COLUMBIA | SIPA
Center for Environmental Economics and Policy

CEEP Working Paper Series
Working Paper Number 33

August 2024

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https://ceep.columbia.edu/sites/default/files/content/papers/n33.pdf

Electricity Consumption: The Role of Grid Reliability in Appliance Ownership and Usage in Rwanda*

Joel Mugyenyi[†] Gabriel Gonzalez Sutil[‡] Vijay Modi[§]

This version: August 5, 2024

Abstract

This study investigates household-level electricity consumption in Rwanda, focusing on the relationship between electricity reliability, residential appliance ownership and usage behaviors. Leveraging a unique dataset and employing instrumental variables for reliability, we explore how households adjust their appliance inventory in response to unreliable grid conditions. Our findings reveal that while electricity reliability affects the types of appliances owned, it does not significantly impact the total number of appliances. Specifically, unreliable electricity reduces, on average, the likelihood of owning low-consumption, affordable devices such as smartphones, TVs, and decoders. Higher-income households in areas with low reliability are more likely to invest in alternative appliances that are less dependent on the grid, such as music systems, while lower-income households tend to favor appliances like sewing machines. Furthermore, our analysis of the conditional electricity demand suggests that reliability has minimal impact on appliance usage among households already possessing appliances. Importantly, income emerges as a major barrier to both appliance ownership and usage. These results suggest that while electricity reliability is an important factor, its impact on residential electricity consumption is limited when affordability constraints due to low income are prominent. This study offers valuable insights for policymakers aiming to enhance residential electricity consumption in Sub-Saharan Africa, emphasizing the need to focus reliability interventions in higher-income areas to maximize benefits.

JEL Codes: Q41; O13; D12
Keywords: Energy; Electricity Demand; Grid Reliability; Electric Appliances; Rwanda

1 Introduction

Access to electricity can significantly enhance the well-being of households in Sub-Sahara Africa but only if they acquire and actively use electric appliances (Lenz, Munyehirwe, Peters, & Sievert, 2017; Richmond & Urpelainen, 2019). Residential electricity consumption is driven by preferences for energy services, which in turn depend on the availability and usage of electric appliances (Auffhammer & Wolfram, 2014; Dubin & McFadden, 1984; Nielsen, 1993). However, the unfortunate reality is that households in Sub-Saharan Africa own few and a limited variety of appliances, even years after electrification efforts (Adesina et al., 2020; Lenz et al., 2017). These deficiencies

*This paper was formerly titled "Electricity Consumption: The role of grid reliability in appliance ownership in Rwanda", publicly available since February, 2024. For valuable feedback and insightful comments, we express our gratitude to Nathan Williams, Jeffrey Shrader, members of the Quadracci Sustainable Engineering Lab and Shrader Lab, and all discussants and participants at the 20th Columbia Africa Conference (2023). We are also deeply thankful to the National Institute of Statistics Rwanda (NISR) for generously providing access to the essential data used in this study.

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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 & Cosgrove-Davies, 2019).[1] This reality underscores the importance of not only expanding electricity access but also increasing the ownership and active utilization of a diverse range of appliances by households in Sub-Saharan Africa. This paper examines the demand for electric appliances, emphasizing their critical role in residential electricity consumption.

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 (Hashemi, 2022; McRae, 2010; Meeks, Omuraliev, Isaev, & Wang, 2023). Theoretical models indicate that the demand for durable goods, like appliances, stems from the services they provide through ownership (Dubin & McFadden, 1984). Thus, households are likely to respond to an unreliable service by refraining from purchasing certain appliances, anticipating that frequent outages will hinder their regular use.[2] Since the current state of the electricity sector in most African countries is characterized by pervasive reliability challenges (Blimpo & Cosgrove-Davies, 2019; Day, 2020; IEA, 2022), the quality of the electricity service can then be a factor contributing to the lack of appliance ownership in Sub-Saharan Africa. However, adoption patterns are less straightforward in poorer and rural contexts typical of Sub-Saharan Africa. First, low reliability might only decrease ownership indirectly by reducing households' income rather than having a direct effect, as households may not fully internalize the quality of the service when deciding on appliance purchases (Dang & La, 2019). Second, households might not conform to theoretical predictions if they are rule-of-thumb, myopic, or bounded rational consumers (Himarios, 2000).[3] Lastly, appliance ownership might not solely be driven by the demand for energy services; social status could also play a role (Ramakrishnan, Kalkuhl, Ahmad, & Creutzig, 2020). Nonetheless, empirical studies on how service reliability impacts appliance ownership are limited due to challenges in accessing reliability data. In this context, the central question remains: How does reliability affect appliance ownership in Sub-Saharan Africa, and consequently, how can investments in reliability influence electricity consumption?

In order to contribute to the literature we assess how the state of electricity reliability impacts ownership of a wide range of appliances in Rwanda using a unique data set and state-of-the-art instrumental variables for reliability. According to the Rwanda electricity distribution plan (REG, 2021), the distribution network suffers from poor reliability and quality of supply which is attributed to under-investment. 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. Appliance data at the household-level was obtained from the Integrated Household Living Conditions Surveys (EICV). Our key explanatory variable is grid reliability which we measure with the frequency of outages per day. We use administrative reliability data from the Rwanda Energy Group (REG) which we link with house locations using non-public GPS location of interviewed household, accessible via an agreement with the National Institute of Statistics of Rwanda (NISR). Additionally, we instrument our reliability measures with lightning activity, specifically,

[1] This reality, as a consequence, diminishes the incentives to connect households and invest in grid expansion. In Rwanda, the main principle adopted for financing transmission lines was an "80-10-10" shared financing policy. Under this policy, 80% of the capital requirements would be sourced from the government and the development partners; 10% from the utility's retained earnings, and 10% from customer connection charges.

[2] An outage is a complete stoppage within the distribution system, preventing end users' consumption of electricity services. Planned outages are either for regular repairs and maintenance, which are typically of limited duration and scheduled for off-peak months. Unplanned outages are typically due to infrastructure breakage, malfunction, and overloaded distribution systems.

[3] For some reason, consumers might not able to account for the future or form expectations with available information (Himarios, 2000)

lightning radiance and strikes frequency. Our models also include household control variables and fixed effects in an additive approach.

Our results demonstrate that households adapt to low reliability levels in Rwanda. A larger frequency of outages per day is associated with a decreased probability of households owning certain appliances, such as smart-phones, TVs, and decoders. These results highlight the significant influence of unreliable electricity supply on household decisions, with families likely factoring in potential disruptions that could affect regular appliance usage. Additionally, our analysis reveals distinct patterns across different income brackets. Higher-income households in low-reliability areas demonstrate a higher likelihood of owning appliances like music systems, while lower-income households in thse areas have a higher probability of owning items such as sewing machines. These appliances rely less on electricity from the grid and are less affected by an intermittent power supply. Interestingly, the frequency of outages does not significantly impact the total number of appliances owned by the household. This underscores that the influence of reliability on the ownership of key appliances primarily affects the type of appliance rather than the overall quantity. These results support the notion that households exhibit forward-thinking behavior in their decisions regarding appliance ownership and that households weigh factors like reliability when making adoption choices. Such insights are crucial for policymakers and utility providers seeking to improve electricity consumption in Rwanda and similar contexts.

From a policy perspective, our results suggest that residential electricity consumption in Rwanda could be influenced through investments in reliability. While our study indicates that the direct effect of outage frequency on appliance ownership is relatively modest - such as a 4% reduction in the probability of owning a television, a 5% reduction for decoders, and a 6% reduction for smartphones with each additional outage per day- these small changes in ownership can potentially translate into substantial impacts on overall electricity consumption. [4] This is especially true if the affected appliances are crucial contributors to residential energy demand. Moreover, investments in reliability can indirectly influence electricity consumption through other channels, such as encouraging the use of newly adopted and existing appliances. Our extended analysis, which models electricity consumption as a conditional demand function, allows us to estimate mean consumption for appliances for the average household Larsen and Nesbakken (2004) while identifying the drivers of appliance usage (Matsumoto, 2016a). We use data from the Integrated Household Living Conditions Surveys (EICV) and complement it with non-public administrative data from the Rwanda Energy Group.

Our extended analysis reveals that the frequency of power outages does not significantly impact appliance usage among households that already own appliances. This finding can be interpreted in a couple of ways. First, households may adapt to unreliable electricity by adjusting their consumption patterns, utilizing appliances primarily when electricity is available. This adaptive behavior suggests that while outage frequency may disrupt usage patterns temporarily, it does not fundamentally alter the overall utilization of appliances over time. Secondly, our results could indicate that the duration of outages, rather than their frequency, could play a more critical role in influencing appliance usage. Longer outages may pose greater challenges to households, impacting their ability to use appliances effectively even if outages occur infrequently. Therefore, reducing the frequency of outages would have limited impact in augmenting household-level consumption for those already possessing appliances. We leave the study of the mechanisms behind our results for future research.

We contribute to the literature in several ways. The existing literature on households' appliance ownership has predominantly examined the relationship between household's income and

[4] It is important to note that the modest impact of outage frequency on appliance ownership may stem from several factors. For instance, households might not heavily prioritize future reliability when making decisions. Additionally, they may have inaccurate expectations about grid reliability or face budget constraints that limit their ability to invest in appliances despite improvements in reliability.

the adoption of specific appliances, anticipating their role in driving household electricity demand growth (see Auffhammer and Wolfram (2014) and Gertler, Shelef, Wolfram, and Fuchs (2016)). Nonetheless, considerable variability in appliance ownership persists across income levels, and non-income factors play a crucial role (Debnath, Bardhan, & Sunikka-Blank, 2019; Rao & Ummel, 2017). Our findings not only shed light on the influence of reliability on appliance ownership but also present descriptive evidence highlighting the impact of 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 shows 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 (Blimpo & Cosgrove-Davies, 2019; Burgess, Greenstone, Ryan, & Sudarshan, 2020; Meeks et al., 2023). In this sense, understanding residential consumers' responses to experiencing changes in electricity quality has attracted attention by researchers. Meeks et al. (2023) explores appliance ownership and reliability in Nepal, Hashemi (2022) investigates the same in Kyrgyz Republic, and McRae (2010) in Colombia. These studies indicate that households in middle-income countries significantly respond to unreliable services by refraining from purchasing certain appliances. Our study extends this inquiry to low-income countries, 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. Finally, we explore the role of reliability on appliance ownership. Previous studies have only analized the role of family structure and economic status of households in determine appliance usage (see Matsumoto (2016a)).

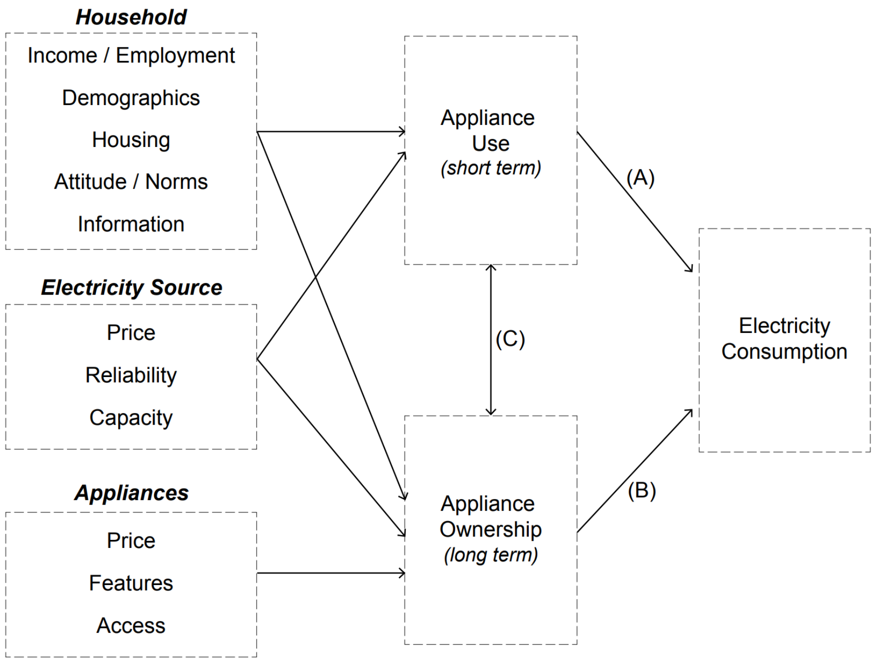
Understanding residential consumers' responses to experiencing changes in electricity quality is also important for electricity planning and demand forecasting. In practice, residential electricity demand once households connect to the grid is rarely estimated and residential electricity demand projections typically involve assumptions about average electricity use per consumer or estimate this applying a constant average income elasticity of demand estimates for developing countries (Kemausuor, Adkins, Adu-Poku, Brew-Hammond, & Modi, 2014; Pachauri et al., 2013; Ramana & Kumar, 2009). However, our results suggest that reliability measures should be accounted for in demand and planning models in low-income countries. Indeed, average estimates mask vast heterogeneity.

The subsequent sections of the paper are organized as follows. In the next section, we delve into the existing literature. Section 3 provides an overview of the data employed in our analysis of appliance ownership. In section 4, we outline our methodology and present the ensuing results. Section 5 delves into the examination of the impact of reliability and other factors on appliance-level electricity consumption, elucidating key implications for policy. Finally, in section 6, we present our conclusions.

2 Electric Appliances and Residential Electricity Consumption

This paper examines the demand for electric appliances, emphasizing their critical role in residential electricity consumption (see Figure 1). Electricity itself does not directly enters into households' utility functions; rather, it serves as a critical input that enables electric appliances to provide essential energy services for individuals (Atkeson & Kehoe, 1999; Dubin & McFadden, 1984; Sievert & Steinbuks, 2020). Essentially, households own appliances and utilize them to obtain "necessary" energy services at varying intensities (Dubin & McFadden, 1984; Nielsen, 1993), as illustrated by arrow (A) in Figure 1. It is essential to note that appliance ownership is a prerequisite for appliance use; households cannot utilize appliances they do not own or have access to, depicted by arrow (c) in Figure 1-. Moreover, appliances continue to consume energy passively, even when not actively used, a phenomenon termed energy vampire consumption. This indirect consumption is represented by arrow (B) in the bottom-right of Figure 1. These insights underscore the pivotal role of appliance ownership in shaping patterns of residential electricity consumption.

Figure 1: Determinants of household's electricity consumption



The economic theory of demand for durable goods posits that demand for appliances arises from the flow of services provided by using them, where utility is best characterized as indirect (Dubin & McFadden, 1984). Additionally, households face fixed costs associated with acquiring appliances. Therefore, the optimization problem becomes complex: households must weigh the benefits of each appliance against expectations of future usage, energy prices, and other considerations. Consequently, appliance ownership is expected to be influenced by a multitude of factors in a complex interplay, with various variables impacting households' decision-making processes when purchasing appliances (Lenz et al., 2017). The following section delves into the current understanding of how different socioeconomic and other factors influence household appliance demand, while also highlighting the unresolved questions pertinent to our study.

2.1 Factors Driving the Demand for Electric Appliances

Early work (see Farrell (1954)) assumed an S-shaped relationship between income and the share of households who own appliances in a model based on a log-normal distribution of "acquisition thresholds". A household must save to acquire the appliance, and this delays the appliance acquisition to a higher income. Past a certain income threshold, households become much more likely to acquire appliances[5]. Gertler et al. (2016) show that a rise in income has a linear relationship with ownership of low-level (i.e. low cost) appliances, and the non-linear relationship is only for major appliances as for example refrigerators (i.e high costs). This suggests that households wait

[5] Low-income households do not allocate additional income to acquire energy-using assets

until they have enough income to purchase high cost and long lifespan appliances which are not replaced frequently, but not low cost appliances. This intuition is similar to the one introduced by Khandker, Barnes, and Samad (2009), where households are more likely to adopt simple electric lighting appliances initially and invest in more energy-intensive appliances over time as households are able to save up for appliance purchases.

While most studies examine the impact of total household income on appliance ownership, Matsumoto (2016a) analyses households' income structure and its effect on appliance ownership. The author finds that in double-income households, non-labor income, such as pension income, lowers the likelihood of dishwasher ownership; yet, labor income raises it. Moreover, wives' income, and non-labor income, increase the number of televisions while a husband's income decreases it. Finally, Wolfram, Shelef, and Gertler (2012) explains that households at very low levels of income are less able to self-finance the appliance, and credit constraints is hence important barrier to appliance adoption at lower income levels.

Income is a key predictor of appliance take-up, but non-income drivers might matter as well. Recent evidence from other studies suggests that appliance diffusion can remain low despite rising incomes (Debnath et al., 2019), and that non-income drivers can be important determinants of appliance choice (see Richmond and Urpelainen (2019) for a review). In this context, understanding these drivers can be helpful to identify barriers to appliance ownership and residential energy demand growth within countries. Yet, empirical evidence of these drivers are limited, and since adoption patterns can be less straightforward among relatively poorer rural households, empirical evidence on appliance ownership is important to guide policy-makers and utilities, specially, in Sub-Saharan Africa..

First, ownership of key appliances is expected to be limited under poor housing conditions. Matsumoto (2016a) finds that households owning a detached house have more appliances, excluding PCs and cellular phones. In addition, the authors find that home ownership has a positive impact on the ownership of appliances in Japan. In a similar way, O'Doherty, Lyons, and Tol (2008) found that homeowners are more likely to have more appliances. In certain situation, adoption of appliances might depend on the context and exogenous variables to the household (McNeil & Letschert, 2010). For example, the usefulness of an fan or air conditioner is climate dependent. That is, adoption might depend on climate and geographic variables. Yet, dwelling size and structure has not been extensively studied.

Second, household willingness to adopt appliances is not necessarily straightforward if they wrongly perceive the benefit of using the appliance and have limited information about them. Bos, Chaplin, and Mamun (2018) reviews several electrification programs over different period of times and found that sometimes it takes several years for household to internalize the value of appliance usage. However, households can be persuaded by those individuals already using appliances (Hanna & Oliva, 2015). This effect is know as the "demonstration effect" (Bos et al., 2018). In this context, education might affect ownership of key appliances as more educated household might have more information. Dhanaraj, Mahambare, and Munjal (2018a) recently found that refrigerator ownership was higher among more educated households.

Finally, appliance ownership is expected to be driven by demographic variables, but the evidence of how gender and households' demographics affect appliance ownership is scant on the literature. Rao and Ummel (2017) found that race and religion together, among other household characteristics, help explain the heterogeneity in appliance ownership at lower income levels in Brazil and South Africa. However, religion was not found significant at all by Richmond and Urpelainen (2019) who studies appliance uptake in India. In addition, the author finds that gender of the decision maker is a significant factor affecting appliance choice.

This study focus on the role or power reliability as a key factor driving the demand for electric appliances. Theory suggests that a principle barrier limiting ownership of key durable goods might an unreliable electricity service (McRae, 2010). Indeed, a low quality electricity service limits appliances usefulness, which can reduces the demand for them (McRae, 2010). Previous evidence for middle income countries corroborate this claim (see Meeks et al. (2023), Hashemi (2022), and McRae (2010)). However, such patterns might not be the same for Sub-Saharan African countries. First, low service quality could decrease the ownership of electricity appliances only through lower household's incomes as affordability is a main constraint (Dang & La, 2019). Moreover, previous literature has found that there is a large share of rule-of-thumb, myopic, and bounded rational consumers in general (Himarios, 2000), and hence, one can expect that adoption patterns are not the same in low-income countries. Indeed, Ramakrishnan et al. (2020) shows that end-users base their consumption decisions not only on available budget and direct use value, but also on their social environment. They find that while income and household demographics are predominant drivers of appliance take-up, household's perception of status emerges as a key social dimension influencing the take-up in India. The main goal of this paper is to provide empirical evidence of the role of reliability on households' appliance demand in low-income settings. We do this by studying appliance ownership in Rwanda leveraging a combination of household level survey data and electricity utility data.

3 Data Description

Estimating the relationship between electricity service quality and household outcomes is typically challenging. Measuring electricity relability is difficult due to common data limitations: utilities may not record outages and, if they do, they may lack incentives to share such data (Meeks et al., 2023). As a result, most prior economics research on electricity quality has either employed data on self-reported electricity quality, which is prone to misreporting, or used electricity shortages as a proxy for outages (Meeks et al., 2023).[6] We overcome these data challenge through a novel dataset which combines public data with proprietary data on electricity outages at the feeder level obtained directly from the Rwanda Energy Group (REG).[7]

The proprietary reliability dataset comprises information on electricity outages for feeder lines from 2016 to 2020, encompassing details such as outage duration, date of occurrence, underlying cause of the outage, and the substation and feeder line implicated.[8] The electricity network consists of many long radial feeder lines in Rwanda; in extreme cases, these lines are longer than 300 km.[9] Faults on such feeders would result in wide-spread outages affecting many households. Complementing this information, the Ministry of Infrastructure collects data for a collection of 52,418 low voltage electricity conductor lines. Each of these lines is characterized by attributes including its parent substation and feeder line, as well as its inherent nature (whether it is underground or overhead), length, and voltage capacity. By leveraging the corresponding substation and feeder line designations, we link outages at the feeder lever with low voltage conductor lines which we use to estimate outages for each individual low voltage line. The geographical distribution of these lines is visually depicted in Figure 2.

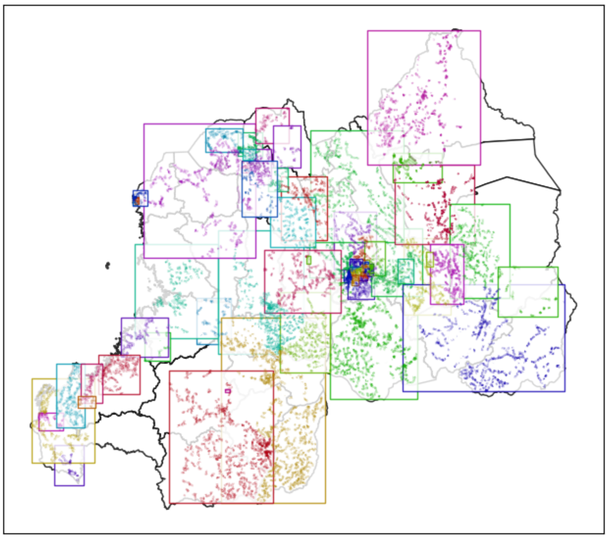
[6] A power outage entails the temporary disruption of electricity supply, affecting either a portion or the entirety of a power grid. Various factors, such as an imbalance between demand and supply, can contribute to the occurrence of a power outage. In contrast, a power shortage occurs when the existing electricity supply falls short of meeting the overall demand.

[7] Rwanda Energy Group Limited (REG), is a government-owned holding company responsible for the import, export, procurement, generation, transmission, distribution and sale of electricity in Rwanda

[8] The number of unique feeders in each year are as follows: 53 in 2016, 63 in 2017, 73 in 2018, 92 in 2019 and 77 in 2020. The reason for these changes is that grids are updated every year meaning that new feeders are getting added, or long feeders are being divided.

[9] An electricity feeder line is a power line that carriers electricity from a substation to individual customers or smaller substations.

Figure 2: Distribution Feeder lines



*Note: In the plot, the lines sharing the same feeder affiliation are represented by the same color, and a bounding box is drawn around them to show each feeder's coverage area. The areas of coverage of feeders further from the capital, Kigali, which is at the center of the country, tend to be larger than those closer to Kigali. The smallest feeder has an area of 1.25*km^2 *while the largest feeder covers an area of 3320*km^2*.*

In the last step, we assign the grid reliability statistics to each household. For this, a collaborative effort was initiated in conjunction with the National Institute of Statistics of Rwanda (NISR).[10] The primary objective of this collaborative endeavor was to establish a closest-distance association between the geographical locations of households and the network of low-voltage lines. To realize this objective, a meticulous process was undertaken wherein household GPS coordinates were matched to the nearest low-voltage distribution line within a proximity range of 800 meters. This specific range was determined in alignment with the prevailing connection policy enforced by the utility company, which delineates that low voltage connections are confined to within an 800-meter radius of the nearest distribution transformer (REG, 2020). In case the GPS locations of a low-voltage line are missing, we use the closest medium-voltage line that would supply a low-voltage line connection to a household. After this proximity-based matching process, each individual household was duly assigned the pertinent outage statistics attributed to the matched feeder line.

We combine this data with public information on household characteristics and appliance ownership. The Integrated Household Living Condition Survey (EICV) is a nationwide cross-section survey initiated in 2000 and conducted every five years. We used the most recent survey, which was completed in 2016/2017. The data was gathered using questionnaires conducted over a 12-month cycle from October 2016 to October 2017.[11] At the national level, there were 1,260 sample villages and 14,580 sample households.[12] In the urban strata, there are 245 sample villages and 2,526 sample households; in the rural strata, there are 1,015 sample villages and 12,054 sample households. 540 households are sampled from the 3 districts comprising the capital city Kigali. From the remaining 27 districts in the country, 480 households are sampled.

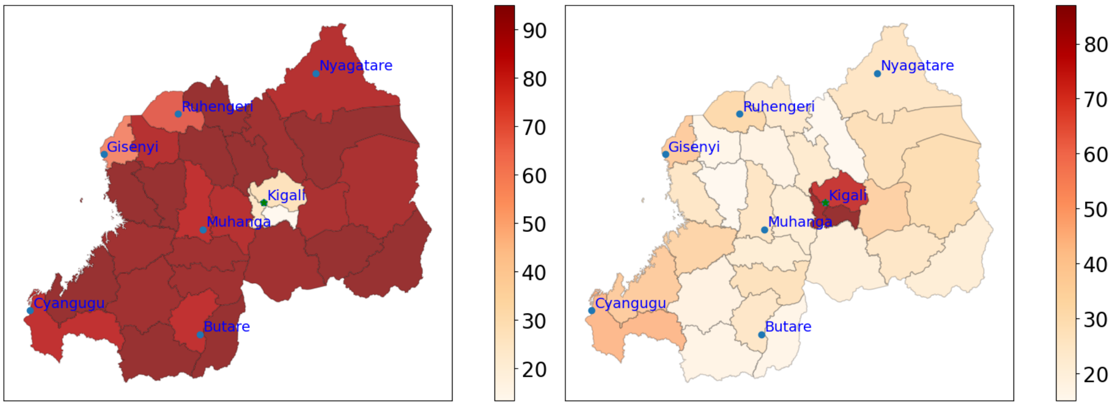
[10]The National Institute of Statistics of Rwanda (NISR) does not disclose household GPS coordinates in the public domain. Therefore, a dedicated visit to their headquarters in Kigali, Rwanda, was essential to securely execute this alignment procedure within their internal systems

[11]The 2016/2017 EICV data was collected in 10 cycles in order to represent seasonality in the income and consumption data.

[12]The 2023 census has found more than 3 million households in Rwanda.

The EICV inquiries surveyed households about the following appliances: radio, mobile phones, televisions, satellite dishes, decoders, music systems, computers, printers, laundry machines, electric fans, fridges, hotplates, and cookers. We study appliance ownership for grid-electrified households. The survey defines electricity access as a household with a grid connection or access to another technology, including solar, batteries, etc. In the survey, 9,775 households do not have access to electricity, and 4,799 households have access to electricity (33% of surveyed households). Of those with access to electricity, 3,600 are connected to the electricity grid. Over 70% of sampled households in Kigali report having access to an electricity source, but the electricity access rate is much lower in the rest of the country, as shown in Figure 3.

Figure 3: Spatial distribution of survey



(a) Share rural households　　(b) Share electrified households

Note: Figure (a) presents the concentration of rural households by district, and figure (b) shows the electrification rate of the sampled households by district. The dots show major cities in the country; the capital city, Kigali, is at the center of the country. Households sampled from the three districts comprising the capital, Kigali, are predominantly urban (Kicukiro, Gasabo, and Nyarugenge). Rubavu district, which hosts Gisenyi, a major commercial hub bordering the Democratic Republic of Congo, has the next highest concentration of urban households outside of the capital, Kigali. The rest of the districts in the country are predominately rural.

Using this data, we constructed several appliance ownership measures following Richmond and Urpelainen (2019) and Matsumoto (2016a). First, we calculated the total number of appliances owned by each household. Second, appliances were categorized according to the service provided (i.e., household usage), capital cost, and wattage level.[13] The categorizations are shown in Table 1. Note that these categories are also associated with electricity consumption. Appliances in category 4 are expected to consume more electricity due to higher wattage requirements. Finally, we generated two distinct variables to capture aspects of household appliance ownership: a binary variable indicating whether a household possesses a particular appliance and a numeric variable representing the quantity of each type of appliance owned by the household. The utilization of the binary variable is motivated by the understanding that ownership of at least one unit of each appliance type reflects the household's inclination to invest in that specific category. Concurrently, the second variable quantifies the extent of ownership for each appliance within the household.

[13]The wattage of an appliance refers to the amount of electrical power it consumes or uses. It is measured in watts (W)

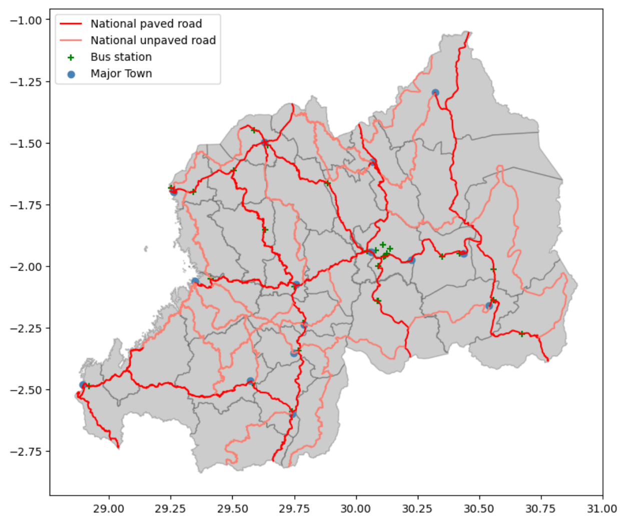
Table 1: Appliance Categories

Category	Appliance(s)		Cost	Use	Wattage
0	No appliances		-	-	-
1	Analogue 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

The EICV survey contains information on households' well-being and expenditure, including living conditions, education, health, housing conditions, consumption, deposits, and loans. We use this information to construct income and non-income drivers at the household level, including household composition (number of females, children, seniors, and age and nationality of the head of household), house ownership (type of house, years in the dwelling and whether the household is the owner or not of the house), as well as several income variables including expenditure, savings, and job stability.

Simultaneously, we use information on house locations, particularly access to markets and major cities. The key issue in accessibility measurement is the definition of the cost distance, which employs the geographic principle of "*friction of distance*", which posits that there is a cost associated with traversing any location, and this cost correlates with distance. We compute the distance from each household to the nearest major city and market to operationalize this concept. Geospatial data about economic infrastructure facilitate this calculation, encompassing commercial centers and major cities, as illustrated in Figure 4, sourced from the Ministry of Infrastructure of Rwanda. In our analysis, we opt for the Euclidean distance, representing an unconstrained straight line, as opposed to alternative measures like Geodesic distance, where travel is constrained to the surface of a sphere. This choice is deliberate, as these alternative measures exhibit a high degree of correlation with the Euclidean distance and convey an equivalent amount of information.

Figure 4: Transport and major towns in Rwanda

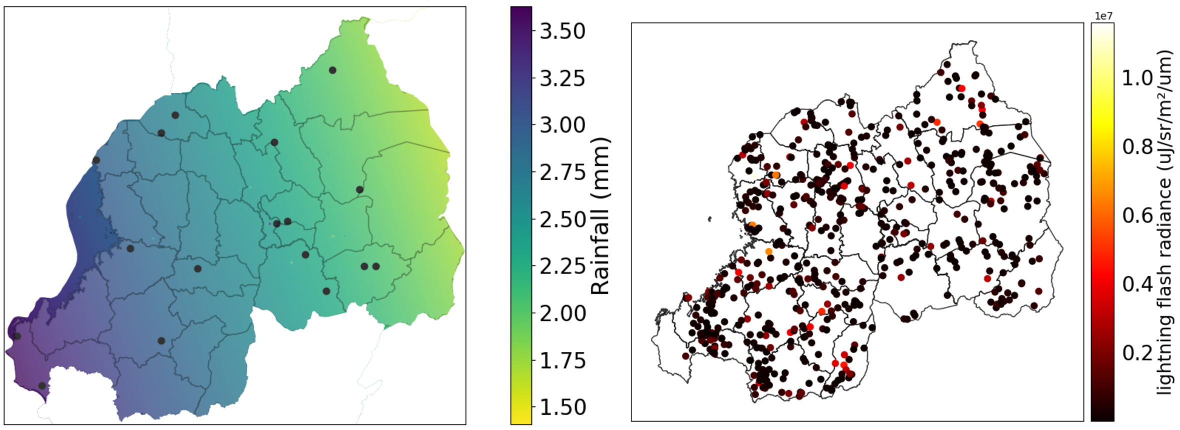


Finally, we use rainfall and lightning data to characterize weather and lightning activity in different country regions. We obtained rainfall data from the Rwanda Meteorology Agency, which monitors and maintains datasets on weather and climate patterns in Rwanda. The agency has a data request portal through which researchers and other academics can request datasets spanning the last forty years. Through the data request portal, we obtained forty years of daily rainfall data from eighteen rainfall stations spread across the country. We calculated the average rainfall at each point in the country using geostatistical interpolation technique explained in Appendix I. The locations of the rainfall stations and the resulting distribution of average rainfall are presented in Figure 5 (a). We observe that the east is drier than the west, where rainforest is more common. These results are consistent with the values reported by the Rwanda Meteorological Agency[14].

Instrumental variables for assessing reliability were derived from lightning data, utilizing the Tropical Rainfall Measuring Mission (TRMM) Lightning Imaging Sensor (LIS) satellite dataset.[15] Specifically designed to observe and analyze lightning activity in tropical regions, the TRMM mission, a collaborative effort between NASA and the Japan Aerospace Exploration Agency (JAXA), was operational from 1998 to 2015 (Blakeslee, 1998). For this study, we use the last three years of lightning data from 2013 to 2015 to obtain the frequency, location, and intensity of lightning events across Rwanda.

Our dataset contains 592 lightning events, including all the flashes (strikes) recorded by the imaging sensor. Figure 5 (b) visually presents the distribution of lightning strikes across Rwanda during 2013-2015, illustrating the widespread occurrence of strikes throughout the country. Leveraging this data, we allocated lightning event statistics to the feeder region using bounding boxes as depicted in Figure 2. We calculated the average yearly 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.

Figure 5: Rainfall and lightning activity



(a) Mean annual rainfall (mm)

(b) Lightning Events (2013-2015)

Note: Figure (a) presents the mean rainfall in Rwanda. Each dot is one weather station recording data on rainfall. Figure (b) presents all the lightning strikes in Rwanda. Each dot is a unique lightning flash recorded by the satellite TMMR, while the color shows the strike's intensity.

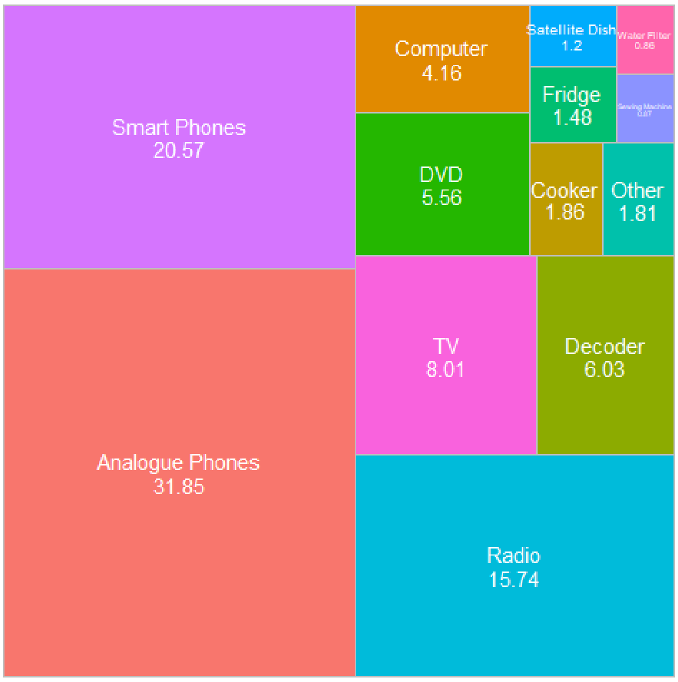
[14] https://www.meteorwanda.gov.rw/index.php?id=30

[15] Instrumental variables are used in statistical analysis to address endogeneity by providing a substitute variable that is correlated with the endogenous explanatory variable but uncorrelated with the error term, ensuring consistent estimation of regression coefficients.

3.1 A Closer Look

From October 2016 to October 2017, our sample of 3,600 grid-electrified households owned a total of 15,510 appliances recorded in the data. Figure 6 shows the composition of this stock of appliances. We categorize mobile phones with internet access as smartphones and those without as analog phones. Figure 6 shows that our sample's total stock of appliances is mainly composed of mobile phones, radios, and televisions(TV). This observation is consistent with previous literature for Rwanda and Sub-Sahara Africa (Bos et al., 2018; Lenz et al., 2017; Muza & Debnath, 2021).

Figure 6: Composition of appliance stock Rwanda



Note: This figure represents the share of appliances owned by a sample of 3,600 grid-electrified households in Rwanda. "Other" appliances include printers, cameras, electric fans, hotplates, music systems, and laundry machines.

Figure 6 provides no insights on household appliance ownership. For this reason, Table 2 presents the number of grid-electrified households that own at least one appliance. The table shows that almost 4% of the households own no appliances, signifying a noteworthy yet modest fraction reliant solely on electricity for lighting in their residences. Among households with at least one appliance, the data indicates an average ownership of 4 appliances, with a maximum of 27 appliances owned by a single household. Remarkably, 86.70% of the households possess more than one appliance. The table also shows the penetration rates and the number of units owned for various appliances identified in the EICV dataset. Radios and mobile phones are prevalent possessions among households; however, other appliances exhibit lower ownership rates. Additionally, for households owning a particular appliance type, the average ownership is typically one unit, except for mobile phones, where the average ownership is nearly 2 per household. This observation will be important in determining the approach to modeling appliance ownership.

Table 2 shows that appliance ownership is limited both in quantity and variety in Rwanda. To understand this reality, Figure 7 presents the composition of appliances owned by households across the different appliance categories defined in Table 1. Figure 7(a) shows the share of households who own at least one appliance for each category; Figure 7(b) presents the distribution of units per category for those households who own at least one appliance for each category. Both

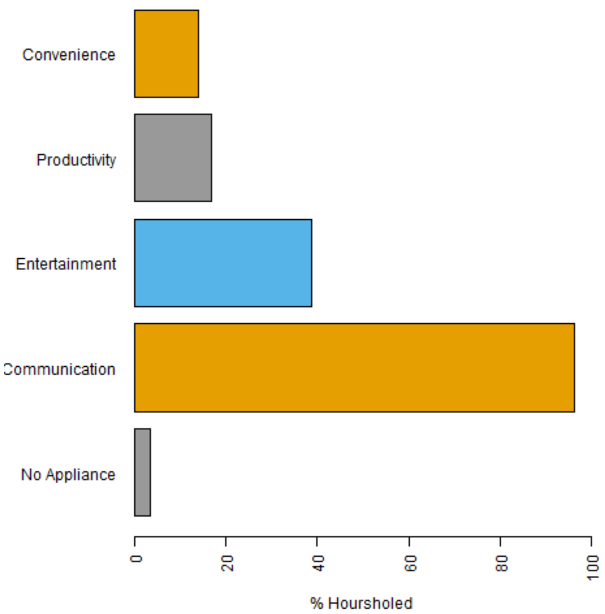
Table 2: Appliance distribution among electrified households

	Penetration		Households who own the appliance				
	Number	%	Mean	St. Dev.	Min.	Max.	HHs > 1 (%)
Any	3,480	96.670	4.440	3.330	1	27	86.70
Analogue Phones	2,955	82.080	1.840	1.100	1	11	52.83
Radio	2,324	64.560	1.150	0.430	1	5	13.08
Smart Phones	1,976	54.890	1.770	1.100	1	10	49.04
TV	1,322	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

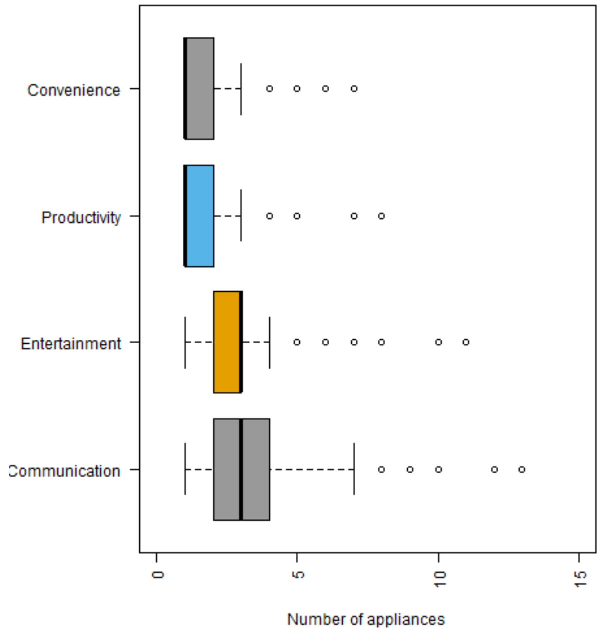
Note: The values in this table were calculated using the 3,600 grid-electrified households in the EICV sample. The number of appliances was only calculated for households with at least 1 appliance of each category.

plots illustrate a clear dominance of communication and entertainment appliances over other categories. This suggests that a few households have ascended the appliance ladder towards more expensive and electricity-consuming devices. Few households possess convenience and productivity appliances, and the number of units owned by those households is also lower for these two categories compared to communication and entertainment appliances.

Figure 7: Ownership by appliance category



(a) Share of households



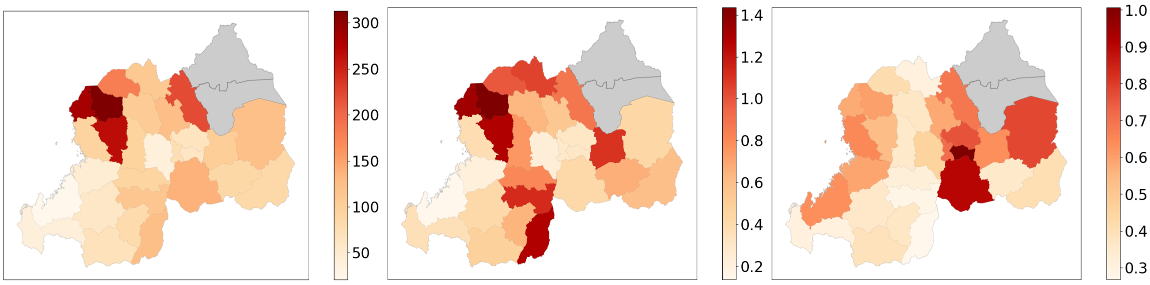
(b) Number of units

The aforementioned adoption patterns suggest that limited affordability is pivotal in constraining households from acquiring more expensive appliances. This outcome is unsurprising, given the prevalence of extreme poverty among several households in Rwanda (Sievert & Steinbuks, 2020). To contextualize, the average prices for cookers and ovens stood at 410 USD in 2018, while refrigerators and washing machines commanded average prices of 540 USD and 420 USD, respectively (Source: Statista Market Insights[16]). Considering that the average annual income in 2018 was 780 USD (Sally Smith & Prates, 2020), a substantial portion of the monthly income is necessitated to acquire these appliances. For some households, this financial constraint translates into the limited use of electricity solely for lighting purposes. Consequently, it stands to reason that higher incomes and improved access to credit could potentially enhance appliance ownership in the country, subsequently contributing to increased electricity consumption.

This paper analyzes non-income factors, specifically reliability, which might be important in explaining residential appliance take-up. Despite having better measures than other African countries, low electricity grid reliability could contribute to limited adoption patterns of certain appliances in Rwanda. Figure 8 presents three statistics characterizing grid reliability at the district level in Rwanda. These variables are the total annual outage time in hours, the average daily outage frequency, and the duration per outage in hours. Note that figure 8 presents district averages for the exposition, but there is significant within district variation which we exploit in our statistical models.

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

Figure 8: Average Reliability metrics per district - 2017



(a) Annual outage time (hrs) (b) Frequency (number per day) (c) Duration per outage (hrs)

Figure 8 reveals large geographic heterogeneity in reliability quality in 2017. Districts located at the nation's geographical center tended to experience a higher availability of electricity, coupled with a reduced frequency of outages in this particular region. On the other hand, households in the southern and northern districts suffered the most frequent outages, while households in the south-central and western parts of the country suffered the longest outages. We are missing reliability data for the two most northern districts in our data set. There are 144 grid-connected households in these two districts, which we dropped from our regression analysis due to this missing data.

In this context, it can be expected that improvements in reliability would increase incentives to buy and/or use appliances, and hence, electricity consumption and welfare impacts from electricity access would increase. Indeed, households could be adapting to low reliability by buying fewer appliances. Moreover, the stock of appliances owned by households might depend on the reliability level in the area where the household lives; for example, household in low reliability ares could favor appliances which rely less on the grid over other type of appliances. The next section explain our empirical strategy to study the role of reliability on appliance ownership.

4 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.

4.1 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. 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[17]

[17]The Poisson model relies on two strong assumptions. First, an event happening in a period of time has a constant

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

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 won't 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, Hall, and Griliches (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.[18] 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.

Equation 1 includes several control variables aiming to control for household characteristics. First, we control for household income using the logarithm of the monthly expenses. Data on expenditures are more reliable than data on income, particularly for households at the low end of the distribution who may have substantial informal and non-monetary income. Expenditure data is highly correlated with income. Additionally, we include a control for the total savings owned by the household, recognizing that savings play a crucial role in determining the household's capacity to finance appliances and signify varying levels of wealth among households. The EICV survey contains details on household employment, such as the nature of contracts and payment frequency. We also incorporate control variables for the average turnover of jobs across household members, recognizing that households with frequent job changes may experience heightened uncertainty in their income sources. Previous authors suggest that uncertainty of future income might affect households' electricity uptake and consumption (Blimpo & Cosgrove-Davies, 2019).

Next, we control for several demographic variables at the household level. First, we control for the gender of the decision makers with a dummy variable, which takes value 1 if the head of the household is female. Households with female decision-makers may exhibit distinct intra-household dynamics, influenced by historical roles where women have traditionally been primary caretakers with limited involvement in other facets of Rwandan society (Izabiliza, 2003). Additionally, women tend to exhibit lower levels of expenditure, which are likely to impact and curtail appliance adoption (Richmond & Urpelainen, 2019). We also control for the number of children,

probability (stationarity). Second, the model assumes that the occurrence of an event does not affect the probability of a second event of happening (indendependence). Under these assumption, the conditional variance is the same as the conditional expectation (equidispersion).

[18]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 minutes in the period 2016/2017 with a standard deviation of 7.4 minutes.

women, and senior members in the household. Given the direct health impacts of indoor air pollution from cooking, lighting, and heating in rural contexts, seniors, women, and children are particularly vulnerable. Acknowledging their heightened susceptibility, we recognize that realizing the benefits of improved indoor air quality may require overcoming financial and informational barriers (Richmond & Urpelainen, 2019).

The level of education and skills at the household level can be an important driver of appliance ownership. (Dhanaraj, Mahambare, & Munjal, 2018b) recently found refrigerator ownership was higher among more educated households. Enhanced education levels may afford individuals greater knowledge about appliances and their applications. Given that these variables can exhibit geographical variations, potentially correlated with reliability, we introduce a dummy variable that takes the value of 1 if the head of the household has attended school. Additionally, we include two supplementary dummy variables: one indicating the presence of a business within the household and another signifying the involvement of household members in high-skill occupations.

We also control for house characteristics and access to major towns and markets. Limited access to major towns and markets may result in reduced exposure to household appliances and commerce (Richmond & Urpelainen, 2019), making it more likely that households with such access are inclined to acquire certain appliances. Firstly, we introduce a dummy variable, taking the value of 1 if the household is located in a rural area, as these areas typically exhibit smaller exposure and access to appliances compared to urban areas. Secondly, we incorporate the Euclidean distance to the nearest major town and trade center. Furthermore, we address house characteristics. We include the number of rooms, recognizing that larger households might possess the same appliance multiple times. Next, we introduce a dummy variable for houses with multiple buildings, reflecting the potential for duplicated appliances. Considering the dynamic nature of appliance ownership, household owners are more likely to acquire less easily moved appliances, so we incorporate a dummy variable, taking the value of 1 if the household owns the house. Lastly, we introduce a variable controlling for the number of years the household has resided in the current location.

We incorporate controls for mean rainfall in the household's locality, recognizing that the utilization of household members' time can be influenced by local climatology Sakah, du Can, Diawuo, Sedzro, and Kuhn (2019a). Certain appliances may have varying levels of value under specific weather conditions (Cabeza, Ürge-Vorsatz, Ürge, Palacios, & Barreneche, 2018). [19] Rwanda, a small tropical country with consistently warm temperatures throughout the year, exhibits four primary climatic regions: eastern plains, central plateau, highlands, and regions around Lake Kivu. Although temperature variations within districts are limited due to the country's small size, variations across disctricts are adequately captured by the district fixed effects. In contrast, rainfall patterns exhibit considerable diversity within districts, ranging from 1,000 to 1,400 millimeters (40 to 55 inches) annually, depending on the area.[20] To account for this, we introduce a control for mean rainfall in the household's vicinity, defined as the average across a 5kmx5km grid.

Finally, we introduce a control for the utility's capacity to restore service, gauged by the average duration of outages in the area. Anticipated to exhibit heterogeneity across regions and correlation with outage frequency, the utility's proficiency in service restoration is crucial. This proficiency, linked to the duration of outages, may influence households' preferences for using certain appliances (McRae, 2010). Utilizing the average duration of outages from 2016 to 2017, we incorporate this control variable to assess the utility's response time.[21] Although the cause of

[19] For example, fans are more valuable in hotter regions, while some appliances, such as TV satellite dishes, can be negatively affected by rainfall.

[20] The wet season months in Rwanda are from March to May and from September to December.

[21] 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.

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 2,706 grid-connected households for which complete variable information is available.

Table 3: Summary statistics (Number of Obs = 2,706)

Variable	Mean	St. Dev.	Min.	Max.
Reliability				
Average duration without electricity (hrs/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

In the second part of the analysis, we empirically study the effect of reliability on the composition of appliances owned by the household, that is, the ownership of key appliances. A challenge in studying individual appliances in our setting is that the penetration rate of most appliances is low, and therefore, the data has an abundance of zeros, surpassing the accommodation capacity of a typical count distribution (Hilbe, 2014).[22] Indeed, the penetration rate for most appliances is below 30% (see Table 2). In this context, we rely on the models which conceptualize the ownership of key appliances as a hurdle model (see Feng (2021) for a discussion).[23] In this model, appliance ownership is viewed as a two-step decision: households initially determine whether to acquire an appliance -a yes or no decision-, and among those willing to invest, they subsequently decide on the quantity to procure. An advantage of this conceptualization is that it allows for the factors determining the ownership of a certain device to differ from the factors influencing how many units are owned (Ščasný & Urban, 2009). Then, this conceptualization allows us to study the decision of owning a certain appliance and the decision to own additional units of a particular kind of appliance as separate decisions.

To model the willingness of a household to invest in different types of appliances, we let y_{ij}^{ℓ}

[22]Excess of zero counts are described as zero-inflated in the statistics literature (Hilbe, 2014).

[23]Such a model overcomes this problem by not constraining the intensive and extensive problem to be the same. Moreover, this model deals with the situation of many zeros

be the number of appliances ℓ owned by the household and define $q_{ij}^{\ell} = 1[y_{ij}^{\ell} > 0]$ as a dummy variable which takes the value 1 if the appliance ℓ exists in the household. Although nonlinear models are commonly employed for discrete choice outcome variables, we opt for linear models in this context. This choice mitigates the risk of incidental parameters, which can arise due to fixed effects and clustering, and improves the interpretability of the results.[24] Although conditional logit models could be used, addressing panel-fixed effects through a likelihood function transformation (see Chamberlain (1980)), certain appliances in our dataset are owned by very few households (see Table 2), constituting what is known as rare events in the literature. This rarity can introduce bias in binary nonlinear models (see King and Zeng (2001)). As our primary interest lies in utilizing statistical models to understand directional and relative relationships between variables, we are less concerned about bias in our linear models with binary outcome variables. Consequently, our fixed-effects models for each appliance type ℓ are expressed as follows:

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

where X_{ij}, Z_{ij}, and α_j are defined as in Equation 1. Each coefficient can vary by appliance in this specification, and we estimate this model as seemingly unrelated equations.

Apart from the question of the presence or absence of a particular appliance in the household, we are also interested in how many appliances of a particular type the household possesses, conditional on having invested in the appliance. Following the Poisson distribution, conditional on having invested at least once in appliance ℓ, the probability of owning y_{ij}^{ℓ} units of appliance ℓ is given by

$$Pr(Y = y_{ij}^{\ell}|X_{ij}, Z_{ij}, \alpha_j, q_{ij}^{\ell} = 1) = \frac{(E[Y|X_{ij}, Z_{ij}, \alpha_j, q_{ij}^{\ell} = 1])^{y_{ij}^{\ell}} \cdot e^{-E[Y|X_{ij}, Z_{ij}, \alpha_j, q_{ij}^{\ell}=1]}}{y_{ij}^{\ell}!} \tag{3}$$

where $E[Y^{\ell}|X_{ij}, Z_{ij}, \alpha_j, q_{ij}^{\ell} = 1] = e^{X_{ij}\beta_{\ell} + Z_{ij}'\Gamma_{\ell} + \alpha_j}$. We then fit a standard fixed-effects count model on the subsample of those who have invested in the appliance under analysis. There are two challenges when estimating equation 3. Firstly, in our sample, households typically own few appliances more than once (see Table 2), implying that a limited number of appliances can be adequately modeled following Equation 3.[25] Secondly, as previously mentioned, only a small fraction of households own the majority of appliances. Given this scenario, the subset of households that have invested in more than one appliance is generally too modest to effectively estimate Equation 3. Consequently, our examination of key appliance ownership mainly revolves around the binary decision of whether the household owns a particular appliance. We exclusively present estimates of Equation 3 for those appliances where we have sufficient observations for estimation and where we anticipate a Poisson distribution, namely, phones, computers, and radios.

4.1.1 Identification

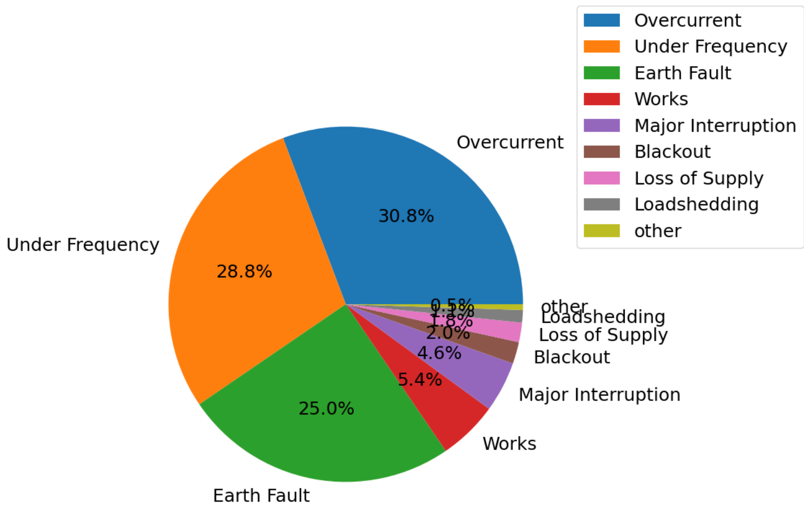
Estimating the relationship between electricity reliability and household outcomes is typically challenging. Service quality is often endogenous and correlated with household characteristics. Two key factors contribute to this complexity. Firstly, the non-random nature of household locations, influenced by regional factors such as weather and economic activity (Pawar & Jha, 2023;

[24] Linear panel data models use the linear additivity of the fixed effects to difference them out and circumvent the incidental parameter problem present in nonlinear models such as the fixed-effect ordered logit model Richmond and Urpelainen (2019).

[25] Following our data, these appliances are phones, computers, sewing machines, printers, cameras, and radios. Modeling as count data other appliances might not be accurate since the data does not follow a Poisson distribution. Maximum likelihood models require fully-specified models, and misspecification leads to violations of the information matrix equality

Sinha, Caulkins, & Cropper, 2018). These factors play an important role in determining the reliability levels of an electric system. Figure 9 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).[26] Radial networks usually have long feeder lines, making them more susceptible to outages.

Figure 9: Main causes of outages



Moreover, inevitable measurement errors occur when capturing power infrastructure quality (Chen, Jin, Wang, Guo, & Wu, 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).

In this context, fixed-effects can eliminate the time-invariant effects, but the endogeneity problem still cannot be solved. Similarly, our control variables fail to capture for unobserved heterogeneity of, for instance, differences in financing schemes within districts (across sectors), or other unobserved variables at the household level which might be correlated with household location. Consequently, our identification strategy relies on the use of two instrumental variables that characterize the lightning activity in the different parts of the country: average radiance of lightning strikes[27] and the number of lightning strikes.[28]

[26] 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).

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

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

Lightning disturbances are usually a major problem for electricity networks and cause service interruptions (Rezinkina, Babak, Gryb, Zaporozhets, & Rezinkin, 2022). For example, lightning damage accounts for about 65% of distribution network failures in South Africa (Andersen & 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). Hence, when a lightning strike hits close to the electricity network, the following events may occur: line overvoltages that exceed the insulation capabilities; transient currents that propagate through the network[29]; damages in transformers, poles, conductors, insulators, substations, and transformers due to high currents, voltages, and intense heat; and temporary disruptions in the grid due to line tripping, automatic reclosing, or protection system operations. Finally, lightning strikes can induce high electromagnetic fields that can affect the operation of the grid.

We instrument the outage frequency with the average frequency of lightning strikes. Previous evidence has found that in areas with high lightning density, the frequency of power outages is higher (Chisholm & Cummins, 2006). Additionally, we introduce a second instrument: the average intensity of the lightning in the region measured by the average radiance of the lightning flashes. The probability of observing a grid failure is directly associated with the intensity of the lightning strikes. Summary statistics are presented in Table 4.

Table 4: Instrumental Variables (Number of Obs = 2,706)

Variable	Mean	St. Dev.	Min.	Max.
Average Lightning Radiance (millon uJ/sr/m^2/um)	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.

Our reduced-form equation for reliability is given by

$$X_{ij} = W_{ij}'\Pi + Z_{ij}'\Lambda + \alpha_j + \varepsilon_{ij} \tag{4}$$

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[30] and the Cragg-Donald Wald-F statistic[31].

[29]Transients create high-frequency harmonics and voltage spikes into the power system. They can disrupt sensitive equipment, leading to malfunctions, faults, or even tripping of protective devices

[30](Staiger & Stock, 1997) establish 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. Hence, we use a value of 10 for the F-statistic as the threshold for the relevance test because we want the IVs to be strongly significant (not just significant). Moreover, we want the first-stage F-statisitc to be above 10 so that the relative bias of 2SLS, relative to OLS, is less than 10% (using the instruments have a real advantage).

[31]Critical values are presented at the bottom of the table

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
Overidentification	
J-Statistic	0.918
$\chi^2(1)$ p-value	0.3379
Observations	2,706
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)

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.[32] Similarly, the intensity of a lightning strike depends on the electric charges inside the clouds. These factors are random, and hence, difficult to correlate with economic and social characteristics which might influence households location (Gunther, 2023). Our assumption, yet, 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 across 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 in Table 5. The results show that we fail to reject the null hypothesis that the instruments are exogenous, meaning they are good instruments.

It's 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. 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 (Rivers & Vuong, 1988; Wooldridge, 1997). In this approach, bootstrap standard errors are employed to accommodate the uncertainty stemming from the first stage.

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

4.2 Empirical Results

This section presents our empirical results. First, we discuss the role of reliability in appliance ownership. Then, we provide descriptive evidence of other drivers of household demand for appliances. In this second part of the analysis, we are cautious about how we interpret the regression results, as coefficients cannot be understood as casual but as a correlation.

4.2.1 The Role of Reliability in Ownership

Table 6 presents the regression results for households' total appliance ownership, specifically highlighting the estimated relationship between total appliance ownership and reliability. We employ conditional fixed-effects Poisson models to analyze the total number of appliances. Each column presents a different specification, and we present the estimated coefficients and the incidence-rate ratios obtained by exponentiating the coefficients. Additionally, we present the results when the instrumental variables are used through the inclusion of the control function. Finally, we explore an alternative model using conditional fixed-effects negative binomial regression. The assumptions of the Poisson regression are quite restrictive: stationarity and independence. This results in the fact that the mean is the same as the variance. Hence, we relax these assumptions in the last columns of Table 6 by allowing for overdispersion.

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	10076.80	7987.79	25062.76	35460.09	83673.86	34979.94
Log pseudolikelihood	-7109.56	-5468.70	-5358.95	-5300.72	-5205.33	-5193.05	-5192.44	-5193.49
Observations	2,706	2,706	2,706	2,706	2,706	2,706	2,706	2,706
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

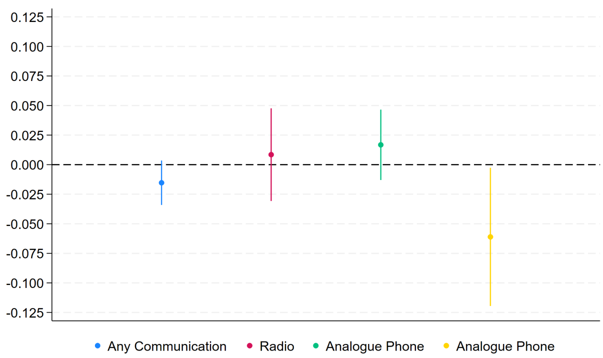
Note: Bootstrapped standard errors in parenthesis. Total number of appliances include radios, phones, TV, decoder, satellite dishes,cookers, fridges, DVDs, music systems, computers and printers, cameras, hotplates, electric fans, laundry machines, water filters and sewing machines. *** p<0.01, ** p<0.05,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

The results in Table 6 underscore the importance of accounting for household characteristics when studying how reliability affects household outcomes. We can observe that the coefficient for the frequency of outages becomes negative as we include additional control variables. Similarly, controlling by the residual of the first-stage regression reduces the magnitude of the coefficients towards zero, indicating that unobservables would bias the coefficient if we do not account for the endogeneity of reliability. In our preferred model, the two-step conditional fixed-effects Poisson model, we observe a negative relationship between the total number of appliances owned by households in Rwanda and our variable of interest, although it is not statistically significant. This outcome aligns with the results from other models that encompass all control variables.

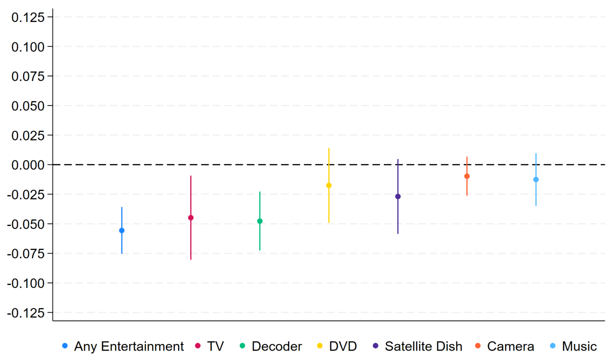
Our results suggest that the frequency of outages does not significantly impact the number of appliances owned by households in Rwanda. One possible explanation is that households might lack information about grid quality or perceive the true system quality differently. If this were the case, we wouldn't observe any effect of reliability on the composition of the appliance stock. Alternatively, the results in Table 6 may be a consequence of affordability constraints. Given the low median income in Rwanda relative to appliance costs, households may experience limited demand for appliances due to budget constraints, and variations in reliability may not significantly influence the overall number of appliances they own. Nevertheless, households can still adapt by substituting between appliances, affecting their appliance stock composition.

Figure 10 presents the change in the probability of households investing in different appliance categories, including key appliances, based on differences in the frequency of outages in their respective areas. The plotted coefficients quantify the disparity in willingness to invest in each category for households residing in areas with varying outage frequencies. Appendix 2 provides all regression results for the variables used in the empirical study for a comprehensive overview.

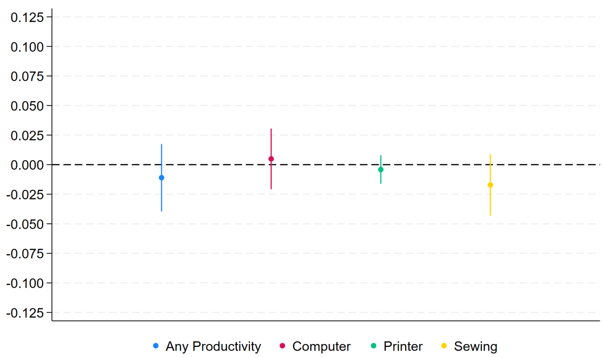
Figure 10: Reliability and Willingness to Invest in Appliances



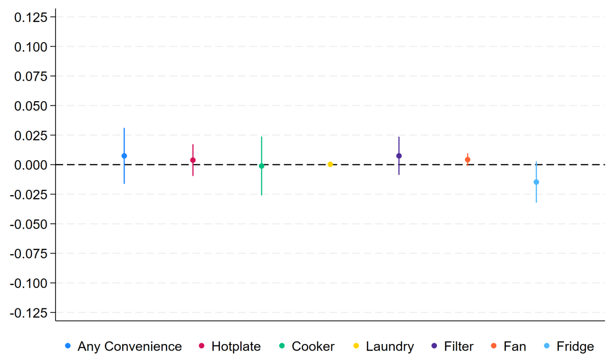
(a) Communication



(b) Entertainment



(c) Productivity



(d) Convenience

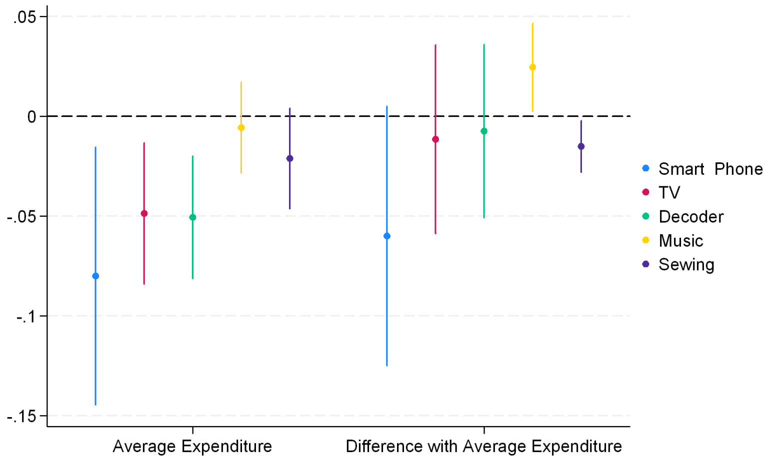
Note: Dots represent the point estimate. Vertical lines are the 95% confidence intervals. For regression tables, please refer to Appendix 2.

As depicted in figure 10, the likelihood of a household investing in a television or decoder diminishes as outage frequency increases. Specifically, our results show that one additional outage per day reduces the probability of owning a television by 4%, and for decoders, the change is nearly 5%.[33] The absence of electricity impedes households from watching television, and since these appliances typically serve as the primary entertainment sources, their ownership is negatively influenced by reliability. The scenario is intriguing for communication appliances, as indicated by Figure 10 (a). In areas with robust reliability, households do not exhibit a notably higher probability of investing in these appliances than those with poor reliability. However, a higher frequency of outages is associated with a lower share of households owning a smartphone -i.e., one extra outage per day decreases the probability of a household investing in this type of phone by 6%. This phenomenon can be attributed to the fact that smartphones are more energy intensive than analogue phones and therefore would require more frequent charging, which becomes challenging in areas with poorer reliability.

Appendix 2 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, Figure 11 presents the estimated coefficients obtained by interacting our reliability variable with the demeaned logarithm of expenditure. The reason for using the demeaned expenditure is that no household has expenditure level zero. We re-run the first stage by using a non-linear function of our instruments given our interaction term to avoid the ”forbidden” regression. The coefficients on the plot below are the second-stage coefficients. The first set of coefficients, denoted as Average Expenditure, depict the changes in the probability of investing in key appliances when reliability is worse by one unit at the average expenditure level. It’s important to note that these coefficients are consistent with those in Figure 10. On the right side of the plot we present the additional effect of outage frequency when for a household which has an income above or below the average income.

Figure 11: Expenditure, Income, and Willigness to Invest in Appliances



The figure highlights nuanced patterns in household appliance investments based on income levels. Specifically, the probability of investing in smartphones, televisions, and decoders decreases for households with average expenditure, and there is no statistical difference for household above or below the average expenditure level. Moreover, the results show that the probability

[33]The larger estimated coefficient for decoders than for televisions can be explained by the fact that televisions, in general, are necessary for decoders.

of investing in music equipment rises for those household with above-average expenditure. Conversely, households with below-average expenditure are more likely to invest in sewing machines. These findings suggest adaptive behavior among households, with a tendency to steer away from appliances heavily reliant on the electricity grid (e.g., smartphones, televisions, and decoders). Wealthier households lean toward music equipment, often equipped with independent power sources, while less affluent households opt for treadle sewing machines, known for their minimal electricity consumption.

Finally, Table 7 presents the impact of reliability on the number of units owned by households for key appliances, focusing solely on appliances with sufficient data to estimate Equation 3. The coefficients for all appliances are negative, except for analogue phones; however, none of the coefficients achieve statistical significance. This implies that the investment intensity in these appliances is not substantially influenced by reliability.

Table 7: Number of Key Appliances Owned by Households

		Phone		
	Radio	Analogue	Smart	Computer
Frequency of Outages (number/day)				
Point Estimate	-0.053	0.086	-0.014	-0.043
	(0.048)	(0.066)	(0.081)	(0.187)
Incidence Ratio	0.948	1.089	0.985	0.958
Control Variables				
Income and employment	Y	Y	Y	Y
Demographics	Y	Y	Y	Y
Head of Household	Y	Y	Y	Y
Dwelling and ownership	Y	Y	Y	Y
Location	Y	Y	Y	Y
District FE	Y	Y	Y	Y
Wald	2684.00	78688.24	48160.64	1012.43
Log pseudolikelihood	-652.00	-1067.03	-711.15	-142.91
Observations	656	829	579	150
Number of district	26	26	26	18
Mean observations per group	25.1	31.9	22.3	8.3

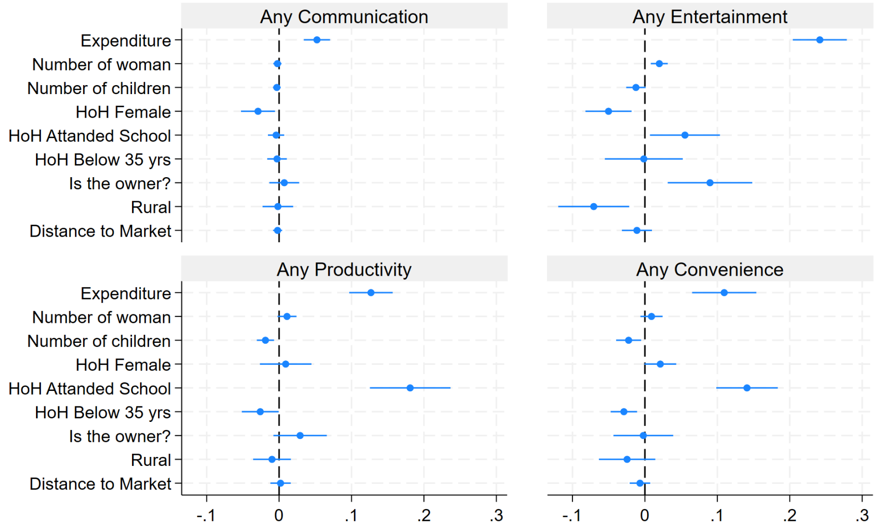
Note: Two-step conditional fixed-effects models were used to estimate these models. Standard errors are boostrapped. *** p<0.01, ** p<0.05, * p<0.1

Overall, our findings indicate that households in Rwanda exhibit forward-looking behavior, adapting to low reliability levels by fine-tuning the composition of their appliance stock rather than altering the total number of units owned. Given the prevalent affordability challenges in Rwanda, households may face limitations in acquiring additional appliances. Wealthier households seem to pivot towards music devices, while less affluent households turn to sewing machines. This adaptive behavior underscores households' strategic optimization of expected utility, factoring reliability into their appliance selection process. Thus, households navigate low reliability by adjusting their appliance mix within similar cost ranges.

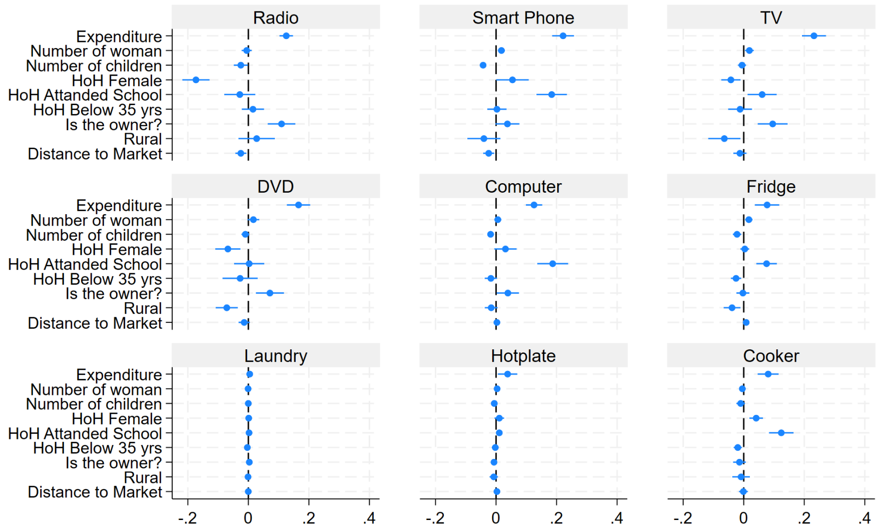
4.2.2 Other Factors Affecting Appliance Ownership

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 3 presents the regression tables. We summarized the results for appliance ownership of key appliances in Figure 12.

Figure 12: Other Drivers of Appliance Ownership



(a) Categories



(b) Key Appliances

Figure 12 shows a substantial positive correlation between household financial variables and appliance ownership, except laundry machines which could be attributed to their high cost or cultural considerations. As shown in the regression tables presented in Appendix 3, households experiencing high job turnover among members tend to possess fewer appliances, indicating the impact of financial uncertainty on household appliance ownership. These findings suggest that programs offering subsidies for appliances could have a profound impact on increasing appliance ownership. However, it is noteworthy that not only income levels but also the associated uncertainty play a crucial role.

Demographic characteristics of the households also show a significant relationship with the dependent variables. 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 entertainment, support with chores, or home-based productive activities. Homes with many children, on the other hand, have a negative significative relationship with the number of appliances in the home as well as the probability of investing in smartphones, fridges, and computers, among others. These households might be expected to devote a larger portion of their expenditure toward their children's needs, like education and health care.

The age and gender of the head of the household play significant roles in determining the household's appliance ownership. The regression table in Appendix 3 highlights a noteworthy pattern: female heads of households and those below the age of 35 exhibit a negative and statistically significant relationship with the total number of appliances owned by the household. This finding may be attributed to existing socioeconomic disparities between genders, where female heads of households could face lower incomes and limited access to resources compared to their male counterparts. Younger heads of households might also experience lower financial stability, contributing to their reduced ownership of appliances. Additionally, the results presented in Figure 12 shed light on distinct demographic based expenditure patterns. Specifically, households led by females tend to own more convenience appliances but fewer entertainment appliances. Notably, female-headed households show a higher likelihood of owning cookers, possibly reflecting traditional gender roles in Rwandan society where women are primarily responsible for household tasks, including cooking.

Education levels of the head of the household significantly influence the types of appliances owned, revealing important insights into household appliance ownership patterns. Specifically, households led by individuals with higher education tend to own more appliances. In addition, the likelihood of a household investing in specific categories of appliances, such as entertainment (e.g., TVs), productivity (e.g., computers), and convenience (e.g., cookers and refrigerators), increases with the education of the head of the household. This positive correlation can be attributed to several factors. Educated heads of households are likely to possess more information about the benefits of various appliances, enabling them to make informed decisions about their utility. Additionally, their higher level of education may equip them with the necessary skills to operate certain appliances, particularly those in the productivity category, such as computers.

Lastly, 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, the stability brought about by long-term homeownership 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.

5 Linking Appliance Ownership to Usage and Electricity Consumption

We extend the analysis by assessing how residential electricity consumption correlated with the ownership of key appliances. Our empirical results suggest that the composition of the stock of appliances owned by households is affected by low reliability. This implies that investment in improving reliability could potentially impact residential electricity consumption in Rwanda. We quantify these empirical results in terms of electricity consumption by estimating the appliance-specific electricity consumption. Although the point estimates from the previous section are relatively low, the overall impact could be significant if the appliances affected by reliability issues represent substantial consumption levels. We follow the conditional demand model proposed by Larsen and Nesbakken (2004) and Matsumoto (2016a). We also use this model to assess the effect of reliability on appliance usage, recognizing that both appliance ownership and usage determine residential electricity consumption. However, there remains a gap in understanding how households specifically use their appliances at there homes (Matsumoto, 2016a), and low reliability might also affect electricity consumption through appliance usage. Therefore, we use our extended analysis to explore the role of reliability in influencing appliance use dynamics.

5.1 The conditional demand model

Since households' electricity consumption depends on both appliance ownership and how these appliances are used once owned, merely regressing electricity consumption on appliance ownership variables would yield biased results. While we could control for factors influencing appliance use in the demand equation[34], doing so would result in biased and inconsistent estimates due to the simultaneous nature of consumption decisions and appliance ownership (Dubin & 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 offers a solution by allowing us to estimate appliance-specific consumption for the average household while accounting for appliance use.

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 k^{th} appliance ℓ for household i is observed through direct metering. The appliance-usage equation is then

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

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 m^{th} 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

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

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

[34]Several factors might affect households' ability to use appliances, including, but not limited to, service characteristics (Blimpo & Cosgrove-Davies, 2019) and household characteristics (Matsumoto, 2016b).

$$y_i = \sum_{\ell=1}^{L} y_i^\ell \cdot D_i^\ell = \sum_{\ell=1}^{L} \alpha_\ell \cdot (K_i^\ell \cdot D_i^\ell) + \sum_{\ell=1}^{L}\sum_{m=1}^{M} \gamma_{\ell,m}(C_{i,m} - \bar{C}_{K^\ell,m}) \cdot (K_i^\ell \cdot D_i^\ell) + \mu_i \tag{7}$$

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 Equation 7 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.

5.1.1 Electricity Consumption Data

To estimate the conditional demand model we use the EICV data explain in Section 3. However, the EICV data presents some challenges for studying electricity consumption. First, the data does not directly provide household electricity consumption in kilowatt-hours (kWh) but reports monthly electricity expenditure. We converted expenditure values into consumption quantities for each household using the country's tariff, as explained in detail in Appendix 3. Secondly, data is susceptible to misreporting and measurement errors, which impact inference and potentially introduce bias (Bruckmeier, Riphahn, & Wiemers, 2019; Meyer, Román-Palacios, & Wiens, 2018). To address this issue, we conducted a validation procedure to address these issues using proprietary data from the Rwanda Energy Group (REG). The REG dataset comprises customer prepaid electricity transactions data collected from 2013 to 2019 for 777,023 unique meter IDs installed between 1996 and 2020.[35] Access to this data was obtained through a data sharing agreement with the Rwanda Energy Group[36].

In order to validate the EICV consumption data, we first matched the survey data and REG data sets to quantify the discrepancy between a respondent's reported electricity expenditure and their actual electricity consumption. Then, we study the relationship between this measurement error and different covariates at the household level. Under the classical measurement errors assumption, a noise measure of the dependent variable will increase the noise of the residual but won't bias the estimates. However, measurement error in the dependent variable that is correlated with the dependent variables (non-classical measurement error) usually does lead to biased estimates (see Bound, Brown, Duncan, and Rodgers (n.d.) for a general framework on the topic).[37] The details of this validation procedure is presented in the Appendix 3 together with the regression results. Our analysis concludes that the variance of the error term, which affects our infer-

[35]In Rwanda, most electricity purchases are carried out using the prepaid electricity framework. Under the prepaid framework, customers purchase electricity units through a mobile telecom network, typically using a mobile or web application if purchasing through the Internet. Otherwise, USSD quick codes can be used for offline customers (Mwaura, 2012). REG maintains a record of each customer transaction with corresponding customer details such as the customer's name, consumer category, transaction timestamps, corresponding taxes and fees, and customer's meter location details such as administrative district and GPS coordinates. Our data includes 85% residential households while the remainder is non-residential (it does not include large industrial meters). The data for residential consumers is used to validate the reported consumption data.

[36]This agreement was signed by e-Guide, a collaboration between engineering research groups at 5 Universities. The following e-GUIDE professors have provided access to this data: Vijay Modi (Columbia University), Nathan Williams (RIT), Barry Rawn (CMU-Africa), and Jay Taneja (UMass Amherst). We are thankful for their support and collaboration.

[37]The bias, in more general cases, can always be thought in terms of regression coefficients from regressing the measurement errors on the mis-measured covariates.

ence, is expected to increase significantly as the variance of the measurement error is 447.60 KWh. Moreover, we find that the measurement error is not random and correlated to ownership status and the number of laundry machines, phones, satellite dishes and printers owned by the home.

In this context, there is a trade-off between the EICV data and the administrative data. The reported data present measurement error which will affect our hypothesis tests and might lead to bias estimates. One solution to this situation would be to use the administrative data for those household we were able to match between dataset. Unfortunately, only 693 households are matched, and hence, we are concern by sample selection bias[38] Appendix 3 also presents the regressions for the sample selection analysis. Unfortunately, selection is not random under our matching process. Consequently, we estimate the conditional demand using analysis on both data sets and compare the results. In addition, we conduct a two-step Heckman selection correction to our model when using the administrative data.

5.1.2 Empirical Estimates

Table 8 presents our residential electricity consumption analysis results. Models 1, 2, and 3 use the reported consumption data in EICV, while model 4 uses the administrative data. Model 1 encompasses solely appliance ownership variables, while models 2 and 3 incorporate usage drivers. Most of the coefficients are robust when comparing between the administrative data and the reported consumption, which can suggest that the attenuation bias is not a big concern. Yet, there are some important differences across the models which can be explained by the different samples we use to estimate the models. Our preferred model is model 3. The reason is that the regression with the administrative data uses sub-samples and estimates might be driven by very few observatios as the conditional demand model assigns households to appliance group K^{ℓ}. Robust standard errors are enclosed in parentheses.

In model 3, we observe positive coefficients for appliance ownership, except for sewing machines and cameras.[39] The results highlight significant electricity consumption for certain appliances, notably hotplates, fridges, and laundry machines. Specifically, our findings suggest that, on average, households consume 16.44 kWh per month on hotplates, 19.58 kWh on fridges, and 38.40 kWh on laundry machines. Comparatively, these estimates for fridges are lower than reported figures for other countries; for instance, research in Japan indicates consumption ranging from 49.33 to 72.08 kWh per month for fridge usage Matsumoto (2016b). Similarly, a study in Ghana reports an average consumption of 31 kWh for refrigerators (Sakah, du Can, Diawuo, Sedzro, & Kuhn, 2019b). Ghana and Japan are admittedly much wealthier than Rwanda.

Moreover, our estimation results show that a household, on average, consumes 5.46 kWh of electricity per month from using a television. Smartphones are associated with higher electricity consumption compared to analogue phones. Specifically, a typical household consumes 1.90 kWh per month for a smartphone and 0.64 kWh per month for an analogue phone. This discrepancy suggests that smartphones require more frequent recharging due to their higher energy demands. It's worth mentioning that the consumption from the remaining appliances is not statistically significant, indicating that only a few households utilize these appliances.

Notably, the results above show that the top three consuming appliances are lights[40], TVs, and smartphones, with ownership rates of 36.7%, 54.8%, for TVs and smartphones, respectively (refer to Table 2). The substantial ownership rates of TVs and smartphones, coupled with their average consumption levels (Table 8), explain their significant shares relative to other household appliances. Conversely, despite an 82% ownership rate, analogue phones contribute minimally

[38] If the sample is truncated in a nonrandom way, then OLS suffers from selection bias.

[39] However, model 1, which does not account for intensity of usage, shows negative coefficients for water filters and radios. It's noteworthy that model 4 also indicates a negative coefficient for radios.

[40] Please note that number of rooms in a household is used as a proxy to determine the number of lights in the household.

to aggregated appliance-level household consumption due to their low consumption levels. Although laundry machines, hotplates, and fridges are classified as demand-intensive appliances, their consumption levels remain minimal owing to their low levels of household ownership.

Table 8: Electricity Consumption Analysis

	Reported Consumption (KWh/month)			Administrative
	Model 1	Model 2	Model 3	Data
Communication				
Radio	-0.179 (0.466)	0.257 (0.413)	0.130 (0.395)	-2.071* (1.152)
Analogue phones	1.655*** (0.374)	0.637** (0.271)	0.595** (0.256)	0.656 (0.693)
# Outage freq. (number/day)		-0.003** (0.001)	-0.003** (0.001)	0.0002 (0.003)
# Expenses (log RWF)		0.620 (0.435)	0.792*(0.437)	2.337** (0.916)
# Children (number)			-0.186 (0.138)	-0.348 (0.342)
Smart phones	2.60*** (0.456)	1.897*** (0.407)	2.148*** (0.383)	0.810 (0.934)
# Outage freq. (number/day)		-0.003* (0.002)	-0.004*** (0.002)	-0.003 (0.003)
# Expenditure (log RWF)		1.400*** (0.422)	1.390*** (0.448)	1.753* (0.983)
# Children (number)			0.178 (0.189)	0.301 (0.487)
Entertainment				
TV	6.172*** (0.665)	5.460*** (0.838)	5.209*** (0.829)	6.184** (2.703)
# Outage freq. (number/day)		0.003 (0.004)	0.002 (0.003)	-0.001 (0.009)
# Expenditure (log RWF)		2.460** (1.004)	2.144** (0.985)	0.758 (3.013)
# Children (number)			-0.328 (0.348)	-0.568 (1.733)
# Seniors (number)			4.005*** (1.501)	5.875** (2.955)
Music system	0.633 (2.591)	0.964 (2.092)	1.022 (2.019)	19.176 (11.995)
Camera	1.098 (4.007)	-1.150 (3.609)	-0.965 (3.618)	-11.917* (6.321)
Productivity				
Computer	4.827*** (1.528)	2.445 (1.534)	2.151 (1.417)	12.549*** (2.471)
# Outage freq. (number/day)			0.014* (0.007)	0.006 (0.015)
# Expenditure (log RWF)		1.022 (1.619)	2.069 (1.772)	6.438* (3.286)
# Members (number)			-0.607 (0.760)	-3.938*** (1.170)
# Children (number)			0.676 (1.329)	0.805 (1.855)
Sewing Machine	-0.451 (0.568)	-0.472 (0.520)	-0.589 (0.544)	3.633 (3.661)
Convenience				
Hotplate	24.894*** (7.181)	16.444*** (6.280)	15.601** (6.248)	-5.248 (11.891)
# Outage freq. (number/day)		-0.023 (0.097)	-0.017 (0.092)	0.151 (0.200)
# Expenditure (log RWF)		28.147** (11.555)	29.402** (12.593)	28.395 (26.385)
# Members (number)			-2.243 (3.425)	-8.282 (8.582)
# Females (number)			0.438 (5.911)	19.179 (16.112)
Cooker	3.510* (2.039)	1.945 (1.721)	2.023 (1.822)	0.729 (2.732)
Fridge	20.419*** (3.186)	19.582*** (3.213)	19.585*** (3.180)	23.665*** (4.885)
# Outage freq. (number/day)		0.057 (0.039)	0.047 (0.035)	-0.003 (0.029)
# Expenditure (log RWF)		10.658*** (2.716)	11.079*** (2.607)	9.444 (5.926)
Laundry machine	57.440*** (20.267)	38.404** (15.563)	36.675** (15.781)	5.409 (7.876)
# Outage freq. (number/day)		-0.202 (0.411)	-0.221 (0.411)	-2.463*** (0.802)
# Expenditure (log RWF)		43.679* (23.832)	43.082* (24.529)	224.090*** (82.272)
Water Filter	-0.379 (3.000)	0.588 (2.536)	0.774 (2.582)	-0.859 (8.401)
Number of rooms (lights)	0.568** (0.232)	0.669*** (0.200)	0.713*** (0.241)	0.540 (0.689)
Constant	3.536*** (0.812)	4.628*** (0.623)	4.363*** (0.776)	1.478 (3.686)
Inverse Mill's Ratio				Y
Observations	2,906	2,906	2,906	496
R^2	0.523	0.603	0.610	0.697
Adjusted R^2	0.520	0.599	0.605	0.672
F Statistic	226.074*** (df = 14; 2891)	161.962*** (df = 27; 2878)	124.684*** (df = 36; 2869)	28.416*** (df = 37; 458)

Note: White's robust standard error in parenthesis. For models 3 and 4, we control for the inverse Mill's Ratio to account for sample selection. In our first step, we regress a dummy which takes value 1 if the household survived the matching procedure on a set of variables which predict selection. These variables are number of members, gender of the head of household, number of children, a dummy which takes value of 1 if the household is rural, number of years in the dwelling, a dummy which takes value 1 if there are multiple households in multiple houses, total savings, distance to major towns, and dummies for the district.
*p<0.1; **p<0.05; ***p<0.01

Models 2 and 3 in Table 8 underscore the significance of usage variations among households in determining residential electricity consumption. The adjusted R^2 for these models is higher compared to that of model 1, indicating that incorporating controls for appliance use enhances the explanatory capability of the empirical model. Given the space constraints in this paper, we concentrate on two variables - households' income and reliability. Our findings suggest that the impact of reliability on appliance use is negligible. Specifically, model 3 reveals that monthly electricity consumption from both analogue and smartphones decreases by 0.003 kWh and 0.004 kWh, respectively, for each additional outage.

While the role of reliability on appliance use is negligible, model 3 in table 8 shows that higher-income households use televisions and phones more intensively. This finding could be attributed to two possible explanations. Firstly, high-income households may have the financial capacity to purchase more electricity at a given tariff level compared to low-income households. The second explanation is straightforward: high-income households may allocate their time differently than low-income households. Notably, the income effect is more pronounced for smart-phones than for analogue phones, with smart phones requiring higher electricity consumption and being more significantly impacted by additional income.

The impact of income is significant for convenience appliances. Model 3 reveals that a typical household consumes 15.601 kWh of electricity per month from a hotplate, and consumption increases by 29.40 kWh for each additional unit of expenditure. Additionally, higher income is associated with increased electricity consumption from fridges and washing machines, possibly because lower-income households may struggle to afford the electricity required to operate such appliances and use them sparingly.

5.2 Quantifying Reliability Changes

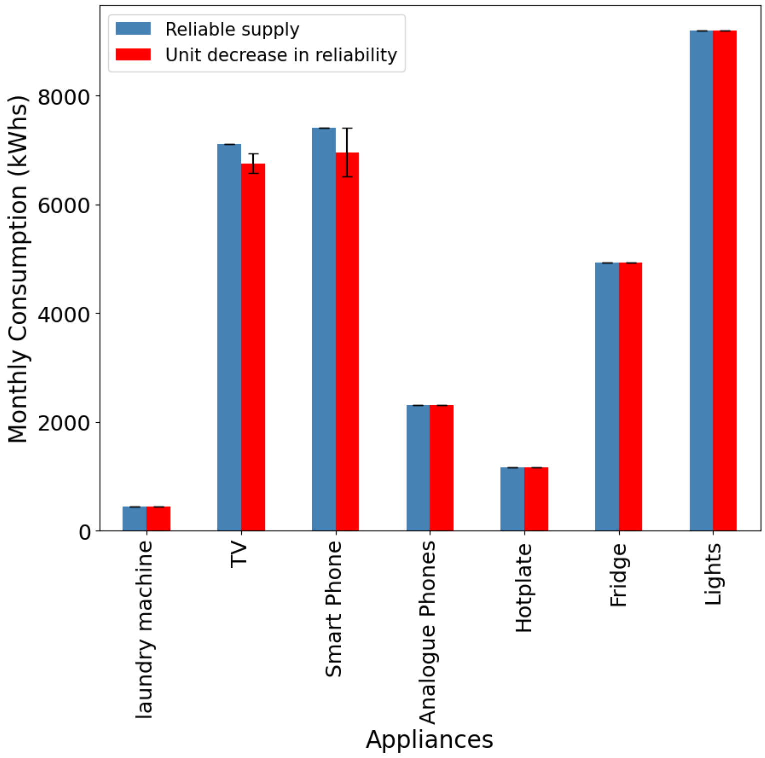
We quantify the effect of reliability investments by estimating the expected electricity consumption from K_i^ℓ units of appliances ℓ for any household i as

$$E\left[y_i^\ell | K_i^\ell, C_{i,m}\right] = \begin{cases} 0 & \text{if } K_i^\ell = 0 \\ K_i^\ell \left(\hat{\alpha}_\ell + \sum_{m=1}^{M} \hat{\gamma}_{\ell,m}(C_{i,m} - \bar{C}_{K^\ell,m})\right) & \text{if } K_i^\ell > 0 \end{cases} \tag{8}$$

where $\hat{\alpha}_\ell$ and $\hat{\gamma}_{\ell,m}$ are the coefficients presented in Table 8, and K_i^ℓ is the number of appliances ℓ owned by household i. Equation 8 provides a framework for estimating the residential electricity consumption of various appliances, considering the characteristics of the specific household. We leverage this equation to quantify our empirical findings from the previous section and draw policy implications. Figure 10 in section 4.2 suggests that a decrease in reliability would lead to reduced ownership rates for TVs and smartphones, on average. Given that these two appliances, along with lights, are the highest contributors to aggregate household-level consumption for the average household (i.e. high $\hat{\alpha}_\ell$), a decrease in their ownership could result in large impacts on the residential consumption.

Using our empirical results and equation 8, we estimate household's consumption at the appliance level for all grid-connected and presented in figure 13. The blue bars represent the baseline level which is the observed consumption; the red bars is the consumption we would have observed if reliability was 1 unit less than the observed one. The number of households selected to not have the appliance was determined following the results from section 4.2, and we assume any household has the same probability of not having the appliance. The vertical lines represents the range for the possible aggregate consumption under this counter-factual scenario. It is important to note that this is a simplified exercise which aims to quantify our results in terms of consumption to provide context to the discussion. A structural model would be required to estimate changes in consumption and welfare gains from reliability investment. Such model exceed the objective of this paper.

Figure 13: Aggregate household consumption



Note: The above figure depicts the consequences of a one-unit reduction in reliability on aggregate household consumption across all grid-connected surveyed households. The combined household consumption is presented at the appliance level. The blue bars represent consumption levels under a reliable electricity supply, while the red bars depict consumption levels following a one-unit decrease in reliability.

From Figure 10 in section 4.2, we observed that a decrease in reliability would lead to reduced ownership rates for TVs and smartphones. Given that these two appliances, along with lights, are the highest contributors to aggregate household-level consumption (Figure 13) 13), a decrease in their ownership results in an average decrease in aggregate household consumption of approximately 800 kWh. According to Joel Mugyenyi (2024), households in Rwanda consumed an average of 22 kWh per month in 2016-2017. As such, a unit decrease in reliability results in a reduction in aggregate consumption equivalent to the aggregate monthly consumption of 36 households. In concise terms, a unit decrease in reliability would have the equivalent impact of loss of consumption for 1% of the households connected to the grid surveyed in EICV2016/2017.

Following our empirical results, it is reasonable to conclude that investments in grid reliability alone may have a limited impact on enhancing household consumption levels. If policymakers aim to boost household consumption, a more effective strategy would involve increasing ownership rates of demand-intensive appliances, such as fridges, laundry machines, and hotplates. Making these appliances more accessible, perhaps through credit schemes, and reducing the operational costs through more affordable tariffs could significantly contribute to elevating household consumption levels. Moreover, to achieve higher levels of residential consumption on the grid, efforts should be directed towards making electricity more affordable for the average household.

6 Conclusions and Discussion

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.

Our results highlight that electricity reliability influences the composition of the appliance stock owned by households in Rwanda. Households, in response to low grid quality, adjust the types of appliances they own based on their energy needs. Specifically, while reliability does not notably affect the ownership of high-consumption appliances such as washing machines and refrigerators, it does reduce the ownership of lower-consumption and less expensive items like televisions, smartphones, and decoders. In this context, we observe that higher-income households are more likely to own music systems, whereas lower-income households tend to own sewing machines. Despite the modest impact of reliability on the ownership of certain appliances, it does not significantly affect the usage of appliances among households that already possess them. Instead, income emerges as the predominant factor influencing electricity consumption, indicating that affordability is a more critical barrier to higher consumption levels than grid reliability.

This paper suggests that improving grid reliability may only have a modest effect on increasing household electricity consumption. A more effective strategy would involve making both electricity and appliances more affordable. This could be achieved through enhanced access to credit for appliance purchases and targeted subsidies to lower electricity costs. Addressing both aspects of affordability holds promise for increasing household electricity usage and expanding energy access. However, it is important to note that this study does not explore other potential impacts of improved reliability, such as the increased ability of households to engage in productive activities, which could boost their income in the medium to long term. Additionally, since reliability is correlated with household location, changes in reliability might affect migration patterns within the country. Furthermore, the paper does not examine the role of reliability in commercial and industrial electricity consumption. These questions are left for future research.

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Appendix 1: Data Description and Cleaning

Integrated Household Living Conditions Survey (EICV)

- Expenditure - The expenditure variable was constructed by consolidating reported expenditure items from surveyed households. Participants were queried about their spending over the past year on durable items like clothes, accessories, furniture, and school-related expenses (uniforms, supplies, and tuition). Monthly expenditures on transport, leisure, health, beauty care, communication, and housing (including rent and electricity) were also elicited. To ensure consistency, all expenditure-related responses were transformed into a monthly cadence and aggregated into a single variable, offering an overview of each household's expenditure level

- Demographics - Several variables from the survey were employed to characterize the demographics of households. These include gender, encompassing the sex of the household head and the overall gender makeup; the highest level of education attained by the household head and members; the age composition of household members (children under 16 and the elderly above 60); details about the dwelling, such as the number of rooms and construction material; and a variable denoting the nationality of the household head.

- Finances - Binary variables were created to identify households involved in various financial activities, including ownership of businesses, employment status of members, presence of debt, savings in a bank account, and receipt of money transfers from friends or family. Another variable categorizes households engaged in either large-scale or small-scale agriculture. The skill level of household members is determined using reported occupation responses and classified into low, medium, or high skill levels according to the Intermation Standard Classification of Occupations ISCO-08. Additionally, the stability of a respondent's job is inferred from the number of jobs held in the recent past.

- Appliance ownership - Households were surveyed about ownership of common household appliances, and binary variables were created to indicate ownership of each appliance within the household. This approach allows for a detailed understanding of the possession of specific household items.

Reliability Data

Reliability and grid infrastructure geo-spatial datasets were provided by the Rwanda Energy Group (REG). The reliability data encompasses reported outages, indicating both the time of occurrence and resolution. Additionally, it includes information on feeder outage causes, reported at the feeder level - the finest resolution on the grid. Each feeder is uniquely identified by a name and originates from a substation. The dataset spans five years, from 2016 to 2020, and is aggregated into a cohesive dataset using feeder names and origin substations to track feeders over time. The geo-spatial dataset contains feeder names, corresponding origin substations, and the spatial extent of each feeder.

Through our collaboration with the National Institute of Statistics in Rwanda (NISR), we integrated REG data with the EICV household survey data. The matching process required our physical presence in Rwanda due to the sensitive nature of the data, and it was conducted on NISR internal computers. For the matching technique, we adopted a straightforward approach. Household reliability was determined based on a household's proximity to a feeder. Each household was assigned the reliability value of the nearest feeder, subject to a constraint: the household had to be within an 800-meter proximity to the feeder. This constraint aligns with REG installation requirements, as households more than 800 meters away from the closest transformer cannot be connected to the grid. This careful consideration helps minimize the probability of erroneously assigning households to distant feeder lines, especially in cases where certain grid lines may not be captured within our dataset.

Rainfall Data and Spatial Interpolation

The Rwanda Meteorological Agency maintains a comprehensive historical dataset of daily rainfall collected at 18 rainfall stations distributed across Rwanda, as depicted in 5 (a). Our study has access to a 40-year daily historical record of rainfall at each station. However, the agency acknowledges occasional gaps in its daily collection of station rainfall data, which are addressed by filling them with derived outputs from satellite images collected at resolutions of 4km by 4km.

To interpolate and estimate rainfall across the entire country, we employ Kriging, a geostatistical technique known for spatial interpolation, prediction, and estimation, as depicted in 5 (a). In this process, the values of rainfall at unobserved locations are estimated using recorded rainfall data from the designated rainfall stations. Kriging involves mathematical modeling of the spatial correlation structure through a variogram, which quantifies the spatial variability of the data. The variogram is then utilized to optimize the weights assigned to observed points when predicting values at unsampled locations.

For the implementation of Kriging, we utilize pykrige, a specialized Python library for Kriging. This library offers various variogram models such as linear, Gaussian, exponential, and power. After visual inspection, we selected a ”power” model for our sample as it provided the best fit to the observed data. Using the modelled variagram, we interpolated the data to the full extent of the country. We then assigned rainfall data to each household given households location.

Lightning Data

The Lightning Imaging Sensor (LIS) is an advanced space-based lightning detection instrument situated aboard NASA's Earth Observing System (EOS) Tropical Rainfall Measuring Mission (TRMM) satellite. Designed to operate seamlessly in both day and night conditions, the LIS records the precise time of lightning occurrences, measures radiant energy, and estimates their locations with exceptional efficiency. As the TRMM satellite speeds through space at an astonishing 7 kilometers per second (nearly 16,000 miles per hour), it provides LIS with a unique vantage point, allowing for observations of a specific point on Earth or a cloud for approximately 90 seconds during each overhead pass.

Despite the relatively brief observation duration, this timeframe is sufficiently long for LIS to accurately estimate the flashing rate of most storms. The instrument's capabilities encompass recording the time of occurrence, measuring radiant energy, and determining the precise location of lightning events within its expansive field-of-view. Notably, the TRMM LIS detection efficiency demonstrates a range from 69% near noon to 88% at night.

The TRMM Lightning Imaging Sensor (LIS) dataset, collected by the LIS instrument on the TRMM satellite, serves as a valuable resource for discerning the distribution and variability of total lightning in Earth's tropical and subtropical regions. This dataset finds application in severe storm detection, comprehensive analysis, and investigations into lightning-atmosphere interactions. With its high detection efficiency during both day and night, the LIS instrument has proven instrumental in advancing our understanding of lightning phenomena (Blakeslee, 1998).

Appendix 2: Regression Tables

This appendix presents the complementary regression tables.

Table 9: Regression Results Communication Appliances

	Any	Radio	Analogue Phone	Smart Phone
Frequency Outages	-0.015	0.008	0.017	-0.061**
	(0.010)	(0.020)	(0.015)	(0.030)
Expenditure	0.052***	0.125***	0.089***	0.222***
	(0.009)	(0.011)	(0.020)	(0.018)
Savings	-0.002***	-0.001	-0.003	-0.004**
	(0.001)	(0.002)	(0.002)	(0.002)
Has business	0.014*	0.061***	0.033**	0.014
	(0.008)	(0.019)	(0.015)	(0.018)
High Skill Job	-0.006	0.012	0.016	0.112***
	(0.004)	(0.026)	(0.015)	(0.023)
Job Instability	-0.029***	-0.019	-0.063***	-0.028
	(0.010)	(0.012)	(0.014)	(0.017)
Number of female	-0.002	-0.006	0.034***	0.018***
	(0.003)	(0.008)	(0.006)	(0.006)
Number of children	-0.003	-0.025**	-0.008	-0.043***
	(0.003)	(0.012)	(0.005)	(0.005)
Number of seniors	-0.044***	0.014	-0.051***	-0.087***
	(0.014)	(0.027)	(0.017)	(0.017)
HoH is female	-0.029**	-0.173***	-0.080***	0.054**
	(0.012)	(0.023)	(0.017)	(0.027)
HoH is Rwandese	0.045	0.095	0.030	-0.079
	(0.035)	(0.076)	(0.067)	(0.062)
HoH High Education	-0.004	-0.028	-0.099***	0.184***
	(0.006)	(0.026)	(0.017)	(0.026)
HoH youth	-0.003	0.015	-0.004	0.003
	(0.007)	(0.019)	(0.016)	(0.016)
Number of Rooms	0.002	0.022***	0.036***	0.011*
	(0.004)	(0.007)	(0.007)	(0.006)
Multiple Households	0.017	-0.015	0.027	0.005
	(0.011)	(0.035)	(0.039)	(0.026)
Mutiple houses	-0.001	0.020	0.001	0.006
	(0.007)	(0.022)	(0.026)	(0.024)
Is owner	0.007	0.110***	0.019	0.038*
	(0.011)	(0.023)	(0.018)	(0.020)
Years in dwelling	0.000	0.002**	-0.001	0.001
	(0.001)	(0.001)	(0.002)	(0.001)
Rural	-0.002	0.028	-0.002	-0.040
	(0.011)	(0.031)	(0.016)	(0.028)
Distance Trade Center	-0.002	-0.025***	0.007	-0.024***
	(0.003)	(0.009)	(0.007)	(0.009)
Distance Town	0.007	0.026*	-0.001	-0.023
	(0.006)	(0.014)	(0.013)	(0.017)
Rainfall	0.103	0.145	-0.043	0.263
	(0.068)	(0.136)	(0.156)	(0.180)
Duration outage	0.000	-0.001	0.000	-0.002
	(0.000)	(0.001)	(0.001)	(0.001)
District FE	Yes	Yes	Yes	Yes
Observations	2,706	2,706	2,706	2,706
R-squared	0.090	0.107	0.150	0.296
Number of district	26	26	26	26

Note: Robust standard errors in parentheses.These are clustered at the district level.
*** p<0.01, ** p<0.05, * p<0.1

Table 10: Regression Results Entertainment Appliances

	Any	TV	Decoder	DVD	Satellite Dish	Camera	Music
Frequency Outages	-0.056***	-0.045**	-0.048***	-0.018	-0.027*	-0.010	-0.013
	(0.010)	(0.018)	(0.013)	(0.016)	(0.016)	(0.008)	(0.011)
Expenditure	0.242***	0.232***	0.177***	0.166***	0.055***	0.021***	0.013**
	(0.019)	(0.020)	(0.015)	(0.020)	(0.011)	(0.004)	(0.005)
Savings	-0.002	-0.001	0.003	-0.000	0.010***	0.009***	0.008***
	(0.001)	(0.002)	(0.003)	(0.003)	(0.003)	(0.001)	(0.002)
Has business	0.062***	0.053***	0.038***	0.056***	-0.006	-0.005	0.002
	(0.014)	(0.014)	(0.013)	(0.014)	(0.012)	(0.007)	(0.005)
High Skill Job	0.022	0.016	0.053**	0.017	0.022	0.017**	0.017*
	(0.031)	(0.028)	(0.027)	(0.030)	(0.018)	(0.007)	(0.010)
Job Instability	-0.044***	-0.046***	-0.021**	-0.040***	0.004	0.016**	0.003
	(0.010)	(0.009)	(0.010)	(0.013)	(0.005)	(0.006)	(0.004)
Number of female	0.020***	0.019**	0.019**	0.017*	-0.000	0.002***	0.000
	(0.006)	(0.007)	(0.008)	(0.010)	(0.004)	(0.001)	(0.003)
Number of children	-0.012*	-0.006	-0.007	-0.010	-0.005	-0.004**	-0.001
	(0.007)	(0.007)	(0.007)	(0.007)	(0.003)	(0.002)	(0.003)
Number of seniors	-0.014	-0.007	0.018	-0.042*	0.016	-0.000	0.002
	(0.019)	(0.018)	(0.019)	(0.024)	(0.018)	(0.007)	(0.004)
HoH is female	-0.050***	-0.042***	-0.034*	-0.068***	-0.005	0.004	-0.008
	(0.016)	(0.016)	(0.018)	(0.021)	(0.010)	(0.004)	(0.008)
HoH is Rwandese	0.009	0.029	-0.018	0.072	-0.011	-0.018	0.027**
	(0.064)	(0.068)	(0.069)	(0.097)	(0.080)	(0.036)	(0.011)
HoH High Education	0.055**	0.061**	0.070***	0.003	0.041***	0.039***	-0.013*
	(0.025)	(0.024)	(0.026)	(0.025)	(0.015)	(0.012)	(0.007)
HoH youth	-0.002	-0.012	-0.051**	-0.027	-0.007	-0.017**	0.004
	(0.027)	(0.020)	(0.021)	(0.030)	(0.009)	(0.008)	(0.006)
Number of Rooms	0.047***	0.041***	0.037***	0.030***	0.015***	0.004	0.003
	(0.007)	(0.007)	(0.008)	(0.006)	(0.005)	(0.006)	(0.002)
Multiple Households	-0.045**	-0.046**	-0.024	-0.017	-0.039*	-0.039***	0.003
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.003)	(0.009)
Multiple houses	0.069***	0.077***	0.044**	0.077***	0.039***	0.029***	-0.026**
	(0.025)	(0.027)	(0.022)	(0.028)	(0.011)	(0.007)	(0.012)
Is owner	0.090***	0.096***	0.081***	0.071***	0.009	0.001	-0.004
	(0.030)	(0.025)	(0.022)	(0.024)	(0.012)	(0.011)	(0.007)
Years in dwelling	-0.000	0.000	0.000	-0.000	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)
Rural	-0.071***	-0.064**	-0.056	-0.071***	-0.024**	-0.007	0.000
	(0.025)	(0.027)	(0.035)	(0.019)	(0.012)	(0.006)	(0.010)
Distance Trade center	-0.011	-0.013	0.005	-0.014	0.001	0.001	0.002
	(0.011)	(0.011)	(0.012)	(0.009)	(0.006)	(0.003)	(0.002)
Distance Town	-0.004	-0.011	-0.015	0.002	0.004	-0.004	-0.004
	(0.009)	(0.010)	(0.010)	(0.012)	(0.007)	(0.006)	(0.006)
Rainfall	0.263**	0.259**	0.354***	0.134	0.014	-0.036	-0.055
	(0.118)	(0.126)	(0.113)	(0.153)	(0.049)	(0.049)	(0.040)
Duration outage	-0.002	-0.001	-0.000	-0.001	-0.002	-0.000	0.000
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,706	2,706	2,706	2,706	2,706	2,706	2,706
R-squared	0.347	0.335	0.285	0.212	0.135	0.102	0.033
Number of district	26	26	26	26	26	26	26

Mote: Robust standard errors in parentheses. These are clustered at the district level.
*** p<0.01, ** p<0.05, * p<0.1

Table 11: Regression Results Productivity Appliances

	Any	Computer	Printer	Sewing
Frequency Outages	-0.011	0.005	-0.004	-0.017
	(0.015)	(0.013)	(0.006)	(0.013)
Expenditure	0.127***	0.126***	0.009**	0.005
	(0.015)	(0.014)	(0.004)	(0.005)
Savings	0.006***	0.006***	0.007***	-0.001
	(0.002)	(0.002)	(0.002)	(0.000)
Has business	0.016*	-0.021**	-0.003	0.047***
	(0.010)	(0.009)	(0.003)	(0.005)
High skill job	0.094**	0.101***	0.006	-0.010
	(0.037)	(0.038)	(0.005)	(0.008)
Job Instability	0.018*	0.016*	0.007**	0.000
	(0.009)	(0.009)	(0.003)	(0.006)
Number of female	0.011	0.006	0.001	0.007**
	(0.007)	(0.006)	(0.002)	(0.003)
Number of Children	-0.019***	-0.018***	-0.000	-0.004
	(0.006)	(0.005)	(0.002)	(0.003)
Numer of seniors	0.008	0.004	0.009**	0.013
	(0.013)	(0.013)	(0.004)	(0.009)
HoH is female	0.009	0.031*	0.000	-0.022***
	(0.018)	(0.019)	(0.005)	(0.008)
HoH is Rwandese	0.080*	0.095**	0.013*	-0.005
	(0.043)	(0.046)	(0.007)	(0.022)
HoH High Education	0.181***	0.187***	0.007**	-0.002
	(0.028)	(0.026)	(0.003)	(0.010)
HoH youth	-0.026**	-0.017*	-0.006	-0.010
	(0.013)	(0.010)	(0.004)	(0.008)
Number of Rooms	0.019***	0.017***	0.002	0.004
	(0.006)	(0.005)	(0.001)	(0.002)
Multiple households	-0.013	-0.034*	0.003	0.019
	(0.016)	(0.018)	(0.006)	(0.014)
Multiple houses	0.022	0.038*	0.009	-0.017**
	(0.026)	(0.023)	(0.009)	(0.008)
Is owner	0.029	0.039**	-0.005	-0.010
	(0.019)	(0.019)	(0.003)	(0.008)
Years in Dwelling	0.000	0.000	-0.000	0.000
	(0.001)	(0.001)	(0.000)	(0.000)
Rural	-0.010	-0.016	-0.003	0.002
	(0.013)	(0.011)	(0.002)	(0.009)
Distance Trade Center	0.002	0.003	0.003	0.001
	(0.007)	(0.005)	(0.002)	(0.004)
Distance Town	-0.019*	-0.021**	0.002	-0.003
	(0.011)	(0.009)	(0.003)	(0.006)
Rainfall	-0.171*	-0.177**	-0.004	0.030
	(0.088)	(0.080)	(0.011)	(0.070)
Duration outage	-0.001*	-0.001	-0.000	-0.000
	(0.001)	(0.001)	(0.000)	(0.001)
District FE	Yes	Yes	Yes	Yes
Observations	2,706	2,706	2,706	2,706
R-squared	0.254	0.296	0.084	0.029
Number of district	26	26	26	26

Note: Standard errors in parenthesis. These are clustered at the district level.
*** p<0.01, ** p<0.05, * p<0.1

Table 12: Regression Results Convenience Appliances

	Any	Hotplate	Cooker	Laundry	Filter	Fan	Fridge
Frequency Outages	0.007	0.004	-0.001	0.000	0.007	0.004	-0.015*
	(0.012)	(0.007)	(0.013)	(0.001)	(0.008)	(0.003)	(0.009)
Expenditure	0.110***	0.038**	0.081***	0.005	0.031***	0.011**	0.077***
	(0.023)	(0.016)	(0.018)	(0.003)	(0.011)	(0.005)	(0.021)
Savings	0.011*	0.014***	0.010***	0.008***	-0.000	0.001	0.013**
	(0.005)	(0.005)	(0.003)	(0.002)	(0.001)	(0.002)	(0.006)
Has business	0.008	-0.013***	-0.018*	0.001	0.015	-0.001	0.005
	(0.010)	(0.005)	(0.010)	(0.001)	(0.010)	(0.003)	(0.007)
High Skil Job	0.040***	0.006	0.029*	-0.001	0.030***	0.005	0.029
	(0.015)	(0.006)	(0.016)	(0.003)	(0.008)	(0.004)	(0.025)
Job Instability	0.021**	0.013**	0.018***	0.001	0.006	0.003***	0.016*
	(0.010)	(0.006)	(0.007)	(0.001)	(0.004)	(0.001)	(0.009)
Number of female	0.009	0.004***	-0.005	-0.001	0.000	0.000	0.017***
	(0.008)	(0.001)	(0.006)	(0.001)	(0.004)	(0.002)	(0.006)
Number of children	-0.022**	-0.006**	-0.010	-0.000	-0.004	-0.003*	-0.022***
	(0.009)	(0.002)	(0.007)	(0.000)	(0.003)	(0.001)	(0.007)
Number of seniors	0.004	-0.004	-0.000	0.002	0.011	-0.006**	0.011
	(0.009)	(0.004)	(0.010)	(0.002)	(0.011)	(0.003)	(0.010)
HoH is female	0.021*	0.011	0.041***	0.001	0.005	-0.007***	0.004
	(0.011)	(0.008)	(0.011)	(0.003)	(0.010)	(0.002)	(0.007)
HoH is Rwandese	-0.034	-0.060**	0.044	-0.033	-0.005	0.022***	-0.100**
	(0.045)	(0.029)	(0.036)	(0.032)	(0.035)	(0.008)	(0.049)
HoH High Education	0.141***	0.011**	0.124***	0.002	0.027***	0.003	0.076***
	(0.022)	(0.005)	(0.021)	(0.003)	(0.009)	(0.008)	(0.017)
HoH youth	-0.029***	-0.003	-0.020***	-0.003***	-0.022***	-0.006	-0.025***
	(0.009)	(0.006)	(0.007)	(0.001)	(0.006)	(0.004)	(0.009)
Number of rooms	0.031***	0.006	0.017***	-0.002*	0.008**	0.000	0.022***
	(0.005)	(0.004)	(0.005)	(0.001)	(0.003)	(0.002)	(0.007)
Multiple households	-0.063***	-0.028**	-0.045**	-0.003	-0.020**	-0.004	-0.061***
	(0.017)	(0.013)	(0.021)	(0.003)	(0.009)	(0.007)	(0.014)
Multiple houses	0.016	-0.000	0.023	-0.000	0.000	-0.007	0.017
	(0.019)	(0.021)	(0.026)	(0.006)	(0.012)	(0.008)	(0.023)
Is owner	-0.002	-0.007*	-0.014	0.003	-0.001	-0.009	-0.003
	(0.021)	(0.004)	(0.011)	(0.003)	(0.012)	(0.006)	(0.011)
Years in dwelling	0.000	-0.000	0.000	0.000	0.000	0.000*	-0.000
	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
Rural	-0.025	-0.007	-0.009	-0.001	0.001	0.001	-0.039***
	(0.020)	(0.007)	(0.015)	(0.001)	(0.013)	(0.008)	(0.014)
Distance Trade Center	-0.007	0.003	-0.001	-0.000	-0.000	-0.002	0.008*
	(0.007)	(0.002)	(0.007)	(0.001)	(0.005)	(0.002)	(0.004)
Distance Town	0.003	0.004	0.002	0.002*	-0.010	0.003	0.004
	(0.013)	(0.004)	(0.010)	(0.001)	(0.008)	(0.003)	(0.009)
Rainfall	-0.124	-0.022	-0.040	0.002	-0.073	0.025	-0.106
	(0.095)	(0.033)	(0.065)	(0.004)	(0.086)	(0.025)	(0.075)
Duration Outage	-0.002**	-0.001	-0.002***	-0.000	0.000	0.000	-0.002
	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,706	2,706	2,706	2,706	2,706	2,706	2,706
R-squared	0.240	0.154	0.189	0.169	0.060	0.018	0.248
Number of district	26	26	26	26	26	26	26

Note: Standard errors in parenthesis. These are clustered at the district level.
*** p<0.01, ** p<0.05, * p<0.1

Appendix 3: Validation of Reported Electricity Consumption Data

This section explains how the reported electricity expenditure data in EICV was validate using administrative data on electricity consumption for the Rwanda Energy Group. We first transformed the reported expenditure data into consumption data in KWh. We then matched the reported and administrative data. Finally, we conducted statistical analysis of the misreported values.

Transforming Expenditure Data into Consumption Data

We use the residential electricity tariff structure in Rwanda to transform our Expenditure Data into Consumption Data. In 2016, every household paid a tariff 182 RWF/KWh. For households surveyed in 2016, we dived the reported expenditure by the tariff level at that moment. In January 2017, a block tariff was introduced in which the household paid a tariff of 89 RWF/kWh for the first 15 kWh. That is, for the first 15 kWh, the expenditure can never be above 1,335 RWF. For the next 35 kWh, the household pays a tariff of 182 RWF/kWh (the expenditure for the following 35 units can never be above 6370). Any additional unit above the first 50 kWh pays a tariff of 189 RWF/kWh. In this context, suppose that for household i the expenditure is y_i:

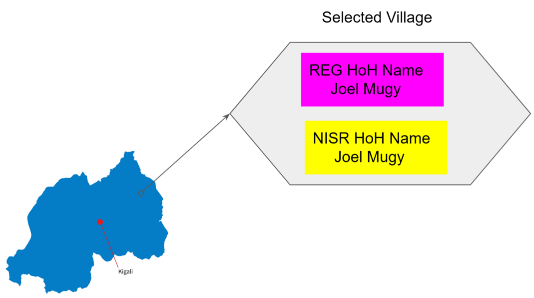
- If $y_i > 7,705$, $y_i - 7,705$ pays a tariff of 189 RWF/kWh and consumption is then 50 + $(y_i - 7,705)/189$
- If $1,335 < y_i < 7,705$, $y_i - 1,335$ pays a tariff of 182 RWF/kWh and consumption is then 15 + $(y_i - 1,335)/182$
- If $y_i < 1,335$, y_i pays a tariff of 182 RWF/kWh and consumption is then $y_i/89$

Matching, Data Validation, and Inverse Mill's Ratio

In both the EICV and REG datasets, the names, administrative and GPS locations are recorded for each household. Unfortunately, meters are not located at the house in several cases but on the grid pole. Hence, using GPS location to match the datasets will produce significative errors. Instead, we combine head of households names and GPS data for our matching process in a two-step algorithm.

The smallest administrative unit in Rwanda is a village. Villages common to both datasets are identified and within selected villages, respondents common to both data sets are chosen. In EICV, each household head is identified and we have access to the recorded names. In REG's data, all electricity purchases are attached the the owner of the house who is typically the household head. Therefore, given that the household head's name is listed in both datasets, it can be used as a common identifier to match households in one dataset to another. Yet, these names are not the same. Figure 14 presents an example of how the household names are display in each dataset.

Figure 14: Head of Household Names



In this context, we implement a "fuzzy" string matches to identify similar names in villages common to both data sets. A similarity score is then assigned based on the number of words which are matched. Figure 15 presents an example for the similarity score. We finally consider that names in each data set are a "match" if they have a similarity score higher than 80 implying a majority of the names are similar.

Figure 15: Fuzzy String matching

String one	String Two	Score
YANKEES	NEW YORK	14
NEW YORK METS	NEW YORK MEATS	96

We then use the GPS data to improve the matching algorithm. We calculate the distance between the houses corresponding to the matched names and the meter ID. In many cases, the meter is not installed in the house but in the electricity pole. In Rwanda, customer electricity meters especially in residential settings are typically located at the closest electricity pole which according to REG electricity connection standards should be within a 40 meter distance to the house receiving the electricity connection (REG, 2020). Hence, only matches that are within a 40 meter distance to one another are maintained, and matches outside this threshold are discarded. The reason for this decision is that people in the same village might have the same name, but the probability of two household living within 80 meters one from the other and having the same name is small.

Figure 16: Distance house to meter location

Figure 17 presents the result from our matching algorithm. Out of the 3,600 grid electrified housedholds in the EICV dataset, 693 household are matched to the REG data set. For the matched results, the respondent's consumption recorded in the month the EICV interview was conducted is compared to the respondent's reported electricity expenditure to determine the level of over or under reporting.

Figure 17: Matching Result

Dataset	**Sample Count**
Original EICV5 (2016-2017)	*14580 unique households (3600 connected to Grid)*
REG GPS	*672,561 customers*
EiCV5 - REG GPS match	1880 unique households matched
EICV5 - GPS - Consumption match	964 unique households matched
REG Consumption (2016-2017) (40 m distance threshold)	*693 unique households matched*

In this context, we are worried about sample selection bias. That it, we may have a latent variable that is only observed based on some other condition, which we will call a selection equation given by

$$s_{ij} = 1(z'_{ij}\omega + \eta_{ij} \geq 0) \tag{9}$$

where $s_{ij} = 1$ if the dependent variable s observed by the econometrician. In this case, the bias is given by the Inverse Mills ratio. We present the results for equation (9) below. As we can observe in out data, selection is not random and correlated to household characteristics.

Table 13: Inverse Mill's Ratio Regression

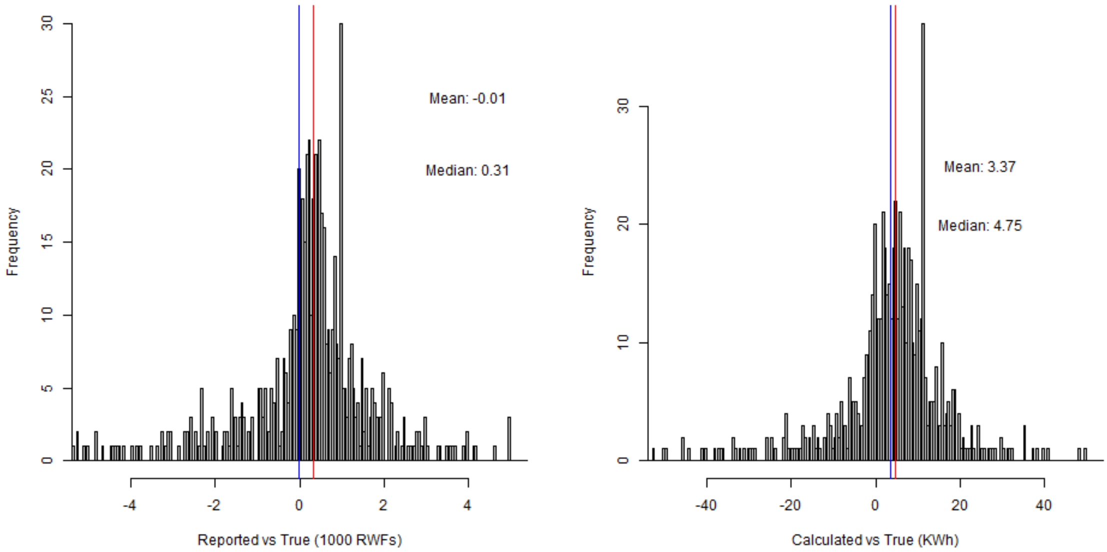
	Dependent variable: household was matched		
	OLS	Logit	Probit
Duration Outage	0.026**	0.173*	0.026**
	(0.013)	(0.103)	(0.013)
Frequency Outage	−0.010	−0.167	−0.010
	(0.016)	(0.121)	(0.016)
Expenditure	0.001	−0.306***	0.001
	(0.003)	(0.029)	(0.003)
Savings	−0.002	−0.015	−0.002
	(0.003)	(0.021)	(0.003)
Has business	0.009	0.138	0.009
	(0.014)	(0.113)	(0.014)
High Skill	−0.021	−0.131	−0.021
	(0.021)	(0.175)	(0.021)
Job Instability	−0.014	−0.281**	−0.014
	(0.011)	(0.109)	(0.011)
Number of female	0.010	0.058	0.010
	(0.007)	(0.050)	(0.007)
Number of children	−0.016**	−0.078*	−0.016**
	(0.006)	(0.046)	(0.006)
Number of seniors	−0.058***	−0.359***	−0.058***
	(0.018)	(0.122)	(0.018)
HoH is female	−0.029	−0.333**	−0.029
	(0.018)	(0.152)	(0.018)
HoH High Education	−0.011	−0.083	−0.011
	(0.020)	(0.179)	(0.020)
HoH youth	−0.021	−0.267*	−0.021
	(0.016)	(0.136)	(0.016)
Number of Rooms	0.005	0.051	0.005
	(0.006)	(0.045)	(0.006)
Multiple Households	0.007	0.072	0.007
	(0.020)	(0.206)	(0.020)
Multiple Houses	0.014	0.221	0.014
	(0.020)	(0.189)	(0.020)
Is owner	0.295***	2.862***	0.295***
	(0.020)	(0.216)	(0.020)
Years in dwelling	0.002**	0.009	0.002**
	(0.001)	(0.006)	(0.001)
Rural	−0.057***	−0.490***	−0.057***
	(0.017)	(0.136)	(0.017)
Distance Trade Center	0.005	0.050	0.005
	(0.008)	(0.064)	(0.008)
Has TV	0.064***	0.557***	0.064***
	(0.021)	(0.154)	(0.021)
Has phone	0.008	0.067	0.008
	(0.007)	(0.050)	(0.007)
Has radio	−0.004	−0.012	−0.004
	(0.011)	(0.082)	(0.011)
Has satellite dishe	−0.030	−0.221	−0.030
	(0.030)	(0.218)	(0.030)
Has decoder	−0.007	−0.003	−0.007
	(0.021)	(0.155)	(0.021)
Has filter	−0.064*	−0.404	−0.064*
	(0.034)	(0.264)	(0.034)
Has laundry machine	0.103	0.653	0.103
	(0.105)	(0.797)	(0.105)
Has computer	−0.011	−0.076	−0.011
	(0.015)	(0.113)	(0.015)
Has printer	0.062	0.671	0.062
	(0.068)	(0.560)	(0.068)
Has cooker	−0.0001	0.009	−0.0001
	(0.025)	(0.189)	(0.025)
Has fridge	0.054*	0.416*	0.054*
	(0.032)	(0.241)	(0.032)
Has hotplate	−0.014	0.248	−0.014
	(0.051)	(0.406)	(0.051)
Has music system	−0.092**	−0.870**	−0.092**
	(0.041)	(0.407)	(0.041)
Has camera	0.024	0.099	0.024
	(0.038)	(0.304)	(0.038)
Observations	3,072	3,072	3,072
R^2	0.328		
Log Likelihood		−1,171.048	−1,163.726
Residual Std. Error	0.355 (df = 3038)		
F Statistic	43.706*** (df = 34; 3038)		

*p<0.1; **p<0.05; ***p<0.01

Non-classical Measurement Error

Figure 18 presents a frequency histogram visualizing the measurement error in the survey report and our consumption estimates for 693 matched households.

Figure 18: Measurement error in EICV 5



(a) Monthly expenditure

(b) Monthly consumption

Note: The figure shows that the measurement error depicts a normal distribution for both monthly reported electricity expenditure and monthly consumption. In the case of reported electricity expenditure, the mean difference is close to zero showing that on average the respondent's reported electricity expenditure don't suffer from under or over reporting but rather mirror a close approximation of their actual electricity consumption. In the case of the calculated monthly consumption, the mean difference is 3.37 while the median is 4.75. The reason of these larger differences might be due to taxes which are charged by the utility but we do not account in our estimates for electricity consumption.

In order to study the measurement error in our consumption data we regress the estimated measurement error on several observables, including the number of appliances. Below are the results. The results show that the measurement error is correlated to the number of some appliances owned by the household. In addition, household who own their home seem to have larger measurement error. For this reason, we need to be careful about non-classical measurement error.

Table 14: Non-classical measurement error

	Dependent variable: measurement error	
	Expenditure	Consumption
	(1)	(2)
Duration Outage	0.133	0.861
	(0.318)	(1.789)
Frequency Outages	0.180	1.943
	(0.365)	(2.052)
Expenditure	−0.112	−0.420
	(0.101)	(0.567)
Savings	−0.019	−0.077
	(0.050)	(0.281)
Has business	−0.423	−2.333
	(0.353)	(1.986)
High Skill	0.289	1.443
	(0.581)	(3.264)
Job instability	0.220	1.483
	(0.364)	(2.044)
Number of female	−0.180	−1.227
	(0.163)	(0.919)
Number of children	−0.001	0.176
	(0.151)	(0.848)
Number of seniors	−0.404	−2.204
	(0.403)	(2.268)
HoH female	−0.117	−0.765
	(0.521)	(2.927)
HoH High Education	0.145	0.895
	(0.591)	(3.320)
HoH youth	−0.112	0.210
	(0.453)	(2.547)
Number of rooms	−0.131	−0.504
	(0.144)	(0.809)
Multiple households	−0.753	−4.832
	(0.622)	(3.497)
Multiple houses	−0.164	−1.415
	(0.564)	(3.170)
Is owner	1.373*	8.450**
	(0.751)	(4.221)
Years in dwelling	0.022	0.140
	(0.021)	(0.120)
Rural	0.218	−1.460
	(0.440)	(2.473)
Distance Trade Center	−0.016	−0.324
	(0.234)	(1.315)
Has tv	−0.495	−2.327
	(0.496)	(2.786)
Has phones	0.377**	1.968**
	(0.161)	(0.905)
Has radio	0.002	0.119
	(0.258)	(1.451)
Has satellite dish	−1.899***	−9.759***
	(0.655)	(3.682)
Has decoder	0.566	2.480
	(0.501)	(2.814)
Has filter	−0.267	0.211
	(0.851)	(4.783)
Has laundry	6.479***	33.228***
	(1.776)	(9.983)
Has computer	−0.662**	−3.373*
	(0.325)	(1.826)
Has printer	4.730**	21.532**
	(1.849)	(10.395)
Has cooker	0.700	4.090
	(0.619)	(3.478)
Has fridge	−0.141	−2.460
	(0.672)	(3.776)
Has hotplate	−0.578	−4.189
	(1.226)	(6.890)
Has music system	−0.730	−2.221
	(1.450)	(8.152)
Has camera	−1.275	−6.987
	(0.957)	(5.377)
Observations	571	571
R^2	0.096	0.110
Adjusted R^2	0.038	0.053
Residual Std. Error (df = 537)	3.847	21.627
F Statistic (df = 34; 537)	1.670**	1.942***
Note:		*p<0.1; **p<0.05; ***p<0.01