DOCUMENTOS DE TRABAJO

BILTOKI

D.T. 2009.02

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Documento de Trabajo BILTOKI DT2009.02
Editado por el Departamento de Economía Aplicada III (Econometría y Estadística)
de la Universidad del País Vasco.

Depósito Legal No.: BI-1934-09
ISSN: 1134-8984
URN: RePEc:ehu:biltok:200902

Choice experiment study on the willingness to pay to improve electricity services

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June 2009

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Abstract

Modern forms of energy are an important vehicle towards poverty alleviation in rural areas of developing countries. Most developing countries' households heavily rely on wood fuel which impact their health and social–economic status. To ease such a dependency, other modern forms of energy, namely electricity, need to be provided. However, the quality of the electricity service, namely reliability, is an important factor in reducing this dependency. This paper discusses a choice experiment valuation study conducted among electrified rural households located in Kisumu, Kenya, in which the willingness to pay (WTP) to avoid power outages or blackouts was estimated. A mixed logit estimation was applied to identify the various socio-economic and demographic characteristics which determine preferences to reduce power outages among a household's users. In conclusion, several of the socio-economic and demographic characteristics outlined in this paper were identified and can assist service differentiation to accommodate the diverse households' preferences towards the improvement of the electricity service.

JEL Classification: Q56; C25

Key Words: developing country, rural, power outages, willingness to pay, random parameter logit

Running Head: S.*Abdullah, P. Mariel/Choice experiment on WTP*

Introduction

Nearly 80% of developing countries' households use traditional fuels such as wood fuel and kerosene, which have adverse effects on their social–economic conditions and health well-being. Kenya is not an exception: the firewood dependency is such that 90% of households rely heavily on these sources compared to other modern form like electricity. Indeed, the household electrification level at the national average is 14%; the urban and rural areas (1999) stand at 42% and 4% respectively (Kenya National Bureau of Statistics (KNBS), 2000). This level is below the average SSA electrification level of 17% (Global Network on Energy for Sustainable Energy Development (GNESD), 2002). The government's goal is to increase rural electrification to 20% by 2010. According to the International Monetary Fund Kenya Poverty Strategy Paper, the rural electrification programme (REP) aims to increase rural electrification levels from 4% to at least 40% by 2020. However, political interferences have been reported which are undermining the REP development and implementation and contributing to add to expansion costs (Sanghvi and Barnes, 2001). Some of the key socio-economic and environmental benefits of electricity include: reduced indoor air pollution, income generation and reduced deforestation, as well as indirect benefits, such as those regarding security and education. These benefits can be reaped as long as the supply of electricity is reliable in the system. Indeed, electricity supplies in most developing countries are erratic with high frequencies of black outs or power outages coupled with long periods of outages.

In power markets, reliability has been described as 'the ability of a power system to provide service to customers, whilst maintaining the quality and price of electricity at an acceptable level' (Tinnium et al., 1994).[1] The delivery of electricity services, in terms of quality and quantity, as demanded by the consumer, is dictated by the performance of the electricity system providing this service.[2] Unreliable systems have costs that have to be taken into account in power planning, as interruptions have a value to users. In developing countries these frequent and longer outages have indirect costs (Munasinghe, 1980) primarily related to lighting rather than cooking needs.[3] Some of the outage costs faced by residential users include: leisure time costs (Munasinghe, 1980), inconvenience costs and consumable costs (LaCommore and Eto, 2006).

Valuing energy services, particularly clean energy such as electricity, is important for policy planning and improving the socio-economic conditions, environment and well being of households. What motivates this study is the use of the choice experiment (CE) method to examine the willingness to pay (WTP) values to improve electricity services because there is a dearth of energy literature on valuation work based in SSA. Numerous stated preference studies such as contingent valuation (CV) and CE have been completed in developed regions, namely: North America and Europe. According to a World Bank report, the bank has funded environmental valuation of projects in developing countries and recorded a high number of studies involving water supply, sanitation and flood protection. By contrast, the energy, transport and agriculture sectors have received less attention (Silva and Pagiola, 2003).

Hence, this study examines WTP to avoid unannounced interruptions in electricity service, using the data of 202 households in Kisumu District, Kenya. As a result, this study applies the CE method to provide new evidence about demand for improved electricity in the context of a developing country, using the electricity service's characteristics to value reliability. Moreover, CE is an important exercise because of the lack of market information/data from electricity distributors about reliability costs, particularly to users whose households are heavily dependent on traditional fuels. In Kenya, the Kenya Power Lighting Company (KPLC), the sole electricity distributor, has reported that the total number of outages (both technical and non-technical) experienced by electrified customers in all sectors averages out at 11,000 a month (Electricity Regulatory Board (ERB), 2005). However, the verification of the frequency and length of outages experienced by residents was difficult to ascertain, because these 11,000 incidents across the country were the total interruptions experienced in residential as well as the industrial and commercial sectors. In developed countries the reliability is quite high, for instance, in the Netherlands the average outage for low voltage consumers is 26 minutes per year (Bloemhof et al., 2001) and in the US the average duration of interruptions is 106 minutes (LaCommare and Eto, 2006). In the US, 70% of outages are caused by weather-related events (floods, lightning, ice storms), and the rest by animal damaging incidents (Energy Information Administration (EIA), 2004).

The main research objective is to investigate the cost of electricity necessary for rural households in order to avoid power outages. As a result, the key research questions explored in this paper are: (1) what are the socio-economic demographic factors that influence the WTP to avoid power outages? (2) What are the implications of such estimates for stakeholders and decision-makers? The answers to these research questions are pertinent to the local electricity distributor, namely KPLC, as well as the Energy Regulatory Commission (ERC) and private distributors for service differentiation, improvement and development.

The paper is structured into four main sections: a theoretical framework, survey methodology, data results and discussion and conclusion.

1. Theoretical framework

The goal of this study is to analyze service improvement using CE, where specific characteristics or attributes of the service are represented as choices and the respondents' selection determines the WTP values. CE comprises a number of choice sets which vary according to the levels of attributes or characteristics, and these describe the features of the goods to be estimated. The selection of the preferred choice is decided implicitly, by the trade-off a consumer makes among the different alternatives being offered in all given choice sets.

The underlying theory of goods possessing characteristics or properties was documented by Lancaster (1966): goods do not provide utility but have characteristics; goods consist of numerous characteristics some of which may be shared by at least one good; and the characteristics differ in combination and/or in separation. The attributes and number of levels and characteristics and/or features are important in constructing choice profiles. Hanley et al. (1998) noted that price is typically one of the attributes in the choices. Additionally, one of the choice sets generally includes the status quo, where this choice provides no difference in the good being offered. This position is a 'do nothing' scenario (Hanley et al., 2001), also known as the 'business-as-usual' position, as it does not vary across the choice sets (Mogas et al., 2006).

Some of the CE applied in the energy sector in developed countries include: Alvarez-Farizo and Hanley (2002), An et al. (2002), Aravena et al. (2006), Arkesteijn and Oerelemans (2005), Beenstock et al. (1998), Bergmann et al. (2006), Carlsson and Martinsson (2008), Goett et al. (2000), Han et al. (2008), Longo et al. (2008), Ladenburg et al. (2005) and Roe et al. (2001). In reviewing some of these studies, the WTP estimates were significant and varied according to: income, age, renewable energy sources (green electricity, wind farms and biomass), service attributes and power outages and/or fluctuations. Moreover, nearly all these studies included questionnaires that were divided into at least three parts: 'warm up' questions, WTP questions and socio-economic demographic (SED) questions. Most of the studies included some SED information, such as: head of household, age, race, education levels, employment, urbanization, marriage status, with/out children, home owner (or renter), electricity payers and membership of an environmental organization.

According to Carlsson and Martinsson (2008), a linear random utility function is assumed, where the indirect utility for the household *n* for alternative *j* consisting of a deterministic component v_{nj} and a random part, ε_{nj} is:

$$U_{nj} = v_{nj} + \varepsilon_{nj} = \beta' a_j + \gamma (I_n - c_{nj}) + \varepsilon_{nj} \tag{1}$$

where a_j is a vector of attributes in alternative *j*, β is the corresponding parameter vector, I_n is income, c_{nj} is the cost associated with the alternative *j*, γ is the marginal utility of income and ε_{nj} is an error term.

Owing to the linearity of income in the utility function, the marginal WTP for an attribute is the ratio between the attribute's coefficient and the cost or payment coefficient, which is formulated as:

$$MWTP = \frac{\beta}{\gamma} \qquad (2)$$

In this study, the status quo or ‘do nothing’ position is included in the utility function to estimate the WTP values. However, its exclusion leads to a marginal rate of substitution between the two unlabelled choices in which the marginal price for each of the attributes is estimated by dividing the attribute coefficient by cost coefficient (Alberini et al., 2007).

2. Choice experiment survey: The case of Kisumu District, Kenya

Kisumu district is the third largest city in Kenya and was selected because of its political and economic vigour, relative to the other districts in Nyanza. Kisumu represents around 13% of Nyanza’s total population of 5,051,562, whereas at the national level its population comprises 2% of Kenya’s total population (KNBS, 2007), see *Table 1*. The rural population in Kisumu is 36 %, compared to that of urban areas of around 64 % (Ministry of Finance and Planning (MoFP) 2002). In Kisumu there are four divisions, namely: Kadibo, Kombewa, Maseno and Winam. Winam division, being the largest, contains as much as 54% of the total population. Consequently, most of the household interviews were collected from this division.

Table 1: Socio-demographic statistics at district, province and national level

	Kisumu District	Province Level	National Level
Total population 2006	650,846	5,051,562	35,514,542
Rural population 2002 (%)	36.03%	87.10%	67.20%
Urban population 2002 (%)	63.97%	9.15%	32.80%
Annual income per capita 2004 (KSh.)	17,535	12,616	24, 836
Electrification cover 1999 (%)	11.62%	4.80%	13.50%

Source: World Bank 2004, MoFP 2002

It was difficult in this study to obtain the electrified household sampling framework from the sole electricity distributor, the KPLC, owing to so-called red tape regulations. The KPLC household listing is possibly an unrepresentative sample, because in most cases the electricity connection is subscribed to by house landlords and less frequently by tenants. In addition, the household listing may over-represent landlords who own more than one property in an area, thus lowering a single home owner's chance of being selected (Salant and Dillman, 1994).

Subsequently, an alternative sample design was chosen based on a cluster listing implemented by the KNBS census, namely the Kenya National Sampling Survey and Evaluation Programme (NASSEP). Cluster sampling involves the selection of interviewees from a group. The advantage of cluster sampling is that it reduces the travel costs (Champ, 2003). There were 33 clusters in Kisumu district, of which 13 were defined as rural and, of these, 9 were identified as being electrified from the present wave: NASSEP IV. The remaining 11 electrified clusters were identified from the previous wave, namely NASSEP III. This was possible because the clusters sampled in each wave were different. Thus, in total, twenty electrified clusters were identified for the survey.

Electricity as a service consists of attributes that respondents identify and value in relation to their preferences. In this study, the policy change introduced to electrified households represents the service improvements by increasing reliability and also permitting other electricity distributors to enter into the market (the entry of other distributors may improve service reliability). The reliability characteristics or attributes of an improved electricity service, as described by the participants in focus group discussions (FGDs), included: reduced number of outages, decreased length of outages and advanced announcement of outages.

The key design element in CE construction is the identification of attributes or characteristics that distinguish alternatives. One common characteristic selected during the FGDs was reliability. For each reliability characteristic identified several distinct levels were established. These levels identify the position of preference among respondents. Four attributes, namely: price, type of provider, number of planned outages (blackouts) and duration of outage, were considered important among the FGDs' participants. These attributes, however, were not ranked during the FGDs, but rather participants were requested to rank these characteristics in the questionnaire. Nevertheless, it should be noted that in the electrified FGDs some participants were willing to pay extra to reduce outages or blackouts, from as little as KSh 10 to as much as KSh 100.

Among the FGDs' members the outages, commonly known as blackouts, were variously reported as being erratic, frequent and intermittent in nature. Participants noted that during the rainy seasons the number of outages increased and were at this time perceived as natural phenomena. During the non-rainy season participants had difficulty distinguishing when and for how long the outages occurred. That is to say, they were unsure whether the outages were occurring at night or during the day, or at weekends or on weekdays. However, the groups were able to estimate the total number of outages experienced in a week. The FGDs' members reported that the average frequency of blackouts occurring in a week ranged from two to four, with an average duration of four to eight hours. Among the FGDs' participants, households would experience electricity shortages for an average period of five hours. Outages varied according to the time of day or day of the week. However, these outage characteristics were not further explored in the CE. For CE design purposes, the average number of outage occurrences in a month, rather than a week, was used to reduce the cognitive burden of recalling from memory. The respondents expressed the opinion that there was no link between the duration of the announced outages and their frequency. That is to say, participants in the discussions distinguished the frequency (number of times) and length of outages (duration in hours), but did not associate the two.

The distinction between announced and unannounced outages or blackouts was emphasized in the experiment. During the FGDs, respondents prioritized advanced warning as an important attribute of electricity use. A warning in advance effectively provides the time to allocate resources elsewhere in order to ameliorate the cost of electricity loss. For instance, an advanced warning, known here as a planned warning, may allow a household to purchase alternative fuel to cope with the electricity loss, for both lighting and heating. Additionally, advanced warning may enable a shift of resources from one activity to another, particularly for households dependent on electricity for income-generating purposes. The shift of resources to cope with electricity loss was considered by the FGDs' participants as economic loss to households' income and time.

For the cost attribute, in Kenya the average number of electricity units consumed by rural households is 45 kWh per month (Ministry of Energy (MoE), 2002). In this CE study, the average rural household in Kisumu district is assumed to consume an average of 50 kWh, paying a monthly total cost of approximately KSh. 300 (US$ 4.47) inclusive of all tax charges. Therefore, the price level proposed above the average consumption of 50 kWh is divided into four levels: KSh. 30, KSh. 50, KSh. 80 and KSh. 120. There was a strong inclination among the FGDs' participants to have other electricity distributors in the market. At present, the sole distributor, the KPLC, is perceived as a monopolistic organization, despite the government stake of only 40% (Eberhard and Gratwick, 2005). Nevertheless, the FGDs' participants favoured community and private dealers in the photovoltaic and grid-electricity markets. Consequently, the levels of providers were divided into two categories: a 100% private and a community-based model.

Table 2 shows the attributes, namely: cost or price, type of provider supplying electricity and duration and frequency of outages, expressed either qualitatively or quantitatively for varying levels.

Table 2: Key service attributes for the improvement of grid-electricity

Attribute	Description	Detail	Variable Type	Levels	Value
Price	Price above the monthly bill for 50 kWh	Amount paid above the average monthly charge of KSh. 300. Note, the total charge is inclusive of all tax and other levy charges.	Continuous	4	KSh. 30 KSh. 50 KSh. 80 KSh. 120
Type of provider	Other distributor of electricity	Two types of suppliers: 100% private and community	Qualitative	2	Private Community
Number of planned 'blackouts'	Indicates the average number of outage occurrences experienced at household level per month for non-rainy season with warning	Frequency of blackout in a month with warning	Discrete	3	2 3 5
Duration of outage	Average number of hours (out of 24) experienced for an outage or 'blackout'	Length of the power outages (Hours)	Continuous	3	1 2 3

For this study the full factorial design generated 72 alternatives. However, to avoid cognitive burden and task complexity for the respondents, the use of orthogonal fractional-factorial design was applied and 16 choice profiles were created. The choice profiles selected were cross-checked to eliminate any dominant choices. Thereafter, the 16 alternatives were divided into two split groups, each consisting of 8 choice profiles (excluding the status quo).

As shown in *Table 3*, the three choices offered to respondents included two unlabelled choices and an 'either' option, also referred to as status quo or current situation. For generic or unlabelled formats, households were unable to associate the two options (alternatives 1 and 2) to any specific programmes, that is to say, they were unable to brand the alternatives available, however, they could identify 'neither' as being the status quo.[4]

Table 3: Example of choice set from the Kisumu energy household survey electrified questionnaire

	Profile A	**Profile B**	**NEITHER**
Price in KSh. (additional amount per month)	KSh. 80	KSh. 120	No expenditure
Type of provider	Private	Community	No provider
Number of planned blackouts (monthly)	5	5	Current number of planned blackouts
Duration of blackout (hours)	3	2	Current duration of blackouts
RESPONDENT CHOICE (please tick one)	☐	☐	Neither A nor B ☐

3. Results and discussion

The analysis used 202 questionnaires completed by households, yielding 808 observations, as each respondent had to make four choices. Prior to the empirical analysis, the data were orthogonally coded, such that all values for each attribute summed to zero (Hensher et al., 2005).

The main variables of interest used in this study, as shown in *Table 4*, are monthly gross income, age, number of rooms and years of residence in the area in continuous format. The dummy variables of interest include: being married, and whether the respondent is unemployed, is a male respondent, possesses a bank account, engages in farming activities, owns their own home, is interested in setting up a business, has a home business and is the household head. Using the variance inflation factor (VIF) to examine multicollinearity, the variables of interest show that they are uncorrelated, as all VIFs are below 30 and this signifies non-collinearity in regression analysis.

Table 4: Summary of variables used in the models

Description	Mean	Std.Dev.	Min.	Max.	Cases	VIF
Gross monthly income	25,342	27,394	500	23,5000	202	3.4351
Highest education level	11.5920	3.3170	0	16	201	0.0002
Age	37.6337	12.1576	19	78	202	0.0086
Number of rooms	4.2090	2.2099	1	15	201	0.0002
Household size	5.5693	2.5369	1	15	202	5.6101
Years of stay	16.8384	18.8819	3	50	198	0.2104
	Dummy variables					
Married	0.7822	0.4129	0	1	202	16.3932
Unemployed	0.0693	0.2540	0	1	202	0.0001
Sex male	0.4356	0.4959	0	1	202	4.5382
Bank account	0.7030	0.4570	0	1	202	5.4536
Engage in farming	0.6436	0.4790	0	1	202	6.2463
Own home	0.5842	0.4930	0	1	202	8.2774
Interest in business	0.1238	0.3294	0	1	202	13.2424
Home business	0.2970	0.4570	0	1	202	6.7248
Household head	0.5644	0.4959	0	1	202	6.1295

Note: varying sample sizes for missing responses.

A multinomial logit model (MNL) is recommended as the first step in determining the right attributes and their functional forms (Hensher and Greene, 2003). First, a simple fixed parameter logit (in this case MNL specification) including only the attribute variables is estimated, in order to have a first insight into the analyzed data. As shown in equation *(4)*, the deterministic part of equation *(1)* is in this case defined as:

$$V_{nj} = \beta_1 + \beta_2 Cost_{nj} + \beta_3 Frequency2_{nj} + \beta_4 Community_{nj} + \beta_5 Duration_{nj} \qquad (4)$$

Hensher et al. (2005) suggested that for an unlabelled experiment a constant term should not be included for all the alternatives available, because they are unbranded. However, for this study a constant term has been assigned to the status quo option, because it is considered as labelled and identifiable by the respondents. The indirect utility functions of the other two alternatives do not include any constant terms, as they are produced from the same experimental design.

Presented in *Table 5* are the results of the MNL, which indicate that all attributes' estimations are significant at the 1% level and have the expected signs.[5] For the cost attribute, this coefficient is negative, as expected, because the utility of selecting an increase in service reliability decreases with higher payments. Respondents preferred fewer outages with shorter duration, as indicated by the positive and significant signs for frequency and duration of outage. Moreover, the respondents favoured a community provider over a public or private entity.

Table 5: Multinomial logit model using maximum likelihood estimation

	Coefficient	Std. Error	t-statistic
Constant	0.4059***	0.0929	4.37
Frequency (2 outages per month)	0.6726***	0.0950	7.08
Community distributor	0.1647***	0.0570	2.89
Duration of outage (1 hour per outage)	0.2533***	0.1138	2.23
Cost	-0.0060***	0.0015	-4.10
Log-likelihood	-856.53		
N	808		

***, **, * indicate that the coefficients are statistically significant at the 1%, 5% and 10% levels respectively.

The interaction of SED variables with attributes as shown in equation (*5)* accounts for group heterogeneity among individuals and that is why their inclusion improves the fit of the simple model with attributes only (see equation (*4*)). The interactions of the SED variables – age, income and education level, household size, employment and marital status, bank account holder, gender, interest in business and years of residence in the area – with the attributes – cost, frequency, duration and community provider – resulted in both significant and insignificant effects. The MNL estimations involved numerous trials with different combinations of the attributes and SED variables. The results of these trials are presented by *equation (5)* and the corresponding estimates are in *Table 6*.

$$V_{nj} = \begin{array}{l} \beta_1 + \beta_2 Cost_{nj} + \beta_3 Frequency2_{nj} + \beta_4\ Community_{nj} + \beta_5\ Duration_{nj} + \beta_6 Cost_{nj}.HouseholdSize_n \\ + \beta_7 Cost_{nj}.YearsofLiving_n + \beta_8 Cost_{nj}.Age_n + \beta_9\ Cost_{nj}.Unemployed_n + \beta_{10} Cost_{nj}.BankAccount_n \\ + \beta_{11}\ Cost_{nj}.EngageinFarmng_n \end{array} \quad (5)$$

All estimated coefficients in the above model are of expected sign and are significant at the 5% level. The overall fit of the model with SED variables is much better in comparison with the model without SED variables according to the log-likelihood, which improves from -856.53 to -812.45.

Table 6: Multinomial logit model with SED variables

	Multinomial Logit Model			
	Coefficient	Std. Error	t-statistic	Expected Sign
Constant	0.4632***	0.0953	4.86	
Frequency (2 times per month)	0.7000***	0.0979	7.15	+
Community distributor	0.1672***	0.0577	2.90	+
Duration of outage (1 hour per outage)	0.2839***	0.1163	2.44	+
Cost	-0.0143***	0.0042	-3.38	-
Interaction term with cost				
Household size	0.0011**	0.0004	2.58	+
Years of residence in the area	-0.0002**	0.000063	-2.47	-
Age of respondent	-0.0002**	0.000092	-2.04	-
Unemployed	-0.0108**	0.0043	-2.50	-
Bank account holder	0.0116***	0.0023	5.10	+
Engage in farming	0.0060**	0.0023	2.60	+
Log-likelihood	-812.45			
N	792			

***, **, * indicate the coefficients are statistically significant at the 1%, 5% and 10% levels respectively, using the P-values in maximum likelihood estimation.

Moreover, the MNL model reveals that households preferred to reduce the number of outages to two for one hour per month, as long as the electricity was provided by a community distributor. The significant and negative coefficient of the interaction term obtained from the cost and age variables, i.e. age of respondent, indicates that older individuals were less likely to pay for service reliability. One possible reason for this negative relationship, as revealed in the FGDs, is the decline in confidence in government policies in the area among older participants. Also, this negative effect is displayed for households who had been resident in the area for longer. Moreover, the unemployed have a negative coefficient, indicating that they were likely to choose not to pay for service reliability, compared to their counterparts. Other cost interactions that are significant and positive emerge for bank account holders and those engaged in farming and imply that, *ceteris paribus*, they were more likely to pay for service improvements for electricity. Additionally, the larger the household, the more likely they were to prefer to pay for service reliability. One reason for this increase is that larger families, unlike smaller ones, rely on electricity for housework and demand more electricity to accommodate the varied needs of the family members. The ASC for the status quo is positive and significant, implying that a fair proportion of the respondents preferred to maintain the current situation, i.e. did not favour a change.

The classical econometric specification for estimating CE, the multinomial logit (MNL) model (McFadden, 1974, Louviere et al., 2000), is generally overcome by the random parameter logit (RPL) specification (Train, 2003). In the RPL model, a random term whose distribution over individuals depends on underlying parameters is added to a classical utility function associated with each alternative. This should be done only after accounting for heterogeneity among individuals by SED variables and in cases where we do not have information in the data set to treat the remaining heterogeneity. Its popularity has kept growing in spite of some problems related to inference and model selection (Brownstone, 2001).

RPL, unlike the MNL model, allows for the specification of unobserved heterogeneity among individuals. The task in this model is to find variables and a mixing distribution that take into consideration the other components of utility, which correlate over alternatives or are heteroskedastic (Train, 2003). In this study, when repeated MLE trials were conducted, two parameters, namely twice-monthly frequency of outages and community distributor, emerged as being random in the applied model. The Lagrange Multiplier test of McFadden and Train (2000) was used here to verify the possible randomness of all parameters.[6] Moreover, a zero-based (asymptotic) *t*-test of the estimated standard errors corresponding to both random coefficients was combined with above stated test.

An inappropriate choice of the distribution type may bias the estimated means of the random parameters. This problem may be overcome using Fosgerau and Bierlaire's (2007) semi-nonparametric test for mixing distributions in discrete choice models. This procedure tests if a random parameter of a discrete choice model follows an *a priori* postulated distribution. Given that the true distribution may be different from the postulated distribution, this procedure expresses the true distribution in a semi-nonparametric fashion using Legendre polynomials (also known as SNP terms). The number of SNP terms must be chosen in advance and a higher number of SNP terms makes the alternative hypothesis more general at the expense of a higher computational demand. Fosgerau and Bierlaire (2007) argue that two or three SNP terms give a large degree of flexibility sufficient for most empirical applications. The model with *a priori* postulated distribution is a special case of the model with the true distribution and, consequently, a simple likelihood ratio test for nested hypotheses can be applied here.

Based on this procedure, uniform, normal, triangular and lognormal distributions of the random parameters were tested as shown in *Table 7*, using the free software package Biogeme (Bierlaire, 2003, 2008). The information contained in the data is insufficient to reject the null hypothesis that one of the four assumed distributions underlies the two random parameters at 5% significance level. That is why the level of significance was raised to 15% and subsequently the uniform and normal distributions of the two random parameters were clearly rejected for two or three SNP terms. The lognormal distribution for community distributor coefficient was also rejected, hence the acceptance of triangular distribution for this coefficient. The tests did not give clear results for the case of the frequency of outage coefficient, because the null hypothesis of triangular and lognormal distribution cannot be rejected in both cases at the selected 15% significance level. As mentioned above, triangular distribution is preferred in this study as it averts the long tail issue because it is symmetrical in form and bounded on either side (Hess et al., 2006). This view is also shared by Hensher et al. (2005) who propose triangular distribution for random parameters in order to guarantee unchanged signs on the random coefficients by restricting their spreads to equal the estimated mean values.

Table 7: Fosgerau and Bierlaire's (2007) test for the choice of mixing distribution

Uniform distribution					Normal distribution				
	Community distributor		*Frequency of outage*			*Community distributor*		*Frequency of outage*	
SNP terms	*LR*	*p-value*	*LR*	*p-value*	*SNP terms*	*LR*	*p-value*	*LR*	*p-value*
1	0.514	0.473	0.060	0.803	1	0.508	0.476	1.980	0.160
2	3.664	0.160	2.330	0.312	2	5.990	0.108	2.950	0.229
3	5.494	0.139	5.660	0.130	3	7.810	0.192	6.320	0.097
Triangular distribution					Lognormal distribution				
	Community distributor		*Frequency of outage*			*Community distributor*		*Frequency of outage*	
SNP terms	*LR*	*p-value*	*LR*	*p-value*	*SNP terms*	*LR*	*p-value*	*LR*	*p-value*
1	0.864	0.353	1.340	0.248	1	0.57	0.451	1.350	0.246
2	1.242	0.537	1.370	0.504	2	4.40	0.111	3.240	0.198
3	1.446	0.695	2.670	0.446	3	6.18	0.103	2.780	0.427

The other step investigated is the correlation and preference heterogeneity between parameters, particularly for the random parameters among the choice of alternatives. Indeed, allowing the two random parameters to correlate means that there are unobserved effects among alternatives for a given choice of situations. In this study the two random parameters presented non-significant correlation.

Moreover, the RPL allows for testing for heterogeneity around the mean of the random parameter by estimating the standard deviation parameter for each random parameter with the interactive covariates, i.e., the SED variables. The six interactive covariates included already in the model, as well as other available SED variables in our database, were tested as possible causes of heterogeneity around the mean but no heterogeneity was found at the 5% and 10% levels.

Table 8 depicts the estimation of the RPM with the estimated fixed and random (in italics) coefficients for attributes and fixed parameters of SED variables being all significant and of expected signs. The signs of the estimated coefficients of all attributes and the interactive terms are similar to the previous models of MNL. Moreover, for the random parameters the mean and standard deviation are positive and highly significant at the 1% level. The slight increase of log-likelihood implies an improved overall fit of RPM, compared to the previous MNL model. However, what distinguishes RPM as an advanced model from MNL is the highly significant standard deviation of the random parameters at 1%, indicating that there is a structural advantage in RPM.

Table 8: Random parameter model (RPM) with covariates (the extended model)

	Random parameter model (RPM)		
	Mean Coefficient	Std. Error	t-statistic
Constant	0.4704***	0.0970	4.85
Frequency (2 times per month)	0.7151***	0.1027	6.97
Community distributor	0.1731***	0.0609	2.84
Duration of outage (1 hour per outage)	0.2865***	0.1168	2.45
Cost	-0.0144***	0.0042	-3.40
Household size	0.0011***	0.0004	2.58
Years of residence in the area	-0.0002***	0.0001	-2.47
Age of respondent	-0.0002**	0.0001	-2.04
Unemployed	-0.0108***	0.0044	-2.49
Bank account holder	0.0116***	0.0023	5.09
Engaged in farming	0.0060***	0.0023	2.61
Standard deviation of random parameters			
Frequency (2 times per month)	0.3576***	0.0513	6.97
Community distributor	0.0866***	0.0304	2.84
Log-likelihood	-811.85		
N	792		

***, **, * indicate the coefficients are statistically significant at the 1%, 5% and 10% levels respectively.

The simulation of WTP, as presented in this section, is an unconditional one. In other words, these estimates are generated out-of-sample populations by randomly sampling each individual from the full distribution (Hensher et al., 2005; Hoyos et al., 2009; Krinsky and Robb, 1986). *Table 9* presents WTPs for the RPM model in which both the random nature of two parameters as well as the effect of SED variables was included.

The simulation of WTP, according to the various attributes and not taking into account the SED variables but allowing for the random nature of the attribute coefficient, is shown in *equation (6)*.

$$WTP_{attribute} = - \frac{\hat{\beta}_{attribute} + \hat{\sigma}_{attribute}.t_1}{\hat{\beta}_{\text{cost}}} \qquad (6)$$

$\hat{\beta}_{attribute}$ represents the mean coefficient for the random parameter and $\hat{\sigma}_{attribute}$ is the derived standard deviation of the random parameter, whereas t_1 represents the triangular distribution used in the analysis. In the case of a non-random parameter, i.e. the duration of the outage being one hour, the estimated coefficient $\hat{\beta}_{attribute}$ is used and $\hat{\sigma}_{attribute}$ is assumed to be zero.

As some SED variables were included in the RPM, the simulated WTPs were estimated, taking them into account. As the values of the SED variables enter into the WTP formula we have to define a base scenario which will be used as a benchmark for WTP comparisons. In the base scenario the three dummy variables (unemployed, bank account holder and engaged in farming) were set to zero and the other SED variables were included at their mean values. In this way, by setting the dummy variables to one, the effect of employment, owning a bank account and engaging in farming activities on WTP with respect to the base scenario can be examined, when the household size, years of residence and age of respondent are at their mean values (6, 16.84 and 37.64 respectively). Additionally, for further analysis' sake, some arbitrary values for these SED variables were selected, i.e. age was set at 60 years to indicate older members, years of residence at 25 to signify longer residence in the area and 10 household members to imply a large family.

Thus, WTP for the base scenario is then defined as

$$\mathrm{WTP}_{\mathrm{attribute}} = -\frac{\hat{\beta}_{attribute} + \hat{\sigma}_{attribute} * t}{\hat{\beta}_{\mathrm{cost}} + \hat{\beta}_{Household} * 6 + \hat{\beta}_{Years} * 16.84 + \hat{\beta}_{Age} * 37.63 + \hat{\beta}_{Unemp} * Unemp + \hat{\beta}_{Bank} * Bank + \hat{\beta}_{Farm} * Farm} \qquad (7)$$

where unemployed (*Unemp*), bank account (*Bank*) and engaged in farming (*Farm*) are set to zero.

Table 9 shows the mean WTPs for the two attributes corresponding to the random parameters: two outages per month (FRQ2) and community provider (simulated using 50,000 random numbers of the triangular distribution) and fixed WTP for the one hour per outage attribute. The first column depicts the mean WTPs for the attribute two outages per month (FRQ2) in different scenarios. For the base scenario *(equation (7)),* we get a mean WTP of KSh. 38.24. For household size set at 10, the mean WTP is higher (KSh. 50.05) which is about 31% more than the base case scenario of 6 household members. It transpires that the mean WTP for the 60 year olds falls to KSh. 30.86. Moreover, the value of the mean WTP for those who has lived in the area for 25 years was also lower than the base mean WTP at KSh. 35.17.

Table 9: Simulated WTP from the random parameter model (RPM) with socio-economic/demographic influences (in KSh)

	Two outages per month (FRQ2)	Community provider	One hour per outage (HR1)
	Mean WTP	Mean WTP	Mean WTP
Base scenario	38.24	9.26	15.32
	(7.84)	(1.89)	
Age (60)	30.86	7.48	12.36
	(6.33)	(1.52)	
Years of residence (25)	35.17	8.49	14.09
	(7.24)	(1.74)	
Household size (10)	50.02	12.09	20.04
	(10.25)	(2.47)	
Unemployed	24.27	5.86	9.71
	(4.97)	(1.19)	
Bank account holders	100.64	24.39	40.37
	(20.53)	(5.01)	
Engaged in farming activities	56.3	13.62	22.56
	(11.44)	(2.77)	

Note: Simulated standard errors in parentheses.

Moreover, there was a positive effect – an increase of 47% more than the base case, with a mean WTP of KSh. 56.30 – among those who were engaged in farming activities. Conversely, a significant negative impact, that is to say a 37% decrease of the mean WTP of KSh. 24.27 from the base case scenario, was observed among those who were unemployed, i.e. 7% of the sample. Additionally, a substantial increase of 263% to the mean WTP was observed for those who held a bank account (74% of the sample) at an estimated mean WTP of KSh. 100.64. This positive and the over-emphasis of this variable can be attributed to an income bias. In Kenya most bank account holders are employees in the government institutions and private sector or small business owners and workers. Because of their occupations, these people generally own and depend on electrical appliances and equipment for their personal and professional use. Consequently, longer and frequent outages have bigger impact on this group than on other households who have lower income, no bank account and fewer electrical appliances and equipment.

For the other attribute variable corresponding to the second random parameter, i.e. community provider (COMPR), it is apparent that the SED interactive variables affect the mean WTP estimates in a similar way. However, all these estimates are substantially lower than those for the outages per month scenario. Regarding the fixed attribute variable of an outage of one hour's duration, the effects of the SED interactive variables on the estimated WTP values are similar to those of the random attributes variables.

Figure 1 illustrates the box plot of the simulated WTPs of the attribute two outages per month (FRQ2) and offers more information than the mean values in the first column of *Table 9* as it depicts in a convenient way the five-number summaries (minimum, lower quartile, median, upper quartile and maximum) of the 50,000 generated WTPs. As illustrated in the box plot, for those aged 60 and who have lived in the area for 25 years, the median WTP estimates are closer to each other with little variation between these two groups. Moreover, those who are unemployed and with 10 household members and, above all, those who are bank account holders and engaged in farming, have estimated WTPs with a wider spread and their medians are very different compared to other groups. This illustration is helpful for policy-makers as well as decision-makers in utility markets who are interested in seeing the variation of median WTP estimates according to socio-economic influences.

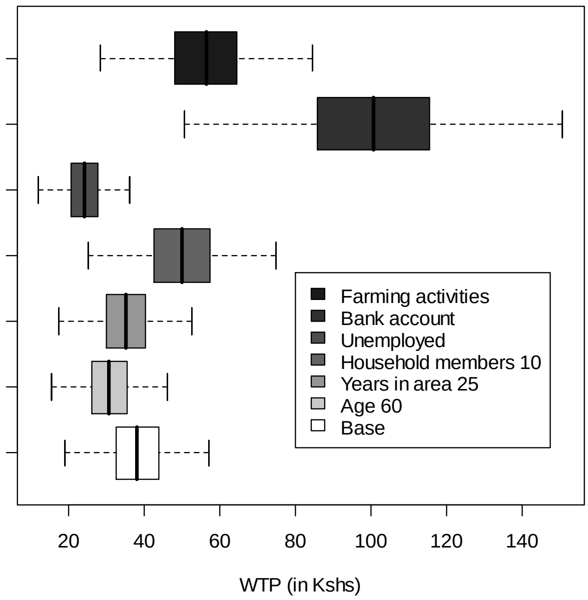

Figure 1: Simulated RPM WTP for the random attribute two outages per month (FRQ2)

4. Conclusion

The importance of identifying heterogeneity among the households with regards to SED variables is that when it is found it demonstrates that there are different preferences which influence choices. That is to say, the valuing of different goods and services is determined by these preferences and this is the same in the case of the decision regarding the reliability of the electricity services. The RPL model allowed for the possibility of finding some of the unobserved heterogeneity, by locating the preferences associated with SED factors. Such factors, when interacted with cost, revealed that the household size, age, years of residence in the area, employment status, farming activities and whether the respondents were bank account holders impacted on the mean WTP. For this survey, the estimations of the mean WTP for the RPM with SED influences would suggest that those who are unemployed, older and have been living in the area longer, would be disinclined to pay above their monthly electricity bill to improve service reliability. Conversely, individuals who hold a bank account, engage in farming activities and who have a larger family, would prefer to pay an extra amount above their monthly bill to improve reliability. In one study customers valued reliability in similar ways, in that larger households, people who work at home and high-income earners had higher outage costs or higher value of service (Woo et al., 1991). In another study, Doane et al. (1998) found outage costs varied with customer location, customer ownership of appliances and the amount of time that household members spent at home.

Understanding the role of SED factors provides insights into households' preferences towards electricity service reliability, which in turn can help decision-makers in the utility companies design new products and services, thus enabling them to target their provision at consumers' preferences in an informed way. The results of this study also support the targeting of social groups, especially farmers and those involved in subsistence agriculture, who revealed a higher WTP to connect/improve electricity services as compared to other groups. Indeed, in a country in which farming activities and agriculture are the backbone of the economy, in order to meet the challenges of electricity connection not only poor households must be targeted but also other social groups, such as horticultural farmers, fishermen and livestock rearers. This position of offering differentiated rates for outage reliability is supported by Doane et al. (1988) with regards to a WTP survey of electricity reliability for households in the San Francisco area, in which they found SED influenced consumers' attitudes towards service reliability. Moreover, such revelations can assist in directing institutional and policy strategies towards service improvements for electricity, particularly in rural areas.

One primary question regarding the policy conclusion is: should the reliability charges be varied among end-users depending on their preferences? It may well be acceptable to charge electricity users varying tariffs for different levels of consumption, but charging them differently regarding service reliability, based on SED factors, would be considered unfair. That is to say, if such a situation was permitted, then some of the aforementioned SED groups would resent the utility companies for increasing the charges without improving the service reliability. Moreover, some electricity users, perceiving these charges as discriminatory, would not be prepared to cooperate with future WTP surveys, fearing that there would be further increases in charges with no accompanying improvement in reliability. It could be plausible to charge different reliability costs according to the different sectoral needs, these being residential, commercial and industrial.

Another policy implication regarding reliability is: what amount does the KPLC incur or charge to maintain system reliability and to what extent should they charge for reliability? In July 2008 the KPLC announced that a World Bank energy sector recovery project fund of around KSh. 10 billion (US$ 0.149 billion) would 'improve the overall quality and reliability of electricity' (World Bank, 2008), hence reducing technical and non-technical losses and saving the company KSh. 1 billion

(US$ 15,000) by the end of the project in 2009 (KPLC, 2008). How much of these funds are allocated for reliability improvements for the household systems is difficult to obtain, because the KPLC does not disseminate this information. Thus, it is difficult to determine how much of the service improvement costs are passed on to the consumers who are, therefore, unaware of what they are paying towards reliability.

Nevertheless, the issue of trust among users and providers is important for service improvement. In this vein, various surveys conducted in developing countries by the World Bank have revealed that, regarding power outages, consumers' WTP is higher if the electricity quality is better and more reliable, but lower if the price increases and the quality remains poor (Townsend, 2000). The developed countries, unlike developing countries, have been able to cater for specific users, owing to the use of advanced technology in their power systems. That is, the development of new rates and service options has allowed for the unbundling of electricity services, including their reliability (Caves et al., 1990). All in all, technological advancement in improving service reliability incurs costs for both producers and generators. However, it is unclear what proportion of these costs should be passed on to users, specifically in developing countries where these remain largely undetermined. In conclusion, the development of differentiated energy services for varied sectors and customers in developing countries should be investigated further and also be encouraged by conducting sectoral energy-based assessments, to assess their respective energy requirements for all electricity users.

Acknowledgement

The authors are grateful to the Royal Economic Society (RES) for the small expenses budget provided in this study and all households and enumerators in Kisumu District who participated in this study. They also acknowledge the financial support from the Department of Education of the Basque Government through grant IT-334-07 (UPV/EHU Econometrics Research Group) and from Spanish Ministerio de Educación and FEDER (SEJ2007-61362).

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[1] According to Woo et al. (1991), reliability is defined as 'ability to deliver uninterrupted service on demand, to whatever degree required'. This is distinguished from 'service quality' which refers to electricity being provided at 'acceptable frequency and voltage ranges'.
[2] Renner and Fickert (1999) distinguished the difference between reliability and power quality as the former meaning 'electricity is available when it is needed' and the latter meaning 'the characteristics in terms of continuity and voltage of the supplied electricity as delivered to customers at supply terminals under normal operating conditions' (cited in Osborne and Kawann, 2001).
[3] Traditional fuels are still used by electrified households for cooking, owing to cultural factors, habits and preferences.
[4] Alpizar et al. (2001, p. 21) discussed in detail the advantages and disadvantages of labelling and generic designs. One advantage of a generic or unlabelled format is that respondents are able to focus on attributes, rather than specific labels, particularly when the marginal rates of substitution of attributes are important.

[5] The MNL on the additional two attributes, namely frequency (5 times per month) and hours of outage (3 hours per outage), are highly insignificant in this and all subsequent estimations and hence they are omitted.

[6] McFadden and Train (2000, p. 456) propose creation of artificial variables:

$z_{tj} = \frac{1}{2}(x_{tj} - x_{tc})$, with $x_{tc} = \sum_{j \in c} x_{tj} p_j$, where t is a parameter where heterogeneity exists, c is the set of alternatives offered and p_j the conditional logit choice probability for alternative *j*. The null hypothesis of fixed parameters is rejected when coefficients for artificial variables are significantly different from zero which can be tested using the Wald or LR test.