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Raul Jimenez M.

Inter-American Development Bank
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Are Blackout Days Free of Charge? Valuation of Individual Preferences for Improved Electricity Services

Raul Jimenez M.*

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Abstract

Low-quality infrastructure services are persistent in developing countries, a situation mainly affecting the poorest households in contexts of high rates of informal access and heavily subsidized services. This paper exploits choice experiments, specifically designed for formal and informal users, to examine whether households in this situation are willing to pay for electricity service improvements. The analysis takes place in urban Dominican Republic, a country with one of the highest rates of electricity theft and lowest quality of services. The results strongly indicate that households value service improvements, showing average willingness to pay around US$9 for informal users, and 22 percent for formal users with service deficiencies. The estimated valuations are significantly heterogeneous across households, and such variance is mainly explained by household income, satisfaction with the electricity service, and household characteristics, such as family size and dwelling size. These results indicate substantial welfare losses derived from low-quality electricity services equivalent to over 35 percent of the direct fiscal subsidy to the utilities.

JEL codes: C25; C93; D12; Q41.

Keywords: Willingness to pay; Choice experiments; Hypothetical bias; Stated preferences; Mixed logit; Quality of electricity services; Electricity subsidies; Informal electricity access.

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* Inter-American Development Bank and Department of Economics, University of Rome Tor Vergata, rjmori@gmail.com. The findings, interpretations, and conclusions herein are strictly those of the author and should not be attributed in any manner to his affiliated institutions. This paper has benefited from comments by Franco Peracchi, Andrea Guerrero, seminar participants at the University of Rome Tor Vergata, Osmel Manzano, and an anonymous peer reviewer. I gratefully acknowledge the support of Jorge Mercado, Tomas Serebrisky and Ariel Yepez at the Inter-American Development Bank. The field work was financed by the operations RG-K1348 y RG-T2417. Special thanks to Tomas Sandoval and his team, who implemented the survey. Andrea Guerrero and Lenin Balza also provided valuable support during the survey preparation. All remaining errors are the author's responsibility.

1. Introduction

Low-quality infrastructure is increasingly recognized as a barrier for development. Even as developing countries are reaching close to universal access to electricity services, offering reliable and affordable supply has remained a challenge (Briceno et al. 2004; Fay and Morrison 2007). This situation is particularly latent among the poorest income groups, who usually tend to connect informally at the cost of facing the worst quality of service (Mimmi and Ecer 2010). As a consequence, such groups experience large welfare costs. For example, Chakravorty et al. (2014) estimate that a 32 percent increase in hours of service per day rises nonagricultural incomes by 38.6 percent. In addition to being associated with illegal connections, low-quality infrastructure is nonetheless highly subsidized, representing a severe financial problem for utilities (see McRae (2015) for the case of Colombia). Jimenez et al. (2014) estimate that electricity losses, mainly due to electricity theft, are around 0.3 percent of the gross domestic product (GDP) of the Latin America region.

If low-quality electricity services translate into losses for utilities and users, why does this situation persist? One potential explanation is that most illegal users are too poor to connect. As an interrelated factor, tolerance toward electricity theft may be exploited in search of political gains (Golden and Min 2012). It may be the case that users prefer free or cheap electricity services, regardless of the associated welfare losses. The trade-off between cost of services and preferences of users, taking into account their income level, represents a behavioral and policy relevant question: do households conform to low-quality services or are they willing to pay for improvements?

To address this question, I designed a choice experiment in urban Dominican Republic that randomly varied alternative electricity services with different levels of attributes. The attributes included the number, length, and timing of outages; voltage stability; cost of service; punctuality in delivering bills; and response time to claims. All the choice situations included a status quo option that allowed the users to stay in their current situation. The alternatives were intended to present the users with multiple trade-offs between attributes, including scenarios of service improvements at higher costs. The design also took into account the differences in types of services received by formal and informal clients. The model allows for heterogeneity in users' preferences, and examination of the role of income in attitudes toward the attributes of electricity services. Through the generated experimental data, I estimate the willingness to pay (WTP) for service improvements, and study its variation across households.

State preference methods represent a suitable approach for studying individual choices for infrastructure services. These types of services provide conditions under which respondents can be expected to provide honest answers. On this point, Carson et al. (Carson and Groves 2007; Carson et al. 2006) point out that choices related to infrastructure services can be more readily incentive compatible than those for private goods, because in the first case the payment is usually mandatory. That is, respondents are expected to be more careful in their choices, because they later would have to face one of such scenarios, reducing potential strategic behavior in the choice situations. Further, the stated preferences approach is useful for considering all the welfare effects, by including nonmarket effects. By contrast, revealed preference methods are difficult to apply, due to the nature of these services. Electricity services are natural monopolies, where end-users have few options in the type of service received and take-up is compulsory. At the same time, these services are regulated, such that significant variability in the quality of service should not be expected. Even if sufficient variability is observed, it may be strongly endogenous, meaning that the allocation of better services would go to areas with differentiated characteristics.

The case study constitutes an ideal and timely context to valuate consumer preferences for different characteristics of the electricity services. Urban Dominican Republic has one of the highest rates of electricity loss in the world, mainly because of informal connections, and one of the lowest levels of quality and reliability. Together with highly subsidized electricity tariffs, this situation translates into financial losses for the utilities that represents annual fiscal subsidies that represent between 0.6 and 0.8 percent of the GDP. Although over the last several years, the utilities have made efforts to reduce these problems, progress has been slow such that only 50% of household receive uninterrupted services. At the same time, the country presents significant variability in the quality of electricity services across its territory. In turn, such variability and the efforts are widely known among users, contributing to enhancing the credibility of the choice situations by the respondents.

The main results of this study suggest that, regardless of their economic situation, users facing service deficiencies are willing to pay for improvements. In the sample of 2,479 users, only 10 percent chose to stay in the status quo. Those users were mostly formal clients, and 50 percent of them already had good quality service. The estimated average willingness to pay among informal users is US$9, while for formal users it is around 22 percent of their current monthly bill (US$5 on average). However, the estimated valuations vary widely across individuals. Factors explaining this variance include family size, dwelling size, users' satisfaction, and income. Household income plays a substantial role in shaping users' preferences and their capacity to pay. The study found that the elasticity of WTP with respect to income is around 0.1. In addition, this paper shows that accounting for individual heterogeneity in the modeling, is not only more realistic, but also improves the performance of the estimations, allowing to elicit more reliable results. A relevant variable that appears to capture such heterogeneity is the household income. Overall, the results are robust to various specifications, estimation methods, and assumptions about the individuals' heterogeneity.

This study joins a growing literature on the valuation of electricity attributes based on stated preferences methods (Blass et al. 2010; Hensher et al. 2014; Carlsson et al. 2011; Abdullah and Mariel 2010; Morrison and Nalder 2009; Carlsson and Martinson 2007, 2008; Yu et al. 2009). This literature has considered fewer attributes, and it has mainly been concentrated on developed countries. Therefore, the findings on the preferences of end-users, and estimates of their WTP for improved services, are hardly comparable or valid for the context under analysis. To my knowledge, Abdullah and Mariel (2010) is the only application to a developing country, Kenya; however, also in this case, end-users were already clients of the utility. Regarding the attributes used in previous articles, it is important to differentiate between experiments aimed at investigating valuations in households and firms. In the former case, the attributes used are mainly related to reliability, including price, number of blackouts, and their average duration. These findings suggest so far that households seem not to perceive the quality characteristics of the provided services. In contrast, in the case of firms, quality dimensions, such as brownouts, surges, and customer service (e.g., notice of service failure, time in telephone queue) are also relevant (Morrison and Nalder 2009).

Unlike previous stated preferences experiments, I am able to model and quantify the role of income in users' preferences and valuations. This paper also contributes to the literature by distinguishing between formal and informal users, with ad hoc experimental designs that allow for examining their disposition to become clients, and studying the determinant of the heterogeneity in preferences. To the best of my knowledge, this is the first paper to do so, representing a timely and relevant application for public policy aimed at increasing improved formal access to utility services.

The remainder of the paper proceeds as follows. Section 2 presents background on the case study. Section 3 describes the modeling of the individual choices, estimation method, and experimental design. Section 4 describes the sample and the data. Section 5 discusses the results, focusing on the heterogeneity in individual valuations, and the attribute profiles of their preferred services. Section 6 concludes.

2. Background of the Case Study

Electricity distribution services in the Dominican Republic are mainly provided by state-owned utilities, in a difficult business environment characterized by poor physical infrastructure, substantial electricity theft, and low payment rates. This situation translates into one of the lowest levels of quality of electricity services in the world. During 2015, formal users experienced 35 interruptions per month of an average length of 3.3 hours.[1]

Electricity users can be broadly divided into formal and informal. Formal users are classified by the utilities according to the hours of electricity available per day. Of a total of around two million of clients, 900,000 have service 24 hours a day; 63,000, 21 hours; 300,000, 18 hours; and around 640,000, around 16 hours. In addition, the utilities estimate that around 400,000 households are informal users, which usually face the lowest quality of services (CDEEE 2014). This group has no metering or contracts, implying that they do not pay for the electricity consumed. This consumption is registered as electricity losses by the utilities.

The current composition of electricity users has a long history, which is important for understanding individual perceptions toward services. Since the mid-1900s, the expansion of new connections to the growing urban population has been undertaken mainly under political mandate, largely intended to gain public opinion support, and with severe investment capacity constraints. This gave place to low-quality electricity provided at low cost or free of charge. Many households connected over these many decades were usually not registered as regulated clients. Thus, the origin of today's main sources of electricity losses can arguably be classified as theft, since households were connected by the utility. In this situation, the type of electricity services received by clients is, to a great extent, exogenous.[2]

Electricity tariffs in the country are heavily subsidized. On average, as of 2015, the electricity tariffs are around 20 percent below cost recovery levels, meaning that even formal clients do not pay the full cost of the electricity supplied. Further, tariffs are defined by consumption blocks, where the lowest block, between zero and 200 kilowatt-hours (kWh)/month, is charged a variable cost per kWh of around US$0.1. This block gathers 80 percent of residential consumption, meaning that most of the population receives indirect tariff subsidies. In addition, to reduce the vulnerability of poorer households, since 2009,

[1] Based on information from the Superintendencia de Electricidad, http://sie.gob.do/mercado-minorista/estadisticas.

[2] The process by which households were connected through the years but never registered as formal clients is documented, for example, in Mercado (2017), and broadly expressed in the media. See, for example, www.cne.gob.do/noticia/dice-herencia-maldita-no-deja-que-poblacion-pague-la-energia.

the government has implemented an electricity cash transfer program to households identified as below the national poverty line. This subsidy reaches up to US$10 for monthly electricity expenses, which, at the previous tariff, is equivalent to around 90 kWh of consumption per month. Regardless of the subsidized tariffs, expenditures on electricity services constitute a high proportion of income among clients who report positive electricity expenditures, potentially implying affordability problems. Electricity expenditure represents 12 and 4 percent of total household income for the first and fifth quintiles, respectively.[3]

The electricity distribution sector exhibits severe financial deficiencies. In 2015, the cost recovery index was around 66 percent, with electricity losses of around 31 percent. This situation translates into significant operational costs for the utilities, requiring yearly fiscal transfers, which in 2015 were US$417 million, or 0.61 percent of GDP.[4]

3. Methodology

This section discusses the modeling of individual choices, the estimation method, and the design implemented to generate the experimental data.

3.1 Conceptual Background

The random utility model provides an appealing framework to disentangle consumers' preferences, so their choices and valuations can be studied in a way that is compatible with standard consumer demand theory. Under this approach, the utility that an individual n obtains from alternative j, in each choice situation s, can be expressed in terms of an observable and a non-observable stochastic component. Assuming linearity and independence between the two components:

$$U_{njs} = V(X_{njs}) + \varepsilon_{njs} \tag{1}$$

where X represents the vector of attributes of the relevant alternatives (k) for consumer decision making. In this application, X may include the number of outages and cost of electricity services, among others. I further assume that the observable component is linear in those attributes such that

$$U_{njs} = \begin{cases} \sum_k \beta_{nk} x_{n0sk} + \varepsilon_{n0s}, if\ j = 0\ (current\ situation) \\ \sum_k \beta_{nk} x_{njsk} + \varepsilon_{njs}, if\ j \neq 0\ (alternatives) \end{cases} \tag{2}$$

[3] Own estimation based on the Dominican Republic's national expenditure survey of 2007.
[4] Own calculations based on *Informe de Desempeno*, *Anexo 2015*, www.cdeee.gob.do/transparencia/estadisticas-institucionales.

where $\beta_{n,k}$ represents the preference weight of a change in a given attribute. For the cost of services, the corresponding parameter ($\beta_{n,cost}$) represents the monetary value of a unit of utility. Everything else constant, it is expected that a reduction in power outages or a reduction in costs of electricity services will increase the utility of consumers, therefore increasing the probability that they choose the alternative offering such advantages. However, a reduction in power outages can come at an increase in cost, a trade-off that needs to be evaluated by the consumer in deciding whether to leave or stay in the status quo.

This presentation allows the parameters to vary by individual. The parameters represent the preference weight that each individual attaches to each attribute, and attribute levels. These values are relevant for studying the heterogeneity among consumers and the potential implications of the adoption of alternatives with different characteristics, as well as for examining differences in valuations across segments of the population.

In addition to idiosyncratic elements, heterogeneity in the preference weights may be explained by differences in individuals' observable characteristics, such as income, education, gender, and so forth. Following Greene (2012), the mean of the random parameters—those allowed to vary in the population—can be specified as a function of the variables of interest. This approach provides great flexibility, as preferences can be directly modeled as a function of some observable variables, while maintaining a stochastic component. A particularly relevant variable in the context of public utilities in developing countries is income, as it is directly related to users' capacity to afford service improvements. Therefore, I allow the mean of the random parameter to depend on household per capita income and its square. Assuming an additive linear structure, it can be expressed as[5]

$$\beta_{nk} = \beta_k + \delta_{1,k} z_n + \delta_{2,k} z_n^2 + \sigma_k \nu_{nk} \tag{3}$$

where the individual preference weight depends on a common fixed term for each attribute (β_k), and its income (z_n) and income squared (z_n^2). The population mean of each parameter is composed by $\beta_k + \delta_{1,k} z_n + \delta_{2,k} z_n^2$. ν_{nk} is the individual-specific heterogeneity, and σ_k is the standard deviation of the parameter β_{nk} around the population mean. Therefore, in this model, heterogeneity is allowed to arise from individual income differences and an unobservable component for which the distribution among individuals is assumed.

Equation 3 allows to study the relationship between income and preferences, capturing

[5] There are other ways to account for individual characteristics in modeling their choices; for example, income can be entered directly into equation 2. However, as income does not vary across individuals at a given point in time, it needs to enter as a constant specific alternative (otherwise, the alternatives would not provide variability for estimation). Therefore, this approach is suitable only for labeled experiments and does not allow for direct study of the effects of income on the attributes of individual parameters.

the potential presence of nonlinearity. A priori, it is unclear whether and how the attribute parameters depend on income. For example, although the parameter for frequency of outages is logically expected to be negative (for all users), how this parameter depends on income is a matter of empirical investigation. Richer users may find outages more inconvenient, as they rely more heavily on electric appliances, and the net income effect would be negative ($\partial\beta_{n,outages}/\partial z < 0$). By contrast, users could have greater tolerance if they are able to afford backup mechanisms against unreliable electricity services. Similarly, a priori it is unknown whether the price parameter would depend on income, although it may be expected that consumers with higher incomes would be less sensitive to a price change ($\partial\beta_{nk}/\partial z < 0$). However, while the income effect may smooth the aversion toward greater number of outages or higher prices, those parameters should be expected to behave rationally along the income distribution, and accounting for nonlinearity allows the examination of such behavior. Therefore, in the case of price, it is expected that $\delta_{1,k} > 0$ and $\delta_{2,k} < 0$, such that the outage and price parameters will be bounded below zero.[6]

WTP is expressed as a ratio of the attribute of interest over the cost parameter. This ratio captures the monetary value of a change in each attribute. For those attributes considered to have random taste, the WTP of individual n for attribute k is

$$WTP_{nk} = \frac{\beta_{n,k}}{\beta_{n,cost}} = \frac{\beta_k + \delta_{1,k}z_n + \delta_{2,k}z_n^2}{\beta_{cost} + \delta_{1,cost}z_n + \delta_{2,cost}z_n^2} \tag{4}$$

For attributes with a fixed parameter, the valuation is just $WTP_k = \beta_k/\beta_{n,cost}$. That is, in equation 4, there are two sources of variation, while in the former expression the variation in valuation only depends of the cost parameter. It is interesting to evaluate how, and in which magnitude, the WTP would change with income, the general expression takes the following form

$$\frac{\partial WTP_{nk}}{\partial z_n} = \frac{\beta_k\left(\delta_{1,k} - \delta_{1,cost}\right) - z_n^2\left(\delta_{1,k}\delta_{2,cost} - \delta_{2,k}\delta_{1,cost}\right)}{(\beta_k + \delta_{1,cost}z_n + \delta_{2,cost}z_n^2)^2} \tag{5}$$

As previously, the direction and magnitude of the change require empirical evaluation, and may depend on the position of the individual in the income distribution.

The proposed framework is relatively general; however, it is interesting to compare its performance and estimations against more restricted ones. A more restricted framework would be a model in which the parameters are assumed to be fixed among users (i.e., by dropping the suffix n from equation 2); I call this model 1. The parameters can also be

[6] In the context of electricity services, there is little discussion of the effects of a negative price parameter on the entire income distribution. Other services or products may give place to the opposite hypothesis if, for example, price is perceived to signal status, and acquiring the services provides greater utility to consumers.

allowed to vary following a random distribution but not depending on individual characteristics. In model 2, I keep the price parameter fixed, while allowing the other parameters to be random. In model 3, I also allow the price parameter to vary.[7] In model 4, the random parameters are allowed to depend only on the first-degree income. Model 5 exploits all the flexibility described in equations 2 and 3.

Characterizing the status quo. The utility of the status quo is not assumed to be zero. This assumption is suitable in some cases and debatable in others. In applications where the good does not exist or it is known that the individual does not have it, it is reasonable to assume the status quo utility is constant or zero. However, if the individual already has the good, assuming a fixed base utility would imply that attributes are at a fixed level for all individuals. If this is not the case, such assumption resembles a problem of non-observable service characteristics in the "current situation," potentially leading to estimation bias. In this application, users already have electricity services of different characteristics, obtaining differentiated utilities; therefore, the effects that the alternatives have on individuals' decisions depend on the relative levels of the attributes (compared with the current situation). The data set that was collected allows including the characteristics of the status quo, and evaluating the performance of the estimations accounting for such attributes against the usual practice of normalizing it to zero.

As an aside. Obtaining negative WTP estimates is recurrent in the literature, representing a controversial issue. In many applications, negative estimates are theoretically unexpected and difficult to explain (e.g., Cameron and Quiggin 1994, 1998; Lockwood et al. 1996). For example, in this application, WTP for fewer interruptions is expected to be positive, meaning that a greater number of interruptions and higher prices cause disutility. Negative WTP would imply that the change in one of these attributes actually causes positive utility, challenging most working hypotheses based on rational behavior. To avoid negative WTP, many applications restrict the range that the estimated parameters can take, generating positive WTP estimates by statistical construction. Two things are assumed: rational behavior (at least congruent with economic theory), and a suitable experimental setting, that is, there are no non-observable factors affecting the estimations. I proxy rationality with a cognitive score and examine it in relation to the estimated WTP. With respect to non-observables, I compare estimations in which the status quo is normalized to zero with estimations that consider the characteristics of the status quo.

From the behavioral viewpoint, however, heterogeneity in preferences should allow for

[7] In WTP estimations, it is common to restrict the price parameter, to avoid the denominator taking values close to zero, returning abnormal valuation for attributes.

a variety of different behaviors, including those leading to negative estimates (Hanemann and Kanninen 1999). Bohara et al. (2001) perform several simulations, and conclude that negative WTP can be a legitimate result. That is, negative WTP may signal attitudes or opinions. For example, an environmental tax is a case where negative WTP estimates have been common, suggesting that people may be signaling through their choices that they do not want/believe in those instruments. In this application, negative WTP estimates may reflect that some users are willing to face lower quality of services to reduce the monthly cost they pay, or that they are accustomed to their current situation. That is, the disutility of the price effect dominates the utility from a service improvement (i.e., some individuals are not disposed to face the trade-off between the increased cost of the services and the improved quality).

3.2 Estimation Method

As utilities are not observed, individual n's decision about an alternative j in a choice situation s is modeled as a discrete choice:

$$y_{njs} = \begin{cases} 1, \; U_{njs} > U_{ngs} \; for \; all \; j \neq g \\ 0, otherwise, \end{cases} \tag{6}$$
$$n = 1, \dots, N \; ; s = 1, \dots, S \; ; j = 1, .., J$$

where U_{njs} is defined by equation 2. In the main empirical specification, it is assumed that the unobserved stochastic component ε_{njs} is independently and identically distributed type I extreme value across choice situations, individuals, and alternatives. This distributional assumption implies that $\varepsilon^{*}_{njs} = \varepsilon_{njs} - \varepsilon_{ngs}$ follows the logistic distribution (for all $j \neq g$). With this assumption, the conceptual framework matches the random parameter logit (RPL) model with heterogeneity in the means of the random parameters (McFadden and Train 2000; Train 2009). The parameters are allowed to vary per individual, but are constant across choice situations. Conditional on observing β_n, the probability that respondent n chooses alternative j in experiment s is given by the standard logit:

$$P_{njs}\left(y_{njs} = 1 | \; \beta_n\right) = \frac{\exp(V_{njs})}{\sum_j \exp(V_{njs})} \tag{7}$$

As equation 7 implies $P_{njs}\left(U_{njs} - U_{ngs} > 0\right)$, the variability used for estimation comes from variation in the levels of the attributes within the alternatives. Any individual-specific characteristic that does not vary between alternatives (e.g., age, income) is partialed out when taking differences between utilities/choices. The probability that a respondent has made a certain sequence $\{j | y_{njt} = 1\}$ of choices is represented by:

$$L_n(\beta_n) = \prod_s \prod_j (P_{nis})^{y_{njs}} \tag{8}$$

Assuming independence between respondents, the log-likelihood can be expressed as:

$$\log E(L) = L_n^*(\beta_n) = \sum_n \log E(L_n^*) \tag{9}$$

As β is not observed, the unconditional choice probability is the integral over all its possible values of the parameters:

$$E(L_n^*) = \int_\beta^{\cdot} L_n^*(\beta_n) f(\beta) d\beta \tag{10}$$

This expression, the mixed logit probability, can be viewed as a weighted average of the logit formula evaluated over the distribution of β given by the mixing distribution $f(\beta)$. Since equation 10 does not have a closed form, the parameters are estimated by simulated maximum likelihood.

Selecting distributions for the random parameters. For the case of RPL, without heterogeneity in the mean of the parameter, $f(\beta)$ reflects that the parameters are distributed as random variables without a deterministic component. The assumption on the preferred distribution for each random coefficient can be derived from theory. For instance, the coefficients for cost or outages (defined from lower to higher number of interruptions) are expected to be negative for all end-users, if nobody prefers higher cost of services and higher number of interruptions. In this context, using unrestricted distributions allows coefficients to take implausible signs (i.e., a positive sign for the price parameter). Also, distributions with infinite range, such as normal or lognormal, allow for extreme implausible parameter values, generating much less precise estimations. Further, from the computational viewpoint, distributions with thick tails are more demanding.

The restricted triangular distribution allows to fix the end-points of the distribution to zero and 2β, such that there is no free variation, and the variance takes the value of the scaling parameter (of the mean). However, this distribution provides empirical freedom, because the parameters can be positive or negative, while the variation is determined by the mean estimation of scaling (Greene, 2016). Further, assuming distributions that restrict the parameter space, such as this, helps particularly in small-sample applications. Therefore, I assume that the coefficients follow a restricted triangular distribution.

Comparing performances with different assumptions. Alternative estimation models match different assumptions laid out in the conceptual framework. Model 1 corresponds to the multinomial logit model, while the RPL (without mean heterogeneity) with different specifications for random variables corresponds to model 2 (price parameter is fixed) and model 3 (price parameter is also random). The RPL with heterogeneity in the means, with a different specification for the deterministic component of the mean parameter, corresponds to models 4 and 5.

3.3 Experimental Design

Identification of attributes and levels. A key stage in implementing choice experiment (CE) is the correct identification of attributes and levels that are meaningful for end-users. Only if those attributes and the ranges of their corresponding levels are correctly defined will the scenarios will be realistic to the respondents. To identify the attributes and their levels, I carried out exhaustive fieldwork, which involved 60 in-depth interviews accompanied by closed questionnaires, and complemented with field visits and interviews with experts. Details of this work are presented in Jimenez et al. (2016). I identified the following seven attributes: number of interruptions per month, monthly cost of service, lengths of outages, voltage stability, billing punctuality, timing of outages, and response to claims. Table 1 summarizes these attributes and their levels per type of end-user. These attributes correspond to x_{njsk} in equation 2. Prices for informal end-users are expressed as amounts, while for formal end-users prices are expressed as an additional percentage of the current average electricity bill.

Choice sets. Having identified the attributes and defined their levels, I proceeded to construct the choice sets, that is, to produce a combination of attributes and attribute levels that would be presented to the respondents. There are several options that can be broadly divided into full-factorial, orthogonal, efficient, and Bayesian designs (see Rose et al. 2009). The full-factorial design provides the entire space of possible combinations of the attributes and their levels; however, such design may return an unmanageably large number for empirical applications. In this application, the full-factorial design returns 21,168 possible combinations for informal and 15,120 for formal users. Orthogonal designs are broadly used in empirical applications; however, it is argued that such designs can produce several choice situations with dominant alternatives, which do not add information to the experiment, other than testing rationality. Efficient designs would outperform orthogonal designs, generating choice tasks to maximize the amount of information about the parameters of the relevant attributes. A key input for this type of design is the priors on the estimated parameters, with the drawback that incorrect priors could lead to greater inefficiencies. Bayesian efficient designs allow specifying the parameters as random variables, providing greater flexibility and reducing the risk of inefficiency (Bliemer and Rose 2010).

Therefore, I produced a Bayesian efficient design. As this approach requires priors on the parameters of the distribution to be used, I followed the next steps to find the most suitable priors. (i) I generated 120 alternatives using a Bayesian efficient design with priors from the literature, using a multinomial model (MNL). I used the same "baseline" priors for formal and informal users. During the pilot of the questionnaires, the alternatives, in blocks of three (plus a status quo), were applied to 30 respondents. (ii) With these data, the new parameters were estimated using an MNL model, separately for formal and informal users. The final priors were chosen from these estimates, and from previous estimation in the literature, assuming an MNL and a normal distribution for frequency of blackouts, cost, and length of blackouts.[8] Annex 1 presents the priors. The choice sets were computed using N-Gene 1.1.2.

It is important to mention that the service characteristics experienced by the respondents were not known with certainty a priori, so the choice sets were not designed with such information. Information on the characteristics of the services was collected during the survey. For estimation, x_{n0sk} contains the following services characteristics: outages, cost, voltage, and length of interruptions.

The design took into account the estimation of main effects, and two-way interaction effects between the number of blackouts and length. For each type of user, I generated a total of 200 choice alternatives, clustered into 50 groups of three choice sets.[9] That is, each respondent would face three choice situations, each one containing four alternatives, one of which is the status quo.[10] As ex ante the characteristics of the electricity services received by the household, and the type of user (formal/informal), are not known, the status quo was labeled "as currently" and each "choice set" was pre-allocated sequentially to each questionnaire's number to avoid discretional applications by the surveyors. The alternatives were unlabeled, as they were preferred when the focus was to elicit WTP for specific attributes and avoiding order bias between alternatives (Hensher, Rose, and Greene 2005). However, order bias can also appear if respondents only pay attention to the first attributes appearing in the list within each alternative. To avoid this potential problem, I randomly sorted the attributes within each choice situation.

[8] Using a simple model (MNL in this case) is a recommended practice, as RPL may take a significant amount of time.

[9] To have enough degrees of freedom to estimate such specification, only 80 choice alternatives (choice alternatives or treatment combinations) would be required for informal users and 82 choice alternatives for formal clients.

[10] The number of alternatives by choice set and the number of choice sets by respondent were selected to avoid tiredness of respondents. Different combinations were tried during the pilot interviews, including three, four, and five alternatives per choice set (all including the status quo), and three and four choice sets per respondent. Surprisingly, the respondents showed great interest in participating in the experiments.

The CE literature highlights that the presence of the status quo option may limit rationality, producing a tendency of respondents to stay in status quo (Hartman et al. 1991). In addition, from the experimental viewpoint, a status quo option may imply the presence of other unobserved factors, not included in attributes, which may lead to over-selection of the current situation. I expect that adding characteristic of the current services reduce the potential presence of such bias. Further, I followed the procedure by Scarpa et al. (2005), under which alternative specific constants (ASC) are added to capture potential unobservable influences. If this indicator is significant, it would suggest the presence of status quo bias.

4. Sampling Frame and Data

The surveys were implemented during November 2015 and early March 2016, obtaining a sample of approximately 2,500 households. The interviews were distributed in seven cities of the Dominican Republican, which concentrate around 67 percent of total urban households. Annex 2 shows the distribution of the sample by city. Since there was no previous list of households to survey, the distribution of the sample was randomly selected based on the official Territorial Administrative Division (2012). In the first stage, I randomly selected "sub-districts," which are geographical units composed of between 150 and 1,000 households. Within each sub-district, I randomly selected "areas" composed of around 40-100 households. Depending on the size of the sub-district, between four and 15 households were randomly selected for interviewing.[11]

The interview consisted of the application of a closed questionnaire and the CE. Based on the characteristics of the household's electricity service, the interviewer applied the corresponding CE for formal or informal clients. The rule to apply a CE designed for informal clients was: if the end-users do not have a contract or if they do not pay for the services. Otherwise, the interviewer applied the choice sets designed for formal clients. The rate of respondents accepting the interview was 77 percent. Of those accepting the interview, 4 percent stopped the interview at some point.[12] All interview rejections were replaced to reach a target sample size of 2,500.

The summary statistics for the final sample are presented in Table 2, which shows that

[11] The number of households to be interviewed per area was selected to reach a power of 80 percent in case of implementing a follow-up survey. The selection of each household followed a standard field procedure: count 10 households from each strong point. A strong point is any place that is distinctive in a given neighborhood and may be used as a reference point for location purposes (e.g., a police station, a church).

[12] Following a random selection process, a total of 3,427 doors were knocked, of which 610 households rejected the interview, and 217 did not answer.

formal and informal users are markedly different. On average, households with informal electricity connections tend to have lower incomes and face poorer quality electricity supply. Consistently, their satisfaction with the services is lower. Both groups are also different in ownership of appliances and characteristics of the dwelling, such as type of dwelling and number of rooms. Differences between family characteristics, such as gender and schooling of the household head, and family size, are not statistically different. Neither is the difference in the cognitive indexes between the two groups.[13]

5. Results

5.1 Estimated Preference Weights

Tables 3 and 4 report the parameters' estimates for informal and formal end-users, respectively. They are estimated using the software NLOGIT 6. The first column in each table presents the estimations for the multinomial logit, which imposes parameter homogeneity across individuals. The next columns relax this assumption, applying the mixed logit model, but with different assumptions on the distribution of the random parameters. After testing different specifications, I selected number of interruptions, cost of energy services, voltage stability, and length of blackouts as attributes with random parameters. Those parameters are assumed to have a restricted triangular distribution. However, to show the relevance of heterogeneity in preferences, column 2 considers cost of service as a fixed parameter. Column 3 allows individuals to have different tastes for cost of services. In column 4, it is further assumed that the means of the random parameters depend on income. Column 5, which is the preferred specification, also includes income squared, to test nonlinearity of the preferences of the end-users.

Throughout the estimations, the mean parameters have the expected signs; however, their statistical significance presents some differences between types of end-users. On the one hand, number of interruptions, average monthly payment, voltage stability, and length of blackouts always have a significant effect on individuals' decisions. On the other hand, response time to claims has an effect only on informal users, while billing punctuality and timing seem to be relevant only for formal users. In the case of timing of blackouts, this specification only indicates that they are relevant for individual decisions. To appreciate the time of day during which blackouts are preferred to occur if they have to, this attribute needs to be entered as a factor variable. The results are shown in Figure 1, for the MNL model, suggesting that the less preferred time of occurrence of interruptions is at night for formal

[13] This index is constructed based on eight questions. The questionnaire is in Spanish, and is available upon request.

users, while nonsignificant preferences are detected for informal users.

The heterogeneity in preferences is strongly statistically significant, as measured by the standard deviation of the random parameters. As heterogeneity is gradually allowed, the chances of reproducing the actual sequence of individual choices continually improves (i.e., the fit of the model improves; see the log likelihood, R-squared, and Akaike information criterion at the bottom of Tables 3 and 4). For example, the inclusion of the price parameter as random in model 3 shows that respondents indeed have very heterogeneous attitudes toward service cost, and increases the likelihood of the model, particularly for informal users. Recall, that in using a restricted triangular distribution, the estimated standard deviations for the random parameters are equal to the scaling parameters. Annex 3 presents the same regressions assuming an unrestricted normal distribution for all parameters. The parameters for the mean and nonrandom components, and the standard deviation, are similar in sign and statistical significance. However, in these specifications, income is not systematically significant.

For the heterogeneity in the mean, the results in columns 3 and 4 indicate that income plays an important role in explaining heterogeneity in individual preferences and shaping their attitudes toward electricity services. In these models, the population mean of the parameters can be computed directly following equation 3. For example, from model 5, at the average income for informal users, the interruptions parameter is -0.05, while the price parameter is -0.06. For formal users, the corresponding estimates are -0.17 and -7.66, respectively. The positive sign of the first-degree income parameter suggests that for wealthier households, "aversion" to interruptions, service cost, voltage instability, and length of interruptions decreases. That is, the first-degree income effect seems to offset the negative impact of higher number of outages, probably due to greater capacity to cope with them. However, the coefficient for squared income tends to have negative signs, indicating that the overall income effect is bounded, as theoretically expected.[14]

Table 5 presents the average elicited WTP per attribute based on the coefficients previously estimated. I report only the sum of WTP for outages, voltage, and length of interruptions, as the significances of those attributes are consistent across all models. For informal users, the average monthly WTP ranges between US$11.8 (model 2) and around US$8.7 (model 5). In the case of formal users, expressed as a share of their current electricity bill, it ranges from an additional 43 percent (model 2) to 22 percent (model 5). Noticeably, in both cases, the bulk of WTP is explained by the high valuation of voltage. Overall, as

[14] Including income and income squared in the mean of the parameter distributions increases the log-likelihood only marginally.

greater heterogeneity is allowed, estimated WTP tends to decrease, particularly when income is accounted for, suggesting the relevance of including this variable.

5.2 Heterogeneity in Estimates of Willingness to Pay

This subsection takes advantage of models 3 to 5, which generate the full distribution of WTP across individuals. As before, WTP is the sum of valuations for outages, voltage, and length of outages, and expressed in monthly U.S. dollars.[15] Figure 2 presents the unconditional distribution of the WTP estimates for the different models implemented here. As can be observed, the distributions differ between models and, consistent with the previous calculations, the modalities of the distributions tend to shift to the left as the estimations account for greater heterogeneity and income is included. The modalities are closer to zero in the case of formal clients, which is expected, as in this case it represents an additional amount to pay. Models 2 and 3 restrict the range of the estimated parameters; therefore, WTP only takes positive values. In the cases of models 4 and 5, where the mean depends on household per capita income, around 10 percent of the respondents have negative WTP (informal and formal).

Negative WTP. As discussed in the methodology section, the meaning of negative WTP is a matter of empirical and theoretical debate. Here, negative estimates are interpreted as reflecting not having a disposition for leaving the status quo, because of the following reasons. First, around 90 percent of the respondents with negative WTP are already formal clients, and 50 percent of all negatives already have the best quality of service. Second, the proportion of respondents with negative WTP decreases as they face better quality of services, suggesting that the alternative scenarios were not attractive enough, given a price increase.

To explore further the nature of the negative estimates of WTP, I compare the previous results with those obtained from ignoring the characteristics of users' current services, therefore normalizing the corresponding utility to zero (see Annex 4). In this case, the share of respondents with negative WTP is slightly higher, around 13 percent of the sample. Annex 5 presents the differences in distribution of the estimated WTP between the two specifications, showing that valuations are greater once the actual characteristics of the status quo are observed. The main message is that in the presence of high variability, such as in this application, choice experiments should account for the attributes of the status quo. That is, it is not that respondents choosing to stay in the status quo do not want an

[15] For informal users, the ratio of the coefficient directly provides the value in U.S. dollars. In the case of formal users, WTP is calculated over the average of the past three electricity bills, as reported for the household.

improvement, but that they already receive a relatively good quality of service.

To investigate if irrationality plays a role in explaining the negative estimates, I generate a dichotomous variable that equals 1 if the estimated WTP is negative, and regress it against a cognitive index. The results are presented in Annex 6, where no systematic correlation between the variables is detected.[16]

Status quo bias. Annex 7 presents the regression of model 5, adding ASC for each alternative. In these regressions, I dropped alternative 3 to avoid perfect multicollinearity. The results show that only the ASC for status quo is significant; however, the sign is negative for formal and informal clients. That is, contrary to the expected direction of the bias over-selection of the status quo, the results indicate that respondents tend to reject the typical low quality of services provided. This effect is stronger for informal users, which may also be interpreted as the absence of some "cultural factors" by which Dominicans would prefer not paying and keeping low-quality services.

WTP per income quartile. To simplify the presentation, in the following, the analysis concentrates on the results of the more general model 5. Table 6 presents the estimated WTP per income group, as well as their corresponding share of current electricity expenditures and household income. Households in the poorer quartiles (I and II) tend to present higher WTP, sacrificing a larger share of their income for accessing improved electricity services. Formal clients in the lowest income group would pay US$7 in addition to their current monthly bill, altogether representing around 19 percent of their income. The amount of WTP for the richest income groups is lower, US$3.5, mainly because these households tend to have good electricity services. Informal users in the poorest income group would pay around US$9, or 8.5 percent of their income. The observed patterns in income share along income quartiles are similar to the empirical distribution at the national level in the Dominican Republic and in Latin American countries.[17] It is also noticeable that for all income groups, the elicited amounts that informal users would pay represent a lower share of their income than that for formal users.[18] On average, informal users would pay around 4.3 percent of their income. That is, individuals choose services profiles that imply affordability. This finding may be interpreted in favor of the experimental technique applied here, as it may suggest that respondents evaluate the choice scenarios realistically as a function of their financial capacity.

[16] This variable is relevant for capturing the respondent's ability, being a proxy for rationality. For example, the variable is strongly correlated with income, even conditional on respondents' characteristics such education, age, and so forth.
[17] See, for example, Jimenez et al. (2016), and Jimenez et al. (2017).
[18] It is assumed that the WTP of informal users is the amount they would pay monthly, while that for formal users, is the income share of the current bill amount.

5.3 Determinants of WTP across Individuals

It has been shown that there are meaningful differences in the distribution of WTP between formal and informal users, and by income groups within each type. In this subsection, I examine the extent to which the variance in users' valuations can be explained by a rich set of household characteristics. Table 7 presents the results of a set of OLS regressions. The dependent variable is the individual WTP estimates of model 5, pooling formal and informal users. Each column gradually adds covariates of interest: per capita household income (column 1), type of user (column 2), satisfaction with the service (column 3), ownership of appliances (column 4), a set of household characteristics (column 5), and a set of dwelling characteristics (column 6).[19] WTP and income are expressed in natural logarithms. In these regressions, negative WTP is ruled out. That is, I exclude users who are not willing to leave the status quo, so the estimations should be considered conditional on reporting positive disposition to pay.

This examination indicates that household per capita income, type of user, and service perception account for most of the variation in WTP among individuals. Income is significantly and positively associated with the additional amount that users are willing to pay for service improvements. Across specifications, the income coefficient is around 0.2, representing an elasticity around 0.10.[20] These results also indicate that informal users would pay 70 percent more than the average WTP, which is consistent with the previous descriptive examination.

With respect to users' perceptions, higher service satisfaction seems to be positively associated with WTP. Further, when the interaction with being an informal user is added, the main effect persists, indicating that users tend to reward good quality services. However, the interaction is negative, although weakly statistically significant, logically suggesting that informal users who are satisfied with the service have no incentive to leave their current situation.[21]

The progressive inclusion of control variables changes the magnitude of the estimated coefficients only marginally. These results are robust to including ownership of appliances, characteristics of the service, characteristics of the household, and characteristics of the

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[19] These regressions do not include the amount of electricity expenditure, because the dependent variable is calculated with this variable.

[20] Given the income distribution, it is expressed in U.S. cents per household member.

[21] As shown in a related paper (Jimenez 2017), satisfaction with electricity service is strongly related to the attributes of electricity services.

dwelling. Among these variables, owning a fan, family size, and dwelling size appear to have a positive influence on valuations. As a robustness check, Annex 8 presents similar estimates using as the dependent variable the estimated WTP under model 3, which rules out the possibility of obtaining negative WTP.

5.4 Effects of Electricity Attributes on Choosing Service Improvements

This section examines the predicted probabilities to identify the preferred composition of attribute levels. I identify services profiles corresponding to the 1st, 25th, 50th, 75th, and 99th percentiles. Figure 3 presents the estimated probabilities for informal (panel A) and formal users (panel B), showing that profiles with better quality of service have higher chances of being selected, particularly with respect to voltage stability and interruptions. For formal users, service cost is expressed as the additional share of their current usual bill. In general, users seem to be more disposed toward giving up quality of commercial attributes (i.e., punctuality of bill delivery, response time to claims) than the cost or reliability of the electricity supply.

For informal users, who tend to have three daily blackouts, the least preferred profile, with the lowest probability of being selected at the 1st percentile, is that of one blackout per week for 12 hours, with very unstable current voltage, delays in response to complaints, some delays in bill delivery, and a (high) monthly cost of US$46. The profile at the 50th percentile, with 20 percent chance of selection, also dominates in all attributes to the previous one except for punctuality in bill delivery. The profile at the 75th percentile dominates the 1st percentile in all attributes, and, while this was not intended in the experimental design, it shows the rationality of the respondents. In contrast, the profile at the 99th percentile suggests that users are quite disposed to trade lower prices for an additional interruption per month and lower quality of commercial attributes.

That users are more inclined toward trade-offs in the levels of commercial attributes than in reliability can also be observed in the case of formal users. Between the 75th and 99th percentiles, these respondents give up delays in response time to claims and bill delivery for fewer interruptions and greater current stability.

Although the distribution of the predicted probabilities looks similar between types of users, recall that most of the informal users choose not to stay in the status quo, while around 15 percent of the formal respondents choose to stay, which would be explained because they already have a reliable quality of service.

6. Conclusions and Potential Policy Implications

Low-quality electricity services, informal access, and highly subsidized electricity supply are interrelated and persistent problems in developing countries. This situation implies significant costs for the utilities, government, and poorer segments of the population, who generally are the most affected and have the lowest means to cope with service deficiencies. Understanding the demand-side view of the trade-off between low quality and cheap or free service represents a basic input to the design of effective policies aimed to escape this low-quality infrastructure trap. With the goal of contributing toward that end, this paper exploits a stated preferences experiment to study individuals' valuations for improved electricity supply in the Dominican Republic, a country with one of the highest rates of electricity theft and lowest quality of services.

The results strongly suggest that poor households are willing to pay for improved services, in particular, that informal users are disposed to become clients. The most conservative estimates indicate that the average formal end-user would pay an additional 22 percent of what they currently pay, a figure close to the indirect tariff subsidy. Informal users would pay around US$9, which is close to the direct subsidy delivered by the government as a cash transfer. Interestingly, a significant part of these estimates is explained by the valuation for voltage stability, probably because of the relevance of this attribute for protecting the electric appliances owned by households. These elicited WTPs are sound from the budgetary viewpoint, as they represent between 8.8 and 4.3 percent of household income, respectively. Nonetheless, in the case of the first income quartile, the income share that users would pay for improvement is as high as 19 percent, potentially implying higher vulnerability of the poorest households.

The estimates are nonetheless highly heterogeneous. In addition to the type of end-user (formal, informal), income plays a significant role in shaping users' preferences and valuations. Although the first-degree income effect seems to smooth the negative shock associated with low-quality services, the second-degree effect increases aversion to poor services. All in all, the cross-sectional estimates of the average income elasticity of WTP are around 0.1, indicating that households are willing to pay for improvements according to their economic conditions. Another variable that is positively and strongly associated with estimated WTP is users' satisfaction, which has a main effect of around 18 percent, sending the message that users reward good quality of services.

Potential policy implications. WTP for improved services is a key parameter for public policy, as well as, for private utilities, which is frequently used to evaluate the cost effectiveness of projects and the optimal mix of attribute levels. The estimates in this paper are thus potentially of interest in several Latin American countries facing high rates of electricity theft and low-quality electricity services. The estimates may be directly applicable to evaluating potential infrastructure projects in the context under analysis. For example, a direct policy question is how much would be the aggregate gains of increasing quality and charging for it. To provide a hint to this question, I expand the estimated WTP to the population of customers corresponding to an equivalent quality of service. This calculation corrects for the proportion that have negative WTP, assuming that they would not pay additional amounts. Table 8 presents these calculations based on the estimates from model 5, showing the average WTP and the aggregate annual amount that such additional payments would represent. The value of low-quality electricity service is equivalent to around US$163 million per year, which is over 35 percent of the fiscal transfer to the public utilities in 2015. Although this figure does not fully pay for the entire estimated fiscal subsidy, it does contribute to relieving the financial flows of the electricity sector. This figure only captures WTP of residential customers; other sectors, such industry and services, would benefit from improvements in the quality of electricity supply and would correspondently have sizeable WTP.

Policy design needs to take into account heterogeneity. This study shows that informal end-users tend to be poorer and have consistently lower WTP. Therefore, the question remains whether such an average amount would be enough to cover the costs of providing improved service, and at the same time satisfy users' energy needs. At the current electricity tariffs, the amount that informal users would pay represents 80 kWh/month, which is around where the greater density of consumption concentrates. This quantity seems reasonable according to the literature. However, the lowest income group would be greatly vulnerable to price shocks, suggesting that subsidies may still be required to ensure affordability and reduce energy poverty.

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Tables and Figures

Table 1: Attributes and Attribute Levels

Attribute	Labels	
Frequency of blackouts	Once every two months	
	One per month	
	one every two weeks	
	one per week	
	dos per week	
	every two days	
Amount of monthly payment for electricity service	Informal	Formal
	RD$500	15%
	RD$1000	20%
	RD$1500	35%
	RD$2000	50%
	RD$2500	100%
	RD$3000	
	RD$3500	
Voltage stability	Very Unstable	
	Instability occasionally	
	Very stable	
Length of blackouts	1 hour or less	
	2 hours	
	3 hours	
	6 hours	
	8 hours	
	10 hours	
	12 hours	
Puntuality in delivery of bills	Always delays	
	delays in occasions	
	Punctual	
Timing of the blackouts	Morning	
	Afternoon	
	Night	
	Dawn	
Response time to claims	Delays in response	
	Quick response	

Table 2: Descriptive Statistics

Variables	Formal Users		Informal Users		All		Mean Test
	mean	sd	mean	sd	mean	sd	Diff.
Number of Interruptions per month	36.71	29.82	58.34	22.78	41.25	29.81	-21.574***
Length of total interruptions (hours)	5.28	2.49	5.6	2.2	5.3	2.4	-0.323**
Income per capita, US$	197.0	283.2	153.2	182.9	187.8	265.9	45.974***
Monthly electricity bill, US$	22.0	23.8	0.0	0.0	17.4	23.0	31.105***
Perception on Voltage Stability (1:unstable; 3:stable)	1.39	0.59	1.64	0.67	1.44	0.62	-0.252***
Gender Household Head (male:1)	0.55	0.50	0.58	0.49	0.55	0.50	-0.03
Age of household head	52	14	46	15	51	14	6.470***
Schooling of household head	8	5	8	4	8	5	0
Family size	3.7	1.7	3.7	1.7	3.7	1.7	0.0
Cognitive Score (min: 0, max:12)	6.02	0.78	5.98	0.71	6.01	0.76	0.05
Refrigerator (1/0)	0.92	0.28	0.78	0.41	0.89	0.31	0.132***
TV (1/0)	0.95	0.21	0.91	0.29	0.94	0.23	0.044**
Fan (1/0)	0.85	0.36	0.84	0.37	0.85	0.36	0.01
Type of dwelling (1:household; 0:Otherwise)	0.92	0.27	0.85	0.36	0.91	0.29	0.070***
Number of bedrooms	2.55	0.75	2.10	0.75	2.45	0.77	0.440***
Meter (1/0)	0.73	0.44	0.05	0.22	0.59	0.49	0.688***
Perception of price fairness (1:fair, 0:unfair)	0.32	0.47	0.27	0.44	0.31	0.46	0.044*
Satisfaction with electricity serv. (1:Satisfy, 0:Unsatisfy)	0.73	0.44	0.59	0.49	0.70	0.46	0.142***

Note: Total of 2,496 observation, 513 informal users, and 1,930 formal users. There are 13 nonresponses for electricity expenditures, and 24 nonresponses for household income. Diff. = mean differences between formal and informal users. * p < 0.05, ** p < 0.01, *** p<0.001.

Table 3: Main Results for Informal End-Users

	Log(WTP for improved electricity services)				
	(1)	(2)	(3)	(4)	(5)
A. Mean/Non-random component of the parameters					
Interruptions	-.01052***	-.04807***	-.05469***	-.09030***	-.14087***
	(0.002)	(0.005)	(0.005)	(0.008)	(0.014)
Average montly payment	-.03316***	-.03959***	-.06131***	-.09448***	-.11978***
	(0.002)	(0.002)	(0.004)	(0.007)	(0.01)
Voltage stability	.25316***	.32096***	.38055***	.42012***	.42767***
	(0.041)	(0.047)	(0.051)	(0.104)	(0.158)
Length of interruptions	-.07595***	-.09718***	-.12561***	-.21128***	-.18907***
	(0.01)	(0.011)	(0.012)	(0.025)	(0.035)
Billing Punctuality	-0.025	0.002	0.001	0.007	-0.006
	(0.042)	(0.044)	(0.047)	(0.05)	(0.052)
Timing	0.016	0.021	0.007	0.002	0.000
	(0.028)	(0.03)	(0.033)	(0.035)	(0.036)
Time response to claims	.19133***	.17105**	.18416**	.21315***	.21389**
	(0.068)	(0.07)	(0.076)	(0.08)	(0.083)
Constant	.65313***	-.51367**	-0.059	0.232	1.02475***
	(0.2)	(0.207)	(0.234)	(0.255)	(0.3)
B. Standard deviation of the random parameters					
Interruptions		.04807***	.05469***	.09030***	.14087***
		(0.005)	(0.005)	(0.008)	(0.014)
Average montly payment			.06131***	.09448***	.11978***
			(0.004)	(0.007)	(0.01)
Voltage stability		.32096***	.38055***	.42012***	.42767***
		(0.047)	(0.051)	(0.104)	(0.158)
Length of interruptions		.09718***	.12561***	.21128***	.18907***
		(0.011)	(0.012)	(0.025)	(0.035)
C. Heterogeneity in mean with income					
Income					
Interruptions				.01231***	.04717***
				(0.002)	(0.007)
Average montly payment				.01150***	.03035***
				(0.001)	(0.005)
Voltage stability				-0.014	-0.040
				(0.033)	(0.069)
Length of interruptions				.03856***	.04092**
				(0.008)	(0.016)
Income square					
Interruptions					-.00370***
					(0.001)
Average montly payment					-.00269***
					(0.0006)
Voltage stability					0.007
					(0.005)
Length of interruptions					-.00241**
					(0.001)
Log likelihood	-2,016	-1,965	-1,888	-1,831	-1,779
McFadden Pseudo R-squared	0.070	0.098	0.134	0.160	0.184
AIC/N	2.575	2.510	2.412	2.345	2.284

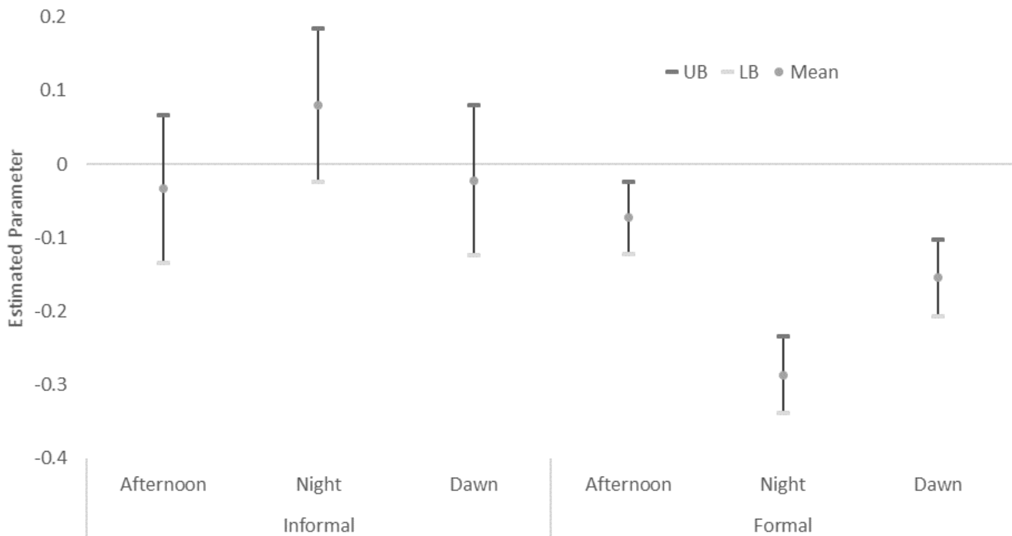
Note: (1) = multinomial logit; (2) = random parameter logit (RPL); (3) and (4) = RPL and RPL with heterogeneity in parameter means depending on income, respectively. ***, **, * denote significance at 1%, 5%, 10% level. Total observations = 1,572. Total respondents = 524. Based on 500 replications using Halton draws sequences.

Table 4: Main Results for Formal End-Users

	Log(WTP for improved electricity services)				
	(1)	(2)	(3)	(4)	(5)
A. Mean/Non-random component of the parameters					
Interruptions	-.02545***	-.06388***	-.06126***	-.13072***	-.41750***
	(0.001)	(0.004)	(0.004)	(0.013)	(0.02)
Average montly payment	-1.75770***	-1.90640***	-4.05785***	-9.02069***	-16.1993***
	(0.091)	(0.097)	(0.271)	(0.538)	(0.698)
Voltage stability	.59973***	.69430***	.90144***	1.14848***	3.37284***
	(0.034)	(0.042)	(0.049)	(0.083)	(0.155)
Length of interruptions	-.06042***	-.06334***	-.10838***	-.15783***	-.12170***
	(0.005)	(0.005)	(0.007)	(0.01)	(0.013)
Billing Punctuality	0.026	.05068**	.06131**	.05464*	.06272*
	(0.024)	(0.025)	(0.026)	(0.028)	(0.033)
Timing	-.10350***	-.09954***	-.09831***	-.11295***	-.15721***
	(0.016)	(0.017)	(0.018)	(0.019)	(0.023)
Time response to claims	0.025	0.026	0.050	.07452*	.19422***
	(0.034)	(0.035)	(0.037)	(0.04)	(0.047)
Constant	-0.062	-.54894***	0.005	.38063**	.77488***
	(0.099)	(0.106)	(0.127)	(0.156)	(0.168)
B. Standard deviation of the random parameters					
Interruptions		.06388***	.06126***	.13072***	.41750***
		(0.004)	(0.004)	(0.013)	(0.02)
Average montly payment			4.05785***	9.02069***	16.1993***
			(0.271)	(0.538)	(0.698)
Voltage stability		.69430***	.90144***	1.14848***	3.37284***
		(0.042)	(0.049)	(0.083)	(0.155)
Length of interruptions		.06334***	.10838***	.15783***	.12170***
		(0.005)	(0.007)	(0.01)	(0.013)
C. Heterogeneity in mean with income					
Income					
Interruptions				.00859***	.10363***
				(0.001)	(0.005)
Average montly payment				.80355***	3.29205***
				(0.063)	(0.132)
Voltage stability				-0.021	-.83901***
				(0.018)	(0.04)
Length of interruptions				.00802***	-0.001
				(0.002)	(0.004)
Income square					
Interruptions					-.00681***
					(0)
Average montly payment					-.14475***
					(0.0025)
Voltage stability					.05975***
					(0.001)
Length of interruptions					0.000
					(0.0001)
Log likelihood	-7,522	-7,199	-7,199	-7,009	-6,600
McFadden Pseudo R-squared	0.082	0.122	0.122	0.145	0.195
AIC/N	2.546	2.436	2.436	2.374	2.237

Note: (1) = multinomial logit; (2) = random parameter logit (RPL); (3) and (4) = RPL and RPL with heterogeneity in parameter means depending on income, respectively. ***, **, * denote significance at 1%, 5%, 10% level. Total observations = 5,916. Total respondents = 1,972. Based on 500 replications using Halton draws sequences.

Figure 1: Parameters for Timing of Interruptions



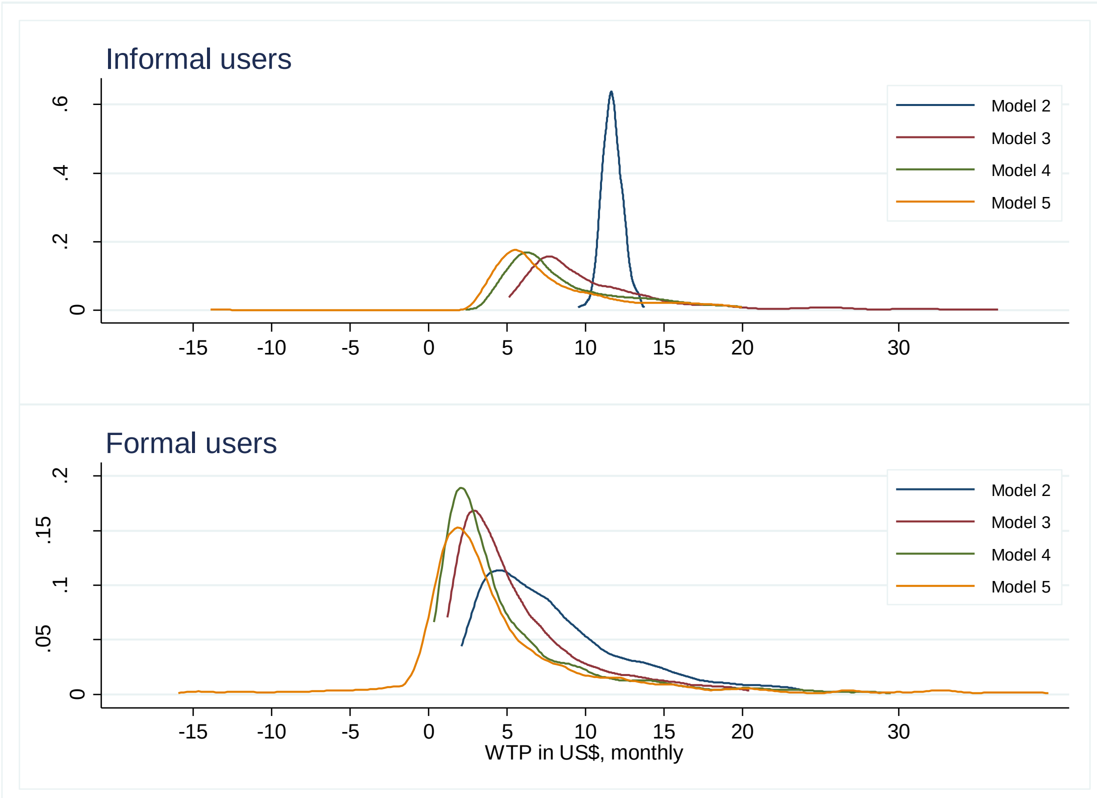
Note: Estimated parameters for timing of outages as factor variable in model 1. Base value is occurrence of outage during the morning. UB = upper bound, mean estimated plus one standard error; LB = lower bound, mean estimated minus one standard error.

Table 5: Average Willingness to Pay for Electricity Improvements

	Informal (in monthly US$)					Formal (as a % of average electricity bill)				
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 1	Model 2	Model 3	Model 4	Model 5
Interruptions	0.317	1.215	0.891	0.621	0.761	0.014	0.033	0.015	0.016	0.022
Voltage stability	7.648	8.126	6.208	5.882	6.225	0.341	0.364	0.222	0.164	0.183
Length of interruptions	2.293	2.458	2.049	1.743	1.693	0.034	0.033	0.027	0.020	0.016
Billing Punctuality	-0.725	0.043	0.013	0.113	0.100	0.015	0.027	0.015	0.008	0.008
Timing	-0.483	-0.537	-0.111	-0.037	-0.002	0.059	0.052	0.024	0.017	0.021
Time response to claims	5.780	4.330	3.004	3.258	2.115	0.014	0.014	0.012	0.011	0.025
ΣWTP All	14.83	15.64	12.05	11.58	10.89	0.48	0.52	0.32	0.24	0.28
ΣWTP (Interruption, Voltage, length)	10.26	11.80	9.15	8.25	8.68	0.39	0.43	0.26	0.20	0.22

Note: Calculations based on Tables 3 and 4.

Figure 2: Distribution of Individual WTP Estimates



Note: Kernel density estimates of individual WTP estimates with models 1 to 5. For presentation purposes, this figure trims the top and bottom 5 percent of the distribution.

Table 6: Willingness to Pay by Income Quartile: Bill and Income Shares

Income Quartile	Formal			Informal			All		
	WTP	Current Bill Share	Income Share	WTP	Current Bill Share	Income Share	WTP	Current Bill Share	Income Share
I	7.3	40.6	19.4	9.3	.	8.5	7.8	40.6	16.7
II	4.1	23.6	7.2	12.7	.	4.4	6.1	23.6	6.6
III	6.4	29.3	5.9	6.0	.	1.5	6.3	29.3	5.0
IV	3.5	3.3	3.1	8.9	.	1.1	4.4	3.3	2.8
Total	5.3	24.0	8.8	9.3	.	4.3	6.2	24.0	7.9

Note: Willingness to pay (WTP) estimates of model 5. All values are monthly calculations. The top and bottom 1 percentiles were trimmed in the calculations. The "current" electricity bill was calculated as the average of the past three months. Informal users do not pay for the electricity service. The shares of current bill and income are averages for households per quartile.

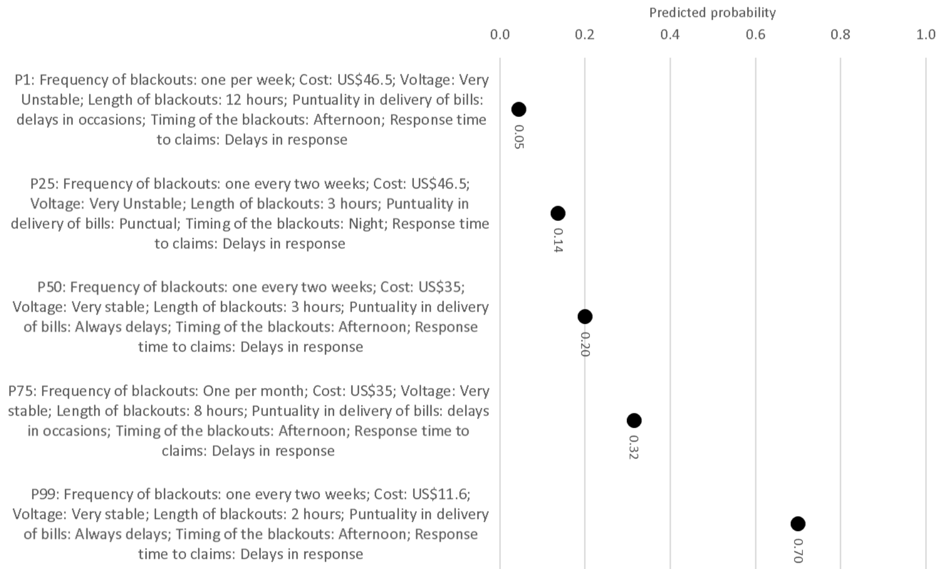
Table 7: Determinants of WTP across Individuals

	Dependent: log(WtP for better electricity services)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Ln(US$per capita hh income/100+2)	0.198**	0.242***	0.234***	0.231***	0.188**	0.231***	0.184**
	(0.063)	(0.062)	(0.062)	(0.062)	(0.062)	(0.065)	(0.065)
Informal user		0.721***	0.720***	0.677***	0.707***	0.729***	0.849***
		(0.038)	(0.038)	(0.063)	(0.065)	(0.065)	(0.071)
Satisfaction with service		0.164***	0.186***	0.222***	0.187***	0.186***	0.190***
		(0.041)	(0.041)	(0.052)	(0.054)	(0.054)	(0.054)
Prices fairness perception			-0.145***	-0.228***	-0.206***	-0.192***	-0.153**
			(0.041)	(0.048)	(0.049)	(0.049)	(0.049)
Informal*Satisfaction				-0.160*	-0.162*	-0.147	-0.171*
				(0.077)	(0.079)	(0.080)	(0.080)
Informal*Fairnes perception				0.402***	0.395***	0.362***	0.344***
				(0.082)	(0.083)	(0.084)	(0.084)
refrigerator					0.136*	0.107	0.070
					(0.059)	(0.059)	(0.060)
tv					0.083	0.049	0.045
					(0.074)	(0.073)	(0.071)
fan					0.219***	0.205***	0.185***
					(0.049)	(0.049)	(0.049)
Number of interruption per month					-0.000	-0.000	0.000
					(0.001)	(0.001)	(0.001)
Hours of service per day					-0.013	-0.013	-0.013
					(0.009)	(0.009)	(0.009)
Household size						0.051***	0.036**
						(0.012)	(0.012)
Gender of the household head						-0.097*	-0.091*
						(0.039)	(0.039)
Age of the household head						0.002	0.000
						(0.002)	(0.002)
Schooling of the household head						0.008	0.005
						(0.005)	(0.005)
Cognositive index						0.035	0.026
						(0.027)	(0.027)
Own electricity meter							0.128*
							(0.055)
Type of dweling (house=1)							-0.121
							(0.070)
Number of rooms in the dwelling							0.139***
							(0.028)
Constant	1.540***	1.214***	1.262***	1.270***	1.032***	0.522*	0.484
	(0.077)	(0.083)	(0.084)	(0.086)	(0.137)	(0.234)	(0.247)
Observations (respondents)	2250	2250	2248	2248	2248	2248	2248
Adj. R-squared	0.005	0.097	0.101	0.107	0.118	0.127	0.139

Note: The willingness to pay (WTP) estimates are based on model 5. In this model, the mean is assumed to depend on income, and the random component is assumed to have a restricted triangular distribution. The dependent variable is ln(WTP_i+2) for each individual i as generated by model 5. Robust standard errors are in parentheses.

Figure 3: Estimated Probability of Services Profiles

Panel A: Informal Users



Panel B: Formal Users

Note: Estimated probability for attributes' levels combination corresponding to the 1st, 25th, 50th, 75th, and 99th percentiles of the predicted probability distribution under model 5.

Table 8: Aggregate Welfare Loss for Low-Quality Electricity Services

Type of Circuit*		Average Montly WTP (US$)	Annual Welfare Loss (Million, US$)
Clients	A	7.59	72
	B	5.99	4
	C	4.42	15
	D	4.52	30
Informal clients		9.30	42
Total Welfare loss			**163**

Note: Estimations are based on model 5. These estimates are averaged by type of client (formal, informal) and circuit. The type of circuit and the number of clients within each circuit were reported by the regulator (CEEDE) in June 2014. Each circuit reflects the hours of service that each user typically receives. The number of informal clients is approximated based on the declaration of the regulator. These calculations expand the sample to the total clients per circuit, and aggregate the elicited willingness to pay (WTP). Per type of circuit and user, the equivalent share of the sample declaring negative WTP is assumed not to pay an additional amount.

ANNEXES

Annex 1: Priors for the Efficient Bayesian Designs: Choice Sets

Attributes	Distribution of the parameter	Informal		Formal	
		Mean	Variance	Mean	Variance
Outages	Normal	[U,-.8,-0.5]	[U,.07,.2]	[U,-.1,-0.05]	[U,.075,.094]
Cost of service	Normal	[U,-1.2,-0.02]	[U,.02,.34]	[U,-.35,-0.02]	[U,.02,.34]
Voltage stability	Fixed	1.3		0.22	
Outage length	Normal	[U,-.78,-0.03]	[U,.055,.45]	[U,-.42,-0.03]	[U,.13,.45]
billing punctuality	Fixed	0.57		0.57	
Timing of outages	Fixed	0.58		0.58	
Time response to claims	Fixed, No prior				

Note: U = uniform distribution. Prior upper and lower bounds were selected based on pilot regression results and literature review.

Annex 2: Distribution of the Sample

Provicen (urban)	Number of Households	%
Distrito Nacional	180	7.21
Puerto Plata	300	12.02
San Cristobal	400	16.03
San Pedro de Macoris	190	7.61
Santo Domingo	688	27.56
Santiago	439	17.59
Valverde	299	11.98
Total	2496	100

Note: The survey was implemented between December 2015 and March 2016.

Annex 3: Main Results: Assuming an Unrestricted Normal Distribution

A. Informal End-Users

	Log(WTP for improved electricity services)				
	(1)	(2)	(3)	(4)	(5)
A. Mean/Non-random component of the parameters					
Interruptions	.01042***	-.04054***	-.04704***	-.05123***	-.07317***
	(0.002)	(0.006)	(0.007)	(0.01)	(0.015)
Average montly payment	.03315***	-.04664***	-.06672***	-.07002***	-.08633***
	(0.002)	(0.003)	(0.005)	(0.007)	(0.013)
Voltage stability	.25199***	.38165***	.40175***	.30692***	0.244
	(0.041)	(0.063)	(0.067)	(0.116)	(0.172)
Length of interruptions	.07599***	-.11034***	-.11518***	-.13184***	-.11190***
	(0.01)	(0.015)	(0.016)	(0.027)	(0.042)
Billing Punctuality	-0.025	0.007	-0.010	-0.008	-0.011
	(0.042)	(0.052)	(0.056)	(0.056)	(0.056)
Timing	-0.005	-0.002	-0.016	-0.015	-0.016
	(0.031)	(0.037)	(0.04)	(0.04)	(0.04)
Time response to claims	.18972***	.16962**	.19816**	.19988**	.20723**
	(0.068)	(0.082)	(0.089)	(0.089)	(0.089)
Constant	.66802***	1.18285***	1.63697***	1.62664***	1.61681***
	(0.216)	(0.295)	(0.363)	(0.364)	(0.367)
B. Standard deviation of the random parameters					
Interruptions		.07160***	.07272***	.07277***	.07116***
		(0.006)	(0.007)	(0.007)	(0.007)
Average montly payment			.04989***	.05009***	.05182***
			(0.005)	(0.005)	(0.005)
Voltage stability		.61453***	.60089***	.59567***	.60754***
		(0.114)	(0.133)	(0.133)	(0.133)
Length of interruptions		.16402***	.12725***	.12703***	.12888***
		(0.021)	(0.027)	(0.027)	(0.028)
C. Heterogeneity in mean with income					
Income					
Interruptions				0.002	.01286*
				(0.003)	(0.007)
Average montly payment				0.001	.01045*
				(0.002)	(0.006)
Voltage stability				0.038	0.067
				(0.038)	(0.077)
Length of interruptions				0.007	-0.005
				(0.009)	(0.02)
Income square					
Interruptions					-.00092*
					(0.001)
Average montly payment					-0.001
					(0.0006)
Voltage stability					-0.001
					(0.005)
Length of interruptions					0.001
					(0.001)
Log likelihood	-2,016	-1,811	-1,760	-1,759	-1,755
McFadden Pseudo R-squared	0.070	0.169	0.192	0.193	0.195
AIC/N	2.576	2.318	2.255	2.258	2.258

Note: (1) = multinomial logit; (2) = random parameter logit (RPL); (3) and (4) = RPL and RPL with heterogeneity in parameter means depending on income, respectively. ***, **, * denote significance at 1%, 5%, 10% level. Total observations = 1,572. Total respondents = 524. Based on 500 replications using Halton draws sequences.

Annex 3 Main Results: Assuming Unrestricted Normal Distribution

B. Formal End-Users

	Log(WTP for improved electricity services)				
	(1)	(2)	(3)	(4)	(5)
A. Mean/Non-random component of the parameters					
Interruptions	.02545***	-.25382***	-.25732***	-.25141***	-.01326***
	(0.001)	(0.016)	(0.016)	(0.018)	(0.003)
Average montly payment	..75770***	1.29583***	-6.91457***	-7.06657***	-1.78982***
	(0.091)	(0.083)	(0.404)	(0.457)	(0.148)
Voltage stability	.59973***	-.09027***	1.59894***	1.50166***	.62160***
	(0.034)	(0.008)	(0.095)	(0.125)	(0.071)
Length of interruptions	.06042***	-2.67217***	-.14876***	-.13110***	.05018***
	(0.005)	(0.122)	(0.01)	(0.013)	(0.014)
Billing Punctuality	0.026	0.022	0.021	0.021	-.05323**
	(0.024)	(0.032)	(0.036)	(0.036)	(0.026)
Timing	.10350***	-.11253***	-.15380***	-.15381***	-.18334***
	(0.016)	(0.021)	(0.024)	(0.024)	(0.018)
Time response to claims	0.025	0.025	0.057	0.055	-0.033
	(0.034)	(0.045)	(0.051)	(0.051)	(0.038)
Constant	-0.062	-0.220	.93999***	.92569***	-0.098
	(0.099)	(0.141)	(0.192)	(0.191)	(0.101)
B. Standard deviation of the random parameters					
Interruptions		.30366***	.29508***	.29793***	.03484***
		(0.018)	(0.021)	(0.021)	(0.002)
Average montly payment			6.31817***	6.23233***	0.001
			(0.408)	(0.4)	(3.409)
Voltage stability		1.73909***	1.86326***	1.84685***	0.003
		(0.11)	(0.127)	(0.129)	(0.647)
Length of interruptions		.17020***	.15599***	.15480***	.16323***
		(0.011)	(0.015)	(0.015)	(0.008)
C. Heterogeneity in mean with income					
Income					
Interruptions				-0.003	-.01090***
				(0.003)	(0.001)
Average montly payment				0.069	.11691**
				(0.073)	(0.048)
Voltage stability				0.029	-.07306***
				(0.029)	(0.028)
Length of interruptions				-.00565*	-.04849***
				(0.003)	(0.005)
Income square					
Interruptions					0.000
					(0)
Average montly payment					-.02910***
					(0.0021)
Voltage stability					.01594***
					(0.002)
Length of interruptions					.00179***
					(0.0003)
Log likelihood	-7,522	-6,304	-6,304	-6,299	-7,222
McFadden Pseudo R-squared	0.082	0.231	0.231	0.232	0.119
AIC/N	2.546	2.135	2.135	2.135	2.448

Note: (1) = multinomial logit; (2) = random parameter logit (RPL); (3) and (4) = RPL and RPL with heterogeneity in parameter means depending on income, respectively. ***, **, * denote significance at 1%, 5%, 10% level. Total observations = 5,916. Total respondents = 1,972. Based on 500 replications using Halton draws sequences.

Annex 4: Main Results – Assuming Restricted Triangular Distribution, normalizing status quo

A. Informal End-Users

	Log(WTP for improved electricity services)				
	(1)	(2)	(3)	(4)	(5)
A. Mean/Non-random component of the parameters					
Interruptions	-.04166***	-.05686***	-.06848***	-.11683***	-.12760***
	(0.008)	(0.01)	(0.01)	(0.02)	(0.029)
Average montly payment	-.03623***	-.04337***	-.06334***	-.08487***	-.11352***
	(0.002)	(0.002)	(0.004)	(0.006)	(0.009)
Voltage stability	.31661***	.54558***	.50465***	.90544***	1.49347***
	(0.047)	(0.053)	(0.054)	(0.094)	(0.151)
Length of interruptions	-.08038***	-.11504***	-.14356***	-.18805***	-.12469***
	(0.011)	(0.013)	(0.013)	(0.023)	(0.038)
Billing Punctuality	0.003	0.016	0.025	0.021	0.002
	(0.043)	(0.045)	(0.048)	(0.051)	(0.053)
Timing	0.010	0.025	0.014	0.005	-0.005
	(0.031)	(0.032)	(0.034)	(0.036)	(0.037)
Time response to claims	.17911***	.19547***	.19208**	.21641***	.22271***
	(0.068)	(0.071)	(0.076)	(0.08)	(0.083)
Constant	1.15470***	1.20146***	2.26460***	2.52165***	2.77023***
	(0.228)	(0.242)	(0.277)	(0.293)	(0.314)
B. Standard deviation of the random parameters					
Interruptions		.05686***	.06848***	.11683***	.12760***
		(0.01)	(0.01)	(0.02)	(0.029)
Average montly payment			.06334***	.08487***	.11352***
			(0.004)	(0.006)	(0.009)
Voltage stability		.54558***	.50465***	.90544***	1.49347***
		(0.053)	(0.054)	(0.094)	(0.151)
Length of interruptions		.11504***	.14356***	.18805***	.12469***
		(0.013)	(0.013)	(0.023)	(0.038)
C. Heterogeneity in mean with income					
Income					
Interruptions				.01839***	.03087**
				(0.006)	(0.013)
Average montly payment				.00716***	.02525***
				(0.001)	(0.004)
Voltage stability				-.16560***	-.57976***
				(0.031)	(0.083)
Length of interruptions				.01866***	-0.002
				(0.006)	(0.015)
Income square					
Interruptions					-0.002
					(0.001)
Average montly payment					-.00200***
					(0.0004)
Voltage stability					.04205***
					(0.008)
Length of interruptions					.00155*
					(0.001)
Log likelihood	-2,015	-1,982	-1,906	-1,876	-1,847
McFadden Pseudo R-squared	0.070	0.090	0.126	0.139	0.152
AIC/N	2.574	2.532	2.435	2.402	2.370

Note: (1) = multinomial logit; (2) = random parameter logit (RPL); (3) and (4) = RPL and RPL with heterogeneity in parameter means depending on income, respectively. ***, **, * denote significance at 1%, 5%, 10% level. Total observations = 1,572. Total respondents = 524. Based on 500 replications using Halton draws sequences.

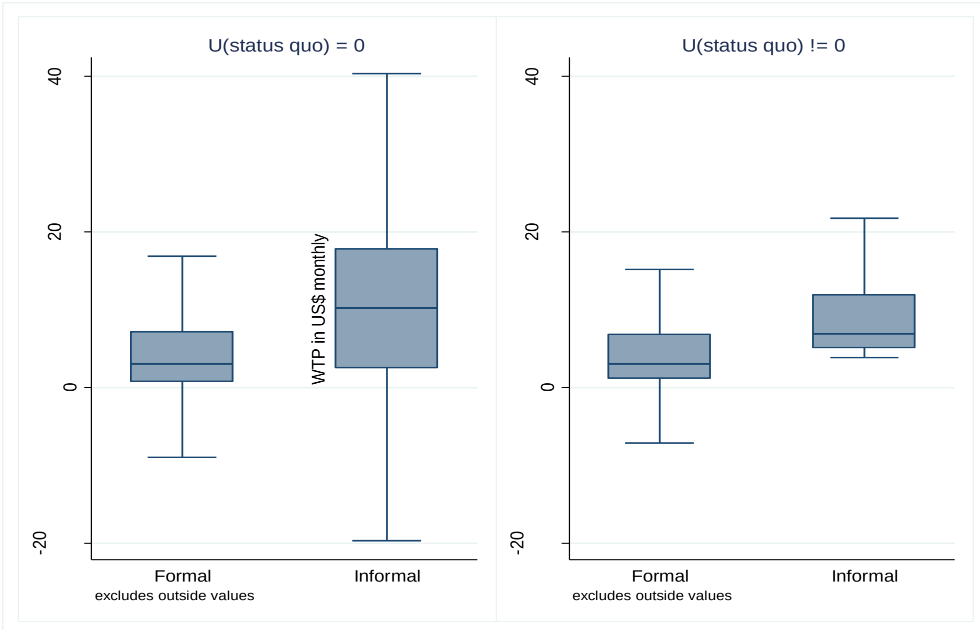
Annex 4: Main Results – Assuming Restricted Triangular Distribution, Normalizing Status Quo

B. Formal End-Users

	Log(WTP for improved electricity services)				
	(1)	(2)	(3)	(4)	(5)
A. Mean/Non-random component of the parameters					
Interruptions	-.15805***	-.19518***	-.24632***	-.27161***	-.42705***
	(0.016)	(0.02)	(0.021)	(0.034)	(0.048)
Average montly payment	-2.15282***	-3.03660***	-5.53919***	-8.86108***	-12.2011***
	(0.099)	(0.119)	(0.289)	(0.455)	(0.627)
Voltage stability	.80571***	1.54426***	1.60898***	1.87874***	2.96795***
	(0.041)	(0.038)	(0.041)	(0.054)	(0.098)
Length of interruptions	-.06942***	-.09418***	-.14637***	-.19657***	-.20896***
	(0.005)	(0.007)	(0.008)	(0.011)	(0.013)
Billing Punctuality	-0.013	.05652**	.07066**	.06726**	.06740**
	(0.023)	(0.027)	(0.029)	(0.03)	(0.032)
Timing	-.09272***	-.08326***	-.08487***	-.09976***	-.13563***
	(0.016)	(0.018)	(0.02)	(0.021)	(0.022)
Time response to claims	0.000	0.019	0.038	0.057	.11312**
	(0.035)	(0.04)	(0.042)	(0.044)	(0.046)
Constant	-.66664***	-1.66566***	-.81675***	0.079	1.42271***
	(0.154)	(0.141)	(0.169)	(0.186)	(0.207)
B. Standard deviation of the random parameters					
Interruptions		.19518***	.24632***	.27161***	.42705***
		(0.02)	(0.021)	(0.034)	(0.048)
Average montly payment			5.53919***	8.86108***	12.2011***
			(0.289)	(0.455)	(0.627)
Voltage stability		1.54426***	1.60898***	1.87874***	2.96795***
		(0.038)	(0.041)	(0.054)	(0.098)
Length of interruptions		.09418***	.14637***	.19657***	.20896***
		(0.007)	(0.008)	(0.011)	(0.013)
C. Heterogeneity in mean with income					
Income					
Interruptions				0.002	.05886***
				(0.008)	(0.015)
Average montly payment				.69696***	2.04325***
				(0.062)	(0.135)
Voltage stability				-.12882***	-.73566***
				(0.011)	(0.034)
Length of interruptions				.01205***	.02608***
				(0.002)	(0.004)
Income square					
Interruptions					-.00347***
					(0.001)
Average montly payment					-.07940***
					(0.006)
Voltage stability					.03557***
					(0.002)
Length of interruptions					-.00143***
					(0.0001)
Log likelihood	-7,719	-6,844	-6,844	-6,726	-6,502
McFadden Pseudo R-squared	0.058	0.165	0.165	0.180	0.207
AIC/N	2.612	2.316	2.316	2.278	2.203

Note: (1) = multinomial logit; (2) = random parameter logit (RPL); (3) and (4) = RPL and RPL with heterogeneity in parameter means depending on income, respectively. ***, **, * denote significance at 1%, 5%, 10% level. Total observations = 5,916. Total respondents = 1,972. Based on 500 replications using Halton draws sequences.

Annex 5: Distribution of WTP, Model 5



Annex 6: Logit Regression of Negative WTP on Cognitive Index

	Dependent: 1 if WTP<0		
	(1)	(2)	(3)
Cognitive index	-0.168	0.001	-0.191
	(0.101)	(0.296)	(0.108)
Informal user	-0.484*		
	(0.233)		
Hours of service per day	0.010	0.064	-0.004
	(0.028)	(0.064)	(0.029)
Number of interruption per month	-0.006*	-0.028***	-0.003
	(0.003)	(0.008)	(0.003)
Ln(income)	1.253***	1.211***	1.267***
	(0.128)	(0.334)	(0.142)
Household size	0.075	-0.021	0.085
	(0.045)	(0.131)	(0.049)
Schooling of the household head	0.040*	0.007	0.044*
	(0.016)	(0.046)	(0.018)
Contant	-2.911***	-2.944	-2.880***
	(0.642)	(1.809)	(0.688)
N	2496	524	1972

Note: ***, **, * denote statistical significance at 1%, 5%, 10% level. Standard errors in parenthesis.

Annex 7: RPL Estimates with ASC – Status Quo Bias

	Dependent: log(WtP for better electricity services)	
	Informal	Formal
Mean/Non-random component of the parameters		
Interruptions	-.14042***	-.39476***
	(0.014)	(0.017)
Average montly payment	-.11897***	-14.1402***
	(0.01)	(0.672)
Voltage stability	.41916***	3.81422***
	(0.158)	(0.174)
Length of interruptions	-.18821***	-0.016
	(0.035)	(0.014)
Billing Punctuality	-0.002	0.031
	(0.052)	(0.033)
Timing	-0.004	-.18422***
	(0.037)	(0.022)
Time response to claims	.21786***	.12485***
	(0.083)	(0.046)
Constant Alternatina 1	-0.132	-.11479**
	(0.09)	(0.051)
Constant Alternatina 2	-.15971*	-0.043
	(0.088)	(0.049)
Constant Status quo	-1.10138***	-1.01622***
	(0.322)	(0.171)
Heterogeneity in mean with income		
Income		
Interruptions	.04708***	.10433***
	(0.007)	(0.005)
Average montly payment	.03027***	2.66186***
	(0.005)	(0.118)
Voltage stability	-0.038	-.97590***
	(0.069)	(0.043)
Length of interruptions	.04059**	-.02831***
	(0.016)	(0.004)
Income square		
Interruptions	-.00369***	-.00678***
	(0.001)	(0.0003)
Average montly payment	-.00269***	-.11069***
	(0.0006)	(0.0024)
Voltage stability	0.007	.07688***
	(0.005)	(0.001)
Length of interruptions	-.00247**	.00069***
	(0.001)	(0.0001)
Log likelihood	-1,777	-6,668
McFadden Pseudo R-squared	0	0
AIC/N	2.284	2.260

Note: ***, **, * denote statistical significance at 1%, 5%, 10% level. Regression are based on model 5. Regression for informal users contains 1,572 observations for 524 respondents. Regression for formal users contains 5,916 observations for 1,972 respondents. Based on 500 replications using Halton draws sequences.

Annex 8: Determinants of WTP across Individuals

	Dependent: log(WtP for better electricity services)					
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(US$per capita hh income/100+2)	0.297***	0.347***	0.346***	0.290***	0.301***	0.240***
	(0.037)	(0.036)	(0.036)	(0.032)	(0.034)	(0.032)
Informal user		0.680***	0.724***	0.786***	0.805***	1.023***
		(0.021)	(0.035)	(0.035)	(0.037)	(0.037)
Satisfaction with service		0.159***	0.176***	0.006	0.009	0.037
		(0.025)	(0.032)	(0.033)	(0.032)	(0.030)
Informal*Satisfaction			-0.069	0.030	0.039	0.001
			(0.044)	(0.045)	(0.045)	(0.044)
refrigerator				0.146***	0.107**	0.057
				(0.037)	(0.037)	(0.037)
tv				0.075	0.033	0.025
				(0.048)	(0.047)	(0.043)
fan				0.181***	0.159***	0.129***
				(0.030)	(0.030)	(0.029)
Number of interruption per month				-0.006***	-0.006***	-0.004***
				(0.000)	(0.000)	(0.000)
Hours of service per day				-0.017***	-0.018***	-0.015**
				(0.005)	(0.005)	(0.005)
Household size					0.050***	0.034***
					(0.007)	(0.007)
Gender of the household head					-0.015	-0.003
					(0.022)	(0.021)
Age of the household head					0.004***	0.001
					(0.001)	(0.001)
Schooling of the household head					0.013***	0.008**
					(0.003)	(0.003)
Cognitive index					0.047**	0.039**
					(0.015)	(0.015)
Own electricity meter						0.309***
						(0.027)
Type of dwelling (house=1)						-0.121**
						(0.037)
Number of rooms in the dwelling						0.146***
						(0.015)
Constant	1.530***	1.209***	1.197***	1.326***	0.667***	0.479***
	(0.047)	(0.048)	(0.049)	(0.080)	(0.136)	(0.135)
Observations (respondents)	2423	2423	2423	2423	2423	2423
Adj. R-squared	0.031	0.221	0.221	0.295	0.322	0.381

Notes: The willingness to pay (WTP) estimates are based on model 3. It assumes a restricted triangular distribution for random parameters. The dependent variable is ln(WTP_i+2) for each individual *i* as generated by model 5. Robust standard errors are in parentheses.