Theoretical Economics Letters, 2017, 7, 1940-1949
http://www.scirp.org/journal/tel
ISSN Online: 2162-2086
ISSN Print: 2162-2078

Effect of Adjacent Product Price on Customer's Willingness to Pay of Focal Brand: A Bayesian Approach

Atanu Adhikari

Indian Institute of Management Kozhikode (IIMK), Kozhikode, India
Email: atanu.adhikari@iimk.ac.in

How to cite this paper: Adhikari, A. (2017) Effect of Adjacent Product Price on Customer's Willingness to Pay of Focal Brand: A Bayesian Approach. *Theoretical Economics Letters*, 7, 1940-1949.
https://doi.org/10.4236/tel.2017.77131

Received: September 9, 2017
Accepted: November 24, 2017
Published: November 27, 2017

Abstract

Psychological researchers, while studying internal reference price, have dealt with different types of psychological effects like attraction effect and compromise effect. While studying consumer reference price and willingness to pay, marketing researchers have focused on consumers' perception about a brand by evaluating several attributes of that brand. Our research investigates the incremental effect on consumers' willingness to pay in a context where an adjacent price is present, for instance, when a medium priced brand is associated with a high price brand than a moderately high priced brand. Unlike other pricing research, this research deals with consumer's individual level heterogeneity as price sensitivity and consumers' willingness to pay for a particular brand since they vary among individual. Hierarchical Bayes methodology is used to incorporate such heterogeneity. The study shows significant difference in consumers' utility and her willingness to pay when a medium priced brand is compared with a high priced brand as against a moderately high priced brand.

Keywords

Brand-Choice Decision, Willingness to Pay, Internal Reference Price, Consumer Heterogeneity, Hierarchical Bayes

1. Introduction

Consumer makes purchase decision in different ways while buying a brand. Consumers have their own preferences for product features, which they used to select a few brands. Preferred features are compared and weights are assigned for the final decision making. Selected brands are then evaluated based on price-benefit paradox and then selected for purchase.

Behavioral aspect of consumers in pricing research has received more focus since early 80s. Utility theory of consumer surplus provides a better understanding of the behavioral aspect of pricing research. Consumer surplus is used to form the reference price which is considered to have a unique value for a given segment. For a particular product category, the whole population behaves in a similar way in terms of both price sensitivity and choice rules; varied price effects across individual or within individual are not considered for the research

During a purchase, a consumer faces prices of several products which vary from low range to high. A consumer can modify her reference price and willingness to pay based on the price of other products. This research deals with the change in the effect of consumers' willingness to pay when a product with the price in low range is placed with a product that has moderately price range than to a product that has high price range.

2. Literature Review

Consumer's evaluation of brand under uncertainty is supported by their justification in terms of most preferred attribute [1] [2]. Psychological research showed that consumers act differently while choosing a product. Among two equal utility brands the consumer tends to buy a brand which is superior in terms of important attributes. These attributes are evaluated based on price-utility paradox and the comparative winner takes the purchase share. The prediction of consumer choice behavior is difficult as the utility of a brand is weighted summation of individual preference of several attributes. However, this evaluation is often uncertain as in most cases consumers are unaware about the benefit of the product until they use. On the contrary, money spent, for such utility is often certain and foregone in advance (Japtura *et al.* 2014).

Several researchers [3] [4] studied the role of attraction effect in brand-choice decision making. They argued that the choice probability of dominating alternative is affected by the presence of inferior alternative in a set. In other words, the products with superior attributes are preferred more than the products with inferior attributes. However these researchers used experimental research to study the phenomena. 20 experimental researches had a very limited number of sample size as well as small number of alternatives with few factors. this has consequently resulted diluted effect of comparative attraction of dominated alternative since the choices were small and the noise of complicating factors may not have significant unit level variation [3] [5].

Choice justification is another branch of research in the field of brand-choice behavior. When a choice selection is followed by explanation to second person; individual try to find reasons for justification. While psychological researches do show many reasons of justification (Hall and Lindzey, 1978; Kaura *et al.*, 2013), the primary referred reason is found to be being rational while evaluating related attribute. Economic literature [6] also provided enough support in terms of utility maximization while consumers select a choice. Consequently, a price-utility effect plays a major role in consumer's brand evaluation (Ha, 2006; Mahamood, 2014).

Studies on anchoring effect found that consumers anchor themselves with independent motivation while evaluating a completely different product. Complete body of significantly, reference price literature also has its base with psychology. Pricing research on incidental price and willingness to pay [7] documented that a highly priced product, which is completely unrelated can also influence the willingness to pay off a less valued product. Monroe [8] pointed out that while price of substitute product affect the expected demand, previous price of the product also influence internal reference price of the consumer. Primary reason for this is related and unrelated anchoring effect. Change in consumers' reference price is based on association of a product along with other products. Monroe [9] found that consumer's reference price varies based on other price stimuli, while describing consumers' subjective perception.

Above review leads us to investigate the impact of several price levels on brand-choice decision making. Hence the objective is to study whether there is any difference in consumers' utility and her willingness to pay when a medium priced brand with no inferior attribute is compared with a high priced brand as against a moderately high priced brand. Our study attempts to propose that there is some association between given product alternative with a high priced product alternative in brand-choice decision and it may inflate the willingness to pay of the given product. In other words we also propose that as the price differential between two associated choice alternatives increases, the willingness to pay of the lower alternative increases. This study tries to explore explores the argument that when a consumer is given a choice set of several alternatives of brands, she makes her reference price based on the higher priced alternative and estimates the price of lower priced alternative from that anchor.

3. Consumer Level Heterogeneity

Reference price modeled aggregate level effect almost all researchers [10]. The Difference across between the consumers is not captured both in reference price as well as in psychological literature. Price effects are estimated by aggregating data of entire sample or few segments and then single parameter or few segment level parameters are estimated. The effect studied reports total effect or segment level effect, but not individual effect. The important aspects like how utility relation, price sensitivity, loss aversion and brand preference differ across individuals are also examined in this study. Understanding consumer level heterogeneity is required while dealing with pricing policies, demand estimation and similar researches. Here the individual level heterogeneity is taken into consideration during the parameter estimation. Since the price sensitivity and willingness to pay are individual specific, individual heterogeneity in preference call for market segmentation that will to cater to specific consumer requirement. However, data deficiency exists in studies on consumer preference due to consumer heterogeneity [11]. Earlier studies shows [12] [13] that hierarchical Bayes (HB) individual estimates are more consistent and reliable than the estimates of finite-mixture models.

4. The Study

Three products were selected from a pilot study. These three product square automobile detergent powder and wrist watch. Automobile was elected because it has both tangible and intangible product features which consumers give almost equal weighted while selecting their automobile. Detergent powder is a frequently purchased product and selected by the consumers primarily because of that tangible attributes like cleaning ability, fragrance comma softness et cetera. Wrist watch was selected because of higher degree of intangibility of its features which consumers consider while buying the product.

Table 1 represents the attributes and levels of these 3 products below. Since full factorial design is too large in number for realistically data collection, fractional factorial design has been used to identify the choice sets for the respondents to respond. The experimental design was not strictly orthogonal nor was strictly level balanced since the objective of the research was to see the effect of anchor points on willingness to pay of a particular alternative choice set. Since profiling the part of utility of the choice set was not primary objective, search method would give more precise estimate of utilities. Hence, we needed choice sets that are distinct in terms of price compare ability while sacrificing the orthogonality and level balancing to some extent. However, required corrective

Table 1. (a) Automobile; (b) Detergent powder—1 kg pack; (c) Wristwatch.

(a)

Brand	Hundai, Mercedes, Toyota, Skoda
Engine Capacity	1500 cc, 1600 cc, 2400 cc, 3300 cc
Type	Small SUV, Medium SUV, Large SUV and Sedan
Mileage (Km/Ltr)	18, 16, 14
Price	750,000; 1,100,000; 1,250,000; 1,500,000; 3,000,000

(b)

Type	Commercial, Fine, Supreme,
Brand	Ariel, Surf, Rin
Price	80; 100; 170

(c)

Look	Ordinary, Official, Ornamental
Band	Chromium Plating, Leather, Gold Coated
Brand	HMT, Titan, Richo
Price	1200; 2500; 15,000; 60,000

measures were taken by measuring design efficiency to keep it within acceptable limit as prescribed by the previous researchers. Huber and Zwerina [14] pointed out that, minimal overlap is important to reduce the probability of duplicating an attribute level in different alternatives of a choice.

Sixteen choice Set Square given to the respondents for their response. Out of these 16 choice sets 4 sets for experimental which was repeated twice. Remaining 8 sets where for filler sets. Filler sets were used to eliminate response bias. The first position in each of the four experimental choice sets where allotted to anchor alternative. The alternative under study is kept in second position and rest 8 alternatives where mixed alternatives. Anchor prices were recorded separately to capture the price sensitivity.

42 respondents participated in the survey. Two dependent variables were collected for each choice profile. These two dependent variable square willingness to pay and intention to buy a price variable was used as a proxy for dependent variable, willingness to pay. Both the dependent variables were measured using 7 point Likert scale. Respondents were required to provide their opinion about the price of the second alternative of the choice set in a 7 point Likert scale. The value of this major varies from very low to very high. Similarly the dependent variable intention to buy was measured in a 7 point scale that arranged from not at all by to definitely buy.

5. Individual Level Estimates Using Hierarchical Bayes

In the last one decade application of Bayesian methodology of application used has occupied significant area in the area marketing research have witnessed wide usage of the application of Bayesian methodology. The usefulness of Bayesian method was recognized quite long back, however, computational limitation was the main hurdle in its application. This computational burden can be solved by Markov Chain Monte Carlo (MCMC) simulation method facilitated to overcome computational burden of which uses models drawn from stepwise conditional distributions. MCMC method is facilitates a chain process drawing from arbitrary posterior distribution that converges to target distribution. Consequently, several marketing issues like intra-unit behavior, consumer level heterogeneity could be considered for more efficient marketing decisions.

A basic problem in marketing research is limited amount of individual level information to calculate consumer specific parameters as well as predict preferences is an important problem in the area of marketing research. This is due to large number of attribute and many levels in each attribute which call for higher number of observations for estimation.

Aggregate level information pooling is a method is based on the fixed effect model which assumes that the parameters are same across all respondents. This particular assumption focuses on mean value of the estimate and does not consider individual level heterogeneity. This is a naive simple and easy way of estimating price related parameters. The process of Marketing action often needs to calculate individual level information for better understanding of consumer preference and purchase decision. Hence, a random-effect model which that assumes that the parameters follow a probability distribution of heterogeneity across respondents is required for practical application.

A hierarchical Bayes random effect model helps in estimating individual specific parameters as well as aggregate level under limited data for dealing with individual specific parameters and limited data, Hierarchical Bayes Random Effect Model is useful. In such model, individuals are considered as independent conditional on unit level parameters. However, the priors induced for HB estimation at individual level are not independent prior. Individual parameters are considered as drawn from the whole population which is one way of mixing distribution.

The likelihood of individual parameter $\{\theta_i\}$ and the common parameter of mixing distribution τ can be written as:

$$L(\{\theta_i\},\tau) = p(\text{data}/\theta_i,\tau) = \prod_{i=1}^{N} p(\text{data}/\theta_i)\, p(\theta_i/\tau) \quad (1)$$

"*i*" denotes the ith consumer of total *N*, *L* is likelihood function, θ_i is individual parameter vector and $p(\theta_i/\tau)$ is the mixed distribution of individual parameter conditional on τ, a common parameter that comes from population. Inference about the parameter τ can be calculated by marginalizing likelihood through integrating out the parameter vector:

$$L(\tau) = \prod_i \int p(y_i/\theta_i)\, p(\theta_i/\tau)\, \mathrm{d}\theta_i$$

Given the joint prior of parameter vector θ_i of i'th individual the posterior distribution can be written as

$$p(\theta_1,\theta_2\cdots,\theta_N/y_1,y_2,\cdots,y_N) \propto \left[\prod_i p(y_i/\theta_i)\right] \times p(\theta_1,\theta_2\cdots,\theta_N/\tau)$$

τ is hyper-parameter on which prior is based. Due to insufficient data point at individual level, specification of functional form and prior hyper-parameters are important for individual level analysis. Rossi and Allenby [15] suggested that this process is useful in choice data sets where many consumers evaluates all the alternatives presented and most standard choice models do not have a bounded ML estimate as likelihood may be asymptotic in certain direction in parameter space. In such situation, largely, the prior determines the inference about the consumer.

Evaluating the joint distribution of prior parameter $p(\theta_1,\theta_2\cdots,\theta_N/\tau)$ is difficult due to its high dimensionality. One way of simplifying the form of the prior distribution is assuming they are independent to each other conditional on τ. Hence, we can write above equation with assumption of independence as:

$$p(\theta_1,\theta_2\cdots,\theta_N/y_1,y_2,\cdots,y_N) \propto \left[\prod_i p(y_i/\theta_i)\right] \times p(\theta_i/\tau)$$

Once we consider the conditionality of the prior on the hyper-parameter, it is necessary to define its behavior, *i.e.* distribution and conditionality of the hyper-parameter. Assessing the prior hyper-parameter is also a challenging task. In case of normal prior, a large standard deviation serves the purpose. Rossi and

Allenby [16] suggested a prior on the scaled version pooled model information matrix. The prior covariance is then scaled ("shrinked") and used to represent the expected information in one observation. This follows shrinkage phenomenon and posterior estimates like the one posterior means ($\tilde{\theta}_i = E\left[\theta_i/\text{data}, \text{prior}\right]$) are concentrated towards the prior means and less on ML estimates (*i.e.* $\hat{\theta}_j$).

Hence, to model individual level heterogeneity, we require two stages of prior; first stage to model prior parameter value and second stage to model the parameter on which the first stage prior is conditional. It can be represented through a hierarchical form. So the hierarchical Bayes model in this research consists of unit level likelihood function and two stages of priors:

Likelihood: $p\left(y_i/\theta_i\right), i = 1, 2, \cdots, N$ (No. of respondents)

First stage prior: $p\left(\theta_i/\tau\right)$

Second stage prior: $p\left(\tau/\omega\right)$

Then we can write the joint posterior for the hierarchical Bayes model as follows:

$$P\left(\theta_1, \cdots, \theta_m, \tau/y_1, \cdots, y_m, \omega\right) \propto \left[\prod p\left(y_i/\theta_i\right) p\left(\theta_i/\tau\right)\right] \times p\left(\tau/\omega\right)$$

where $\left(\theta_1, \cdots, \theta_m\right)$ are individual level (for ith individual) parameter vector and $y_1, \cdots, y_m$ are individual level data vector. In above model, the individual level priors are not independent, rather calculated based on super-population distribution with an assumption that individual alone cannot influence the prior dependence. However, the description of the consumers requires information about θ_i and τ. Only the knowledge of heterogeneity by way of assuming distribution often insufficient to evaluate optimum marketing decision under less individual level information. Bayesian approach solves this problem by estimating τ by maximizing its likelihood function given in Equation (1) and then applying $p\left(\theta_i/\tau = \hat{\tau}\right)$ as prior in the analysis of an individual's conditional likelihood. So, $P\left(\theta_i/\text{data}\right) \propto P\left(y_i/\theta_i\right) P\left(\theta_i/\tau = \hat{\tau}\right)$. For reasonably large sample size, τ can be correctly estimated and any individual cannot influence its estimate.

Huber [17] study on hierarchical Bayes with survey data and Natter and Feurstein [18] with real world purchase data find that hierarchical Bayes outperforms latent class model and aggregate model in terms of correctness of parameter estimation (RMSE) and predicting hold out choices as it incorporates heterogeneity in the model. This supports that incorporation of heterogeneity in the consumer choice model have higher predictive power. Aggregate models underestimate the standard error of the parameter estimates in presence of heterogeneity.

6. Analysis

Sawtooth Software is used in this research for The HB analysis is carried out using Sawtooth Software. An identity matrix is assumed as prior covariance matrix which indicates a prior variance of 1 for all parameters. Large prior variance pays more importance on data-fitting of each individual and less importance on borrowing data (Sawtooth software manual, 2006) from others. An identity matrix ensures a proper balance between two data-fitting and borrowing of data. We maintained the default option of prior degrees of freedom, 5 is maintained and less degrees of freedom helps to restrict impact of prior variance. As the research is exploratory in nature and very little information is available about the prior parameter, we considered less degree of freedom to restrict the impact of prior variance.

All categorical the independent variables that are categorical, coded through "effect coding". In dummy variable coding, one level of each attribute which is deleted attribute takes the value zero. In effect coding, the deleted level has an implied value which is equal to suggests that the negative value of summated coefficients of rest levels in that category. Hence, with effect coding, the sum of coefficients of all levels of any attribute is zero.

7. Result and Discussion

20,000 iterations are performed in each case through HB regression procedure is devised for performing 20,000 iterations in each case. Every 10^{th} draws are saved to calculate mean part-worth of every respondent and the result is saved to calculate the mean part-worth of each attribute across all respondents To calculate the mean part-worth of every respondent and each attribute, 10^{th} draws are saved across. No parameter constraint both in value and sign is imposed in the analysis Parameter constraint does not matter in both value and sign of the results. In terms of Willingness to pay and in choices of medium priced study alternatives with high priced reference (anchor) alternatives are significantly higher ($p < 0.01$) in all three studies. It means that consumers perceive utility of an alternative when it is associated with a high priced alternative which is significantly higher than and also when the same alternative is associated with moderately high priced alternative. At the same time, the intention to buy the alternative under study is not significantly different in two both cases ($p > 0.05$). It also suggests that people's intension to buy a moderately priced alternative do not vary with the association of a higher priced alternative than that of a moderately priced alternative. Correlation between part-worth utilities in two both cases is insignificant. This advocates the usefulness and effectiveness of this is where filler choice sets are made use of. A possible explanation is that when similar types of choice sets are faced by the respondent, as per standard form in memory one choice set is immediately supplemented by another similar choice set. No significant insignificant correlations suggest that respondents' evaluation of study alternative along with each anchor alternative (*i.e.* with high price and moderately high price) was independent to each other and hence bias free.

Evaluated score of willingness to pay were significantly different with value (at $p < 0.01$) with value of 19. 3 and 23.5 (Maximum possible score for each respondent in both cases would be 28 and minimum will be 4). However, we found that significant positive correlation between two cases This which suggest that willingness to pay is consistently high among respondents when the study alternative is associated with moderately high priced one than that of high priced one.

8. Conclusions and Future Research

Above all, the findings support reveal that consumers compare their choice alternatives with the one close to them and form an opinion about its utility that modifies their reference price accordingly. It is quite consistent with the standard notion of it is human behavior. They compare things and form an opinion about one, which is consistent with our findings. The study considered the effect of higher price anchor on medium priced brand and found that by considering the effect of higher price anchor on medium priced brand, there is a significant positive impact in consumers' willingness to pay. Unlike other studies on reference pricing research and studies on consumers' willingness to pay, we have considered consumer level heterogeneity as individuals vary in terms of utility and price reference.

Further studies can be carried to research and to investigate whether there is any negative impact of association of lower priced brand on medium to moderately high priced brand. Currently, we are working on a similar project to investigate the effect of such lower anchor pricing and see the effect on consumer's willingness to pay. However, this kind of research also requires inclusion of aspects like individual level heterogeneity to study the individual specific effect. Nunes and Boatwright [6] conducted a study in that line but did not repost as they and did not find any significant result. The study considered aggregate level effect and did not include individual level heterogeneity.

References

[1] Montgomery, H. (1983) Decision Rules and the Search for a Dominance Structure: Towards a Process Model of Decision Making. In: Humphreys, P.C., *et al.*, Eds., *Analyzing and Aiding Decision Process*, North-Holland, Amsterdam. https://doi.org/10.1016/S0166-4115(08)62243-8

[2] Slovic, P. (1975) Choice between Equally-Valued Alternatives. *Journal of Experimental Psychology: Human Perception and Performance*, **1**, 280-287. https://doi.org/10.1037/0096-1523.1.3.280

[3] Huber, J. and Puto, C. (1983) Marketing Boundaries and Product Choice: Illustrating Attraction and Substitution Effects. *Journal of Consumer Research*, **10**, 31-44. https://doi.org/10.1086/208943

[4] Simonson, I. (1989) Choice Based on Reasons: The Case of Attraction and Compromise Effects. *Journal of Consumer Research*, **16**, 158-174. https://doi.org/10.1086/209205

[5] Ratneshwar, S., Shocker, A.D. and Stewart, D.W. (1987) Towards Understanding the Attraction Effect: The Implication of Product Stimulus Meaningfulness and Familiarity. *Journal of Consumer Research*, **13**, 520-533. https://doi.org/10.1086/209085

[6] Samuelson, P.A. and Nordhaus, W.D. (2001) Microeconomics. ISE Editions, McGraw-Hill Education, New York.

[7] Nunes, J.C. and Boatwright, P. (2004) Incidental Prices and Their Effect on Willingness to Pay. *Journal of Marketing Research*, **41**, 457-466. https://doi.org/10.1509/jmkr.41.4.457.47014

[8] Monroe, K.B. (1990) Pricing: Making Profitable Decisions. 2nd Edition, McGraw Hill, New York.

[9] Monroe, K.B. (1973) Buyers' Subjective Perceptions of Price. *Journal of Marketing Research*, **10**, 70-80. https://doi.org/10.2307/3149411

[10] Mazumdar, T., Raj, S.P. and Sinha, I. (2005) Reference Price Research: Review and Propositions. *Journal of Marketing*, **69**, 84-102. https://doi.org/10.1509/jmkg.2005.69.4.84

[11] Adhikari, A. and Rao, A.K. (2013) Individual Preference and Bargaining Behavior in Families' Buying Decisions of Restaurant Service. *Cornell Hospitality Quarterly*, **54**, 248-261. https://doi.org/10.1177/1938965512459801

[12] Allenby, G.M. and Ginter, J. (1995) Using Extremes to Design Products and Segment Markets. *Journal of Marketing Research*, **32**, 392-403. https://doi.org/10.2307/3152175

[13] Lenk, P., DeSarbo, W., Green, P.E. and Young, M. (1996) Hierarchical Bayes Conjoint Analysis: Recovery of Part-Worth Heterogeneity from Reduced Experimental Design. *Marketing Science*, **15**, 173-191. https://doi.org/10.1287/mksc.15.2.173

[14] Huber, J. and Zwerina, K. (1996) The Importance of Efficient Utility Balance if Efficient Choice Design. *Journal of Marketing Research*, **33**, 307-317. https://doi.org/10.2307/3152127

[15] Rossi, P.E. and Allenby, G.M. (2003) Bayesian Statistics and Marketing. *Marketing Science*, **22**, 304-328. https://doi.org/10.1287/mksc.22.3.304.17739

[16] Allenby, G.M. and Rossi, P.E. (1999) Marketing Models of Consumer Heterogeneity. *Journal of Econometrics*, **89**, 57-78.

[17] Huber, J. (1998) Achieving Individual Level Predictions from CBC Data: Comparing ICE and Hierarchical Bayes. Presentation Given at Advance Research Technique Forum (Understanding Taken from Sawtooth Software Technical Papers).

[18] Natter, M. and Markus, F. (2002) Real World Performance of Choice Based Conjoint Models. *European Journal of Operation Research*, **137**, 448-458.