricity per month than those that live in traditional mud houses. In both Tobit models, number of rooms is significantly and positively correlated with electricity consumption ($p < 0.01$).

3.3.2. *Income and price factors*

The estimated parameters in Tables 5 and 6 show that electricity consumption is positively and significantly related to income for both customer groups; where a 1% increase in the income of a household is associated with a 1.28% increase in monthly electricity consumption; and a 1% change in income of a productive user is associated with an 8.9% change in monthly electricity consumption. As in previous studies [11,12,18,31,33], this result indicates that income plays a major role in determining electricity consumption; however the electricity consumption of SMEs is more income elastic (responsive) than that of households. This is further supported by the marginal elasticity estimates in Tables 7 and 8; where a 1% increase in income is associated with 1.37% increase in consumption for households but a 9.09% increase for productive users.

The price of electricity is positively and significantly associated with electricity consumption for SMEs but not for households. However, it is important to note that the electricity tariff rate in Ethiopia changes slabwise depending on consumption level. As such, price may not necessarily dictate consumption; rather increase in consumption results in higher tariff slab. Accordingly, the marginal effects of price/tariff rate in

Tables 5 and 6 can be interpreted as 'a 20 kWh increase in monthly consumption results in a one slab increase in the tariff rate for households ($p = 0.19$); while a 47 kWh increase in monthly consumption results in a one slab increase in the tariff rate for SMEs ($p = 0.003$). This suggests that consumption does not necessarily change with price (price inelastic) but price changes significantly with consumption for SMEs. In the same vein, the marginal elasticity of price in Table 8 is interpreted as 'for every 28% increase in monthly consumption of SMEs, the tariff rate increases by one slab' ($p < 0.01$). In contrast, for households, the change in monthly consumption has not, once again, led to significant change in tariff rate (Table 7). This is probably because the increase in monthly household consumption is negligible, and that it only slightly raises the tariff slab.

3.3.3. Appliance ownership/stock and use

Customers' ownership and stock of electrical appliances is positively and significantly associated with electricity consumption in both households and SMEs. Both models agree that appliance-rich customers have significantly higher consumption than appliance-poorer ones. Yet, there appears to be a difference in the influence of different appliances on electricity consumption of households and SMEs. For households, *number of space cooling fans ($p < 0.01$)* and *cooking with electricity ($p < 0.01$)* are positively and significantly correlated with electricity consumption. For SMEs, *number of refrigerators ($p < 0.05$), number of other appliances ($p < 0.05$)* and *number of space cooling fans ($p < 0.1$)* are positively and significantly related with electricity consumption. Note that '*other appliances*' denotes the various appliances and machines that are mostly used by SMEs but not regressed separately in the models including compressors, electric drills, welding machines, hair dryers and other productive use machines. According to the parameter estimates of the *household model (1),* for every space cooling fan owned, the household's mean monthly electricity consumption increases by 22%. Similarly, households who use electricity for cooking consume 20% more than those that do not. The marginal effect estimates for appliance factors for SMEs (Table 6), by contrast, indicate that for every additional *refrigerator*, *cooling fan* and *other appliances*, the mean monthly electricity consumption of SME increases by 7%, 11.6%, and 25.6% respectively. These findings demonstrate that appliances ownership and stock plays a crucial role in determining the electricity usage of both households and SMEs.

Private SHSs and DGs ownership has a negative relationship with electricity consumption in the households model, though insignificant coefficients. This is likely due to the limited contribution of SHS and limited use of DGs and, thus, their marginal role of reducing electricity consumption. As a result, MG electrified households with their own SHS and DG are almost as dependent on electricity from the MG as those without. However, it was also found that some productive users in Omorate with private SHS and DGs were able to access 24-h and sufficient electricity by combining the MG power supply with their private SHSs and DGs. It should be noted that the metered data in this study does not include electricity derived from private SHSs and DGs. The total electricity consumption of those households and SMEs using private SHSs and DGs may hence be higher than those relying on MG alone, as shown by a recent study in Bangladesh [12].

3.3.4. Load-shedding and location factors

Another important finding of this study is the significant and positive association between load-shedding and electricity consumption in both models. Contrary to previous research [31,34], households and SMEs faced with extended load-shedding hours and power outages consumed significantly more electricity than those with uninterrupted power supply. The empirical results suggest that, compared to households in Tum (where there is no load-shedding), households in Omorate consume a significantly higher (50% more) amount of electricity per month ($p < 0.1$). Similarly, SMEs in Omorate consume a significantly higher (33% more) amount of electricity per month ($p < 0.01$) than SMEs in Tum (reference category). The findings suggest two probable phenomena. The first is that the electricity requirement of rural households and SMEs is significantly influenced by local context-specific demand factors including the local climatic conditions, economic and business activities, and accessibility of appliances. The second could be that faced with prolonged daily power outages, consumers in Omorate go into a consumption spree (energy hoarding) during the hours when power is available. To maximize their energy consumption and hoarding when it is available, these customers have equipped themselves with a variety of high power appliances including freezers, refrigerators, compressors and rechargeable LEDs. This behavior of 'energy hoarding' was also confirmed during our field visits and door-to-door surveys.

Location is also a major confounding factor in this research. It embodies the local sociocultural setting, temperature, livelihoods, security and the differences between the two sites in terms of access to electrical appliances, appliance markets, cost of appliances and price of fuels. Location is also a proxy variable for many other variables omitted from the Tobit regression models due to their multicollinearity. In this sense, the empirical results in Tables 5 and 6 confirm the findings of the consumption analysis presented in Table 4. In Omorate, where appliances are relatively cheaper and more accessible, and the mean annual temperature is above 28 °C, many households and SMEs own and use space cooling fans, refrigerators and deep freezers, therefore consume more electricity. A concern repeatedly expressed by most households and SMEs in Tum, in contrast, was the extremely high cost and general lack of access to appliances in local markets.

4. Discussion and policy implications

Findings from the load curve and demand analyses show that the daily load profiles of the two towns have distinctly different characteristics and patterns. While the load (demand) curve at Omorate is interrupted by load-shedding for more than half of the day (due to the discrepancy between the MG's generation capacity and the demand), the load curve at Tum is complete and uninterrupted throughout the day. Yet, MG customers at Omorate are consuming almost twice as much as those at Tum, in spite of the fact that the MG at Omorate has a lower installed capacity (375 kWp) than the MG at Tum (550 kWp); and that both MGs have similar number of customers. This is because the energy demands of both households and SMEs at Omorate are significantly higher than those of households and SMEs at Tum (see Fig. 5). The main explanation for this is that the two locations have different characteristics when it comes to energy demand variables such as consumer's income level; stock of electrical appliances, access to appliance markets, type and number of productive users, local climatic conditions and lifestyle. These differences have direct impact on the load (demand) profiles of the two towns.

The high energy consumption even with protracted load-shedding in Omorate and conversely the low consumption in Tum have important policy implications. It underscores that PV based rural electrification in SSA should be based on adequate knowledge and practical understanding of the main drivers of demand for electricity, and accurate assessments of the load profile of customers. The large share of SMEs in the total electricity consumption relative to their number, on the one hand, shows the important role of productive use in ensuring sufficient electricity demand for the proliferation of commercially viable MGs. On the other hand, it underlines the need to identify and implement targeted policies and suitable demand side management strategies (such as load-shifting, differential and time based pricing, energy efficiency) to ensure reliability of electricity supply for SMEs without compromising the demands of households and public institutions. At present, the price of electricity in rural Ethiopia is determined irrespective of the time of the day.

The empirical results show that the energy consumptions of ordinary households and businesses are influenced by distinct yet interconnected sets of factors. However, the significance of effect of each factor differs markedly between the two user groups. While income and price are key factors, it seems that electricity consumption is income-inelastic for households but elastic for SMEs, and price-inelastic (not necessarily elastic) both for households and SMEs. The income inelasticity of household electricity consumption suggests that rural households in Ethiopia are increasingly seeing electricity as a basic need (essential good), to the point where they are willing to meet their demand regardless of the price. The price inelasticity of consumption, on the other hand, could be in part because, being a developing nation, Ethiopia uses a progressive seven-slab tariff structure for household and SMEs-level electricity services based on the amount of energy consumed per user per month. Hence, an increase in consumption is rather an indication of an increase in affordability, provided that supply is reliable. As a result, SMEs end up paying higher prices than ordinary households since they consume more electricity. Similar income and price inelasticities in electricity demand were reported by previous researches in rural villages in India [15] and South Africa [35].

The large coefficient estimates for appliance ownership in both models indicates that appliances ownership is a key influencing factor of electricity consumption, as was reported by prior studies [18,35,36]. Interestingly however, the influence of space cooling fans and electric cookstoves was more significant for households; while refrigerators, cooling fans and other (productive use) appliances were more significant for SMEs. These results in turn point to the important role of businesses and local climate in determining demand for electricity. While the availability of electricity is a requirement, the findings demonstrate that the quantity of electricity consumed is more a function of the type of end use of the electricity (productive or domestic), the customer's stock of appliances, and other relevant demand variables including the cost of appliances and local climate. In line with our findings, Gaunt et al. [37] documented that the cost of appliances is one of the main obstacles to electricity consumption in rural areas of SSA. Mudakkar et al. [38] reported that extreme temperatures were major drivers of electricity consumption in South Asian countries. Along similar lines, Luo et al. [39] in Tanzania reported on the significant influence of location on household electricity consumption.

In addition, the findings of this study point to a unique behavior of distributed renewable MG customers where, when faced with prolonged hours of load-shedding, they tend to hoard as much electricity as they need during those hours when electricity is available using various electrical appliances and power storage devices. Although consumers' tendency to hoard when an essential good becomes scarce is not a new occurrence, we believe that the observed behavior of planned daily electricity hoarding in response to load-shedding by these off-grid communities in SSA is a little-known and interesting finding of this study that is worth modelling theoretically in further studies. Furthermore, despite the widely held belief that decentralized MGs might not be economically viable in SSA due to insufficient demand for electricity [7], the high consumption levels and unmet demands found at Omorate suggest otherwise.

The empirical results presented in this study are mostly based on cross-sectional data, and hence are explanatory rather than causal. Since data was available only for 8 month period of the mini-grids' operation, the study was unable to capture the dynamic nature of electricity demand over a longer time period. This is significant since electricity consumption is typically linked to changes in the customers' sociodemographics, awareness, appliance stock and accessibility, and overall economic development in the region.

5. Conclusions and future work

In summary, findings from this study show that most of the variation in electricity consumption of customers of distributed PV mini-grids in the study area is driven by the user type (household or SMEs), stock of electrical appliances, income level, tariff rate and location-specific variables, including climatic conditions and access to appliances. The study has demonstrated that in the context of off-grid rural East Africa, electricity consumption from mini-grids is influenced more by supply-side and context-specific non-income factors than traditional income and price factors. In particular, the study has revealed the significance of influence of location and productive use on the demand for electricity, and the need to account for these factors in mini-grid sizing. The study also suggests that harnessing the potential of off-grid mini-grids requires guaranteeing accessibility and affordability of appliances.

Future research work might include in-depth investigation of the electricity consumption behaviors of customers vis-à-vis energy hoarding and other load-shedding coping mechanisms; study on the contribution of load-shifting and other DSM strategies to mitigate power outages and interruptions in Omorate during peak demand hours. If not, how can the generation capacity of the MG in Omorate be expanded in most optimal way to achieve the twin objectives of lowest cost and reliable supply?

Credit author statement

We certify that both authors have participated sufficiently in this research work from intellectual conception, and design of the research objectives to data collection, analysis and interpretation of the data and writing of the manuscript. The contribution of each author is provided hereafter.

Yibeltal T. Wassie: Conceptualization, Methodology, Field data collection and investigation, Formal analysis, Writing - original draft, and Writing - review and editing, **Erik O. Ahlgren**: Conceptualization, Methodology, Resources, Writing - review and editing, Visualization, Supervision, Project administration, and Funding acquisition.

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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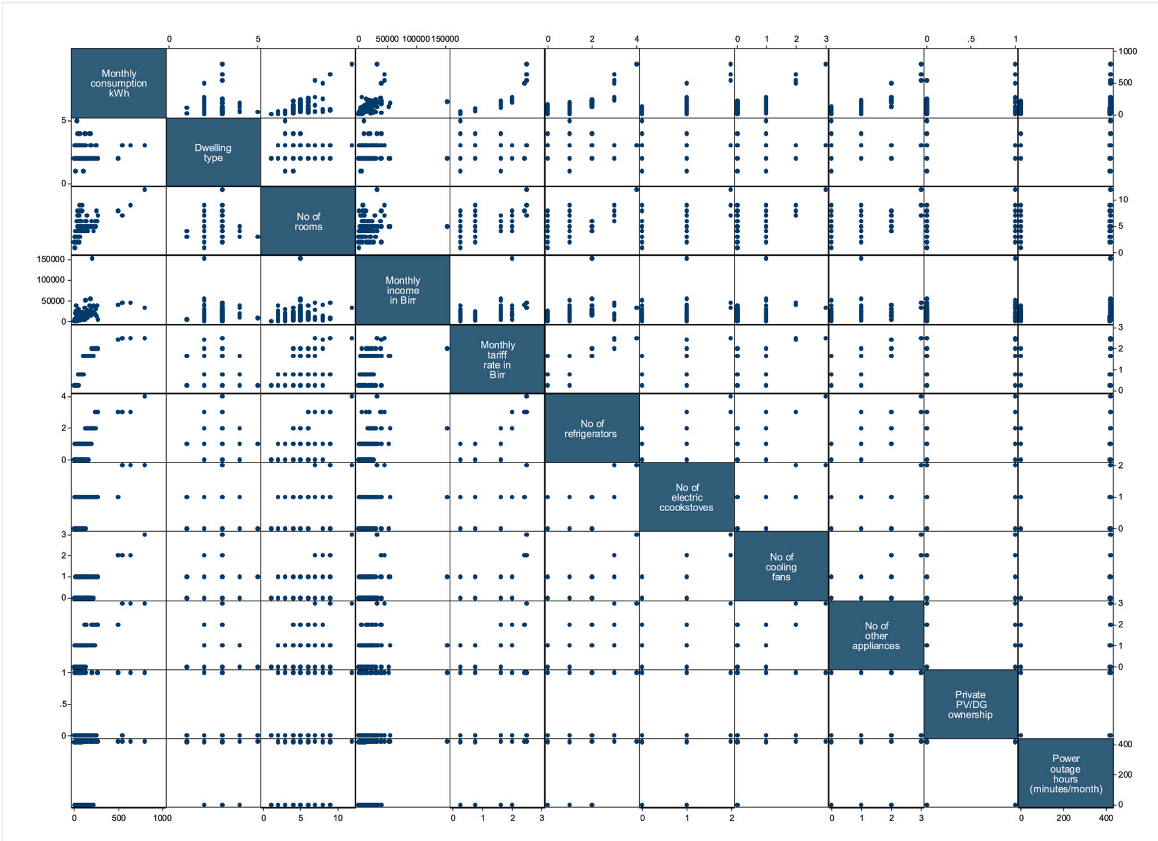
Appendix I

Photos of the PV mini-grid infrastructure in Omorate, with electricity usage measurements from a small bar and restaurant owner with an EEU bill invoice and a refrigerator stocked with cool beers ready to be served (Photo by Yibeltal T. Wassie, 2021).

Appendix II

A scatterplot matrix of bivariate relationships between combinations of the key variables used in the econometric analyses.



Appendix III. Types of small and medium productive users/enterprises (SMEs) in the study area

SMEs/productive users (sample size = 90)	Freq.	%
Retail goods and cold drinks stores	24	26.7
Fast food, beverages and traditional coffee shops	12	13.3
Bars, restaurants, and traditional ‘beer-like’ beverage makers	11	12.2
Beauty salons for men and women	10	11.1
Hotels and pensions	7	7.8
Mobile phone charging and electronic shops	5	5.6
Garage, wood and metal workshops	3	3.3
Motorcycle and bicycle repair service	3	3.3
Juice bars and sport/game zones	3	3.3
Bakeries	3	3.3
Photo studios	3	3.3
Photocopy, computer and printing services	2	2.2
Tailoring	2	2.2
Private clinic/pharmacy	2	2.2

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