Reliability, Appliance Choice, and Electricity Demand*

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Abstract

I estimate a model of the household demand for electricity that includes both the short-run consumption decision and the long-run choice of the appliances that the household owns. I use a discrete factor approximation for the correlation between the unobserved components of the individual appliance choice and electricity consumption decisions. The reliability of electricity service enters demand directly through its effect on current-period consumption, and indirectly through its effect on the appliances owned by the household. I use the model to show that improvements in the reliability of electricity supply in Colombia would affect demand primarily through changes in household appliance portfolios.

1 Introduction

Economic growth has dramatically increased the number of households in developing countries with the income and desire to emulate developed-country lifestyles.

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However, these aspirations are often constrained by the availability of adequate infrastructure. Congestion, pollution, and inadequate public services are defining characteristics of everyday life in many countries. In this paper I show how one such limitation—the provision of a reliable electricity supply—affects the long-run residential demand for electricity. In particular, I demonstrate the effect of unreliable electricity on ownership of electrical appliances and residential demand for electricity in Colombia, and show that the largest impacts from reliability improvements arise from changes in household appliance portfolios.

As with demand for other forms of energy, the residential demand for electricity is derived from the household's demand for appliance services. In the short-run, the appliances owned by the household are fixed, and the household decides the length and intensity of usage for each appliance. In the long-run, the household can change the portfolio of appliances that they own. The reliability of electricity service affects both these short-run and long-run decisions. In the short-run, during a power outage, the household's consumption of electricity is zero. However, the services provided by some appliances—such as clothes washing or food preparation—can be shifted to a later time, so the effect of the outage on total electricity consumption is diminished. Reliability also affects the household's choice of appliances. For example, frequent outages would reduce the benefit for the household from ownership of refrigerators and televisions.

In this paper I use data for more than 83,000 households in Colombia to jointly model the choice of appliances and the demand for electricity. The data includes household-level information on dwelling characteristics, demographics, and appliance holdings. This is matched to billing data for individual households that includes the metered electricity consumption and the billed amount each month. In addition, the household-level data is matched to transformer data that includes information on the total number and length of electrical outages each month.

This data set provides a rich environment for the analysis of household demand for electricity in a developing country. Colombia is an ideal environment in which to examine the effect of supply reliability on electricity demand. Wholesale market reforms and generation investment have created sufficient system capacity to meet demand in all periods. However, there are large differences in the quality of distribution networks, providing substantial variation across households in the number and length of electricity outages.

I model the probability of ownership of seven appliances using a multivariate logit model. Ownership of each individual appliance depends on household and dwelling size, household expenditure, climate, and the reliability of electricity service. The reliability of service is measured as both the average number and average length of outages over the previous twelve months. I allow for correlation in the unobservable component of the ownership decisions for each appliance using a discrete factor approximation.

I model the demand for electricity using a discrete-continuous framework that incorporates non-linearity in the price schedule. Electricity demand depends on appliance holdings, household demographics, geographical variables, and again the reliability of electricity service. The discrete factor approximation from the appliance choice equations also enters the electricity demand equation. This allows for correlation between the unobservable component of electricity demand and the unobservable component of the appliance choices.

The estimation results show that unreliable electricity service affects not just the electricity demand in a single month, but also the portfolio of appliances owned by the household. The probability of ownership of every appliance is decreasing in the average number of outages. I show that a 50 percent reduction in the number and length of electrical outages would lead to a mean increase of 2.3 percent in the demand for electricity. More than 85 percent of this increase is the result of additions to appliance stocks due to the improved service reliability. This result illustrates that the largest effect of infrastructure quality improvements is due to changes in the capital stock of households.

The results also show a statistically significant and positive correlation in the unobserved components of the individual appliance choice equations and the electricity demand equation. Dubin and McFadden (1984) discuss the potential endogeneity of the appliance variables used in electricity demand estimation that arises from this correlation. In their application they estimated a joint model of water and space heating choice and electricity demand. Nonetheless, many subsequent papers treat appliance choices as exogenous or model the choice of only one or two appliances. The methodology in this paper, using a mixture maximum likelihood model, enables the consistent estimation of the demand for electricity by modeling the correlation across a much broader range of appliance choices and demand.

This paper contributes to the literature on the effect of infrastructure quality in developing countries, by demonstrating the changes in household appliance stocks that arise from improved reliability of electricity supply. Similar issues in the context of unreliable water service are analyzed by Baisa, Davis, Salant, and Wilcox (2010), who calibrate a model of residential water storage in Mexico City to calculate the welfare benefits of providing regular water deliveries. Klytchnikova (2006) estimates the short-run demand for household energy services (electricity, gas, kerosene, and firewood) in Azerbaijan, in the presence of intermittent supply. Munasinghe (1980) combines a theoretical model with survey data for a small sample of households in Brazil to show that the principal cost of power outages for residential users is the loss of leisure activities.

The effect of unreliable electricity service on industrial users in developing countries has received more attention. Fisher-Vanden, Mansur, and Wang (2009) study the effect of rolling blackouts on the productivity of industrial firms in China. Foster and Steinbuks (2010) analyze the prevalence of self-generation by firms in Africa and show that improvements in supply reliability would have a relatively small effect on generator ownership. Jyoti, Ozbafli, and Jenkins (2006) calculate the cost of power outages using five years of data from three factories in Nepal.

The results from this paper have important implications for development policy. Infrastructure investments have a large fixed cost component, and the low demand for infrastructure services by poor households may suggest that such investments are unprofitable in the absence of government subsidies. Consequently, government programs such as universal service funds are used to provide infrastructure in low-income areas. However, if demand is sufficiently elastic with respect to service quality, there may be less need for such subsidies. In the context of this paper, upgrading electricity distribution networks may be unprofitable if demand is held fixed at existing levels, but profitable at higher levels of demand from additional appliance purchases by households in response to the improved reliability.

The remainder of this paper is organized as follows. Section 2 provides background information on electricity reliability in Colombia. Section 3 describes the outage, household characteristic, and electricity usage data used in the analysis. Section 4 provides the set-up of the econometric model of appliance choice and electricity demand. Section 5 describes the estimation results. Finally, Section 6 concludes.

2 Reliability of Electricity Supply in Colombia

Electricity is supplied through a highly complex and interconnected system, conventionally divided into three components: generation (the production of power), transmission (the transportation of power over long distances), and distribution (the local delivery of power to customers). Interruption of electricity supply to end users may be the result of insufficient capacity or equipment failures at any of these stages.[1]

Unlike many developing countries, generation capacity in Colombia has been sufficient to supply all electricity demand since 1993. Generation in Colombia is dominated by hydroelectricity and has historically been vulnerable to periods of reduced rainfall. In 1983 and 1992–93, low hydro inflows due the climate phenomenon *El Niño* led to generation shortfalls and widespread blackouts. About 14 percent of the normal annual demand was rationed in 1992, and a state of social and economic emergency was declared. This crisis was the impetus for deregulation of the electricity industry. New investment in thermal generation greatly reduced the vulnerability of the system to water shortages. Subsequent *El Niño* events in 1997–98, 2002–03, and 2009–10 did not cause any blackouts.[2]

Transmission network outages have been a significant source of reliability problems in the Colombian electricity system. A major contributor to these outages has been attacks on transmission lines by the guerrilla groups FARC and ELN. These attacks have been greatly reduced by improvements in the security situation in Colombia: the number of damaged or destroyed transmission pylons fell from 483 in 2002 to 77 in 2009.[3] Investment in new transmission lines has also reduced capacity constraints on major interconnections between different regions.

Problems in the distribution network are the cause of nearly 90 percent of power outages for typical consumers in the United States (Brown, 2009). They are also

[1] This paper considers only reliability. A perfectly reliable electricity supply is one without any interruptions, where interruptions are defined as a sustained period in which the voltage magnitude is zero. However, even if supply is not interrupted, fluctuations in voltage may create problems for certain categories of electrical equipment. Power quality is the measure of these deviations from a perfect sinusoidal voltage (Brown, 2009, p.43).

[2] In comparison, the neighboring countries of Ecuador and Venezuela, which are also highly dependent on rainfall for hydroelectric generation, suffered widespread rolling blackouts as a result of the 2009 *El Niño* ("Dark truth about Latin American energy", BBC News, November 20, 2009 `http://news.bbc.co.uk/2/hi/americas/8368785.stm`).

[3] XM Compañía de Expertos en Mercados S.A. E.S.P, "Informe de Operación y Administración del Mercado", 2005 and 2009.

the largest source of customer outages in Colombia. Distribution outages may be caused by equipment failures, trees, animals, lightning, accidents, sabotage, as well as scheduled interruptions for maintenance. While many of these causes are random and uncontrollable events, the amount of investment in the distribution network affects the resulting number and length of customer interruptions. For example, a device known as a recloser can be installed to automatically reenergize a distribution circuit following a temporary fault.[4] Installation of spare capacity may allow faulty equipment to be replaced without interrupting service to customers. For distribution networks in the United States, more than half of the total capital cost is for equipment and capacity to provide higher reliability (Brown, 2009).

Figure 1 shows the trend for demand lost due to all outages, as well as demand lost due to transmission system outages, from mid-2003 to 2008.[5] In 2008, the total unmet demand due to system outages (both planned and unplanned) was 49.1 GWh, an average of 4.1 GWh per month. This was 0.09 percent of the total electricity demand of 53870 GWh in 2008. For comparison, unmet demand due to system outages was 0.17 percent of total electricity demand in 2004. The upper line shows an estimate of the total demand lost at a local transformer level. In 2008, this total unserved demand was approximately 314 GWh, or 0.58 percent of total demand. The difference between the two lines represents demand lost due to outages in local distribution networks. That is, distribution network outages comprised 84 percent of total demand lost due to all outage causes in 2008.

Figure 2 shows the mean number of outage hours per month in 2005, by distribution area. For each transformer and month, firms report the number and length of outages in five categories: programmed, unprogrammed, force majeure, temporary, and other.[6] These reports are used by the regulator to calculate reliability indices for each transformer. If these indices repeatedly exceed regulatory bounds, the firm is required to pay compensation to all consumers served by the transformer. However,

[4]Over 80 percent of faults in an overhead distribution system are temporary, lasting a few seconds or less (Gers and Holmes, 2004).

[5]System outages are calculated from daily reports from the system operator of unmet demand due to transmission network events. Total outages are calculated by summing out outages across all distribution network transformers. For each transformer and month, the proportion of outage-hours in the month (p) and the total demand for the month (Q) are known. The demand lost due to outages is estimated as $\frac{pQ}{1-p}$.

[6]The "other" category may include outages due to generation or transmission events, safety or security reasons, expansion work on low-voltage distribution networks, or customer non-compliance with contract conditions.

the calculation of these indices excludes force majeure, temporary, and other outages.[7] Consequently, the firm has an incentive to classify outages, wherever possible, into one of these excluded categories. The graph shows that for the three regions with the greatest outage duration, a very high proportion of outages were reported in the uncompensated categories.

Figure 3 and Table 1 show the trend of mean monthly outage hours broken down by customer category. For this analysis, I define major users as those with their own transformer and more than 50 MWh of consumption per month. Reliability for major users and urban areas has consistently been much greater than for rural areas. However, reliability improvements in rural areas have reduced this gap: the mean length of outages in rural areas fell from 20.6 hours per month in 2003 to 11.5 hours per month in 2008.

Figures 4 and 5 show the geographical distribution of outages during 2005. The maps show the transformer-level data aggregated to the municipality level. The greatest number and length of outages were in the northern coastal region, the northeastern lowlands, and the south of Colombia. Nonetheless, there was substantial variation in reliability, even for neighboring municipalities served by the same distribution network.

This variation in reliability is unlikely to be caused by geographical differences in consumer demand. One common factor that affects both demand and reliability is weather. Outages are more common in hot regions, such as the northern coast of Colombia. Demand is also higher in these regions, because of greater usage of refrigeration, fans, and air conditioning. Nonetheless, hot weather can directly cause equipment failure and outages, by reducing the capacity of lines and transformers to transfer heat to their surroundings (Brown, 2009, p.147). Furthermore, because Colombia is a tropical country, there is much less annual variation in weather conditions. In any case, a correlated spike in demand across households would not necessarily cause an outage. Distribution equipment is able to function at levels greatly in excess of its nameplate capacity, although at a cost of increasing its future probability of failure (Brown, 2009, p.108).

[7]Ministry of Mines and Energy, Resolution 96 (2000), Article 2.

3 Data

The data set collected for this investigation provides an extremely rich environment for the analysis of household demand for electricity in a developing country. It comprises monthly electricity billing data, matched at a household level to cross-section data on household characteristics including appliance holdings, dwelling characteristics, and demographics. These data are combined with monthly reliability information for the distribution transformer serving the household.

The base data frame is a complete listing of the residential electricity bill recipients in Colombia in March 2004. This data set links all the other data sources: household characteristics, billing data, and distribution network data. It includes information on the dwelling address, the subsidy classification, and the identification code for the service transformer supplying the dwelling, as well as the firm and customer identification codes that match to the billing data.

Microdata on household characteristics are from the 2005 Amplified (Long-Form) Census, undertaken by the National Statistical Department ("DANE") over a 10-month period between May 2005 and March 2006. The amplified version of the census includes an additional 34 questions not in the regular version that was applied to the entire population. For small counties or towns, the extended version of the census was used for everyone. For larger counties and cities, a probabilistic sample (generally about 5–10 percent) was chosen to received the extended version.

I matched the census microdata to the billing data identification codes for approximately 150,000 urban households. For these matched households, I obtained their monthly electricity bills over the six-year period January 2003 to December 2008. These billing data include information on the start and end of the billing cycle, the billed consumption, the meter and connection type, any subsidy or contribution amounts, and the total charge. I use a subsample of 83661 households that have complete metered consumption data for the six months before and six months after the date of the census interview.

Using the subsidy classification and reported amounts from the electricity bills, combined with additional price schedule information from the regulator, I infer the price schedule faced by the household each month. Every neighborhood in Colombia is classified into one of six socioeconomic strata based on external characteristics of the dwellings. The bottom three strata receive a subsidy of approximately 50, 40, or

15 percent for between 130 and 200 kWh of consumption each month. Consequently, households in these strata face a non-linear price schedule, paying a low price p^L for the first Q_{sub} units of consumption and p^H for all subsequent units.

The billing data was matched to a database containing monthly information on all distribution service transformers in Colombia. The transformers are the final stages of the local distribution networks, in which the voltage is stepped down to the level at which it can be used by households. Since the losses when transmitting electricity at such low voltages are very large relative to high voltage transmission, these service transformers are generally located within a few hundred meters of the end user. The transformer database includes information on the geographical position of the transformer (longitude, latitude, and altitude), transformer capacity, the number of users and their demand for that month, and the number and total length of outages for that transformer and month.

4 Model and Estimation Methodology

In this section I describe the joint model of appliance ownership and electricity demand that I estimate with the household and outage date. I use a discrete factor approximation to model the potential correlation in the unobserved components of the individual appliance equations and the electricity demand equation.

4.1 Appliance Ownership Model

The set of appliances owned by a given household is determined by observable factors such as climate, the price and quality of electricity supply, the household's income, and demographic factors such as the number and age of household members. However, the appliance choice may also be affected by unobservable factors. For example, a household whose members are particular fans of soap operas may be more likely to own a television. The problem this creates for estimating the household demand for electricity, discussed by Dubin and McFadden (1984), is that the unobserved component in the appliance choice problem also enters the appliance-level demand equation. Continuing the example, the soap opera fans will watch more television and so consume more electricity than an otherwise identical household with different tastes.

I model the household's choice of appliance holdings using a multivariate logit model. The probability that household j owns appliance i is given by equation (4.1).

$$\text{Prob}(A_{ij} = 1) = \frac{\exp(\boldsymbol{\lambda_i'} \boldsymbol{z_j} + \rho_i \theta)}{1 + \exp(\boldsymbol{\lambda_i'} \boldsymbol{z_j} + \rho_i \theta)} \tag{4.1}$$

$\boldsymbol{z_j}$ is a vector of household-specific characteristics including household and dwelling size, household expenditure, and the mean number and length of electricity outages. The term $\rho_i \theta$ allows for correlation across appliance choices within a household, as well as correlation between the appliance choices and the demand for electricity.[8]

4.2 Electricity Demand Model

The model for electricity demand incorporates appliance holdings, household demographics and income, electricity price, and the monthly duration of outages. Appliance ownership enters directly and through interactions with household income. Equation (4.2) shows the equation for the observable components in the model.

$$\bar{q}_{jt} = \sum_{i=1}^{M} A_{ij}(\alpha_i + \gamma_i y_{jt}) + \zeta w_{jt} + \beta p_{jt} + \boldsymbol{\delta' z_{jt}} \tag{4.2}$$

In this equation i indexes the M individual appliances, which include a composite baseload appliance that is found in all households. A_{ij} is an indicator variable that is 1 if household j owns appliance i, and zero otherwise. y_{jt} is the income of household j in period t, w_{jt} is the length of electricity outages faced by household j in period t, and p_{jt} is the marginal price of electricity.[9] $\boldsymbol{z_{jt}}$ is a vector of characteristics of household j in period t.

Equation (4.3) shows the electricity demand for household j in period t, q_{jt}, given a marginal price of electricity p_{jt} and expenditure y_{jt}.

$$q_{jt} = \bar{q}_{jt}(p_{jt}, y_{jt}, .) + \rho_D \theta + \eta_{jt} + \varepsilon_{jt} \tag{4.3}$$

As described in Section 3, the household faces a non-linear price schedule with

[8] The data used for this paper does not contain information on the capital cost of each appliance, so it is not possible to embed the appliance choice decision within a utility maximization framework.

[9] For simplicity I refer to the variable y_{jt} as "income". In the data used for estimation this variable is household expenditure—specifically, the household's response to one of nine discrete categories for the level of income that is required to cover its monthly expenses.

a price p_{jt}^L for the first Q_{sub} units of consumption in a month, and a price p_{jt}^H for all subsequent consumption in the month. If the household chooses to consume on the second tier of the price schedule, its marginal price is p_{jt}^H but it has a lower marginal price for the first Q_{sub} units of consumption. I treat this reduced price on the inframarginal units as a transfer to the household and include this in the income variable, as shown in equation (4.4).

$$y_{jt}^H = y_j + Q_{sub}(p_{jt}^H - p_{jt}^L) \tag{4.4}$$

Of the three error components in equation (4.3), $\rho_D\theta$ and η_{jt} are assumed to be known by the household and used in the choice of the price schedule step. The θ term is the same unobservable θ that appears in Equation (4.1), and ρ_D (where D refers to demand) is a single parameter that measures the contribution of the unobservable θ to electricity demand. The additional error term ε_{jt}, which is not known by the household, may result in final consumption being on a different step to the one chosen by the household. This term represents the difficulty faced by the household in observing and optimizing its day-to-day appliance-level consumption of electricity.

Equation (4.5) shows the discrete and continuous components of the household demand for electricity.

$$q_{jt} = \begin{cases} \bar{q}_{jt}(p_{jt}^L, y_{jt}, .) + \rho_D\theta + \eta_{jt} + \varepsilon_{jt}, & \bar{q}_{jt}(p_{jt}^L, y_{jt}, .) + \rho_D\theta + \eta_{jt} < Q_{sub} \\ \bar{q}_{jt}(p_{jt}^H, y_{jt}^H, .) + \rho_D\theta + \eta_{jt} + \varepsilon_{jt}, & \bar{q}_{jt}(p_{jt}^H, y_{jt}^H, .) + \rho_D\theta + \eta_{jt} > Q_{sub} \\ Q_{sub} + \varepsilon_{jt}, & \text{otherwise} \end{cases} \tag{4.5}$$

θ enters both the electricity demand equation (4.5) and the appliance choice equations (4.1). It is assumed to have the discrete distribution shown in equation (4.6).

$$\theta = \begin{cases} \theta_1 & \text{with probability } p_1 \\ \theta_2 & \text{with probability } p_2 \\ \theta_3 & \text{with probability } 1 - p_1 - p_2 \end{cases} \tag{4.6}$$

E(θ) is assumed to be zero, restricting the value of θ_3 to be $\frac{-\theta_1 p_1 - \theta_2 p_2}{1 - p_1 - p_2}$.

All of the parameters of the distribution of θ (θ_1, θ_2, p_1, and p_2) are estimated in the maximum likelihood procedure. This definition of θ allows for heterogeneity across households, and is a major advantage of the discrete factor methodology.

η_{jt} is assumed to be distributed $N(0, \sigma_\eta^2)$ and ε_{jt} is assumed to be distributed $N(0, \sigma_\varepsilon^2)$. η, ε and θ are assumed to be independent.

Given these assumptions on the distribution of η_{jt} and ε_{jt}, combined with the discrete-continuous demand in equation 4.5, I construct the portion of the likelihood function that corresponds to electricity demand.[10] This is combined with the logit likelihoods from equation (4.1) for the 128 possible combinations of the seven appliances. Finally, the full likelihood contribution for each household is the sum of three individual components that correspond to the three possible values of θ in equation (4.6).

The overall contribution to the log likelihood of one household j is given by equation 4.7.

$$\begin{aligned}
L_j = &\log \sum_{k=1}^{3} p_k \left[\sum_{b=0}^{2^M-1} \prod_{i \notin A(b)} \left(\frac{1}{1+\exp(\boldsymbol{\lambda_i'} \boldsymbol{z_j} + \rho_i \theta_k)} \right)^{1-A_{ij}} \prod_{i \in A(b)} \left(\frac{\exp(\boldsymbol{\lambda_i'} \boldsymbol{z_j} + \rho_i \theta_k)}{1+\exp(\boldsymbol{\lambda_i'} \boldsymbol{z_j} + \rho_i \theta_k)} \right)^{A_{ij}} \right] \\
&\times \prod_{t=1}^{T} \Bigg[\frac{1}{\sigma_\nu} \phi \left(\frac{q_{jt} - \bar{q}_{jt}^L - \rho_D \theta_k}{\sigma_\nu} \right) \Phi \left(\frac{Q_{sub} - \bar{q}_{jt}^L - \rho_D \theta_k}{\sigma_\eta \sqrt{1-\tau^2}} - \frac{\tau (q_{jt} - \bar{q}_{jt}^L - \rho_D \theta_k)}{\sigma_\nu \sqrt{1-\tau^2}} \right) \\
&\quad + \frac{1}{\sigma_\nu} \phi \left(\frac{q_{jt} - \bar{q}_{jt}^H - \rho_D \theta_k}{\sigma_\nu} \right) \left(1 - \Phi \left(\frac{Q_{sub} - \bar{q}_{jt}^H - \rho_D \theta_k}{\sigma_\eta \sqrt{1-\tau^2}} - \frac{\tau (q_{jt} - \bar{q}_{jt}^H - \rho_D \theta_k)}{\sigma_\nu \sqrt{1-\tau^2}} \right) \right) \\
&\quad + \frac{1}{\sigma_\epsilon} \phi \left(\frac{q_{jt} - Q_{sub}}{\sigma_\epsilon} \right) \left(\Phi \left(\frac{Q_{sub} - \bar{q}_{jt}^H - \rho_D \theta_k}{\sigma_\eta} \right) - \Phi \left(\frac{Q_{sub} - \bar{q}_{jt}^L - \rho_D \theta_k}{\sigma_\eta} \right) \right) \Bigg]
\end{aligned} \tag{4.7}$$

$$\begin{aligned}
\text{where } \tau &= \frac{\sigma_\eta}{\sigma_\nu} \\
\bar{q}_{jt}^L &= \bar{q}_{jt}(p_{jt}^L, y_{jt}, .) \\
\bar{q}_{jt}^H &= \bar{q}_{jt}(p_{jt}^H, y_{jt}^H, .)
\end{aligned}$$

and b indexes the 2^M possible bundles, $A(b)$, of the M appliances.

[10] See McRae (2010) for further details of this derivation.

4.3 Estimation Methodology

There are seven appliances (or uses of electricity) for which I model the ownership decision: refrigerator, washing machine, television, computer, air conditioning, fan, and the use of electricity as the primary energy source for cooking. These appliances were selected either because they are owned by a large proportion of households, or because their consumption of electricity is relatively large.

I estimate the model with a single month of data for each household (so that $T = 1$). The billing cycle that I use for each household is the one that is closest in time to the date of the census interview. I drop households with an average monthly consumption for the six months before and after the census interview exceeding 1000 kWh. The parameter ρ_1, the effect of θ on the household's decision to buy a refrigerator, is normalized to 1.

Initial values for the estimation are obtained by fixing θ to be zero and estimating the appliance choice logit equations and the electricity demand equation separately. I held these initial values constant and estimated the parameters of the θ distribution. Finally, I relaxed all parameters and estimated the combined model using the BHHH algorithm with analytic gradients.

5 Results

The results for the maximum likelihood estimation of equation (4.7) are shown in Table 2 to 7. There are three sets of results corresponding to different assumptions on the common unobservable term θ. First, I set θ equal to zero and estimate the model without this common unobservable across the appliance and demand equations. Second, I estimate the parameters of the distribution of θ and ρ_i for each of the appliance equations, but set $\rho_D = 0$ so that θ does not enter electricity demand. Finally, I estimate the full model in equation (4.7) with the common unobservable θ across the appliance and demand equations.

Table 2 shows the coefficient estimates for the appliance choice equations with $\theta = 0$. Without the common unobservable term across the seven appliance choices, these results are equivalent to an independent binomial logit model for each of the individual appliance equations. Table 3 shows the appliance choice estimates with the common unobservable across the appliances, but not entering into the electricity demand equations. Finally, Table 4 shows the appliance choice estimates from the full model. In all of the tables, the coefficients are interpreted as the expected change in the log of the odds of ownership for that appliance, for a unit change in the dependent variable, holding the other variables constant.[11] Positive values of the estimated coefficients in the table correspond to variables that increase the probability of ownership of the appliance. Table 5 provides transformed coefficients from Table 4 to show the effect on the odds of ownership, rather than the log of the odds, for each appliance.

For all three versions of the model, larger families are less or equally likely to own each of the appliances except for a television.[12] Larger dwellings and higher total household expenditure increase the probability of owning each of the appliances, except for choice of cooking with electricity. Living in hotter regions increases the probability of owning a fridge, air conditioner, and fan.

The reliability of electricity supply—measured here as the log of the mean number of outages over the previous year and the log of the mean monthly length of outages over the previous year—has a large effect on the ownership choice for every appliance modeled. A higher number of outages reduces the probability of owning each of the appliances, and a greater length of outages reduces the probability of owning every appliance except fans. Although the length of outages has a positive effect on fan ownership, the coefficient is small compared to all of the other estimates. Interestingly, in Table 4, the length of outages has a relatively larger effect on fridge ownership while the number of outages has a relatively larger effect on computer ownership. This is consistent with the anticipated cost of outages on fridge and computer usage.

Comparing the appliance choice estimates for the three different assumptions on θ, there is no change in the sign of the estimates for any of the models. However, with the exception of electric cooking, there are large changes in the magnitude of the estimates for all appliances when the common unobservable is added to the model (Table 2 to 3). Conversely, there are only very minor changes to the estimates once the common unobservable is also incorporated into demand (Table 3 to 4).

Table 6 shows the estimates of the electricity demand equation in the model. In this table the results for the three sets of assumptions on θ are shown in different columns. Column 1 shows the demand estimates with $\theta = 0$, Column 2 shows the demand estimates with θ in the appliance choice equations but not demand ($\rho_D = 0$),

[11] The odds of ownership is a monotonic transformation, $\frac{p}{1-p}$, of the probability of ownership for that appliance.

[12] The expenditure measure is based on nine binned values of monthly household expenditure and is not adjusted for household size. Holding expenditure constant, an increase in the number of household members therefore reduces per capita expenditure.

and Column 3 shows the demand estimates for the full model.

For the results in Column 3, the total length of outages during the billing cycle has a negative effect on consumption: an hour of outage reduces electricity consumption for the month by 0.271 kWh. Over a full month this outage effect corresponds to a consumption of 195 kWh, slightly above the sample mean consumption of 173 kWh. The constant terms for each of the appliance ownership variables are positive, although the coefficients for computer, fan and television are small and not statistically significant. However, the interactions of the fan and computer variables with the household expenditure variable are positive and statistically significant.

The expenditure term, without any appliance interactions, is positive and statistically significant. The range of values for the expenditure variable is 0.1 to 5.0 (equivalent to US$42 to US$2,110 per month). The interaction between expenditure and refrigerator ownership is negative: for households with a refrigerator the effect of income on electricity consumption is about half as large as for households without a refrigerator. One interpretation of this result is that refrigerator usage is insensitive to changes in income compared to the usage of other appliances. Another possible interpretation is that poorer households have older, more inefficient refrigerators that use more electricity. Despite the negative interaction terms between expenditure and some appliances, the combined effect of expenditure on electricity consumption is positive for every combination of appliances.

Comparing the results for the three sets of demand estimates, there is little change between Column 1 and Column 2. That is, adding a common unobservable into the seven appliance equations has a large effect on the estimates in those equations, but little effect on the demand estimates. Conversely, there is a large change in the magnitude of many of the estimates between Column 2 and Column 3. Incorporating θ in the demand equation, and so accounting for the correlation in the unobservables between appliance choice and electricity demand, results in potentially important changes in the magnitudes of the estimated demand parameters. For example, the expenditure and outage estimates are larger in magnitude. All of the constant terms for the individual appliances are smaller in magnitude. For computers, televisions, and fans, these terms are no longer statistically significantly different from zero in Column 3. There are also changes in the magnitude of many of the interaction terms between appliances and expenditure: larger in magnitude for washing machines and televisions, smaller in magnitude for fridges, air conditioners, and computers.

For the final part of the results from equation (4.7), Table 7 shows the parameter estimates for the discrete factor distribution of θ as well as the parameters ρ_i and ρ_d in the appliance and demand equations. The first column is empty because it corresponds to the case of $\theta = 0$. The second column shows the estimates without the common unobservable in the demand equation (so $\rho_D = 0$). The third column shows the results for the full model. There is little change to the parameters of the discrete factor distribution with the addition of ρ_D. This stability in the estimated factor distribution demonstrates that it is identified by the correlation across appliances in the unobservable determinants of appliance holdings. It is not sensitive to the specification of the non-linear model of electricity demand.

There are eight equations in the model: the seven appliance choice equations for the decision to own a refrigerator, washing machine, air conditioner, fan, electric cooking, computer, and television, and the electricity demand equation. The variance-covariance matrix of the disturbance terms in the eight equations is shown in equation (5.1).

$$\begin{bmatrix} 1+\rho_1\sigma_\theta^2 & \rho_1\rho_2\sigma_\theta^2 & \cdots & \rho_1\rho_7\sigma_\theta^2 & \rho_1\rho_D\sigma_\theta^2 \\ & 1+\rho_2^2\sigma_\theta^2 & \cdots & \rho_2\rho_7\sigma_\theta^2 & \rho_2\rho_D\sigma_\theta^2 \\ & & \ddots & & \vdots \\ & & & 1+\rho_7^2\sigma_\theta^2 & \rho_7\rho_D\sigma_\theta^2 \\ & & & & \rho_D^2\sigma_\theta^2+\sigma_\eta^2+\sigma_\epsilon^2 \end{bmatrix} \tag{5.1}$$

where $\sigma_\theta^2 = p_1^2\theta_1^2 + p_2^2\theta_2^2 + (1-p_1-p_2)^2\theta_3^2$

Table 8 shows the estimated covariance matrix for the model disturbances, and Table 9 shows the estimated correlation matrix. The unobserved components of the appliance choice equations are all positively correlated with each other and also with the unobserved component of the electricity demand equation. All of the correlations are statistically significantly different from zero at conventional levels. The smallest correlation across the appliance choices is between electric cooking and the other appliances. This demonstrates why the electric cooking estimates changed by only a small amount once the θ term was included in the model.

Table 10 demonstrates the importance for the economic analysis of accounting for correlation in the unobservables in the appliance equations. It shows the actual and predicted probability of ownership of every combination of the seven modeled appliances. The observed probability is the number of households that own both appliances, divided by the total number of households in the sample. The predicted probability is the sample mean of the product of the probabilities of ownership for each household and appliance, calculated from the logit formula. For example, 30.7 percent of households in the sample own both a fridge and a fan. For the model with no common unobservable, the mean predicted probability of owning a fridge and a fan is 33.7 percent. For the model with the common unobservable, this probability is 31.4 percent.

For most combinations of appliances, there is little difference in the predicted probabilities from the models with and without the common unobservable. However, for a few appliance pairs (such as fridge/fan, fridge/television, and washing machine/computer), this difference is large. The third and fifth columns show the squared difference between the predicted and observed probabilities, normalized by the observed probability. The sum of these terms for the model with no common unobservable is 1.750, compared to the sum for the model with the common unobservable of 0.458. Overall, the appliance choice model with the common unobservable does a better job of matching the observed outcomes.

Table 11 shows the results of a counterfactual analysis in which the number and length of outages (both in the current month and in the long-term average) is reduced by 50 percent. The top block shows the effect of the outage reduction on the probabilities of appliance ownership, calculated from the sample data using the appliance choice equations. Ownership rates of all appliances are predicted to increase after the reduction in outages, with the largest percentage point increase in washing machine ownership and the smallest in air conditioner ownership.

In the second block of Table 11, I show two results for the counterfactual change in electricity demand. If there is no change in the appliance holdings of households as a result of the 50 percent reduction in outages, then demand would increase by 0.5 kWh, from 173.1 kWh to 173.5 kWh per month. This increase is solely as a result of the reduction in current period outages that enter through the outage minutes term in Table 6. The final row in Table 11 shows the change in electricity demand if appliance stocks adjust as predicted by the appliance choice model. Demand would increase to 177.0 kWh per month. Of this increase in demand, about 85 percent corresponds to the change in appliance stocks and about 15 percent to the direct effect of outages on electricity consumption.

Table 12 shows the results of a counterfactual 10 percent increase in total household expenditure. There would be a slight increase in the probability of ownership of all appliances. Electricity demand is predicted to increase by a mean of 2.0 kWh per month as a result of the higher expenditure. However, only about 15 percent of this increase corresponds to additional consumption from new appliances. Most of the increase is due to higher electricity consumption from the existing appliance portfolio, or from the addition of small appliances in the baseload that are not included in the model.

6 Conclusion

Unreliable infrastructure has detrimental effects on the well-being and the prospects for economic advancement for millions of families in developing countries. In this paper I have shown that an unreliable electricity supply has both a short-run and a long-run effect on electricity demand. Power outages affect electricity consumption in the short-run, because some uses of electricity cannot be shifted to other times. In the long-run, power outages affect electricity consumption by reducing the benefits from appliance ownership. Modeling these two effects requires estimation of the correlation in the unobserved components of the individual appliance choice equations and the electricity demand equation. I have shown that reliability improvements affect demand primarily through changes in the household's appliance portfolio. Consideration of the effect of distribution infrastructure investments on long-run electricity demand may be important in designing policies for funding such investment.

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Table 1: Monthly Mean Number and Length of Outage, by Customer Category and Year

Year	Monthly Outage Duration (hours)			Monthly Number of Outages		
	Major	Urban	Rural	Major	Urban	Rural
2003	1.9	5.9	20.6	1.6	3.5	8.6
2004	2.1	4.4	16.0	1.7	3.7	9.2
2005	2.1	4.4	12.6	1.7	3.8	7.6
2006	1.8	4.1	13.3	1.6	3.4	7.8
2007	2.3	4.0	10.8	1.5	3.0	6.5
2008	2.1	4.3	11.5	1.7	3.7	7.2

Major consumer category includes all transformers with a single user and more than 50 MWh/month consumption. Urban and rural categories are all other transformers in urban and rural areas, respectively. Number of outages excludes minor outages of less than one minute in duration. The department of Boyacá and parts of Antioquia are excluded due to missing data.

Table 2: Appliance Choice Estimates with No Common Unobservable

	Fridge	Wash	A/C	Fan	Cook	Comp	TV
Hh members	-0.034	-0.005	-0.083	-0.050	-0.159	-0.030	0.044
	(0.0050)	(0.0047)	(0.0111)	(0.0055)	(0.0074)	(0.0061)	(0.0057)
Rooms	0.577	0.401	0.251	0.241	-0.138	0.349	0.436
	(0.0086)	(0.0065)	(0.0142)	(0.0077)	(0.0088)	(0.0075)	(0.0096)
Apartment (0/1)	0.238	0.563	0.184	0.353	0.669	0.483	0.373
	(0.0314)	(0.0230)	(0.0588)	(0.0297)	(0.0267)	(0.0253)	(0.0372)
Expenditure (m pesos)	1.035	0.746	0.451	0.362	0.060	0.782	0.815
	(0.0204)	(0.0114)	(0.0191)	(0.0136)	(0.0130)	(0.0110)	(0.0221)
Av. temperature (deg C)	0.018	0.006	0.025	0.045	-0.074	0.019	0.018
	(0.0060)	(0.0049)	(0.0149)	(0.0053)	(0.0054)	(0.0058)	(0.0065)
Elevation (000m)	0.422	-0.440	-2.777	-4.482	2.846	-0.201	-0.275
	(0.0591)	(0.0494)	(0.1265)	(0.0721)	(0.0941)	(0.0594)	(0.0690)
Elevation squared	-0.242	0.179	0.692	0.697	-0.959	0.175	0.106
	(0.0168)	(0.0138)	(0.0368)	(0.0249)	(0.0251)	(0.0159)	(0.0200)
Log(1 + no. outages)	-0.190	-0.500	-0.553	-0.672	-0.668	-0.327	-0.255
	(0.0230)	(0.0206)	(0.0521)	(0.0232)	(0.0316)	(0.0255)	(0.0263)
Log(1 + outage hours)	-0.415	-0.189	-0.102	0.040	-0.592	-0.296	-0.247
	(0.0195)	(0.0179)	(0.0412)	(0.0196)	(0.0351)	(0.0235)	(0.0224)

Each column shows the estimates for the ownership equation of the particular appliance, from a model with no common unobservable. Each equation is equivalent to an independent logit for ownership of that appliance. Estimates of the electricity demand equation in this model are shown in Column 1 of Table 6. Standard errors are computed from the covariance of the analytic first derivatives. Number of observations = 83434.

Table 3: Appliance Choice Estimates with Common Unobservable for Appliance Equations Only

	Fridge	Wash	A/C	Fan	Cook	Comp	TV
Hh members	-0.046	-0.002	-0.103	-0.060	-0.161	-0.038	0.054
	(0.0067)	(0.0067)	(0.0118)	(0.0063)	(0.0074)	(0.0072)	(0.0069)
Rooms	0.821	0.627	0.293	0.288	-0.139	0.450	0.527
	(0.0139)	(0.0112)	(0.0155)	(0.0089)	(0.0088)	(0.0093)	(0.0119)
Apartment (0/1)	0.325	0.867	0.207	0.416	0.672	0.634	0.457
	(0.0428)	(0.0335)	(0.0620)	(0.0337)	(0.0268)	(0.0308)	(0.0450)
Expenditure (m pesos)	1.198	1.109	0.551	0.420	0.061	1.014	0.765
	(0.0265)	(0.0199)	(0.0218)	(0.0156)	(0.0131)	(0.0149)	(0.0243)
Av. temperature (deg C)	0.029	0.007	0.031	0.054	-0.075	0.020	0.029
	(0.0083)	(0.0071)	(0.0152)	(0.0061)	(0.0054)	(0.0069)	(0.0080)
Elevation (000m)	0.737	-0.710	-3.006	-5.590	2.824	-0.357	-0.298
	(0.0813)	(0.0719)	(0.1340)	(0.0876)	(0.0942)	(0.0700)	(0.0855)
Elevation squared	-0.392	0.284	0.745	0.919	-0.954	0.247	0.129
	(0.0233)	(0.0200)	(0.0386)	(0.0280)	(0.0251)	(0.0188)	(0.0247)
Log(1 + no. outages)	-0.297	-0.782	-0.631	-0.823	-0.669	-0.413	-0.357
	(0.0318)	(0.0308)	(0.0552)	(0.0266)	(0.0316)	(0.0299)	(0.0326)
Log(1 + outage hours)	-0.664	-0.290	-0.118	0.047	-0.588	-0.320	-0.354
	(0.0275)	(0.0260)	(0.0443)	(0.0222)	(0.0352)	(0.0271)	(0.0278)

Each column shows the estimates for the ownership equation of the particular appliance, from a model with a common unobservable across the seven appliance equations. Estimates of the electricity demand equation in this model are shown in Column 2 of Table 6, and estimates of the discrete factor distribution are shown in Column 2 of Table 7. Standard errors are computed from the covariance of the analytic first derivatives. Number of observations = 83434.

Table 4: Appliance Choice Estimates with Common Unobservable for Appliance and Demand Equations

	Fridge	Wash	A/C	Fan	Cook	Comp	TV
Hh members	-0.043	-0.003	-0.105	-0.060	-0.162	-0.041	0.057
	(0.0068)	(0.0067)	(0.0118)	(0.0063)	(0.0074)	(0.0072)	(0.0069)
Rooms	0.831	0.627	0.289	0.287	-0.139	0.450	0.534
	(0.0140)	(0.0112)	(0.0155)	(0.0089)	(0.0088)	(0.0094)	(0.0119)
Apartment (0/1)	0.294	0.857	0.206	0.414	0.672	0.634	0.429
	(0.0425)	(0.0334)	(0.0619)	(0.0336)	(0.0268)	(0.0308)	(0.0448)
Expenditure (m pesos)	1.203	1.105	0.549	0.420	0.062	1.017	0.767
	(0.0266)	(0.0197)	(0.0217)	(0.0156)	(0.0131)	(0.0149)	(0.0243)
Av. temperature (deg C)	0.029	0.008	0.032	0.054	-0.075	0.020	0.028
	(0.0083)	(0.0071)	(0.0152)	(0.0060)	(0.0054)	(0.0069)	(0.0080)
Elevation (000m)	0.729	-0.701	-2.992	-5.573	2.824	-0.357	-0.310
	(0.0813)	(0.0719)	(0.1339)	(0.0874)	(0.0942)	(0.0701)	(0.0854)
Elevation squared	-0.389	0.283	0.741	0.915	-0.953	0.248	0.131
	(0.0233)	(0.0199)	(0.0386)	(0.0279)	(0.0251)	(0.0189)	(0.0247)
Log(1 + no. outages)	-0.286	-0.776	-0.628	-0.817	-0.669	-0.412	-0.347
	(0.0318)	(0.0307)	(0.0552)	(0.0265)	(0.0316)	(0.0300)	(0.0326)
Log(1 + outage hours)	-0.672	-0.297	-0.120	0.049	-0.587	-0.323	-0.355
	(0.0276)	(0.0260)	(0.0443)	(0.0222)	(0.0352)	(0.0271)	(0.0278)

Each column shows the estimates for the ownership equation of the particular appliance, from a model with a common unobservable across the seven appliance equations and the demand equation. Estimates of the electricity demand equation in this model are shown in Column 3 of Table 6, and estimates of the discrete factor distribution are shown in Column 3 of Table 7. Standard errors are computed from the covariance of the analytic first derivatives. Number of observations = 83434.

Table 5: Odds Ratio for Estimates for Appliance Choice Model with Discrete Factor Distribution

	Fridge	Wash	A/C	Fan	Cook	Comp	TV
Hh members	0.96	1.00	0.90	0.94	0.85	0.96	1.06
	(0.0065)	(0.0067)	(0.0107)	(0.0059)	(0.0063)	(0.0069)	(0.0073)
Rooms	2.29	1.87	1.33	1.33	0.87	1.57	1.71
	(0.0321)	(0.0209)	(0.0206)	(0.0119)	(0.0076)	(0.0147)	(0.0203)
Apartment (0/1)	1.34	2.36	1.23	1.51	1.96	1.89	1.54
	(0.0570)	(0.0787)	(0.0761)	(0.0508)	(0.0524)	(0.0582)	(0.0688)
Expenditure (m pesos)	3.33	3.02	1.73	1.52	1.06	2.76	2.15
	(0.0886)	(0.0596)	(0.0376)	(0.0237)	(0.0139)	(0.0412)	(0.0522)
Av. temperature (deg C)	1.03	1.01	1.03	1.06	0.93	1.02	1.03
	(0.0085)	(0.0071)	(0.0157)	(0.0064)	(0.0051)	(0.0071)	(0.0083)
Elevation (000m)	2.07	0.50	0.05	0.00	16.84	0.70	0.73
	(0.1686)	(0.0357)	(0.0067)	(0.0003)	(1.5863)	(0.0490)	(0.0627)
Elevation squared	0.68	1.33	2.10	2.50	0.39	1.28	1.14
	(0.0158)	(0.0264)	(0.0810)	(0.0697)	(0.0097)	(0.0242)	(0.0281)
Log(1 + no. outages)	0.75	0.46	0.53	0.44	0.51	0.66	0.71
	(0.0239)	(0.0141)	(0.0294)	(0.0117)	(0.0162)	(0.0199)	(0.0230)
Log(1 + outage hours)	0.51	0.74	0.89	1.05	0.56	0.72	0.70
	(0.0141)	(0.0193)	(0.0393)	(0.0233)	(0.0195)	(0.0196)	(0.0195)

Estimates are reported as the odds ratio and calculated as $\exp(b)$ where b is the coefficient from Table 4. Standard errors are computed from the standard errors in Table 4 using the following formula from the delta method: $\exp(b)\mathrm{se}(b)$.

Table 6: Parameter Estimates for Electricity Demand Model with Discrete Factor Distribution

	(1)	(2)	(3)
Expenditure (m pesos)	20.506	20.504	24.952
	(3.0953)	(3.0936)	(3.1998)
Price (pesos/kWh)	-1.053	-1.053	-1.054
	(0.0209)	(0.0209)	(0.0209)
Outage minutes	-0.003	-0.003	-0.005
	(0.0010)	(0.0010)	(0.0011)
Refrigerator	61.025	61.022	47.987
	(2.6314)	(2.6305)	(3.2386)
Washing machine	24.806	24.802	13.305
	(2.0557)	(2.0565)	(2.7533)
Air conditioner	54.851	54.855	49.248
	(3.4544)	(3.4592)	(3.5717)
Fan	11.565	11.565	4.047
	(2.2018)	(2.2020)	(2.5377)
Electric cooking	42.769	42.772	42.442
	(2.6878)	(2.6943)	(2.6926)
Computer	8.332	8.334	1.026
	(2.3419)	(2.3425)	(2.5467)
Television	16.626	16.625	5.068
	(3.1536)	(3.1434)	(3.6381)
Expenditure × refrigerator	-13.001	-13.000	-12.453
	(2.4654)	(2.4670)	(2.4619)
Expenditure × washing machine	-1.404	-1.403	-2.458
	(1.4010)	(1.4020)	(1.4210)
Expenditure × air conditioner	4.511	4.510	3.491
	(1.5902)	(1.5918)	(1.5992)
Expenditure × fan	7.446	7.446	7.539
	(1.1281)	(1.1284)	(1.1310)
Expenditure × electric cooking	-0.327	-0.327	-0.264
	(1.2747)	(1.2752)	(1.2805)
Expenditure × computer	5.247	5.246	4.054
	(1.2261)	(1.2266)	(1.2561)
Expenditure × television	1.779	1.779	2.575
	(3.0029)	(3.0020)	(3.0137)
Household members	10.647	10.647	10.465
	(0.2470)	(0.2469)	(0.2483)
Rooms in dwelling	10.053	10.053	12.606
	(0.3524)	(0.3525)	(0.5159)

Table 6: Parameter Estimates for Electricity Demand Model with Discrete Factor Distribution (continued)

	(1)	(2)	(3)
Elevation (000m)	-60.854	-60.858	-66.082
	(5.3882)	(5.3888)	(5.4860)
Elevation squared	21.572	21.573	22.977
	(1.6474)	(1.6475)	(1.6695)
Av. temperature (deg C)	-0.721	-0.721	-0.564
	(0.3418)	(0.3418)	(0.3435)
State capital	10.925	10.929	12.991
	(1.4274)	(1.4275)	(1.4773)
Constant	191.946	191.928	203.948
	(10.6403)	(10.6359)	(10.8435)
σ_η	113.500	113.495	112.951
	(0.5274)	(0.5275)	(0.5525)
σ_ϵ	61.749	61.747	61.815
	(0.8381)	(0.8382)	(0.8370)
Stratum FEs	Y	Y	Y
Region FEs	Y	Y	Y

Notes: Column 1 shows the estimates of the demand parameters for the model with no common unobservable. Column 2 shows the estimates for the model with a common unobservable across the appliance choice equations, but not between appliance choice and electricity demand ($\rho_D = 0$). Column 3 shows the estimates for the full model in Equation (4.7). Standard errors are computed from the covariance of the analytic first derivatives. Number of observations = 83434.

Table 7: Parameter Estimates for Discrete Factor Distribution

	(1)	(2)	(3)
θ_1		2.886	2.922
		(0.0768)	(0.0774)
θ_2		-0.115	-0.138
		(0.0263)	(0.0266)
θ_3		-3.579	-3.604
		(0.0765)	(0.0774)
p_1		0.202	0.205
		(0.0057)	(0.0056)
p_2		0.656	0.653
		(0.0051)	(0.0050)
p_3		0.142	0.141
		(0.0037)	(0.0037)
ρ_2 (washing machine choice)		1.083	1.059
		(0.0346)	(0.0339)
ρ_3 (air conditioner choice)		0.663	0.645
		(0.0261)	(0.0254)
ρ_4 (fan choice)		0.610	0.597
		(0.0174)	(0.0171)
ρ_5 (electric cooking choice)		0.052	0.053
		(0.0088)	(0.0087)
ρ_6 (computer choice)		0.718	0.709
		(0.0213)	(0.0211)
ρ_7 (television choice)		0.790	0.787
		(0.0226)	(0.0227)
ρ_D (electricity demand)			8.136
			(1.3079)
Log-likelihood	-708053	-697491	-697475

Notes: Column 1 shows the estimates for the model with no common unobservable. Column 2 shows the discrete factor distribution estimates for the model with a common unobservable across the appliance choice equations, but not between appliance choice and electricity demand. Column 3 shows the discrete factor distribution estimates for the full model in Equation (4.7). Standard errors are computed from the covariance of the analytic first derivatives. Number of observations = 83434.

Table 8: Estimated Covariance Matrix for Model Disturbances

	Fridge	Wash	A/C	Fan	Cook	Comp	TV	Demand
Fridge	2.273 (0.0300)	0.665 (0.0215)	0.405 (0.0175)	0.375 (0.0127)	0.033 (0.0055)	0.445 (0.0148)	0.495 (0.0173)	5.111 (0.8276)
Wash		2.350 (0.0303)	0.429 (0.0182)	0.397 (0.0124)	0.035 (0.0058)	0.472 (0.0143)	0.524 (0.0164)	5.414 (0.8748)
A/C			1.906 (0.0176)	0.242 (0.0101)	0.022 (0.0036)	0.287 (0.0122)	0.319 (0.0132)	3.296 (0.5409)
Fan				1.869 (0.0091)	0.020 (0.0033)	0.266 (0.0084)	0.295 (0.0094)	3.050 (0.4925)
Cook					1.647 (0.0006)	0.024 (0.0039)	0.026 (0.0043)	0.272 (0.0618)
Comp						1.961 (0.0130)	0.351 (0.0110)	3.624 (0.5855)
TV							2.034 (0.0166)	4.023 (0.6511)
Demand								16620.500 (75.3654)

Standard errors (shown in parentheses) are computed from the covariance of the analytic first derivatives.

Table 9: Estimated Correlation Matrix for Model Disturbances

	Fridge	Wash	A/C	Fan	Cook	Comp	TV	Demand
Fridge	1.000 (0.0000)	0.288 (0.0066)	0.195 (0.0069)	0.182 (0.0049)	0.017 (0.0028)	0.211 (0.0054)	0.230 (0.0061)	0.026 (0.0042)
Wash		1.000 (0.0000)	0.203 (0.0070)	0.189 (0.0047)	0.018 (0.0029)	0.220 (0.0051)	0.240 (0.0057)	0.027 (0.0044)
A/C			1.000 (0.0000)	0.128 (0.0046)	0.012 (0.0020)	0.149 (0.0054)	0.162 (0.0057)	0.019 (0.0030)
Fan				1.000 (0.0000)	0.011 (0.0019)	0.139 (0.0038)	0.151 (0.0040)	0.017 (0.0028)
Cook					1.000 (0.0000)	0.013 (0.0021)	0.014 (0.0023)	0.002 (0.0004)
Comp						1.000 (0.0000)	0.176 (0.0046)	0.020 (0.0032)
TV							1.000 (0.0000)	0.022 (0.0035)
Demand								1.000 (0.0000)

Standard errors (shown in parentheses) are computed using the delta method from the covariance of the analytic first derivatives.

Table 10: Observed and Predicted Appliance Combinations With and Without Common Unobservable

Ownership probability	Observed	No common unobservable		Common unobservable	
		Predicted	$\frac{(P-O)^2}{O}$	Predicted	$\frac{(P-O)^2}{O}$
Fridge +					
Washing machine	36.7	37.1	0.006	37.4	0.013
Air conditioner	3.1	3.3	0.004	3.4	0.019
Fan	30.7	33.7	0.285	31.4	0.014
Electric cooking	10.6	11.4	0.055	10.7	0.001
Computer	19.5	20.5	0.047	20.5	0.046
Television	77.2	82.7	0.386	77.8	0.004
Washing machine +					
Air conditioner	2.3	1.9	0.097	2.6	0.042
Fan	14.0	12.7	0.132	14.9	0.055
Electric cooking	6.2	6.1	0.002	6.3	0.000
Computer	15.7	13.2	0.382	16.4	0.034
Television	36.7	36.4	0.002	37.8	0.031
Air conditioner +					
Fan	2.7	2.2	0.086	2.6	0.005
Electric cooking	0.4	0.3	0.025	0.3	0.008
Computer	1.7	1.2	0.131	1.8	0.009
Television	3.1	3.2	0.003	3.4	0.035
Fan +					
Electric cooking	2.1	2.0	0.006	2.1	0.000
Computer	6.9	6.3	0.055	7.7	0.081
Television	33.8	32.8	0.029	34.1	0.002
Electric cooking +					
Computer	3.7	3.7	0.000	3.8	0.001
Television	11.0	11.1	0.002	11.2	0.005
Computer +					
Television	19.6	20.2	0.016	20.7	0.054
$\sum \frac{(P-O)^2}{O}$			1.750		0.458

Observed appliance ownership probabilities are based on the proportion of households in the sample owning both appliances. Predicted appliance ownership probabilities are the sample mean of the product of the probabilities from the logit formula for each appliance. For each model, the squared difference between the predicted and observed appliance ownership probabilities is shown, normalized by the observed appliance ownership probability. The bottom row shows the sum of these squared normalized differences across all appliance pairs.

Table 11: Change in Appliance Choices and Electricity Demand from a 10 percent Increase in Household Expenditure

	Before	After	Difference
Appliance ownership (%)			
Fridge	81.7	85.2	3.5
Washing machine	37.1	42.8	5.7
Air conditioner	3.2	4.3	1.1
Fan	37.1	40.7	3.6
Electric cooking	11.9	15.9	4.0
Computer	19.7	22.7	3.0
Television	88.9	91.1	2.2
Electricity demand (kWh)			
Appliances held fixed	172.5	178.4	5.8
Appliance holdings changed	172.5	179.5	6.9

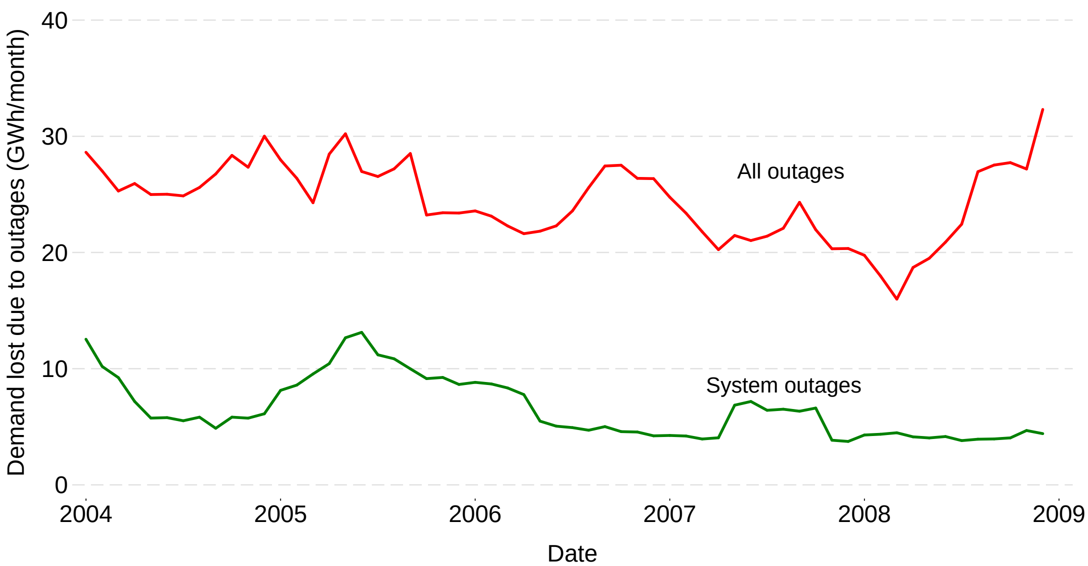
Appliance ownership probabilities are the sample mean of the probabilities from the logit formula for each appliance. Electricity demand with appliances held fixed is based on a single draw of ε and η. Demand with appliance holdings changed is based on draws of uniform random numbers to determine appliance ownership given the estimated probabilities, then the draw of ε and η to calculate electricity demand given those appliances.

Table 12: Change in Appliance Choices and Electricity Demand from a 10 percent Increase in Household Expenditure

	Before	After	Difference
Appliance ownership (%)			
Fridge	81.7	82.6	0.9
Washing machine	37.4	38.8	1.3
Air conditioner	3.2	3.4	0.2
Fan	36.8	37.3	0.4
Electric cooking	12.0	12.0	0.1
Computer	20.0	21.2	1.2
Television	88.8	89.3	0.5
Electricity demand (kWh)			
Appliances held fixed	173.1	174.4	1.3
Appliance holdings changed	173.1	175.1	2.0

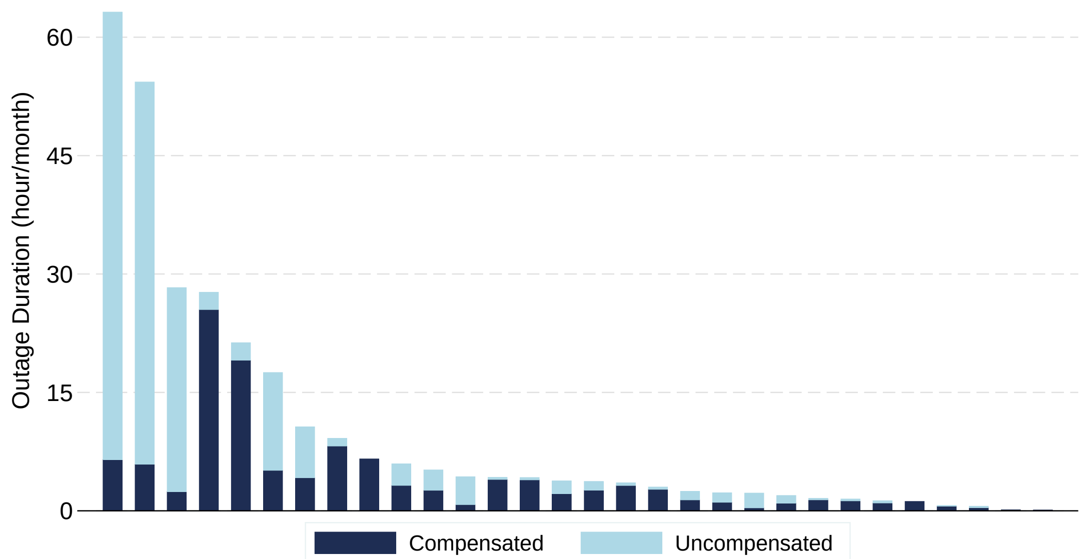
Appliance ownership probabilities are the sample mean of the probabilities from the logit formula for each appliance. Electricity demand with appliances held fixed is based on a single draw of ε and η. Demand with appliance holdings changed is based on draws of uniform random numbers to determine appliance ownership given the estimated probabilities, then the draw of ε and η to calculate electricity demand given those appliances.

Figure 1: Electricity Demand Unserved due to Outages, Six-Month Moving Average



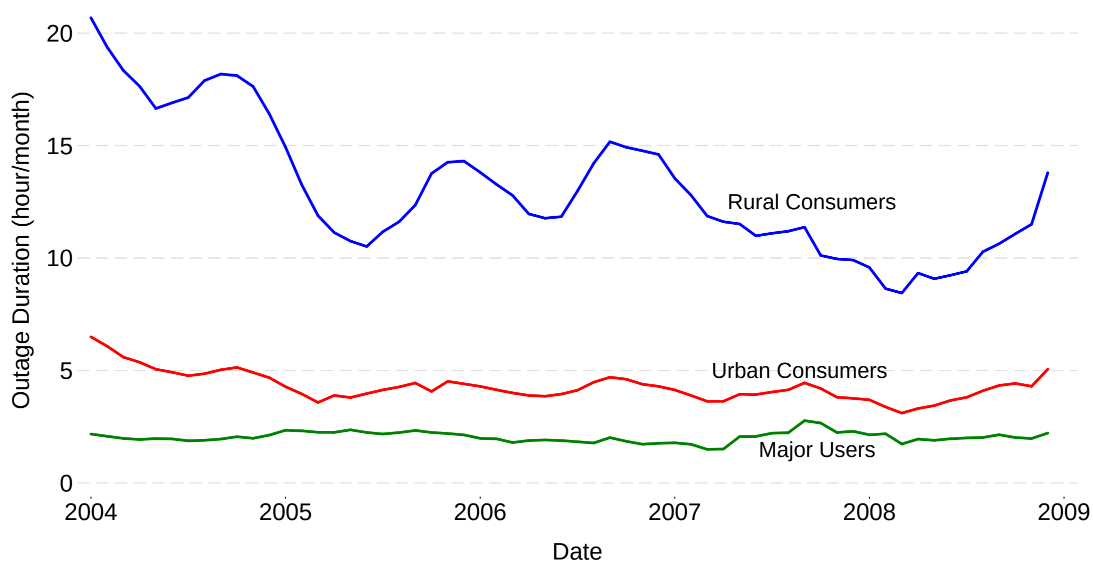
Notes: Total unserved demand, shown in the top line, is the sum of transformer-level estimates based on monthly outage hours and monthly electricity demand. System unserved demand, shown in the bottom line, is obtained from daily reports by the system operator of unmet demand caused by events on the national transmission network. Both lines are six-month moving averages of the monthly figures.

Figure 2: Mean Monthly Outages by Distribution Area and Type, 2005



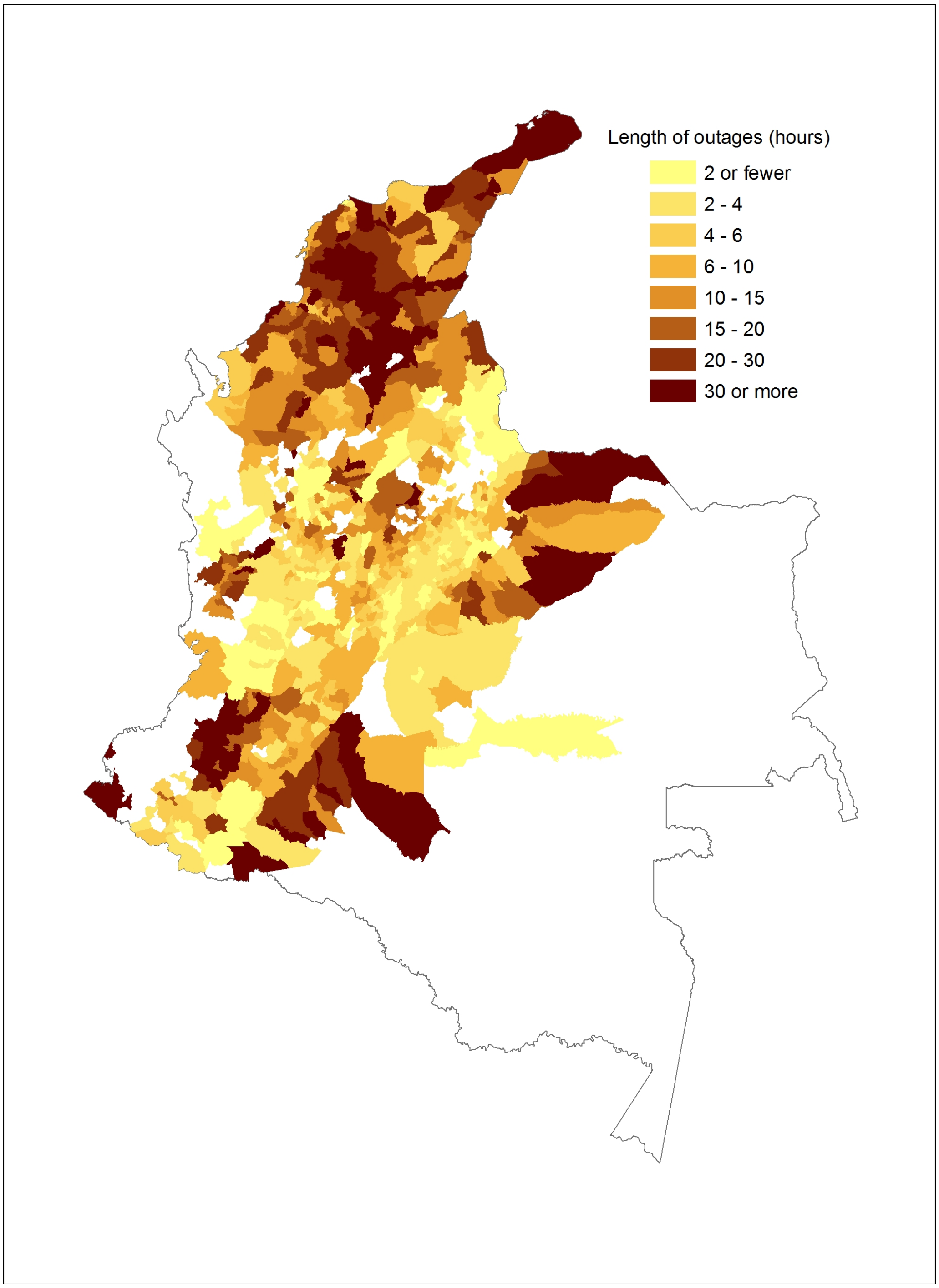
Notes: Each bar represents a distribution area (which in some cases is served by more than one firm). The total height of the bar represents the mean monthly outage hours for 2005, across all transformers in the area, weighted by the number of users at each transformer. The dark region represents outages reported as "programmed" and "unprogrammed", which are include in the calculation of reliability measures for the purpose of compensating users. The light region represents outages reported as "minor", "force majeure", and "others", which are excluded from the compensation calculation.

Figure 3: Mean Monthly Outage Hours, by Transformer Category, Six-Month Moving Average



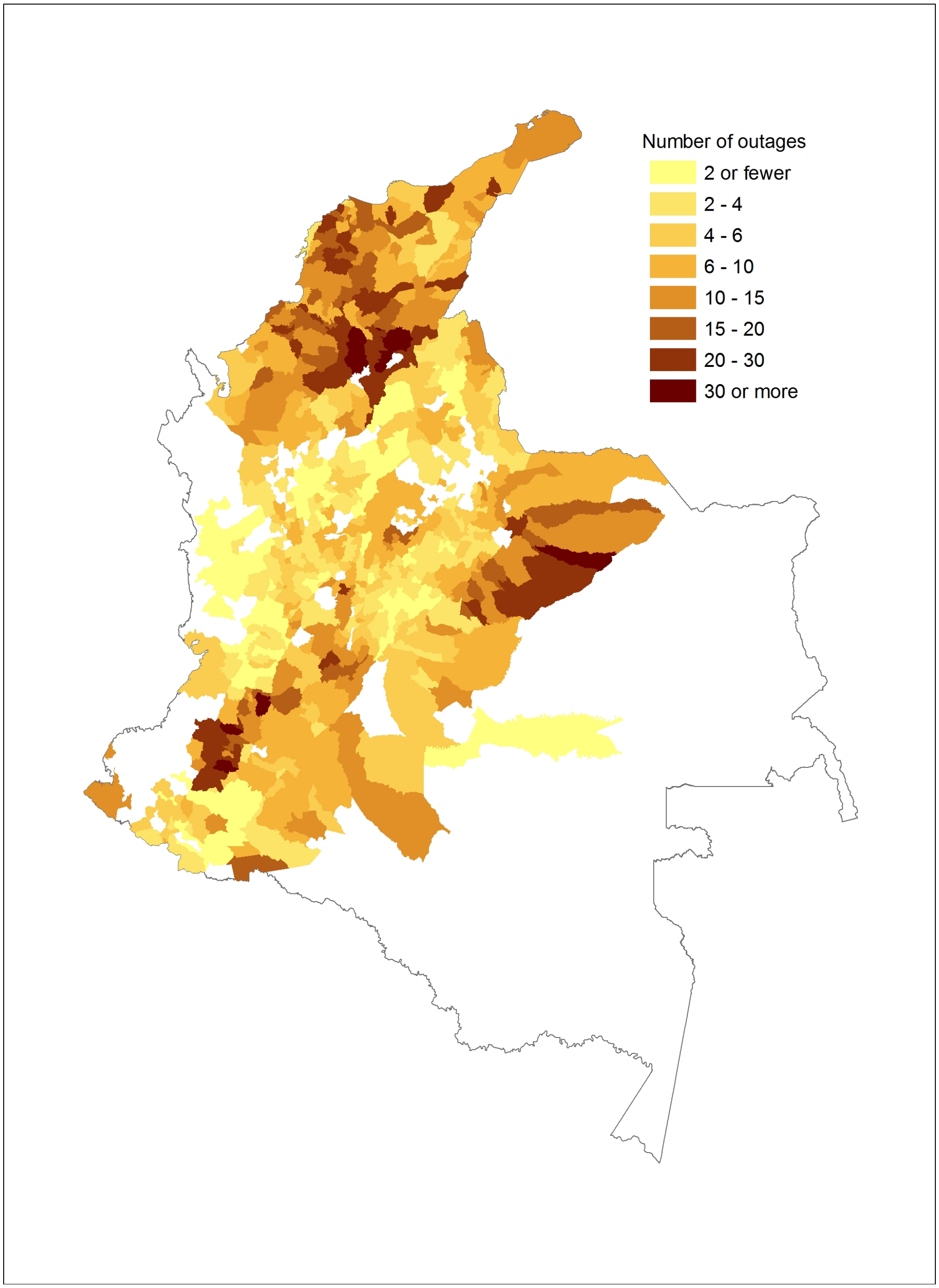
Notes: Each line shows the six-month moving average of the number of outage hours each month, for each distribution transformer in the category, weighted by the transformer demand. The major user category includes all transformers with a single user and more than 50 MWh/month consumption.

Figure 4: Mean Monthly Outage Hours in 2005, by Municipality



Notes: The map shows the mean monthly outage hours in 2005 for each municipality, calculated as the average across all transformers and months in the municipality, weighted by the number of users on each transformer. Areas in white either do not have data available for 2005, or are not connected to the national transmission network.

Figure 5: Mean Monthly Number of Outages in 2005, by Municipality



Notes: The map shows the mean number of outages each month in 2005 for each municipality, calculated as the average across all transformers and months in the municipality, weighted by the number of users on each transformer. Areas in white either do not have data available for 2005, or are not connected to the national transmission network.