Econometric Analysis of Household Electricity Demand in Peru*

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November 2006

Abstract

The following paper estimates a demand function using household-level data in Peru, using a method that combines two traditions widely used in public utilities estimation: the modelling of increasing block tariff schemes and the choice of appliance stocks. We find this approach is rather innovative in the literature, as both methodolgies have always been considered separately. Results show that price sensitivity increases with the complexity of the appliance portfolio and that poorer households consuming in the lower block tariff show the highest price and income elasticities, regardless of their appliance portfolio choice. Those results validate the implementation of tariff discounts for poorer households.

JEL Classification: C25, L94, O54

Keywords: Discrete choice, electricity demand, Peru.

1 Introduction

In the Peruvian case, the regulatory scheme makes necesary the estimation of a demand function with the objective of making predictions in order to obtain a regulated tariff. Since the enactment of the Electricity Concessions Law in 1992, various models have been used in order to reach this objective. However, those models, which have mainly used aggregated data (such as macroeconomic variables), have shown evident limitations when used with other regulatory purposes. More specifically, the homogeneity assumption among different types of agents makes it difficult to ascertain the magnitude of price response differences between households located in urban and rural areas, as well as among poor

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and non-poor households. Those models also don't take into account the new increasing block tariff structure introduced by the electricity subsidy scheme in 2001 (FOSE)[1], which includes a different price for households consuming less than 100 kWh per month. Therefore, the estimation of models with aggregated data introduces serious biases when trying to make more detalied policy decisions.

The notorious limitations of models with aggregate information have sparked the growth of demand models estimated using disaggregated data. Those models allow for the explicit modelling of consumers' decision processes, so price and income elasticities can be readily estimated with less biases than aggregated models. In turn, the elasticities can be used to simulate policy measures, calculating the change in consumer surplus. Following this line, the main objective of this paper is to estimate an econometric model which could be used to simulate policy measures like those introduced by the FOSE.

As it's well known, one of the main disadvantages of disaggregated demand models is the notorious lack of information. This paper uses a household survey conducted by the Peruvian Energy Regulator (OSINERG) during the first three months of 2003. The sample of about 5400 households was matched with electric utilities' price and consumption records, providing national and urban / rural areas representativity.

This paper is divided in five sections. The first one carries a brief literature review on electricity demand models in a historical context, focusing on the various existing aggregate and disaggregate demand models. The second section briefly describes the survey used in the estimation process and makes a characterization of average consumption levels by region. In the third section we describe the theoretical model in which the econometric specification is based, showing the main results in the fourth section. Section five concludes.

2 Literature Review

When analyzing electricity demand, there are various criteria in which to determine a classification. The first one is related to the required statistical information, that is, if the data used in the estimation process comes from aggregate (or macro), sectoral or disaggregate sources. The second criteria is related to the temporal dimension of the demand function being estimated, namely, if it allows durable goods or energy sources substitution over time or not. Lastly, the third criteria is based on an historical perspective, linking the diverse demand studies with certain demand shocks, regulatory policies, as well as advances in econometric theory. In this line, Table 1 shows a brief description of each of those three categories.

[1] The subsidy scheme, called Fondo Social de Compensacion Electrica (FOSE) implies a substantial price discount for residential customers with consumption levels that are less than 100 kWh per month and is financed by non-residential customers and residential customers with monthly consumption levels above 100 kWh. This discount is higher in rural areas (up to 75%). For a more detailed descrption and a first evaluation of the program, see Gallardo and Bendezu (2005).

From a standpoint of the information used, the first group includes the studies which use aggregate data, such as total electricity sales, GDP, average electricity price, among others[2]. On the other side, works that use semi-aggregate data seek to estimate electricity demand at the sectoral level or by trying to determine the behavior of electricity sales over different regions of a country. Finally, disaggregate estimation procedures use household or firm-level data. It is well known that the main advantage of these works is the explicit modeling of the agents' choices and responses to price and income changes, which are taken as given in the other two categories[3].

Table 1
Classification of Demand Studies

	Classification		
	Aggregate	**Semi - Aggregate**	**Disaggregate**
Type of Data Used	Heavy use of macroeconomic data.	Sectoral or regional information	Household (or firm) - level data
	Short Run		**Long Run**
Coverage	Fixed appliance stocks. Limited substitution possibilities.		Explicit modelling of appliance portfolio choices. Possibility of substitution among energy sources.
	Before 1973	**1973-1986**	**1987 onwards**
Historical	First electricity demand studies.	Oil price crisis (1973) and PURPA (1978) generate a series of studies oriented to measure households' responses to price changes.	The liberalization of electricity markets in UK and USA revive the interest in demand studies.

The distinction between short and long run arises from the nature of electricity demand. Various authors have shown that electricity does not provide direct utility for an individual or firm. It is the use of appliances (durable goods) which are electricity-operated the one that gives an agent certain level of utility. In this sense, the possibility of adjustment in the appliance stocks is the one that raises this distinction. The short-run demand doesn't allow for the posibility of appliance substitution, while the long-run demand does. Therefore, a long-run demand function should incorporate the mechanism in which agents decide

[2] For a brief literature review on aggregate electricity demand models until the early 1970s see Taylor (1976). A brief revision of the international and Peruvian experience using aggregate data can be found in Gallardo, Coronado y Bendezú (2003).

[3] The main disadvantage of estimating a model with disaggregate information is the aggregation problem. More specifically, the heterogeneous individual demands of each agent are summed horizontally, obtaining as a result price elasticities that could be very different from the individual behavior of each household, causing biases. In addition, this problem hides the decision process that underlies appliance use patterns.

when to purchase an appliance or when to substitute it with a more efficient one.

Finally, the first two classifications don't consider any special issues raised by the economic context in which demand is estimated. More specifically, regulatory policies might shape the price structure, incorporate certain supply restrictions that might ultimately influence in the way households' respond to price changes. Any demand analysis is incomplete if it doesn't take account these facts. In some sense, the data-based, the long-short run and the "historical" classifications overlap each other. Some answers regarding the analysis of some policy measures can be answered using any combination of these three classifications.

When using the historical point of view, there are three stages that could be identified, each one related with certain events which occured in the American economy. The first one ranges from the 1950s to the 1973 oil crisis. The second one goes from 1973, goes through the enactment of the Public Utilities Regulatory Act (PURPA) in 1978 and ends in the early 1980s, and the last one starts in 1983 until present. During the 1950s, we can find certain works which use semi-aggregate and disaggregate data, such as the papers of Houthakker (1951), followed by Fisher and Kaysen (1962), Wilson (1970) and Anderson (1972). Those works didn't take into account any pricing schedules, such as increasing block tariffs (IBTs) or time-of-day pricing (TOD), mostly because there were almost inexistent in the U.S. They only tried to determine which were the main determinants of energy demand and whether they were different among distinct types of users or regions.

The oil crisis of 1973 represented a major change in the cost structure of public utilities (since a percentage of electricity is generated using fossil fuels), leading to the introduction of demand management programs. In order to do this, a deep understanding of the consumer characteristics was necesary, and demand models played a major role for this task. In this period we can mention the work of Halvorsen (1975), Taylor (1976), McFadden, Puig and Kirshner (1977), Murray et. al. (1978), Battalio et. al. (1979), Hausman et. al. (1979), Aigner and Hausman (1980), Parti and Parti (1981), Westley (1983), Dubin and McFadden (1984), Dubin (1985) and McFadden, Miedema y Chandran (1986). Those papers introduced new methodologies to deal with the increasing availability of new micro data, such as demand modelling with increasing block tariff and consumers' choice among different price segments or appliance categories.

Finally, the deregulation in the electricity sector, started in the U.K., and the eventual fate of the California liberalization process led to a third wave of papers, of which Belanger et. al (1997), Wolak (2001), Reiss and White (2001) and Filippini and Pachauri (2002) are worth mentioning. In the following lines we examine in more detail each one of these papers, concentrating in their main characteristics as well as obtained results.

2.1 Pre-1973 Period

As said before, the first group of papers bases their estimation on semi-aggregate information, because of the relative scarcity of information from household surveys[4]. The literature review made by Taylor (1976) makes a superb review of most of the studies surveyed here, so we will only make a brief revision.

One of the first electricity demand estimations was the one made by Houthakker (1951), who uses a sample of United Kingdom regions for the 1937-38 period. According to Taylor (1976), this work estimates cross-section equations for each year of the sample, using a double-logarithmic functional form. One of the main problems of this approach was the treatment of the tariff structure, composed of IBTs, as well as the absence of an appliance demand equation. In the first place, Gabor (1955) mentions that an IBT implies a kinked budget constraint, and the assumption of constant marginal or average prices leads to biased and inconsistent estimates. The solution carried by Houthakker was to estimate electricity demand usng the marginal price corresponding to the consumers located in the highest price tier. In order to identify demand, those prices were introduced in the equation with a two year lag. Finally, it also considered the influence of appliance holdings by introducing some proxy variables to control for this fact.

In the United States, Fisher and Kaysen (1962) estimate electricity demand using state-level data for the 1945-1957 period. They obtained consumption information directly from the regulator and were the first in explicitly distinguishing among short and long run demand. Elasticities were estimated, confirming the intuition that substitution posibilities make demand more elastic in the long run. Finally, Wilson (1970) and Anderson (1972) estimate electricity demand using regional-level data. Both employ appliance stocks as explanatory variables and use as a price proxy the average price or the Typical Electric Bill (TEB) for households consuming in the highest price tiers[5]. The elasticities obtained in those studies show a very high dispersion, which could indicate problems of misspecification due to the treatment of price strucutres.

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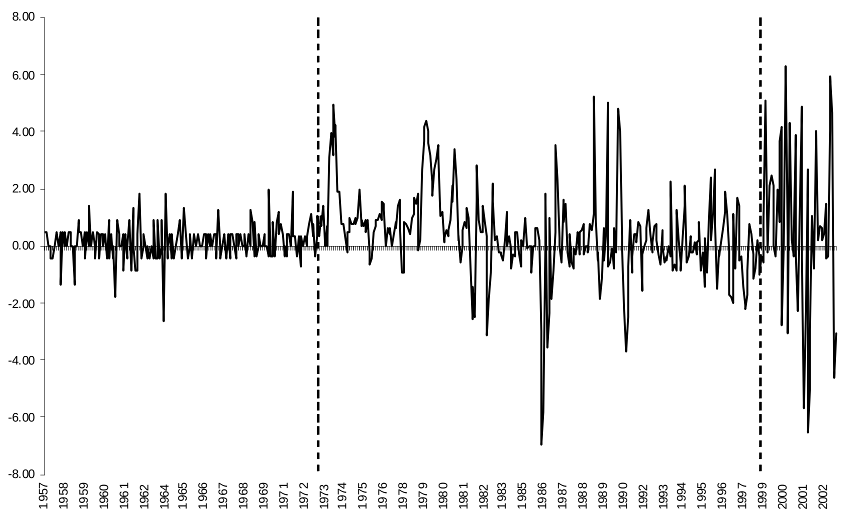
[4] For example, one of the most important household surveys in the U.S., the Panel Study for Income Dynamics (PSID), started in 1968. Only during the 1970s there began to appear household surveys explicitly designed to measure energy consumption. Those first surveys were paid by electricity distribution firms.

[5] The Typical Electric Bill concept was widely used in the first demand estimations. A TEB includes a fixed charge plus a quantity that depends proportionally to the quantity consumed. In the U.S., there were various TEBs, each one related with a consumption tier (Halvorsen, 1975).

2.2 The Oil Crisis, Demand Management Policies and Introduction of Discrete Choice Models: 1973 – 1986

During this period, the oil shocks of 1973 and 1979[6], as well as the introduction of a new regulatory scheme[7] in the United States substantially increased the volatility of electricity prices. More specifically, price variance increased over 270% if compared to the pre-1973 period, as shown in Figure 1. This new context caused a surge of studies, whose main objective was to find the determinants of electricity demand, as well as finding residential and commercial users' response to price changes. The factors mentioned above, as well as the increased availability of micro-level data, created a fertile ground for those papers. In this period, there was at least one paper published per year.

Figure 1
Volatility in the U.S. Energy Consumer Price Index: 1957-2003



Note: Includes both electricity and fuel prices. Electricity CPI as a separate series is available only from 1978 (after the enactment of PURPA).

Source: U.S. Federal Reserve System.

[6] The 1973 oil shock was caused by a drastic reduction of supply from the OPEP members in response to the Yom Kippur war. In that time, the price suffered a substantial increase, affecting the American economy in an adverse way, which was largely oil-dependent. In the electricity sector this caused an increase in oil substitutes, such as coal, which in turn caused higher electricity prices. There is abundant literature on the effects of that shock. For more details, see Hamilton (1999).

[7] One of the main characteristics of this new scheme, the Public Utilities Regulatory Policy Act (PURPA) was the ability of distribution firms to directly buy electricity from generation firms. This caused an increase in the price pass-through from generators to final consumers (Hunt, 2001).

During this period two currents can be distinguished. The first one is related to the explicit introduction of non-linear price structures (IBTs, for example), and the other one concentrates on alternative demand management policies, such as TOD and energy conservation programs. As the complexity of the functional forms derived from the use of more sophisticated schemes increased, discrete choice procedures based on maximum likelihood estimation were prevalent.

In the field of non-linear price structures, the most important work is that of Taylor (1976), who makes a complete review of all the electricity demand literature prior to 1973. Also, he mentions some methodological issues related to the estimation when considering non-linear price structures using micro data. According to Taylor, that problem had been considered by authors in the pre-1973 period, but with few success. The presence of nonlinearities in the budget constraint makes it almost impossible to identify the demand equation unless some assumptions about prices are made. Therefore, estimated elasticities will have biases if coming from a demand equation that is not well identified. Taylor mentions that the use of marginal prices and various measures of TEB have incurred in this problem, although he mentions that is was a common way to do econometrics at the time[8].

A year before, Halvorsen (1975) had made some remarks on the necesity of taking into account the tariff structure when estimating correctly identified demand equations. In order to solve this problem, he introduces a separate equation for the energy marginal price, which has quantity and other supply covariates as other expainatory variables Both equations were supposed to be estimated simultaneously, by 2SLS. The sample contains semi-aggregate information for 48 U.S. states for the period 1961-1969, and the estimated values suggest that electricity demand in the long run has a price elasticity equal to -1, while income elasticity is about 0.5. Murray et. al. (1978), by using a similar methodology, developed a series of econometric models for the state of Virginia.

Halvorsen's model would be criticized by McFadden, Puig and Kirschner (1977), who propose a modification to it. For these authors, the use of instruments in order to solve the simultaneity problem gives consistent estimates of the demand function parameters, but only if the appliance holding and usage decisions are considered as exogenous. If this is not true, they suggest that the probabilities of choosing alternative appliance portfolios should be included as instruments in the demand equation. In addition, the introduced specification allows for the calculation of price elasticities for each portfolio. Results show that price elasticity is higher when a household has more energy-intensive appliances. The introduction of the choice probabilities among distinct bundles will be of special importance in subsequent work.

[8].However, Taylor mentions that the demand estimation problem when a household faces a nonlinear budget constraint is more a theoretical than a practical issue. According to him, if this characteristic was really taken into account, no residential demand equation could be estimated. Given the lack (at the time) of econometric techniques that could tackle this problem, the estimation results obtained at the time seemed valid.

In this same line, the paper of Parti and Parti (1980) models households' consumption by implementing a method that allows estimation of consumption for each appliance. The total appliance stock is considered as an observed variable, but the consumption for each one is considered as a latent variable. By estimating a model that introduces a set of dummies for each appliance, the authors obtain price elasticities for the consumption of each appliance. Thus, the model allows to analyze appliances' consumption changes derived from variations in households' characteristics, something that engineering-based models cannot do.

The work of Dubin and McFadden (1984) explicitly introduces the discrete-continous framework in electricity demand estimation, jointly with the contributions stated by McFadden et. al. (1977)[9]. In this context, they derive the demand for electricity from a utility maximization framework. When considering the demand for electricity as a derived demand, the introduction of a two-stage methodology is straightforward. The first stage models the household choice among appliances, while the second stage uses the predicted choice probabilities as correction terms a-la-Heckman in the continous demand equation. Dubin and McFadden try to model the choice between energy-intensive appliances, such as space and water heating systems, but their extension to lower-intensity ones is also possible.

As said above, demand management programs acquired more relevance during this period. Since the enactment of PURPA in 1978, electricity prices became more volatile for final consumers. In addition, certain regions of the U.S. implemented a price system that made differences between peak and off-peak consumption hours. Lillard and Acton (1981), mention that the enactment of the PURPA required an evaluation of current tariff schemes, as well as diverse alternatives, for all of the U.S. states. Of all the available alternatives (11 in total), there were schemes such as TOD pricing and other non-linear pricing methods. In addition, energy conservation programs were also introduced.

The TOD scheme was subject from various studies, like the ones done by Hausman et. al. (1979) and Aigner and Hausman (1980). Those papers were among the first that incorporate non-linear price modelling in electricity demand[10]. The first study assumes that, for each time of day, electricity is treated as a different good and tries to model the demand equations according to these facts. On the other hand, Aigner and Hausman (1980) estimate a demand equation that takes into account the sample selection bias present in this type of experiments. The corrected specification was then estimated by the methods explained in Hausman et. al. (1979). Regarding energy conservation programs and efficiency in electricity consumption, Dubin, Miedma and Chandran (1986), employ a combination of econometrics and engineering models with the purpose of calculating the introduction effect of conservation systems on households' en-

[9] A similar approach is taken in Hanneman (1984), even though through a more theoretical level.

[10] The application of microeconometric models to electricity demand was part of a much broader context, in which those models were also used for transportation choice studies, house purchase decisions and labor market studies. See Hausman (1985).

ergy consumption[11].

Latin America wasn't exempt from these huge amount of studies. Westley (1985) estimates a residential electricity demand equation for Paraguay, obtaining less elastic demands than those observed in developed countries. One remarkable characteristic of this paper is the use of the demand equation to measure outage costs through consumer surplus variation.

2.3 Liberalization of Electricity Markets: 1986 onwards

After 1986, electricity demand studies entered into a more than less prolonged hiatus. In the 1990s, the electricity market deregulation process started in England and Wales, as well as in the United States implied in some cases a higher price volatility that had its impact on final consumers. Just as in the 1970s, there was a new set of works which tried to determine the main determinants of household electricity demand . However, the main difference with the previous period is that household-level data was much more available, as well as higher computing power, that could made sophisticated methods more accesible to researchers.

The norm during this period was to incorporate the techniques developed during the 1970s and early 1980s, which were now incorporated into standard packages. Thus, Belanger et. al. (1996) estimate a residential demand model in the line of Dubin and McFadden (1984) for the Canadian province of Québec, even though incorporating a more complex specification based on multinomial probit models. On the other hand, Pachauri (2002) estimates a residential demand model for India, far less sophisticated than prevalent models at the time.

Reiss and White (2001) work deserves special attention. Those authors depart from the standard two-stage modeling of electricity demand, trying to incorporate all the available information of IBTs into a single likelihood function. In strict sense, they follow the tradition started by Hausman (1979, 1985) in labor markets and apply them to electricity demand. While keeping off appliance purchase decisions (i.e. taking appliance stocks as given), they estimate a demand function using GMM techniques. For them, the choice of each price segment is alike to a Tobit model or a sample selection correction model, in which the censoring occurs not in the tails of the distribution, but in the middle of it. The obtained estimators don't suffer from the biases coming from the average/marginal price definition that plagued the pre-1973 studies (Taylor, 1976), as well as some problems of the second period, such as the appropiate choice of instruments (Halvorsen, 1975; McFadden et.al., 1977).

2.4 What have we learned?

Since Houthakker (1951) and the literature review by Taylor (1976), household demand models have focused in two main problems, related both with micro-

[11] In a similar fashion, Train (2003) employs bayesian techniques in electricity demand estimation.

economic choice theory and econometric issues.

- Price modeling, given that regulatory schemes often create non-linear prices (of which IBTs are the most prevalent).
- The influence of appliance stock holdings and purchase decisions in price and income elasticities.

In order to solve the first problem, three different approaches have been tried. The first one suggests the inclusion of average or marginal prices as exogenous variables (Houthakker, 1951; Fisher and Kaysen, 1967; Halvorsen, 1975). In the second half of the 1970s, the solution provided by (McFadden et. al., 1977) was to incorporate marginal prices and instrumentalizing them by all the prices in the tariff structure, so that consistent estimates of relevant elasticities could be obtained. Finally, Reiss and White (2001) suggest to include all relevant prices into an expression for a given household expected consumption. Also, after the introduction of econometric techniques compatible with non-linear budget constraints (Hausman, 1985), there are more important tools that could be used to solve the simultaneity problem and correctly estimate the demand equation.

Table 2
Price and Income Elasticities Obtained in Previous Work

Study	Country	Type of Information Used	Short-Run Elasticities	
			Price	Income
Houthakker (1951)	UK	S	-0.89	1.17
Wilson (1970)	USA	S	-1.33	-0.46
Anderson (1972)	USA	S	-0.91	1.13
Halvorsen (1975)	USA	S	1.52 to 3.70	0.72 to 1.65
McFadden et. al. (1977)	USA (Washington)	D	-0.25 to -0.52	0.22
Murray et.al. (1978)	USA (Virginia)	S	-0.26 to -1.43	NA
Aigner and Hausman (1980)	USA (Arizona)	D	0.02 to -0.79	NA
Lilard and Acton (1980)	USA	D	-0.06	0.02
Parti and Parti (1980)	USA (California)	D	-0.28 to -1.24	0.13 to 0.17
Westley (1983)	Paraguay	D	-0.56	0.42
Dubin and McFadden (1984)	USA (California)	D	-0.25 to -0.31	0.008 to 0.01
Dubin et.al. (1986)	USA (Florida)	D	-0.07 to -0.84	0.25 to 0.83
Belanger et.al. (1996)	Canada	D	-0.02	0.08
Reiss and White (2001)	USA (California)	D	-0.39	0.00
Filippini and Pachauri (2002)	India	D	-0.16 to -0.39	0.65 to 0.69

Note: S: Semi-aggregate data, D: Disaggregate (household-level) data.

Regarding the second problem, the choice of certain appliance stocks became consistent with the development of microeconoic theory. The econometric modelling of choice behavior was developed after the introduction of flexible functional forms and duality theory. Discrete choice models, sample selection corrections and discrete-continous combinations (McFadden, 1973, 1974; Heckman, 1974, 1979; Hanemann, 1984) allow to introduce this component on electricity demand estimation, providing estimates of electricity consumption for appliance portfolios, or even for each appliance.

However, these two "traditions" have not been reconciled, since either one or other approach was carried on separately. This paper tries to combine them into a single model.

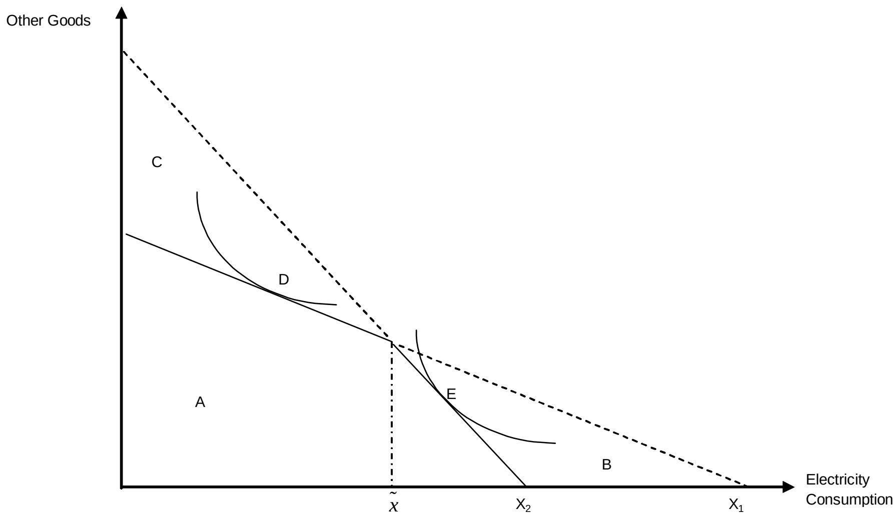
3 Theoretical Model

According to the literature, the typical tariff schemes for electricity pricing are three: (i) constant rates, (ii) increasing block rates and (iii) decreasing block rates. In the first case, users pay the same price irrespective of the quantity consumed in kWh. The second approach makes the consumer pay more for each additional kWh, while the third one implies an inverse relationship between price and quantity consumed.

Under IBTs, the linear budget constraint has kinks at each cutoff point. To explain better this situation, suppose a consumer that is endowed with a certain amount of money and faces the problem of allocating each one in the most efficient way, according to his preferences between electricity (x_1) and a composite good (x_2). As an example, let´s suppose that electricity is priced according to a two-block increasing tariff scheme: the first one has a price of p_1^A, for a consumption under $\overline{x}_1$ kWh, while the second has a price of p_1^B for any quantity consumed over $\overline{x}_1$ kWh, with $p_1^A < p_1^B$. The composite good has a price of p_2. For simplicity, this is assigned a value of 1. Under these assumptions, the budget restriction is similar as the solid line shown in Figure 2.

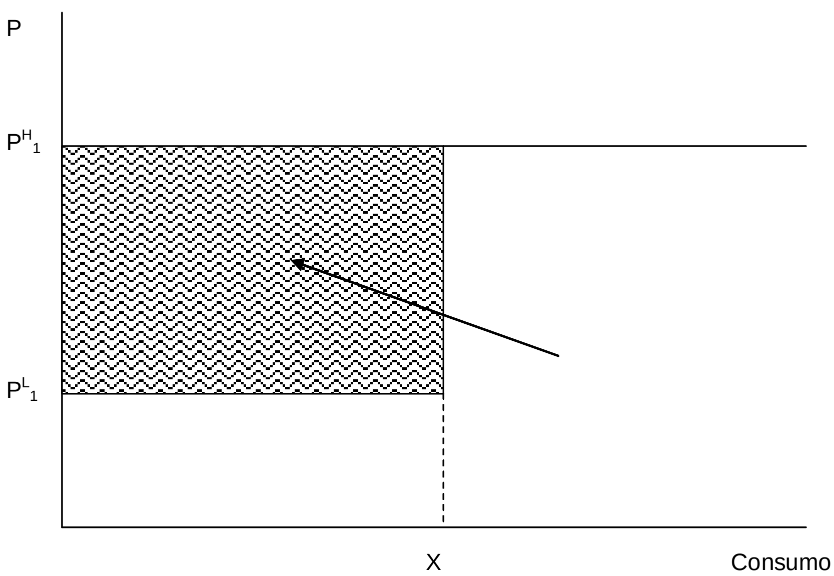
The area A, which defines the feasible combinations, is the intersection of two different sets. The first one corresponds to a price of p_1^A for each kWh consumed (areas A and B), while the second one corresponds to a price p_1^B (areas A and C). However, the income, given by the intersection of the budget constraint with the vertical axis, is different. In the first case, the income is given by y, that is, the real consumers' income, while in the second case the income could be y^* (called "virtual income" in the literature). It is clear that, if all of the consumption was priced at p_1^B and income were y, the relevant budget constraint would be given by yx_3, which is incorrect. According to this price scheme, there are three options for the consumer to follow, represented by his utility function. Some of them will choose a consumption level lower than $\overline{x}_1$, others will consume at the kink, while others will consume more than $\overline{x}_1$. In this context, the virtual income is a concept based in the electricity supply for a given household. In the example given above, the supply function is similar to the one shown on Figure 3.

Figure 2
Allocation under Increasing Block Tariffs



Source: Based on Moffitt (1986).

Figure 3
Virtual Income



Source: Based on Hanemann and Stavins (2001).

According to this, any household that consumes x_1, with $x_1 > \overline{x}_1$ could pay an amount given by $(x_1 - \overline{x}_1)\, p_1^B + p_1^A$, while if the household pays p_1^B for all the quantity consumed, the total payment comes given by $p_1^B x_1$. The difference between those two payments is equal to $x_1 p_1^A - \overline{x}_1 p_1^B$. This difference might be interpreted as a transfer that is added to the consumer's income. In formal terms, the virtual income can be obtained by the following way:

$$
\begin{aligned}
y - p_1^A x_1 - p_1^B(\overline{x}_1 - x_1) &= \overline{y} - p_1^B x_1 && (1)\\
\overline{y} &= y - p_1^A x_1 - p_1^B(\overline{x}_1 - x_1) + p_1^B x_1 && (2)\\
\overline{y} &= y - x_1\left(p_1^B - p_1^A\right) && (3)
\end{aligned}
$$

Having done this precisions, the consumer problem can be represented by the following equations:

$$
\begin{array}{ll}
\max U(x_1, x_2) & \\
s.t. & \begin{array}{rll} p_1^A x_1 + x_2 = y & if & x_1 < \overline{x}_1 \\ x_1\left(p_1^B - p_1^A\right) = \overline{y} - y & if & x_1 \geq \overline{x}_1 \end{array}
\end{array}
$$

Note that the second restriction includes the virtual income component. After the optimization procedure, the obtained results are the following:

$$
\begin{array}{rll}
\frac{\partial U/\partial x_1}{\partial U/\partial x_2} = p_1^A & if & x_1 < \overline{x}_1 \\
\frac{\partial U/\partial x_1}{\partial U/\partial x_2} = p_1^B - p_1^A & if & x_1 \geq \overline{x}_1
\end{array} \tag{4}
$$

Consequently, the consumer might maximize his utility in any of the points of the budget constraint, depending on his marginal substitution ratio. Given those assumptions, from equation (4) we can derive a conditional demand function for electricity as follows:

$$
\begin{array}{rll}
x_1 = x_1\left(p_1^A, y, z\right) & if & x_1 < \overline{x}_1 \\
x_2 = x_2\left(p_1^B, \overline{y}, z\right) & if & x_1 \geq \overline{x}_1
\end{array} \tag{5}
$$

However, those demand equations don't take into account the fact that a household might choose between different appliance categories. Therefore, we will assume that any given household faces m different portfolios for each price block, denoted by $i = 1, ..., m$. According to Dubin and Robledo (2006), a

simple way to obtaining two closed-form expressions from (5) is to obtain an indirect utility function. Assuming that there are r price segments (denoted by $r = A, B$), an indirect utility function of this form might be employed (Dubin and McFadden, 1984):

$$
\begin{aligned}
v_r^i &= \left(\alpha_{0r}^i + \frac{\alpha_{1r}^i}{\beta_r^i} + \alpha_{1r}^i p_{1r} + \beta_r^i(\overline{y}_r - r_i) + \eta_r\right)\exp\left(-\beta_r^i p_{1r}\right) - \alpha_5 \ln p_2 + \varepsilon_{ir} && (6)\\
&= V_r^i + \varepsilon_{ir} && (7)
\end{aligned}
$$

Where p_{1r} is the electricity price for each tariff segment, $\overline{y}_r$ is virtual income, r is the rental price of each appliance category, and η_r and ε_{ir} are error terms. Note that there are $r \times m$ indirect utility function specifications.

Using Roy's identity, an expression for the first and second segment demands and appliance category i can be obtained:

$$x_{1A}^i = a_{0A}^i - \frac{\alpha_{1A}^i}{\beta_A} + \alpha_{1A}^i + \alpha_2^i p_2 + \beta_A (y - r_i) + \eta_A \tag{8}$$

$$x_{1B}^i + \overline{x}_1 = a_{0B}^i - \frac{\alpha_{1B}^i}{\beta_B} + \alpha_{1B}^i + \alpha_2^i p_2 + \beta_B (\overline{y} - r_i) + \eta_B \tag{9}$$

All the equations seen at the moment are conditional on the choice of a given appliance portfolio. The error term has the following properties: $E(\eta_r) = 0$, $Var(\eta_r) = \sigma_r^2$ and $cov(\eta_r, \eta_s) = \sigma_{rs}$ for $r \neq s$. However, $E(\eta_r \mid i)$, the expected value conditional to the appliance category chosen is not equal to zero (Dubin and McFadden, 1984), and it's given by:

$$E(\eta_r \mid i) = \sum_{j \neq i}^{m} \left[\sigma \frac{\sqrt{6}}{\pi} R_j\right] \left[\frac{P_{j|r} \ln P_{j|r}}{1 - P_{j|r}} + \ln P_{j|r}\right] \tag{10}$$

Now we must find how this probability is computed. Let's consider the probability of choosing portfolio i and price block $r = A, B$.

$$P_{ir} = \Pr\left\{(\varepsilon_{1r}, ..., \varepsilon_{mr}, \eta_r) : V(i, \overline{y}_r - r_i, p_{1r}, \varepsilon_{ir}, \eta_r) > V\left(j, \overline{y}_j - r_j, p_{1r}, \varepsilon_{jr}, \eta_r\right), \forall j \neq i\right\} \tag{11}$$

Replacing the functional form assumed for $V(\bullet)$, we have that:

$$\begin{aligned} P_{ir} &= \Pr\left\{(\varepsilon_{1r}, ..., \varepsilon_{mr}, \eta_r) : V_r^i + \varepsilon_{ir} > V_r^j + \varepsilon_{jr}, \forall j \neq i\right\} \\ &= \Pr\left\{\varepsilon_{jr} - \varepsilon_{ir} > V_r^i - V_r^j, \forall j \neq i\right\} \end{aligned}$$

If we assume that ε_{mr} has an independent extreme value distribution, we can estimate the probability that a household has chosen an appliance category i:

$$P_{i|r} = \Pr\left(\varepsilon_{jr} - \varepsilon_{ir} < V_r^i - V_r^j, \forall j \neq i\right) \tag{12}$$

$$= \frac{\exp\left(U_r^i/\theta\right)}{\sum_{j=1}^m \exp\left(U_r^j/\theta\right)} \tag{13}$$

where $\theta = \frac{\lambda\sqrt{3}}{\pi}$.This result gives us the probability of choosing a particular appliance portfolio, given that a particular price segment has already been chosen. In this sense, the demand equations for a particular appliance category i should be reexpressed as:

$$x_{1A}^i = a_{0A}^i - \frac{\alpha_{1A}^i}{\beta_A} + \alpha_{1A}^i + \alpha_2^i p_2 + \beta_A (y - r_i) + \sum_{j \neq i}^{m} \gamma_j \left[\frac{P_{j|A} \ln P_{j|A}}{1 - P_{j|A}} + \ln P_{j|A}\right] + \eta_A^* \tag{14}$$

$$x_{1B}^{i}+\overline{x}_{1}=a_{0B}^{i}-\frac{\alpha_{1B}^{i}}{\beta_{B}}+\alpha_{1B}^{i}+\alpha_{2}^{i}p_{2}+\beta_{B}\left(\overline{y}-r_{i}\right)+\sum_{j\neq i}^{m}\gamma_{j}\left[\frac{P_{j|B}\ln P_{j|B}}{1-P_{j|B}}+\ln P_{j|B}\right]+\eta_{B}^{*} \tag{15}$$

The $m\times 2$ simultaneous equation system can be consistently estimated using 3SLS, given the estimated probabilities $P_{j|r}$ and the possible contemporaneous correlation among error terms. Due to the influence of other exogenous variables in electricity consumption, a matrix $\mathbf{s}$ could be introduced**,** which includes additional factors that explain electricity consumption, such as households' members and dwelling characteristics.

From the above equations the elasticities of interest can be calculated. In first place, the price elasticity for each one of the price segments can be obtained from the following way:

$$\in\left[x_{ir}^{j},p_{1r}\right]=\alpha_{1r}^{i}\frac{p_{1r}}{E\left(x_{1r}^{i}\mid p_{2},y_{r},\mathbf{s}\right)} \tag{16}$$

where the expected consumption and the coefficient α_{1r}^{i} are estimated from the model. On the other hand, income elasticity can be obtained by replacing income and the estimated coeficient β_r in the above formula.

$$\in\left[x_{ir}^{j},\overline{y}_{r}\right]=\beta_{r}\frac{\overline{y}_{r}}{E\left(x_{1r}^{i}\mid p_{2},y_{r},\mathbf{s}\right)} \tag{17}$$

Similar expressions can be obtained for other elasticities, such as substitution effects among different price blocks and appliance portfolios.

4 Empirical Implementation

4.1 The Data

The information used in the estimation procedure comes from a household survey conducted by the Peruvian Energy Regulatory Agency (OSINERG) during the first three months of 2003, interviewing 10243 households along the Peruvian territory. The sample size was determined using the variance of households' total expenditure in energy during the year 2001, obtained from the Peruvian National Institute of Statistics' household survey (INEI in Spanish). Given the characteristics of the sample, it allows to make inferences at the departamental level, as well as in rural and urban areas.

The survey instrument was divided in six sections, four of them used in the estimation procedures. The first part compiles information regarding households' demographic characteristics (sex, age, marital status, education). In the second part, data on a given household income sources and expenditure is contained. Part three is related to the measurement of the physical characteristics of the dwelling and appliance stock characteristics. Finally, the last part includes questions regarding energy consumption and use. This section included information on the households' customer number assigned by electricity distribution firms, in order to match their characteristics with monthly consumption records provided by the firms (from November 2001 to March 2003). In terms of the work carried out by the survey firm, the methodology used was a direct interview to all of the household members in the first two sections, while interviewing only the household head in the remaining sections. On the other hand, the price of electricity for all segments was obtained directly from the OSINERG. The existence of 17 distribution firms supplying electricity to Peruvian households guarantees that there will be enough variance to obtain meaningful estimates.

The combined database which was used on the estimations came as a product of the merging between the OSINERG's household survey, the electricity firms' historical consumption records and regulated prices, also obtained from OSINERG. Since the introduction of the FOSE in November 2001, there are three different prices for each distribution system: a fixed charge, a price for consumption under 100 kWh per month and another price for the marginal consumption above 100 kWh per month. However, there was a problem when trying to match each household with the price structure it faces, since prices in each distribution prices are set on engineering criteria, which usually don't coincide with political division criteria used in the survey sampling process. In order to do an appropiate match, additional information coming from distribution network designs had to be used. In some cases, even that information wasn't enough to make the matching, so the price of adjacent regions had to be imputed, controlling for their socioeconomic characteristics. Also, when matching consumption records with the customer number provided by each household, there were some issues with typos and missing values in those numbers, so ultimately 86% of households with electricity could be identified in the database (6,200 out of 7,190 households).

Having said this, we can make a classification of all the variables involved in the estimation procedure. The first category includes all of the basic variables, such as the quantity demanded by each household, price, income and appliance portfolio choices. The second category includes exogenous variables that, according to the literature, have influenced in electricity demand, such as household members' and dwelling characteristics. The third group includes a set of multiplicative dummies. Due to the notorious heterogeneity in electricity demand, it was necesary to include multiplicative dummies that interact with price and income, in order to determine if there is any significant difference between poor and non-poor households.

Finally, the estimation procedure involves the choice between m appliance portfolios, as well as the determination of a variable r which indicates the users' cost of capital for each of them. The survey incorporated a series of questions regarding the number of appliances that each household had, as well as the "age" of each appliance. A deeper examination of the various household characteristics made it possible to determine four appliance categories, each of the latter includes the previous ones. The first one is the most common among poorer households both in rural areas, and involves a set of lightbulbs and a transistor radio. The second portfolio comprises the first one, as well as TV and refrigerator ownership. The third portfolio is more common of a middle-class household and includes representative appliances such as a stereo, computer and a microwave oven. Lastly, the appliances used by richer households were considered in the fourth portfolio and include electric stoves, electric heating systems and pool equipments. Most of the households (52.4%) declared having appliances included in portfolio. No 2, while only 2.8% of households use the additional appliances included in portfolio No. 4. For each of these portfolios, purchase prices were obtained according to the equipment age, and we assumed that the equipment cost was the annual payment that one of these households had to make if he purchased it on credit.

4.2 Estimation Results

As said in Part 3, the first stage of the estimation procedure involves the estimation of a nonlinear multinomial logit. In order to estimate it with standard logit techniques we followed the procedure introduced by Fadder et. al. (1992). This procedure consists of an iteratieve procedure based on a first-order Taylor expansion in order to obtain a linear version of the model which can be readily estimable in any standard econometrics package. They prove that, if the derivatives of the nonlinear function are bounded in an interval that contains both the starting values and the maxima, the procedure should converge rapidly.

Having said this, the starting values for the iterative procedure were taken from a standard (linear) logit specification. Using a tolerance of 1×10^{-5}, the procedure converged after the 11^{th} iteration. Results, shown in Table 3, represent the appliance portfolio choices, whch are estimated taking the price blocks as given[12]. Because of the theoretical specification exposed in Section 3, we estimated the first model with income and first segment price, while the second model was estimated with the "virtual" income and using the price of the second block. As always, identification issues for this kind of models don't allow us to present equations for all available choices, but to condition them on a given category. In this case, the selected category was portfolio No. 2, which includes lightbulbs, a transistor radio, at least one TV and a refrigerator. All of the variables included in the model are statistically different from zero.

[12] The posibility of conditioning first on the choice of appliances is also plausible.

Table 3
Nonlinear Multinomial Logit (First-Stage) Results

Dependent Variable: Appliance Portfolio Choice

Variables	First Price Block			Second Price Block		
	Portfolio 1	Portfolio 3	Portfolio 4	Portfolio 1	Portfolio 3	Portfolio 4
Household's income	-0.001	0.001	0.001			
	[0.000]***	[0.000]***	[0.000]***			
Household's "virtual" income				-0.001	0.001	0.001
				[0.000]***	[0.000]***	[0.000]***
Electricity price (first block)	7.244	-5.819	-16.806			
	[0.418]***	[0.299]***	[0.898]***			
Electricity price (second block)				4.328	-5.167	-11.939
				[0.163]***	[0.158]***	[0.563]***
No of people in household	-0.038	-0.057	-0.292	-0.026	-0.059	-0.297
	[0.007]***	[0.005]***	[0.016]***	[0.007]***	[0.005]***	[0.016]***
Household's head age	0.010	0.003	0.035	0.011	0.002	0.035
	[0.001]***	[0.001]***	[0.002]***	[0.001]***	[0.001]***	[0.002]***
Dwelling is used for economic activity	0.046	-0.232	-0.474	0.056	-0.220	-0.449
	[0.031]	[0.023]***	[0.061]***	[0.031]*	[0.023]***	[0.061]***
Rural Area	1.087	-0.780	-1.935	1.127	-0.741	-1.812
	[0.028]***	[0.031]***	[0.162]***	[0.027]***	[0.031]***	[0.155]***
Constant	-4.787	0.942	1.378	-4.468	1.270	1.087
	[0.137]***	[0.093]***	[0.288]***	[0.099]***	[0.077]***	[0.254]***
Observations		69124			69124	
Log likelihood		-59561.99			-58825.58	
LR chi2(18)		16919.01			18391.83	
P-value		0.0000			0.0000	
Pseudo R2		0.1244			0.1352	

Standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Source: Authors' own calculations.

When analyzing the choice probabilities, the only portfolio which has a negative relationship with income is the first one. All others have a positive relationship, in the sense that a household with a higher income is more likely to choose the third or fourth portfolio. The relationship between prices and portfolio choices is also of interest. It seems that the first and second portfolio is among the less preferable of households in a context of lower prices. More specifically, an increase in prices in both segments increases the probability that a household chooses a more basic portfolio. Therefore, the presence of higher electricity prices is a deterrent for any given household to acquire more appliances.

Two other variables that are worth mentioning are the presence of any other economic activity inside the dwelling that the household occupies (such as a small store, shoemaking, handicrafts, etc.). There is extensive evidence that, in developing countries, mixed-use dwellings (both for living and other activities) are among the poorest ones. While they might posess some energy-intensive equipment, the income generated by those activities is not enough to take them above the poverty line. This result is also reinforced by the effect generated by rural areas: any household living in a rural setting is more likely to choose a "basic" portfolio. Other variables such as the number of people in the household and the household's head age are used as controls.

Table 4 shows the results of the demand estimation model. Due to the nature of the model, only the coefficient signs and its relative magnitude can be analyzed, but not the elasticities. Regarding the price and income coefficients in both price segments and for all appliances, results show that the price elasticities are greater for the more energy-intensive portfolios located in the first price block. Of that group, the poorer households are the ones that have the largest price elasticities in absolute value, with no major difference across portfolios. When analyzing income elasticities, we found that those choosing to consume in the first block are the most sensitive to changes in income. Again, poorer households consuming in this segment have the largest income elasticities of all households. In contrast, households consuming in the second block seem to be less sensitive if income changes. These results confirm previous empirical research, in the sense that price and income elasticities are -on average- inverse related with income levels. In the specific Peruvian case, price elasticity is larger in poorer households because of the availability of alternative energy sources for lighting (such as kerosene lamps, candles or batteries) that can offset the reduced consumption levels already observed. Following this logic, the price elasticity is lower in households with more income, who have less substitution possibilities, since they mostly live in urban areas.

The same logic can be applied to income elasticities. Poorer households have larger price elasticities since changes in income are translated into appliance purchases and, therefore, a higher electricity consumption. As in other developing countries, Peruvian households have small appliance stocks, so that those increases in income can be used to change -say- from portfolio 1 to portfolio 3. When a household reaches a certain point in its income, further increases don't cause a higher electricity consumption, since most appliances have already been purchased. Only modest increases can be expected, which are related to usage decisions.

Finally, the other variables included in the regression deserve some explanation. The number of people living in the household is also a proxy for income, since families with more members are known to be poorer in average. The influence of this variable is more pronounced in the second segment. Other two variables that serve as controls are the presence of a fixed telephone line and the number of rooms in the dwelling. Those two have a positive influence in electricity consumption, as expected from other studies. The use of the dwelling for some economic activity has also a positive influence on demand, since some of the equipment used for those small businesses is energy-intensive or is used more hours than in a regular household. Another control variable was the household's head age. This variable is a rough proxy of the "age" of the household: one might expect that older household heads have also older wifes/husbands and older sons. Therefore, because of the time elapsed since the formation of the household it might have acquired more equipment, thus resulting in a higher demand. In this sense, younger households should have less consumption than older ones, and that is what is observed in the table.

Table 4
Demand Equation Estimation Results

Dependent Variable: Electricity Consumption (kWh / month)

Variable	First Block				Second Block			
	Portfolio 1	Portfolio 2	Portfolio 3	Portfolio 4	Portfolio 1	Portfolio 2	Portfolio 3	Portfolio 4
Electricity price (first block)	-116.450	-114.594	-119.757	-120.156				
	[3.521]***	[3.542]***	[3.467]***	[3.466]***				
Electricity price (first block) * Poor Household	-73.566	-73.366	-73.945	-73.978				
	[1.641]***	[1.642]***	[1.641]***	[1.641]***				
Electricity price (second block)					-51.696	-53.118	-57.434	-55.133
					[2.602]***	[2.621]***	[2.579]***	[2.577]***
Electricity price (second block) * Poor Household					-4.17	-4.288	-4.865	-4.604
					[1.958]**	[1.961]**	[1.960]**	[1.958]**
Household income	0.004	0.004	0.003	0.003				
	[0.000]***	[0.000]***	[0.000]***	[0.000]***				
Household income * Poor Household	0.019	0.019	0.019	0.019				
	[0.001]***	[0.001]***	[0.001]***	[0.001]***				
Household "virtual" income					0.01	0.01	0.009	0.009
					[0.000]***	[0.000]***	[0.000]***	[0.000]***
Household "virtual" income * Poor Household					0.006	0.006	0.006	0.006
					[0.001]***	[0.001]***	[0.001]***	[0.001]***
No of people in household	-0.266	-0.110	-0.553	-0.584	-1.038	-1.19	-1.698	-1.44
	[0.077]***	[0.078]	[0.074]***	[0.074]***	[0.127]***	[0.128]***	[0.125]***	[0.125]***
Household's head age	-0.069	-0.094	-0.022	-0.017	0.006	0.032	0.118	0.074
	[0.009]***	[0.010]***	[0.009]**	[0.009]*	[0.016]	[0.016]*	[0.016]***	[0.015]***
Dwelling is used for economic activity	2.985	3.066	2.827	2.813	4.175	4.101	3.83	3.963
	[0.260]***	[0.261]***	[0.261]***	[0.261]***	[0.439]***	[0.440]***	[0.439]***	[0.439]***
Fixed telephone line in household	12.298	12.299	12.294	12.294	14.247	14.251	14.253	14.25
	[0.154]***	[0.154]***	[0.154]***	[0.154]***	[0.259]***	[0.259]***	[0.259]***	[0.259]***
No of rooms in household	1.922	1.922	1.922	1.922	0.994	0.994	0.995	0.995
	[0.069]***	[0.069]***	[0.069]***	[0.069]***	[0.116]***	[0.116]***	[0.116]***	[0.116]***
P11		0.640	-1.234	-1.352				
		[0.057]***	[0.085]***	[0.080]***				
P21	0.662		2.098	2.191				
	[0.081]***		[0.145]***	[0.157]***				
P31	-1.904	-3.026		0.261				
	[0.206]***	[0.244]***		[0.045]***				
P41	1.348	2.021	0.142					
	[0.094]***	[0.125]***	[0.024]***					
P12						-0.484	-2.484	-1.544
						[0.103]***	[0.160]***	[0.106]***
P22					-0.423		2.201	1.242
					[0.148]***		[0.254]***	[0.223]***
P32					-4.719	-3.495		-1.896
					[0.319]***	[0.298]***		[0.138]***
P42					1.778	1.086	-1.155	
					[0.113]***	[0.153]***	[0.074]***	
Constant	77.117	78.596	74.323	74.049	116.151	114.829	109.487	112.022
	[1.074]***	[1.090]***	[1.103]***	[1.097]***	[1.346]***	[1.409]***	[1.434]***	[1.381]***
Observations	68230	68230	68230	68230	68230	68230	68230	68230
R-squared	0.2909	0.291	0.2907	0.2906	0.1419	0.1418	0.1419	0.1419
Chi-squared	28612.01	28612.52	28518.18	28503.45	11766.4	11689.83	11774.96	11781.68
P-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Source: Authors' own calculations.

4.3 Elasticities

The elasticities were obtained following the formulas presented in the last section. Table 5 reports the obtained results, by income deciles (where the first decile represents the poorest households and the tenth decile represents the richest ones). It can be seen that the households located in the lower segments of the income distribution are the ones with the greatest price elasticities, which in some cases is near unity (as in the first decile), and gradually decreases as households earn more. For example, households located in deciles 9 and 10 have price elasticities of -0.20 and -0.17 respectively, while the households in the middle segment of the distribution have values of -0.30 aproximately. When analyzing income elasticities, it can be seen that households from the deciles 1 to 5 have a higher income elasticities than the others. However, if those values are examined in detail, it can be seen that income elasticity grows from 0.26 in the first decile to 0.33 in the fourth decile, then declines to 0.16 in the 7th decile and grows again to 0.26 in the 10th decile. In contrast to the price elasticities, which were monotonically decreasing, income elasticities are not. The explanation to this might reside in the fact that the households located in the first decile place less emphasis on increasing their electricity consumption rather than satisfying other basic necesities. As income levels increase, households allocate more of their newly available income to electricity consumption, but this diminishes again as they purchase more appliances. Finally, the households located in the highest deciles acquire more luxury items that lead to a higher electricity consumption.

Table 5
Income and Price Elasticities - Average Effects (By Income Deciles)

Decile	Price		Income	
1	-0.9357	***	0.2693	***
2	-0.7317	***	0.3323	***
3	-0.5840	***	0.3556	***
4	-0.4640	***	0.3346	***
5	-0.3529	***	0.2578	***
6	-0.2665	***	0.1710	***
7	-0.2334	***	0.1694	***
8	-0.2077	***	0.1726	***
9	-0.1982	***	0.2039	***
10	-0.1653	***	0.2552	***
Total	**-0.3170**	*******	**0.2349**	*******

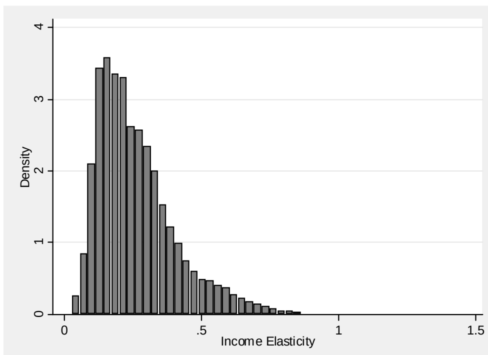
Note: * significant at 10%; ** significant at 5%; *** significant at 1%.
Source: Authors' own calculations.

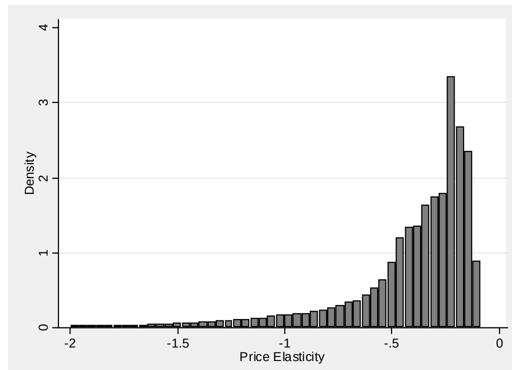
Figure 3 shows the distribution of price and income elasticities[13]. In both cases, it can be seen that a great percentage of the elasticities lie in a range between 0 and 0.5 (in absolute value). However, it can be seen that some households have price elasticities that exceed unity. Those elasticities correspond to poor households that have consumption levels that are slightly above the 100 kWh break. This result might suggest that some households could react

[13] Due to the presence of some outliers, both graphics are truncated in order to show relevant values.

to a change in prices by switching to the inmediate lower block. However, due to the fact that about 60% percent of Peruvian households don't know their consumption levels but only their expenditure, this fact should be reviewed in more detail.

Figure 3
Distribution of Income and Price Elasticities





Source: Authors' own calculations.

5 Conclusions

By using an approach that combines the existence of increasing block prices and households' choices among different appliance portfolios, this paper has estimated a demand function for electricity employing household data. This approach, suggested by Dubin and Robledo (2006), is a generalization of the Dubin and McFadden (1984) framework for block tariffs. The estimation can be carried using a two-step procedure with available econometric packages, in deep contrast with the use of maximum likelihood or GMM procedures presented in Reiss and White (2001).

The results show that price and income elasticities in the Peruvian case are -0.31 and 0.23 respectively. Those values hide a substantial heterogeneity, in the sense that some households have price or income-elastic demands. We also have found that both income and current electricity prices have a strong effect on the appliance portfolio choices. What do we learn from these results? In first place, the poorest households have the highest price and income elasticities, regardless of the block in which they consume. In this sense, any policy that gives those households a lower price might increase welfare among that group. The analysis of the portfolio choices shows that "starter" households that have just accessed to the service are also more sensitive to price. Those households are mostly located in the distribution firms' expansion areas, so any special measure that takes into account this group could also be benefical. Finally, other results show that there might be some strategic behavior on part of the households because the higher elasticities are concentrated near the 100 kWh thresholds. This increased knowledge of household electricity consumption validates cross-subsidy programs like the FOSE.

However, there are some limitations that might be improved in future research. In first place, the determinants of the choice among different portfolios should be investigated in detail. Also, we are implicitly assuming that there is an unidirectional relationship among income and energy consumption. The experience in developing countries shows that energy consumption might also influence income generation, in the case that some economic activity is carried inside the dwelling. Therefore, any explicit modelling of this situation is necesary in order to obtain more precise estimates of price and income elasticities.

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