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Electricity consumption: The role of grid reliability in appliance ownership and usage in Rwanda☆

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ABSTRACT

Using household survey data and electricity reliability data, this study analyzes the relationship between grid reliability and appliance ownership and usage in Rwanda, a low-income country in Sub-Saharan Africa. We estimate the effect of reliability on household appliance ownership by employing lightning as an instrumental variable for grid reliability. The findings reveal that while grid reliability has a limited effect on the total number of appliances owned, it significantly influences the types of appliances households choose to acquire. Higher outage frequencies are linked to reduced ownership of entertainment devices, such as televisions and decoders, particularly in low-income households. Conversely, high-income households in low-reliability areas tend to reduce their ownership of high-energy, costly appliances, like fridges and cookers. The study further explores how appliance ownership affects electricity consumption by estimating the conditional demand. The findings suggest that improving grid reliability could modestly enhance electricity consumption among wealthier households, though complementary policies targeting the affordability gap are needed to encourage low-income households to increase their consumption as well. Consistent with prior research, income remains a significant barrier to both appliance ownership and usage in low-income households.

1. Introduction

Access to electricity can significantly enhance the well-being of households in Sub-Sahara Africa (SSA) but only if they acquire and actively use electric appliances (Richmond and Urpelainen, 2019; Lenz et al., 2017). Residential electricity consumption is driven by preferences for energy services, which in turn depend on the availability and usage of appliances such as refrigerators, televisions, and cooking devices (Dubin and McFadden, 1984; Nielsen, 1993; Auffhammer and Wolfram, 2014). However, even after gaining access to electricity, many households in SSA own a limited variety of appliances, leading to low levels of electricity consumption (Lenz et al., 2017; Adesina et al., 2020). These deficiencies not only diminish the impact of electrification programs on households' well-being but also pose challenges for the financial viability of distribution utilities due to low residential electricity consumption (Blimpo and Cosgrove-Davies, 2019). The limited appliance ownership observed in SSA highlights the need for interventions that extend beyond merely expanding access to electricity. Instead, understanding what drives appliance ownership and usage is critical for improving both household welfare and the sustainability of electricity sectors in these contexts.

A large body of literature has focused on the relationship between household income and the adoption of electric appliances, finding that income is a major determinant of ownership (Farrell, 1954; Gertler et al., 2016; Khandker et al., 2009). As income rises, households tend to acquire more appliances, particularly durable and higher-cost items like refrigerators and televisions. While income is undoubtedly important, recent research suggests that rising incomes alone may not be sufficient to drive appliance ownership and residential electricity demand (Debnath et al., 2019). Non-income factors, such as credit constraints (Wolfram et al., 2012), housing conditions (Matsumoto, 2016a; O'Doherty et al., 2008), social influence (Hanna and Oliva, 2015), and education levels (Dhanaraj et al., 2018), can also play critical roles in determining household adoption of appliances. Additionally, external factors like climate can shape appliance ownership decisions (McNeil and Letschert, 2010), while limited information about the benefits of appliances may further restrict household adoption and use (Bos et al., 2018). Finally, the type of electricity access matters. Households with

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grid connections are significantly more likely to own large appliances than those using off-grid systems like solar home kits (Lee et al., 2016), highlighting the importance of electricity infrastructure for appliance adoption in low-income settings. A comprehensive review by (Richmond and Urpelainen, 2019) explores various non-income drivers that affect appliance adoption, underscoring the complexity of the factors influencing household appliance adoption beyond income alone.

While low income is a key variable explaining low appliance ownership, economic theory suggests that an unreliable electricity supply reduces the incentive to acquire new appliances. Theoretical models indicate that the demand for durable goods, like appliances, stems from the services they provide through ownership (Dubin and McFadden, 1984). Thus, frequent electricity outages undermine the utility of appliances, acting as a disincentive for households to invest in them, even when they have the financial means.[4] Studies from middle-income countries such as Nepal, Kyrgyzstan, and Colombia demonstrate that households often respond to poor reliability by limiting their acquisition of electricity-dependent appliances (Meeks et al., 2023; Hashemi, 2022; McRae, 2010). However, the role of reliability of electricity supply in shaping appliance ownership remains underexplored in low-income and rural contexts typical of SSA. In such contexts, adoption patterns are not straightforward and the relationship between reliability and appliance ownership can be particularly complex. Poor electricity reliability may indirectly suppress appliance adoption by reducing household income, as frequent outages constrain productive activities and income-generating opportunities (Dang and La, 2019). Beyond income effects, households may fail to internalize the full impact of service quality when making purchasing decisions, deviating from theoretical predictions. Behavioral factors, such as myopia, bounded rationality, and reliance on social cues, further complicate decision-making (Himarios, 2000; Ramakrishnan et al., 2020). For instance, households might prioritize appliances that confer social status over those that directly improve utility. Additionally, external factors like climate, housing conditions, and household demographics may shape adoption patterns (McNeil and Letschert, 2010; Matsumoto, 2016a).

Relatively few studies have examined how electricity reliability influences household appliance adoption, particularly in the residential sector of low-income countries. By contrast, much of the existing literature on outages has focused on their broader economic consequences. Numerous studies show that unreliable electricity reduces output, productivity, and revenues in firms across SSA and other developing regions (Alam, 2013; Moyo, 2012; Estache, 2005; Abeberese et al., 2021; Allcott et al., 2016; Cole et al., 2018; Hardy and McCasland, 2021). These impacts also extend to labor markets, as (Mensah, 2024) finds that outages reduce skilled and non-agricultural employment opportunities. This broader economic context underscores the importance of electricity reliability not only for firm performance but also for fostering economic development.

Equally important is the role that appliance ownership can play in generating social welfare gains for households. Appliances such as modern cooking equipment, washing machines, and refrigerators reduce domestic burdens and free time for labor market participation, particularly for women (Bhargava and Kerr, 2022; Tewari and Wang, 2021; Omotoso and Obembe, 2016; Su and Azam, 2023). Similarly, appliances can reduce child labor and improve educational outcomes (Malhi et al., 2025; Kerr, 2019). (Dhanaraj et al., 2018) highlights how refrigerators improve nutrition and food security by enabling food preservation, while (Shi et al., 2022) shows that increased refrigerator uptake improves child health outcomes. (De Cian et al., 2025) finds that owning an air conditioner increases residential electricity consumption, with associated welfare gains including improved productivity, better sleep during hot seasons, and potentially life-saving reductions in heat-related illnesses. Our study complements this literature by examining how reliability constraints shape household access to appliances that deliver these broader social and economic benefits, an issue of particular importance in SSA, where persistent service quality challenges remain widespread across many countries (Mugyenyi et al., 2024a,b; Afrobarometer, 2022; Day, 2020; Blimpo and Cosgrove-Davies, 2019; Burgess et al., 2020).

While prior work has demonstrated the negative impacts of outages on firm productivity and welfare, and has documented the welfare gains from appliance ownership for households, relatively little is known about how electricity reliability influences appliance adoption decisions in low-income SSA residential settings. Our study addresses this gap by examining the role of electricity reliability in shaping appliance ownership and usage among Rwandan households. Specifically, we ask: **How does electricity reliability affect household decisions regarding appliance ownership and usage in low-income settings?** In doing so, we contribute to the literature by focusing not only on the role of reliability in determining electricity usage but also on its influence on the adoption of appliances in the first place. We address this research question using a unique combination of household survey data and administrative data on electricity reliability from Rwanda. The household-level survey data, obtained from the Integrated Household Living Conditions Surveys (EICV), includes detailed information on appliance ownership. The administrative data, provided by the Rwanda Energy Group (REG), allows us to measure the frequency of power outages. By linking these datasets through geographic information, we can rigorously assess the relationship between reliability and appliance ownership. To account for potential endogeneity in electricity reliability, we use lightning strikes frequency and radiance as an instrumental variable, following recent studies on grid reliability (Meeks et al., 2023; Andersen and Dalgaard, 2013; Mensah, 2024).

We follow previous literature and evaluate two outcome variables: a count of electric appliances (size) and the ownership of specific appliances (composition) (see (Richmond and Urpelainen, 2019) and (Matsumoto, 2016a)). We use conditional fixed-effects Poisson models and linear fixed-effects probability models to investigate the household appliance stock. Our results indicate that grid reliability has a minimal impact on the total number of appliances owned by Rwandan households. However, higher outage frequencies reduce ownership of certain appliances, particularly entertainment devices like televisions (by 4%) and decoders (by nearly 5%), as well as smartphones. This effect is more pronounced for low-income households, who are more likely to reduce ownership of entertainment appliances under low reliability, while high-income households are less affected. Yet, in low-reliability areas, high-income households avoid costly, power-dependent appliances like fridges and cookers, possibly substituting with alternatives.

In addition to examining the relationship between reliability and appliance ownership, we also analyze how reliability affects appliance usage, as reflected in household electricity consumption. We model electricity consumption using a conditional demand function, following the approach of (Larsen and Nesbakken, 2004), which is designed to estimate the mean electricity consumption at the appliance level among households. We also identify key drivers of appliance usage, following the methods of (Matsumoto, 2016a). Our analysis further reveals that, while outages have limited effects on appliance usage among current owners, grid reliability indirectly affects household consumption through its influence on appliance ownership. High-income households show reduced ownership of energy-intensive devices, while low-income households are primarily impacted in terms of low-energy appliances like smartphones and TVs. This suggests that targeted reliability improvements for wealthier households could enhance overall electricity consumption, though complementary support for low-income households to acquire appliances is also essential to reduce energy poverty

[4] An outage is a complete stoppage within the distribution system, preventing end users' consumption of electricity services.

and promote equitable access. Balancing these strategies across income groups is key to an effective and inclusive energy strategy in Rwanda.

The existing literature on households' appliance ownership has predominantly examined the relationship between household income and the adoption of specific appliances, anticipating their role in driving household electricity demand growth (see (Auffhammer and Wolfram, 2014), (Farrell, 1954), (Gertler et al., 2016), (Khandker et al., 2009), (Matsumoto, 2016a) and (Wolfram et al., 2012)). While low income is a key variable explaining low appliance ownership, non-income factors also shape appliance adoption (Rao and Ummel, 2017; Debnath et al., 2019). Poor housing conditions can limit ownership, as homeowners and residents of detached homes are more likely to invest in appliances than renters (Matsumoto, 2016a; O'Doherty et al., 2008). External factors, such as climate, can also drive adoption, with appliances like fans and air conditioners more common in warmer regions (McNeil and Letschert, 2010). Finally, behavioral and informational barriers further constrain adoption. Households may lack information about appliance benefits or fail to fully internalize their value, although social influences, such as observing neighbors' usage, can accelerate adoption (Bos et al., 2018; Hanna and Oliva, 2015). This paper explores the role of reliability on appliance ownership while providing descriptive evidence on other non-income drivers, such as gender, household composition, education, and dwelling characteristics. In particular, we find that demographic characteristics of the households, specifically the age of the members and the gender of the head of household, also show a significant relationship with ownership of key appliances.

We also contribute to a small but growing literature on households' response to electricity reliability improvements. Despite increased electricity access in the 21st century, many developing countries still face challenges in ensuring satisfactory service quality (Meeks et al., 2023; Blimpo and Cosgrove-Davies, 2019; Burgess et al., 2020). In this sense, understanding residential consumers' responses to experiencing changes in electricity quality has attracted the attention of researchers. (Meeks et al., 2023) explores appliance ownership and reliability in Nepal, (Hashemi, 2022) investigates the same in Kyrgyz Republic, (Cissé, 2025) in Senegal and (McRae, 2010) in Colombia. These studies indicate that households in developing countries significantly respond to unreliable services by refraining from purchasing certain appliances. Our study extends this inquiry to a low-income country, specifically analyzing appliance ownership in Rwanda. The adoption patterns in low-income rural settings are nuanced. Moreover, our study sets itself apart by leveraging novel administrative data and instrumental variables to enhance identification.

The remainder of the paper is organized as follows. Section 2 describes the data used in our analysis of appliance ownership. Section 3 outlines the empirical methodology and presents the key results. Section 4 examines how reliability and other factors influence appliance-level electricity consumption. Section 5 offers a broader interpretation of the findings, and Section 6 concludes.

2. Data description

Estimating the relationship between electricity service quality and household outcomes is often challenging, primarily due to the difficulty of accurately measuring electricity reliability. Utilities may not consistently record outages, or, if they do, may lack the incentive to share such data with external researchers (Klytchnikova and Lokshin, 2009). Consequently, previous research has relied on indirect measures of electricity quality, such as self-reported data, which is susceptible to misreporting (Carranza and Meeks, 2021), proxies like electricity shortages (Meeks et al., 2023), or satellite imagery of nighttime lights, which suffers from limitations such as infrequent overpass intervals (Mann et al., 2016).

To overcome these data limitations, we utilize a novel dataset that combines public data with proprietary outage records at the feeder level from the Rwanda Energy Group (REG), a government-owned vertically integrated utility. This dataset provides detailed information on outages from 2016 to 2020, including the duration, occurrence date, cause, and affected substation and feeder line.[5] Rwanda's electricity network consists of many long radial feeder lines, some extending over 300 km. Outages on these lines can impact wide areas and affect a large number of households.

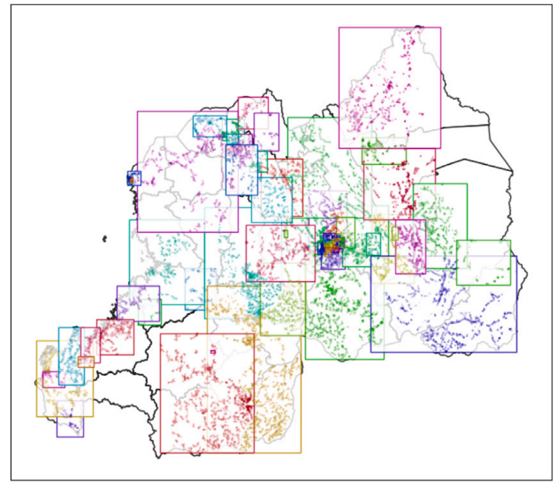


Fig. 1. Distribution feeder lines.
Note: Feeder lines are represented by different colors, with a bounding box indicating each feeder's coverage area. Feeders farther from Kigali (the capital) tend to cover larger areas. The smallest feeder covers 1.25 km^2, while the largest spans 3320 km^2. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

In addition, we integrate additional data from REG, which maintains a record of 52,418 low-voltage electricity conductor lines. These lines are linked to their corresponding substations and feeder lines. By mapping outages from the feeder level to the low-voltage lines, we estimate outage exposure for each line, as shown in Fig. 1.[6] This mapping allows us to connect feeder-level outages to specific households served by these low-voltage lines.[7]

We complement this reliability data with household-level information from the Integrated Household Living Condition Survey (EICV), a national cross-sectional survey conducted every couple of years. For this analysis, we draw on the 2016/2017 EICV round, covering 14,580 households across 1,260 sample villages. The survey collected data on household characteristics and appliance ownership, such as radios, televisions, fridges, and cookers, among others. For our analysis, we focus on the 3600 households with a grid electricity connection, which represent 25% of the surveyed households. Fig. 2 illustrates the spatial distribution of the survey data, highlighting the grid electrification rates across Rwanda's districts. Note that this does not include off-grid electrification, particularly solar systems. This electrification rises to 33% once these alternative systems are taken into account (see Appendix Table A2)

To assign grid reliability statistics to individual households from the survey dataset, we collaborated with the National Institute of Statistics of Rwanda (NISR), the agency responsible for implementing the EICV

[5] We have outage data from 2016 to 2020, however, we only utilize 2016 and 2017 data which matches the time period of our survey. The number of unique feeders tracked each year is as follows: 53 in 2016, and 57 in 2017. The increase likely reflects efforts to meet growing electricity demand as Rwanda expands grid access.

[6] A limitation of our approach is that its limited in its ability to identify outages at specific low voltage locations.

[7] Feeder level/lines operate at the medium voltage level.

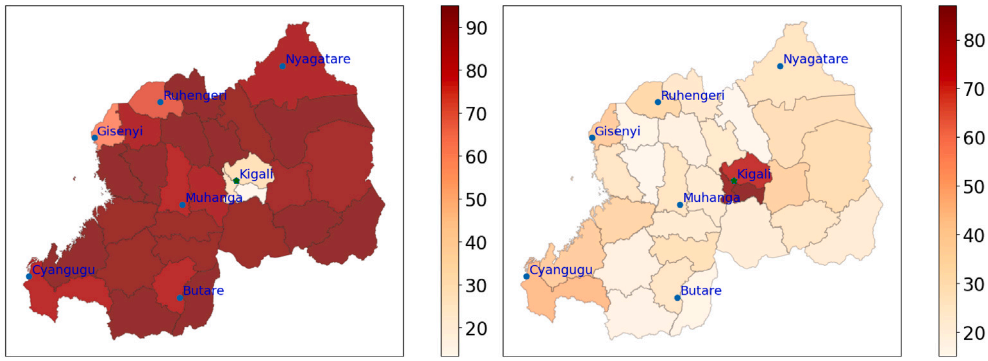


Fig. 2. Spatial distribution of survey.
Note: Figure (a) shows the rural concentration by district (%), and figure (b) shows the grid electrification rate by district (%). Major cities/towns, including the capital, Kigali, are indicated by dots.

surveys.[8] We matched household GPS coordinates to the nearest low-voltage line within an 800-m range, reflecting the utility company's connection policy (REG, 2020). Through this process, each household was assigned outage statistics based on the nearest feeder line.

We constructed measures of appliance ownership among grid connected households following (Richmond and Urpelainen, 2019) and (Matsumoto, 2016a). These include the total number of appliances owned by each household, as well as categorization of appliances based on service type, capital cost, and wattage. Table 1 presents the appliance categories.[9] We also created two variables: a binary indicator for whether a household owns a particular appliance, and a numeric count of each appliance type. In our analysis, we also include EICV data on household socioeconomic status, income, and access to infrastructure. The distance to major cities and markets is calculated using the Euclidean distance measure, which represents the straight line distance between a household and key infrastructure locations, as illustrated in Fig. 3. Lastly, we incorporate weather data, including rainfall and lightning activity. Rainfall data comes from the Rwanda Meteorological Agency, with 40 years of daily records from 18 stations across the country. Using these records, we estimate average rainfall through geostatistical interpolation (Murphy and Krajnik, 2017) (detailed in Appendix A), as shown in Fig. 4(a). The interpolated rainfall estimates align with the official figures reported by the Rwanda Meteorological Agency.[10]

Lightning data, obtained from the Tropical Rainfall Measuring Mission (TRMM), cover 2013–2015 and provide lightning frequency and intensity (Blakeslee, 1998; Earth Data, 2023). These lightning events are mapped to feeder regions and serve as an instrumental variable for assessing electricity reliability (Fig. 4(b)). Our dataset contains 592 lightning events, including all the flashes (strikes) recorded by the imaging sensor. Fig. 4(b) visually presents the distribution of lightning strikes across Rwanda during 2013–2015, illustrating the widespread occurrence of strikes throughout the country.

Using these data, we assign lightning event statistics to the feeder region using bounding boxes as depicted in Fig. 1. We calculated the average annual number of strikes in the area and the average radiance (intensity) of all the flashes in the area. We then assign these values to each household in the feeder region and, hence, our lightning data measures lightning activity in the grid area, which serves electricity to the household.

Table 1
Appliance categories.

Category	Appliance(s)		Cost	Use	Wattage
0	No appliances		–	–	–
1	Feature phones Radio	Smart phones	Low	Communication	Low
2	TVs Satellite dish Music system	Decoders DVD player Camera	Medium	Entertainment	Low
3	Computer Sewing Machine	Printer	Medium	Productivity	Medium
4	Fridge Hotplate Fan	Laundry machine Cooker Water Filter	High	Convenience	High

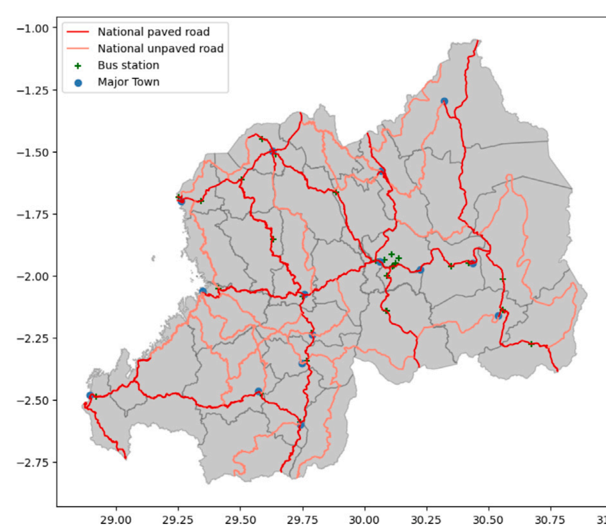


Fig. 3. Transport and major towns in Rwanda.

2.1. A closer look

From October 2016 to October 2017, our sample of 3600 grid-electrified households owned a total of 15,510 appliances recorded in the data. Fig. 5 shows the composition of this appliance stock, dominated by mobile phones, radios, and TVs. This distribution aligns with findings from other studies on appliance ownership in Rwanda and Sub-Saharan Africa (Lenz et al., 2017; Bos et al., 2018; Muza and Debnath, 2021).

[8] The NISR does not disclose household GPS coordinates publicly; therefore, the matching process was conducted at their headquarters in Kigali.
[9] We define phones with internet capabilities as smartphones and those without as feature phones.
[10] https://www.meteorwanda.gov.rw/index.php?id=30.

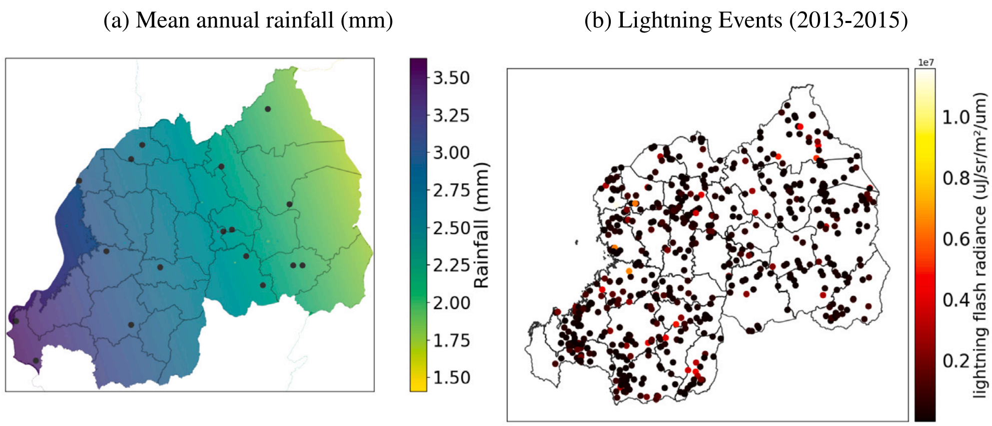


Fig. 4. Rainfall and lightning activity.
Note: Figure (a) shows mean annual rainfall in Rwanda. Each dot is one weather station recording data on rainfall. Figure (b) presents lightning strikes, with color indicating intensity. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

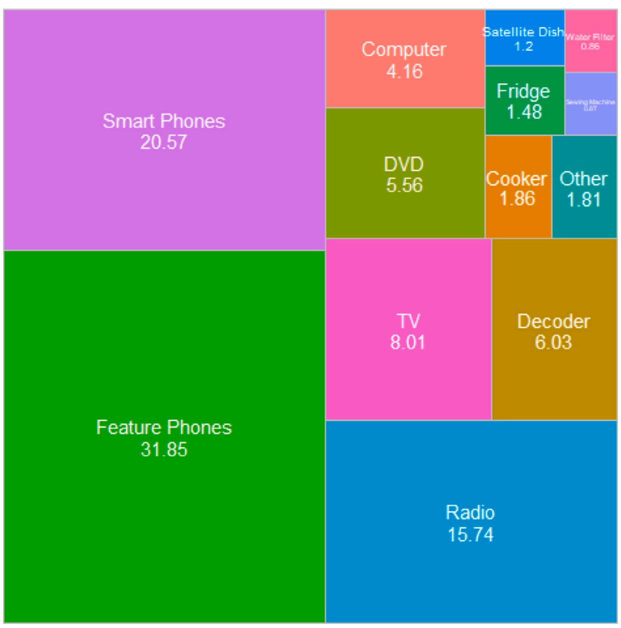


Fig. 5. Composition of appliance stock Rwanda.
Note: This figure shows the share of appliances owned by a sample of 3600 grid-electrified households in Rwanda. "Other" appliances include printers, cameras, electric fans, hotplates, music systems, and laundry machines.

To better understand household appliance ownership, Table 2 presents the number of households that own at least one appliance. On average, households own 4 appliances, with nearly 87% owning more than one. Radios and mobile phones are the most common, while other appliances have lower penetration rates. Appliance ownership is generally low in Rwanda, both in quantity and variety.[11] Fig. 6 breaks down ownership across various appliance categories. Fig. 6(a) shows the share of households owning at least one appliance per category, while Fig. 6(b) illustrates the distribution of units within each category for those households. The data reveals that communication and entertainment devices dominate, while more expensive, energy-intensive appliances like cookers and refrigerators are much less common. This suggests that only a small number of households have moved up the "appliance ladder".[12]

This pattern likely reflects the financial constraints faced by many households. The high cost of appliances, coupled with low average incomes (Sievert and Steinbuks, 2020), limits purchases of more expensive items. For example, in 2018, the average cost of a cooker was $410 USD, a refrigerator $540 USD, and a washing machine $420 USD (Statista Market Insights)[13]). In contrast, Rwanda's average annual income was only $780 USD in 2018 (Sally Smith et al., 2020), making it difficult for households to afford these appliances. As a result, electricity usage remains largely limited to basic needs like lighting and phone charging. Increases in household income or better access to credit could potentially lead to higher appliance ownership and, consequently, greater electricity consumption.

Despite having better measures than other African countries (Blimpo and Cosgrove-Davies, 2019), Rwanda still faces challenges with electricity reliability. Fig. 7 shows the variation in grid reliability across districts, presenting three key metrics: total annual outage time, daily outage frequency, and outage duration per incident. Though the data is aggregated at the district level for clarity, there is significant within-district variation, which is leveraged in our statistical analysis. We are missing reliability data for the two northernmost districts in our sample, affecting 144 grid-connected households. These households were excluded from the regression analysis due to the missing data.

3. Appliance ownership and reliability

In this section, we study the role of reliability in appliance ownership. Ideally, we would model how the probability of buying a given appliance changes as the grid reliability faced by each household changes over time (see (Meeks et al., 2023) for an example). Regrettably, the nature of our available data precludes the execution of such a longitudinal study. Instead, we conduct a cross-sectional analysis comparing appliance ownership across regions with different reliability levels. We also analyze other drivers, including income, demographics, education, gender, and dwelling characteristics.

[11] See Appendix A for ownership rates amongst households with access to non grid-electricity.

[12] We use the concept of the appliance ladder to describe how households incrementally adopt appliances as their income improve, with low-income households typically acquiring basic devices first and moving toward energy-intensive appliances over time.

[13] https://www.statista.com/outlook/cmo/household-appliances/major-appliances/rwanda#price.

Table 2
Appliance distribution among electrified households.

	Penetration		Households who own the appliance				
	Number	%	Mean	St. Dev.	Min.	Max.	HHs > 1 (%)
Any	3480	96.670	4.440	3.330	1	27	86.70
Feature phones	2955	82.080	1.840	1.100	1	11	52.83
Radio	2324	64.560	1.150	0.430	1	5	13.08
Smart phones	1976	54.890	1.770	1.100	1	10	49.04
TV	1322	36.720	1.030	0.190	1	3	3.03
Decoder	982	27.280	1.050	0.230	1	4	4.28
DVD player	897	24.920	1.060	0.400	1	10	3.90
Computer	520	14.440	1.360	0.710	1	6	26.35
Cooker	301	8.360	1.050	0.270	1	4	4.65
Fridge	242	6.720	1.040	0.240	1	3	3.31
Satellite dish	198	5.500	1.040	0.190	1	2	3.54
Water filter	146	4.060	1.000	0.000	1	1	0.00
Sewing machine	109	3.030	1.370	1.020	1	8	18.35
Camera	79	2.190	1.130	0.430	1	4	10.13
Hotplate	73	2.030	1.030	0.160	1	2	2.74
Music system	71	1.970	1.060	0.290	1	3	4.23
Electric fan	30	0.830	1.000	0.000	1	1	0.00
Printer	24	0.670	1.120	0.340	1	2	12.50
Laundry machine	11	0.310	1.090	0.300	1	2	9.09

Note: The values in this table were calculated using the 3600 grid-electrified households in the EICV sample. Appliance counts are based on households owning at least one unit in each category.

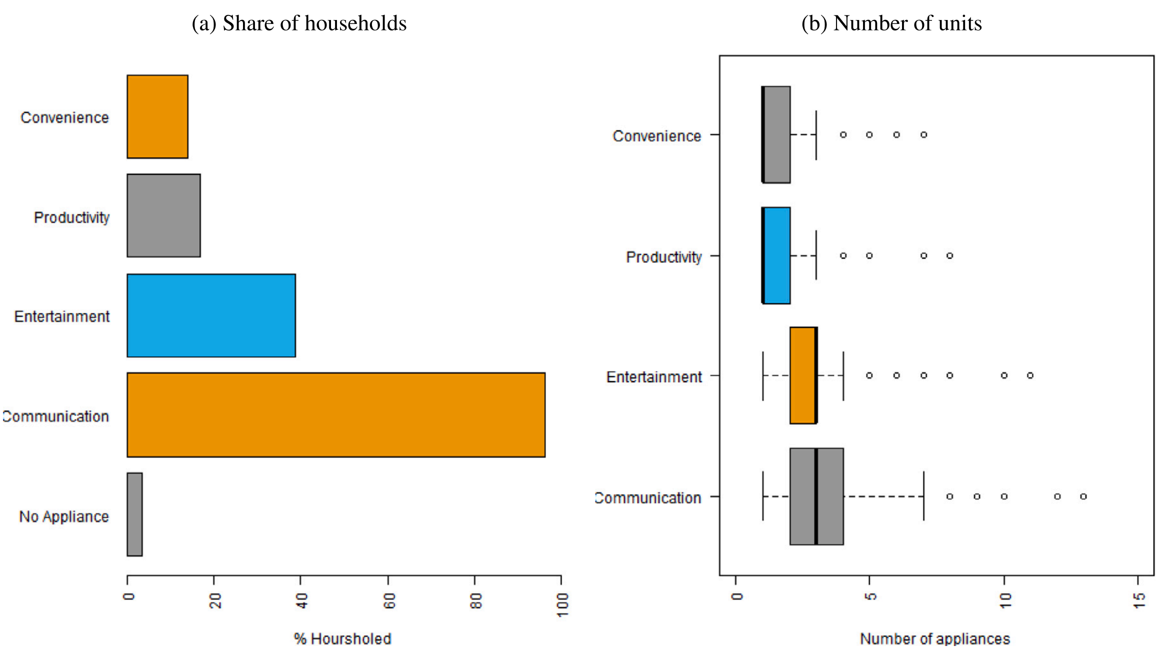


Fig. 6. Ownership by appliance category.

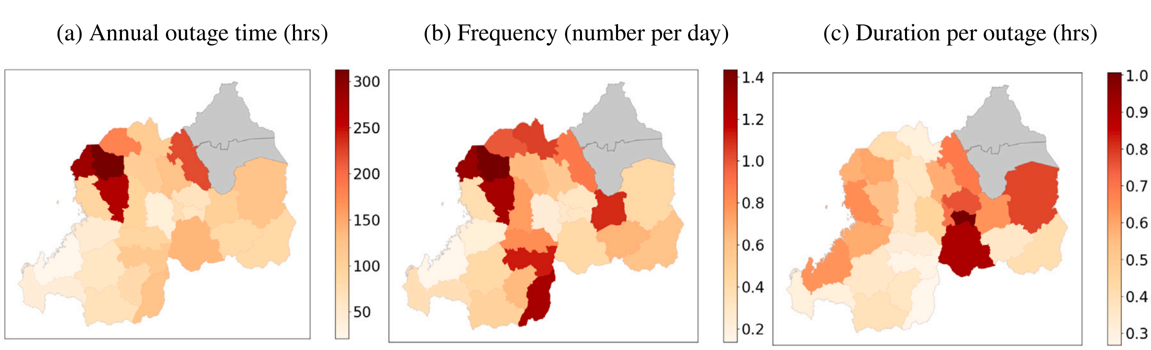


Fig. 7. Average reliability metrics per district - 2017.

3.1. Research design

Our research design follows (Richmond and Urpelainen, 2019) and (Matsumoto, 2016a), but it also considers the intricacies of our particular case, appliance ownership in Rwanda, characterized by its limited prevalence, resulting in certain appliances being owned by only a few households and consequently generating an abundance of zeros in our dataset. This section explains our empirical strategy.

First, we analyze the role of reliability on the total number of appliances owned by households by studying the intensity at which households invest in appliances with a conditional fixed-effects Poisson model.[14] Let y_{ij} be the total number of household-owned appliances i in district j. Under the Poisson assumptions, the probability of owning y_{ij} units of appliances is given by Eq. (1)

$$Pr(Y = y_{ij}|X_{ij}, Z_{ij}, \alpha_j) = \frac{(E[Y|X_{ij}, Z_{ij}, \alpha_j])^{y_{ij}} \cdot e^{-E[Y|X_{ij}, Z_{ij}, \alpha_j]}}{y_{ij}!} \tag{1}$$

where $E[Y|X_{ij}, Z_{ij}, \alpha_j] = e^{X_{ij}\beta + Z'_{ij}\Gamma + \alpha_j}$ represents the anticipated number of appliances, dependent on a series of variables. Here, X_{ij} is the grid reliability; Z_{ij} is a vector of control variables that include both income and non-income drivers; α_j are district fixed effect to capture common characteristics for households within the district. We do not use village fixed effects since villages are generally very small, so our data will not have enough within-village variation. Note that even though Poisson models are inherently nonlinear, using the linear index and the exponential link function leads to multiplicative separability, allowing us to estimate the model with fixed effects. We employ the conditional maximum likelihood methodology proposed by (Hausman et al., 1984) to estimate this model.

We derive our measure of grid reliability, referred to as outage frequency, from the average number of outages over the 24-month period spanning 2016 and 2017.[15] Unfortunately, we lack an extensive time series predating 2016/2017, prompting us to rely on the average for these two years to construct variables that encapsulate grid reliability. However, it is important to note that the stability of reliability metrics across time is a hallmark, given that outage occurrences predominantly hinge on factors like weather conditions, vegetation interference, animal disruptions, feeder length, and various other determinants that exhibit minimal temporal variability. In this context, our parameter of interest is β, which measures the change in the log of the expected number of appliances owned by a household when reliability improves by one unit. Using the point estimates, we also calculate the incidence ratio rate, which measures the increase in the expected number of appliances owned by the household as reliability improves by 1 unit by exponentiating the regression coefficient.

Eq. (1) includes control variables that account for household characteristics affecting appliance ownership. Household income is captured by the log of monthly expenditures, which is a reliable income proxy, particularly for households with informal or non-monetary income sources (Cope et al., 2012). Additionally, total savings serves as an indicator of wealth, reflecting a household's financial capacity to acquire appliances. The EICV survey provides data on employment stability, and we include the average turnover of jobs within the household. Job turnover reflects income uncertainty, which may impact electricity consumption and appliance ownership, as prior studies have suggested (Blimpo and Cosgrove-Davies, 2019).

Demographic controls include variables for the gender of the household head (dummy for female), the number of children, women, and seniors, who may face higher health risks from poor indoor air quality. Controlling for these demographics helps account for variation in health priorities and the associated financial and informational barriers to improving indoor air quality (Richmond and Urpelainen, 2019). Education and skills are key drivers of appliance ownership (Dhanaraj et al., 2018). We include a dummy for households where the head has attended school, as well as dummies for business ownership and high-skill occupations, recognizing that these characteristics are likely correlated with knowledge of and access to appliances.

Household location and structure are also controlled for in the analysis. A dummy for rural location captures limited exposure to appliances in non-urban areas, while the distance to major towns reflects access to markets where appliances are sold. Additionally, the number of rooms and a dummy for multiple-building residences account for potential redundancy in appliance ownership. Homeownership and years at the current location are also included to capture stability and the likelihood of investing in less portable appliances. Climatic factors are represented by mean local rainfall, acknowledging that climate can influence appliance usage, such as fans in warmer areas or outdoor equipment affected by rainfall (Sakah et al., 2019). Although temperature variation within Rwanda is modest, rainfall patterns differ substantially across regions, from 1000 to 1400 mm annually.

Finally, we control for the utility's capacity to restore service by including the average outage duration in the area. This measure reflects the utility's responsiveness, which may affect appliance usage preferences (McRae, 2010). While this variable may be endogenous, it provides an important indicator of utility performance.[16] Although the cause of a power outage can influence the restoration duration, the average outage duration is a reliable metric for evaluating the utility's overall responsiveness to outages.

The variables used in the analysis are summarized in Table 3. Specifically, our regression models incorporate data from 2706 grid-connected households for which complete variable information is available.

In the second part of the analysis, we empirically examine how electricity reliability affects household appliance ownership. Due to low appliance penetration rates, most below 30% (Table 2), the data contains an excess of zeros, a condition known as zero inflation (Hilbe, 2014). To address this, we conceptualize appliance ownership as a two-step decision: first, whether to acquire an appliance (a yes/no choice), and second, the quantity of units if the decision to acquire is affirmative. This approach recognizes that the factors influencing the ownership of an appliance may differ from those affecting the number of units owned (Ščasnỳ and Urban, 2009).

For modeling, we define $y^{\ell} ij$ as the count of appliance ℓ owned by household i in district j, and use the indicator variable $q^{\ell} ij = 1[y^{\ell}_{ij} > 0]$ to denote ownership. Despite the prevalent use of nonlinear models for discrete outcomes, we use linear models here to mitigate the incidental parameters problem associated with fixed effects in nonlinear settings, improving interpretability (Richmond and Urpelainen, 2019). While conditional logit models could handle panel-fixed effects through a likelihood function transformation (see (Chamberlain, 1980)), the low ownership rates of certain appliances (Table 2) classify them as rare events, which can bias binary nonlinear estimates (King and Zeng,

[14] The Poisson model relies on two strong assumptions. First, an event happening in a period of time has a constant probability (stationarity). Second, the model assumes that the occurrence of an event does not affect the probability of a second event happening (independence). Under this assumption, the conditional variance is the same as the conditional expectation (equidispersion).

[15] Within our dataset, these years have the worst reliability performance. Indeed, there is a substantial improvement in grid reliability in the proceeding years (i.e. 2018, 2019 and 2020). We rely on outage frequency and not outage duration because outage frequency is highly correlated with the total hours a household does not have access to electricity in a given year. In Rwanda, the average duration of an outage was 20 min in the period 2016/2017 with a standard deviation of 7.4 min.

[16] Unfortunately, we could not find good instruments for the duration, and hence, we are cautious in analyzing the coefficient for this variable. We expect this variable to be endogenous.

Table 3
Summary statistics (Number of Obs = 2706).

Variable	Mean	St. Dev.	Min.	Max.
Reliability				
Average duration without electricity (h/year)	116.920	92.750	17.260	496.500
Average Frequency (outages/day)	1.069	0.837	0.064	2.91
Average Outage Duration (min/outage)	20.040	7.410	9.670	67.110
Income and employment				
Expenditure (log RWF month)	11.570	0.930	8.790	14.580
Savings (million RWF)	0.250	2.320	0	99
Has business (dummy)	0.450	0.500	0	1
Job instability (number of jobs/member)	1.480	0.620	1	7
Involves in high skill occupation (dummy)	0.190	0.370	0	1
Demographics				
Female (number)	2.310	1.580	0	13
Children (number)	1.860	1.640	0	9
Seniors (number)	0.140	0.410	0	3
Head of Household				
Female (dummy)	0.190	0.390	0	1
Below 35 years old (dummy)	0.430	0.490	0	1
Rwandese (dummy)	0.990	0.100	0	1
Attended School (dummy)	0.250	0.440	0	1
Dwelling and ownership				
Number of rooms (count)	3.760	1.610	1	10
Multiples houses (dummy)	0.180	0.380	0	1
Multiples households (dummy)	0.280	0.450	0	1
Number of years in house (count)	6.850	8.850	0	63
Own house (dummy)	0.560	0.500	0	1
Location				
Rural (dummy)	0.450	0.500	0	1
Distance to major town (km)	9.600	7.900	0.050	43.860
Distance to trade center (km)	1.780	1.540	0.010	9.990
Mean rainfall (mm)	2.600	0.370	1.850	3.690

2001). Our focus on the direction and relative strength of relationships between variables justifies using linear models for binary outcomes.

Thus, we specify the fixed-effects model for appliance ownership as:

$$q_{ij}^{\ell} = X_{ij}\beta_{\ell} + Z_{ij}'\Gamma_{\ell} + \alpha_j + \varepsilon_{ij} \tag{2}$$

where X_{ij}, Z_{ij}, and α_j are defined as in Eq. (1). We estimate each appliance model as seemingly unrelated equations.

3.1.1. Identification

Estimating the relationship between electricity reliability and household outcomes is typically challenging. Service quality is often endogenous and correlated with household characteristics. Two key factors contribute to this complexity. Firstly, the non-random nature of household locations, influenced by regional factors such as weather and economic activity (Sinha et al., 2018; Pawar and Jha, 2023). These factors play an important role in determining the reliability levels of an electric system. Fig. 8 shows that overcurrents, under-frequency, and earth faults are the predominant causes of outages in our data, and these are the consequence of regional factors such as weather, vegetation, and electricity demand. Secondly, the reliability of the grid is dependent on utility decisions, including maintenance and grid design, demonstrating substantial regional variations that correlate with household characteristics (Meeks et al., 2023). Indeed, the distribution network design typically adopts radial feeders for rural areas in Rwanda, in contrast to networked feeders commonly seen in urban locales (REG, 2021).[17] Radial networks usually have long feeder lines, making them more susceptible to outages.

[17] The distribution network can have radial or networked configurations. Radial networks lack interconnections with alternative supply points, while networked networks boast multiple connections to diverse supply sources. Radial networks are used in rural Rwanda due to the isolated nature of rural loads, making the use of network feeders economically less feasible (REG, 2021).

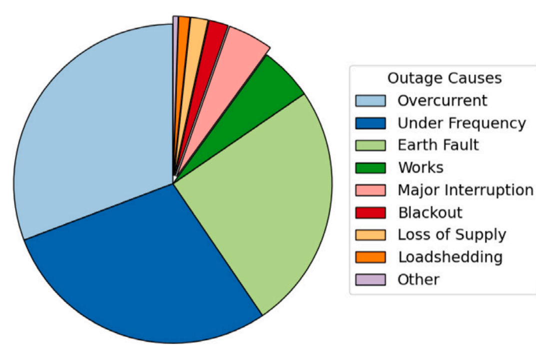


Fig. 8. Main causes of outages.

Inevitable measurement errors occur when capturing power infrastructure quality (Chen et al., 2023). Despite possessing novel reliability data, our data set may not precisely align with localized outages, which often go unnoticed in utility tracking. Achieving a comprehensive match between these measured outages and household-level outages proves challenging, particularly given extensive feeder lines that stretch over considerable distances and branch into multiple distribution spurs serving smaller communities. This inherent limitation poses a methodological challenge. Our use of feeder outages serves as a proxy to characterize the "standard" service quality experienced by households. As acknowledged in econometrics literature, measurement errors in the independent variable result in attenuation bias (Bollen, 1989; Wooldridge, 2010).

While our model controls for district unobservables, it does not fully address endogeneity. Consequently, our identification strategy relies on the use of two instrumental variables that characterize lightning

Table 4
Instrumental variables (Number of Obs = 2706).

Variable	Mean	St. Dev.	Min.	Max.
Average lightning radiance (millon μJ/sr/m²/μm)	0.500	0.260	0.100	2.120
Frequency lightning (count/year)	7.170	8.590	0.330	27

Note: Summary statistics were calculated across each household in our data. Lightning. values assigned to each household represent the "typical" lighting activity in the region where the household lives.

activity in the different parts of the country: the average radiance of lightning strikes[18] and the number of lightning strikes.[19]

Lightning disturbances are usually a major problem for electricity networks and cause service interruptions (Rezinkina et al., 2022; Minnaar et al., 2012; Alvehag and Soder, 2010; Mensah, 2024). For example, lightning damage accounts for about 65% of distribution network failures in South Africa (Andersen and Dalgaard, 2013). The energy carried by a single lightning bolt is immense, averaging around 1 gigavolt with a typical current of 10,000 to 30,000 amperes (Gunther, 2023). The heat produced can also be substantial, reaching temperatures five times higher than the surface of the Sun (Rezinkina et al., 2022). Strikes near the grid can cause overvoltages, disrupt transformers, poles, and substations, or induce electromagnetic fields affecting grid operations.

Our first instrument is the frequency of lightning strikes, as prior studies have shown that areas with high lightning density often experience more frequent power outages (Chisholm and Cummins, 2006). Our second instrument is the average intensity of lightning strikes, measured by radiance. Higher-intensity strikes are more likely to lead to grid failures. Table 4 provides summary statistics for these instruments.

Our reduced-form equation for reliability is given by

$$X_{ij} = W_{ij}'\Pi + Z_{ij}'\Lambda + \alpha_j + \varepsilon_{ij} \tag{3}$$

where X_{ij} is the outage frequency, W_{ij}' are our instruments, Z_{ij} are the control variables from our structural equation, and α_j district fixed-effects. Table 5 presents the results of our first-stage reduced-form regression. As observed in the table, the coefficients are positive and significant, which means that the average number of outages increases with the frequency and intensity of lightning strikes. Furthermore, the results affirm the instruments' relevance, substantiated by both the F-statistics and the Cragg-Donald Wald-F statistic.[20]

Our identification assumption is that our instruments are exogenous and uncorrelated with the structural error term, conditional on the control variables. This assumption is grounded on the random nature of lightning, which can strike anywhere, as noted by (Oceanic and Administration), 2020) and (Gunther, 2023). The occurrence of lightning strikes depends on the specific buildup of positive and negative charges between clouds and the ground.[21] Similarly, the intensity of a lightning strike depends on the electric charges inside the clouds. These factors are random and therefore difficult to correlate with economic and social characteristics that could influence the location of the households (Gunther, 2023). Our assumption would fail if there are differences in other factors leading to thunderstorm development, and cloud formation specifically, within the country. Factors influencing cloud formation include meteorological conditions such as warm temperatures and strong solar radiation. Solar radiation and temperature do not present significant differences in Rwanda, a relatively small country. For these reasons, we believe our identifying assumption is a plausible one. To support this claim, we present the J-statistic and p-value for the over-identification test for each regression model in Appendix B. The results show that we fail to reject the null hypothesis that the instruments are exogenous at 5%

Table 5
First-stage results.

Dependent variable: Frequency of outages (number/day)	
Lightning radiance	0.463**
	(0.202)
Lightning frequency	0.069***
	(0.006)
Relevance and Weak-IV Test	
F-statistic	401.89
Cragg-Donald Wald-F statistic[a]	1477.14
Observations	2706
Number of district	26
Mean observations per group	104.1

Note: All the exogenous variables from the structural equation are including in the first-stage regression, including the district-fixed effects. Clustered standard error at the district level in parenthesis. *** p < 0.01, ** p < 0.05, * p < 0.1.
[a] Stock-Yogo (2005) weak IV F–test critical values for single endogenous regressor: 19.93 (10% maximal IV size); 11.59 (15% maximal IV size); 8.75 (20% maximal IV size).

It is essential to note that, for our linear models, we implement 2SLS fixed effects models. However, the 2SLS approach is not valid for nonlinear models and may not produce a consistent estimate. In cases where the second-stage equation involves nonlinearity, as seen in our Poisson models, the predicted endogenous variable from the first-stage regression can become correlated with the residuals (Cameron and Trivedi, 2013; Wooldridge, 1999). To address this challenge, we opt for the Control Function Approach (CFA), a two-step process where we incorporate the predicted residuals from the first stage into the second stage (Wooldridge, 1997; Cameron and Trivedi, 2013; Wooldridge, 1999). The implementation of the CFA is valid in the case of Poisson Regression given the multiplicative separability of the second stage and the linear model in the first, relying on the normality assumption of the residuals of this stage (Cameron and Trivedi, 2013; Wooldridge, 1999). In this approach, bootstrap standard errors are employed to accommodate the uncertainty stemming from the first stage.

3.2. Empirical results

This section presents the empirical findings of our study. We begin by examining the impact of electricity reliability on household appliance ownership. Following that, we provide descriptive insights into other determinants of household appliance demand. In this latter analysis, we interpret the regression coefficients as correlations rather than causal effects, due to limitations in establishing causality.

3.2.1. The role of reliability in ownership

Table 6 displays the regression results on the relationship between total appliance ownership and reliability. Each column represents a different model specification, showing estimated coefficients and their incidence-rate ratios obtained by exponentiating the coefficients. In addition, we present results incorporating instrumental variables through a control function approach and compare with an alternative conditional fixed-effects negative binomial model to account for potential overdispersion in appliance ownership data. The Poisson model assumes equidispersion (mean equals variance), which we relax in the final columns of Table 6.

[18] Radiance is used to characterize diffuse emission and reflection of electromagnetic radiation, and to quantify emission of neutrinos and other particles.

[19] The rank condition establishes that we need at least 1 valid instruments for the identification of the model.

[20] (Staiger and Stock, 1997) establishes the rule-of-thumb for this test: if the F-statistic is less than 10, the instruments are weak, and no valid statistical inference can be made.

[21] This allows positive charges below to attract them, creating powerful discharges of electricity known as lightning.

Table 6
Reliability and total number of appliances.

	Conditional fixed-effects poisson						FE + CFA	
	Mod. 1	Mod. 2	Mod. 3	Mod. 4	Mod. 5	Mod. 6	Poisson	Neg. Bin.
Frequency of outages (number/day)								
Point estimate	0.0001	0.010	0.003	0.001	−0.010	−0.028	−0.055	−0.056
	(0.052)	(0.037)	(0.033)	(0.031)	(0.023)	(0.019)	(0.054)	(0.055)
Incidence ratio	1.000	1.010	1.002	1.001	0.999	0.971	0.946	0.946
Control variables								
Income and employment		Y	Y	Y	Y	Y	Y	Y
Demographics			Y	Y	Y	Y	Y	Y
Head of household				Y	Y	Y	Y	Y
Dwelling and ownership					Y	Y	Y	Y
Location						Y	Y	Y
District FE	Y	Y	Y	Y	Y	Y	Y	Y
Wald	0.00	3568.56	10 076.80	7987.79	25 062.76	35 460.09	83 673.86	34 979.94
Log pseudolikelihood	−7109.56	−5468.70	−5358.95	−5300.72	−5205.33	−5193.05	−5192.44	−5193.49
Observations	2706	2706	2706	2706	2706	2706	2706	2706
Number of district	26	26	26	26	26	26	26	26
Mean observations per group	104.1	104.1	104.1	104.1	104.1	104.1	104.1	104.1

Note: Bootstrapped standard errors in parenthesis. Total number of appliances include radios, phones, TV, decoder, satellite dishes,cookers, fridges, DVDs, music systems, computers and printers, cameras, hotplates, electric fans, laundry machines, water filters and sewing machines. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The results in Table 6 highlight the importance of household characteristics when examining the effect of reliability on appliance ownership. As additional control variables are added, the frequency of outages shows a negative association with appliance ownership, though not statistically significant in the final specifications. This shift suggests that controlling for unobserved factors through instrumental variables minimizes potential biases from endogeneity in the reliability variable. The preferred model, the two-step conditional fixed-effects Poisson, shows a negative but non-significant association, consistent across all fully controlled models.

These results imply that, overall, the frequency of outages has minimal influence on the number of appliances owned by Rwandan households. One possible explanation is limited awareness of grid reliability, or households may perceive reliability differently. Alternatively, affordability constraints could play a role: With low median incomes relative to appliance costs, budget limitations may suppress demand for appliances, regardless of grid reliability. However, households may still adapt by shifting the types of appliances they own, influencing the composition of the appliance stock.

Fig. 9 illustrates the relationship between outage frequency and the probability of investing in specific appliance categories. The figure displays coefficients that quantify differences in ownership probability based on reliability in various regions. Detailed regression outputs can be found in Appendix B.

As shown in Fig. 9, higher outage frequencies correlate with lower ownership rates for entertainment appliances, such as televisions and decoders. Specifically, one additional outage per day is associated with a 4% reduction in the likelihood of owning a television and a nearly 5% reduction for decoders.[22] The lack of reliability deters households from investing in these entertainment sources. In contrast, Fig. 9(a) reveals no substantial relationship between reliability and ownership of communication appliances. However, a higher outage frequency significantly reduces the likelihood of owning energy-intensive devices like smartphones, which require more frequent charging, an issue in regions with low reliability.

Appendix B presents the regression table with all the coefficients. From those tables, we can observe that both fridges and satellite dishes are significant at 10% significance level but not 5%. The point estimates in both cases is negative. This result suggests that there is a negative effect on the composition of the stock of appliances owned by the households, yet the uncertainty associated with these two coefficients is larger and we need to allow for more type I error in our tests in order to determine reject the null hypothesis. For this reason, we follow the 5% confidence level in the rest of the analysis.

To complement these results, Fig. 10 presents the estimated coefficients from interacting our reliability variable with a dummy variable capturing household income level. Here, we define a "high" income household as one with expenditure above the sample median, coded as 1; "low" income households are those with expenditure below the median, coded as 0. This interaction produces our new variables of interest: reliability interacted with the income dummies.

To avoid the "forbidden regression" issue, we rerun the first stage using a non-linear functional form of our instruments. Specifically, we introduce two endogenous variables defined by the interaction of reliability with the income dummies. Separate first-stage regressions are conducted for each endogenous variable, with instruments also interacted with the endogenous terms. The coefficients in Fig. 10 represent second-stage estimates (detailed regression outputs are available in Appendix B). The left side of the plot shows the effects on low-income households, highlighting changes in the probability of investing in key appliances with a one-unit decrease in reliability. On the right, the plot presents coefficients for high-income households.

The figure reveals nuanced patterns in appliance investments based on income level. For low-income households, the likelihood of investing in televisions, and decoders declines with lower reliability, whereas high-income households show no significant changes in ownership of these appliances under similar conditions. This pattern likely stems from two factors. First, the cost of these appliances may be manageable for high-income households, making them less sensitive to reliability constraints, whereas for low-income households, even modestly priced appliances can strain budgets if usage is unreliable. Second, high-income households may have more flexibility in appliance usage due to their distinct consumption patterns and employment types, allowing them to adjust usage based on power availability, a flexibility often unavailable to low-income households.

Additionally, Fig. 10 shows that high-income households in areas with low reliability are less likely to own fridges and cookers, which is not observed for low-income households, who generally do not own these higher-cost appliances regardless of reliability. This suggests that high-income households in less reliable regions are more inclined to use alternative energy sources for cooking and to forego fridge ownership due to inconsistent power, indicating that these appliances are both costly and require shifts in consumption patterns when reliability is low.

In conclusion, these findings emphasize that both income and reliability strongly influence household appliance investments. Low-income

[22] The larger effect size for decoders likely stems from televisions being a prerequisite for decoders.

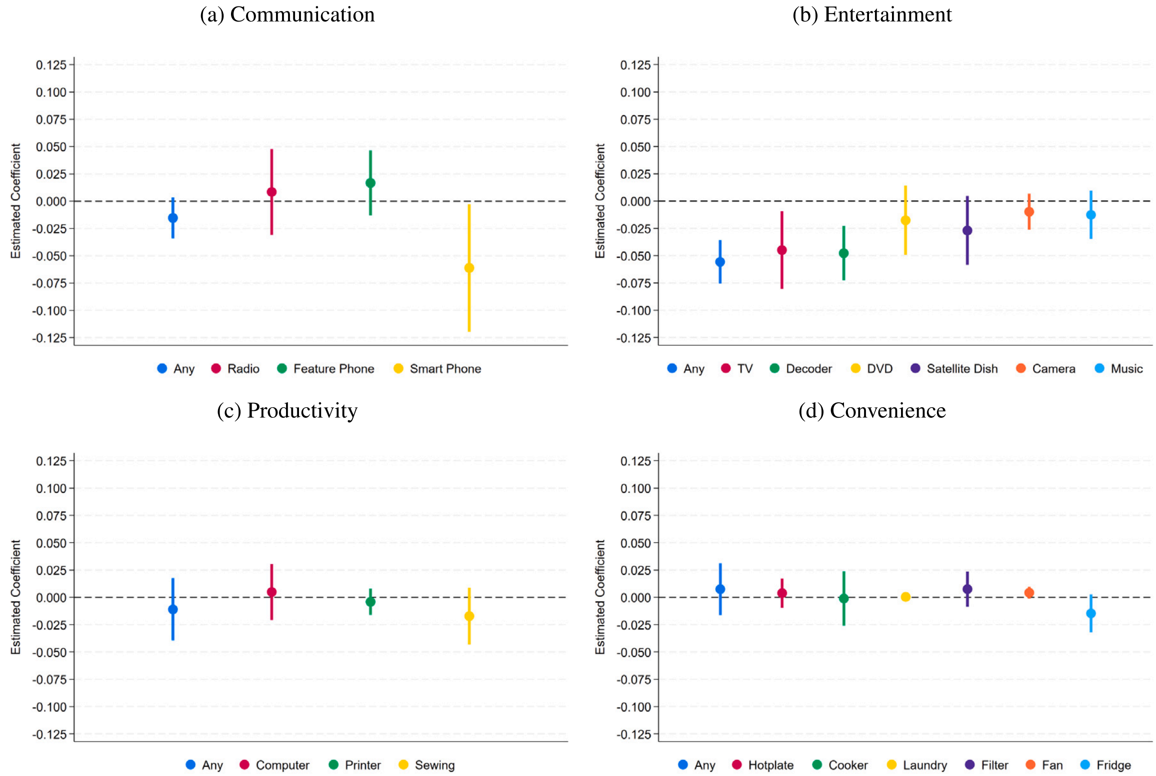


Fig. 9. Reliability and willingness to invest in appliances.
Note: Dots represent the point estimate. Vertical lines are the 95% confidence intervals. Clustered standard errors at the district level were used to construct the confidence intervals. For regression tables, please refer to Appendix B. J-statistics and p-values for the over-identification tests are also presented in Appendix B.

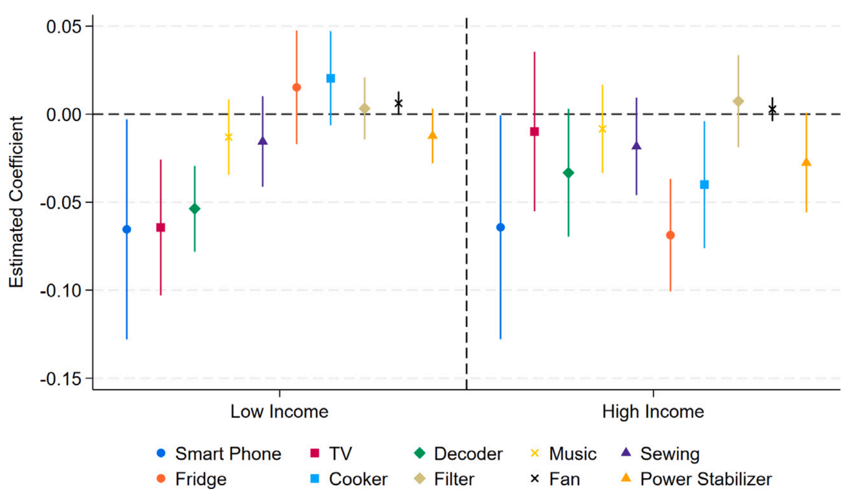


Fig. 10. Expenditure, income, and willigness to invest in appliances.
Note: Dots represent the point estimate. Vertical lines are the 95% confidence intervals. Clustered standard errors at the district level were used to construct the confidence intervals.

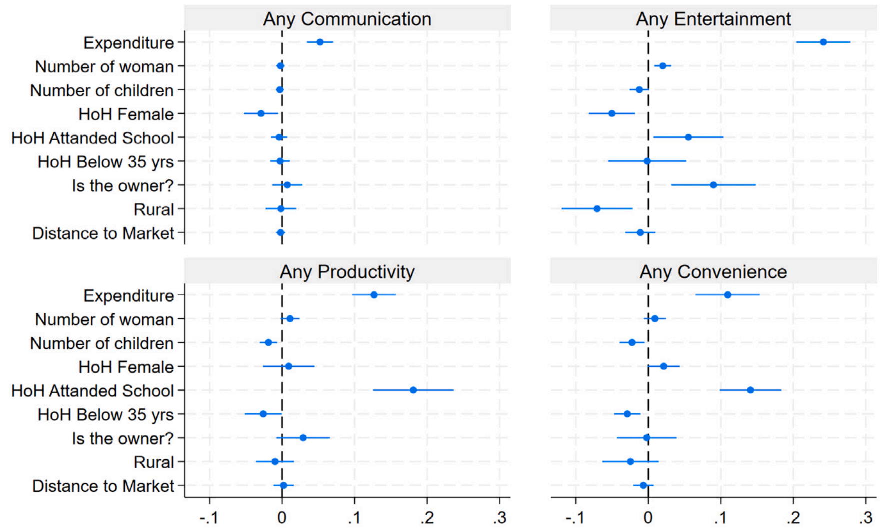
households face greater constraints in owning appliances under low reliability, while high-income households adapt by reducing ownership of costly, power-dependent appliances.

3.2.2. Other factors affecting appliance ownership

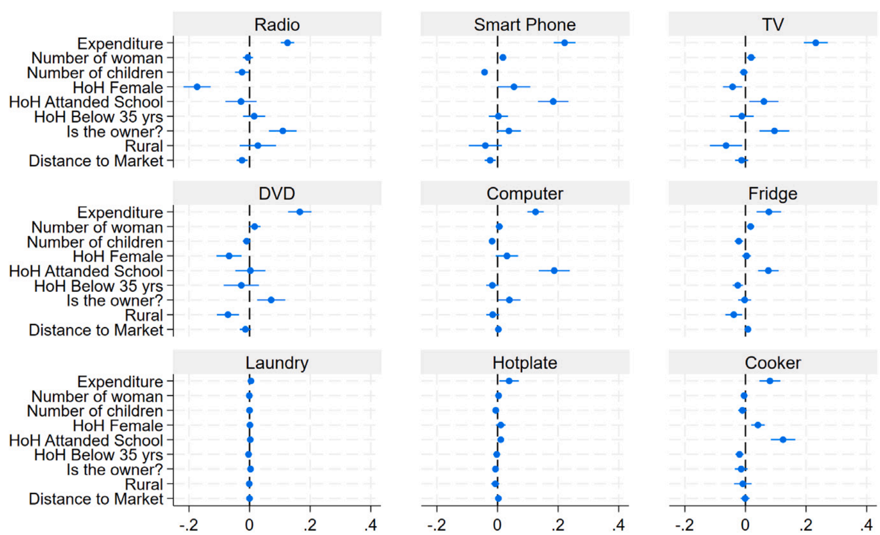
This section provides descriptive evidence of other drivers of appliance ownership. Note that these results are not casual and should be interpreted with care. Appendix B presents the regression tables. We summarized the results for appliance ownership of key appliances in Fig. 11.

Fig. 11 shows a substantial positive correlation between household financial factors and appliance ownership, excluding laundry machines, which may be due to high costs or cultural factors. As shown in the regression tables presented in Appendix B, households experiencing high job turnover tend to own fewer appliances, underscoring the role of financial stability in appliance ownership. This suggests that subsidy programs targeting appliances could be effective in increasing ownership, especially where financial uncertainty limits access.

Demographic characteristics of the households and education level also show a significant relationship with the dependent variables.



(a) Categories



(b) Key Appliances

Fig. 11. Other drivers of appliance ownership.
Note: Dots represent the point estimate. Vertical lines are the 95% confidence intervals. Clustered standard errors at the district level were used to construct the confidence intervals. Regression tables are presented in Appendix B.

Historical gender roles, where women traditionally take on caretaking responsibilities in Rwandan homes (Izabiliza, 2003), could explain why households with more females tend to invest in more appliances, possibly for home-based productivity. Homes with many children show a lower probability of owning a variety of appliances, likely due to prioritizing spending on children's needs. The head of household's age and gender are also relevant. Female-led households and those headed by individuals under 35 are associated with lower appliance ownership, reflecting socioeconomic challenges such as lower incomes or financial stability. However, female-led households tend to prioritize convenience appliances like cookers, which may align with traditional household roles in Rwandan society. Education levels of household heads are linked to greater appliance ownership, especially in categories like entertainment, productivity, and convenience. Higher education levels likely enhance both the awareness of and ability to use these appliances effectively.

Finally, dwelling characteristics, such as the number of rooms in a house, exhibit a positive and significant relationship with the dependent variable. Larger houses are associated with a higher likelihood of owning appliances, particularly items such as televisions, suggesting that the spatial requirements of a household influence the demand for appliances. Additionally, homeowners also have a positive and significant relationship with the ownership of entertainment appliances. The stability brought about by long-term home ownership may encourage households to acquire more appliances over time. In contrast, rural households and multiple families sharing a home are less likely to have an extensive collection of appliances.

4. Linking appliance ownership to usage and electricity consumption

We further analyze how residential electricity consumption correlates with appliance ownership. Our findings indicate that low reliability impacts the mix of appliances that households own, suggesting that investments to improve reliability may influence residential electricity demand in Rwanda. By estimating appliance-specific electricity consumption, we assess the broader implications of reliability on household electricity use. Following the conditional demand model by (Larsen and Nesbakken, 2004) and (Matsumoto, 2016a), we assess the role of both appliance ownership and usage in driving electricity consumption, acknowledging that reliability may affect both factors.

4.1. The conditional demand model

Household electricity use depends on appliance ownership and usage patterns, so simply regressing electricity consumption on ownership would lead to biased results. Several factors influence appliance use, including household and service characteristics (Blimpo and Cosgrove-Davies, 2019; Matsumoto, 2016b), which complicate estimation due to simultaneity between consumption decisions and ownership (Dubin and McFadden, 1984). Addressing this simultaneity problem requires identifying instrumental variables that influence the purchase decision but not the usage decision. However, finding a valid instrument for each appliance is impractical given the diversity of appliances. The conditional demand model addresses this challenge by estimating average appliance-specific consumption while accounting for appliance use patterns.

Assume a household can own $\ell \in L$ different types of appliances. We follow the hurdle model explained in our empirical section, in which a household first invests in each appliance and then decides the amount of units. Let D_i^ℓ be a dummy that takes the value 1 if a household i owns appliance ℓ, and let $K^\ell > 0$ be the number of units of that appliance owned by the household. We assign each household owning $K^\ell > 0$ units of appliances ℓ to group K^ℓ and we estimate the intensity of the use of appliance ℓ within group K^ℓ. For this, assume that electricity consumption for the kth appliance ℓ for household i is observed through direct metering. The appliance-usage equation is then

$$y_{ik}^\ell = \alpha_\ell + \sum_{m=1}^{M} \gamma_{\ell,m}(C_{i,m} - \bar{C}_{K^\ell,m}) + \varepsilon_{ik}^\ell \tag{4}$$

where the parameter α_ℓ measures the electricity required for an appliance of type ℓ for the mean household, and ε_{ik}^ℓ is an independent and identically distributed error term. The parameter $\gamma_{\ell,m}$ measures the effect of the mth observable characteristic $C_{i,m}$ on the use of appliance ℓ. This variable can be the household socioeconomic characteristics as well as other factors. In this model, $\bar{C}_{K^\ell,m}$ is the mean characteristic for households in group K^ℓ. Therefore, the second term is the adjustment to appliance consumption due to usage on account of other variables. This equation enables us to investigate, for instance, whether high-income households utilize each appliance ℓ more intensively than their low-income counterparts and whether households in areas with low reliability use certain appliances less intensively than those in areas with good reliability.

Given that each household owns K_i^ℓ units of the appliance, we assume each unit has the same energy requirements, and the effect of household characteristics on appliance usage is the same for all K_i^ℓ units. Therefore, the total electricity consumption of appliance ℓ is

$$y_i^\ell = y_{ik}^\ell \cdot K_i^\ell = \alpha_\ell \cdot K_i^\ell + \sum_{m=1}^{M} \gamma_{\ell,m}(C_{i,m} - \bar{C}_{K^\ell,m}) \cdot K_i^\ell + \omega_i^\ell \tag{5}$$

where $\omega_i^\ell = K_i^\ell \cdot \varepsilon_{ik}^\ell$. Given that there are L varieties of appliances, the total electricity consumption of household i becomes

$$y_i = \sum_{\ell=1}^{L} y_i^\ell \cdot D_i^\ell = \sum_{\ell=1}^{L} \alpha_\ell \cdot (K_i^\ell \cdot D_i^\ell) + \sum_{\ell=1}^{L} \sum_{m=1}^{M} \gamma_{\ell,m}(C_{i,m} - \bar{C}_{K^\ell,m}) \cdot (K_i^\ell \cdot D_i^\ell) + \mu_i \tag{6}$$

where $\mu_i = \tau + \omega_i^\ell \cdot D_i^\ell$, and τ is the consumption due to unobserved appliances. Since all the variables in Eq. (6) are observed, we can estimate it by least squares.

In this model, the parameters of interest are α_ℓ and $\gamma_{\ell,m}$. The parameter α_ℓ represents the electricity consumption associated to one unit of appliance ℓ for the mean household. That is, this variable measures how much electricity of a unit of appliance ℓ is expected to consume at the mean household. On the other hand, the parameter $\gamma_{\ell,m}$ are the deviations in consumption from the mean due to usage differences across households. In other words, this method allows us to explain the intensity of appliance usage in terms of *variations* in the different household-level characteristics, for example, income and reliability. Hence, we can also estimate how appliance use is expected to change due to reliability changes.

To estimate the conditional demand model, we use the EICV data described in Section 3. However, this data presents some challenges for studying electricity consumption. First, it does not directly provide household electricity consumption in kilowatt-hours (kWh) but instead reports monthly electricity expenditure. We converted these expenditure values into consumption quantities for each household using the national tariff, as detailed in Appendix A. Nonetheless, the data is susceptible to misreporting and measurement errors, which could impact inference and introduce potential bias (Bruckmeier et al., 2019; Meyer et al., 2018).

4.1.1. Empirical estimates

Table 7 presents the results of our residential electricity consumption analysis. Models 1, 2, and 3 utilize EICV reported consumption data. Model 1 includes only appliance ownership variables, while Models 2 and 3 incorporate additional usage drivers. Model 3 is our preferred model. Robust standard errors are shown in parentheses.

In Model 3, we observe positive coefficients for appliance ownership, except for sewing machines and cameras.[23] The results highlight significant electricity consumption for certain appliances, notably hotplates, fridges, and laundry machines. Specifically, our findings suggest that, on average, households consume 15.6 kWh per month on hotplates, 19.58 kWh on fridges, and 36.6 kWh on laundry machines. Additionally, our estimates indicate that households consume an average of 5.2 kWh per month from television use. Smartphone use is associated with higher electricity consumption compared to feature phones, with households averaging 2.1 kWh per month for smartphones and 0.6 kWh for feature phones. This suggests that smartphones require more frequent charging due to their higher energy demands. Consumption from other appliances is not statistically significant, indicating limited usage by households.

Models 2 and 3 in Table 7 emphasize the importance of usage variations among households in determining electricity consumption. The higher adjusted R^2 values in these models, compared to Model 1, indicate that controlling for appliance usage improves the model's explanatory power. Due to space constraints, we focus on two key variables: household expenditure and electricity reliability. Additionally, we include demographic variables for appliances whose usage is hypothesized to increase with larger household sizes.

The findings suggest a negligible impact of reliability on appliance use; Model 3 indicates that monthly electricity consumption for feature and smartphones decreases by 0.003 kWh and 0.004 kWh, respectively, with each additional outage.

While the effect of reliability on appliance use is minimal, Model 3 in Table 7 reveals that higher-income households use televisions and phones more intensively. This could be due to two factors: higher-

[23] However, model 1, which does not account for the intensity of usage, shows negative coefficients for water filters and radios.

Table 7
Electricity consumption analysis.

	Reported Consumption (kWh/month)		
	Model 1	Model 2	Model 3
Communication			
Radio	−0.179 (0.466)	0.257 (0.413)	0.130 (0.395)
Feature phones	1.655*** (0.374)	0.637** (0.271)	0.595** (0.256)
# Outage freq. (number/day)		−0.003** (0.001)	−0.003** (0.001)
# Expenses (log RWF)		0.620 (0.435)	0.792*(0.437)
# Children (number)			−0.186 (0.138)
Smart phones	2.60*** (0.456)	1.897*** (0.407)	2.148*** (0.383)
# Outage freq. (number/day)		−0.003* (0.002)	−0.004*** (0.002)
# Expenditure (log RWF)		1.400*** (0.422)	1.390*** (0.448)
# Children (number)			0.178 (0.189)
Entertainment			
TV	6.172*** (0.665)	5.460*** (0.838)	5.209*** (0.829)
# Outage freq. (number/day)		0.003 (0.004)	0.002 (0.003)
# Expenditure (log RWF)		2.460** (1.004)	2.144** (0.985)
# Children (number)			−0.328 (0.348)
# Seniors (number)			4.005*** (1.501)
Music system	0.633 (2.591)	0.964 (2.092)	1.022 (2.019)
Camera	1.098 (4.007)	−1.150 (3.609)	−0.965 (3.618)
Productivity			
Computer	4.827*** (1.528)	2.445 (1.534)	2.151 (1.417)
# Outage freq. (number/day)			0.014* (0.007)
# Expenditure (log RWF)		1.022 (1.619)	2.069 (1.772)
# Members (number)			−0.607 (0.760)
# Children (number)			0.676 (1.329)
Sewing Machine	−0.451 (0.568)	−0.472 (0.520)	−0.589 (0.544)
Convenience			
Hotplate	24.894*** (7.181)	16.444*** (6.280)	15.601** (6.248)
# Outage freq. (number/day)		−0.023 (0.097)	−0.017 (0.092)
# Expenditure (log RWF)		28.147** (11.555)	29.402** (12.593)
# Members (number)			−2.243 (3.425)
# Females (number)			0.438 (5.911)
Cooker	3.510* (2.039)	1.945 (1.721)	2.023 (1.822)
Fridge	20.419*** (3.186)	19.582*** (3.213)	19.585*** (3.180)
# Outage freq. (number/day)		0.057 (0.039)	0.047 (0.035)
# Expenditure (log RWF)		10.658*** (2.716)	11.079*** (2.607)
Laundry machine	57.440*** (20.267)	38.404** (15.563)	36.675** (15.781)
# Outage freq. (number/day)		−0.202 (0.411)	−0.221 (0.411)
# Expenditure (log RWF)		43.679* (23.832)	43.082* (24.529)
Water Filter	−0.379 (3.000)	0.588 (2.536)	0.774 (2.582)
Number of rooms (lights)	0.568** (0.232)	0.669*** (0.200)	0.713*** (0.241)
Constant	3.536*** (0.812)	4.628*** (0.623)	4.363*** (0.776)
Observations	2706	2706	2706
R^2	0.523	0.603	0.610
Adjusted R^2	0.520	0.599	0.605
F Statistic	226.074*** (df = 14; 2891)	161.962*** (df = 27; 2878)	124.684*** (df = 36; 2869)

Note: White's robust standard error in parenthesis. *p < 0.1; **p < 0.05; ***p < 0.01.

income households may afford more electricity at a given tariff, or they may allocate their time differently compared to lower-income households. The income effect is more pronounced for smartphones than for feature phones, as smartphones have higher electricity needs and are more sensitive to income increases.

The impact of income is also significant for convenience appliances. Model 3 shows that a typical household consumes 15.601 kWh per month from hotplates, with consumption increasing by 29.40 kWh for each additional unit of log expenditure. Higher income is also associated with increased electricity use for fridges and washing machines, likely because lower-income households may face constraints in affording the electricity required to operate these appliances regularly.

4.2. Consumption and reliability

In this section, we examine the effects of grid reliability on household appliance ownership and its subsequent impact on electricity consumption.

4.2.1. Aggregate appliance consumption across all households

This section describes the calculation of aggregate appliance consumption for all grid-connected households in the survey. Using regression estimates from Table 7, we analyze total household electricity consumption by examining both appliance ownership rates and average monthly consumption estimates. For each household i with appliance type ℓ, expected electricity consumption is modeled using Eq. (7), which provides a framework to estimate monthly consumption based on the presence of various appliances.

$$E\left[y_i^{\ell} \mid K_i^{\ell}, C_{i,m}\right] = \begin{cases} 0 & \text{if } K_i^{\ell} = 0 \\ K_i^{\ell}\left(\hat{\alpha}_{\ell} + \sum_{m=1}^{M} \hat{\gamma}_{\ell,m}(C_{i,m} - \bar{C}_{K^{\ell},m})\right) & \text{if } K_i^{\ell} > 0 \end{cases} \quad (7)$$

Using this model, we compute the monthly aggregate consumption for each appliance type, focusing on commonly owned items like smart-

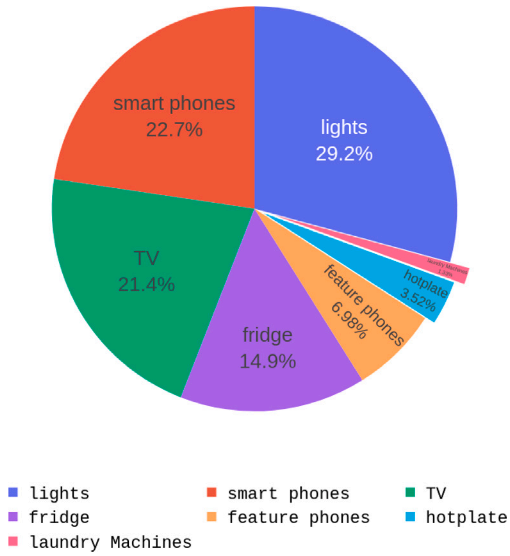


Fig. 12. Aggregate household consumption.
Note: This figure illustrates the proportional contribution of each appliance type to aggregate household electricity consumption across all grid-connected surveyed households.

phones, televisions, lights, feature phones, fridges, and hotplates[24]. This aggregation relies on the expected monthly appliance demand combined with ownership rates across households in the survey. The results, shown in Fig. 12, reveal that widely owned appliances, specifically lighting, smartphones, and televisions, constitute the largest share of the aggregate consumption of household electricity. In contrast, high-energy appliances such as fridges and hotplates contribute less to total consumption due to lower ownership rates, particularly among lower-income households.

We further estimate monthly household-level consumption, where the most commonly owned appliances, phones and lights, result in relatively low consumption levels for many households. Our findings show that the median household consumes approximately 6.3 kWh per month (consumption 15.61 kWh for the average household). For comparison, data from the Rwanda Energy Group reports a higher median monthly consumption of 11 kWh in 2017 (Mugyenyi et al., 2025). This discrepancy suggests limitations in our dataset, which may lack a full inventory of household appliances (e.g. our model does not explain the full variation in the data). Common devices such as electric kettles, irons, and security lights are not captured in our survey, potentially leading to an underestimation of actual household consumption.

Overall, the analysis highlights how appliance ownership patterns drive aggregate consumption: more widely owned but lower-energy appliances contribute significantly to total consumption, whereas high-energy appliances, despite their higher individual usage rates, have a limited impact on aggregate consumption due to their lower prevalence.

4.2.2. *Quantifying reliability effects on appliance consumption*

In the second part of the analysis, we combine the point estimates from Fig. 10 with Eq. (7) to model changes in average household consumption under improved reliability scenarios.

We first modeled how appliance ownership would change in three scenarios: (1) improvement in the reliability of one unit for both low- and high-income households; (2) improvement of one unit for high-income households; and (3) improvement of one unit for low-income households. For each scenario, we used the point estimate presented in Fig. 10 to estimate the number of households that would adopt new appliances for both the low- and high-income samples. This was done by calculating the share of new adopters based on the point estimates and the number of households in our sample.

Given that this analysis only determines the number of potential adopters, we performed 10,000 random draws from households that do not own the key appliances to determine the new adopters. In each simulation, a different pool of potential adopters is determined capturing the fact that usage is different given households' characteristics. In the last step of this simulation exercise, we use the simulated structure for appliance ownership, Eq. (7), and estimates presented in Table 7, to predict the expected change in average monthly consumption relative to the baseline scenario presented in Fig. 12.

Results for this simulation exercise are presented in Fig. 13. In our analysis, uncertainty comes from the simulated ownership structure, but uncertainty with respect to the estimated coefficients used in the calculation are not accounted for.

4.2.3. *Implications for resource allocation in grid reliability improvements*

From the results in Fig. 13 we can observe that the expected change in consumption from reducing the daily frequency of outages for high-income households leads to an expected change in average monthly consumption of 5%, but only of 0.3% in low-income households. This is primarily due to their higher ownership of energy-intensive appliances like fridges. In contrast, lower-income households have fewer energy-intensive appliances, resulting in a smaller absolute reduction in consumption under unreliable grid conditions.

Given the disparity in the impact of reliability on consumption across income groups, we argue that limited financial resources for grid reliability improvements should be strategically allocated. Focusing on wealthier households may yield greater returns in terms of aggregate consumption gains, as these households are more likely to invest in and use energy-intensive appliances when grid reliability improves.

We further argue that a targeted investment approach must be complemented by initiatives that incentivize and subsidize electricity consumption among lower-income households. Promoting greater adoption of energy-intensive appliances, such as those for clean cooking, can enhance overall consumption, alleviate energy poverty, and advance equitable energy access. The observed disparities in consumption highlight the importance of addressing the needs of both ends of the income spectrum to achieve a balanced and efficient outcome in Rwanda's energy sector.

5. Discussion

This study contributes to the growing literature on how electricity reliability shapes appliance ownership and usage in low-income settings. Our findings both complement and contrast with those of recent studies in Senegal and India (Cissé, 2025; Khanna and Rowe, 2024).

In Senegal, (Cissé, 2025) evaluates the effects of reliability improvements using utility billing data and two waves of household surveys. The study finds that improved reliability increased appliance ownership by 9%, with effects becoming significant after two years, and raised electricity consumption by 2.6% per additional hour of supply. These gains were driven primarily by new acquisitions of fans, refrigerators, and laptops, with no significant differences in uptake by income group. Our results are broadly consistent in showing that reliability influences the types of appliances owned. However, we do not find a similar increase in overall appliance ownership, due to the dominance of phones and radios in our dataset, and we observe clear income-based heterogeneity in response to reliability, unlike in (Cissé, 2025).

Similarly, (Khanna and Rowe, 2024) analyzes outages in Delhi using household and utility data over five years. They find that an additional hour of outages per month reduces annual electricity consumption by 4.8%. In contrast, both our results and those from (Cissé, 2025) suggest

[24] The number of rooms is used as a proxy for estimating the number of lights in a household.

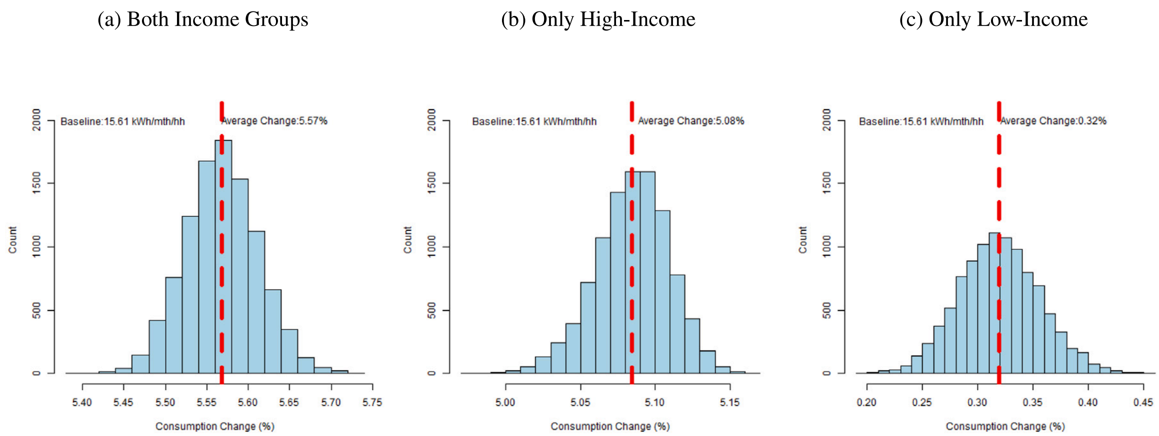


Fig. 13. Consumption and reliability.
Note: Distribution represents the expected change in average consumption at the household level for each of the different scenarios and simulations. The dashed vertical line represents the expected change across the different simulations. Point estimates were used to conduct these estimates, and uncertainty from the estimated coefficients is not accounted for.

that in lower-income SSA contexts, consumption responses to reliability appear to be driven more by appliance acquisition decisions than by changes in usage of existing appliances.

Next, in interpreting income-related patterns in Rwanda, it is important to note the country's Ubudehe system.[25] While household income is categorized through the Ubudehe system, the electricity lifeline tariff, offering discounted rates for consumption under 15 kWh per month, is applied uniformly, regardless of income group. As a result, we do not model subsidy effects by income in our analysis. The income-based heterogeneity we observe is therefore driven by underlying affordability constraints, rather than differential tariff design.

We find that while reliability does influence appliance ownership, the effects are modest. Prior research shows that even among appliance-owning households in Rwanda, electricity consumption remains low (Mugyenyi et al., 2025; Masselus et al., 2024). Subsidies for appliance ownership may offer some benefits, but broader improvements in household incomes and affordability are likely to be more effective in driving both appliance adoption and sustained usage. Strengthening household economic conditions is therefore critical to achieving meaningful and lasting welfare gains.

Several limitations of our study should be noted. First, appliance ownership and electricity consumption data are self-reported and may be subject to recall bias. Second, our analysis is based on a single survey wave, which prevents us from capturing dynamic responses to changes in reliability.[26] Third, while we use lightning frequency as an instrumental variable to strengthen causal inference, potential threats to the exclusion restriction remain. For example, lightning may affect household income through its impact on local economic activity, and variation in grid protection infrastructure (e.g., presence of lightning arrestors) could alter the strength of the first-stage relationship across locations. Additionally, lightning detection data are subject to measurement error, with detection efficiency ranging from 69% to 88% (GHRC, 2023), which may reduce the precision of our estimates. Finally, matching feeder-level outages to households using low-voltage line and GPS data introduces potential measurement error, since outage exposure may vary within a feeder's service area. Nonetheless, we believe our outage data provide a credible proxy for the general reliability conditions experienced by households.

[25] Ubudehe is Rwanda's national system for categorizing households into income-based groups, used to target social programs and monitor poverty. It classifies households into four categories ranging from the poorest (Category 1) to the wealthiest (Category 4).

[26] We do not have access to electricity outage data prior to 2016.

Future research could extend this study in several important directions. First, panel data linking household survey responses to changes in reliability over time would allow for a more precise analysis of dynamic household adjustments to service quality. Second, given the income-related heterogeneity we observe, further work should explore how targeted interventions, such as appliance financing, income transfers, or subsidies, interact with reliability improvements to promote more equitable patterns of appliance adoption and energy use. Finally, the EICV 2016/2017 survey records only the primary electricity source reported by households, without capturing secondary or complementary sources (e.g., solar kits used alongside grid electricity). Understanding how access to multiple electricity sources affects appliance ownership and usage represents an important avenue for future research.

6. Conclusion

This paper investigates the impact of electricity reliability on households appliance ownership and usage in Rwanda, focusing on the well-documented challenge of low appliance ownership and utilization in Sub-Saharan Africa. Utilizing rare access to administrative reliability data linked to household locations, the study provides a unique opportunity to examine how electricity reliability influences both the total number of appliances owned and the ownership of key appliances. We address empirical challenges related to endogeneity and measurement error using a novel set of instrumental variables;specifically, lightning frequency and radiance. These instruments help to mitigate biases, enabling a more accurate assessment of the relationship between electricity reliability and appliance ownership. Moreover, we estimate the conditional demand model to quantify how investments in improving reliability could impact residential electricity consumption. This analysis considers both the effects on appliance ownership and usage, providing insights into how enhanced reliability might influence overall residential electricity consumption.

The findings reveal a nuanced relationship between electricity reliability, appliance ownership, and consumption. While reliability does not significantly affect the overall number of appliances owned, it does influence the types of appliances acquired. Higher outage frequencies are linked to lower ownership of entertainment devices, such as televisions and decoders, especially among low-income households likely constrained by finances and limited usage flexibility. In contrast, high-income households in low-reliability areas reduce ownership of energy intensive appliances, such as fridges and cookers, potentially substituting with alternatives due to the inconvenience of outages. Analysis of electricity consumption shows that widely owned, low-energy appliances, like lighting, smartphones, and televisions, account for a substantial share of household electricity use, while high-energy appliances contribute less overall due to low ownership among low-income households.

Improving grid reliability, particularly for higher-income households, could enhance appliance ownership and electricity consumption. However, reliability improvements alone will not ensure equitable access to electricity's benefits or to the broader social welfare gains that modern appliances can deliver. Complementary policies that promote affordability and encourage appliance ownership among low-income households are critical to achieving inclusive energy outcomes.

By balancing efforts to improve grid reliability with strategies that address affordability and appliance access, policymakers in Rwanda and other Sub-Saharan African countries can foster a more inclusive and sustainable electricity sector, one that supports not only higher consumption but also broader welfare gains in health, education, and gender equity.

CRediT authorship contribution statement

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

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.eneco.2025.108907.

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