Product design

Working assumption: What is a product?

A product is a bundle of attribute levels or features that have utilities to customer (price is considered as attribute as well)

The meaning of : "Designing a product"

Deciding and setting the levels of the attributes.

Performance criteria

1) Sales

2) Revenues

3) Profit

Consider elasticity, demand curve, cash flow-credit (starts up firms), quick cents v.s slow dollars.

Elements to consider

1) What are the product attributes and their levels

2) "Where" is the product positioned in the perceptual map and where it should be positioned.

3) Where are the competitor for the same dimensions

The Conjoint Model

Conjoint is a compensatory multiattribute model - it assumes that weakness on one attribute can be compensated for by strength in another. It assumes that the utility or value for a product can be expressed as a sum of utilities for its features or attributes.

$$U = u(a_1) + u(a_2) + \ldots = \sum_{attributes} utilities$$

Working assumptions:

•Utilities can be measured by consumers' overall evaluation of products where customers make tradeoffs among attributes.

•Customers differs in their preferences and the value they place on different attributes.

•Estimates of the utilities can be used to make market share predictions about new products

An Illustrative Example

(Lehmann, Gupta and Steckel, 1998) P. 541

Consider a situation of shopping a notebook computer, the attributes under your consideration are (ignoring other attributes such as price, for clarity):

1) Processing speed: 100mHz, 133mHz.

2) Hard drive: 2GB or 3GB

3) Memory: 32MB or 64MB RAM

There are 8 different combinations of notebook - defined as *product profiles:*

			Hard drive		
		2GB		**4GB**	
		Memory		**Memory**	
		32MG	64MG	32MG	64MG
processor	100mHz	1	2	3	4
	133mHz	5	6	7	8

Ranking the profiles

Next, we can ask customer to rank or rate, the profiles. The table below present rankings for a hypothetical customer, the profiles are coded as dummy variables.

Product Profile	Processor	Hard Drive	Memory	Rank	Product Utility
1	0	0	0	8	1
2	1	0	0	4	5
3	0	1	0	6	3
4	0	0	1	7	2
5	1	1	0	2	7
6	0	1	1	5	4
7	1	0	1	3	6
8	1	1	1	1	8

Not surprisingly, this customers prefers profile 8, It is the ranking for of other profiles that reveals the customer's preference for various attributes.

Uncovering Attribute Utilities from Overall Utility

Recall The conjoint assumption:

$$U=a+b_1*Processor + b_2*Hard\ Drive + b_3*Memory$$

Using the dummy variables from the table in the last slide for profiles 1-4 we can write down 4 equations with 4 unknowns (a, b_1, b_2, b_3) and solve them:

$$U_1 = a + b_1 \cdot 0 + b_2 \cdot 0 + b_3 \cdot 0 = a$$
$$U_2 = a + b_1 \cdot 1 + b_2 \cdot 0 + b_3 \cdot 0 = a + b_1$$
$$U_3 = a + b_1 \cdot 0 + b_2 \cdot 1 + b_3 \cdot 0 = a + b_2$$
$$U_4 = a + b_1 \cdot 0 + b_2 \cdot 0 + b_3 \cdot 1 = a + b_3$$

$$a = U_1 = 1$$
$$b_1 = U_2 - U_1 = 5 - 1 = 4$$
$$b_2 = U_3 - U_1 = 3 - 1 = 2$$
$$b_3 = U_4 - U_1 = 2 - 1 = 1$$

a, b1, b2, b3 are called ***part-worths***, in practice they are derived by means of a computer algorithms (dummy variable regression, MONANOVA, etc.)

Uses of the Part-Worths

1) We can estimate the relative value our customer attaches to different attributes. In this example, processing speed (b_1=4) is valued more than hard drive capacity (b_2=2) or memory (b_3=1). In fact $b_1>b_2+b_3$.

2) We can use the part-worths to forecast the preferences of this customer for other notebook computers. Note that in the examples we used only the first 4 profiles to compute the part-worths. In order to estimate other profiles we have to plug in the dummy variables:

$$U_5 = a + b_1 \cdot 1 + b_2 \cdot 1 + b_3 \cdot 0 = 7$$
$$U_6 = a + b_1 \cdot 0 + b_2 \cdot 1 + b_3 \cdot 1 = 4$$
$$U_7 = a + b_1 \cdot 1 + b_2 \cdot 0 + b_3 \cdot 1 = 6$$
$$U_8 = a + b_1 \cdot 1 + b_2 \cdot 1 + b_3 \cdot 1 = 8$$

3) We can simulate the impact of new product introductions.

Conjoint Simulation - The Motivation

Consider a market with two existing brands A and B with the attributes (and levels) specified in the table below (using dummy coding); A has a 133mHz (processor = 1) with 2GB (Hard Drive = 0) and 64MB (Memory = 1). Brand B has 1 133 MHz processor, with 4GB hard drive but only 32MB of memory. Assume that we want to introduce a new notebook with 100mHz, 3GB and 64MB.

Brand	Processor	Hard Drive	Memory
A	1	0	1
B	1	1	0
New	0	1	1

What share can the new brand obtain?

and where this share will come from?

Conjoint Simulation - The Principle

From the part-worths estimated earlier, we can obtain ratings or rankings for each product profile, including the new concept. For each customer separately we can determine his choice. The table below presents part-worths and brand utilities for 10 customers. For each customer we can assign a choice of brand A, B or the new concept (assuming a choice rule).

	Part-Worths				Brand Utilities			Brand Chioce	
Customer	**a**	**b1**	**b2**	**b3**	**A**	**B**	**New**	**W/O New**	**With New**
1	1	2	4	1	4	7	6	B	B
2	0	5	1	2	7	6	3	A	A
3	2	2	3	1	5	7	6	B	B
4	1	0	3	4	5	4	8	A	**New**
5	0	2	1	5	7	3	6	A	A
6	1	6	1	0	7	8	2	B	B
7	0	1	3	4	5	4	7	A	**New**
8	1	2	5	0	3	8	6	B	B
9	1	0	6	1	2	7	8	B	**New**
10	2	4	2	0	6	8	4	B	B

Before the introduction the market share is expected to be: A=0.4, B=0.6. When the new brand is introduced: A=0.2,B=0.5, and New=0.3. In other words, the new brand is expected to draw 20% of brand A and 10% of brand B.

Assessing Relative Importance of Each Attribute

Relative importance of an attribute = utility range of that attribute divided by the sum of the utility ranges for all attribute. For example the relative importance of processing speed for a customer is:

$$\frac{b_1}{b_1 + b_2 + b_3} = \frac{4}{7}$$

Relative importances for our 10 customers are given below;

Customer	Processor	Hard Drive	Memory
1	29%	57%	14%
2	63	12	25
3	33	50	17
4	0	43	57
5	25	12	63
6	86	14	0
7	13	37	50
8	29	71	0
9	0	86	14
10	67	33	0

Customers 1,3 and to some extent customer 8 have similar preferences. This data allows segmentation (e.g., by using cluster analysis), and understanding the market structure.

Steps involved

Designing the conjoint study:

- Select attributes relevant to the product or service category.
- Select levels for each attribute
- Develop the product bundles to be evaluated

Obtaining data from a sample of respondents:

- Design the data collection procedure.
- Select a computation method for obtaining part-worth functions.

Evaluating product design options:

- Segment customer based on their part-worth functions
- Design market simulations.
- Evaluate (and select) choice rules.
- Establish the best design for the product.

Computing the part-worth functions

(using dummy variable regression)

$$R_{ij} = \sum_{k=1}^{K} \sum_{m=1}^{M_k} a_{ikm} x_{jkm} + \varepsilon_{ij}$$

j = a particular product or concept included in the study design

R_{ij} = the ratings provided be respondent I for product j

a_{ikm} = part-worth associated with *m*th level of the *k*th attribute

M_k = number of levels of attribute *k*

K = numbers of attributes

x_{jkm} = dummy variable that take on value 1 if *m*th level of the *k*th attribute is present in product j and 0 otherwise

ε_{ij} = error terms, assumed to be normal distribution with zero mean and variance σ^2 for al *i* and *j*

a_{ikm} can be rescaled for more easy interpretation

Conjoint results

The utility of a product *j* to customer *i*:

$$u_{ij} = \sum_{k=1}^{k} \sum_{m=1}^{M_k} a_{ikm} x_{jkm}$$

Note that product *j* can be any product that can be designed using the attributes and levels in the study, including those that were not included in the estimation of the part-worths in the former equation.

Design market simulation:

A major reason for the wide use of conjoint analysis is that once part-worths are estimated from a representative sample of respondents it is easy to asses the likely success of a new product concept under various simulated market conditions. A typical question is what market share would a proposed new product be expected to achieve in a market with several specific existing competitors?

To answer this we have to specify all existing products as combinations of attributes and their levels. Also we have to select the choice rules that transform part-worths into product choices that customers are most likely to make.

Choice rules - maximum utility

•Maximum Utility rule:

under this rule we assume that each customer chooses from available alternatives the product that provides the highest utility value, including a new product concept under consideration. This choice rule is most appropriate for high involvement purchases such as cars, videos etc.

There are two ways to compute the market share according to this choice rule. We can compute the number of customers for whom that product offers the highest utility and dividing this figure by the numbers of customers in the study.

The second way is weighting each customer probability of purchasing each alternative by the relative volume of purchases that the customer makes in the product category:

$$m_j = \frac{\sum_{i=1}^{I} w_i p_{ij}}{\sum_{j=1}^{J} \sum_{i=1}^{I} w_i p_{ij}}$$

I - number of customers participating in the study, *J* - The number of product alternatives available for the customer to choose from, m_i - market share of product *j*, w_i the relative volume of purchase made by customer I, with the average volume across all customers indexed to the value 1, p_{ij} the probability that customer I will choose product j on a single purchase occasion

Choice rules - Share of utility

This rule is based on the notion that the higher utility of the product to the customer, the greater the probability that he or she will choose that product. Thus each product gets a share of a customer's purchases in proportion to its share of the customer's preferences:

$$p_{ij} = \frac{u_{ij}}{\sum_{j}^{J} u_{ij}}$$

where u_{ij} is the estimated utility of product j to customer *i*. We can obtain the market share for product I by averaging p_{ij} across customers.

This choice rule is relevant for low involvement frequently purchased products, such as consumer packaged goods. This rule requires that utilities be expressed as ratio scaled numbers.

Logit choice rule

$$p_{ij} = \frac{e^{u_{ij}}}{\sum_j e^{u_{ij}}}$$

Detailed (Classic) Example - Household Cleaner.

(Green and Wind, 1975)

Spot removers (e.g., for carpets); the following attributes were analyzed:

- Package design (A, B, C)
- Brand Names (K2R, Glory, Bissell)
- Price (1.19$, 1.39$, 1.59$)
- Good Housekeeping seal (yes or no)
- Money back guarantee (yes or no).

For the 3x3x3x2x2=108 possible profiles and orthogonal design (18 profiles) was selected. The design with one customer's ranking is presented below:

Package Design	Brand Name	Price	Seal	Money Back	Ranking
A	K2R	1.19	No	No	13
A	Glory	1.39	No	Yes	11
A	Bissel	1.59	Yes	No	17
B	K2R	1.39	Yes	Yes	2
B	Glory	1.59	No	No	14
B	Bissel	1.19	No	No	3
C	K2R	1.59	No	Yes	12
C	Glory	1.19	Yes	No	7
C	Bissel	1.39	No	No	9
A	K2R	1.59	Yes	No	18
A	Glory	1.39	No	Yes	8
A	Bissel	1.19	No	No	15
B	K2R	1.19	No	No	4
B	Glory	1.39	Yes	No	6
B	Bissel	1.59	No	Yes	5
C	K2R	1.39	No	No	10
C	Glory	1.59	No	No	16
C	Bissel	1.19	Yes	Yes	1

Derivation of the Attribute Utilities

Assuming no interactions the regression model becomes:

Rating = $B_0 + b_1(\textit{package A}) + B_2(\textit{package B}) + B_3(\textit{K2R}) +$
$B_4(\textit{Glory}) + B_5(\textit{Price 1.19}) + B_6(\textit{Price 1.39}) +$
$B_7(\textit{Seal}) + B_8(\textit{Money back})$

With the dummy coding: Package - A=0, B=1, C=2; Brand name - K2R=0, Glory=1, Bissel=2; Price - 1.19\$=0, 1.39\$=1, 1.59\$=2; Sea; - No=0, Yes=1; Money back - No=0, Yes=1.

The dummy coding scheme is presented below:

	Package Design		Brand		Price			
Ranking	A	B	K2R	Glory	1.19	1.39	Seal	Money
6	1	0	1	0	1	0	0	0
8	1	0	0	1	0	1	0	1
2	1	0	0	0	0	0	1	0
17	0	1	1	0	0	1	1	1
5	0	1	0	1	0	0	0	0
16	0	1	0	0	1	0	0	0
7	0	0	1	0	0	0	0	1
12	0	0	0	1	1	0	1	0
10	0	0	0	0	0	1	0	0
1	1	0	1	0	0	0	1	0
11	1	0	0	1	1	0	0	1
4	1	0	0	0	0	1	0	0
15	0	1	1	0	1	0	0	0
13	0	1	0	1	0	1	1	0
14	0	1	0	0	0	0	0	1
9	0	0	1	0	0	1	0	0
3	0	0	0	1	0	0	0	0
18	0	0	0	0	1	0	1	1

Estimated Attribute Utilities in Various methods

	Attribute	Simple Sum	MONANOVA	Regression	Reorded Regression
Package	A	0.1	0.1	-4.5	0
	B	1	1	3.5	8
	C	0.6	0.6	0	4.5
Brand	K2R	0.5	0.3	-1.5	0.5
	Glory	0.5	0.2	2	0
	Bissel	0.7	0.5	0	2
Price	1.19	1	1	7.67	7.67
	1.39	0.6	0.7	5.83	4.83
	1.59	0.1	0.1	0	0
Seal	Yes	0.7	0.3	1.5	1.5
	No	0.5	0.2	0	0
Money	Yes	0.9	0.7	4.5	4.5
	No	0.4	0.2	0	0

Constant = 4.833, R^2=.98

•Simple sums: Estimation of the average value of the dependent variable for each level of each attribute (e.g., Package A appears in six profiles, the average score is (6+8+2+1+11+4)/6=5.33). This set is rescaled to a range of .1 - 1 (by a linear interpolation - 5.33=.1, …)

•The regression suggests that package design is important, with a range of 8 (-4.5 to +3.5), as is the price (range of 7.67).

•Strong preference for package design B and low price the money back guarantee and the seal are relatively unimportant

•We can now estimate any combination, for example: K2R with package design B with a seal, priced at 1,39 and no money back guarantee (4.833-1.5+3.5+4.83+1.5+0=13.16)

Exercise in Conjoint Analysis - Designing a frozen pizza

(Marketing Engineering P. 189)

Assume that frozen pizza can be described by combination of attributes - type of crust, type of topping, amount of cheese and its type, price and other attributes. Suppose that a firm considers 3 types of crust (thin, thick an pan), four types of toppings (veggie, pepperoni, sausage and pineapple), three types of cheese (mozzarella, ordinary, and mixed cheese), quantity of cheese at three levels (regular, double and extra), and price at one of the three levels (32Nis, 36Nis, and 40Nis). The table in the next page enumerates 16 product bundles that form an orthogonal study.

Rank these profiles according to your own preference (taste), obtain your own part-worth function, discuss your preference as comes up from the analysis, and define the "best design" that matches your own choice of preference. How close is it?

An orthogonal design for the frozen pizza analysis

Product bundle #	Crust	Topping	Type of Cheese	Amount of cheese	Price Nis	Perference (yours)
1	Pan	Pineapple	Regular	Regular	40	
2	Thin	Pineapple	Mixed	Extra	36	
3	Thick	Pineapple	Mozzarella	Double	36	
4	Thin	Pineapple	Mixed	Double	32	
5	Pan	Veggie	Mixed	Double	36	
6	Thin	Veggie	Regular	Double	32	
7	Thick	Veggie	Mixed	Extra	40	
8	Thin	Veggie	Mozzarella	Regular	36	
9	Thick	Pepperoni	Mozzarella	Extra	32	
10	Thin	Pepperoni	Mixed	Regular	36	
11	Pan	Pepperoni	Regular	Double	36	
12	Thin	Pepperoni	Mixed	Double	40	
13	Pan	Sausage	Mixed	Double	36	
14	Thin	Sausage	Mozzarella	Double	40	
15	Thick	Sausage	Mixed	Regular	32	
16	Thin	Sausage	Regular	Extra	36	

Segmentation

- *Why do we segment?*
- *When it is mostly important?*

A Definition

Market Segmentation is concerned with individual or intergroup differences in response to marketing mix variables. The managerial presumption is that if these response differences exist, can be identified, are reasonably stable over time and the segments can be efficiently reached the firm may increase its sales and profits beyond those obtained by assuming market homogeneity.

Du-Pont's Definition

"A group of customers anywhere along the distribution chain who have common needs and values - who will respond similarly to our offerings and who are large enough to be strategically important to our business."