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MULTIVARIATE PRICING

Price strategy is the key marketing tool for companies to increase their competitive edge but too often, prices are based on costs, not on customers' perceptions of value.

Value-based pricing is a business strategy which sets selling prices based on the perceived value to the customer, rather than the actual cost of the product, the market price, competitors' prices, or the historical price. Practically speaking, the goal is to align the money spent with the value perceived. For example, the number of users, lifetime spending, number of transactions, value of transaction, return-on-investment, cost saving, revenue; the list can continue.

The most common techniques employ straightforward methods such as: 'Would you pay for this item at this price?'. While the van Westendorf method and conjoint analysis are useful, this article focuses on multivariate pricing techniques that allow flexibility and agility into the pricing models, and therefore can be more widely employed by clients and product managers.

DISCRETE CHOICE MODEL

Discrete choice is a realistic consumer choice exercise that is used when the products themselves are fixed. The main goal is then to ascertain market share in various competitive and pricing situations and to calculate a fluid price function.

Discrete choice analysis consists of a series of questions that ask respondents to choose between two or more hypothetical products or services at different price levels. The resulting model is a simplified description of reality providing a better understanding of how consumers make product decisions.

The model simulates future market states to support product and price level decisions. A well-constructed discrete choice model allows for multiple 'what-if' scenarios within the context of the model, optimises price or brand positions within existing market realities, and figures in 'non-purchase'. The customer views 'real world' choices with the inclusion of competitive brands, which can be set at different prices and target specific competitors with products designed to take share specifically from them.

For example, Bart's Bait Company wants to introduce a new bait into his local market. With discrete choice he will be able to project his market share among his chief competitors. Bart's Bait Skinny Chunk specifies the competitors and a range of prices. Below is an example scenario:

Please choose one of the following:

1. Bart's Skinny Chunk at $2.39
2. Zoom Fat Albert Twin Tail at $2.19
3. E-Bait Big Salty Chunk at $2.39
4. Bracken Bait's Big Critter Craw at $1.89
5. None of the above

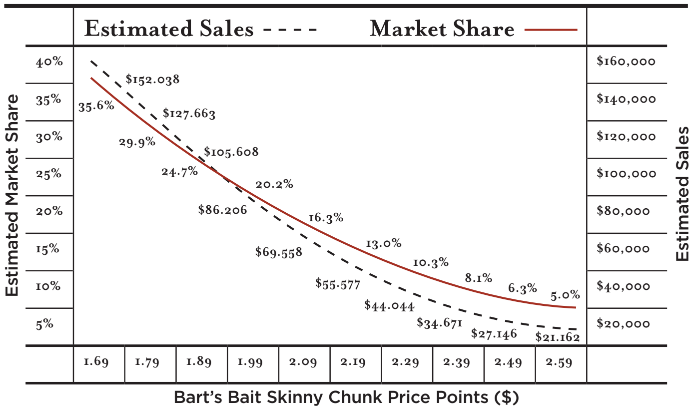
After running the model using a multinomial logistic regression, we then create a simulator which allows Bart's to plug in prices for his Skinny Chunk as well as for the three other competitors in the market. The 'brand space' baseline outputs the initial finding for a discrete model. It shows the calculated market share of each brand when their prices are held at the mid-test points.

Bart's Bait Skinny Chunk can expect about 13% entry market share. With the model and a working simulator, Bart can now project his Skinny Chunk sales. To keep things simple, Figure 1 shows a price curve of Skinny Chunk along 10 price points. With a discrete choice model there are an infinite


$6
$5
$4

number of potential curves, as each one depends on fixed points of the other competitors (in this figure we have kept the competitors each at $2.19.)

FIGURE 1: TESTED PRICE POINTS FOR BART'S BAIT SKINNY CHUNK



Zoom Fat Albert Twin Tail $2.19
E-Bait Big Salty Chung $2.19
Bracken Bait's Big Critter Craw $2.19

Clearly, the lower the price Bart charges, the greater the market share he will gain. However, the lower prices may not be realistic price points, and the higher ones may give Bart too low a sales figure. Moreover, the market might not be stable at $2.19. His competitors may — in fact, will — raise and lower their prices.

MAXIMUM DIFFERENCE

The newest choice in choice modeling is maximum difference analysis or scaling. Maxdiff is based on customer choice or trade-off instead of typical rating scale responses and is the multinomial extension of the traditional method of paired comparisons.

A paired comparison question asks a respondent to make a binary choice, maximum difference has the respondent specify 'best' and 'worst' choices from sets of three or more objects.

This model is easily administered, has multiple levels of analysis, and is a very effective tool in establishing the relative priority of such items as the potential message for a new product, features or benefits of a service, and fundamental customer interests, activities and unmet/future needs.

PRICING APPLICATION

The client, a casual dining restaurant, needed to test price sensitivity for 11 main courses, each at four price points. For example, the customer will see all 11 menu items such as Shrimp and Chicken Gumbo, Factory Burrito Grande, or Beef Ribs at four test price points.

We employed a maximum difference design to test the price ranges. Each respondent saw 15 choice scenarios with varying items and prices. The order of questions was randomised, and price levels were randomly assigned to each attribute. Respondents chose which menu item they would be most likely, and least likely, to choose.

This approach allows us to construct a discrete-choice model similar to the logit model just described. We can construct utilities for each item and a price function, and then build a simulator to model item demand. Figure 2 shows a simulator that contains seven menu items at varying price points.

FIGURE 2: MAXIMUM-DIFFERENCE SIMULATOR

Casual Dining Restaurant			
Market Model	1 = Included	Item Price ($)	Projected Market Share
Shrimp and Chicken Gumbo	1	13.49	16%
Herb Crusted Filet of Salmon	1	13.49	16%
Shrimp Scampi	1	15.49	13%
Double B.B.Q. Bacon Cheeseburger	1	11.99	9%
Teriyaki Chicken	1	12.99	12%
Beef Ribs	1	16.99	24%
Filet Mignon	1	19.99	10%

Examining the outcome, the management can see that beef ribs, at their lowest price point, have a demand of 24%, and that pricing the Double BBQ bacon cheeseburger above $11 will drive demand down below 10%.

MONTE CARLO SIMULATION

This takes into consideration a consumer's price value perception, product, variable fixed costs, and market size. This model is an extension of the Grange-Gabor price where several levels of prices are tested for a given product. Let's say we are testing
a household product. The product managers want to make a decision to price on one of four price points: $3.19, $3.49, $3.79 and $4.09. The pricing module on the questionnaire is constructed as follows–
Given the features of this product, would you be willing to pay $3.49 for it?'
— If 'yes', then ask, "Would you pay $3.79 for it?"

— If ‘no’, then ask , “Would you pay $3.19 for it?”
Continue with ‘Yes’ until the respondent says, ‘No.’ Record the highest ‘Yes’. Continue with ‘No’ until the respondent says, ‘Yes.’ Record that ‘Yes’.
— If ‘Yes’ at top price ($4.09), record top price.
— If ‘No’ at bottom price, ($3.19), record ‘No purchase’.

Rotate the starting points so that all price points begin equally. Also, assume that if a person says ‘Yes’ at a higher price point, say $3.79, they would purchase the product at the lower price points.

This methodology yields penetration of the product at each price point. The Monte Carlo forecast is laid out in an excel spreadsheet.

FIGURE 3: THE MONTE CARLO METHOD

Percentiles %	3.19*	3.49*	3.79*	4.09*
100	597,523	695,832	589,950	267,951
90	2,106,987	2,158,621	2,019,893	1,949,298
80	2,319,575	2,361,291	2,229,070	2,196,493
70	2,481,527	2,515,587	2,387,704	2,382,843
60	2,624,676	2,653,837	2,529,045	2,544,796
50	2,762,286	2,787,369	2,644,762	2,776,234
40	2,902,625	2,923,539	2,803,168	2,960,732
30	3,054,749	3,070,702	2,952,720	3.333.242
20	3,232,977	3,242,015	3,127,511	3,537,269
10	3,477,125	3,474,521	3,368,736	3,821,356
0	5,499,152	5,307,607	5,185,025	6,080,598

*All prices are in US $

THE MONTE CARLO METHOD

In the real world, however, the market is not exactly two million but between 1.75 million and 2.25 million people. Fixed costs actually vary between $1,750,000 to $3,000,000 with a skew towards cost over-runs and the 75% market penetration has a standard deviation of +/- 4%, but at 57% the standard deviation is +/- 6%.

The Monte Carlo method allows the different assumptions (eg fixed costs) to ‘bounce around’ within their limits and records projected revenue for each scenario. If this model is run 1,000,000 times, then 1,000,000 different outcomes for each of the four price points can be recorded. These outcomes are arrayed in a cumulative distribution in Figure 3.

The table is read as follows. At $3.19, the chances of making $2,300,000 or more given the moving parts is about 80%. At $3.49 the chances of making $2,700,000 or more are a little over 50% and this (highlighted in yellow) is often referred to as the ‘expected value’. At this point, $3.49 has the highest expected value.

This table can be used for management to make several decisions. If, for example, they would like to choose the price point at which they can be 80% sure to make the most money, then $3.49 is the winner. However, if management would like to know at which price point they are most likely to make $3,000,000, the winner is the high $4.09, which generates a chance of reaching the revenue goal being just a bit under 40%, higher than the other tested price points.

The strength of this approach is that it allows unlimited ‘what-if’ scenarios. Simply change the parameters in the worksheet, re-run the simulation, produce the output table, and make a price decision.

In the toolbox shown, we are searching for robust pricing methodologies designed to yield extraordinarily accurate price elasticity measures. Powerful pricing simulators give our clients unparalleled flexibility in modeling ‘what if’ pricing scenarios. By utilising any of the methods explored, we demonstrate a useful price optimisation system that determines optimal price points that maximise revenue, share, penetration, and margin with less risk. RW

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