Study of Retail Electricity Consumers' Response and Perception Regarding Electricity Consumption

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Abstract

The price of retail electricity is restricted by regulations and have not increased at a same pace with the ever-growing demand of electricity. However, there exists a considerable amount of consumer surplus that can be harnessed by the electricity industry to improve the quality of service. In this paper we make an attempt to understand some characteristics of household electricity consumer demand. We performed an empirical, descriptive research and used inductive reasoning. Quantitative and qualitative primary data was collected through a questionnaire administered in Microsoft Excel format from 173 respondents. We propose a suitable present and future market segmentation of the retail electricity market based on several demographic and perceptual parameters respectively. We also analyze the demand price relationships and the price elasticities of demand for four appliances. We find that the willingness-to-pay is nearly five times the present average price of electricity. We also present perceptual distances for the future market related to adoption of dynamic prices and renewable energy by consumers.

Keywords: Electricity demand-price relationship, elasticity of demand, segmentation, willingness-to-pay for electricity, perceptual distance

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1. INTRODUCTION AND REVIEW OF LITERATURE

Electricity has become a necessity to the urban, semi-urban and even rural societies around the world. Innovations of various types of electrical appliances have led to the replacement of several household manual activities. However, this high demand for retail electricity have failed to raise its price to high values because of regulations in regulated markets and competitions in the deregulated markets. It seems possible to charge higher prices or different prices to different segments of the market. A knowledge of possible market segments, the demand-price relationships, elasticities and willingness-to-pay (WTP) can help in making better pricing decisions. The knowledge of consumer's willingness-to-accept dynamic pricing of electricity and renewable energy can also help in future policy decisions. This paper aims to address these issues by analyzing data from responses from a survey of 173 individuals in India. A literature survey(Dutta and Mitra, 2017) finds that modification and shift in demand with changing price is possible but mostly with low elasticity of demand. It also registers that WTP can be significantly higher than market price, consumer's willingness-to accept dynamic pricing (DP) increases with enabling technology and segmentation of electricity markets is mostly restricted to residential, commercial and industrial segments.

Consumers are interested in dynamic pricing but are mostly unaware of the specific advantages of such schemes (Dütschke and Paetz, 2013). Survey results state that consumers respond significantly to price signals (Faruqui, Sergici & Wood, 2009) and high prices can induce over 30% peak load reduction (Mak & Chapman, 1993). Demand is elastic in industrial and large commercial sectors but inelastic in residential, agricultural and small commercial sectors (Bose & Shukla, 1999). The upper-middle class of residential consumers is most responsive to price signals (Tiwari, 2000). The demand elasticity varies with household, demographic, lifestyle and geographical variables (Filippini & Pachauri, 2004) (Zhou & Teng, 2013). Low demand elasticity can be dealt with larger price spikes but duration of high price periods in a day does not impact much on the consumer behavior (Wolak, 2011). However, DP can increase consumers price elasticity of demand (Ifland et al., 2012) (Kirschen, 2003). Manual consumption scheduling is cumbersome and can be a cause of low demand elasticity (Kirschen et al., 2000). Hence smart grid technology (Thimmapuram and Kim, 2013) (Roozbehani et al., 2012) and load scheduling models (Mitra and Dutta, 2018) can be helpful in demand-side management with DP.

Enabling technology enhances demand response but people with very low income is inherently adverse to demand response because of the insignificant opportunity to reduce their already very low consumption (Faruqui et al., 2014). A higher peak-to-off-peak ratio within a pricing scheme induces higher load reduction (Charles River Associates, 2005) (Faruqui & Sergici, 2013). Demand response is highest during hot days and from the use of air-conditioner (Letzler, 2007). These factors imply that significant demand response can be observed from financially affluent consumers using air-conditioners during hot weather conditions experiencing a higher peak-to-off-peak ratio. The WTP of retail electricity consumers for reliable electricity supply is generally higher than what they are used to pay. This fact is validated through contingent valuation method (Devicienti et al., 2005) (Twerefou, 2014), choice experiment method (Ozbafli and Jenkins, 2013) and stated preference data method (An et al., 2002).

In this paper we have made the following contributions.

- Cluster analysis is used to form suitable segments for the present market. Such efforts for electricity market segmentation are rare in published literature.
- Factor analysis is performed with the perception data to develop a factor map and derive suitable segments for the future market where dynamic pricing and renewable energy is expected to be adopted.
- Discriminant analysis is performed and a threshold discriminant score and a set of discriminant equations are prescribed for the present and future markets respectively. These values help in discriminating any new consumer into one of the segments in both markets. These threshold parameters are specific for the Indian urban household consumer and may differ in other markets.
- The demand-price relationships and price elasticities are calculated for each segment and separately for four different appliances to capture and compare the consumer behavior in each segment for the different types of appliances.
- The individual willingness-to-pay is converted to market parameters for each appliance to measure the proportion of market that can pay a certain price.
- The perceptual distance among the perceptual responses is calculated to understand the relative efforts needed to introduce the aspects in the future market.

This introduction section is followed by research design, data organization, analysis and discussion followed by conclusion and extension.

2. RESEARCH DESIGN

2.1. RESPONDENTS, AREA OF ENQUIRY AND SAMPLING PLAN

The respondents of this questionnaire were employees of a prominent higher educational institution located at Ahmedabad, India. The sample consisted of 173 respondents who were interviewed over a period of one month. A convenience sampling technique (non–probability sampling) was used for the selection of the sample. The sample selection was based on the availability and willingness of the respondents to attend the interview during short break-times during their office hours. All levels of employees were approached to get a representation from different demographical groups.

2.2. SCOPE OF THE STUDY

The scope of the study is limited to the respondents within an institutional campus, responding during their break-times during office hours and their awareness and perception about their household electricity usage pattern. It is done as an academic study depending on the respondents' memory and willingness to answer a long and complex questionnaire. The quality of information collected from the responses is subjected to the understanding of the respondents about dynamic pricing of electricity and its related advantages and disadvantages.

2.3. RESEARCH METHODOLOGY

The present study is a cross-sectional study based on empirical, descriptive research. Cross-sectional study refers to study of a wide range of subjects at one specific point of time. Empirical research is based on evidences captured in terms of data. Descriptive study method is used to obtain information concerning the current status of a phenomenon with respect to variables or conditions in the situation by interviewing people who are believed to possess the desired information. This research deals with both quantitative and qualitative data. This study is based on the data collected through questionnaire from employed people about their household electricity consumption. The reasoning is inductive, i.e. reasons from specific observations are used to develop general patterns.

2.4. DATA SOURCES

Primary data has been collected directly from the respondents for the purpose of this academic study. Primary data is the raw data collected for research work that represents an official position or opinion. This kind of data is always authoritative because the information collected has not been interpreted or filtered by a second party. We have not used any secondary data in this study.

A structured questionnaire was designed & presented to the respondents. The questionnaire was constructed to be as concise and simple as possible keeping the profile of the respondents in mind. The data has been collected through face-to-face interviews with the help of a MS Excel based file that could be used to calculate and display the monetary effect of responses of the respondents. The questionnaire was a formal one and mostly structured with a few unstructured questions. Responses were oral verbal in most cases where the interviewer explained and asked the questions and recorded the responses. However, in some cases the responses could be considered as written verbal where the respondents preferred to input the responses themselves.

2.5. RESEARCH INSTRUMENT

The primary data was collected through questionnaires administered to employees of an Institute by visiting their offices within the institute campus. The questionnaire was presented in MS Excel format and respondents were allowed to respond in an interactive way by changing their responses regarding perceived consumption depending on the associated expenditure for the same calculated in the same excel sheet. The questions of the questionnaire are provided in the appendix-1.

3. DATA ORGANIZATION, ANALYSIS AND DISCUSSION

3.1. THE GROUPS WITHIN THE SAMPLE

The data collected from the respondents was organized to get an idea of the demographic characteristic of the sample. The sample can be classified into several groups based on education, income and family size. We have registered respondents from secondary to doctoral education level, from less than INR 0.2 million to greater than INR 2 million annual family income and family size (number of members staying in the house) from 1 to 11. The size of the groups in each category is represented in figure-1 through pie charts.

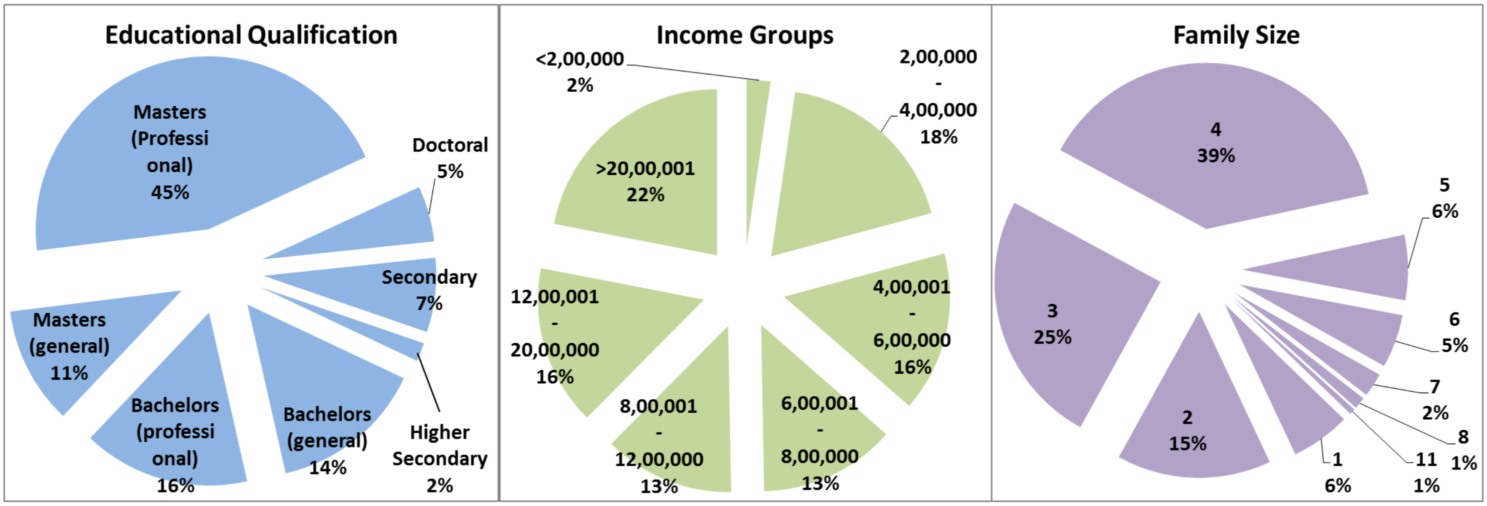
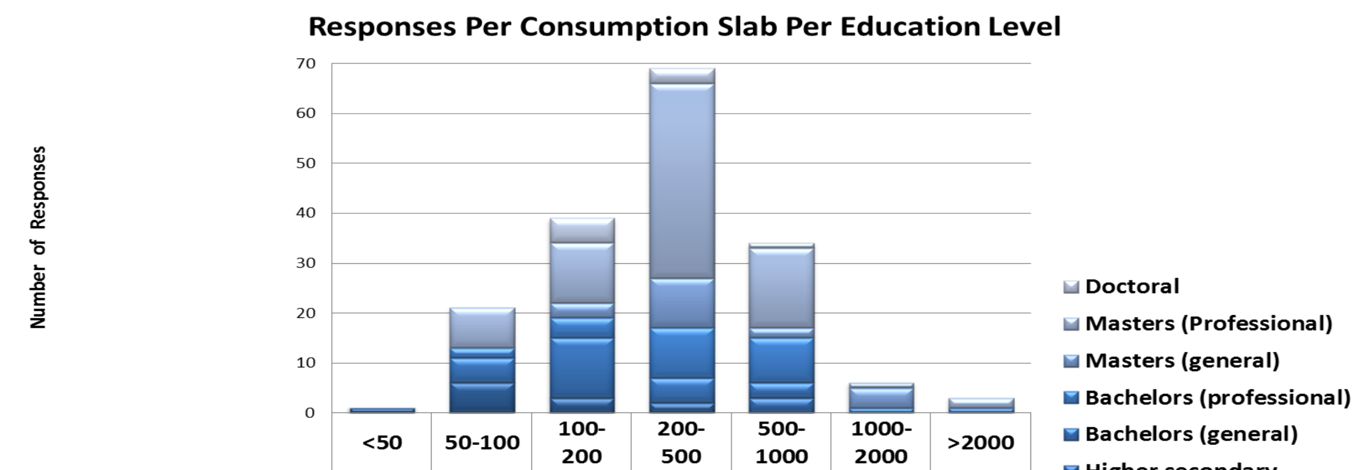


Figure-1: Sample composition with respect to Education Qualification, Income Group and Family Size.

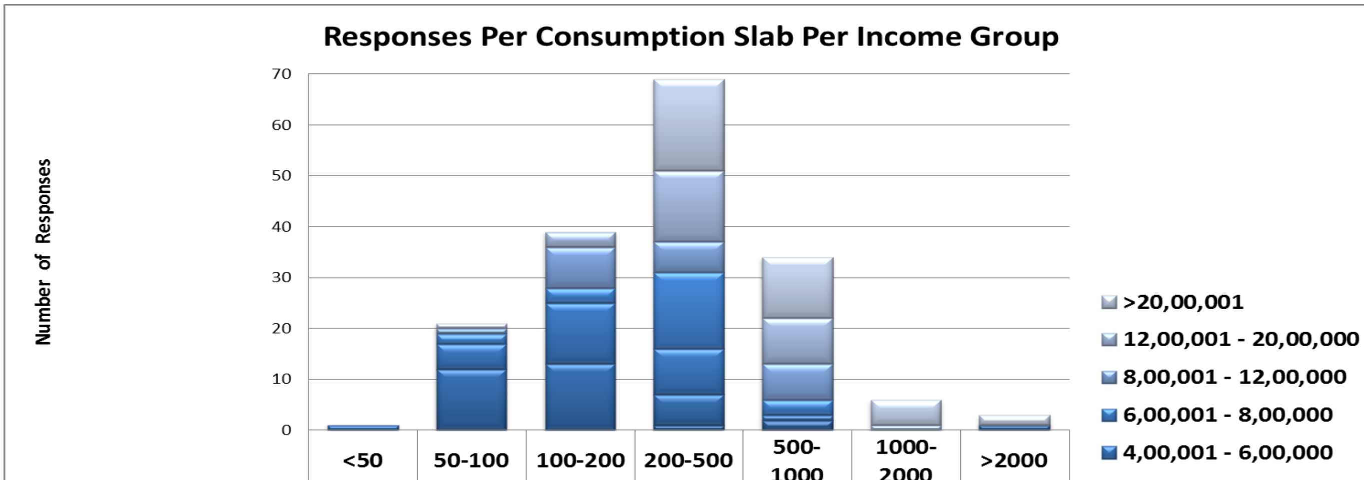
The pie charts clearly shows that the sample has a maximum number of professional master degree holders(45%), followed by professional bachelors(16%), general bachelors(14%) and general masters(11%). The income groups are more or less of similar size with the highest(22%) being more than 2 million annual income. The group with family size of 4(39%) is the largest group folowed by the family size 3(25%) and family size 2(15%). The household electricity consumption during a certain summer period by each education level, each income group and each family size group are depicted in the exhibits 1, 2 and 3 respectively.



	<50	50-100	100-200	200-500	500-1000	1000-2000	>2000
Doctoral	0	0	5	3	1	0	0
Masters (Professional)	0	8	12	39	16	1	2
Masters (general)	0	0	3	10	2	4	0
Bachelors (professional)	0	2	4	10	9	1	1
Bachelors (general)	0	5	12	5	3	0	0
Higher secondary	0	0	0	0	3	0	0
Secondary	1	6	3	2	0	0	0

Consumption Slabs

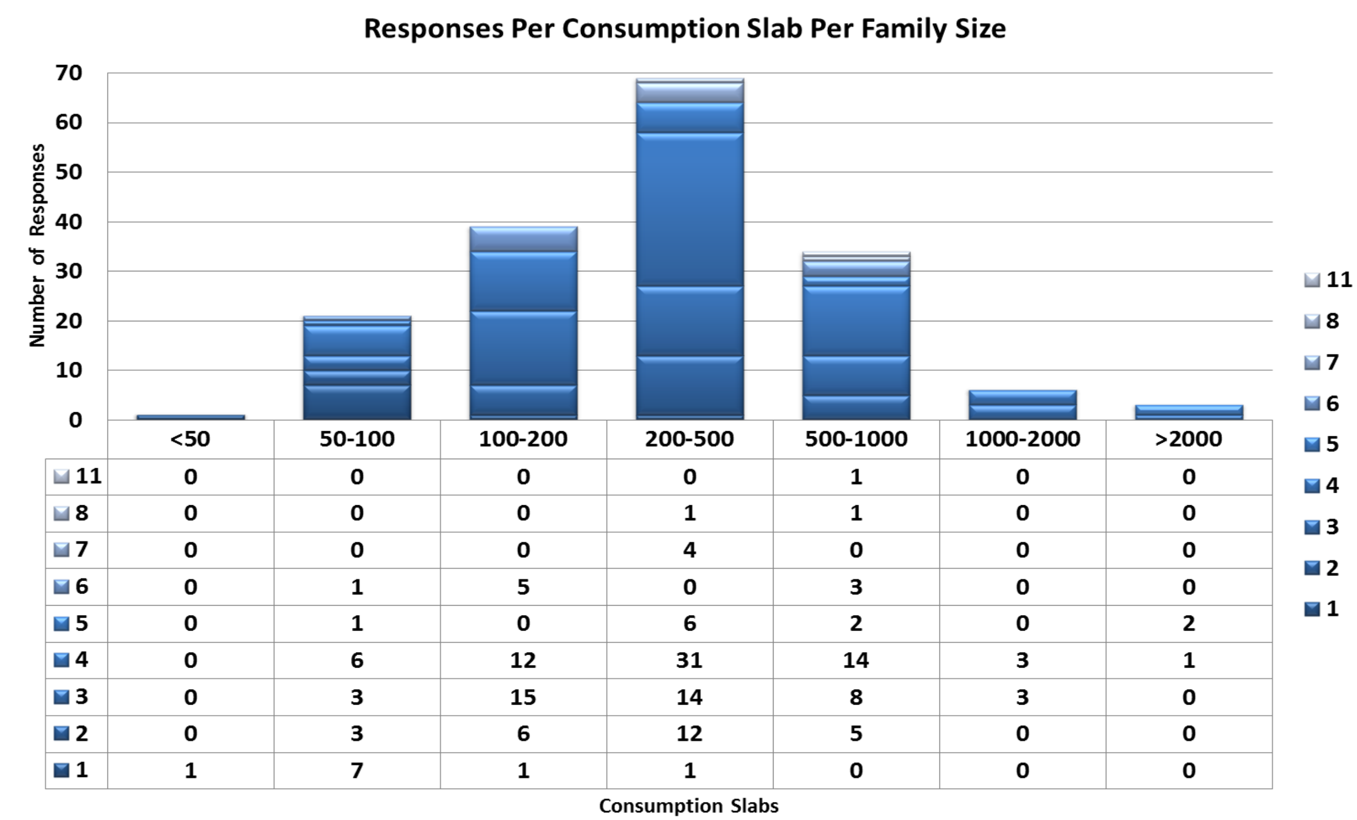
Exhibit-1: Consumption level per Education level.



	<50	50-100	100-200	200-500	500-1000	1000-2000	>2000
>20,00,001	0	1	0	18	12	5	2
12,00,001 - 20,00,000	0	0	3	14	9	1	0
8,00,001 - 12,00,000	0	1	8	6	7	0	0
6,00,001 - 8,00,000	0	2	3	15	3	0	0
4,00,001 - 6,00,000	0	5	12	9	1	0	0
2,00,000 - 4,00,000	1	12	13	6	0	0	0
<2,00,000	0	0	0	1	2	0	1

Consumption Slabs

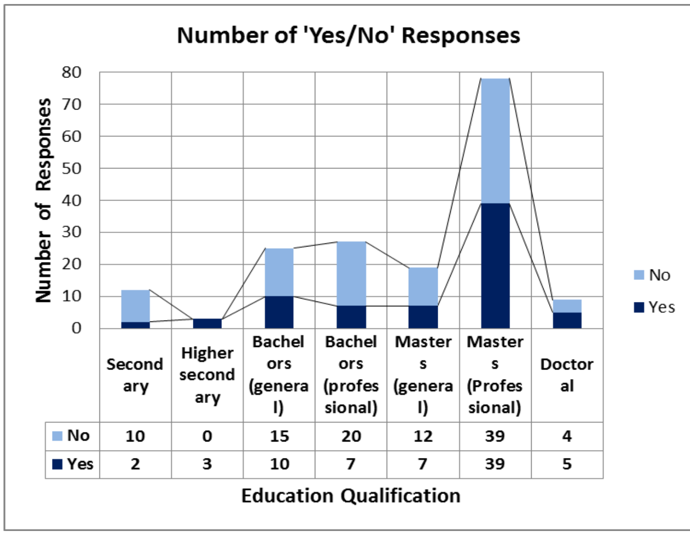
Exhibit-2: Consumption level per income group.



	<50	50-100	100-200	200-500	500-1000	1000-2000	>2000
11	0	0	0	0	1	0	0
8	0	0	0	1	1	0	0
7	0	0	0	4	0	0	0
6	0	1	5	0	3	0	0
5	0	1	0	6	2	0	2
4	0	6	12	31	14	3	1
3	0	3	15	14	8	3	0
2	0	3	6	12	5	0	0
1	1	7	1	1	0	0	0

Exhibit-3: Consumption level per family size.

It can be observed from the above exhibits that the mode of the sample is the consumption slab of 200-500 units. This is also the mode for higher educated groups, higher income groups and most family size groups. However, it seems to shift to lower consumption slabs for lower educated groups and lower income groups. Family size of 1 has a lower mode due to lower consumption requirements. All respondents were consuming electricity in inclining block rate tariff schemes, which is a form of dynamic pricing based on consumption slabs. We tried to figure out if the respondents were aware of the tariff differences with level of consumption and that they were already experiencing a form of dynamic pricing in electricity. The results in yes/no responses, classified in the educational level groups, are summarized in exhibit-4.



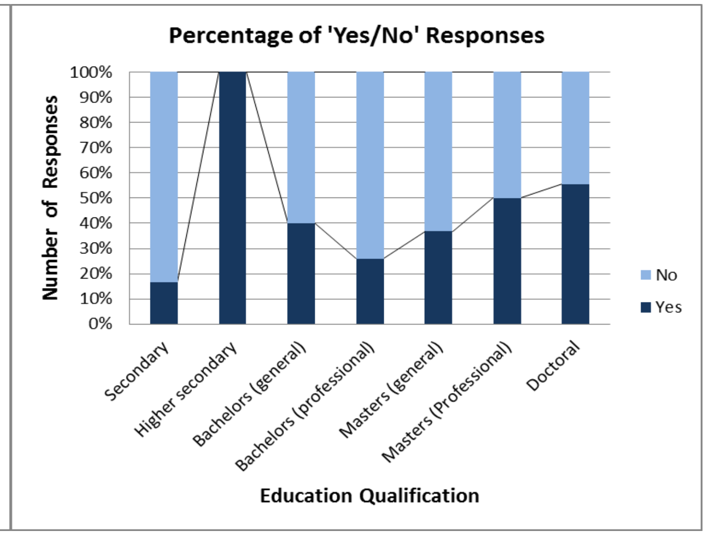


Exhibit-4: Awareness levels towards already implemented dynamic tariffs

The awareness increases steadily with increase in education level as could be seen with the increasing percentage of yes responses with the increasing education level. The awareness at higher secondary level is 100%, but that does not tell much in general as there were only 3 respondents in this group. The overall awareness regarding dynamic pricing is low and hence it seems that a lot of effort will be required to introduce dynamic pricing schemes with frequent price changes in this market.

3.2. SEGMENTATION OF THE MARKET

The respondents could be divided into several segments based on the characteristics that we have discussed in the previous subsection. So we applied cluster analysis in SPSS software to figure out the suitable number of segments and the constituents of the segments. The table-1 shows the number of respondents in each cluster for cluster analysis conducted for 2 clusters to 10 clusters.

Number of Respondants	**Cluster Index**										
Number of clusters	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**Total**
2	92	81	0	0	0	0	0	0	0	0	173
3	46	46	81	0	0	0	0	0	0	0	173
4	46	46	78	3	0	0	0	0	0	0	173
5	46	46	65	3	13	0	0	0	0	0	173

6	20	46	65	26	3	13	0	0	0	0	173
7	20	46	43	26	3	13	22	0	0	0	173
8	20	35	43	26	3	13	22	11	0	0	173
9	20	35	43	13	3	13	22	11	13	0	173
10	20	35	30	13	3	13	13	22	11	13	173

Table-1: Number of respondents in each cluster for different numbers of clusters in the analysis.

We can note that from the 4 segment to the 10 segment cases there are very low volume (3 members) segments. Also having more than 10 segments can be impractical and will further lead to low volume segments. Hence we concentrate on segmentation the market into either 2 or 3 segments where each segment will have a significant number of members. However for 3 segments, segments 1 and 2 are quite close to each other as found from SPSS and visually observed from the dendrogram using Ward linkage in figure 2. Thus the proper segmentation of the sample can be done into 2 segments where each segment is considerably large to be profitable, with significant statistical difference and identifiable to be measurable (which we have explained later). There are two outliers in the sample (respondent 67 and 167) based on Mahalnobis distance that were more than the critical value of 18.47 for 4 variables at p=0.001. Both these outliers belonged to segment 2 and were eliminated from further analysis.

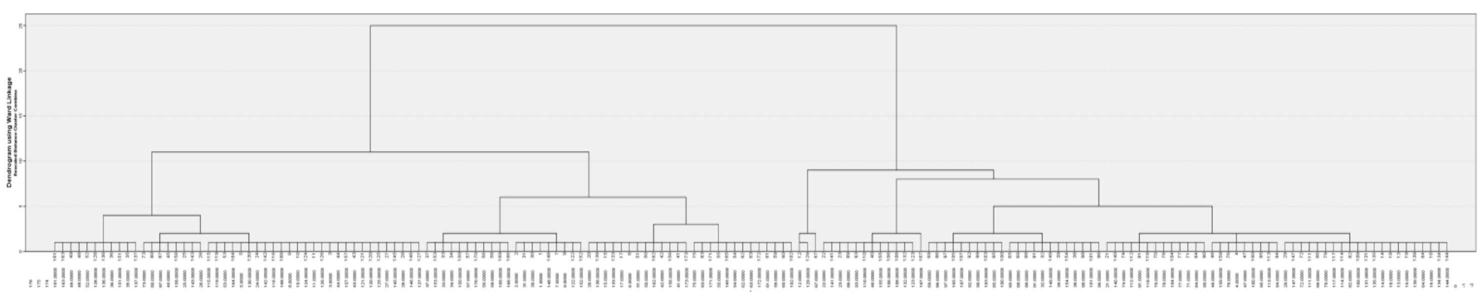


Figure-2: SPSS output of Dendrogram using Ward linkage.

The 2 clusters (or segments) thus obtained were subjected to a discriminant analysis to develop a discriminant function so as to find a definite condition (discriminant score) to classify a new case into one of the following segments. The group statistics are displayed in table- 2a. The segment size is different, i.e. 92 and 79. The values of the mean and the standard deviation also differ considerably for each variable in between the two segments. This is verified from table-2b. The F values are quite large with significance values as zero, hence the difference in the means of the variables in the two segments are significant. We can see that the income is the most important component of the discriminant function and the family size is least important from their lowest and highest values of Wilk's Lambda.

Clusters_2		Mean	Std. Deviation	Valid N (listwise)	
				Unweighted	Weighted
1	Education_Index	4.108696	1.8123903	92	92.000
	Income_Index	3.065217	1.1841847	92	92.000
	Family_size	3.217391	1.2737941	92	92.000
	units_consumed	244.836957	186.6541891	92	92.000
2	Education_Index	5.569620	.8869935	79	79.000
	Income_Index	6.240506	.7879735	79	79.000
	Family_size	3.949367	1.3765316	79	79.000
	units_consumed	581.379747	389.6691662	79	79.000
Total	Education_Index	4.783626	1.6287746	171	171.000
	Income_Index	4.532164	1.8858187	171	171.000
	Family_size	3.555556	1.3681723	171	171.000
	units_consumed	400.315789	341.5193298	171	171.000

Table-2a: Group statistics for the 2 segments.

Tests of Equality of Group Means					
	Wilks' Lambda	F	df1	df2	Sig.
Education_Index	.799	42.552	1	169	.000
Income_Index	.291	411.399	1	169	.000
Family_size	.928	13.026	1	169	.000
units_consumed	.757	54.186	1	169	.000

Table-2b: Test of equality of the group means.

The within-group correlations displayed in table-3 have low values for the predictor variables ensuring that there is sufficient difference between the two segments. Table-4 shows the values of the log determinants are fairly similar, hence it supports the assumption of the homogeneity of the covariance matrices between groups. Since significance is very low, we can say that the group variance is unequal.

Pooled Within-Groups Matrices[a]					
		Education_Index	Income_Index	Family_size	units_consumed
Correlation	Education_Index	1.000	-.006	-.110	-.050
	Income_Index	-.006	1.000	-.177	.298
	Family_size	-.110	-.177	1.000	.085
	units_consumed	-.050	.298	.085	1.000

Table-3: Within-group correlations.

Clusters_2	Rank	Log Determinant	Box's M		111.491
1	4	12.241	F	Approx.	10.862
2	4	11.568		df1	10
Pooled within-groups	4	12.590		df2	129547.175
The ranks and natural logarithms of determinants printed are those of the group covariance matrices.				Sig.	.000

Table-4: Log determinant and Box's M test results

Table-5 shows the high eigenvalue which signifies that the discriminant function can explain a large variation. The high canonical correlation value indicates that the function can discriminate quite well (the perfect value should have been 1 and 0.869 is quite close to 1). A significance value of 0 means that the prediction model is statistically significant. Smaller Wilk's lambda value again indicates greater discriminatory capability of the function.

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation	Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	3.087[a]	100.0	100.0	.869	1	.245	235.096	4	.000

Table-5: Eigenvalue and Wilk's Lambda

The unstandardized coefficients of the variables in the discriminant function are shown in the Table-6a. So the discriminant function can be written as:

$$\text{Discriminant score} = (0.227 \times \text{Education index}) + (0.927 \times \text{Income index}) + (0.272 \times \text{Family size}) + (0.000088 \times \text{Units Consumed}) - 6.29 \quad \ldots\ldots\ldots\ldots\ldots\ldots \text{(1)}$$

We can see from the value of the coefficients of the discriminant function that the income has maximum effect and units consumed has negligible effect on the discriminant score. Table-6b shows the mean discriminant score for both the segments. Table-6c provide us with the prior probabilities of the segments which are the weights attached to the segments based on their size. We need to calculate the difference between the two mean discriminant scores and use the prior probability to arrive at the specific discriminant score that can clearly separate the two segments. Thus this specific discrimination value can be calculated as

$$1.885 - \big((1.885 - (-1.619)) \times 0.462\big) = 0.2662 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(2)}$$

This means a new consumer with discriminant score less than equal to 0.2662 can be considered in segment-1 and a consumer with discriminant score more than 0.2662 can be considered in segment-2.

Table-6a: **Canonical Discriminant Function Coefficients**

	Function
	1
Education_Index	.227
Income_Index	.927
Family_size	.272
units_consumed	.000088
(Constant)	-6.290
Unstandardized coefficients	

Table-6b: **Functions at Group Centroids**

Clusters_2	Function
	1
1	-1.619
2	1.885
Unstandardized canonical discriminant functions evaluated at group means	

Table-6c: **Prior Probabilities for Groups**

Clusters_2	Prior	Cases Used in Analysis	
		Unweighted	Weighted
1	.538	92	92.000
2	.462	79	79.000
Total	1.000	171	171.000

Table-6: Details of the discriminant function.

The classification results in Table-7 shows that in the original sample, 94.6% of the segment-1 members were correctly classified as per the discriminant function and the figure for the segment-2 is

98.7%. In total 96.5% of the cases were correctly classified. These are fairly high values which states that the capability of the function in placing a new case into a group is quite high.

Clusters_2			Predicted Group Membership		Total
			1	2	
Original	Count	1	87	5	92
		2	1	78	79
	%	1	94.6	5.4	100.0
		2	1.3	98.7	100.0
Cross-validated	Count	1	87	5	92
		2	1	78	79
	%	1	94.6	5.4	100.0
		2	1.3	98.7	100.0

Table-7: Predicted group membership.

In the two segments thus formed, segment-2 consists of higher income, higher educated customers with larger family size as compared to segment-1 with the income level playing the biggest role in segmenting.

3.3. THE APPLIANCES CONSIDERED IN THE SURVEY

The consumption of electricity by the respondents was measured for four appliances. This was done to keep the length of the survey reasonably short. We have divided these appliances into three types based on their usage need. The first one is refrigerator which is generally characterized with non-shiftable and non-reducible usage. This means that people need to use the refrigerator during specific hours of the day and in most cases a refrigerator runs for 24 hours everyday. This is due to the necessity of storing food through definite hours of the day. The next two appliances are air-conditioner and cooler. These appliances are for comfort purpose. These might be necessary during specific hours of the day but consumers can cut short on their consumption and go for less costly substitutes like fans if they feel that the operating costs are too high for them. So these are partially shiftable or reducible usage appliances. The fourth appliance is washing machine for which users have much more flexibility in its time of usage.

3.4. THE DEMAND-PRICE RELATIONSHIP

The average price that the customer is paying (referred to as base price henceforth) and the related consumption for each of the four appliances were calculated from the data collected. This knowledge was made available to the respondent in terms of the monetary value of the said consumption. Then five other price points (two lower and three higher than the base price) were presented to the respondent and their preferred consumption level for each price point was recorded. This data gave a series of price-demand points that were plotted in figures 3a and 3b for the two segments.

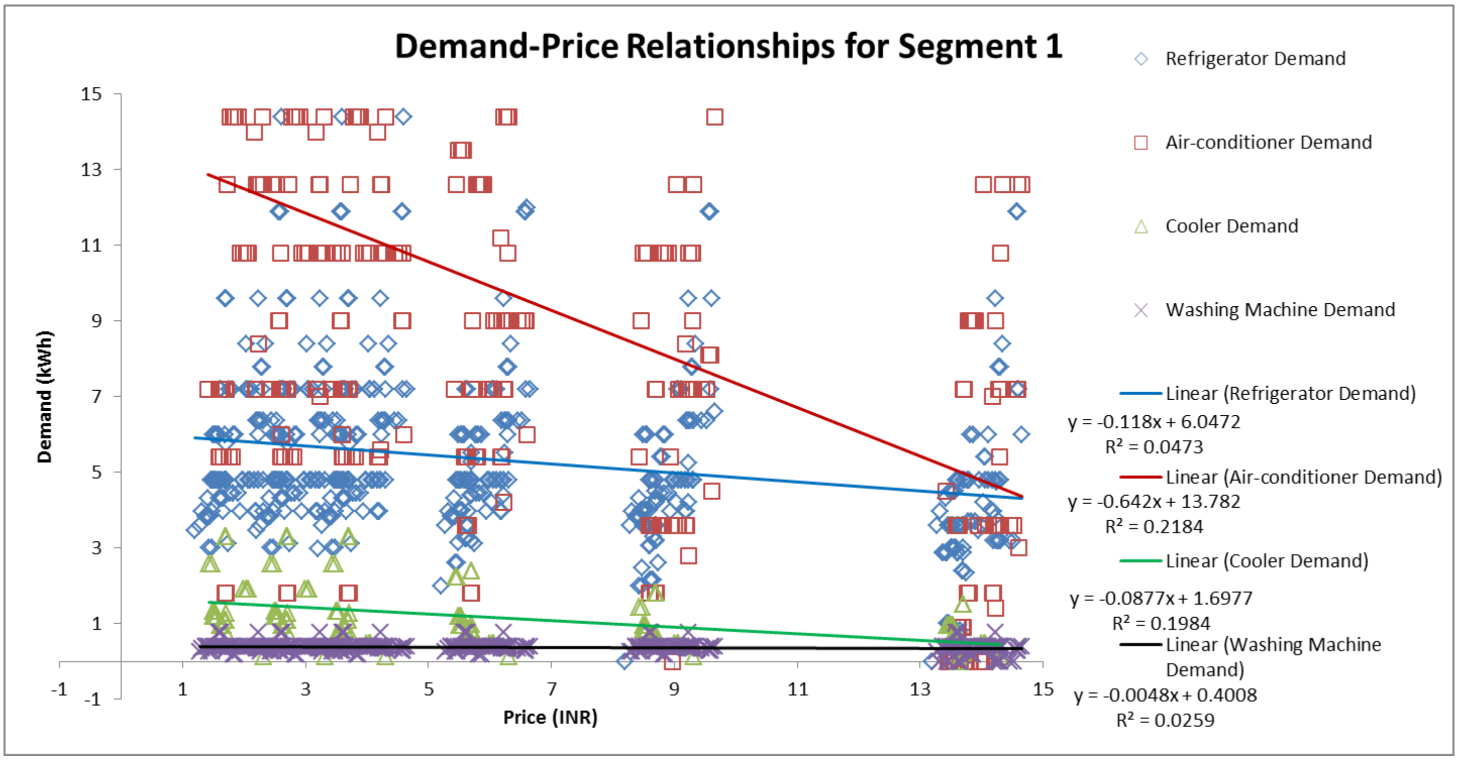


Figure-3a: Demand-price relationship for segment-1.

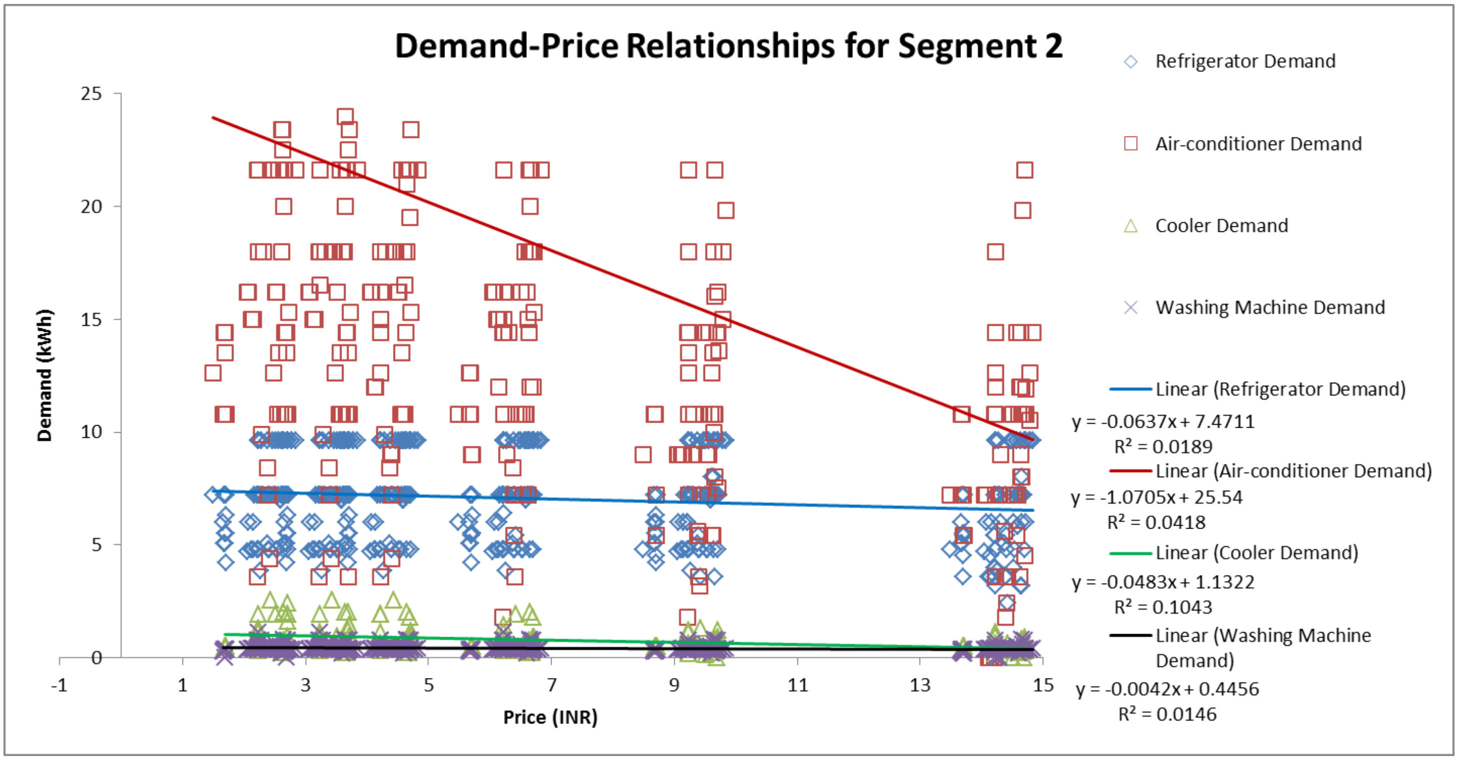


Figure-3b: Demand-price relationship for segment-2.

A linear regression model is developed for each appliance in each segment and the R^2 values for the same are also provided. It can be seen that all the curves have negative slope following the 'law of demand'. In both the segments, the slope of the air-conditioner is highest, followed by that of the refrigerator, the cooler and the washing machine. This shows that the response to prices can be experienced most with air-conditioners; at a higher demand range in segment-2 and a lower demand range in segment-1. This is because of the comfort nature of usage and the high cost of running an air-conditioner. However, cooler being another appliance for comfort purpose, have a much lower slope. This is because the power consumption by a cooler is much lower than that of an air-conditioner. Hence the running expense of a cooler is much lower in high prices even without much consumption reduction. This observation leads to the inference that a higher demand response can be expected with appliances with higher operating expense. The lower slope of the refrigerator is due to its nature of use. Since most consumers feel it to be indispensable, high demand response cannot be expected for it. The slope for washing machine is very low and this is because of very small daily expenditure associated with it. Moreover, the small time of use of washing machine has much less option for further reduction. The slopes of the demand curve in segment-1 are higher for refrigerator and cooler, lower for air-conditioner and almost same for washing machine as compared to segment-2. This means that a greater response for air-conditioner and a lesser response for refrigerator and cooler can be expected in segment-2 over segment-1.

3.5. THE ELASTICITY OF DEMAND

The linear functions in the previous section provide an idea of the price elasticity of demand of the appliances. We figured out that the elasticity of air-conditioner is highest and those of the others are quite low. We then calculated the elasticity value at each price point with respect to the base price for each respondent. Thus a series of elasticity values against each of the price points were obtained and linear regression was carried out on this data. The scatter plot along with the regression equations and the R^2 values are displayed in figures 4a and 4b for segments 1 and 2 respectively. The slope of the elasticity function is positive for the cooler and negative for the refrigerator in both the segments. However the air-conditioner and the washing machine had a negative slope of elasticity in segment-1 and a positive one in segment-2. This means that the incremental change in demand response with respect to increasing price decreases for a cooler and increases for a refrigerator. Thus significant change in electricity demand due to coolers cannot be expected when prices are very high while some small change can be expected for refrigerators. In the case of air-conditioners, incremental demand response slightly increases in segment-1 and slightly decreases in segment-2 with increase in price. This means that the value of money is more to members of segment-1 than of segment-2. The same explanation holds true for washing machine but the values are very small to be significant.

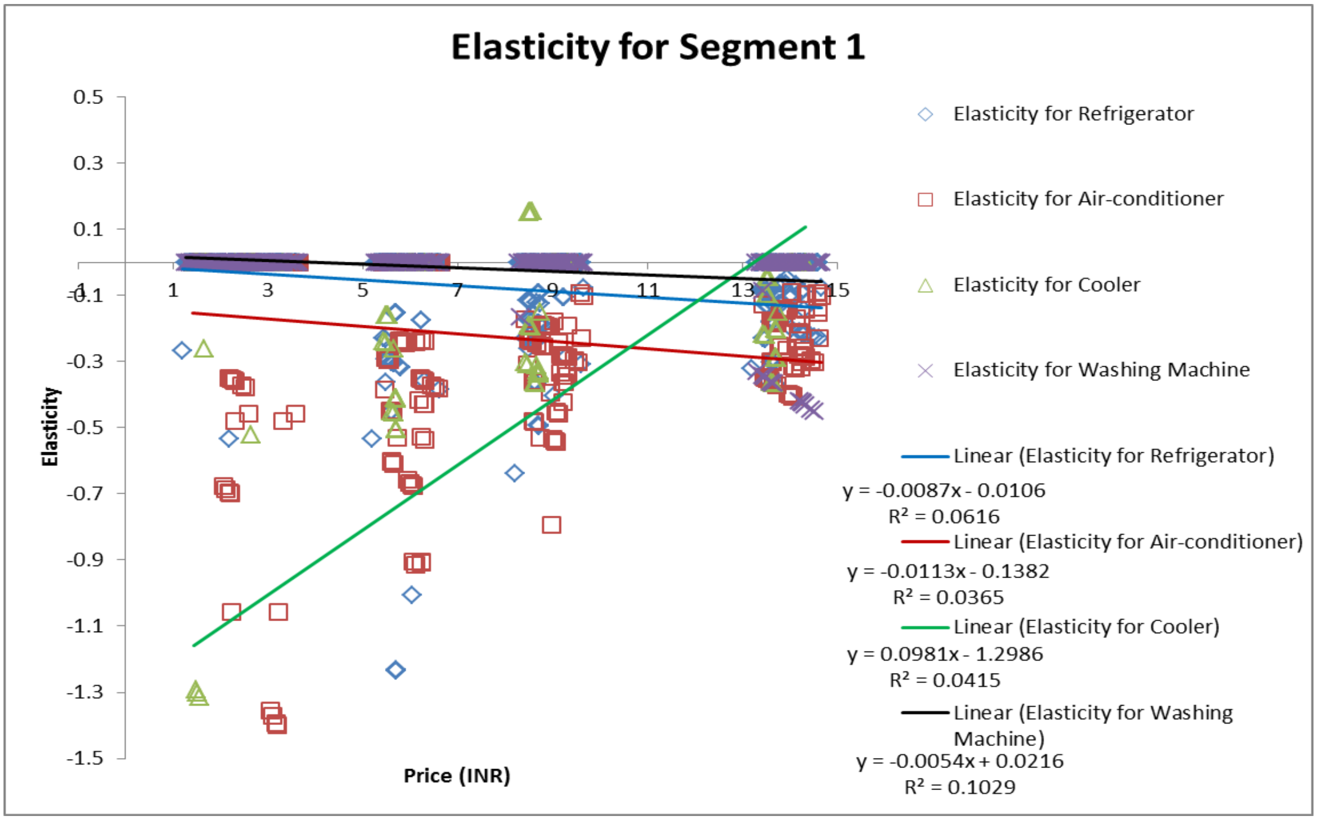


Figure-4a: The demand elasticity in segment-1.

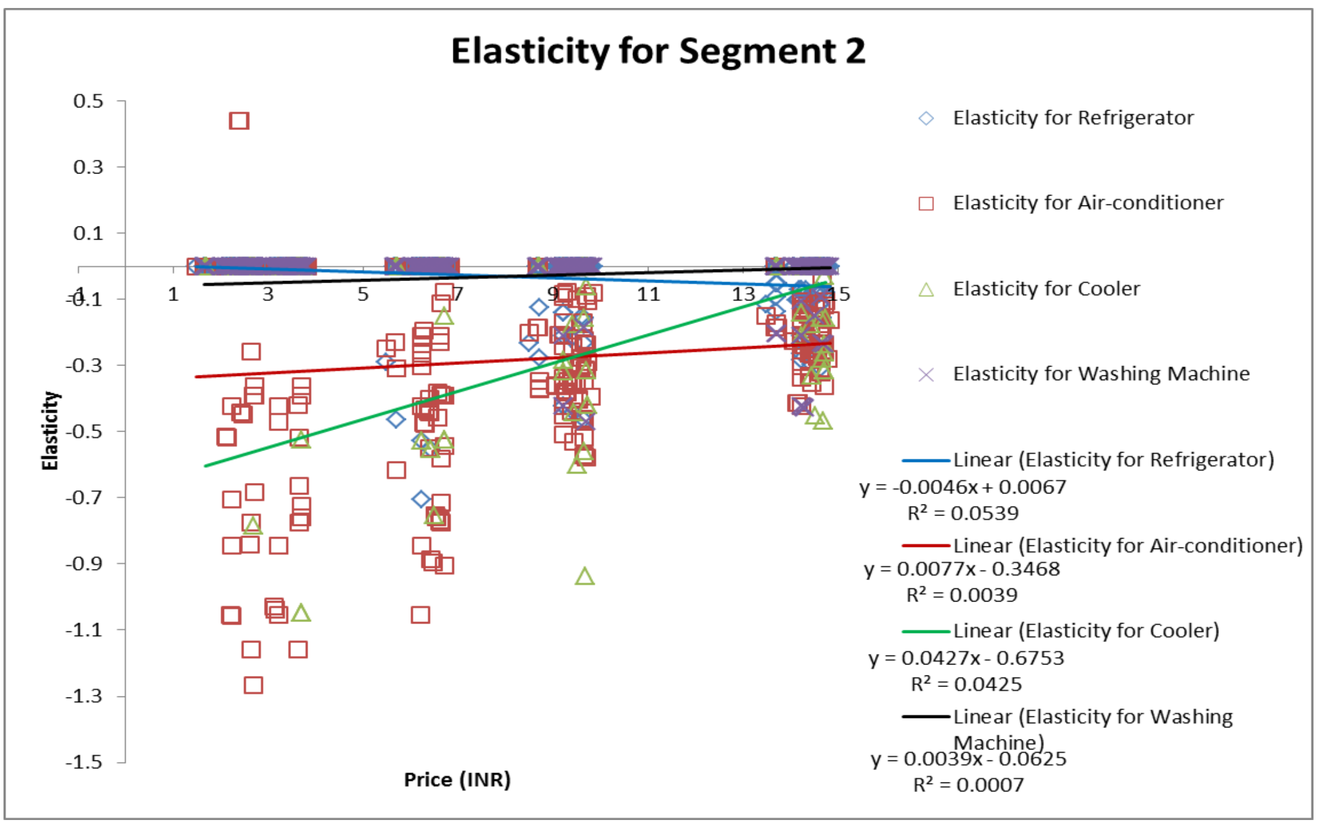


Figure-4b: The demand elasticity in segment-2.

3.6. THE REDUCTION AND SHIFT OF DEMAND

The respondents are presented with a hypothetical situation where they face two price periods in a single day. The original time when they are using an appliance is priced higher than the base price and the rest of the day is priced lower than the base price. The ratio of the higher price to the lower price is termed as price ratio in this paper. The respondent is then asked how he would prefer to consume electricity for each appliance in this situation. The respondent can shift some or whole of the present consumption from the high priced period to the low priced period or can reduce the overall consumption. The percentage reduction of the demand considers difference between present demand at base price and total demand in both the high and low-priced periods summed together. The percentage shift of demand reflects the proportion of total demand of the two periods that is demanded in the low-priced period only. Figures 5a, 5b, 5c and 5d display the plot for percentage reduction and percentage shift in the two segments with the respective linear regression equation and the R^2 values. The curves for reduction has a positive slope in both the segments which means that when the difference in higher price and lower price increases, the overall consumption decreases. The reduction effect is highest in air-conditioner followed by cooler, refrigerator and washing machine. However, the slops of the first three are higher in segment 1 than in segment-2, which means that increasing the price ratio can induce a better demand response in segment-1. An increase in the percentage shift with increasing price ratio can be observed in segment-1 for all the appliances. However, the shift response in washing machine is highest staying close to 100% which is followed by air-conditioner, cooler and refrigerator. In segment-2, there was no shift noticed for refrigerator and for the other appliances, the percentage shift reduced with increase in price ratio although the shift of the washing machine remained close to 100%. It can be concluded that, with increasing price ratio, consumers in segment-1 can be expected to keep reducing their total demand and shifting more of that demand to the low priced periods. However, with increasing price ratio, consumers in segment-2 can be expected to keep reducing their total demand but not shifting much of that demand to the low priced periods. It seems that segment-2 is more specific about time preference of consumption as compared to segment-1.

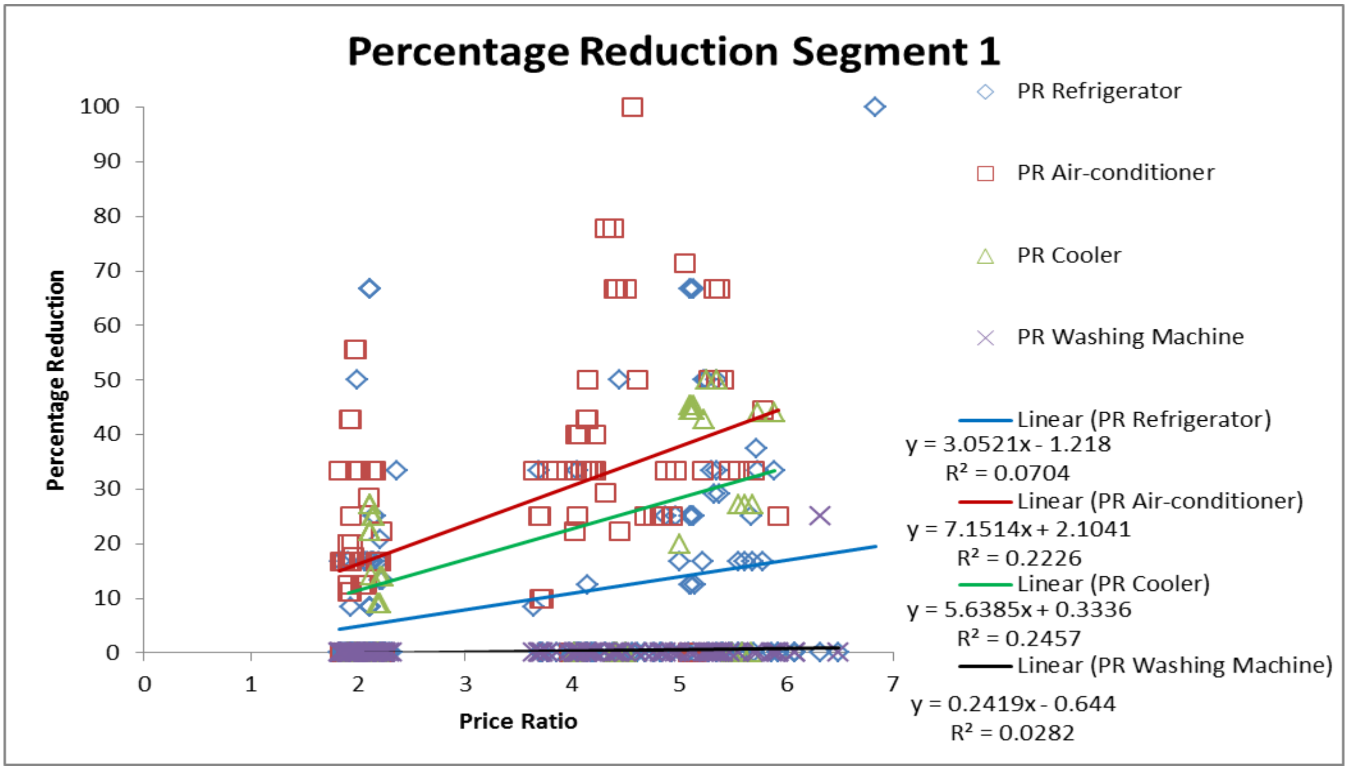


Figure-5a: Percentage demand reduction in segment-1.

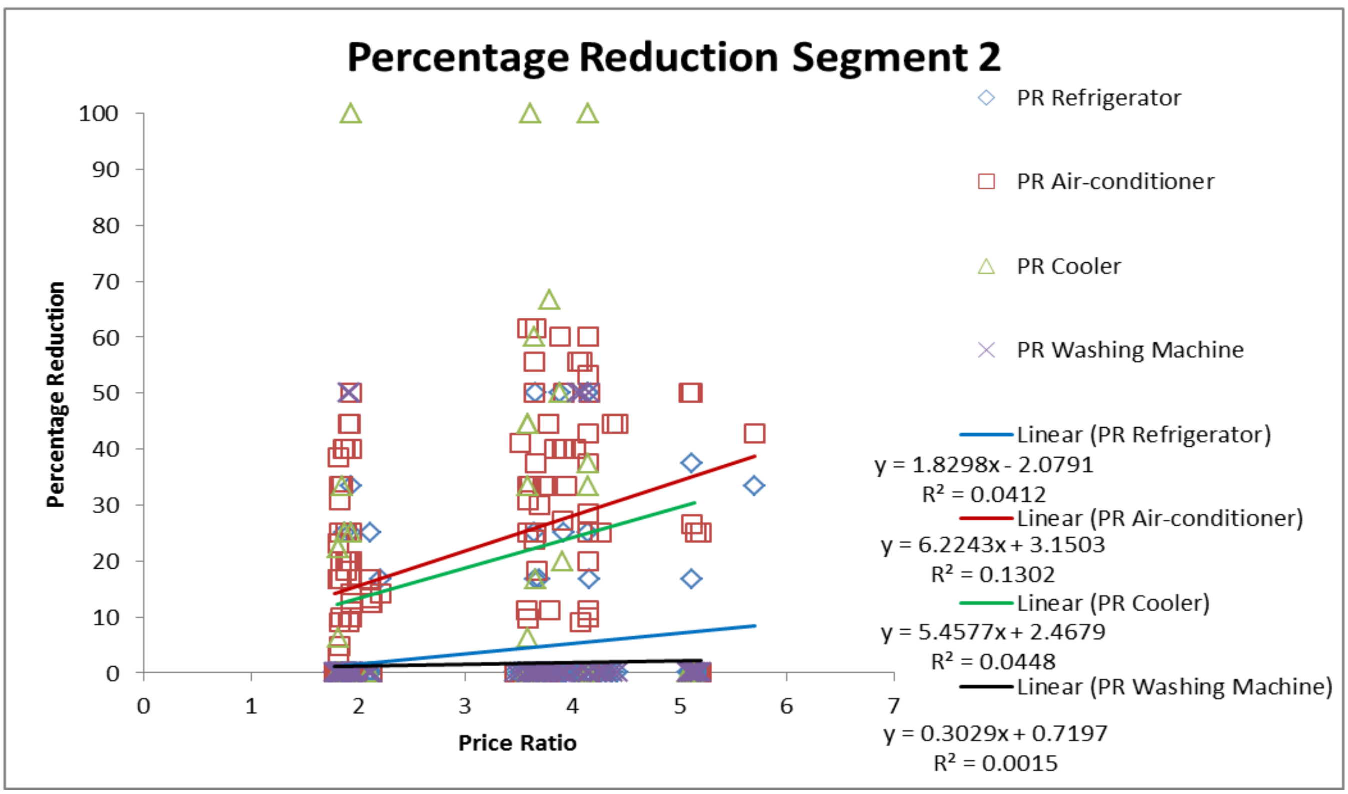


Figure-5b: Percentage demand reduction in segment-2.

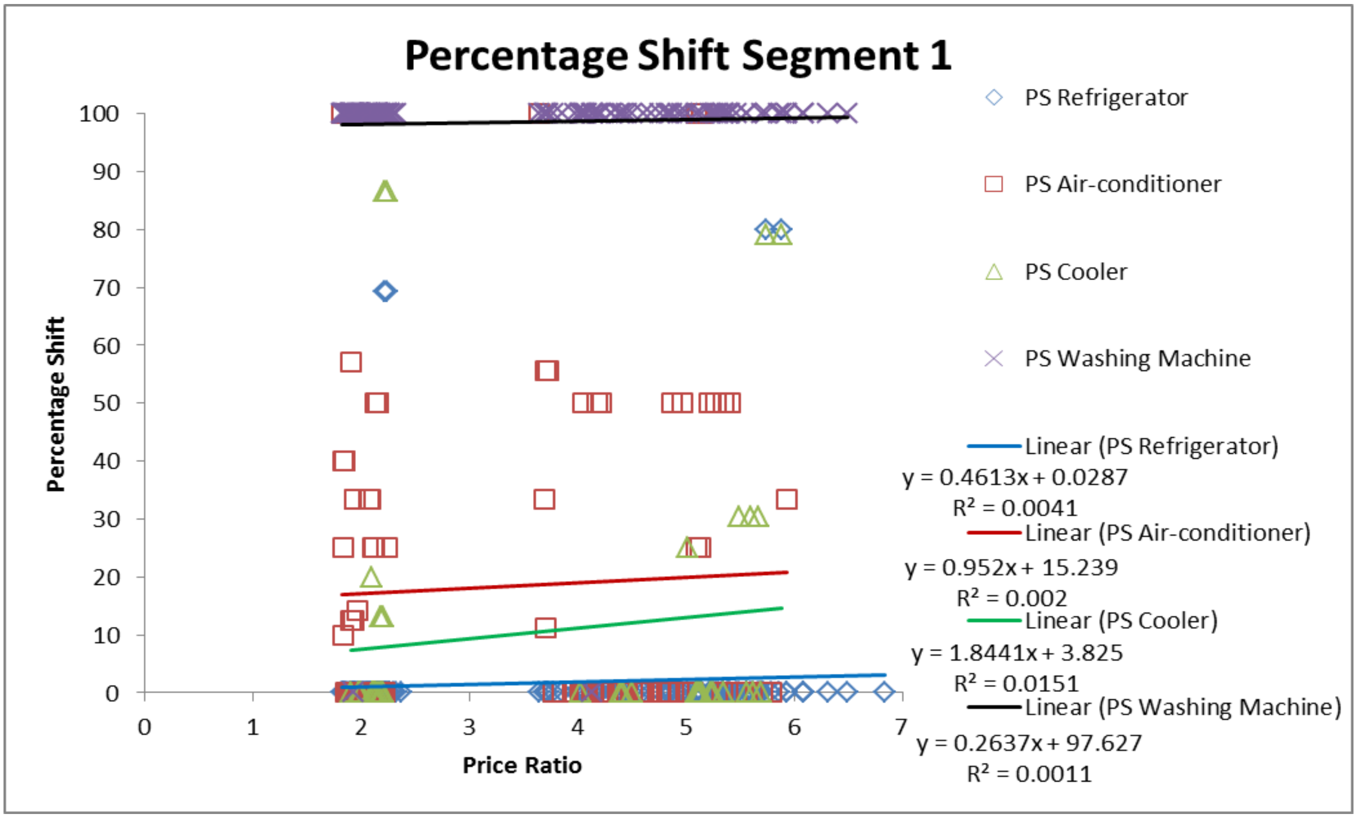


Figure-5c: Percentage demand shift in segment-1.

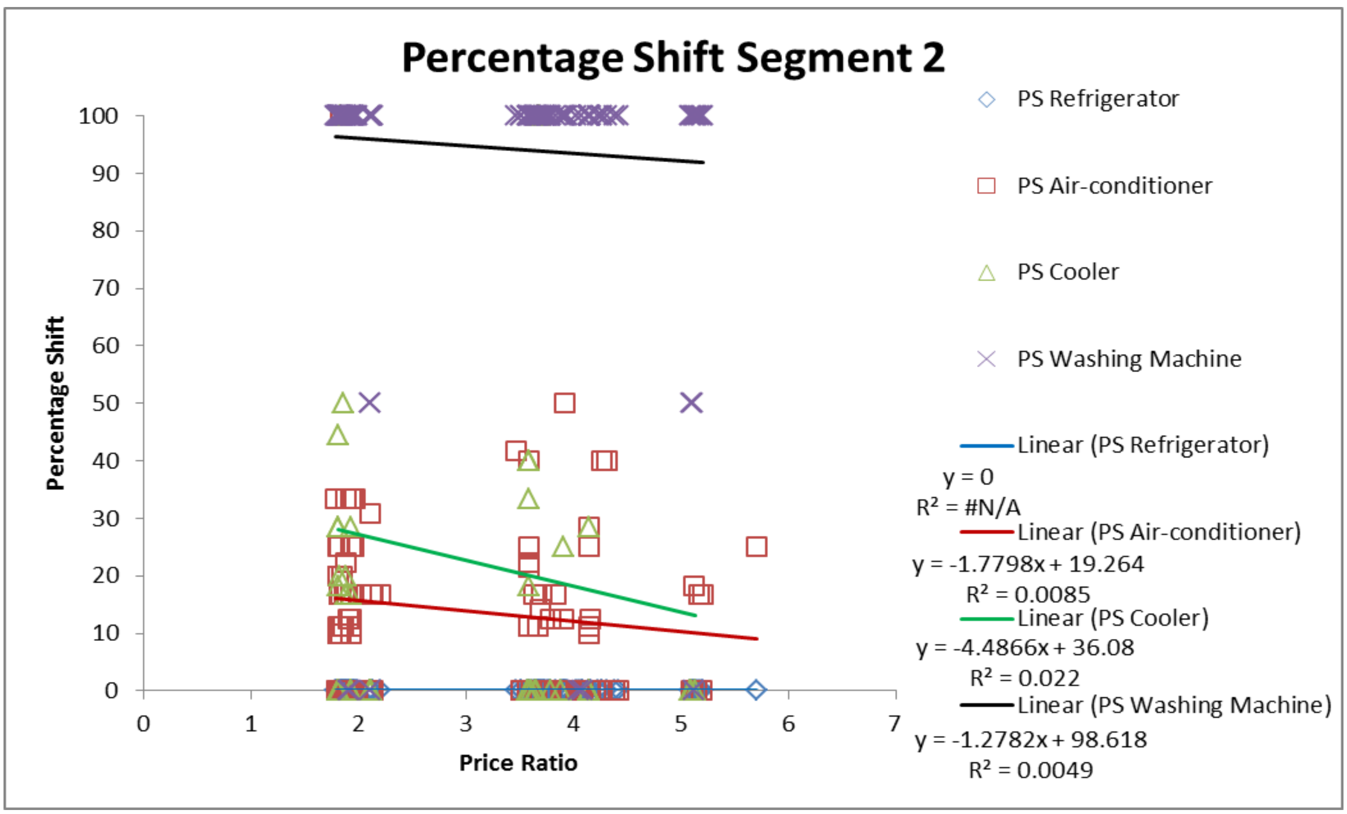


Figure-5d: Percentage demand shift in segment-2.

3.7. THE WILLINGNESS TO PAY

The consumers' willingness to pay (WTP) is known by directly questioning them about what maximum price they are willing to pay for running each appliance. The responses are then tabulated in terms of number of customers responding within price bands. Each price band is of INR 10 and we consider the higher limit of a band as the consumer's reservation price for that appliance. This number value is then converted to percentage value of the total number of customers using that appliance. As seen from Table-8, the reverse cumulative percentage values are then calculated. Note that the numbers showing up against the reservation price 0 (in the shaded row) are consumers not using that appliance and are hence not included in the calculations.

Reservation Price	Refregerator Frequency	Refregerator Percentage of Customers	Percentage of Customers Accepting Price for Refrigerator	Airconditioner Frequency	Airconditioner Percentage of Customers	Percentage of Customers Accepting Price for Airconditioner	Cooler Frequency	Cooler Percentage of Customers	Percentage of Customers Accepting Price for Cooler	Washing Machine Frequency	Washing Machine Percentage of Customers	Percentage of Customers Accepting Price for Washing Machine
0	1			42			127			29		
10	1	0.58139535	100	3	2.290076336	100	0	0	100	3	2.0833333	100
20	10	5.81395349	99.4186047	26	19.84732824	97.70992366	6	13.043478	100	26	18.055556	97.9166667
30	39	22.6744186	93.6046512	53	40.45801527	77.86259542	13	28.26087	86.956522	35	24.305556	79.8611111
40	50	29.0697674	70.9302326	38	29.00763359	37.40458015	12	26.086957	58.695652	28	19.444444	55.5555556
50	60	34.8837209	41.8604651	9	6.870229008	8.396946565	13	28.26087	32.608696	45	31.25	36.1111111
60	8	4.65116279	6.97674419	0	0	1.526717557	1	2.173913	4.3478261	1	0.6944444	4.86111111
70	1	0.58139535	2.3255814	1	0.763358779	1.526717557	0	0	2.173913	3	2.0833333	4.16666667
80	1	0.58139535	1.74418605	0	0	0.763358779	1	2.173913	2.173913	0	0	2.08333333
90	0	0	1.1627907	0	0	0.763358779	0	0	0	0	0	2.08333333
100	2	1.1627907	1.1627907	0	0	0.763358779	0	0	0	3	2.0833333	2.08333333
110	0	0	0	0	0	0.763358779	0	0	0	0	0	0
120	0	0	0	0	0	0.763358779	0	0	0	0	0	0
130	0	0	0	0	0	0.763358779	0	0	0	0	0	0
140	0	0	0	0	0	0.763358779	0	0	0	0	0	0
150	0	0	0	1	0.763358779	0.763358779	0	0	0	0	0	0
Total	172	100		131	100		46	100		144	100	

Table-8: Reverse cumulative percentage values for number of customers with a reservation price.

The reverse cumulative percentage values are plotted against the reservation prices as seen in Figure-6. It can be clearly noted that nearly 100% of the consumers are willing to pay up to INR 20 for operating the appliances. The average price that the consumers are paying at the time of this survey is INR 4.08. This means that almost all consumers can be charged about 500% of the present price for using these appliances. As price increases further, the cumulative percentage of refrigerator users remains highest and that of air-conditioner users remains lowest. The cumulative percentage of cooler user remains higher than that of washing machine users till a reservation price of INR 45, after which the statistics reverses. Thus, refrigerator seems to be a much-needed appliance bearing a high WTP and hence it is mostly non-shiftable and generally runs throughout twenty-four hours a day. The cooler has a high WTP with almost 60% of the consumers willing to pay INR 40. This is because it is a comfort appliance which runs at a lower cost when compared to air-conditioner, which bears a lower WTP (37% of consumers have WTP of INR 40). The washing machine seems to be less necessary than the refrigerator but more important than the air-conditioner.

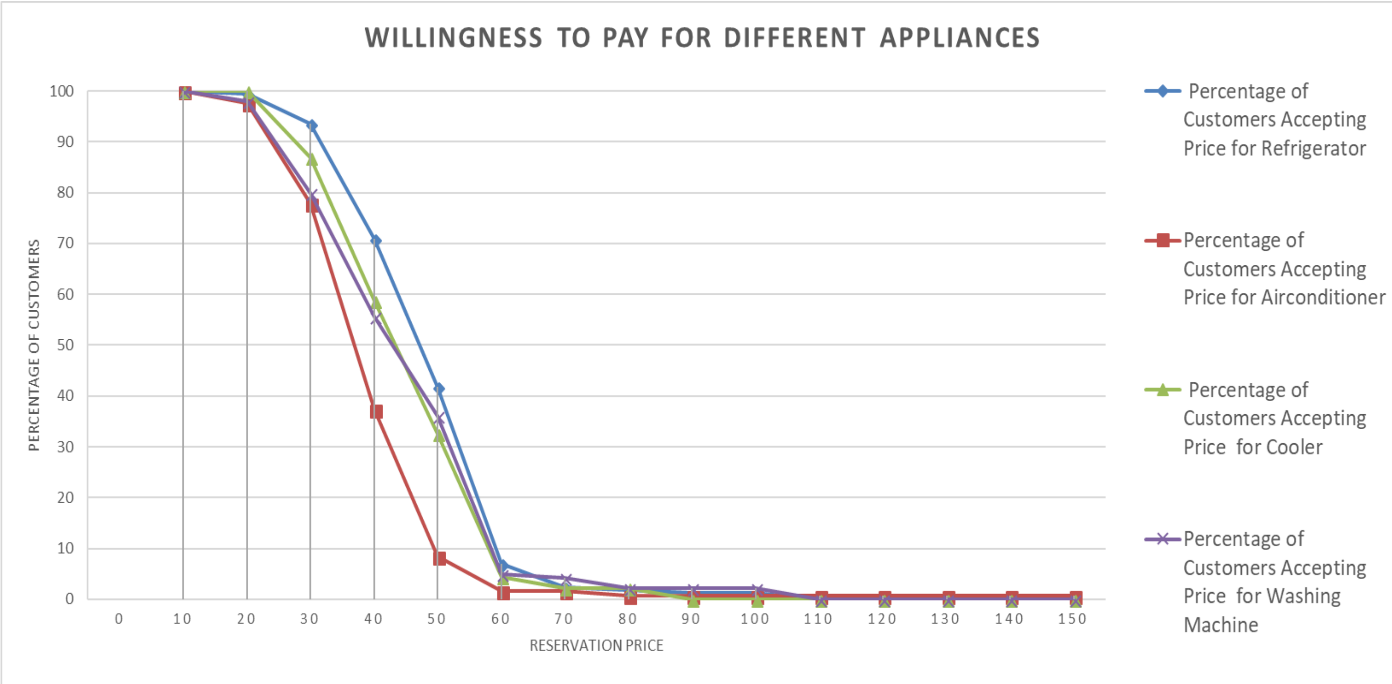
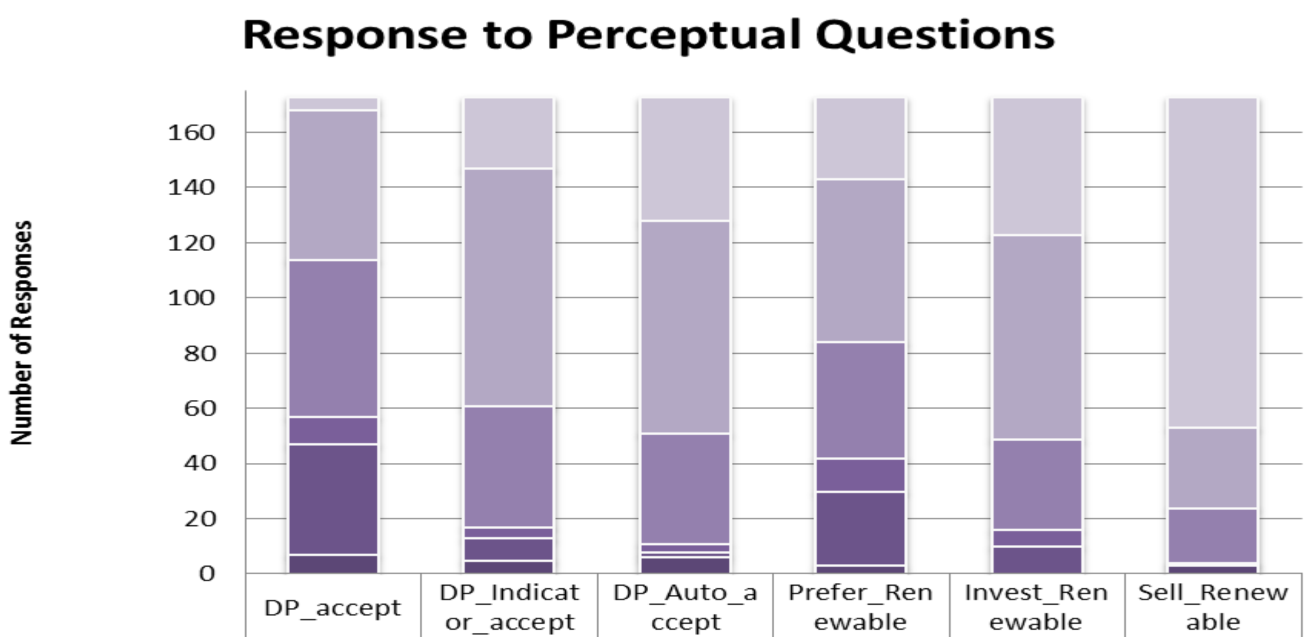


Figure-6: Percentage of the sample willing to pay a price for each appliance.

3.8. THE PERCEPTIONS REGARDING A FUTURE MARKET

The respondents were asked to state their likelihood on a six point scale for three questions on acceptance of dynamic pricing of electricity and three questions on acceptance of renewable energy and renewable energy generators in their home. Exhibit-5 shows the number of responses in each likelihood category for each question.



	DP_accept	DP_Indicator_accept	DP_Auto_accept	Prefer_Renewable	Invest_Renewable	Sell_Renewable
Absolutely	5	26	45	30	50	120
Very likely	54	86	77	59	74	29
May be	57	44	40	42	33	20
May be not	10	4	3	12	6	0
Not very likely	40	8	2	27	10	1
Not at all	7	5	6	3	0	3

Responses

Exhibit-5: Responses to perceptual questions.

It can be seen that while the consumers' willingness to accept dynamic pricing was not very strong, the willingness increased when they had an option of indicator devices that indicate the high priced periods with some sound or display. This attitude of acceptance of dynamic pricing further increased with the option of automation to schedule household electrical loads to reduce expenditure. Most respondents were somewhat interested in using renewable energy even if it costs more than conventional energy. The interest is high for investing in in-house renewable energy generator which gives an opportunity to substitute some grid energy and thus reduce operating expenditure. There is extreme likelihood of acceptance of in-house renewable energy generators if consumers are allowed to sell the excess energy to the grid.

3.9. THE FACTORS OF THE PERCEPTIONS

The responses to the perceptual questions had to concentrated down to lesser number of factors for the ease of further analysis. Hence we conducted factor analysis on this data. Table-9a shows the KMO and Bartlett's test results. Since the KMO measure is more than 0.5, we can proceed for a satisfactory factor analysis. The significance value of zero in the Bartlett's test signifies that the correlation matrix is not an identity matrix. The extraction value in table-9b shows the percentage of the variance in the variables accounted for by the factors. Thus the factors explain a good variance in almost all the variables.

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.658
Bartlett's Test of Sphericity	Approx. Chi-Square	405.883
	df	15
	Sig.	.000

Table-9a: KMO and Bartlett's test results

Communalities		
	Initial	Extraction
DP_accept	1.000	.719
DP_Indicator_accept	1.000	.851
DP_Auto_accept	1.000	.834
Prefer_Renewable	1.000	.644
Invest_Renewable	1.000	.785
Sell_Renewable	1.000	.458

Table-9b: Communalities

The rotation sums of squared loadings in table-10 show that there are only 2 factors whose eigenvalues exceed 1. These two factors account for 40.73% and 30.76% of variance of all variables.

Component	Initial Eigenvalues			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.555	42.590	42.590	2.444	40.732	40.732
2	1.734	28.905	71.495	1.846	30.764	71.495
3	.764	12.740	84.236			
4	.435	7.251	91.487			
5	.329	5.479	96.966			
6	.182	3.034	100.000			

Table-10: The decision of the number of factors.

The highlighted values in table-11a show the variables that have major impact on the values of the factors. The first factor (say F_1), which is highly dependent on the first three variables related to dynamic pricing, can be named as 'customer's inclination towards Dynamic Pricing'. The second factor (say F_2), which is highly dependent on the last three variables related to renewable energy, can be named as 'customer's inclination towards in-house renewable energy'. The two factors can be expressed as equations using the component scores from table-11b. The factor equations will be:

$$F_1 = (0.347 \times DP\ accept) + (0.387 \times DP\ Indicator\ accept) + (0.365 \times DP\ Auto\ accept) - (0.082 \times Prefer\ Renewable) - (0.049 \times Invest\ Renewable) + (0.068 \times Sell\ Renewable) \quad ..\ (3)$$

$$F_2 = -(0.012 \times DP\ accept) - (0.084 \times DP\ Indicator\ accept) + (0.03 \times DP\ Auto\ accept) + (0.445 \times Prefer\ Renewable) + (0.487 \times Invest\ Renewable) + (0.328 \times Sell\ Renewable) \quad ..\ (4)$$

Rotated Component Matrix

	Component	
	1	2
DP_accept	.845	.076
DP_Indicator_accept	.921	-.046
DP_Auto_accept	.899	.157
Prefer_Renewable	-.075	.799
Invest_Renewable	.018	.886
Sell_Renewable	.259	.625

Table-11a: Rotated component matrix

Component Score Coefficient Matrix

	Component	
	1	2
DP_accept	.347	-.012
DP_Indicator_accept	.387	-.084
DP_Auto_accept	.365	.030
Prefer_Renewable	-.082	.445
Invest_Renewable	-.049	.487
Sell_Renewable	.068	.328

Table-11b: Component score coefficient matrix

3.10. SEGMENTING THE PERCEPTUAL MARKET

The factors are calculated using equations 3 and 4 for each respondent and are plotted on a space with the two factors on the two axes as shown in figure-7a. It seems that the two market segments that we dealt with in the previous analyses do not properly differentiate the respondents in this perceptual future market. Hence we divided the space into four parts and formed three segments as seen in figure-7a. Segment-1 represents consumers with low inclination towards dynamic pricing but high inclination towards renewable energy. Segment-2 represents consumers with high inclination towards dynamic pricing but low inclination towards renewable energy. Segment-3 represents consumers with high inclination towards both dynamic pricing and renewable energy. The pie chart in figure-7b shows the volume of the segments. Segment-3 is the largest while segment-2 is smallest.

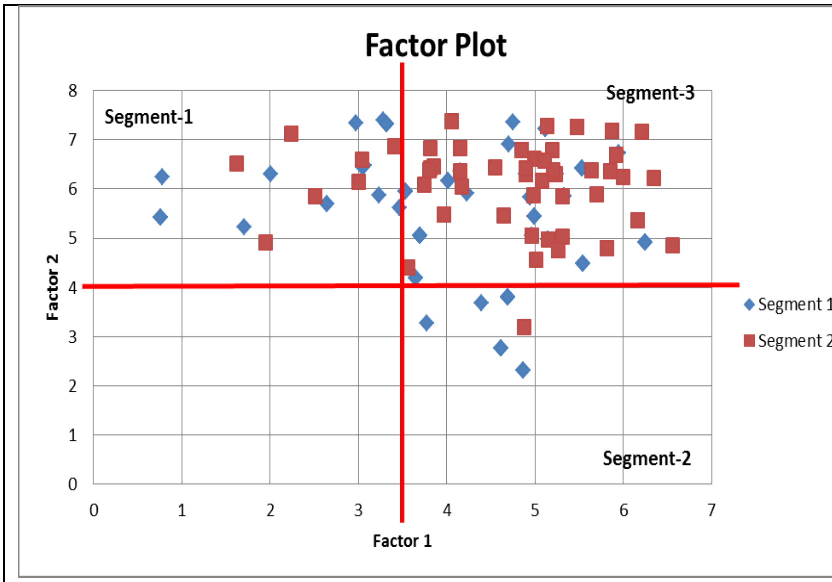


Figure-7a: Plot of the respondents based on factor scores.

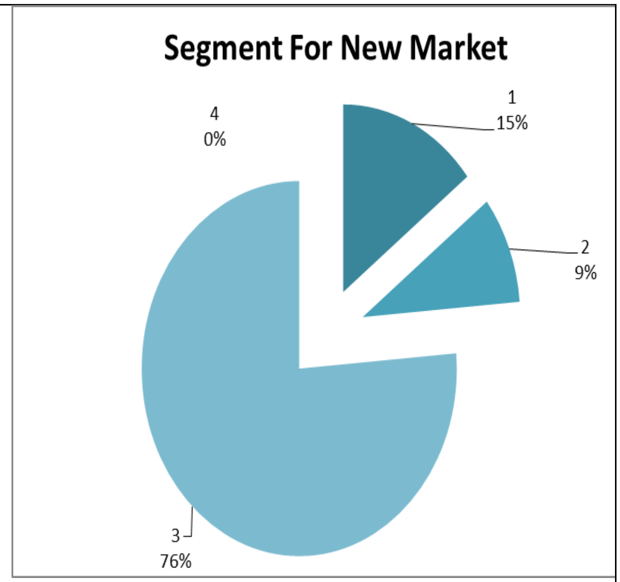


Figure-7b: Pie chart for new segments.

A discriminant analysis was carried out on these newly formed segments to be able to classify any new case in one of these segments. We carried out the discriminant analysis in SPSS in a similar fashion as we have done previously. The results of the analysis show that there are two discriminant functions for the three segments as shown in tables 12a and 12b. Here the high eigenvalues specifies that the discriminant functions can explain a large variation in the variables. The high canonical correlation values indicate that the functions can discriminate quite well. A significance value of 0 specifies that the prediction model is statistically significant. Smaller Wilk's lambda value indicates greater discriminatory capability of the functions.

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	1.875[a]	62.5	62.5	.808
2	1.123[a]	37.5	100.0	.727

Table-12a: Eigenvalues of the two functions

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1 through 2	.164	302.958	12	.000
2	.471	126.081	5	.000

Table-12b: Wilks' Lambda of the two functions

The classification results for the three segments are shown in table-13. The model can explain 88% of segment-1 and 100% of segments 2 and 3 correctly. On a whole, it has classified 98.3% of the cases correctly which verifies a very good discriminatory capability of the model.

Classification Results[a,c]						
Future_Segment			Predicted Group Membership			Total
			1	2	3	
Original	Count	1	22	0	3	25
		2	0	16	0	16
		3	0	0	132	132
	%	1	88.0	0.0	12.0	100.0
		2	0.0	100.0	0.0	100.0
		3	0.0	0.0	100.0	100.0
Cross-validated[b]	Count	1	18	0	7	25
		2	0	16	0	16
		3	0	2	130	132
	%	1	72.0	0.0	28.0	100.0
		2	0.0	100.0	0.0	100.0
		3	0.0	1.5	98.5	100.0
a. 98.3% of original grouped cases correctly classified.						
b. Cross validation is done only for those cases in the analysis. In cross validation, each case is classified by the functions derived from all cases other than that case.						
c. 94.8% of cross-validated grouped cases correctly classified.						

Table-13: Classification results for the analysis.

The analysis gave us two discriminant functions whose coefficients are displayed in table-14a. We can use these values to create the discriminant equations (5) and (6).

$$D_1 = (0.04 \times DP\ accept) + (0.866 \times DP\ Indicator\ accept) + (0.482 \times DP\ Auto\ accept) - (0.439 \times Prefer\ Renewable) - (0.364 \times Invest\ Renewable) - (0.222 \times Sell\ Renewable) - 1.601 \quad \ldots\ldots (5)$$

$$D_2 = (0.201 \times DP\ accept) - (0.028 \times DP\ Indicator\ accept) + (0.394 \times DP\ Auto\ accept) + (0.115 \times Prefer\ Renewable) + (0.553 \times Invest\ Renewable) - (0.749 \times Sell\ Renewable) - 9.808 \quad \ldots\ldots (6)$$

Table-14b shows the mean discriminant scores of the two functions for the groups. We can use the prior probabilities shown in table-14c to develop the equations of the lines that separate the space among the three segments. The territorial map for the segments obtained from the SPSS solution is shown in figure-8. This shows the lines that separate the space defined by the two functions 5 and 6 to discriminate among the segments.

	Function	
	1	2
DP_accept	.040	.201
DP_Indicator_accept	.866	-.028
DP_Automate_accept	.482	.394
Prefer_Renewable	-.439	.115
Invest_Renewable	-.364	.553
Sell_Renewable	-.222	.749
(Constant)	-1.601	-9.808

Table-14a: Canonical Discriminant Function Coefficients

Future_ Segment	Function	
	1	2
1	-3.040	-.998
2	2.160	-2.834
3	.314	.533

Table-14b: Function values at Group Centroids

Future_ Segment	Prior	Cases Used in Analysis	
		Unweighted	Weighted
1	.145	25	25.000
2	.092	16	16.000
3	.763	132	132.000
Total	1.000	173	173.000

Table-14c: Prior Probabilities for Groups

The distance of any point on a line dividing two segments from the centroids of those two segments should be in the proportion of the respective prior probabilities. So, if (D_1, D_2) represent any point on the line dividing segment 1 and 2, using the data from tables 14b and 14c we can write:

$$\frac{\sqrt{\left(D_1-(-3.040)\right)^2+\left(D_2-(-0.998)\right)^2}}{\sqrt{\left(D_1-(2.160)\right)^2+\left(D_2-(-2.834)\right)^2}} = \frac{0.145}{0.092} = 1.5761$$

$$\equiv 1.4841\left({D_1}^2+{D_2}^2\right)-4.6513D_1+12.0839D_2+21.3034=0 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (7)$$

Simmilarly, for any point (D_1, D_2) on the line dividing segment 2 and 3, we can write:

$$\frac{\sqrt{\left(D_1-(2.160)\right)^2+\left(D_2-(-2.834)\right)^2}}{\sqrt{\left(D_1-(0.314)\right)^2+\left(D_2-(0.533)\right)^2}} = \frac{0.092}{0.763} = 0.1206$$

$$\equiv 0.9855\left({D_1}^2+{D_2}^2\right)-4.3109D_1+5.6835D_2+12.6916=0 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (8)$$

Simmilarly, for any point (D_1, D_2) on the line dividing segment 3 and 1, we can write:

$$\frac{\sqrt{\left(D_1-(0.314)\right)^2+\left(D_2-(0.533)\right)^2}}{\sqrt{\left(D_1-(-3.040)\right)^2+\left(D_2-(-0.998)\right)^2}} = \frac{0.763}{0.145} = 5.2621$$

$$\equiv 26.6894\left({D_1}^2+{D_2}^2\right)+168.9796D_1+56.334D_2+283.0904=0 \quad \text{……………………. (9)}$$

Now let us represent the left hand side of the equations 7, 8 and 9 as LHS(7), LHS(8) and LHS(9). For any new case, we need to calculate the discriminant scores D_1 and D_2 from equations 5 and 6. Then these values of D_1 and D_2 needs to be used in equations 7, 8 and 9. Knowing the values of the LHSs, we can allocate the new case to one of the segments depending on the side of the lines it is located, as follows:

If LHS(7) <= 0 and LHS(9) <= 0, then the case belongs to segment 1.

If LHS(7) > 0 and LHS(8) <= 0, then the case belongs to segment 2.

If LHS(8) > 0 and LHS(9) > 0, then the case belongs to segment 3.

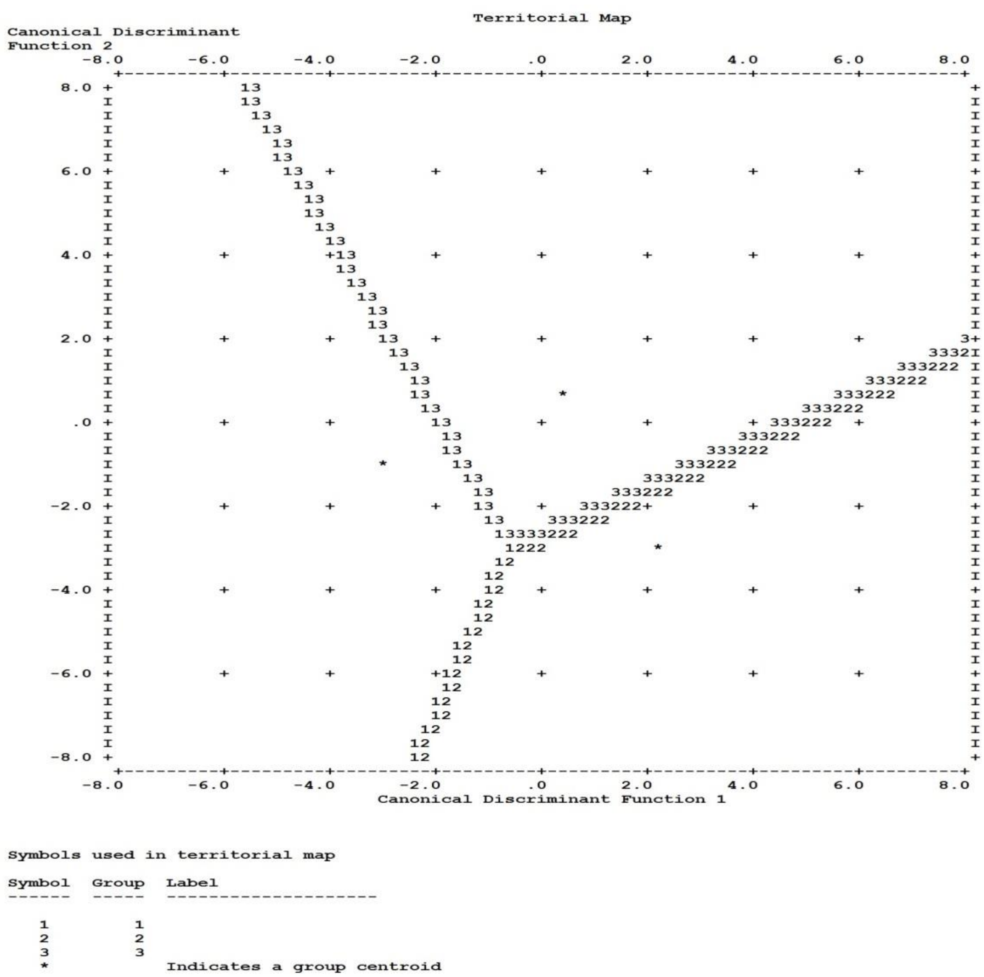


Figure-8: the territorial map for the three segments.

3.11. THE PERCEPTUAL DISTANCE BETWEEN THE ATTRIBUTES

The perceptual questions can be classified into two groups as explained by the factor analysis – 'customer's inclination towards Dynamic Pricing' and 'customer's inclination towards in-house renewable energy'. By comparing the response of consumers for the three questions in the dynamic pricing group, we can develop a perceptual distance plot among the three questions in the three segments. The same can also be done with the three questions of the renewable energy group. The figures are shown in the tables 15 and 16 respectively.

Segment 1 - Dynamic Pricing				
Weighted Response count				
		Higher Ranked Question		
		1	2	3
Lower Ranked Question	1	-	20	27
	2	5	-	15
	3	1	4	-
Proportion of total response				
		Higher Ranked Question		
		1	2	3
Lower Ranked Question	1	-	0.8	0.9643
	2	0.2	-	0.7895
	3	0.0357	0.2105	-
Normalized distance table				
		Higher Ranked Question		
		1	2	3
Lower Ranked Question	1	0	0.8416	1.8027
	2	-0.842	0	0.8046
	3	-1.803	-0.805	0
Average		-0.881	0.0123	0.8691
R*		0	0.8938	1.7506
R**		0	0.5106	1

Segment 2 - Dynamic Pricing				
Weighted Response count				
		Higher Ranked Question		
		1	2	3
Lower Ranked Question	1	-	24	18
	2	0	-	0
	3	0	6	-
Proportion of total response				
		Higher Ranked Question		
		1	2	3
Lower Ranked Question	1	-	1	1
	2	0	-	0
	3	0	1	-
Normalized distance table				
		Higher Ranked Question		
		1	2	3
Lower Ranked Question	1	0	7.9414	7.9414
	2	-7.941	0	-7.941
	3	-7.941	7.9414	0
Average		-5.294	5.2943	0
R*		0	10.589	5.2943
R**		0	1	0.5

Segment 3 - Dynamic Pricing				
Weighted Response count				
		Higher Ranked Question		
		1	2	3
Lower Ranked Question	1	-	119	146
	2	8	-	37
	3	1	3	-
Proportion of total response				
		Higher Ranked Question		
		1	2	3
Lower Ranked Question	1	-	0.937	0.9932
	2	0.063	-	0.925
	3	0.0068	0.075	-
Normalized distance table				
		Higher Ranked Question		
		1	2	3
Lower Ranked Question	1	0	1.5301	2.4675
	2	-1.53	0	1.4395
	3	-2.468	-1.44	0
Average		-1.333	0.0302	1.3023
R*		0	1.3627	2.6349
R**		0	0.5172	1

Table-15: Perceptual distance development table for dynamic pricing questions.

For each consumer, we have calculated how many times a question in a group is ranked more than another. We have added all these values for each segment and this data matrix is represented in the topmost part of tables 15 and 16. The columns represent the questions that have higher ranking than those in the rows in a paired comparison. The second part of the table represents the proportion of total response indicated by the actual numbers. The third part provides the normalized distance of the proportions. We find the average of this normalized distance and then change the origin to zero and the scale to unity. Hence we get a linear scale (Figure 9a and 9b) representing the perceptual distance of each question from one another in the question group.

Segment 1 - Renewable Energy				
Weighted Response count				
		Higher Ranked Question		
		4	5	6
Lower	4	-	8	10
Ranked	5	7	-	6
Question	6	8	5	-
Proportion of total response				
		Higher Ranked Question		
		4	5	6
Lower	4	-	0.5333	0.5556
Ranked	5	0.4667	-	0.5455
Question	6	0.4444	0.4545	-
Normalized distance table				
		Higher Ranked Question		
		4	5	6
Lower	4	0	0.0837	0.1397
Ranked	5	-0.084	0	0.1142
Question	6	-0.14	-0.114	0
Average		-0.074	-0.01	0.0846
R*		0	0.0643	0.1591
R**		0	0.404	1

Segment 2 - Renewable Energy				
Weighted Response count				
		Higher Ranked Question		
		4	5	6
Lower	4	-	15	35
Ranked	5	4	-	21
Question	6	6	3	-
Proportion of total response				
		Higher Ranked Question		
		4	5	6
Lower	4	-	0.7895	0.8537
Ranked	5	0.2105	-	0.875
Question	6	0.1463	0.125	-
Normalized distance table				
		Higher Ranked Question		
		4	5	6
Lower	4	0	0.8046	1.0523
Ranked	5	-0.8046	0	1.1503
Question	6	-1.0523	-1.1503	0
Average		-0.619	-0.1153	0.7342
R*		0	0.5037	1.3532
R**		0	0.3722	1

Segment 3 - Renewable Energy				
Weighted Response count				
		Higher Ranked Question		
		4	5	6
Lower	4	-	106	191
Ranked	5	14	-	106
Question	6	8	15	-
Proportion of total response				
		Higher Ranked Question		
		4	5	6
Lower	4	-	0.8833	0.9598
Ranked	5	0.1167	-	0.876
Question	6	0.0402	0.124	-
Normalized distance table				
		Higher Ranked Question		
		4	5	6
Lower	4	0	1.1918	1.7484
Ranked	5	-1.1918	0	1.1554
Question	6	-1.7484	-1.1554	0
Average		-0.9801	0.0121	0.9679
R*		0	0.9922	1.948
R**		0	0.5094	1

Table-16: Perceptual distance development table for renewable energy questions.

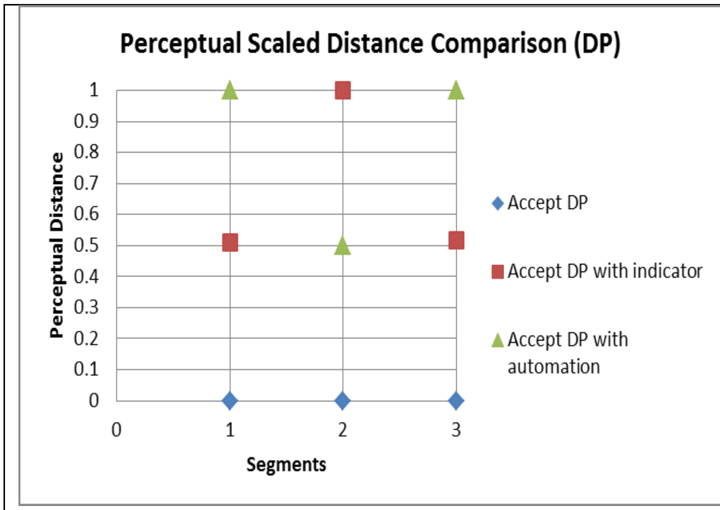


Figure-9a: The representation of perceptual distance between the dynamic pricing questions on linear scale

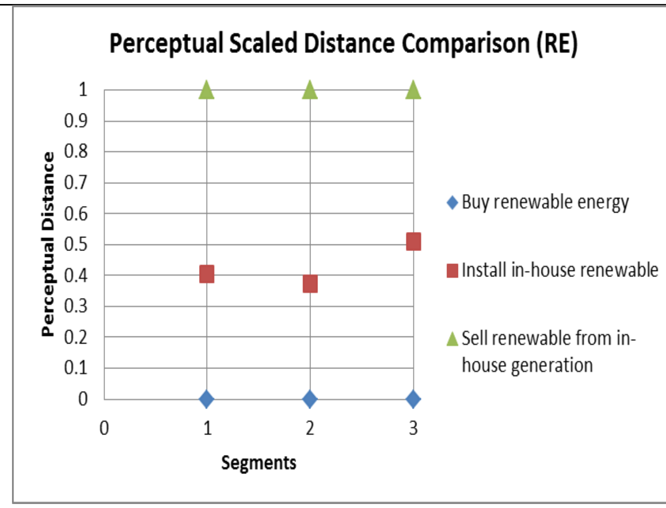


Figure-9b: The representation of perceptual distance between the renewable energy questions on linear scale

The perceptual distance between the willingness to accept only dynamic pricing (DP) and DP with indicator is almost same as that between DP with indicator and DP with automation in segments 1 and 3. The preference of DP with automation is highest in segments 1 and 3 meaning that higher prices can be charged and not much promotional effort will be required for offering automation system with DP to customers of these segments. Segment 2 customers however have highest preference to DP with indicator which means that they are more likely to be satisfied with indicator technology rather than automation technology. Customers of all the segments have highest preference for selling renewable energy that is generated inhouse, however the segments differ in their perception to install an inhouse renewable energy generator. While segment 3 will be the easiest, segment 2 will be the hardest to get an inhouse renewable energy generator installed.

4. CONCLUSION AND EXTENSION

The survey was done with 173 participants, selected through a convenience sampling technique, by the use of a formal and mostly structured questionnaire in Microsoft Excel format in a face-to-face interview setup. We have used inductive reasoning. The following characteristics of the sample are noted:

a) The average annual income of the sample was INR 1 Million and the median was the INR 0.8-1.2 Million group. The groups based on income are almost of equal size.
b) The median education group is that for professional Master degree holders and the same is the largest group.

c) The group based on family size has an average family size of 3.6 and median of 4. The 4-member family forms the largest group in our sample.

d) Most households consume in the range of 200-500 units per month.

e) The overall awareness about dynamic pricing is low but increases with the increasing education level.

The following inferences were drawn from the study:

a) The market can be suitably divided into two distinct segments as seen from a cluster analysis and dendrogram using Ward linkages.

b) The income has the highest impact on discriminant function which is based on the income, education, family size and the consumption level and has discriminated 96.5% of the original sample correctly.

c) A new consumer can be grouped in segment-1 if the discriminant score is less than or equal to the threshold value of 0.2662, else it is grouped in segment-2. Segment-2 consists of higher income, higher educated customers with larger family size as compared to segment-1.

d) The demand-price curves are negatively sloped and the maximum change in consumption with changing price is noted in the air-conditioner. Consumption by air-conditioner is high in segment-2 as compared to segment-1. The consumptions in other appliance types are more or less similar. Segment-1 responds slightly more to price changes than segment-2 in all other appliances other than air-conditioner.

e) Higher demand response can be achieved with appliances that have higher operating expenses and are also shiftable or dispensable.

f) The incremental change in demand response with respect to increasing price decreases for a cooler and increases for a refrigerator.

g) Value of money is more to members of segment-1 than to members of segment-2.

h) The overall consumption decreases when the difference in higher price and lower price increases in a two price-period setup.

i) Increasing the price ratio can induce a better demand response in segment-1 than in segment-2.

j) With increasing price ratio, consumers in segment-1 can be expected to keep reducing their total demand and shifting more of that demand to the low-priced periods. However, consumers in segment-2 can be expected to keep reducing their total demand, to a lesser extent as compared to segment-1, but not shifting much of that demand to the low-priced periods. The consumption shift to low-priced period is nearly 100% for washing machine and negligible for refrigerator.

k) It seems that segment-2 is more specific about time preference of consumption as compared to segment-1.

l) The willingness-to-pay for electricity is INR 20 per unit for all consumers for all appliances, which is 5 times the present average price. At INR 40 per unit, 70% of present refrigerator users, more than 55% of present washing machine and cooler users and less than 40% of the air-conditioner users will still be using the respective appliances.

m) The willingness to accept dynamic pricing in electricity increases with the use of indicator technology and further with the use of automation. The interest for using renewable energy increases with the option of inhouse generation and further increases with the option of selling any excess generation to the grid.

n) A factor analysis is done and the perceptual market is segmented into 3 segments (A, B and C). A discriminant analysis of these three segments correctly discriminates 98.3% of the cases and provides two discriminant functions D1 and D2. From the discriminant scores the total sample space is divided into three segments that is displayed through a territorial map that can classifying any new case into one of these three segments.

o) The perceptual distance of dynamic pricing (DP) with automation from only DP is greatest in segments A and C meaning that higher prices can be charged and not much promotional effort will be required for offering automation system with DP to customers of these segments. Segment-B customers however have highest preference to DP with indicator which means that they are more likely to be satisfied with indicator technology rather than automation technology. Segment-C will be the easiest and segment-B will be the hardest to get an inhouse renewable energy generator installed while the offer will turn interesting to all segments if the option of sale to the grid is made available.

In future studies, the segments defined in the study can be tested with larger and different samples to verify the discriminatory power of the model. More appliance types can be included in future studies to understand appliance specific consumer behavior. Future study on incorporating policy changes to address this lost consumer surplus can be taken up and research on specific marketing tools necessary to introduce dynamic pricing and inhouse renewable energy can be done.

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6. REFERENCES

An, L., Lupi, F., Liu, J., Linderman, M. and Huang, J. (2002). Modeling the choice to switch from fuelwood to electricity. *Ecological Economics*, 42(3), pp.445-457.

Bose, R. and Shukla, M. (1999). Elasticities of electricity demand in India. *Energy Policy*, 27(3), pp.137-146.

Charles River Associates, (2005). Applications Of Dynamic Pricing In Developing And Emerging Economies. [online] The World Bank. Available at: *http://siteresources.worldbank.org/INTENERGY/Resources/ApplicationsofDynamicPricing.pdf [Accessed 8 Jan. 2016]*.

Devicienti, F., Irina, K. and Stefano, P. (2005). Willingness to pay for water and energy: an introductory guide to contingent valuation and coping cost techniques. *Energy and Mining Sector Board, 3. World Bank*. Available at: http://documents.worldbank.org/curated/en/866831468158995793/Willingness-to-pay-for-water-and-energy-an-introductory-guide-to-contingent-valuation-and-coping-cost-techniques [Accessed 21 Sep. 2016].

Dütschke, E. and Paetz, A. (2013). Dynamic electricity pricing—Which programs do consumers prefer?. *Energy Policy*, 59, pp.226-234.

Dutta, G. and Mitra, K. (2017). A literature review on dynamic pricing of electricity. *Journal of the Operational Research Society*, 68(10), pp.1131-1145.

Faruqui, A. and Sergici, S. (2013). Arcturus: International Evidence on Dynamic Pricing. *The Electricity Journal*, 26(7), pp.55-65.

Faruqui, A., Sergici, S. and Akaba, L. (2014). The Impact of Dynamic Pricing on Residential and Small Commercial and Industrial Usage: New Experimental Evidence from Connecticut. The *Energy Journal*, 35(1).

Faruqui, A., Sergici, S. and Wood, L. (2009). Moving toward utility-scale deployment of dynamic pricing in mass markets. *IEE Whitepaper*, *June*. Available at: http://www.edisonfoundation.net/iei/Documents/IEE_Utility-ScaleDynamicPricing_0609.pdf [Accessed 21 Sep. 2016].

Filippini, M. and Pachauri, S. (2004). Elasticities of electricity demand in urban Indian households. *Energy Policy*, 32(3), pp.429-436.

Ifland, M., Exner, N., Doring, N., & Westermann, D. (2012, July). Influencing domestic customers' market behavior with time flexible tariffs. *2012 3rd IEEE PES Innovative Smart Grid Technologies Europe (ISGT Europe)*, Berlin, 2012, pp. 1-7.

Kirschen, D. S. (2003). Demand-side view of electricity markets. *IEEE Transactions on Power Systems,18*(2), pp.520-527.

Letzler, R. (2007). Implementing Opt-in, Residential, Dynamic Electricity Pricing: Insights from Economics and Psychology. ProQuest.

Mak, J. and Chapman, B. (1993). A survey of current real-time pricing programs. *The Electricity Journal*, 6(7), pp.76-77.

Mitra, K. and Dutta, G. (2018). A two-part dynamic pricing policy for household electricity consumption scheduling with minimized expenditure. *International Journal of Electrical Power & Energy Systems*, 100, pp.29-41.

Ozbafli, A. and Jenkins, G. (2013). Estimating Willingness To Pay For Reliable Electricity Supply: A Choice Experiment Study. Available at: http://www.queensjdiexec.org/publications/qed_dp_224.pdf [Accessed 26 Jun. 2015].

Roozbehani, M., Dahleh, M. A., & Mitter, S. K. (2012). Volatility of power grids under real-time pricing. *IEEE Transactions on Power Systems*, *27*(4), pp.1926-1940.

Thimmapuram, P. R., & Kim, J. (2013). Consumers' Price Elasticity of Demand Modeling With Economic Effects on Electricity Markets Using an Agent-Based Model. *IEEE Transactions on Smart Grid*, *4*(1), pp.390-397.

Tiwari, P. (2000). Architectural, Demographic, and Economic Causes of Electricity Consumption in Bombay. *Journal of Policy Modeling*, 22(1), pp.81-98.

Twerefou, D. (2014). Willingness to Pay for Improved Electricity Supply in Ghana. *Modern Economy*, 05(05), pp.489-498.

Wolak, F. A. (2011). Do residential customers respond to hourly prices? Evidence from a dynamic pricing experiment. *The American Economic Review*, Wolak, F. A. (2011). Do residential customers respond to hourly prices? Evidence from a dynamic pricing experiment. *The American Economic Review*, 101(3), pp.83-87.

Zhou, S. and Teng, F. (2013). Estimation of urban residential electricity demand in China using household survey data. *Energy Policy*, 61, pp.394-402.