Queen's Economics Department Working Paper No. 1469

The Effect of Reliability Improvements on Household Electricity Consumption and Coping Behavior: A Multi-dimensional Approach

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10-2021

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Abstract

This study analyzes the extent to which electricity consumers of different income levels would increase electricity consumption and change their coping behavior to deal with power outages in response to electricity reliability improvements. The empirical analysis is conducted in two steps: (1) using an unsupervised machine learning technique, a nationally representative sample of Nepalese households is segmented into similar clusters based on the reliability constraints they face; and, (2) using regression models, the impact of reliability improvements on consumption and coping decisions is estimated. The findings point out that improved reliability is positively correlated with the probability of electric appliance ownership. The interaction of income and reliability-constraint indicators suggests that the unreliable electricity supply constrains households equally at all income levels. Moreover, the results from an ordered probit model with three off-grid backup decision alternatives indicate no association between coping decisions and income in the first two income quintiles. In contrast, higher-income quintiles are associated with significant changes in coping behavior when reliable electricity is available from the grid. Putting this paper's findings into an energy-policy perspective, a connection to the grid by itself does not necessarily translate to realized benefits from electricity consumption. The reliability of the service plays a critical role for households at all income levels.

Keywords: Electricity demand; electricity reliability; coping behavior; k-means clustering analysis; low-income countries; Nepal.

1. Introduction

As low-income countries strive to meet United Nations Sustainable Development Goal 7 (SDG 7, universal access to electricity), residential electricity consumption remains low despite substantial investments in grid expansion programs (Blimpo & Cosgrove-Davies, 2019; Blimpo et al., 2020)[1]. Reliability constraints have been blamed for low electricity consumption (Bhatia & Angelou, 2015; Aidoo & Briggs, 2019; Pelz & Urpelainen, 2020) since insufficient capacity in the generation and transmission segments and overloaded infrastructure in the distribution network cause varying reliability levels for consumers connected to the same national grid[2].

This study investigates the impact of improvements in grid-electricity access on electricity consumption and coping behavior to deal with unreliable electricity supply of households at different income levels[3]. For this purpose, I use a nationally representative sample of Nepalese residential consumers consisting of 4,660 households surveyed in 2017, one year after this country-wide reliability improvements. Nepal has experienced chronic power deficits for more than a decade (2007-2016). However, Nepal's national electricity authority (NEA) has managed to eliminate its seasonal hydropower generation deficits at the end of 2016 by facilitating power imports from India (Hashemi, 2021). This creates a unique environment to study the research question because during the time data collection was conducted, many households across Nepal had improved access to electricity service.

[1] "Universal access to modern energy by 2030" is one of the three key pillars of the Sustainable Energy for All (SE4All) program, an initiative co-chaired by the United Nations (UN) Secretary General and the World Bank President.

[2] Availability of grid-electricity takes into account the timing and duration of supply and reliability considers the frequency of interruptions to supply. Although availability and reliability may be seen as the same issue, addressing them requires different interventions.

[3] Improved access to the grid-electricity supply can be defined in terms of enhanced attributes of electricity that make it more usable for the desired applications. In this paper, I focus on the impact of enhancing the availability and reliability attributes on electricity consumption.

Therefore, I exploit the spatial variation in electricity reliability to identify the impact of reliability improvements on electricity consumption.

More specifically, I segment households into similar groups based on the supply constraints they face using an unsupervised machine learning technique known as K-means clustering. To categorize the different levels of reliability available to households, I group households along three dimensions: available hours of electricity per day (maximum of 24 hours), available hours of electricity during the evening peak-time (6-10 PM, a maximum of 4 hours), and frequency of outages experienced by households in a typical week. Next, I estimate the optimal number of clusters via the K-means clustering technique[4]. The largest cluster comprises 55% of the sample, with the rest of the households are distributed across four clusters, representing 5%, 11%, 10%, and 19% of the sample. The clusters reveal three distinct patterns of grid-electricity constraints: (1) low availability with frequent outages (clusters 1 and 2); (2) high availability with frequent outages (clusters 3 and 4); and (3) high availability without frequent outages (cluster 5).

After identifying household clusters, I investigate the extent to which unreliable access constrains households' electricity demand at different income levels by focusing on the impact of system reliability on electric appliance ownership. The rationale here is that the residential demand for electricity is derived from the household's demand for electric appliance services. Unreliable electricity affects a household's choice of appliances because it reduces the benefit for the household from ownership of such appliances. Therefore, if reliability improvements impact households' purchase decisions and the portfolio of appliances owned, they will also impact electricity consumption (McRae, 2010; Meeks et al., 2021). This approach avoids the

[4] The objective of the K-means clustering technique is to achieve the highest intra-cluster similarity and lowest inter-cluster similarity. Observations are grouped into k homogenous clusters. The first step of the analysis is to determine the optimal number of clusters. I use the elbow method which determines the number of clusters by examining the within-cluster variance as a function of the number of clusters.

potential endogeneity bias due to unobserved factors determining appliance choice and electricity consumption when electric appliance ownership is an independent variable in electricity demand estimation.

I find that improved access to grid electricity is positively correlated with the probability of electric appliance ownership. Furthermore, the interaction of income and supply-constraint indicators in a piecewise regression model suggests that the insufficient capacity of power supply constrains households equally at all income levels. In contrast, the frequency of unplanned service interruptions does not appear to matter at any income level. These findings imply that if electricity from the grid were available 24-hour a day, the average duration of the remaining outages would probably be so short that it would not affect electric appliance ownership decisions.

In addition, I find that the effect of income on appliance ownership is approximately the same across all income quintiles. The importance of this finding is highlighted when I investigate how households' coping behavior changes when they experience different levels of reliability. The results from an ordered probit model with three backup decision alternatives indicate no association between backup decisions and income in the first two income quintiles. On the other hand, higher-income quintiles are associated with significant changes in coping behavior when electricity is available from the grid all day long, and unplanned outages are not frequent. Thus, the increased availability of supply hours from the grid matters more for poor households, for whom the combined ownership cost of both appliances and backup equipment may be prohibitive[5].

The empirical results presented in this paper deliver at least three critical insights to sector planners and decision-makers in the electricity sector. First, previous studies have

[5] Poorer households either do not invest in coping equipment or use low-quality coping equipment (such as kerosene and candles) that provide low-quality lighting services.

analyzed the ex-ante demand for electricity reliability using contingent valuation (proposed hypothetical reliability improvements) and revealed preferences (expenditures on backup alternatives used during outages) surveys (Ozbafli & Jenkins, 2015; Ozbafli & Jenkins, 2016; Niroomand & Jenkins, 2020; Hashemi, 2021). While survey-based studies provide helpful insights to sector planners about the electricity demand, the change in consumers' coping behavior and appliance ownership after actual improvements (ex-post) has remained unexplored in the literature. The findings presented in this study shed some light on how consumers' investment decisions on electric appliances and coping equipment would be affected with enhanced quality of electricity service.

Second, with more progress being made toward achieving SDG7, the findings in this study highlight how unreliable access to electricity constrains the acquisition of household electric appliances. Thus, reliability improvements are expected to increase benefits from electric appliance usage through greater household appliance ownership and, consequently, increased electricity consumption. Moreover, a reliable service eliminates the need for investments in coping equipment, resulting in savings in additional expenditures on top electricity bills to cope with power outages. Previous studies show that there is often a significant willingness to pay (WTP) among consumers for reliability improvements (Kim et al., 2015; Abrate et al., 2016; Ozbafli & Jenkins, 2016; Carlsson et al., 2020; Niroomand & Jenkins, 2020; Hashemi, 2021; Carlsson et al., 2021). Hence, achieving SDG7 goals is impossible if the quality of service is ignored in electrification programs.

Third, consistent with recent studies, the methodology employed in this paper highlights the importance of using a multi-dimensional measurement framework rather than simply counting grid connections when measuring energy access and the associated economic impacts (Bhatia & Angelou, 2015; Mendoza et al., 2019; Pelz & Urpelainen 2020). A focus on counting connections - politically motivated in most cases - without considering household electrical energy service utilization has deteriorated electric utilities' cash flows in low-income countries (Blimpo & Cosgrove-Davies, 2019). Also, such an energy-policy perspective is likely to overestimate electrification projects' benefits by sector planners when conducting cost-benefit analyses of investment projects (Bajo-Buenestado, 2021).

The rest of the paper proceeds as follows. Section 2 provides a brief review of previous studies on different causes of electricity service interruptions. Section 3 describes the empirical methodology used in this paper, followed by a description of the data. In section 4, empirical results are presented and discussed. Lastly, Section 5 concludes the paper and discusses some policy implications.

2. What causes unreliable electricity supply?

Investments in grid extension would increase electrification rates, but in the absence of adequate availability and reliability of power, the grid-connected consumers would experience poor electricity access due to frequent and prolonged outages. In many developing countries, insufficient investments in transmission capacity or seasonal shortages in electricity generation result in long hours of electricity service unavailability (Zhang, 2018). As a result, electric utilities in these countries typically allocate the constrained supply of electricity among customers through rationing programs (also known as load shedding programs). Outages caused by these programs are called planned outages and are announced ahead of time to electricity consumers. Previous studies show that there is often a significant WTP among consumers to eliminate planned outages (Abrate et al., 2016; Ozbafli & Jenkins, 2016; Carlsson et al., 2020; Niroomand & Jenkins, 2020; Hashemi, 2021; Carlsson et al., 2021).

There are, in addition, situations where sufficient electricity is generated and transmitted to distribution networks, but frequent unplanned outages remain[6]. Local substation failure due to capacity overload is the most common cause of unplanned outages (Carranza & Meeks, 2018; Meeks et al., 2021)[7]. Electric utilities upgrade substation capacities to keep up with growing demand over time and to prevent or reduce overloading. The cost of such investments is recovered from adjustments to retail electricity prices. However, there is often political pressure against raising electricity prices in many developing countries. The situation gets worse where access to electricity is viewed as a right. Unaccounted electricity usage (electricity theft) through illegal connections and unpaid electricity bills often becomes a socially accepted part of the system (Burgess et al., 2020). Consequently, electric utilities' cash flows deteriorate, and they postpone essential investments to maintain service reliability (Gertler et al., 2017).

Therefore, the availability and reliability of electricity supply from the same national grid may vary from one locality to another. This variation creates the need for evaluating the reliability issues with a multi-dimensional framework that considers various indicators representing multiple attributes. For instance, power outages may be frequent but last for only a few minutes or several hours. In addition, the time of day when grid electricity is available is an essential factor because the demand for lighting services - the main category of electricity consumption in low-income countries - is highest during the evening hours. Therefore, if grid power is available for extended hours during the day but constrained during the evening, households will still be significantly constrained in their electricity use. In the next section, the

[6] Due to its unexpected nature, the opportunity cost of unplanned outages are often greater than planned outages. Hashemi et al. (2018) estimate the cost to Nepalese industrial firms in the range of US$0.28/kWh up to US$2.88/kWh of electricity not supplied

[7] A distribution substation is the last part of the electricity distribution network that ensures electric power is adequately converted to a usable service voltage for the daily operations of consumers. Each substation is designed for a specific maximum capacity, and the installed protection devices automatically shut down the substation in the occurrence of an overload, leaving all consumers connected to that substation without power. Thus, the frequency with which unplanned power outages occur in a locality is a function of how much overloaded the distribution substations are in that locality.

three indicators that are used in this study to capture the spatial variation in electricity reliability for households residing across Nepal are introduced and explained in detail.

3. Methodology and data

3.1 Methodology

In this paper, differences in system reliability are explored using K-means clustering, an unsupervised data-mining technique with applications in various fields such as market segmentation analysis and social network studies. In the energy economics literature, K-means clustering has been used to analyze smart-meter data to understand residential electricity load profiles and consumption patterns (Trotta, 2020). Estimates of these patterns have been used in load forecasting, tariff design, and demand-response programs (Rhodes et al., 2014; Trotta, 2020). Identifying consumer segments with similar electricity load profiles allows for a broader range of policy analyses in electricity markets, including studies of the advisability of grid expansion and the efficient level of service reliability (Hayn et al., 2014; Thomas et al., 2020).

After identifying the relevant household clusters in terms of service reliability, I exploit the variation in reliability across household clusters to estimate the effect of improvements on high-load electric appliance ownership. The residential demand for electricity is derived from the households' demand for electric appliances. Unreliable electricity affects a household's choice of appliances because it reduces the benefit for the household from ownership of such appliances. Therefore, if reliability improvements impact households' purchase decisions and the portfolio of appliances owned, they will also shift the demand curve for residential electricity. The alternative of estimating the electricity demand, using either electricity bills or hours of consumption as the dependent variables, is likely to yield inconsistent estimates because of the clear endogeneity of appliance ownership as a regressor.

Similarly, it is expected that reliability improvements would change consumers' coping behavior to deal with unreliable electricity service. Households engage in various coping behaviors (ranging from simple technologies like candles to more advanced forms such as diesel generators) when electricity from the grid is not available or when there are fluctuations in the voltage of electricity drawn from the grid (Hashemi, 2021). I exploit the variation in reliability across household clusters to analyze how households' adoption patterns of coping equipment would be affected after reliability improvements.

3.2 Data Description

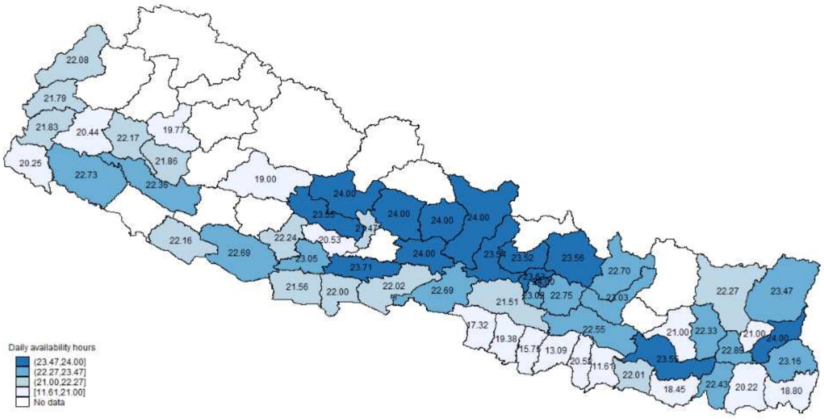
I use a nationally representative survey of Nepalese households collected as part of the World Bank's Multi-Tier Framework (MTF) for Assessing Energy Access Program (World Bank, 2019). The survey was conducted in 2017, one year after the total elimination of load shedding in Nepal through electric power imports from India. The sample design was based on a two-stage stratification to ensure the national representativeness of the sample. In the first stage, the enumeration areas were selected randomly within stratifications, representing urban and rural areas and Nepal's three distinct ecological regions (mountains, hills, and terai). In the second stage, households were randomly selected for interviews from wards chosen in the first stage. The raw dataset consists of 6,000 households, of which 4,660 were grid-connected. I focus only on those grid-connected households in this study. Table 1 presents summary statistics for the 3,847 grid-connected households for which there are no missing data.

The household segmentation variables listed in Table 1 represent three dimensions of system reliability. Households report in the survey that electricity from the grid is available on average for almost 22 hours per day, with a minimum of 7 and a maximum of 24 hours of availability. Moreover, the frequency of outages per week varies greatly across households, with a mean of 7 and a standard deviation of 9.37. The third dimension of reliability is peak-time availability, measured as the hours of grid electricity availability from 6 PM to 10 PM.

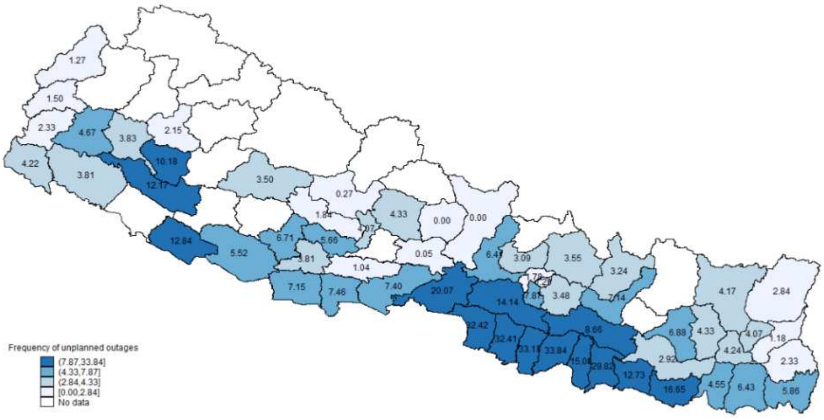
The sample average is 3.56 hours with a standard deviation of 0.68 hours. The three panels in Figure 1 illustrate the district-level average hours of grid electricity availability, frequency of outages, and peak-time availability.

Table 1: Summary statistics

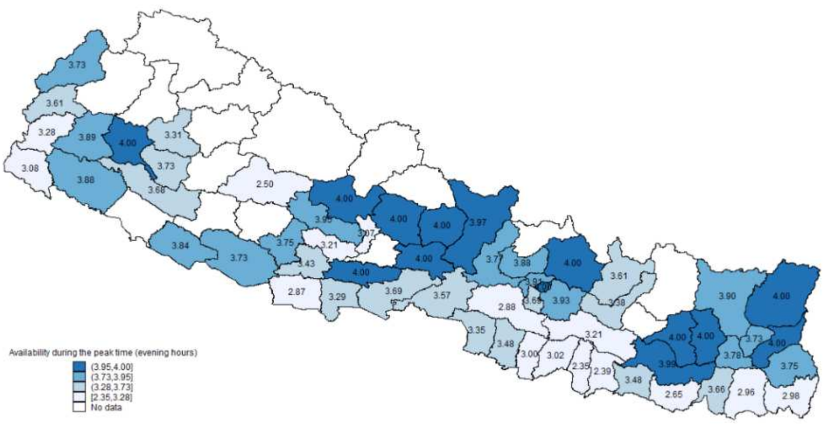
Variable	Mean	St. Dev.	Min	Max
Segmentation variables				
Daily availability of grid electricity	21.93	2.89	7	24
Frequency of outages	6.97	9.37	0	88
Availability during the evening peak time (6 – 10 PM)	3.56	0.68	0	4
Household characteristics				
Electricity bill in a typical month (USD)	4.94	7.43	0.04	77.31
Total number of high-load appliances	1.43	1.94	0	10
Quintiles of total monthly expenditures (USD)				
1st	73.44	19.66	14.28	100.66
2nd	122.09	12.46	100.76	144.19
3rd	166.90	13.81	144.28	192.57
4th	228.20	23.27	192.66	274.00
5th	492.05	415.52	274.17	3,666.48
Backup status				
No backup	0.09			
Only for lighting	0.61			
Both for lighting and appliances	0.30			
Education status of the household head				
No formal education	0.35			
Primary	0.22			
Secondary	0.38			
College education	0.05			
Household head gender				
Female	0.20			
Time spent at home				
Retired / too old to work	0.12			
Housewife/husband	0.11			
Locality				
Urban	0.66			
Rural	0.34			
Number of observations	3,847			



Panel A. Daily availability of grid electricity



Panel B. Frequency of outages



Panel C. Availability of grid-electricity during the evening peak time (6-10 PM)

Figure 1: Grid electricity supply constraints – district-level averages

Households reported a wide variety of electric appliance ownership, ranging from light bulbs and mobile phone chargers, which require only a few watts, to space heaters and air conditioners, which require several kilowatts. Based on the amount of electricity needed to operate, their electric appliances can be categorized as low-power or high-power (see Table 2)[8]. The more high-load appliances a household owns, the higher is its demand for grid electricity for a given level of income. In addition, wealthier households tend to have more high-load appliances because of their higher incomes. As a result, the distribution of the total number of high-load appliance ownership represents skewness in consumption, with a mean and median of 1.46 and 1, respectively.

Table 2: Appliances owned by households in the sample

Appliance type by the power load	
Low-load	High-load
Incandescent Light Bulb	Refrigerator
Fluorescent Tube	Hairdryer
Compact Fluorescent Light (CFL) Bulb	Electric food processor/blende
LED Light Bulb	Electric rice cooker
Radio/CD Players/sound system	Microwave oven
VCD/DVD	Electric Iron
Fan	Washing machine
Computer/ Laptop	Electric sewing machine
Smartphone (internet phone) charger	Air cooler
Regular mobile phone charger	Air conditioner
Black & White TV	Space Heater
Regular Color TV	Electric water heater
Flat color TV	Electric hot water pot/kettle
	Electric Water Pump

Source: Nepal's Multi-Tier Framework Survey (World Bank, 2019)

In electricity markets with frequent power outages, household coping behavior is a strong predictor of current and future electricity demand (Hashemi, 2021)[9]. The households in

[8] According to the World Bank's MTF framework, appliances with load levels less than 200 watts are low-power appliances, and those with load levels greater than 200 watts are high-power appliances.

[9] Coping behavior refers to decisions made by electricity consumers about how to deal with power outages. During blackouts, consumers may use their off-grid coping equipment (such as rechargeable batteries and generators) or delay all electricity-intensive activities until power returns.

the sample reported ownership of a wide range of coping equipment for lighting purposes during blackouts, including disposable batteries (used with flashlights), kerosene lamps, solar lanterns, and solar lighting. Some households also use high-quality coping equipment such as rechargeable batteries, voltage stabilizers, and generators to power their appliances during service outages. The survey asked two questions about each household's coping behavior: whether it uses any backups for (1) lighting only and (2) lighting plus appliances. Based on the responses to these two questions, I define three binary variables for a household's backup status: no backup, backup for lighting only, and backup for both lighting and appliances. While 9 percent of households do not engage in any coping behavior, 60 percent of them back up for lighting only and 31 percent back up for both lighting and appliances.

The survey also collected information about households' characteristics. I use those characteristics documented in the literature as predictors of electricity demand (Lee et al., 2016; Blimpo & Cosgrove-Davies, 2019; Tesfamichael et al., 2020): income, time spent at home, educational attainment, and urban/rural locality. I use the recurring combined monthly expenses reported by households on food, rent, and other services as a proxy for income[10]. I divide households into quintiles of total monthly expenditures. Thirty-three percent of the households in the sample live in rural areas, with the other 67 percent spread across urban areas. Thirteen percent of household heads in the sample report as retired, and 12 percent report as housewives/househusbands. This is relevant because if the household head is a housewife/husband or retiree, electricity demand is likely to be affected because that person spends more time at home.

[10] Other goods and services include medical and pharmacy expenses; cleaning supplies, cosmetics, toiletries, water expenses; mobile phone top-up; internet, land phone, cable, and other household communication; and transportation costs.

4. Results

I use the elbow method developed by Makles (2012) to find the optimal number of clusters. Figure 2 illustrates the within-cluster variance plotted against the number of clusters. The criterion for choosing the optimal number of clusters is to find a point where the marginal decline in within-cluster variance falls to the "elbow" point. For these data, the number of clusters beyond which marginal reductions in within-cluster variance are not significant is five.

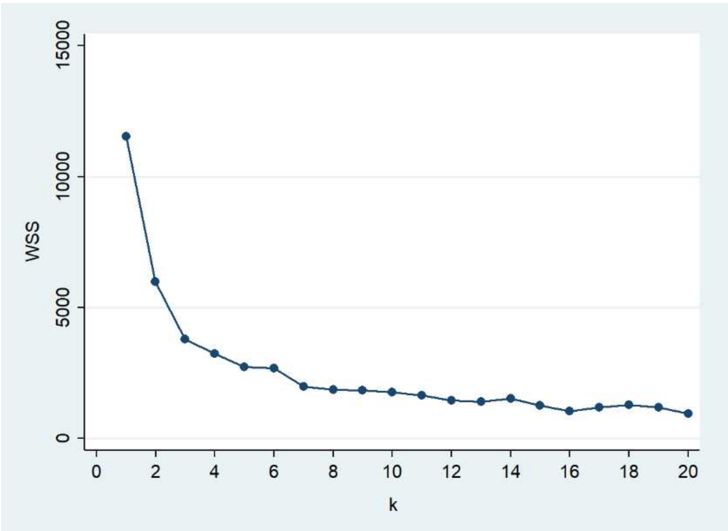


Figure 2: Elbow method outcome - the optimal number of clusters

Table 3 lists the unscaled mean and standard deviation of segmentation variables across the five clusters and the number of observations in each cluster. Cluster 5 is the largest group comprising 55% of the sample. The rest of the sample households are distributed across clusters 1 to 4, representing 5%, 11%, 10%, and 19% of the sample. As shown in Figure 3, overall and peak-time availability hours are significantly less than the sample average for the first group (clusters 1 and 2). While the frequency of outages is above the sample average for the second group (clusters 3 and 4), grid electricity is available for longer hours for the households in this group. Cluster 5 exhibits the lowest variability in the duration of grid-electricity availability (standard deviation of 0.77 hours). Households in this cluster also report an uninterrupted service during the evening peak hours. Based on the segmentation variables, the clusters reveal three distinct system reliability levels: (1) low availability with frequent outages (clusters 1 and 2); (2) high availability with frequent outages (clusters 3 and 4); and (3) high availability without frequent outages (cluster 5).

Table 3: Variation in segmentation variables across clusters

Segmentation variable	Cluster				
	1	2	3	4	5
Daily availability hours (max. of 24 hours)	13.70	18.48	21.40	21.63	23.55
	(3.26)	(2.36)	(1.98)	(1.25)	(0.77)
Frequency of outages	37.09	9.73	12.81	8.44	2.14
	(10.83)	(6.11)	(7.49)	(5.90)	(2.20)
Availability during the peak time (max. of 4 hours)	2.86	2.26	3.99	2.99	4.00
	(0.81)	(0.57)	(0.05)	(0.09)	(0.00)
Number of observations	193	417	392	716	2,129
Percentage of the sample	5%	11%	10%	19%	55%

Figures in parentheses are standard deviations.

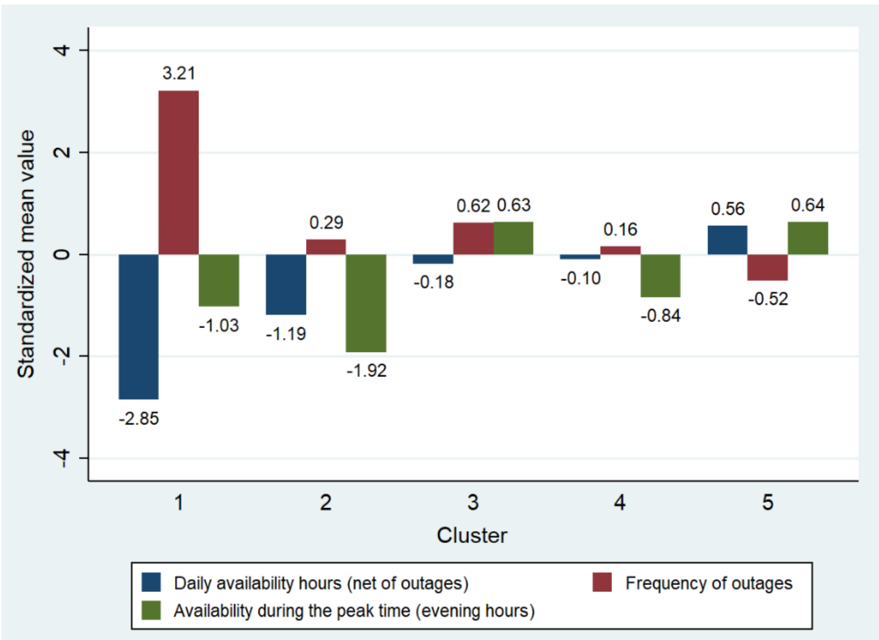


Figure 3: Standardized mean values of segmentation variables by cluster
Note: Variables are standardized to have a mean of 0 and a standard deviation of 1.

Table 4 reports the estimated coefficients for a linear probability model with an indicator for high-load appliance ownership as the dependent variable without applying the K-means clustering method. These estimates imply, counterintuitively, a negative relation between peak-time availability and appliance ownership. Additionally, the frequency of outages is estimated to have only a minimal effect on the likelihood of high-load appliance ownership. Thus, it seems likely that the K-means clustering method offers a better way to characterize grid reliability, essentially because of the way it deals with multicollinearity among system reliability measures. The K-means clustering method achieves that by grouping households into unique clusters of supply constraints instead of using each measure of supply constraint as a separate regressor.

Table 4: Estimates of system reliability impacts without K-means clustering

Variable	OLS Dep. var.: high-load electric appliance ownership
Grid-electricity supply constraints	
Daily availability hours	0.0264*** (0.0035)
Frequency of outages	- 0.0034*** (0.0010)
Availability during the peak time	- 0.0419*** (0.0127)
Controls	YES
Number of observations	3,847

Notes: * p < 0.1 , ** p < 0.05 , *** p < 0.01. Figures in parentheses are robust standard errors. Controls include indicators household's income, housewife/husband, too old to work or retired, female, educational attainment, and rural-urban status.

Table 5 shows the results of a linear piecewise regression model with indicators for reliability clusters and defined breakpoints at income quintiles to allow the marginal effect of income to vary by quintile. I find that extended hours of availability matter equally for all income levels, whereas the frequency of unplanned service interruptions does not matter at any income level. As shown in column 1, although improvements in each supply constraint are associated with a higher probability of high-load electric appliance ownership, the magnitude of these impacts is the same in all income quintiles. In particular, when availability hours are extended, those with and without frequent outages are equally more likely (17 percent) to own high-load appliances. Thus, it appears that once availability is increased, the frequency of unplanned outages does not affect households' appliance ownership decisions. This finding aligns with previous studies which also found supply reliability is poorly associated with household electricity utilization relative to supply availability (Pelz & Urpelainen, 2020).

Moreover, there are no differences in the marginal effects of income across clusters when they are interacted with cluster indicators (column 2). With the most severe constraints as the reference group (low availability with frequent outages), the results indicate that none of the income groups is more constrained than others by service availability. I also estimate separately the impact of each availability measure (daily and peak-time) on appliance ownership. As shown in Tables 6 and 7, I find no statistically significant difference in the impact of reliability on appliance ownership across income levels.

Table 5: System reliability and appliance ownership

Variables	Dep. Var.: High-load electric appliance ownership	
	(1)	(2)
Clusters of grid-electricity supply constraint		
High availability with frequent outages	0.1678***	0.1963
	(0.0222)	(0.1447)
High availability without frequent outages	0.1728***	0.1936
	(0.0205)	(0.1682)
Total monthly expenditures (USD)		
Quintile 1 expenditures	0.0031***	0.0040***
	(0.0006)	(0.001)
Quintile 2 expenditures	- 0.0010	- 0.0025
	(0.0012)	(0.003)
Quintile 3 expenditures	0.0003	0.0018
	(0.0013)	(0.003)
Quintile 4 expenditures	- 0.0013	- 0.0047**
	(0.0009)	(0.0023)
Quintile 5 expenditures	- 0.0001***	0.0013
	(0.0003)	(0.0009)
Interaction between high availability with frequent outages and expenditures		
Quintile 1 expenditures × High availability with frequent outages		- 0.0004
		(0.0018)
Quintile 2 expenditures × High availability with frequent outages		0.0004
		(0.0038)
Quintile 3 expenditures × High availability with frequent outages		- 0.0027
		(0.0041)
Quintile 4 expenditures × High availability with frequent outages		0.0056*
		(0.0029)
Quintile 5 expenditures × High availability with frequent outages		- 0.0030**
		(0.0012)
Interaction between high availability without frequent outages and expenditures		
Quintile 1 expenditures × High availability without frequent outages		- 0.0011
		(0.0016)
Quintile 2 expenditures × High availability without frequent outages		0.0020
		(0.0035)
Quintile 3 expenditures × High availability without frequent outages		- 0.0071
		(0.0037)
Quintile 4 expenditures × High availability without frequent outages		0.0028
		(0.0026)
Quintile 5 expenditures × High availability without frequent outages		- 0.0030***
		(0.0010)
Controls	YES	YES
Observations	3,847	3,847

Notes: * p < 0.1, ** p < 0.05, *** p < 0.01. Figures in parentheses are robust standard errors. Controls include indicators for housewife/husband, too old to work or retired, female, educational attainment, and rural-urban status.

Table 6: Daily availability and appliance ownership

Variables	Dep. Var.: High-load electric appliance ownership	
	(1)	(2)
Grid-electricity supply constraint (ref. group: < 24-hour availability)		
24-hour availability	0.0594***	- 0.0157
	(0.0148)	(0.1143)
Total monthly expenditures (USD)		
Quintile 1 expenditures	0.0032***	0.0029***
	(0.0006)	(0.0008)
Quintile 2 expenditures	- 0.0013	- 0.0006
	0.0012	(0.0015)
Quintile 3 expenditures	0.0006	- 0.0001
	(0.0013)	(0.0017)
Quintile 4 expenditures	- 0.0012	- 0.0016
	(0.0009)	(0.0012)
Quintile 5 expenditures	- 0.0012***	- 0.0006
	(0.0003)	(0.0004)
Interaction between availability and expenditures		
Quintile 1 expenditures × 24-hour availability		0.0006
		(0.00127)
Quintile 2 expenditures × 24-hour availability		- 0.0018
		(0.0025)
Quintile 3 expenditures × 24-hour availability		0.0020
		(0.0027)
Quintile 4 expenditures × 24-hour availability		0.0005
		(0.0018)
Quintile 5 expenditures × 24-hour availability		- 0.0015**
		(0.0007)
Controls	YES	YES
Observations	3,847	3,847

Notes: * p < 0.1, ** p < 0.05, *** p < 0.01. Figures in parentheses are robust standard errors. Controls include indicators for housewife/husband, too old to work or retired, female, educational attainment, and rural-urban status.

Table 7: Peak-time availability and appliance ownership

Variables	Dep. Var.: High-load electric appliance ownership	
	(1)	(2)
Grid-electricity supply constraint (ref. group: < 4 hours of availability between 6-10 PM)		
Peak-time availability (4 hours of availability between 6-10 PM)	0.0309**	0.0220
	(0.016)	(0.1041)
Total monthly expenditures (USD)		
Quintile 1 expenditures	0.0031***	0.0033
	(0.0006)	(0.0010)
Quintile 2 expenditures	- 0.0013	- 0.0012
	(0.0012)	(0.0021)
Quintile 3 expenditures	0.0005	- 0.0013
	(0.0013)	(0.0022)
Quintile 4 expenditures	- 0.0013	0.0005
	(0.0009)	(0.0016)
Quintile 5 expenditures	- 0.0012***	- 0.0014
	(0.0003)	(0.0006)
Interaction between availability and expenditures		
Quintile 1 expenditures × Peak-time availability		- 0.0002
		(0.0013)
Quintile 2 expenditures × Peak-time availability		- 0.0003
		(0.0026)
Quintile 3 expenditures × Peak-time availability		0.0034
		(0.0027)
Quintile 4 expenditures × Peak-time availability		- 0.0031
		(0.0020)
Quintile 5 expenditures × Peak-time availability		0.0003
		(0.0008)
Controls	YES	YES
Observations	3,847	3,847

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Figures in parentheses are robust standard errors. Controls include indicators for housewife/husband, too old to work or retired, female, educational attainment, and rural-urban status

In all specifications, the marginal effect of income on appliance ownership is statistically significant at the first income quintile, holding constant reliability. The importance of this finding is highlighted more when I investigate how a household's coping behavior changes with access improvements. The estimates for an ordered probit model with the three alternative backup decisions as the ranked categories (Table 8) suggest that when the availability and reliability of service are relatively improved, consumers change their coping behavior. In particular, with a reasonably reliable service, when power outages occur, households reschedule their use of electric appliances and use backup for lighting only. This finding is consistent with the findings by Hashemi (2021) that a fully reliable grid provides a reliability level above and beyond any backup equipment that even households with high-quality backup equipment are willing to pay a significant premium on top of their current electricity bills.

Table 8: Supply constraints and coping behavior

Variables	Backup status		
	No backup	Lighting only	Lighting and appliances
Clusters of grid-electricity supply constraint			
High availability with frequent outages	- 0.0156*	- 0.0184*	0.0341*
	(0.0081)	(0.0096)	(0.0176)
High availability without frequent outages	0.0332***	0.0393***	- 0.0726***
	(0.0081)	(0.0091)	(0.0170)
Total monthly expenditures (USD)			
Quintile 1 expenditures	- 0.0002	- 0.0003	0.0005
	(0.0002)	(0.0002)	(0.0005)
Quintile 2 expenditures	- 0.0007	- 0.0009	0.0016
	(0.0004)	(0.0005)	(0.0010)
Quintile 3 expenditures	0.0013**	0.0016**	- 0.0029**
	(0.0005)	(0.0006)	(0.0011)
Quintile 4 expenditures	- 0.0008*	- 0.0009**	0.0017**
	(0.0004)	(0.0004)	(0.0008)
Quintile 5 expenditures	0.0004***	0.0005***	- 0.0009***
	(0.0001)	(0.0001)	(0.0003)
Controls	YES	YES	YES
Observations	3,847	3,847	3,847

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Figures in parentheses are robust standard errors. Controls include indicators for housewife/husband, too old to work or retired, female, educational attainment, and rural-urban status.

However, for poorer households, the marginal effect of income is not significant in backup decisions but is significant in appliance ownership decisions. It can be inferred from these two findings that income constraints limit both appliance ownership and coping decisions. Consistent with Hashemi (2021), although low-income households are willing to pay a relatively significant proportion of their current electricity bills for improved reliability, the absolute value of their WTP is so low that it only justifies adopting low-quality backup services or, in some cases, no backup when the grid is down. In other words, as discussed by Aidoo and Briggs (2018), the marginalized position of the poorer households leads them to bear a disproportionate share of electricity supply unreliability. Thus, it is expected that the impact of increased availability of supply hours from the grid may be more substantial for poorer households.

In summary, the findings presented in this section suggest that household utilization of electrical energy services is strongly associated with improvements in electricity supply availability. The consumption pattern after improvements, however, may vary across income strata. Pelz and Urpelainen (2020) find that improvements in the availability of electricity service for Indian households were associated with a higher likelihood of space cooling and entertainment utilization. However, mechanical loads, thermal loads, refrigeration, and electric cooking remain constrained by low income in rural areas. Hence, residential electricity demand grows with reliability improvements, but differently across income strata.

5. Conclusion and Policy Implications

This paper estimates the extent to which electricity consumers of different income levels would increase their use of high-load appliances and change their coping behavior in response to improvements in grid reliability. The findings highlight that a multi-dimensional measure framework is essential in studying the impact of enhancements in grid-electricity constraints on electricity demand. More specifically, it was observed that although grid-connected households are counted in the electrification statistics, unreliable electricity service significantly constrains their electric appliance ownership and, consequently, electricity consumption. Putting this paper's findings into SDG 7's perspective, a connection to the grid by itself does not necessarily translate to realized benefits from electricity consumption. The availability and reliability of the service play a critical role for households at all income levels.

Moreover, the estimates for an ordered probit model with the three alternative backup decisions suggest that when the availability and reliability of service are relatively improved, consumers change their coping behavior across all income levels. In particular, with a reasonably reliable service, when power outages occur, households reschedule their use of electric appliances and use backup for lighting only. Therefore, the economic benefits from a fully reliable grid extend beyond direct benefits from electricity consumption once consumers decide to remove their coping equipment. For instance, kerosene is a typical coping technology that is associated with the possibility of burn injuries. A reliable supply can minimize or eliminate such incidences.

For policy-making purposes, the findings highlight the importance of tracking the reliability of the new infrastructure during the early stages of grid expansion project evaluation. Otherwise, sector planners will overestimate the benefits of grid expansion projects. For an optimal allocation of available funds in the electricity sector, the efforts by governments and international development organizations should not be focused only on grid expansion but also on allocating some funds to sustain a reliable supply. More accurate electricity demand forecasts and timely investments in expanding distribution substation capacities are examples of such policy.

Finally, this study's findings leave open some other questions for future research. For instance, the impact of reliability improvements on electricity consumption was evaluated right after eliminating power capacity deficits. However, Pelz and Urpelainen (2020) find that each additional year of electricity access leads to incrementally higher ownership rates of electric appliances and an increased likelihood of a higher total stock of appliances. A similar pattern may exist when evaluating the impact of reliability improvements over a more extended period. Therefore, future studies can extend the current analysis by investigating the effect of reliable electricity on changes in appliance ownership patterns over a longer time horizon.

Acknowledgment

I would like to thank William Dougan, Robert Fleck, Andrew Hanssen, Glenn Jenkins, and other Public Economics Workshop participants at John E. Walker Department of Economics, Clemson University, for their valuable comments on earlier drafts of this paper.

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