Price elasticity of Electricity: The case of Urban Maharashtra

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ABSTRACT

With demand exceeding supply, severe peak and energy shortages continue to plague the sector. The case for tariff reform in India is thus clear. There is, however, a need to estimate the impact of tariff revisions on electricity consumption before any such revisions could be implemented. The effects of any price revisions on consumption will depend on the price elasticity of demand for electricity. Our study uses a single equation approach to modelling the residential demand for electricity in four different quarters i.e. July-September, October-December, January-March and April-June. Our model takes care to incorporate not only the conventional socio-economic factors but also demographic and meteorological factors when estimating electricity demand. Our results suggest that the idea of subsidizing the poor in some way other than with electricity deserves attention.

1. Introduction

In the past, several electricity demand studies have been published for India based on aggregate macro data at the country or sub-national / state level. As we all know the underlying theory of consumer demand is based on the behaviour of individual agents; the use of micro data, which reflects individual and household behaviour, more closely, can shed greater light on the nature of consumer responses.

Section1 is the introduction, section 2 deals with the section on data, wherein we primarily discuss the data that we have accessed from the survey on household consumer expenditure and employment-unemployment, survey Round 55, for the year 1999–2000, from the National Sample Survey Organization (NSSO, (2002)) conducted by the Ministry of Statistics and Programme Implementation, Government of India.

In section 3, we postulate that the demand for electricity as a function of the price of electricity, the prices of alternate fuels, income and some demographic variables. The single most important economic variable that is assumed to determine household electricity demand is the total household expenditure or income.

Section 3.2 looks at various meteorological factors such as Temperature, Relative Humidity. A Heat Index which is computed using these two is used as an explanatory variable in the model for computing the price and income elasticities. Section 4 looks at the model that will be used in the calculation of price, income elasticities, into 4 quarters for the period for which the data was collected, namely from July-September 1999, October-December 1999, January-March 2000 and April-June 2000. This is to find out whether there is a significant difference in the price and income elasticities over various time periods. Section 5 looks at the interpretation of the results and the elasticities.

2. Source of Data:

With demand exceeding supply, severe peak and energy shortages continue to plague the sector. The case for tariff reform in India is thus clear. There is, however, a need to estimate the impact of tariff revisions on electricity consumption before any such revisions could be implemented. The effects of any price revisions on consumption will depend on the price elasticity of demand for electricity. Moreover, information regarding the income elasticity of demand for electricity is of importance, especially in the case of a rapidly developing country like India where one can expect to see large increases in the income of households in coming years. In the past, electricity demand studies for India published in international journals have been based on aggregate macro data at the country or sub-national/ state level (see for instance Bose and Shukla (1999), Sengupta (1993) and Roy (1992)).

Some authors have recently shown that the use of micro-level data, which reflects individual and household behaviour more closely, can add detail to an understanding of the nature of consumer responses (see for instance Nesbakken (1999)). Microeconomic approaches to energy and electricity demand modelling also enable an analysis across different heterogeneous household groups and allow for the incorporation of a wide variety of household characteristics within the estimated equations. In other words, the use of micro-level data permits more extensive examination of variation in electricity consumption across demographic and geographic subgroups (Filippini 1999).

The household micro data used in this study are provided by the survey on household consumer expenditure and employment-unemployment, survey Round 55, for the year 1999–2000, from the National Sample Survey Organization (NSSO, (2002)), Ministry of Statistics and Programme Implementation, Government of India. This survey on household consumer expenditure and employment-unemployment is the sixth quinquennial surveys in the series, the last one being conducted in the 50th round (1993-94) of National Sample Survey (NSS). The survey covers the whole of the Indian Union except some of the areas of (i) Ladakh & Kargil districts of Jammu & Kashmir, (ii) interior villages of Nagaland & (iii) villages of Andaman & Nicobar Islands remaining inaccessible throughout the year. The fieldwork of 55th round of NSS is from 1st July, 1999 to 30th June, 2000. The survey period of this round is divided into four sub-rounds, each with duration of three months. The 1st sub-round period is from July to September 1999, 2nd sub-round period is from October to December 1999 and so on for urban Maharashtra, as our model also tries to look at quarter-wise/season-wise consumption of electricity.

3. Demand for electricity

Parametric econometric models of energy demand are commonly used to predict the future energy needs under alternative economic and policy scenarios. Elasticity estimates from such models are used to analyze how changes in energy prices, tax changes, income, weather and other factors might affect the demand for various energy resources. Many econometric studies of residential electricity demand have been conducted over the years, particularly during the 1970s and early 1980s when energy prices were rising rapidly and concerns about energy conservation increased. Recently, deregulation, record cold winter temperatures, unstable oil prices, and continuing global warming concerns have rekindled interest in understanding the demand for electricity, particularly in predicting the impact of price changes on consumption. Given the variety of energy sources used to generate electricity, understanding consumers' responsiveness to electricity price changes can help municipalities, utility companies / boards, and policy makers predict future energy needs and design pricing and taxation policies.

Many models of electricity demand have been estimated over the years in an effort to better understand the market. These models have varied in numerous ways, using different functional forms and estimation techniques, as well as covering different time periods and different parts of the world. One goal of each of these models was to estimate the residential consumers price and income elasticities of demand, but the broad spectrum of estimates can create confusion without more detail about the differences in data and analysis techniques utilized. For example, price elasticities reported in the literature range from 0.076 to -2.01 for the short run and -0.07 to -2.5 for the long run (Espey, 2004).

The literature on electricity demand estimation for the residential sector in India that makes use of micro data is scanty. To our knowledge the only published study is the one that estimates the short-term price and income elasticity of residential electricity demand using household survey data for the city of Mumbai (Tiwari, (2000)) and the other is by Massimo (2004) which looks at the seasonal price and income elasticities of electricity demand in the residential sector of all urban areas of India. There are very few studies from other developing countries as well that estimate electricity demand by making use of micro household data. Jung, (1993) is one example, which presents results from the estimation of an ordered logit model making use of micro census data from Korea.

The residential demand for electricity is a demand derived from the demand for a well-lit house, cooked food, hot water, etc., and can be specified using the basic framework of household production theory. According to this theory, households purchase ‘‘goods’’ on the market which serve as inputs that are used in production processes, to produce the ‘‘commodities’’ which appear as arguments in the household’s utility function. In our specific case, a household combines electricity and capital equipment to produce a composite energy commodity.

We postulate that the demand for electricity depends on the price of electricity, the prices of alternate fuels, income and some demographic variables. The single most important economic variable that is assumed to determine household electricity demand is the total household expenditure or income. The price variables included in the estimated model are the average price for the household. In addition to including average price of electricity, since electricity consumption is likely to be sensitive towards prices of supplementary or alternate fuels, we also include the average price of kerosene and liquid petroleum gas in the estimation of the demand functions. These are also included in the model in order to test the hypothesis of whether these fuels are in anyway complimentary or substitutes to electricity.

In addition to these variables we have included demographic variables such as household members living in the household, age of the head of the household, household type. Most commonly, electricity demand has been estimated using a double-log static model. Our study utilizes analysis to summarize the electricity demand research and determine if there are factors that systematically influence estimates of price and income elasticities.

Also, we will be considering a term called as Heat Index, which is not used much in India, but used more often in United States of America (USA). Heat index or HI is sometimes referred to as the 'Apparent Temperature'. The HI, given in degrees F, is a measure of how hot it feels when relative humidity (RH) is added to the actual air temperature.

3.1 Demand Specification

Price elasticities of electricity demand in the residential sector of all urban areas of Maharashtra are estimated using disaggregate household level survey data. Following Massimo, (1999), we econometrically estimate electricity demand functions for urban Indian households using household data on total household expenditure (as a proxy for income), monetary expenditure on electricity and physical quantity of electricity consumed, average price of electricity, socio-economic dummy variables (such as household size, age of the head of the household) and key climatic factors such as temperature and relative humidity. The objective of undertaking such estimation is to contribute to an understanding of the key factors that influence electricity demand at the household level in urban Maharashtra. After finding out the elasticities, they are used in determining tariffs for different consumer strata, for example, for consumers who are below poverty line, above poverty line and for consumers whose consumption is more than the average per capita consumption.

The functional form suited for estimating household electricity demand, which is explained in section 4 is of the double logarithmic or log-log form. Therefore, the dependent variables and the independent variables both are expressed in terms of their logarithmic values (except for the dummy variables). Now we will list out the dependent variable and the independent variables, which we will be explained one by one, wherein 'i' i.e. LnQuaEle is the dependent variable and the others are the independent variables.

i. **Qele:**

   Qele is the dependent variable and is the quantitiy of electricity consumed (kWh) by a household during the last thirty days.

ii. **Hinc:**

   The total household expenditure or income of the household is the single most important economic variable that is assumed to determine household electricity demand. In order to gauge this in our model we will be taking the logarithm of household data on total household expenditure (as a proxy for income).

iii. **Pele:**

Prices are determined from the sample data as unit values, or in other words, monetary expenditures divided by physical quantities of consumption. The information for a single household is gathered only for one month. Thus, the households in the four quarters datasets are not the same. The price variables included in the estimated model are the average price for the household which is arrived by dividing the monthly expenditure on electricity by the number of units consumed.

iv. **Plpg:**

As electricity consumption is likely to be sensitive towards prices of supplementary or alternate fuels, we also include the average price of liquefied petroleum gas (LPG) in the estimation of the demand functions. The use of these alternative fuels may be for heating water, cooking or lighting.

v. **Pker:**

As explained earlier in case of LPG, electricity consumption is likely to be sensitive towards prices of supplementary or alternate fuel, we also include the average price of kerosene in the estimation of the demand functions. In case of kerosene we have taken both, the one available on Public Distribution System (PDS) and second is the one made available from other sources.

vi. **HI:**

Heat index or HI is sometimes referred to as the "apparent Temperature". The HI, given in degrees F, is a measure of how hot it feels when relative humidity (RH) is added to the actual air temperature. We will explain HI in detail in section 3.2.

vii. **DSclgr:**

In the NSSO data on consumer expenditure there is a variable called as social group, which, gives information whether the family belongs to the backward classes i.e. scheduled caste, scheduled tribes and other backward class. We want to find out whether there is any impact on electricity consumption if a family belongs to the backward classes. If the results are significant, then the government can extend some sort of concessional tariffs to the people from the backward classes. A dummy variable for the people belonging to the backward classes is included into the model.

viii. DHtype:

The **household type** code based on the means of livelihood of a household will be decided on the basis of the source of the household's income during the 365 days preceding the date of survey. For the urban areas, the selected household type codes are as follows:

i. self-employed – 1,
ii. regular wage / salary earning – 2,
iii. casual-labour -3,
iv. others-9

A dummy variable for the people who are self employed and regular wage / salary earning is included in the model in order to take into account the effect on electricity consumption of household.

ix. DHsze:

As we know, there is a strong relationship between the size of the household and the electricity consumption of the household. The average size of the households is 5. Therefore we have taken a dummy variable to control for the difference of the size of household (number of household members. The value of the dummy variable is equal to 1 in case the household has more than 5 (average size) members; otherwise is 0.

x. DSltg:

In the questionnaire given by the NSSO there is a question regarding the primary source of energy for lighting is kerosene-1, other oil-2, gas-3, candle-4, electricity-5, others-6, no lighting arrangement-7. So we have taken a dummy variable wherein we can say that if electricity is used as a major source of lighting then the dummy variable is equal to 1 otherwise 0.

xi. DAge:

The dummy variables are included in the model to control for differences in the age of the household head. The value of the dummy variable is equal to 1 in case the age of the head of the household is less than 45 years and otherwise is 0. We want to test whether the age of the person who heads the household plays any significant difference in electricity consumption.

xii. **DEdu:**

The dummy variable is included in the model to try to find out whether the level of education of the head of the household plays any significant difference in electricity consumption, as being educated and have attained a level of education, say a graduate, then he would be aware of the Demand Supply Management programs and thus reduce his consumption. The value of the dummy variable is equal to 1 in case the education attained is a bachelor's degree and 0 otherwise.

xiii. **DTinc:**

A dummy variable is included in the model to find out whether the head of the household earns his income from economic activity, other sources or whether there is no income.

3.2 Heat Index

The **heat index** (**HI**) or **humidex** is an index that combines air temperature and relative humidity to determine an apparent temperature — how hot it actually feels. The human body normally cools itself by perspiration, or sweating, in which the water in the sweat evaporates and carries heat away from the body. However, when the relative humidity is high, the evaporation rate of the water is reduced. This means heat is removed from the body at a lower rate, causing it to retain more heat than it would in dry air. At high temperatures, the level of relative humidity needed to make the Heat Index higher than the actual temperature is lower than at cooler temperatures. For example, at 80 °F (approximately 27 °C), the heat index will agree with the actual temperature if the relative humidity is 45%, but at 110 °F (roughly 43 °C), any relative humidity reading above 17% will make the Heat Index higher than 110. In general, any person should assume that there is a significant risk of heat illness if the Heat Index for the day is 80 or above.

Heat index is given by the following formula:

$$\left.\begin{aligned}
HI = {} & 16.923 + (1.85212x10^{-1} * T) + (5.37941 * RH) - (1.00254x10^{-1} * T * RH) + \\
& (9.41695x10^{-3} * T^3) + (7.28898x10^{-3} * RH^3) + (3.45372x10^{-4} * T^2 * RH^2) - \\
& (8.14971x10^{-4} * T * RH^2) + (1.02102x10^{-5} * T^2 * RH^2) - (3.8646x10^{-5} * T^3) + \\
& (2.91583x10^{-5} * RH^3) + (1.42721x10^{-6} * T^3 * RH) + (1.97483x10^{-7} * T * RH^3) - \\
& (2.18429x10^{-8} * T^3 * RH^2) + (8.43296x10^{-10} * T^2 * RH^3) - \\
& (4.81975x10^{-11} * T^3 * RH^3)
\end{aligned}\right\} \quad \mathbf{1}$$

where HI = *heat index*

T = *temperature* ^{o}F

RH = *relative humidity (%)*

A good example of the difference between heat index and true temperature would be comparing the climates of Mumbai, which has lower temperatures due to being closer to the Arabian Sea, yet the city has a higher heat index because of the humidity. Likewise, while Pune actually has hotter daytime temperatures, the city has a dry heat, so one doesn't feel as hot. Therefore, in our model we would be using HI instead of the cooling degree days (CDD) and heating degree days (HDD) (Valor 2001), which much more relevant than just temperatures or humidity. Therefore if the HI is going to be greater than 75 then people may feel discomfort and switch on fans, air-coolers and air-conditioners and *vice-versa.*

In our model we have taken the temperature (both high and low) and relative humidity on a daily basis for all the month of our selected period for 10 meteorological centres in Maharashtra, for which the data is taken from the NSSO CD, and used them to calculate the Heat Index. From this heat index if the value is greater than 75 (where the level of discomfort increases and people need to switch on the fan etc.) then we take the difference of the calculated value and 75 and add them for the given period otherwise the value is zero. The meteorological centres are Alibag (Raigad), Chikalthana (Aurangabad), Dahanu (Thana), Mahabaleshwar (Satara), Santacruz (Mumbai), Nasik (Nasik), Parbhani (Parbhani), Pune (Pune), Ratnagiri (Ratnagiri) and Sholapur (Sholapur). The names in parenthesis indicate the city for which the temperatures and relative humidity are used. All the data for the ten meteorological centres was sourced from the Office of Deputy Director General of Meteorology, Indian Meteorological Department, Mumbai.

As our equation is in double logarithmic or log-log form we take the logarithmic value of the summation of the heat index for the particular centre and then incorporate them into the socio-economic and demographic data that we have extracted.

4.0 Model Specification:

In our specific case, a household combines electricity and capital equipment to produce a composite energy commodity. The choice of variables depend on the determinants the residential electricity consumption demand. Other studies for example, Hirst et al. (1982), find that the demand for comfort is a major determinant of monthly consumption. Family size, income, and age of the house are some of the significant determinants of residential electricity consumption. In the short run, the intensity with which consumers use electric appliances depends on their income, housing unit structure, demographic characteristics, seasonal variations, weather, and electricity prices. The area covered in the present study is urban Maharashtra.

In this study, we use a single equation approach to modelling the residential demand for electricity in four different quarters i.e. July-September, October-December, January-March and April-June.

The key explanatory variables that influence household electricity demand were described above. The total household expenditure or income (**Hinc)** of the household is the single most important economic variable that is assumed to determine household electricity demand. The price variables included in the estimated model are the average price for the household. In addition to including average price of electricity (**Pele)**, since electricity consumption is likely to be sensitive towards prices of supplementary or alternate fuels, we also include the average price of kerosene (**Pker)** and LPG (**Plpg)** in the estimation of the demand functions. These are also included in the model in order to test the hypothesis of whether these fuels are in anyway complimentary or substitutes to electricity. Also we have included meteorological variable, heat index (HI), which may play a significant role in the demand for electricity.

A Dummy variable is included in the model to capture the discrete demographic variable for the age of the head of the household (**DAge)**. A dummy variable for the number of household members living in the household (**DHsze)** and the variable regarding the source of lighting (**DSltg)**, are included in the model in order to take into account the effect on electricity consumption.

We have also tried to find whether by taking dummies of various socio-economic variables, like dummy variable for the social group, for a family belonging to the backward class (**DSclgr**), dummy variable for the household type code based on the means of livelihood of a household (**DHtype**), dummy variable to find out whether the level of education of the head of the household (**DEdu**), dummy variable to find out whether the head of the household earns his income (**DTinc**) from economic activity, other sources or there is no income, have a significant role in the demand for electricity.

Estimation of demand function requires the specification of a functional form. While there is no clear consensus in the literature on the functional form that is best suited for estimating household electricity demand, most studies that have adopted a single equation specification have most often used a linear or logarithmic form. The double logarithmic or log-log form offers an appropriate functional form for answering questions about price and income elasticities. The major advantage, of course, is that the estimated coefficients amount to elasticities, which are, therefore, assumed to be constant.

The equation to be estimated for each season is

$$\left.\begin{aligned}\ln Qele = {} & \alpha_0 + \alpha_{Hinc}\ln Hinc + \alpha_{pele}\ln Pele + \alpha_{Plpg}\ln Plpg + \alpha_{P\ker}\ln P\ker + \alpha_{HI}\ln HI + \\ & \alpha_{DSc\lg r} DSc\lg r + \alpha_{DHtype} DHtype + \alpha_{DHsze} DHsze + \alpha_{DSltg} DSltg + \alpha_{DAge} DAge + \\ & \alpha_{DEdu} DEdu + \alpha_{DTinc} DTinc\end{aligned}\right\} \text{---- } \mathbf{2}$$

Since it is reasonable to assume that in a cross-section the observed difference in consumption of electricity represents not only variation in the utilisation rate but also stock adjustment, estimates based on cross-sectional data are conventionally interpreted as long-run elasticities.

5.0 Price elasticities: interpreting the results

Note that in interpreting the coefficients, price elasticity is specified in absolute value; thus a positive coefficient implies a more elastic demand, whereas a negative coefficient implies a less elastic demand. Since the demand for electricity is a derived demand, it is a function of the demand for services provided by electricity-using appliances. Bohi (1981) suggests that aggregated data tend to produce larger long-run price elasticities, whereas disaggregated data tend to produce slightly larger short-run price elasticities. As explained in the earlier chapter, the data that we have used is an aggregated data and thus the estimates of price elasticities are long-run elasticities.

Studies using non-U.S. data estimate the demand for electricity to be less elastic in the short run than those focusing on the U.S., but more elastic in the long run. This suggests that U.S. consumers may be quicker to respond to price changes, but less price sensitive overall in the long run than electricity consumers in other countries (Espey 2004). Results with respect to data years suggest that residential electricity demand was more inelastic in the short run during the energy crises of the 1970s, but not significantly different in the long run compared with either before or after that time. Over time, more and more appliances that consume electricity became a part of daily life, and consumers increasingly rely on appliances, reducing short-run price elasticity. On the other hand, dramatic improvements in the efficiency of many electric appliances has increased the options for consumers in the long run, perhaps offsetting this effect for long-run estimates.

The format of the section is that, initially we look at the results for the various quarters and for the whole year that are derived by using the data of the socio-economic data of the household expenditures survey Round 55, conducted by NSSO and the temperatures and relative humidity data, starting from the month of July 1999 to June 2000 (IMD 2005).

The estimated coefficients and their associated 't' values, obtained using an OLS approach, for the four seasonal household electricity demand models are presented in Table 1 The estimated functions are well behaved. Most of the parameter estimates are statistically significant. The goodness-of-fit (R^2) measure varies between 0.50 and 0.61. The explanatory power of the regressions is reasonably good given the individual cross-sectional data. Since electricity consumption and the continuous regressors are in logarithms, the coefficients are interpretable as demand elasticities. The percentage effects for the dummy variables can be derived by exponential transformation of the coefficients.

Even though we had selected the variables DSclgr, DHsze and DTinc were included in the initial model, the coefficients of these terms were not significant and hence were dropped from the model. Having a DSclgr to be insignificant means that there is no need to dole out special packages to the socially backward people, and which is a major policy implication for the pricing of power in a country, where nearly every action of policy makers is governed by some ulterior motives. Even though the household size that was taken in other studies on determination of elasticities were significant, in our study the dummy of the household size greater than five (median size) members turned out to be insignificant.

Table 1: Residential electricity demand estimates (t-ratios in parentheses)

	First Quarter	t Stat	Second Quarter	t Stat	Third Quarter	t Stat	Fourth Quarter	t Stat	July 1999-June 2000	t Stat
Const.	-2.00909**	(-2.35134)	-2.24207***	(-2.88280)	-2.14278**	(-2.39968)	-2.12403***	(-2.66562)	-1.55834***	(-5.25113)
lnHinc	0.83480***	(18.27556)	0.87613***	(17.99783)	0.88153***	(16.29458)	0.886970***	(17.90994)	0.81352***	(34.29087)
lnPele	-0.68839***	(-7.72867)	-0.58221***	(-5.72858)	-0.60711***	(-5.74662)	-0.54168***	(-5.94978)	-0.61030***	(-13.14660)
lnPker	-0.09161	(-1.15767)	-0.19086**	(-1.83972)	-0.11312	(-0.96900)	-0.13253	(-1.17237)	-0.11719**	(-2.37601)
lnPlpg	-0.50645**	(-2.13160)	-0.68253***	(-2.62499)	-0.65057**	(-2.24037)	-0.68700**	(-2.53829)	-0.69136***	(-9.35245)
lnHI	0.27687***	(6.96896)	0.31015***	(8.26179)	0.30594***	(7.23802)	0.26090***	(5.99252)	0.29721***	(14.82598)
Dhtype	-0.16063**	(-2.05072)	-0.22081***	(-2.61452)	-0.18197*	(-1.79066)	-0.17884*	(-1.79034)	-0.17155***	(-3.80347)
DSltg	-0.47088	(-1.54525)	-0.48607*	(-1.61021)	-0.51581*	(-1.68721)	-0.48157	(-1.60245)	-0.48981***	(-3.19368)
Dage	-0.18718***	(-4.10143)	-0.15972***	(-3.27748)	-0.18489***	(-3.36131)	-0.17622***	(-3.24743)	-0.18847***	(-7.41010)
Dedu	0.20211***	(4.17129)	0.16296***	(3.08589)	0.14044**	(2.42114)	0.11502**	(2.03074)	0.17963***	(6.68797)
Adj. R^2	0.53		0.56		0.58		0.61		0.56	
Obsns.	581		499		401		406		1887	

*, **, *** significantly different from zero at 90%, 95% and 99% confidence level

Note: *First Quarter: July-September 1999.*
Second Quarter: October-December 1999.
Third Quarter: January-March 2000.
Fourth Quarter: April-June 2000.

The price elasticity for electricity is significant in all the five models and carries the expected sign. This suggests that a 1% increase in the price index of electricity will (ceteris paribus) result in approximately a -0.69 decline during the first quarter, -0.58 during the second quarter, -0.61 during the third quarter, -0.54 during the fourth quarter in the consumption of electrciity. If we see the overall picture for the year a 1% increase in the price index of electricity will result in approximately -0.61% decline in household consumption of electricity. It can also be noted that the first quarter in Maharashtra corresponds to the rainy season, the second and third quarter corresponds to the winter with the exception of a month in between of October, where the heat is severe and the fourth quarter corresponds to the summer season. The number of households that we have considered are 581 households, 499 households, 401 households, 406 households and 1887 households for the 1^{st}, 2^{nd}, 3^{rd}, 4^{th} and for the whole year respectively.

Now if we look at the following table 2 it can be seen that the price-inelastic demand for electricity values are slightly lower than those reported in previous study by Tiwari (2000); higher than Fillipini M. (2004) and in between to the values of Bose and Shukla (1999). Therefore, from an energy point of view we can say that there is little room for discouraging residential electricity consumption, using price increases alone.

Finally, these results show that the electricity demand during the summer months is more price-inelastic than the electricity demand during the other seasons of the year. This difference can be explained by the fact that during the summer months, because of the high temperatures, the use of air conditioners and air ventilators is very intense and necessary. The demand for electricity is responsive in all models to the level of income (Y) with an income elasticity of approximately 0.81 to 0.88 across the three seasons. Since this elasticity is below unity, income growth apparently results in a less than proportional increase in electricity demand.

Table 2: Comparison of our estimates with other studies

Author	**Anay Vete**	**Fillipini M. S. Pachauri**	**Tiwari P.**	**Bose & Shukla***	**Sarkar and Kadekodi***
Region	**Urban Maha.**	**Urban India**	**Mumbai**	**19 States**	**India**
Year	(1999-2000)	(1993-94)	(1987-88)	(1997)	(1988)
Income elasticity	0.81 to 0.88	0.60 to 0.64	0.34	0.88	3.06
Price elasticity	-0.54 to -0.69	-0.29 to -0.51	-0.7	-0.65	N.A.

Note: ** references are from a detailed study carried out by the authors' (Bose and Awasthi, 1997)*

An examination of the coefficients on the price of alternate energy fuels that were included in the model provide cross-price elasticities and show that in general there is a complimentary relationship between electricity and LPG as the coefficient on price of LPG is negative and highly significant. However, the coefficient on kerosene price is found to be generally not significant over the various quarters, except for the second quarter. This result is surprising, as one would expect some degree of substitutability between kerosene and electricity, since the former is also used for lighting purposes.

Another important point to be noted from our study is the coefficient of heat index (which is a combination of temperatures and relative humidity) are very significant over all the quarters and thus can be one of the unexplored mechanisms, which can be used in pricing models. Also, when there is a slight tweaking of this heat index, there is a change in the coefficients of the income and price elasticities. There were also some surprising results, wherein education and age significantly influence the electricity consumption of urban Maharashtra households.

6. Conclusion

The electricity demand equation 2 is used for the various quarters, specified earlier for the calculation of elasticities and for the income/slab-wise calculation of elasticities, which can be used in counter-factual exercise for determining tariffs. Thus in this paper we have not only looked at socio-economic factors but also on demographic as well as to the meteorological factors in detail, which according to our hypothesis affects the electricity demand. The changeover from one tariff structure to another is always difficult, since customers who did well under the old tariff tend to regard themselves as having a vested interest in it. Hence, some importance is attached to the impact effect of the changeover and possible tactics for making it more acceptable. Also the conventional wisdom which requires a second look is the notion that poor electricity consumers should be subsidized. Poor people without electricity are worse off than poor people who have it. Hence, the idea of subsidizing the poor in some way other than with electricity deserves attention.

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