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Distributional implications of power sector reforms in the Philippines

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This paper seeks to assess the distributional implications of the power sector reforms in the Philippines to residential consumers of electricity. First, we estimate the demand for electricity, taking into consideration the difficulties that arise from block pricing of electricity. Second, we simulate the impact of power reforms in terms of increasing the prices of electricity, assuming a linear budget set, and using the elasticities from the demand equation. This exercise draws heavily from the duality in consumer theory, which allows us to recover the utility function of individuals and to assess welfare in terms of compensating variation. This paper concludes that an increase in price of electricity will result in higher welfare loss as income increases. However, welfare loss of the poorest is highest among the lower-income groups.

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1. Introduction

Power sector restructuring has been the centerpiece of the Philippine reform policy in the past five years. Following the successful privatization of the country's telecommunications and water industries, and the power sector's vast experience with various privatization schemes—e.g., the build-operate-

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transfer (BOT) scheme—the major restructuring in the sector started in 2001 with the passing of the Electric Power Industry Act of 2001 (EPIRA).

EPIRA started the gut-wrenching reforms in the sector as it dismantled the decades-old monopoly—the National Power Corporation (Napocor)—to seek greater private sector participation in the industry, first, by spinning it off into two separate businesses: generation and transmission. The former is under the operational control of Napocor until its complete sale and privatization, while the latter is under the management of the newly created National Transmission Corporation (TransCo), which will be offered to interested private investors under a franchise/concession contract.

The reforms are being implemented in the midst of the country's macroeconomic problems such as rising fiscal deficits and ballooning debt burden. This essentially means that the government is in a very tight position to provide continuing subsidies and support to Napocor. The government has to do this in the presence of the steadily declining net income of Napocor at the same time that the latter's debt stock is increasing. Napocor cannot rely on its internally generated revenues to maintain and upgrade electricity infrastructure and continue providing services to its customers. It cannot raise its tariff to levels that make it profitable—that is, increasing nominal tariff has failed to raise the firm's profitability as measured by the return on rate base from 1998 onward.

Figure 1. Philippines deficit and debt

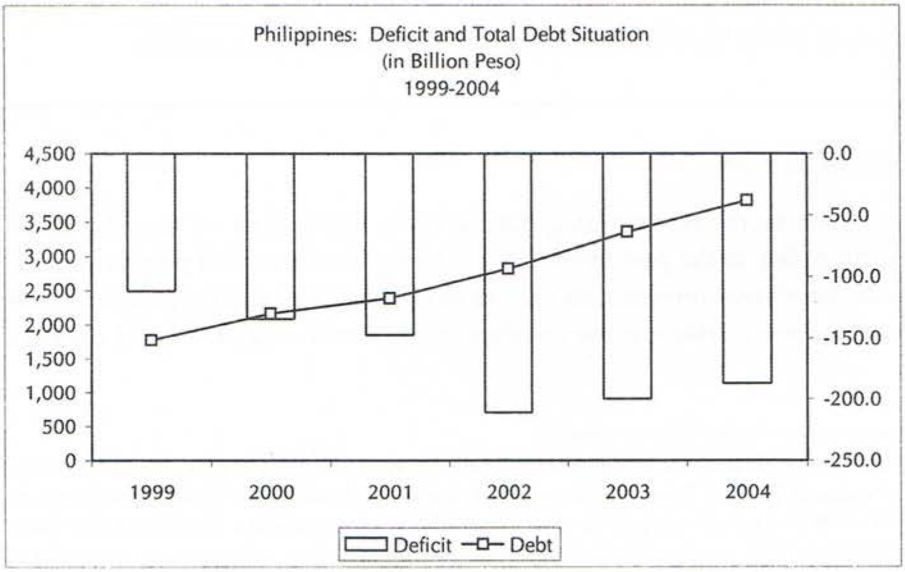


Figure 2. National government's support to Napocor

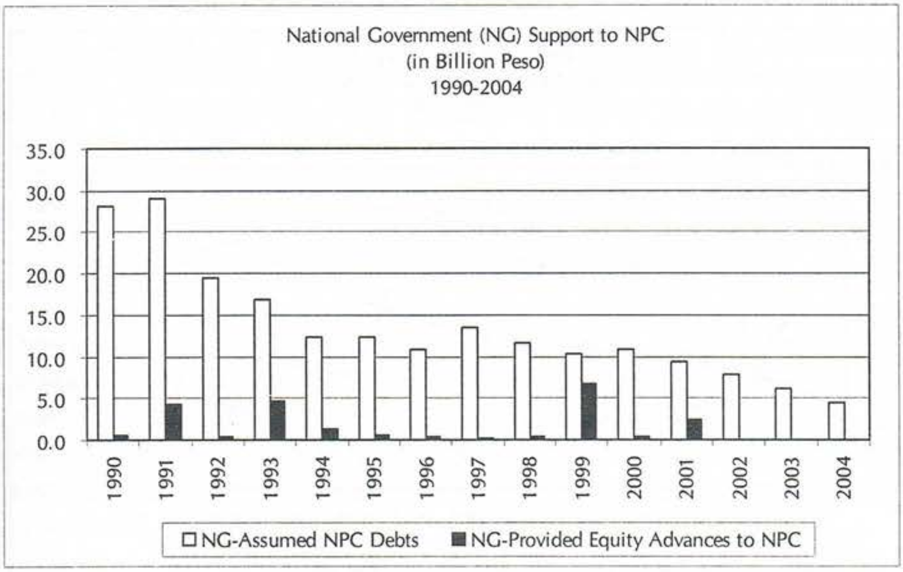


Figure 3. Napocor has been experiencing steadily declining income and increasing long-term debt

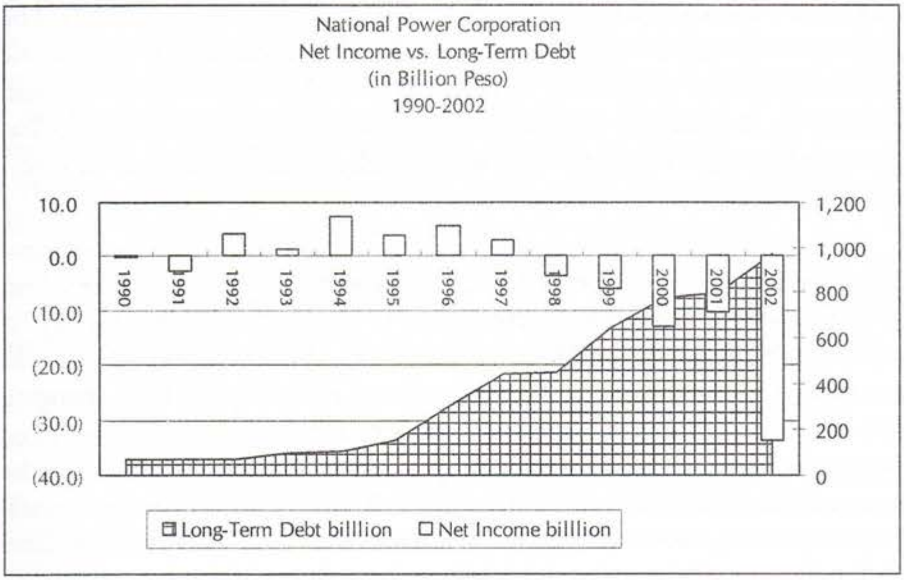
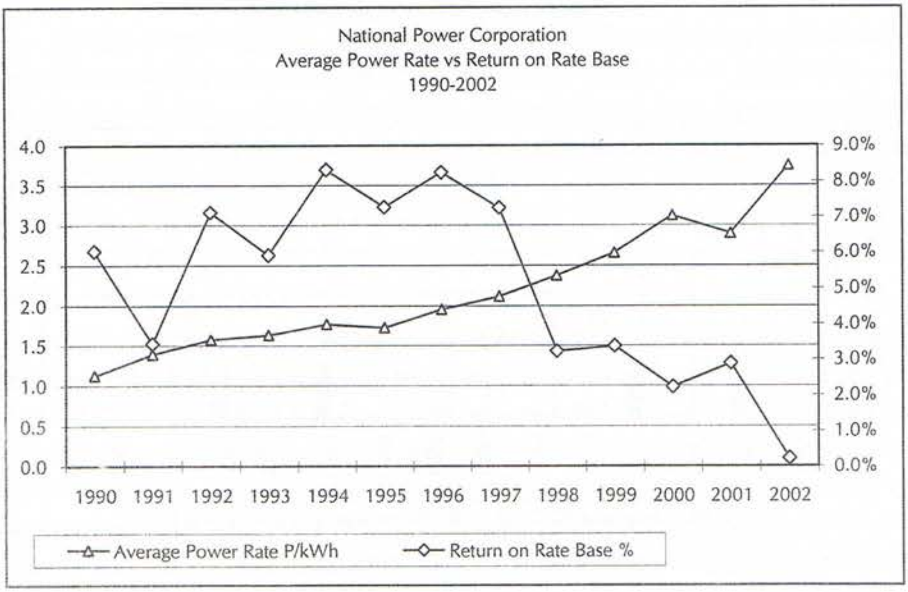


Figure 4. Despite increasing nominal tariff, Napocor remains unprofitable



As the reforms seek to reduce government support to Napocor and to increase the sector's efficiency as a whole by enabling (a) a more competitive structure for the industry and (b) more private sector participation, the dynamics of gradual removal of existing subsidies versus having a more efficient and competitive industry makes it difficult to assess the price change vector. The government maintains that the reforms will bring prices down, while some sectors believe the opposite to be true. However, both sides agree that with the reforms, the price of electricity is expected to reflect its true cost so that the competitive structure will work and the private sector is enticed to invest in the industry.

Given the changes, their impact could be wide ranging. But the potential impact on consumers is one of the most interesting aspects of the reforms, given the government's long involvement in the sector and the history of cross-subsidies among consumer groups, i.e., residential, industrial, and commercial consumers. Since the retail price of electricity has been changing due to reforms, there is a growing need to understand its distributional consequences, which have been the subject of considerable debate. It is to be expected that welfare impacts will vary with families according to how much electricity they consume relative to each family's income. Thus, to appreciate how consumers react to price changes, we first need to understand the demand for electricity and its relation to prices.

This paper has two major parts. The first part estimates the demand for electricity, which tries to address the endogeneity and simultaneity problems inherent in residential electricity demand, as well as nonrandom sample selection. Our treatment casts these interrelated issues along the lines of Hall [1973] and Heckman [1979]. We then estimate the model using the data from the Family Income and Expenditure Survey (FIES), which include household characteristics, total expenditure, and spending on electricity.

The second part focuses on application. We simulate the impact of an increase in price and assess its distributional implications using the well-known dual approach to consumer behavior and its use in measuring the costs and benefits of price and other changes. For this exercise, we will assume a linear budget constraint using the observed market demand curve estimated in part 1, and then derive the corresponding indirect utility function (the expenditure function) and, finally, our measure of welfare (the compensating variation).

2. Estimation of residential electricity demand

2.1. Difficulties in modeling residential demand

Among the difficulties that researchers should tackle are endogeneity and simultaneity problems caused by appliance replacement and, to some extent, dwelling decisions.[1] Cowing and McFadden [1984] noted that electricity is not consumed; rather, it is an input to household production process—to provide heat, cooling, lighting, and other needs. The household technology for electricity consumption, on the other hand, is largely determined by the characteristics of the dwelling and durable equipment. Therefore, the level of electricity consumption is determined by behavioral decisions on utilization, the choice of dwelling, and appliance characteristics, among others. However, replacement and retrofit decisions also depend on electricity price expectations.

Second, there are also endogeneity and simultaneity problems because of multipart tariffs. The latter occurs when the marginal price charged to a consumer changes along with the quantity demanded, and depending on the

[1] While dwelling decision and its relationship with electricity price should be a subject of a more detailed study, in the Philippines, there is no indication that household dwelling decisions are affected by electricity price. See regression runs of dwelling characteristics on electricity price in Appendix A.

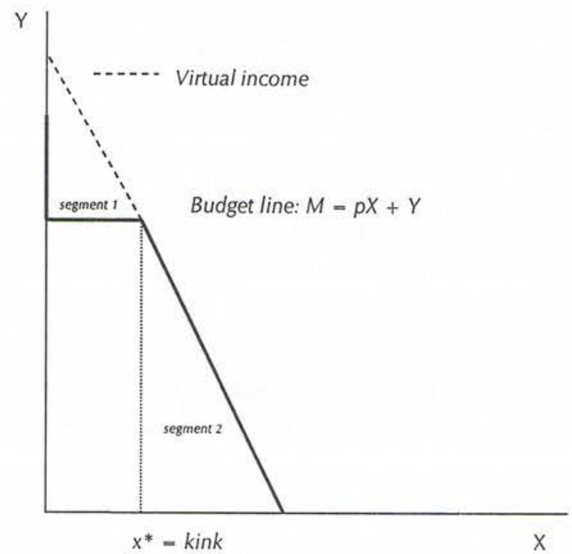
context, these tariffs may exhibit increasing or decreasing marginal prices. The difficulty in empirical work is how to incorporate a complex price schedule into demand specification in a way consistent with economic theory. Taylor [1975] provided a succinct description of the issues in modeling demand for electricity caused by multiblock pricing.

In the Philippines, all residential consumers, except those in the National Capital Region (NCR), pay a fixed amount for the first minimum kilowatt-hour consumption of electricity. These households then pay a marginal amount for the succeeding units consumed. This type of pricing system implies that consumers face a nonlinear, i.e., kinked, budget constraint (see Figure 5). The budget line is drawn, supposing that there are only two goods: electricity denoted by X, and the numeraire good, Y.

The budget line for kinked budget constraint

$$M = Y, \text{ at } X = 0, \qquad (1)$$
$$M = F + Y, \text{ at } 0 < X < x^*,$$
$$M = F + p(X - x^*) + Y, \text{ at } X > x^*.$$

Figure 5. The budget constraint with fixed payment



Segment (1) is the horizontal segment of the budget constraint equal to the fixed charge, F. Segment (2) is the linear segment from the kink; x^* has a slope equal to the price p. Kinked budget constraints create difficulty in estimating demand functions for reasons related to economic theory, which assumes that consumers purchase any desired quantity at a constant price subject to budget constraint. The standard econometric approach to this problem, which traces to Hall [1973], is to linearize the budget constraint. This necessitates computation of the virtual income (see Figure 5) to be the intercept of segment (2) if it is extended to the vertical axis. It is as though households in segment (2) were facing a linear budget constraint with the slope equal to the observed price, p, and intercept m, the virtual income.

Computing the virtual income

$$\begin{aligned} M \quad &= F + p(X - x^*) + F, \\ &= F + pX - px^* + Y. \\ M + px^* - F &= Y + pX, \\ m \quad &= Y + pX, \textit{ m is called the virtual income.} \end{aligned} \tag{2}$$

By computing the virtual income, one can express demand under nonlinear pricing in terms of the ordinary demand function, which assumes a linear budget constraint. However, even if we are able to compute for the virtual income, our demand estimate must consider the problem caused by consumers *sorting themselves between the segments*, i.e., household choosing either (a) to consume less than x^* and pay only the fixed charge, F; or (b) to consume above x^* and pay both the F and the marginal price p for consumption greater than x^*. This sorting makes calculating demand difficult because one must account for the consumer's willingness to switch tariff segments. This also makes virtual income *endogenous* as it now becomes a function of price observed only in segment (2).

It is also difficult to assess the demand for electricity of households in segment (1) or those paying only a fixed amount for electricity. As such, we are constrained to use these observations in our regression, which leads to another special case of sample selection problem called nonrandom sample selection.

These are the difficulties in estimating the demand for electricity, which we have tried to address by implementing the three-step estimation procedure discussed in section 4 below, based on previous approaches to modeling demand for electricity and the estimation of demand for nonlinear budget sets.

2.2. Approaches to modeling demand

A number of studies on electricity demand have tried to present a detailed description of residential energy consumption using different approaches. Houthakker's [1951] study of residential electricity consumption in the United Kingdom is considered one of the pioneering studies on energy demand. It is pioneering in many respects; among them, it is one of the earliest studies on demand that takes into account the econometric implications of two-part tariff by using marginal rather than average price, and considers cross-price or substitution effect of natural gas on electricity demand.

Fisher and Kaysen [1962], on the other hand, authored what is considered the most ambitious early dynamic study of residential energy demand. They distinguished between short-run and long-run electricity demand. In the short run, electricity consumption is estimated as a function of stock and average utilization of electricity-using household appliances. In contrast, the long run is estimated for five different classes of electric appliances: washing machines, refrigerators, irons, ranges, and water heaters. Their results indicated that income and population were among the important determinants of long-run residential demand.

However, Taylor [1975] in his survey of electricity-demand studies lamented the fact that the literature on residential demand for electricity fails to deal adequately with block pricing. He suggested that regressors should include both the marginal and average prices, the latter to account for the income effect arising from the differential between marginal and intramarginal prices. Since then, various demand studies have tried to address the issue of nonlinear pricing. Some of these studies have been strongly influenced by the literature on labor supply that also tried to address closely related issues. Labor supply has been difficult to estimate because of the presence of nonlinear tax schedule and the fact that individuals have different tastes for reasons that cannot be controlled using observable information. Thus demand studies have increasingly employed virtual income, instrumental variable, and two-stage least squares approaches as well as sample selection models—all of which previously appeared in labor supply studies.

Hausman, Kinnucan, and McFadden [1979] analysed the results of the pricing test that attempts to estimate the effect of household electricity demand on time-of-day prices. They took the appliance stock as fixed so that the medium- and long-run response cannot be inferred from the analysis. Their approach uses traditional econometric consumer demand estimation and treats electricity demand within a two-stage budgetary context. They let electricity demand in each period be a different commodity and then estimate the relative household demand across periods conditional on relative prices, the appliance stock, socioeconomic characteristics of households, and the weather. Two-stage least squares (2SLS) is then applied in specifying how the price of electricity was entered into the demand equations. They linearize the budget set—i.e., virtual income—at a reduced-form prediction on monthly consumption. The predicted quantities and the rate schedule are used to form the predicted price variable, which serves as an instrumental variable for the observed marginal price in the second-stage ordinary least squares (OLS) estimation of the demand equation. Their analysis exhibits biases opposite in sign to those of their OLS counterparts.

Reiss and White [2002], in one of their most recent papers, studied electricity demand from a sample of California household. Their paper seeks to develop an estimable model that can be used to evaluate alternative tariff designs. They assume that the demand for electricity is derived from the flow of services provided by a household's durable energy-using appliances, and distinguish between short-run and long-run demand elasticities. The short-run refers to demand behavior taking a household's existing appliance stock as given, while long-run elasticities are meant to incorporate both changes in utilization behavior and any adjustments to the stock of appliances owned by the household. Their approach to modeling electricity demand is conditioning econometric analysis on a household's existing appliance stocks. This allows them to model heterogeneity by specifying electricity-demand function at the level of individual appliances.

Other residential electricity-demand studies also utilized the sample-selection model on the basis of Heckman [1979] to address the block rate structure. The basic idea of sample selection model is that the outcome of variable—say, x—is only observed if some criterion defined with respect to a variable z is met. The common form of the model has two stages. In the first stage the dichotomous variable z determines whether or not x is observed; x is observed only if $z = 1$. In the second stage, the expected value of x, conditional on it being observed, is estimated.[2] However, for this paper we are primarily interested in modeling incidental truncation in which the usual approach is to add an explicit selection equation to the population model of interest:

[2] Summary of Heckman sample selection model from Sweeney [2005].

$$y = x\beta + u, E(u \mid x) = 0 \tag{3}$$

$$s = 1[z\gamma + v \geq 0], \tag{4}$$

where $s_i = 1$ if we observe y and zero otherwise. We assume that elements of x and z are always observed, and we write $x\beta = \beta_0 + \beta_1 x_1 + ... + \beta_k x_k$ and $z\gamma = \gamma_0 + \gamma_1 z_1 + ... + \gamma_m z_m$. The equation can be estimated by OLS, given a random sample. The selection equation (4) depends on observed variables, z_h, and an unobserved error, v. For the following proposed model to work well, x should be a strict subset of z. To estimate: using all n observations, estimate the probit model of s_i on z_i and obtain the estimate for the inverse mills ratio, $\hat{\lambda}_h$. Then, using the selected sample—that is, observations for which s_i=1, say n_1 of them—run the regression of y_i on $x_i, \hat{\lambda}_i$.[3]

Terza and Welch [1982] and Terza [1986] used a two-stage method similar to the one developed by Heckman in analysing increasing block tariffs. Their analysis required a specification that blocks household consumption. In their study the choice of block can be explained with reference to consumer surplus. Two-stage probit approach is applied in estimating demand for electricity that captures the declining block pricing, which consists of (1) estimating probit model of the observed rate block outcomes, and (2) using the probit results to compute for the "correction factor" that they include in the demand equation, which can be estimated by OLS. According to Terza, this correction factor serves to purge the demand equation of the negative correlation between the price variable and the random error term.

A similar approach was suggested by Maddock, Castano, and Vella [1992]. They presented an estimator for generalized selectivity bias based on the sample selection estimator of Heckman, which they call generalized Heckman approach. In the same paper, they applied Burtless and Hausman's [1978][4] technique in dealing with nonlinear prices and concluded that Hausman's method produces perfectly credible results—i.e., the signs are right, the pattern

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[3] Discussion of incidental truncation was taken from Wooldridge [2003:585-589].

[4] Burtless and Hausman [1978] offered a sophisticated technique to analyse labor supply responses under nonlinear income taxation. They examined the negative income tax program that created a nonconvex budget set, and also incorporated the federal income tax that created convex budget sets as well. Their model allowed distribution of preferences for work in the population or individual variations in tastes (heterogeneity), i.e., two individuals who face the same budget sets may prefer to work substantially different amounts. They estimated a two-error model: measurement error and heterogeneity error. The former was assumed to be additive, but the latter was assumed to be located in the income coefficient and constrained to be of theoretically correct sign. Their method necessitated using complex statistical technique in computing the maximum likelihood estimates.

of results is consistent, there is no evidence of heteroskedasticity, and the parameters are about the right magnitudes. They compared the results with alternative methods of estimating electricity demand, and to resolve the difference between the results of the methods they suggested the use of the Heckman approach. They used this model in estimating demand for electricity in Colombia, with a pricing system that includes a connection fee and an increasing five-step block rate structure.

3. Measurement of welfare[5]

We will also discuss the derivation of our measure of welfare before going into the details of our own estimation of demand. Hausman [1981] derived an exact measure of Consumer's Surplus coming from the observed market demand. The derivation of consumer surplus in this way is very appealing as we can use the parameters from the estimated demand to give us a measure of welfare: compensating variation (CV). Compensating variation is defined as the amount of money the household would need to be given at the new set of prices to attain the pre-reform level of utility. Hausman's derivation draws heavily from the duality in consumer theory, which links the primal and dual problem in consumer optimization. The primal problem of consumer choice is when a consumer chooses consumption pattern so as to maximize his or her utility u, subject to given price p and exogenous income y, that is

$$\text{Maximize } u = u(x) \text{ subject to } p \cdot x = y. \tag{5}$$

The dual problem of consumer choice, on the other hand, is the mirror of the primal problem—a consumer chooses consumption pattern so as to minimize his or her expenditure y (total expenditure or income) on consumption, given price p and exogenous utility level u, that is

$$\text{Minimize } y = p \cdot x \text{ subject to } u = u(x). \tag{6}$$

In both problems, optimal values of x are being sought. In the primal problem, the solution is a set of Marshallian demand $x(p,y)$. In the dual problem the determining variables are u and p, thus we have the cost minimizing demand function $h(p,u)$, which is also called the Hicksian demand function. Each of these solutions can be substituted back into their respective problems to give

[5] We are using Hausman's [1981] derivation of consumer's surplus.

(a) the maximum attainable utility $v(p,y)$ from the original problem and (b) the minimum attainable cost $e(p, u)$ of the dual problem. Therefore,

$$v(p,y) = \max [\, u(x);\ p \cdot x = y \,], \tag{7}$$

$$e(p, u) = \min [\, p \cdot x;\ u(x) = u \,]. \tag{8}$$

The function $v(p,y)$ is also called the indirect utility function, while the function $e(p,u)$ can be called the cost or expenditure function. The important property of the expenditure function is that its partial derivative with respect to price gives the Hicksian compensated demand curves,

$$\frac{\partial e(p,\bar{u})}{\partial p_j} = h_j(p,\bar{u}). \tag{9}$$

Another useful property is that of the indirect utility function using Roy's identity, which yields the observed market demand curves as partial derivatives of $v(p, y)$

$$x_j(p,y) = -\frac{\partial v(p,y)/\partial p_j}{\partial v(p,y)/\partial y}. \tag{10}$$

We will use the expenditure function to derive the explicit utility function that will allow us to measure the change in consumer surplus. Using the expenditure function makes computations easy because the arguments of the function depend only on the reform under consideration and are completely independent of preferences. In expenditure function, preferences are described by the form of the function, and opportunities by the values of the arguments of the function. In terms of the expenditure function, compensating variation is defined by

$$\begin{aligned} CV &= e(p^1,u^0) - e(p^0,u^0) \\ &= e(p^1,u^0) - y^0. \end{aligned} \tag{11}$$

To derive the exact compensating variation, the idea is to take the observed market demand curve and to use the Roy's identity from equation (10) to integrate and derive the indirect utility function. Inversion of the indirect utility gives the expenditure function, which allows calculation of the compensating variation in equation (11). We will employ our demand estimates to simulate the impact of reforms, i.e., in this case assuming an increase in the price of electricity.

4. Estimation procedure

4.1. Residential electricity demand

Our model analyses the demand for electricity, taking the household appliance stock and dwelling characteristics as fixed. Our economic variables are the household budget, i.e., price of electricity, virtual income, household characteristics, dwelling characteristics, regional dummies, and year dummy. Our sample is limited to the households that have indicated access to and spending positive amount for electricity. In this paper, we will use the constant elasticity demand specification where Z is the vector of household characteristics, x is the demand for electricity, p is the price of electricity, and y is the total household expenditure or budget,

$$x = e^{Z\gamma} p^{a} y^{b}. \tag{12}$$

Equation (12) is often estimated in log-linear form as

$$\log x = \gamma Z + a\log(p) + b\log(y) \tag{13}$$

We specify the residential demand for electricity as

$$\text{In } kWh = \alpha_0 + a \ln price + b \ln budgetpc + \beta_1 year\,2003 + \\ + \sum_j \gamma_j educ_j + \sum_j \delta_j region_j + \varepsilon \tag{14}$$

The model consists of three steps.[6] The first involves estimating the probit model for household spending below or above the kink. We are basically using equation (4) above; in this case, our selection equation is $s = 1$ if the household spend above the kink, and zero if otherwise. The major implication of using this model is that we should have at least one element in our probit equation that is not also in our demand function, i.e., this variable should affect selection (being above the kink) but does not have partial effect on demand for electricity. In this paper, the excluded variable is the fixed payment[7] for the following reasons:

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[6] We call this henceforth as the three-step methodology.

[7] See Table 1 for details.

(a) Fixed payment does not enter the demand equation because of the linearization of the budget constraint.

(b) Fixed payment, however, may affect whether consumer is above the kink or not.

(c) Fixed payment is completely an exogenous variable since it is determined by the government.

(d) This is time-variant variable, i.e., for some regions, it changes over time.

We will compute the inverse mills ratio from the probit equation, which will be included as one of the explanatory variables in the demand regression. This first-step regression is necessary to capture the impact of dropping some 2,308 households that spend below the kink since there is no way we can ever measure the demand for these observations.[8]

The second step addresses the concern about virtual income's endogeneity. We will be using the real expenditure as instrumental variable for the virtual income. We will regress the virtual income with the real expenditure and take the predicted residuals. The predicted residuals together with the inverse mills ratio are included in the demand equation as one of the regressors to complete our third and final step: demand estimation using ordinary least squares.

4.2. Compensating variation[9]

For this section, we will derive compensating variation using the constant elasticity-demand specification in equation (12). We first need to find the indirect utility function by using the technique of separation of variables to find:

$$v(p,y) = c = -e^{Z\gamma} * \frac{p^{1+a}}{1+a} + \frac{y^{1-b}}{1-b}, \tag{15}$$

where c is the constant of integration, which we set equal to the initial utility level $\overline{u}$. The following are the conditions to check for a valid indirect utility, which arises from consumer maximization: (1) The indirect utility function is continuous and homogenous at degree zero in prices and income. (2) It is also

[8] Dropping 2,308 observations can be considered a problem of incidental truncation, which is addressed by the first-step regression.

[9] Derivation from Hausman [1981].

a decreasing function in prices such that $a \leq 0$ and increasing in income if $b \geq 0$. The other condition that the indirect utility must satisfy is quasi concavity, which is equivalent to the Slutsky condition:

$$\frac{\partial h(p,u)}{\partial p} - \frac{\partial x(p,y)}{\partial p} = x \bullet \frac{\partial x(p,y)}{\partial y},$$

$$s_{11} = \frac{\partial h(p,u)}{\partial p} = x \bullet \frac{\partial x(p,y)}{\partial y} + \frac{\partial x(p,y)}{\partial p}$$

$$s_{11} = x(\frac{a}{p} + \frac{bx}{y}) \leq 0 \,. \tag{16}$$

The expenditure function is

$$e(p,\overline{u}) = \left[(1-b) \bullet (\overline{u} + e^{Z\gamma}) \bullet \frac{p^{1+a)}}{(1+a)} \right]^{1/(1-b)} \tag{17}$$

The compensating variation in terms of expenditure function given in equation (11) is

$$CV\,(p^0, p^1, y^0) = \left\{ (1-b) \bullet \left[\frac{e^{Z\gamma}}{1+a} \bullet (p^{1^{1+a}} - p^{0^{1+a}}) \right] + y^{0^{(1-b)}} \right\} - y^0$$

$$= \left\{ \frac{(1-b)}{(1+a)y^{0^b}} [p^1 x^1 (p^1, y^0) - p^0 x^0 (p^0, y^0)] + y^{0^{(1-b)}} \right\}^{1/(1-b)} - y^0 . \tag{18}$$

According to Hausman [1981], as long as the sign conditions are satisfied by the demand function, we can calculate the consumer's exact surplus, so that the compensating variation for a change in price from p^0 to p^1 using equation (18) is the exact calculation for the compensating variation of loglinear demand that we used in our analysis.[10]

[10] The CV computations assume all other goods as numeraire.

5. Descriptive measures

5.1. Family income and expenditure survey

Our data consist of a pooled cross-section of 2000 and 2003 Family Income and Expenditure Survey (FIES). The 2000 FIES contains 39,000 observations while that of 2003 has 41,000 observations. Our final sample, however, consists of 61,197 observations—households with indicated access to electricity and reported positive spending on electricity. FIES contains information about household total expenditure, income, total fuel spending per fuel group, household members, and dwelling characteristics, etc., which we used in our regression. However, it does not report the quantity of electricity consumed by the household. But this quantity can be calculated using the household expenditure on electricity divided by the price of electricity.

5.1.1. Regional reclassification

We have combined Regions 13 and 3 to enable our three-step model to work. This is to force probit to retain the observations in the NCR, which does not have fixed payment in its pricing schedule. The choice of Region 3 is natural because of its proximity to the NCR. The number of observations based on the new regional classification is given below:

Table 1. Regional classification

New regional classification	*Classification of households by electricity spending*		*Total*
	Below kink	*Above kink*	
1	121	3,585	3,706
2	176	2,567	2,743
4	206	9,829	10,035
5	153	2,876	3,029
6	184	3,916	4,100
7	137	3,568	3,705
8	189	2,630	2,819
9	117	1,800	1,917
10	131	2,778	2,909
11	128	2,888	3,016
12	96	2,521	2,617
14	116	2,157	2,273
15	175	1,076	1,251
16	314	1,979	2,293
3_13*	65	14,719	14,784
Total	**2,308**	**58,889**	**61,197**

*This is the combined regions 3 and 13 or Region 3 and the NCR.

5.1.2. Income categories

The income quartile is computed for the remaining sample based on the household's real total expenditure. This is done by calculating income quartile per year and then combining both years so that there is no need to readjust the expenditure/income to some base year. Table 2 below shows the number of observations per income quartile as well as the mean electricity expenditure (in Philippines peso) and consumption (in kilowatt-hour) per income group.

Table 2. Number of observations, mean electricity spending, and mean electricity consumption by income quartile

Income category	*Number of observations*			*Mean electricity expenditure (PhP)*			*Mean electricity consumption (kWh)*		
	All	*<kink*	*>kink*	*All*	*<kink*	*Test-Stat*	*All*	*<kink*	*<kink*
1st Quartile	15,301	1,790	13,511	1,396.40	395.51	1,529.03	398.58	111.65	436.59
2nd Quartile	15,298	406	14,892	2,658.90	410.01	2,720.24	724.85	111.38	741.58
3rd Quartile	15,300	94	15,206	4,748.40	396.64	4,775.30	1,217.15	108.48	1,224.00
4th Quartile	15,298	18	15,280	11,009.40	462.67	11,021.82	2,614.87	118.06	2,617.81
Total	**61,197**	**2,308**	**58,889**	**4,953.10**	**398.63**	**5,131.60**	**1,238.82**	**111.52**	**1,283.00**

5.2. Price of electricity

We obtained the prices of electricity in effect during the survey period from the Philippine National Electrification Administration (NEA) for all regions except the NCR. The price of electricity in the NCR came from the prevailing price of electricity charged by the Manila Electric Company (Meralco), the main distribution utility in Metro Manila. NEA also reports both the minimum consumption and amount charged by electric cooperatives together with the marginal price paid by households for succeeding consumption. The price of electricity varies with region. Households that enjoy low price of electricity are Regions 12, 11, 10, 9 and 16, while those in Regions 2, 5, 4, 14, 15 (Autonomous Region in Muslim Mindanao) and the NCR are paying the highest price for electricity.

Table 3. Persons in the sample working outside the family farm

Region	*Minimum payment*		*Minimum consumption*		*Rate above the minimum*	
	2003	*2000*	*2003*	*2000*	*2003*	*2000*
1	46.047	46.047	12.6667	12.6667	3.6363	3.6363
2	50.070	50.070	13.2857	13.2857	3.7872	3.7872
3	38.028	38.028	10.6923	10.6923	3.5642	3.5642
4	47.652	47.652	11.9286	11.9286	4.0956	4.0956
5	46.170	46.170	11.6364	11.6364	3.9569	3.9569
6	46.386	46.386	12.0000	12.0000	3.8606	3.8606
7	41.521	41.218	11.5000	11.5000	3.6938	3.6685
8	42.757	42.757	10.4545	10.4545	4.0758	4.0758
9	40.542	39.928	15.0000	15.0000	2.7027	2.6617
10	42.448	41.848	14.8750	14.8750	2.8462	2.8198
11	35.317	34.103	13.3333	13.3333	2.6252	2.5452
12	33.760	33.573	13.7500	13.7500	2.4553	2.4428
13	...	...	...	...	5.7453	4.8400
14	51.773	51.772	12.4000	12.4000	4.1292	4.2372
15	54.731	54.731	15.0000	15.0000	4.1058	4.1058
16	51.662	48.659	14.2857	13.5714	3.5145	3.4663

6. Estimation results

6.1. Demand for electricity

The results of the three-step methodology for all observations are given in Table 4. The coefficient of the price in the third step can be interpreted as the price elasticity of demand while the coefficient of the virtual income is the income elasticity. The elasticities show correct signs: the price elasticity is –0.86, and the income elasticity is 0.91.

The coefficients for the household-head characteristics are significant and showed correct signs as well. Additional household member increases the consumption of electricity, and the household head's age has positive impact on consumption as well. The year dummy is positive but not significant. This may be due to the fact there is not much difference between the prices in 2000 and 2003 for some regions in the Philippines.

The educational-attainment dummies also showed expected signs and significant coefficients—that is, the higher one's education, the higher the electricity consumption. From the data, it appears that highly educated people have either more appliances or more energy-consuming appliances.[11]

[11] See Appendix D: Other descriptive measures for the details of appliance ownership per educational attainment.

On the other hand, regional dummies all resulted in negative signs. This is expected, with the combined NCR and Region 3 as the base region. This may be because most households in this area are generally more affluent and/or have more energy-intensive appliances compared to those in any other region. The coefficient inverse mills ratio (*invmills*) and the residual (*uhat*) are also significant. For the residual, the significant t-statistics means that virtual income is indeed endogenous.

The model was used to estimate demand, including various dwelling characteristics, such as the structure of roofs and walls, but the change in coefficients is very minimal.[12]

We also estimate separate price and income elasticities per income category.[13] As in the previous regression using all observations, OLS gives consistently lower price elasticities per income category, but the income elasticities are almost similar to the results of the three-step. Table 6 shows that the lowest-income group has a relatively inelastic demand second only to the fourth-income quartile.[14] The reason for inelastic demand may be that households in the first quartile compared to other income groups have already very limited appliance ownership; as such even if the price of electricity increases, they no longer have enough freedom to adjust their consumption.[15] In addition, the first and fourth quartiles relatively have the highest income elasticity (0.501 and 0.767).

6.2. Welfare losses

We simulate the impact of a single price change—a 10 percent across-the-board increase in the price of electricity for all regions in the Philippines. This simulation exercise assumes that we have a linear budget set. The compensating variation is computed using the parameter estimates from demand using all observations (i.e., parameters in Table 4), which we will call parameter (a); and per quartile demand parameters (in Table 6 and detailed in Appendix D), which we will call parameter (b).

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[12] See Appendix B: Regression results of three-step methodology comparing runs with and without dwelling characteristics.

[13] See Appendix C for the detailed results of three-step regression per income quartile.

[14] Reiss and White [2002] found that the electricity consumption of the lowest income group has more elastic demand.

[15] See Appendix E: Other descriptive measures for the details of appliance ownership per income category.

Table 4. Regression results for all observation

*First step**			*Second step***			*Third step*		
Variables	*Coefficient*	*z-statistics*	*Variables*	*Coefficient*	*t-statistics*	*Variables*	*Coefficient*	*t-statistics*
fxpay	-0.007	-19.400	lntotexpc	1.000		lnprice	-0.864	-14.660
totmem	0.069	8.920	totmem	0.000	0.660	lnbudgetpc	0.906	122.800
age	0.013	10.790	age	0.000	-3.520	totmem	0.180	80.940
year2003	0.015	0.620	year2003	0.000	-26.050	age	0.006	20.580
primaryd	0.351	4.000	primaryd	0.000	-2.530	year2003	0.004	0.650
hschoold	0.732	8.120	hschoold	0.000	-2.650	primaryd	0.121	3.630
colleged	1.344	13.530	colleged	0.000	-2.780	hschoold	0.247	7.170
nregion01	0.218	2.160	nregion01	0.000	28.610	colleged	0.348	9.400
nregion02	0.193	1.790	nregion02	0.000	47.310	nregion01	-0.145	-7.660
nregion04	0.691	6.940	nregion04	0.000	-108.920	nregion02	-0.274	-12.060
nregion05	-0.117	-1.190	nregion05	0.000	-56.840	nregion04	0.014	0.900
nregion06	0.098	0.990	nregion06	0.000	-25.420	nregion05	-0.234	-9.920
nregion07	-0.260	-2.910	nregion07	0.000	62.980	nregion06	-0.265	-12.780
nregion08	-0.538	-5.980	nregion08	0.000	-53.680	nregion07	-0.243	-12.480
nregion09	-0.666	-7.180	nregion09	0.000	-7.030	nregion08	-0.311	-11.540
nregion010	-0.381	-4.140	nregion010	0.000	-16.250	nregion09	-0.246	-9.430
nregion011	-0.853	-9.610	nregion011	0.000	-59.740	nregion010	-0.333	-14.940
nregion012	-1.030	-11.930	nregion012	0.000	-35.790	nregion011	-0.323	-13.130
nregion014	0.319	2.750	nregion014	0.000	-52.830	nregion012	-0.326	-12.060
nregion015	0.342	2.490	nregion015	0.001	40.700	nregion014	-0.471	-17.280
nregion016	-0.236	-2.460	nregion016	0.000	-54.460	nregion015	-0.314	-10.170
_cons	3.863	20.490	_cons	0.000	1.960	nregion016	-0.292	-11.540
						invmills	0.044	4.490
						uhat	383.946	11.210
						_cons	-2.651	-25.460
Number of observations		*61,197*	*Number of observations*		*58,889*	*Number of observations*		*58,889*
Log pseudo likelihood		*-7408.94*	*F - statistics (21, 58867)*			*Number of censored obs.:*		*2,308*
Pseudo R - squared		*0.1660*	*R - squared*		*1.0000*	*F - statistics (24, 58864)*		*1775.67*
						R - squared		*0.5772*

*This is a probit equation for the probability of household spending above the kink using the variable ***fxpay*** as the excluded variable.

**Second step is regression of the virtual income by the real total expenditure. From this equation we predict the residual, which is used in the third step (the demand equation) as one of the regressors.

Note that the dependent variable in the 3rd step: log of electricity consumption in kWh

Table 5. Comparison of three-step and OLS demand estimation

Variable	*Three-step methodology*		*Ordinary least squares*	
	Coefficient	*t-statistics*	*Coefficient*	*t-statistics*
Lnprice	-0.864	-14.660	-0.647	-25.910
Lnbudgetpc	0.906	122.800	0.906	122.640
Totmem	0.180	80.940	0.183	86.410
Age	0.006	20.580	0.007	23.850
year2003	0.004	0.650	-0.008	-1.360
Primaryd	0.121	3.630	0.137	4.080
Hschoold	0.247	7.170	0.279	8.230
Colleged	0.348	9.400	0.407	11.710
nregion01	-0.145	-7.660	-0.171	-9.900
nregion02	-0.274	-12.060	-0.324	-17.610
nregion04	0.014	0.900	-0.015	-1.210
nregion05	-0.234	-9.920	-0.294	-16.590
nregion06	-0.265	-12.780	-0.311	-18.760
nregion07	-0.243	-12.480	-0.277	-16.290
nregion08	-0.311	-11.540	-0.383	-19.710
nregion09	-0.246	-9.430	-0.227	-8.800
nregion010	-0.333	-14.940	-0.319	-14.420
nregion011	-0.323	-13.130	-0.288	-12.400
nregion012	-0.326	-12.060	-0.278	-11.220
nregion014	-0.471	-17.280	-0.541	-26.650
nregion015	-0.314	-10.170	-0.392	-14.130
nregion016	-0.292	-11.540	-0.351	-16.880
Invmills	0.044	4.490	....	....
Uhat	383.946	11.210	....	....
_cons	-2.651	-25.460	-2.883	-34.190
Number of obs.:	*58,889*		*58,889*	
F-statistics:	*F(24, 58864) = 1775.67*		*F(22, 58866) = 1811.19*	
R-squared:	*0.5772*		*R-squared = 0.5761*	

Table 6. Elasticities per income quartile

Income quartile	*Price elasticity*		*Income elasticity*	
	3-Step	*OLS*	*3-Step*	*OLS*
1st Quartile	-0.960	-0.562	0.501	0.501
2nd Quartile	-1.117	-0.641	0.237	0.238
3rd Quartile	-0.999	-0.663	0.308	0.310
4th Quartile	-0.809	-0.779	0.767	0.749

In terms of total compensating variation, the estimated welfare loss increases as income increases. This is true using both parameters. However, there is a notable difference in mean compensating variation for the second and third quartiles: the compensating variation using the per quartile demand parameters is less than the compensating variation computed using the parameters for all observations.

Figure 6. Mean compensating variation: Comparing CV computed from (a) all observations and (b) per quartile parameters

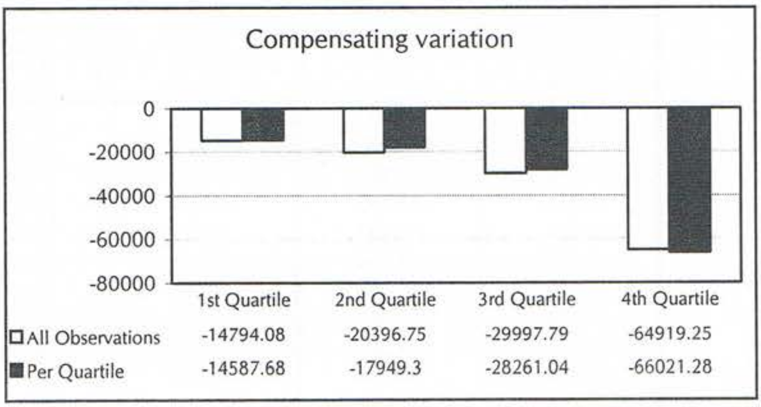


Figure 7. Mean total expenditure per capita

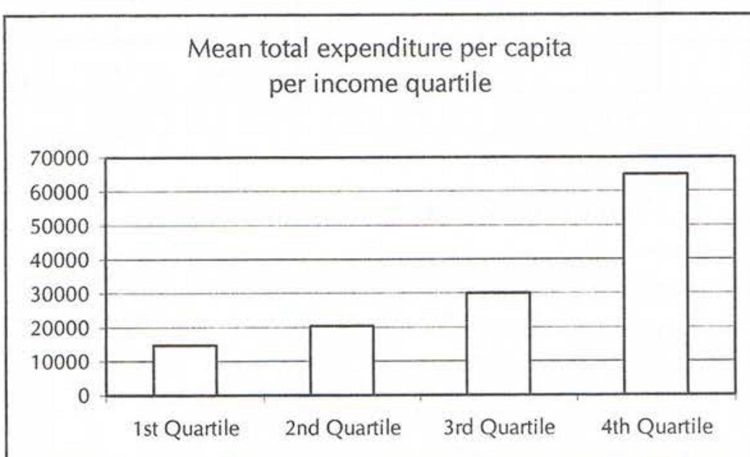


Figure 8. Mean percentage loss using parameter (a): parameters of demand estimated from all observations

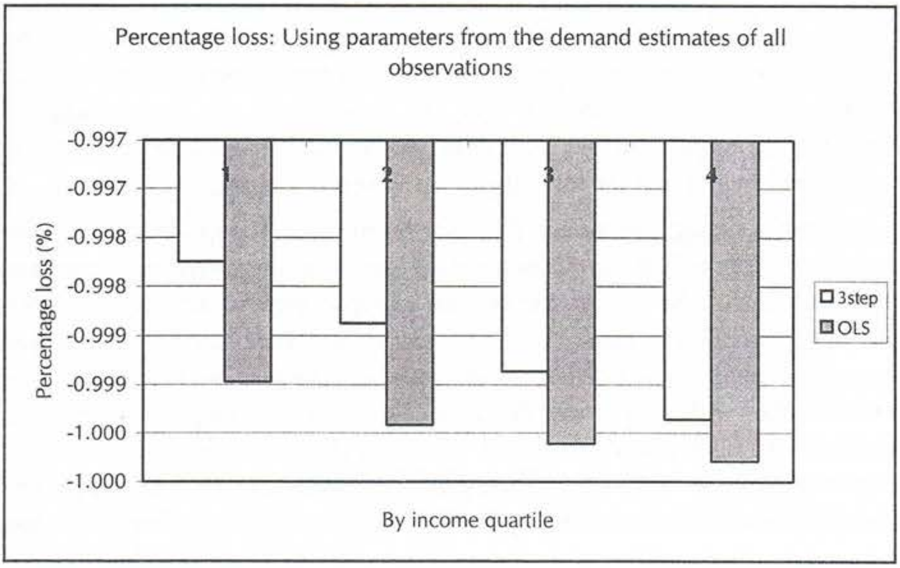
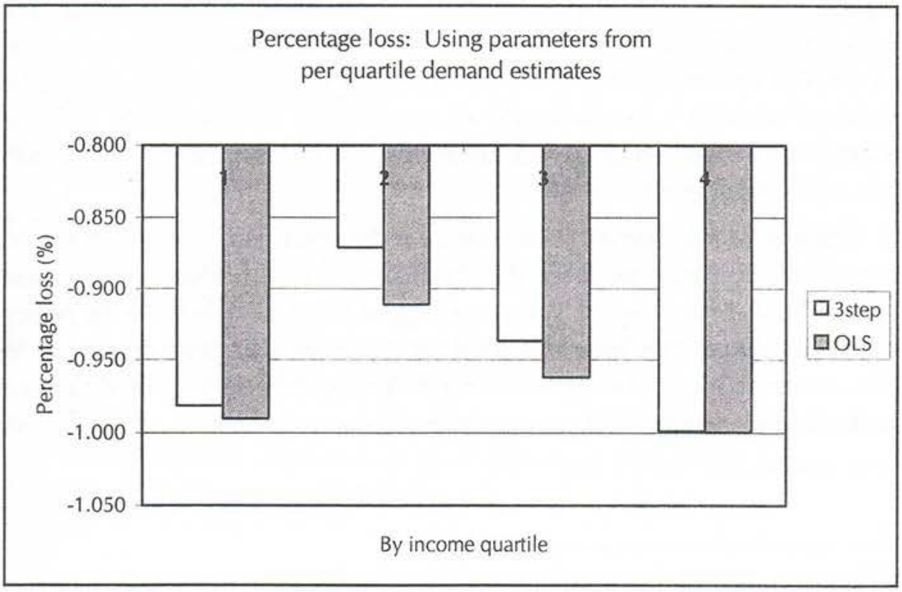


Figure 9. Mean percentage loss using the parameter (b): per quartile demand estimation



But it appears that using the compensating variation alone as a measure of welfare loss gives an incomplete picture of the distributional implications of a price increase. There remains the question of the burden of welfare loss in terms of its proportion to the total household expenditure. As such, we also compute the welfare impacts in terms of percentage loss[16] by dividing compensating variation with the total real expenditure per capita. Figure 8 shows that using parameter (a), our conclusion is unchanged—that is, welfare as measured by percentage loss strictly increases as income increases.

However, using parameter (b), the distributional implications change dramatically. Figure 9 shows the percentage loss increasing as income increases, which means that the loss of the poorest group is greatest among the lower-income groups. This is true for both the OLS and the three-step methodologies. This may imply that the poorest groups lose because they have extremely low income to start with, so that any price increase, which means higher expenditure, translates to a higher percentage loss. This may also imply that the electricity-price subsidies provided this income group will probably mask the impact of a price increase but will not change the real cause of higher welfare loss—low real income.

7. Conclusion

The residential demand curve is estimated with consideration for the difficulties posed by such estimation—the nonlinearity in the budget set caused by fixed payments. This paper has tried to address these issues by using a three-step methodology that deals with the nonrandom selection problem and the endogeneity of household budget used in demand estimation. The residential demand is computed for all observations and compared with the results of OLS. The results are not much different in terms of magnitude and signs of the coefficient.

While there is no explicit calculation for the precise impact of reform on the price of electricity, we made the simulation exercise based on an increase in price because its impact will probably be of utmost interest in policy discussions. As such we have simulated the impact of a 10-percent increase in price, assuming a linear budget set using the parameters of demand estimated for all observations and the parameters per income quartile.

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[16] Or simply, percentage loss is the proportion of welfare loss to real expenditure.

We find that the distributional implication of the price change will depend upon the choice of welfare measure as well as the demand parameters used. Generally, we find that using compensating variation alone, the loss increases as income group rises. However, distributional implications change when we use the parameters of per quartile demand and computing percentage loss instead: the loss of the income group is highest among the lower-income groups. An important policy implication of this finding is on lifeline subsidy implemented by the government, which gives preferential electricity tariffs to marginal consumers of electricity. It appears that the lifeline subsidy, while softening the impact of a price increase on the poorest group, may not be able to address the real cause of higher welfare loss—poverty.

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Appendices

A. Regression of dwelling characteristics with price of electricity

Variables	*Wall1*		*Wall2*		*Wall3*	
	Coefficient	*t-statistics*	*Coefficient*	*t-statistics*	*Coefficient*	*t-statistics*
pricepower	**0.009**	**1.400**	**-0.009**	**-1.560**	**0.001**	**0.430**
fxpay	0.000	-2.210	0.000	2.370	0.000	-0.350
year2003	0.001	0.420	0.001	0.450	-0.003	-3.030
nregion01	-0.060	-6.530	0.066	7.350	-0.006	-2.270
nregion02	-0.047	-4.180	0.056	5.180	-0.010	-3.060
nregion04	-0.013	-1.430	0.015	1.720	-0.002	-0.870
nregion05	-0.088	-8.410	0.093	9.100	-0.005	-1.630
nregion06	-0.231	-24.090	0.233	25.010	-0.003	-0.980
nregion07	-0.126	-14.970	0.130	15.910	-0.004	-1.890
nregion08	-0.117	-11.470	0.128	12.930	-0.011	-4.010
nregion09	-0.180	-15.800	0.185	16.630	-0.005	-1.410
nregion010	-0.068	-7.140	0.069	7.370	0.000	-0.150
nregion011	-0.112	-10.010	0.115	10.580	-0.003	-1.050
nregion012	-0.172	-13.980	0.177	14.700	-0.004	-1.190
nregion014	0.076	5.620	-0.070	-5.360	-0.005	-1.440
nregion015	-0.159	-10.000	0.156	10.060	0.003	0.720
nregion016	-0.075	-6.820	0.079	7.380	-0.004	-1.320
_cons	0.864	24.630	0.120	3.510	0.015	1.560
No. of observations	*61197*		*611197*		*61197*	
F - statistics	*(17,61179)=165.84*		*(17,61179)=191.93*		*(17,61179)=4.78*	
R - squared	*0.0441*		*0.0481*		*0.0013*	

Variables	*Roofs1*		*Roofs2*		*Roofs3*	
	Coefficient	*t-statistics*	*Coefficient*	*t-statistics*	*Coefficient*	*t-statistics*
pricepower	**-0.002**	**-0.370**	**0.000**	**0.030**	**0.002**	**1.320**
fxpay	0.000	-2.670	0.000	2.780	0.000	-0.140
year2003	0.016	5.000	-0.013	-4.320	-0.003	-3.020
nregion01	0.005	0.580	0.003	0.420	-0.008	-3.750
nregion02	0.011	1.030	-0.002	-0.210	-0.009	-3.140
nregion04	0.005	0.630	-0.002	-0.210	-0.004	-1.640
nregion05	-0.185	-19.120	0.192	20.340	-0.007	-2.650
nregion06	-0.138	-15.490	0.143	16.500	-0.005	-2.240
nregion07	-0.067	-8.570	0.069	9.070	-0.002	-1.010
nregion08	-0.158	-16.760	0.169	18.430	-0.011	-4.540
nregion09	-0.204	-19.310	0.210	20.440	-0.006	-2.280
nregion010	-0.073	-8.170	0.075	8.700	-0.003	-1.160
nregion011	-0.050	-4.850	0.054	5.340	-0.004	-1.330
nregion012	-0.120	-10.470	0.124	11.110	-0.004	-1.360
nregion014	0.086	6.910	-0.077	-6.350	-0.009	-2.750
nregion015	-0.119	-8.060	0.121	8.450	-0.003	-0.680
nregion016	-0.213	-20.980	0.222	22.430	-0.009	-3.330
_cons	0.924	28.430	0.068	2.150	0.007	0.870
No. of observations	*61197*		*611197*		*61197*	
F - statistics	*(17,61179)=186.64*		*(17,61179)=207.83*		*(17,61179)=8.18*	
R - squared	*0.0493*		*0.0546*		*0.0023*	

Note: Regressing the wall types on the price of electricity, fixed payment and regional and year dummies resulted in insignificant coefficients. The dwelling types are (a) ***wall1/roofs1***, made of up strong or mixed but strong materials; (b) ***wall2/roofs2***, made up of light or mixed but light materials; and (c) ***wall3/roof3***, made up of makeshift materials or mixed but salvaged materials.

B. Comparison: Results of three-step with and without dwelling characteristics for all observations

Variables	*Without dwelling*		*With dwelling*	
	Coefficient	*t-statistics*	*Coefficient*	*t-statistics*
lnprice	-0.864	-14.660	-0.875	-14.960
lnbudgetpc	0.906	122.800	0.875	115.260
totmem	0.180	80.940	0.176	79.560
age	0.006	20.580	0.006	20.320
year2003	0.004	0.650	0.005	0.800
primaryd	0.121	3.630	0.120	3.600
hschoold	0.247	7.170	0.239	6.990
colleged	0.348	9.400	0.340	9.390
nregion01	-0.145	-7.660	-0.137	-7.430
nregion02	-0.274	-12.060	-0.270	-12.190
nregion04	0.014	0.900	0.019	1.200
nregion05	-0.234	-9.920	-0.224	-9.880
nregion06	-0.265	-12.780	-0.225	-11.510
nregion07	-0.243	-12.480	-0.224	-11.820
nregion08	-0.311	-11.540	-0.302	-11.630
nregion09	-0.246	-9.430	-0.226	-8.570
nregion010	-0.333	-14.940	-0.337	-15.240
nregion011	-0.323	-13.130	-0.314	-12.720
nregion012	-0.326	-12.060	-0.302	-10.980
nregion014	-0.471	-17.280	-0.476	-17.320
nregion015	-0.314	-10.170	-0.303	-9.980
nregion016	-0.292	-11.540	-0.291	-11.870
wall1	....	....	0.165	3.010
wall2	....	....	-0.017	-0.310
roofs1	....	....	-0.051	-0.850
roofs2	....	....	-0.038	-0.630
invmills	0.044	4.490	0.046	4.900
uhat	383.946	11.210	389.335	11.290
_cons	-2.651	-25.460	-2.386	-21.040
No. of observations	*58889*		*58889*	
F - statistics	*F(24, 58864) = 1775.67*		*F(28, 58860) = 1583.23*	
R - squared	*0.5772*		*0.5830*	

Note: The three-step model was also estimated when some dwelling characteristics were included in the regression. But the results are not much different from the results reported in Table 4.

C. Per quartile regression: Three-step estimation results

C.1 1st Quartile

First step*			Second step**			Third step		
Variables	*Coefficient*	*z-statistics*	*Variables*	*Coefficient*	*t-statistics*	*Variables*	*Coefficient*	*t-statistics*
fxpay	-0.007	-23.190	lntotexpc	1.000		lnprice	-0.960	-2.970
totmem	0.011	1.060	totmem	0.000	-1.230	lnbudgetpc	0.501	20.290
age	0.008	5.830	age	0.000	-2.210	totmem	0.106	17.910
year2003	-0.082	-2.630	year2003	0.000	-13.470	age	0.004	5.790
primaryd	0.323	3.220	primaryd	0.000	-0.500	year2003	0.019	1.420
hschoold	0.523	4.960	hschoold	0.000	-0.740	primaryd	0.159	3.870
colleged	0.747	5.890	colleged	0.000	-1.120	hschoold	0.219	4.580
nregion01	0.528	3.720	nregion01	0.000	13.590	colleged	0.266	4.320
nregion02	0.415	2.820	nregion02	0.000	37.910	nregion01	0.019	0.480
nregion04	0.707	5.020	nregion04	0.000	-76.720	nregion02	-0.048	-0.820
nregion05	0.184	1.330	nregion05	0.000	-57.170	nregion04	0.075	1.520
nregion06	0.291	2.110	nregion06	0.000	-29.540	nregion05	-0.069	-1.030
nregion07	-0.047	-0.370	nregion07	0.000	61.570	nregion06	-0.119	-2.100
nregion08	-0.198	-1.560	nregion08	0.000	-55.610	nregion07	-0.059	-1.320
nregion09	-0.337	-2.600	nregion09	0.000	-12.610	nregion08	-0.175	-2.210
nregion010	-0.070	-0.550	nregion010	0.000	-18.920	nregion09	-0.090	-1.080
nregion011	-0.658	-5.420	nregion011	0.000	-57.780	nregion010	-0.186	-2.650
nregion012	-0.687	-5.910	nregion012	0.000	-37.920	nregion011	-0.176	-1.830
nregion014	0.453	2.680	nregion014	0.000	-47.590	nregion012	-0.217	-1.880
nregion015	0.737	4.190	nregion015	0.002	51.800	nregion014	-0.197	-2.230
nregion016	0.075	0.540	nregion016	0.000	-62.610	nregion015	0.145	1.770
_cons	3.812	23.060	_cons	0.000	2.100	nregion016	-0.014	-0.240
						invmills	0.080	1.620
No. of observations		*15,301*	*No. of observations*		*13,511*	uhat	82.618	1.620
Log pseudo likelihood		*-5309.58*	*F - statistics (21, 13489)*			_cons	1.505	3.300
Pseudo R-squared		*0.0503*	*R - squared*		*1.0000*			
						Number of observations		*13511*
						No. of censored observations		*1,790*
						F - statistics (24,13486)		*42.23*
						R - squared		*0.1345*

C.2 2nd Quartile

*First step**			*Second step***			*Third step*		
Variables	*Coefficient*	*z-statistics*	*Variables*	*Coefficient*	*t-statistics*	*Variables*	*Coefficient*	*t-statistics*
fxpay	-0.012	-2.380	lntotexpc	1.000		lnprice	-1.117	-6.890
totmem	-0.022	-1.310	totmem	0.000	-1.650	lnbudgetpc	0.237	5.480
age	0.013	4.480	age	0.000	0.800	totmem	0.019	2.070
year2003	0.028	0.490	year2003	0.000	-31.460	age	0.007	11.260
primaryd	-0.059	-0.230	primaryd	0.000	0.260	year2003	-0.006	-0.520
hschoold	0.103	0.400	hschoold	0.000	0.140	primaryd	0.089	1.310
colleged	0.399	1.450	colleged	0.000	0.100	hschoold	0.216	3.160
nregion01	0.756	1.470	nregion01	0.000	36.380	colleged	0.317	4.510
nregion02	1.072	1.430	nregion02	0.000	94.640	nregion01	-0.072	-2.010
nregion04	1.267	2.090	nregion04	0.000	-237.030	nregion02	-0.224	-5.450
nregion05	0.528	1.010	nregion05	0.000	-132.690	nregion04	0.052	1.530
nregion06	0.972	1.800	nregion06	0.000	-68.230	nregion05	-0.107	-2.410
nregion07	0.247	0.900	nregion07	0.000	162.890	nregion06	-0.203	-5.620
nregion08	0.034	0.100	nregion08	0.000	-127.950	nregion07	-0.199	-5.690
nregion09	-0.193	-0.800	nregion09	0.000	-33.230	nregion08	-0.146	-2.740
nregion010	0.390	1.210	nregion010	0.000	-47.780	nregion09	-0.286	-4.680
nregion011	-0.777	-2.710	nregion011	0.000	-148.880	nregion010	-0.290	-5.480
nregion012	-1.031	-3.050	nregion012	0.000	-95.280	nregion011	-0.289	-4.760
nregion014	0.997	1.180	nregion014	0.000	-130.760	nregion012	-0.349	-5.040
nregion015	1.518	1.470	nregion015	0.001	88.940	nregion014	-0.318	-5.680
nregion016	0.969	1.230	nregion016	0.000	-134.480	nregion015	-0.180	-3.180
_cons	7.373	3.140	_cons	0.000	4.650	nregion016	-0.222	-5.370
						invmills	0.053	3.570
No. of observations		*15,298*	*No. of observations*		*13,511*	uhat	379.026	1.380
Log pseudo likelihood		*-1494.35*	*F - statistics (21, 13489)*			_cons	4.912	9.700
Pseudo R-squared		*0.0913*	*R - squared*		*1.0000*			
						Number of observations		*13511*
						No. of censored observations		*1,790*
						F - statistics (24,13486)		*42.23*
						R - squared		*0.1345*

C.3 3rd Quartile

First step*

Variables	Coefficient	z-statistics
fxpay	-0.01	-1.40
totmem	-0.05	-1.83
age	0.01	1.82
year2003	0.09	0.97
primaryd	0.11	0.29
hschoold	0.46	1.15
colleged	0.54	1.32
nregion01	0.32	0.59
nregion02	0.48	0.62
nregion04	0.73	1.14
nregion05	0.23	0.39
nregion06	0.73	1.13
nregion07	0.12	0.34
nregion08	-0.03	-0.08
nregion09	-0.05	-0.11
nregion010	0.19	0.44
nregion011	-0.27	-0.58
nregion012	-0.96	-2.47
nregion014	0.43	0.50
nregion015	0.11	0.10
nregion016	0.32	0.42
_cons	5.41	2.29
No. of observations		*15,300*
Log pseudo likelihood		*-403.62*
Pseudo R - squared		*0.1368*

Second step**

Variables	Coefficient	t-statistics
lntotexpc	1.000	.
totmem	0.000	2.660
age	0.000	1.560
year2003	0.000	-31.380
primaryd	0.000	0.630
hschoold	0.000	0.600
colleged	0.000	0.730
nregion01	0.000	49.090
nregion02	0.000	90.660
nregion04	0.000	-248.680
nregion05	0.000	-124.630
nregion06	0.000	-72.990
nregion07	0.000	140.260
nregion08	0.000	-122.500
nregion09	0.000	-30.070
nregion010	0.000	-49.360
nregion011	0.000	-142.220
nregion012	0.000	-94.690
nregion014	0.000	-124.900
nregion015	0.001	69.740
nregion016	0.000	-106.700
_cons	0.000	-0.510
No. of observations		*15206*
F - statistics (21, 15184)		
R - squared		*1.0000*

Third step

Variables	Coefficient	t-statistics
lnprice	-0.999	-8.460
lnbudgetpc	0.308	7.380
totmem	0.051	5.990
age	0.009	13.860
year2003	0.000	-0.010
primaryd	0.048	0.560
hschoold	0.183	2.100
colleged	0.280	3.180
nregion01	-0.114	-3.270
nregion02	-0.289	-6.350
nregion04	0.031	1.060
nregion05	-0.207	-4.520
nregion06	-0.284	-7.520
nregion07	-0.279	-7.330
nregion08	-0.264	-5.020
nregion09	-0.280	-4.960
nregion010	-0.413	-8.680
nregion011	-0.415	-8.190
nregion012	-0.354	-6.710
nregion014	-0.404	-7.650
nregion015	-0.475	-6.420
nregion016	-0.396	-8.270
invmills	0.068	3.300
uhat	1536.016	2.810
_cons	4.187	8.760
Number of observations		*15206*
No. of censored observations		*94*
F - statistics (24, 15181)		*50.13*
R - squared		*0.1341*

C.4 4th Quartile

*First step**			*Second step***			*Third step*		
Variables	*Coefficient*	*z-statistics*	*Variables*	*Coefficient*	*t-statistics*	*Variables*	*Coefficient*	*t-statistics*
fxpay	0.004	0.240	lntotexpc	1.000		lnprice	-0.809	-8.610
totmem	0.002	0.030	totmem	0.000	6.830	lnbudgetpc	0.767	38.520
age	0.017	4.730	age	0.000	0.330	totmem	0.151	29.600
year2003	0.232	1.210	year2003	0.000	-23.330	age	0.007	8.530
primaryd	-3.972	-2.180	primaryd	0.000	0.960	year2003	0.059	2.920
hschoold	-3.571	-1.950	hschoold	0.000	1.090	primaryd	0.298	1.450
colleged	-2.807	-1.460	colleged	0.000	1.150	hschoold	0.450	2.270
nregion01	....	....	nregion01	0.000	30.320	colleged	0.587	3.170
nregion02	-6.913	-0.690	nregion02	0.000	37.060	nregion01	....	....
nregion04	-5.570	-0.580	nregion04	0.000	-135.330	nregion02	-0.507	-2.730
nregion05	....	....	nregion05	0.000	-75.390	nregion04	-0.101	-0.720
nregion06	-6.281	-0.670	nregion06	0.000	-51.890	nregion05	....	....
nregion07	-5.933	-0.710	nregion07	0.000	60.250	nregion06	-0.362	-2.170
nregion08	....	....	nregion08	0.000	-60.150	nregion07	-0.430	-2.550
nregion09	....	....	nregion09	0.000	-13.710	nregion08	....	....
nregion010	....	....	nregion010	0.000	-35.020	nregion09	....	....
Nregion011	-3.996	-0.540	nregion011	0.000	-62.880	nregion010	....	....
nregion012	....	....	nregion012	0.000	-62.270	nregion011	-0.543	-3.600
nregion014	-6.812	-0.660	nregion014	0.000	-68.050	nregion012	....	....
nregion015	-5.176	-0.470	nregion015	0.000	31.780	nregion014	-0.759	-4.400
nregion016	-6.910	-0.680	nregion016	0.000	-52.450	nregion015	-1.097	-7.590
_cons	9.251		_cons	0.000	-4.950	nregion016	-0.673	-3.490
						invmills	-0.010	-0.310
						uhat	472.645	0.610
						_cons	-1.003	-1.850
No. of observations		*12,565*	*No. of observations*		*15,280*	*Number of observations*		*12,547*
Log pseudo likelihood		*-1494.35*	*F-statistics (21, 15258)*			*No. of censored observations*		*18*
Pseudo R - squared		*0.0913*	*R - squared*		*1.0000*	*No. of dropped observations*		*2,733*
No. of dropped observations due to collinearity.		*2,733*				*F - statistics (18, 12528)*		*182.49*
						R - squared		*0.3789*

D. Other descriptive measures

D.1 Educational attainment and appliance ownership: All observations

Educational attainment	*Appliance group*				*Total*
	No other appliances	*Entertainment appliances*	*Refrigeration appliances*	*Cooling appliances*	
No grade completed	190	732	213	24	1,159
Completed elementary (or had some elementary)	1,859	12,678	6,230	564	21,331
Completed high school (or had some high school)	1,145	10,274	9,521	926	21,866
Attended college or until graduate school	252	3,618	10,122	2,849	16,841
Total	**3,446**	**27,302**	**26,086**	**4,363**	**61,197**

Note: Appliance categories came from Danao [2001]. It is assumed that cooling appliances are more energy intensive among the appliance groups. This table shows that those who attended college have more energy-intensive appliance than those who did not. The computed correlation between appliance ownership and educational attainment is 0.3380.

D.2 Appliance ownership and income quartile: All observations that includes household spending below the kink

Income quartile	*Appliance group*				*Total*
	No other appliances	*Entertainment appliances*	*Refrigeration appliances*	*Cooling appliances*	
1st Quartile	2,413	10,692	2,060	136	15,301
2nd Quartile	798	9,358	4,800	342	15,298
3rd Quartile	196	5,760	8,719	625	15,300
4th Quartile	39	1,492	10,507	3,260	15,298
Total	**3,446**	**27,302**	**26,086**	**4,363**	**61,197**

D.3 Appliance ownership and income quartile: Only for households that spend above the kink

Income quartile	*Appliance group*				*Total*
	No other appliances	*Entertainment appliances*	*Refrigeration appliances*	*Cooling appliances*	
1st Quartile	1,816	9,533	2,027	135	13,511
2nd Quartile	696	9,077	4,784	335	14,892
3rd Quartile	182	5,690	8,710	624	15,206
4th Quartile	36	1,483	10,501	3,260	15,280
Total	**2,730**	**25,783**	**26,022**	**4,354**	**58,889**

Note: The appliance categories came from Danao [2001]. Higher income households own more energy-intensive appliances than the lower-income categories, i.e., cooling appliance in the fourth income quartile is 3,260 compared to 135 in the first income quartile.