

"A man is
great by
deeds, not by
birth"

-Chanakya

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Adjacent Price Anchoring and Consumer's Willingness to Pay: A Bayesian Approach

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Abstract:

Considerable research on consumers' use of psychological reference points exists in pricing literature. Researchers examining brand choice have reasoned that reference point is based on past prices of the brand. We argue that consumers' reference prices is motivated by the adjacent price of the product at point of display rather than any other reference prices in the context. This research studies the effect of adjacent price on consumers' willingness to pay and purchase intention. This research considers consumer level heterogeneity since price sensitivity and consumers' willingness to pay vary among individual. Hierarchical Bayes methodology is used to incorporate heterogeneity. This study shows significant difference in consumers' willingness to pay when a medium priced brand is placed adjacent to a high priced brand as against adjacent to a moderately priced brand.

Keywords

Brand-choice decision, Willingness to pay, internal reference price, Consumer heterogeneity, Hierarchical Bayes

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Introduction:

Consumer's decision making in real life purchase of a brand are formed several ways. Consumers compare different brands based on their preferred features and keep few selected brands in their decision platform. Preferred features across different alternatives are then compared and weights are assigned on these attributes for final decision making. Selected brands in decision platform are then evaluated on price-benefit paradox and one is selected for purchase.

Since early 80s, pricing research started focusing behavioral aspect of consumers more frequently (Rao, 1993). The basic understanding of behavioral aspect of pricing research is that it considers utility theory through consumer surplus. Consumer's reference price is formed based on their surplus. Pricing research has encountered several models where reference price is considered to have unique value for a given segment. The whole population of the segment behave in similar way in terms of price sensitivity and choice rules for a particular product categories. These researches do not consider to have varied price effects across individual or within individual.

Consumers encounter prices of several products while making a purchase. For example, when we enter into a retail garment store, we come across prices which vary from low range to very high range. A consumer of economic segment, though buy a low range product, often modifies her reference price and willingness to pay based on the price of other displayed garments. In this research, I capture the change in effect on

consumer's willingness to pay when low range product is placed with moderately high priced garment and with high priced garments

Literature review:

Psychological research showed that consumer choice behavior acts in different ways. Montgomery (1983), Slovic (1975) found that consumer's evaluation of brand under uncertainty is supported by her justification in terms of most preferred attribute. Consumers tend to buy a brand which is superior on important attribute from two equal utility brands. However, the attributes that determine the selection of brands are still evaluated in price – utility paradox and the comparative winner takes the purchase share. Difficulty in predicting consumer choice behavior is that the utility of a brand is weighted summation of individual preference of several attributes. This evaluation is often uncertain. In most cases consumers are unaware about the benefit of the product till they use the product. On the contrary, money, that is to be given away for such utility is often certain and foregone in advance (Japtura et al 2014).

Several researchers (Huber and Puto,1983; Simonson, 1989) studied attraction effect in brand-choice decision making. They argued that presence of an inferior alternative in a set increases the choice probability of dominating alternative. In other words, when an alternative in a choice set contain an attribute level which is significantly inferior to other levels, an alternative with higher level attribute dominates. However, Huber and Puto (1983) study and few other studies (Ratneshwar et al., 1987) conducted experiments with small number of alternatives and with few factors. Hence, the

comparative attraction of dominated alternative is often diluted in small choice sets due to noise of complicating factors that may not have significant unit level variation.

There is another stream of research in brand-choice behavior is choice justification. 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 (Samulson, 2004) 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).

Several psychological researches on anchoring effect found that consumers anchor themselves with independent motivation while evaluating a completely different product. Complete body of reference price literature has its base with psychology. Pricing research on incidental price and willingness to pay (Nunes and Boatwright, 2004) documented that a highly priced completely unrelated product may positively influence willingness to pay of a less valued product. Monroe (1990) 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 it is related and unrelated anchoring effect. Change in consumers' reference price is based on association of a product along with other products. While describing consumers' subjective perception of price Monroe (1973) found that consumer's reference price varies based on other price stimuli.

Above review leads one to investigate the impact of several price levels on brand-choice decision making. It means 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. We propose that association of a given product alternative with a high priced product alternative in brand-choice decision may inflate the willingness to pay of the given product. In other words we propose that as the price differential between two associated choice alternatives increases, the willingness to pay of the lower alternative increases. This study 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.

Consumer Level Heterogeneity

Almost all researches in reference price modeled aggregate level effect (Majumder, Raj and Sinha, 2005). Difference across consumers is not captured both in reference price and psychological literature. All these studies calculated price effects by aggregating data of entire sample or few segments and then estimated single parameter or few segment level parameters. The effect studied in these researches essentially postulate total effect or segment level effect, but not individual effect. These studies implicitly However, utility relation, price sensitivity, loss aversion and brand preference differ across individual. Pricing policies demand estimation and similar researches require to understand consumer level heterogeneity. This study considers individual level heterogeneity in parameter estimation. Since the price sensitivity and willingness to pay

are individual specific, heterogeneity in individual preference call for market segmentation to cater to specific consumer requirement. However, studies on consumer preference typically face data deficiency problem while incorporating consumer heterogeneity (Allenby and Rossi, 1999). As found in earlier studies (Allenby and Ginter, 1995; Lenk et al. 1996) that hierarchical Bayes (HB) individual estimates are more stable than the estimates of finite-mixture models.

The Study

We carried out our studies with three different products: Wristwatch, Automobile and detergent power. Wristwatch is selected as it has high degree of intangible property and consumer's emotional appeal plays a vital role in choice decision and willingness to pay. Automobile is a balance mixture of tangible and intangibles attributes and consumers provide almost equal weight in purchase decision. Detergent powder is a product with tangible properties and consumer's choice decision depends on rational appeal of the product. We selected these three kinds of product to measure the variability across types of product choice i.e. emotional, balanced and rational.

Factors and levels of these three products are given in Table-1. Fractional factorial design is used to identify different choice sets for the respondents. We have not tried to make the experimental design level balanced or orthogonal. Our objective in this research is to compare the willingness to pay of a particular alternative in a choice set to see the effect of the anchor point and not to profile the part-worth utility of the choice set. Consequently, we require a choice set that are distinct in terms of price comparability between alternatives which may not be orthogonal or level balanced. However, we have

paid special attention to make the choice sets minimal overlap. Huber and Zwerina (1996) pointed out that minimal overlap becomes important to make optimal utility neutral choice design. It reduces the probability of duplicating an attribute level in different alternatives of a choice. Dazzling

Table - 1

Wristwatch

Brand	Richo , Titan, HMT
Band	Gold coated, Leather, Chromium plating
Look	Ornamental, official, ordinary
Price	Rs 60,000; Rs 15000; Rs2500, Rs. 1200

Automobile

Brand	Mercedes, Skoda, Toyota, Hundai
Type	Sedan, Large SUV, Medium SUV, Small SUV
Engine Capacity	3.3L, 2.4L, 1.8L, 1.5L
Mileage (Km/Ltr)	14, 16, 18
Price	Rs 3,000,000, Rs 1,500,000, Rs 1,250,000 Rs 1,100,000 Rs 750,000.

Detergent powder – 2.2 pound pack

Brand	Surf, Ariel, Rin
Type	Supreme, fine, commercial

Price	Rs. 170, Rs. 100, Rs. 80
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Each respondent evaluated sixteen choice sets out of which four sets were experimental set which was repeated twice and rest eight sets were filler sets. Filler sets are used to eliminate response bias. In all four experimental choice sets, the alternative under study (i.e medium priced alternatives) were kept in second position and anchor alternative (i.e. high and moderately high priced alternatives) were placed in the first position. The rest eight sets were with mixed alternatives. The anchor prices (i.e. high and moderately high price) were recorded for each choice sets separately to calculate price sensitivities.

Forty two respondents took part in the study. Two dependent variables were collected for each choice profiles: willingness to pay and intension to buy. The variable, willingness to pay were surrogated by a price variable. Both variables were captured in seven point Likert scale (Likert, 1931). Respondents were asked to provide their feeling about the price of the second alternative of the choice set in a seven point scale, from 'very low' to 'very high'. Similarly their intention to buy of the second profile was also collected in seven point scale, from 'not at all buy' to definitely buy.

Individual level estimates using hierarchical Bayes:

In last one decade application of Bayesian methodology has occupied significant area in marketing research. The usefulness of Bayesian method was recognized quite long back, however, computational limitation was the main hurdle in its application. Markov Chain Monte Carlo (MCMC) simulation method facilitated to overcome computational burden

of models drawn from stepwise conditional distributions. MCMC method is 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. This is due to large number of attribute and many levels in each attribute call for higher number of observations for estimation.

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

An hierarchical Bayes random effect model helps in estimating individual specific parameters as well as aggregate level under limited data. 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:

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

'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:

$$L(\tau) = \prod_i \int p(y_i / \theta_i) p(\theta_i / \tau) d\theta_i$$

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

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

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 (2003) 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 $p(\theta_1, \theta_2, \dots, \theta_N / \tau)$ 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:

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

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. Rossy and Allenby (1993) suggested a prior on the scaled version pooled model information matrix. The prior covariance is then scaled ('shrunked') and used to represent the expected information in one observation. This follows shrinkage phenomenon and posterior estimates like the one posterior means ($\tilde{\theta}_i = E[\theta_i / \text{data, prior}]$) are concentrated towards the prior means and less on ML estimates (i.e. $\hat{\theta}_i$).

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:

$$\begin{aligned} \text{Likelihood:} & \quad p(y_i / \theta_i) \quad i = 1, 2, \dots, N \text{ (No. of respondents)} \\ \text{First stage prior:} & \quad p(\theta_i / \tau) \\ \text{Second stage prior:} & \quad p(\tau / \omega) \end{aligned}$$

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

$$\begin{aligned} P(\theta_1, \dots, \theta_m, \tau / y_1, \dots, y_m, \omega) \\ \propto \prod p(y_i / \theta_i) p(\theta_i / \tau) \times p(\tau / \omega) \end{aligned}$$

Where $(\theta_1 \dots \theta_m)$ are individual level (for i'th individual) parameter vector and y_1, \dots, 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 can not 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 $p(\theta_i / \tau = \hat{\tau})$ as prior in the analysis of an individual's conditional likelihood. So, $P(\theta_i / \text{data}) \propto P(y_i / \theta_i)P(\theta_i / \tau = \hat{\tau})$. For reasonably large sample size, τ can be correctly estimated and any individual can not influence its estimate.

Huber (1998) study on hierarchical Bayes with survey data and Natter and feurstein (2002) 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 under estimates the standard error of the parameter estimates in presence of heterogeneity.

Analysis

Sawtooth Software is used in this research for HB analysis. 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. We maintained the default option of prior degrees of freedom as 5. 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 independent variables are coded through 'effect coding'. In dummy variable coding, one level of each attribute which is deleted, takes value zero. In effect coding, the deleted level has an implied value which is equal to 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.

Result and discussion

20000 iterations are performed in each case through HB regression procedure. Every 10th 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. No parameter constraint both in value and sign is imposed in the analysis. Willingness to pay 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 consumer's perceive utility of an alternative when it is associated with a high priced alternative is significantly higher than when the same alternative is associated with moderately high priced alternative. At the same time intention to buy the alternative under study is not significantly different in two cases ($p > 0.05$). It 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 cases ranged from 0.17 to 0.25 and is insignificant. This advocates the usefulness and

effectiveness of filler choice sets. 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 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 significant positive correlation between two cases. This 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.

Conclusion and future research

Above findings support that consumers compare their choice alternatives with the one close to them and forms an opinion about its utility that modifies their reference price accordingly. It is quite consistent with the standard notion of human behavior of comparing things and forming an opinion about one. The study considered the effect of higher price anchor on medium priced brand and found that 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.

Research can be done to investigate whether there is any negative impact of association of lower priced brand on medium to moderately high priced brand. 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 considering individual level heterogeneity to study the individual specific effect. Nunes and Boatwright (2004) conducted a study in that line but did not report as they did not find any significant result. Their study considered aggregate level effect and did not include individual level heterogeneity.

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