

## Designing for attribute-level best-worst choice tasks

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1 / 49

### What is the task?

- Show a product described by  $k$  attributes.
- Attribute  $q$  is shown at one of its  $\ell_q$  levels.
- Respondents are asked which feature of the product is *best*
- and which is *worst*.
- Repeat for several product descriptions.

3 / 49

### Overview

- 1 What is the best-worst choice task?
- 2 The model
- 3 The design question
- 4 Contraceptive Choices Example

2 / 49

### Contraceptive products

Describe contraceptives by using 7 attributes

- Product
- Effect on acne
- Effect on weight
- Frequency of administration
- Contraceptive effectiveness
- Effect on bleeding
- Cost

The levels of *frequency of administration* and *contraceptive effectiveness* are nested within Product.

4 / 49

Below is a hypothetical contraceptive product which has the features described. Please read the description of the product and choose which in your opinion is the best feature of this product and which is the worst.

Best		Worst
	Intra-uterine hormonal device	
	Has no effect on acne symptoms	
	May lose up to 1kg in weight	
	Administered once per year	
	1 in 1000 women using this product get pregnant in a 12 month period	
	Cost is \$7 per month	
	Most women using this product experience irregular bleeding	

### The choice set

Given a profile  $(x_1, x_2, \dots, x_k) = \mathbf{x}$   
the implicit choice set of pairs from which a respondent is making a choice is given by:

$$C_{\mathbf{x}} = \{(x_1, x_2), (x_1, x_3), \dots, (x_1, x_k), (x_2, x_3), \dots, (x_{k-1}, x_k), (x_2, x_1), (x_3, x_1), \dots, (x_k, x_1), (x_3, x_2), \dots, (x_k, x_{k-1})\}.$$

### Motivation for the task

- Allows direct comparison of all levels across all attributes.
- Can average effects of all levels for an attribute and talk of the attribute *impact*.
- Can be more acceptable task than the usual DCE, particularly if a choice set has multiple implausible options.
- Even if all options are plausible, task may be less cognitively demanding for some respondents.

### Attribute-level maxdiff model

Marley, Flynn and Louviere (2008)

$BW_{\mathbf{x}}(x_i, x_j)$  - probability that jointly (level  $x_i$  of factor  $F_i$  is chosen as best, level  $x_j$  of factor  $F_j$  is chosen as worst) from profile  $\mathbf{x}$ .

$BW_{\mathbf{x}}$  - best-worst choice probability for profile  $\mathbf{x}$ .

Define  $BW_{\mathbf{x}} \forall \mathbf{x} \in P$

Satisfies *attribute-level maxdiff model* iff  $\exists$  positive scale  $b$  on the attributes such that for every  $\mathbf{x} \in P$  and for any two distinct factors,

$$BW_{\mathbf{x}}(x_i, x_j) = \frac{b(x_i)/b(x_j)}{\sum_{q=1}^k \sum_{r=1, r \neq q}^k (b(x_q)/b(x_r))}.$$

### Incorporating attributes

Let  $b(x_i) = \exp[\beta_{F_i} + \beta_{F_i, x_i}]$ .

Then the set of best-worst choice probabilities,  $BW_x$ , satisfies

- 2-invertibility; that is,

$$BW_x(x_i, x_j)BW_x(x_j, x_i) = BW_x(x_q, x_r)BW_x(x_r, x_q),$$

where  $1 \leq i, j, q, r \leq k$ ,  $i \neq j$  and  $q \neq r$ ;

- 3-reversibility; that is,

$$BW_x(x_i, x_j)BW_y(y_j, y_q)BW_z(z_q, z_i) = BW_z(z_i, z_q)BW_y(y_q, y_j)BW_x(x_j, x_i),$$

where  $x_j = y_j$ ,  $y_q = z_q$  and  $z_i = x_i$ , and  $i \neq j$  and  $j \neq q$ ;

- 4-reversibility; that is,

$$\begin{aligned} BW_x(x_i, x_j)BW_y(y_j, y_q)BW_z(z_q, z_r)BW_w(w_r, w_i) \\ = BW_w(w_i, w_r)BW_z(z_r, z_q)BW_y(y_q, y_j)BW_x(x_j, x_i), \end{aligned}$$

where  $x_j = y_j$ ,  $y_q = z_q$ ,  $z_r = w_r$  and  $w_i = x_i$ , and  $i \neq j$ ,  $j \neq q$  and  $q \neq r$ .

so this  $b$  gives an attribute-level maxdiff model.

### Definition of $\Lambda$

$$n_{(x_1, x_2, \dots, x_k)} = n_C = \begin{cases} 1 & \text{if profile } (x_1, x_2, \dots, x_k) \text{ in BW task,} \\ 0 & \text{if profile } (x_1, x_2, \dots, x_k) \text{ not in BW task.} \end{cases}$$

$N = \sum_C n_C$  is the number of profiles in the experiment.

Let  $t = (x_{q_1}, x_{q_2})$ ,  $s = (x_{q_3}, x_{q_4})$

$$\Lambda_{t,t} = \frac{\pi_t}{N} \sum_{\{C|t \in C\}} \frac{n_C \sum_{\{u \in C|u \neq t\}} \pi_u}{(\sum_{u \in C} \pi_u)^2}$$

and

$$\Lambda_{t,s} = \frac{-\pi_t \pi_s}{N} \sum_{\{C|t \in C, s \in C\}} \frac{n_C}{(\sum_{u \in C} \pi_u)^2}.$$

### Link with the MNL model

Define

$$\pi(F_i x_i, F_j x_j) = \frac{b(x_i)}{b(x_j)} = \exp[\beta_{F_i} + \beta_{F_i, x_i} - (\beta_{F_j} + \beta_{F_j, x_j})]$$

$\pi$  - vector containing the distinct  $\pi(F_i x_i, F_j x_j)$

$$\gamma = \ln(\pi)$$

### As defined $\Lambda$

is information matrix for  $\gamma$

for MNL model

selection probabilities given by  $BW_x$

for profiles in  $P$  and corresponding choice sets  $C_x$

### The entries in $\Lambda$ when $\pi=1$

$$\Lambda_{t,t} = \frac{k(k-1)-1}{N(k(k-1))^2} \sum_{\{C|t \in C\}} n_C$$

and

$$\Lambda_{t,s} = \frac{-1}{N(k(k-1))^2} \sum_{\{C|t \in C, s \in C\}} n_C.$$

### The entries in $36\Lambda$ from profile 0 1 1 when $\pi=1$

Row  $0_1 1_2$  has 5 in column  $0_1 1_2$ .

and has -1 in columns  $0_1 1_3$ ,  $1_2 1_3$ ,  $1_2 0_1$ ,  $1_3 0_1$ , and  $1_3 1_2$

and has 0 in all other columns.

Rows  $0_1 1_3$ ,  $1_2 1_3$ ,  $1_2 0_1$ ,  $1_3 0_1$ , and  $1_3 1_2$  also have 5 on diagonal and -1 in columns corresponding to the entries in the implicit choice set.

All other rows are 0 throughout.

**Example**  $k = 3$  attributes, each with  $\ell_q = 2$  levels

Complete set of profiles is:

000, 001, 010, 011, 100, 101, 110, 111

Consider profile 0 1 1

Implied choice set is (subscript is attribute):

$\{0_1 1_2, 0_1 1_3, 1_2 1_3, 1_2 0_1, 1_3 0_1, 1_3 1_2\} = C$

Number of levels = 2+2+2=6

Number of pairs of levels =  $2 \times 4 \times 3 = 24$

Labels of rows and columns of  $\Lambda$ :

$0_1 0_2, 0_1 1_2, 1_1 0_2, 1_1 1_2, 0_1 0_3, 0_1 1_3, 1_1 0_3, 1_1 1_3,$   
 $0_2 0_3, 0_2 1_3, 1_2 0_3, 1_2 1_3, 0_2 0_1, 0_2 1_1, 1_2 0_1, 1_2 1_1,$   
 $0_3 0_1, 0_3 1_1, 1_3 0_1, 1_3 1_1, 0_3 0_2, 0_3 1_2, 1_3 0_2, 1_3 1_2$

### The first 12 rows of $36\Lambda$

$0_1$ $0_2$	$0_1$ $1_2$	$1_1$ $0_2$	$1_1$ $1_2$	$0_1$ $0_3$	$0_1$ $1_3$	$1_1$ $0_3$	$1_1$ $1_3$	$0_2$ $0_3$	$0_2$ $1_3$	$1_2$ $0_3$	$1_2$ $1_3$	$0_2$ $0_1$	$0_2$ $1_1$	$1_2$ $0_1$	$1_2$ $1_1$	$0_3$ $0_1$	$0_3$ $1_1$	$1_3$ $0_1$	$1_3$ $1_1$	$0_3$ $0_2$	$0_3$ $1_2$	$1_3$ $0_2$	$1_3$ $1_2$
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	5	0	0	0	-	0	0	0	0	0	-	0	-	0	0	0	-	0	0	0	0	0	-
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	-	0	0	0	5	0	0	0	0	0	-	0	-	0	0	0	-	0	0	0	0	0	-
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	-	0	0	0	-	0	0	0	0	0	5	0	-	0	0	0	-	0	0	0	0	0	-
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

## Bringing back $\beta$

$$\gamma(F_i x, F_j y) = \beta_{F_i} + \beta_{F_i x} - (\beta_{F_j} + \beta_{F_j y})$$

Transform  $\Lambda$  to the information matrix for the  $\beta_{F_i}$  and the  $\beta_{F_i x}$ .

Let

$$\beta' = (\beta_{F_1}, \beta_{F_2}, \dots, \beta_{F_k}, \beta_{F_1 0}, \dots, \beta_{F_1 \ell_1 - 1}, \beta_{F_2 0}, \dots, \beta_{F_2 \ell_2 - 1}, \dots, \beta_{F_k 0}, \dots, \beta_{F_k \ell_k - 1}).$$

Define  $X$  by  $\gamma = X \beta$ .

17 / 49

**Example**  $X'$  matrix,  $k = 3$  attributes, each with  $\ell_q = 2$  levels

$0_1$	$0_1$	$1_1$	$1_1$	$0_1$	$0_1$	$1_1$	$1_1$	$0_2$	$0_2$	$1_2$	$1_2$	$0_2$	$1_2$	$0_2$	$1_2$	$0_3$	$1_3$	$0_3$	$1_3$	$0_3$	$1_3$	$0_3$	$1_3$
$0_2$	$1_2$	$0_2$	$1_2$	$0_3$	$1_3$	$0_3$	$1_3$	$0_3$	$1_3$	$0_3$	$1_3$	$0_1$	$0_1$	$1_1$	$1_1$	$0_1$	$0_1$	$1_1$	$1_1$	$0_2$	$0_2$	$1_2$	$1_2$
1	1	1	1	1	1	1	1	0	0	0	0	-	-	-	-	-	-	-	-	0	0	0	0
-	-	-	-	0	0	0	0	1	1	1	1	1	1	1	1	0	0	0	0	-	-	-	-
0	0	0	0	-	-	-	-	-	-	-	-	0	0	0	0	1	1	1	1	1	1	1	1

$0_1$	$0_1$	$1_1$	$1_1$	$0_1$	$0_1$	$1_1$	$1_1$	$0_2$	$0_2$	$1_2$	$1_2$	$0_2$	$1_2$	$0_2$	$1_2$	$0_3$	$1_3$	$0_3$	$1_3$	$0_3$	$1_3$	$0_3$	$1_3$
$0_2$	$1_2$	$0_2$	$1_2$	$0_3$	$1_3$	$0_3$	$1_3$	$0_3$	$1_3$	$0_3$	$1_3$	$0_1$	$0_1$	$1_1$	$1_1$	$0_1$	$0_1$	$1_1$	$1_1$	$0_2$	$0_2$	$1_2$	$1_2$
1	1	0	0	1	1	0	0	0	0	0	0	-	-	0	0	-	-	0	0	0	0	0	0
0	0	1	1	0	0	1	1	0	0	0	0	0	0	-	-	0	0	-	-	0	0	0	0
-	0	-	0	0	0	0	0	1	1	0	0	1	0	1	0	0	0	0	0	-	-	0	0
0	-	0	-	0	0	0	0	0	0	1	1	0	1	0	1	0	0	0	0	0	0	-	-
0	0	0	0	-	0	-	0	-	0	-	0	0	0	0	0	1	0	1	0	1	0	1	0
0	0	0	0	0	-	0	-	0	-	0	-	0	0	0	0	0	1	0	1	0	1	0	1

19 / 49

**Example**  $k = 3$  attributes, each with  $\ell_q = 2$  levels (cont)

$$\beta' = (\beta_{F_1}, \beta_{F_2}, \beta_{F_3}, \beta_{F_1 0}, \beta_{F_1 1}, \beta_{F_2 0}, \beta_{F_2 1}, \beta_{F_3 0}, \beta_{F_3 1}).$$

$$\gamma(0_1, 0_2) = \beta_{F_1} + \beta_{F_1 0} - (\beta_{F_2} + \beta_{F_2 0})$$

with corresponding row of  $X$

$$1 - 0 \ 1 \ 0 - 0 \ 0 \ 0$$

18 / 49

**Example** Reduced  $X'$  matrix,  $k = 3$  attributes, each with  $\ell_q = 2$  levels

$0_1$	$0_1$	$1_1$	$1_1$	$0_1$	$0_1$	$1_1$	$1_1$	$0_2$	$0_2$	$1_2$	$1_2$	$0_2$	$0_2$	$1_2$	$1_2$	$0_3$	$1_3$	$0_3$	$1_3$	$0_3$	$1_3$	$0_3$	$1_3$
$0_2$	$1_2$	$0_2$	$1_2$	$0_3$	$1_3$	$0_3$	$1_3$	$0_3$	$1_3$	$0_3$	$1_3$	$0_3$	$1_3$	$0_3$	$1_3$	$0_3$	$1_3$	$0_3$	$1_3$	$0_3$	$1_3$	$0_3$	$1_3$
1	1	1	1	1	1	1	1	1	0	0	0	0	-	-	-	-	-	-	0	0	0	0	0
-	-	-	-	0	0	0	0	1	1	1	1	1	1	1	1	1	0	0	0	0	-	-	-
-	-	1	1	-	-	1	1	0	0	0	0	1	1	-	-	1	1	-	-	0	0	0	0
-	1	-	1	0	0	0	0	-	1	-	1	1	-	1	-	0	0	0	0	1	-	1	-
0	0	0	0	1	-	1	-	1	-	1	-	0	0	0	0	-	1	-	1	-	1	-	1

Same idea for any situation -  $k - 1$  parameters for the impact factors,  $\sum_q \ell_q - k$  parameters for the levels of attributes.

Call this matrix  $R$ .

20 / 49

## The design question

What set of profiles should we show to get as much information as possible about the scale of the attribute levels?

If we are only fitting main effects, can we get as much information about the attribute levels by showing (the right) subset of all possible combinations of attribute levels, or do we have to show all possible combinations of attribute levels?

21 / 49

**Example**  $k = 3$  attributes, each with  $\ell_q = 2$  levels

Complete set of profiles is:

000, 001, 010, 011, 100, 101, 110, 111

Each profile can be included or not in a BW task.

So there are  $2^8 - 1 = 255$  different possible designs to compare.

For each of these calculate  $\det(F)$ .

23 / 49

## Comparing Designs

To compare designs for their ability to estimate  $\beta$ s, we need  $F$ , information matrix for  $\beta$ s. Get this by calculating

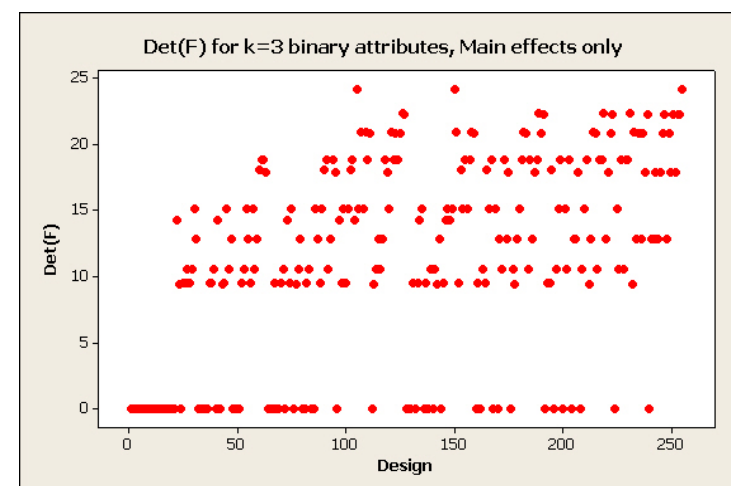
- information matrix for  $\gamma, \Lambda$ ,
- the reduced matrix  $R$
- Evaluate  $F = R' \Lambda R$ .

Use the generalised variance, that is, the determinant of the variance-covariance matrix, to compare designs.

The *D-optimal* design has the smallest determinant of the variance-covariance matrix.

Equivalently, it has the largest determinant for the information matrix.

22 / 49



24 / 49

The best designs are

0 0 0	0 0 1	0 0 0
0 1 1	0 1 0	0 0 1
1 0 1	1 0 0	0 1 0
1 1 0	1 1 1	0 1 1
		1 0 0
		1 0 1
		1 1 0
		1 1 1

$OA[N = 18; \ell_1 = 3, \ell_2 = 3, \ell_3 = 3, \ell_4 = 3; t = 2]$   
subdivided into  $OA[N = 9; \ell_1 = 3, \ell_2 = 3, \ell_3 = 3, \ell_4 = 3; t = 2]$ s

0 0 0 0	0 0 0 1
0 1 1 1	0 1 1 2
0 2 2 2	0 2 2 0
1 0 2 1	1 0 2 2
1 1 0 2	1 1 0 0
1 2 1 0	1 2 1 1
2 0 1 2	2 0 1 0
2 1 2 0	2 1 2 1
2 2 0 1	2 2 0 2

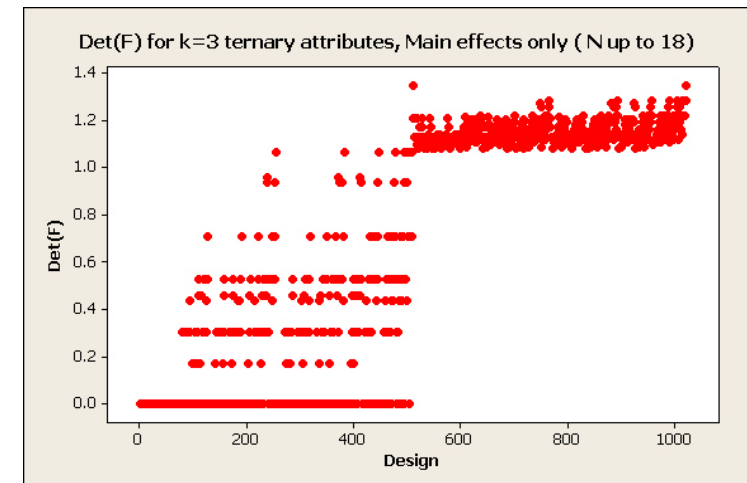
**Orthogonal array -  $OA[N; \ell_1, \ell_2, \dots, \ell_k; t]$**

$N \times k$  array with

elements from a set of  $\ell_q$  symbols in column  $q$  such that any  $N \times t$  subarray has each  $t$ -tuple as a row equally often.  $t$  is the *strength* of the OA.

$OA[N = 8; \ell_1 = 2, \ell_2 = 2, \ell_3 = 2, \ell_4 = 2, \ell_5 = 4; t = 2]$

0	0	0	0	0
0	0	1	1	2
0	1	0	1	1
0	1	1	0	3
1	0	0	1	3
1	0	1	0	1
1	1	0	0	2
1	1	1	1	0



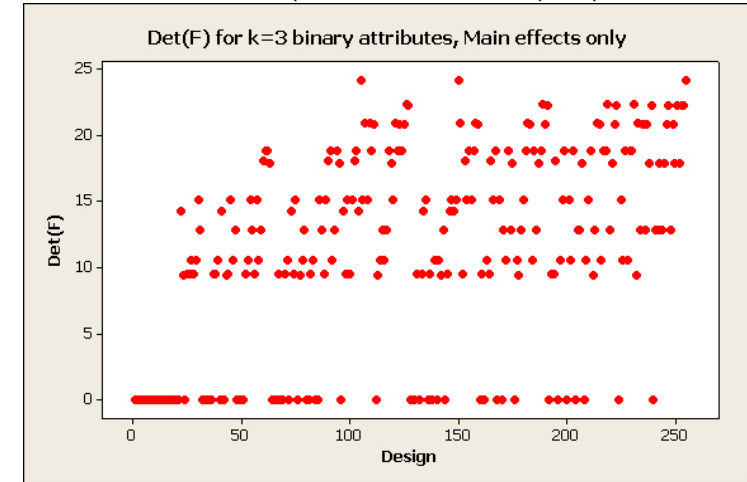
### General result when $\pi=1$

If respondents see all the treatment combinations in the complete factorial, or just those in an orthogonal array with  $t = 2$ , then the information matrix for the attribute-level maxdiff model is

$$\begin{bmatrix} \frac{2}{k-1} I_{k-1} - \frac{2}{k(k-1)} J_{k-1} & \mathbf{0}_{k-1, \ell_1-1} & \cdots & \mathbf{0}_{k-1, \ell_k-1} \\ \mathbf{0}_{\ell_1-1, k-1} & \frac{1}{\ell_1(a-\ell_1)k} I_{(\ell_1-1)} & \cdots & \mathbf{0}_{\ell_1-1, \ell_k-1} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{0}_{\ell_k-1, k-1} & \mathbf{0}_{\ell_k-1, \ell_1-1} & \cdots & \frac{1}{\ell_k(a-\ell_k)k} I_{(\ell_k-1)} \end{bmatrix},$$

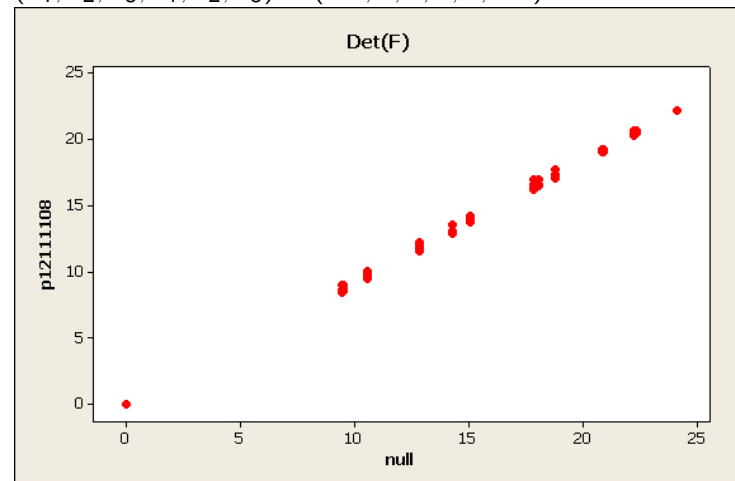
where  $a = \sum_q \ell_q$ .

### Performance when $(0_1, 0_2, 0_3, 1_1, 1_2, 1_3) = (1, 1, 1, 1, 1, 1)$



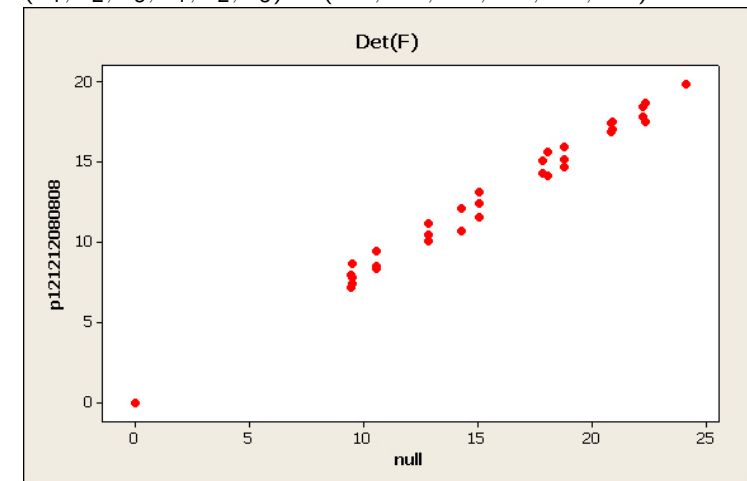
### Performance under alternative hypotheses

$(0_1, 0_2, 0_3, 1_1, 1_2, 1_3) = (1.2, 1, 1, 1, 1, 0.8)$



### Performance under alternative hypotheses

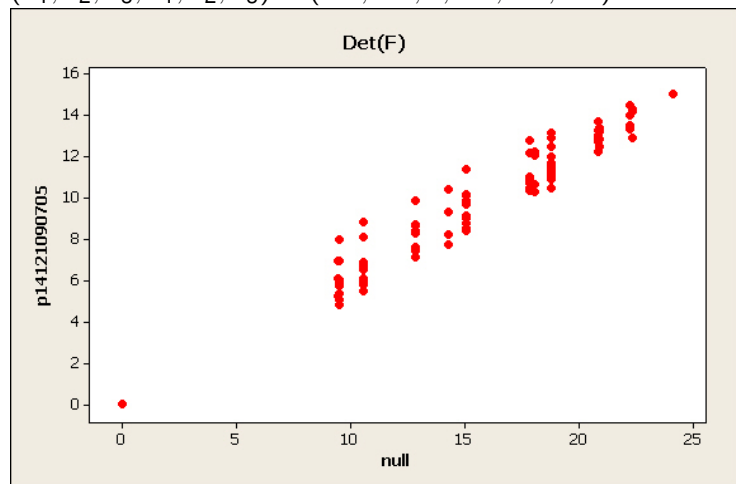
$(0_1, 0_2, 0_3, 1_1, 1_2, 1_3) = (1.2, 1.2, 1.2, 0.8, 0.8, 0.8)$





### Performance under alternative hypotheses

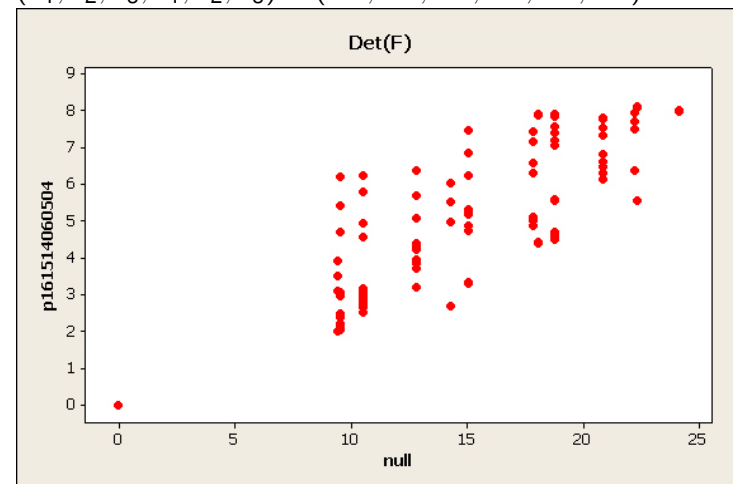
$$(0_1, 0_2, 0_3, 1_1, 1_2, 1_3) = (1.4, 1.2, 1, 0.9, 0.7, 0.5)$$



33 / 49

### Performance under alternative hypotheses

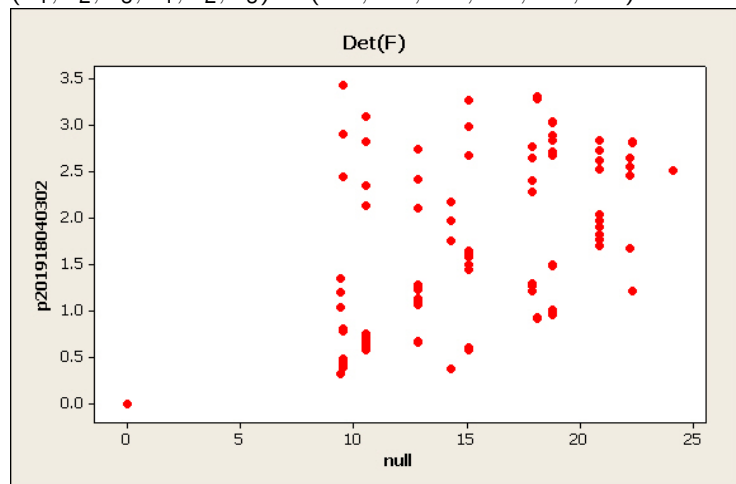
$$(0_1, 0_2, 0_3, 1_1, 1_2, 1_3) = (1.6, 1.5, 1.4, 0.6, 0.5, 0.4)$$



34 / 49

### Performance under alternative hypotheses

$$(0_1, 0_2, 0_3, 1_1, 1_2, 1_3) = (2.0, 1.9, 1.8, 0.4, 0.3, 0.2)$$



35 / 49

### How much is lost by using a non-optimal design?

$(0_1, 0_2, 0_3, 1_1, 1_2, 1_3)$	105	131	219	255
	or 150	or 137		
$(1, 1, 1, 1, 1, 1)$	1	0.830	0.985	1
$(1.6, 1.5, 1.4, 0.6, 0.5, 0.4)$	0.997	0.948	1	0.997
$(2.0, 1.9, 1.8, 0.4, 0.3, 0.2)$	0.940	1	0.962	0.941

Design	000	001	010	011	100	101	110	111
105	0	1	1	0	1	0	0	1
150	1	0	0	1	0	1	1	0
131	1	0	0	0	0	0	1	1
137	1	0	0	0	1	0	0	1
219	1	1	0	1	1	0	1	1
255	1	1	1	1	1	1	1	1

36 / 49

## Can all level orderings be recovered?

Let  $k = 3$  and  $\ell_1 = \ell_2 = \ell_3 = 2$

Suppose that  $0_1 > 0_2 > 0_3 > 1_1 > 1_2 > 1_3$ .

Choice set	Choice	Ordering
$0_1 0_2 0_3$	$0_1 0_3$	$0_1 > 0_2 > 0_3$
$0_1 1_2 1_3$	$0_1 1_3$	$0_1 > 1_2 > 1_3$
$1_1 0_2 1_3$	$0_2 1_3$	$0_2 > 1_1 > 1_3$
$1_1 1_2 0_3$	$0_3 1_2$	$0_3 > 1_1 > 1_2$

from which we can recover the original ordering.

## Practical design advice

Find several candidate designs that do well under the null hypothesis, since then it appears likely that you will be able to estimate everything for any values.

Check by doing a simulation study that a range of values for the levels can be recovered.

## Recovering Orderings (cntd)

Let  $k = 3$  and  $\ell_1 = \ell_2 = \ell_3 = 2$

Suppose that  $0_1 > 0_2 > 1_2 > 0_3 > 1_1 > 1_3$ .

Choice set	Choice	Ordering
$0_1 0_2 0_3$	$0_1 0_3$	$0_1 > 0_2 > 0_3$
$0_1 1_2 1_3$	$0_1 1_3$	$0_1 > 1_2 > 1_3$
$1_1 0_2 1_3$	$0_2 1_3$	$0_2 > 1_1 > 1_3$
$1_1 1_2 0_3$	$1_2 1_1$	$1_2 > 0_3 > 1_1$

from which we can recover

$0_1 > 0_2 > 0_3 > 1_1 > 1_3$  and  $0_1 > 1_2 > 0_3 > 1_1 > 1_3$

but we do not know the relative rankings of  $0_2$  and  $1_2$ .

Having the other 4 profiles from the complete factorial will not help sort this out since  $0_2$  and  $1_2$  are never in the same profile.

Could be addressed by using other designs that did not just consider profiles.

## Contraceptive Choices BW task - The attributes

Attribute	Number of levels
Product	8
Acne	3
Weight	4
Frequency of administration	3
Contraceptive effectiveness	3
Effect on bleeding	8
Cost	4

Levels of *frequency* and *effectiveness* are nested in product.



### 15th Contraceptive product

Below is a hypothetical contraceptive product which has the features described. Please read the description of the product and choose which in your opinion is the best feature of this method and which is the worst.

Attributes	Product description	Which is the best feature of this method?	Which is the worst feature of this method?
Type of product	Patch	<input type="radio"/>	<input type="radio"/>
Effect on Acne	In some women this product worsens acne symptoms	<input type="radio"/>	<input type="radio"/>
Effect on Weight	Some women using this product may lose up to 1 kg in weight	<input type="radio"/>	<input type="radio"/>
Frequency of Administration	Once every 6 months	<input type="radio"/>	<input type="radio"/>
Contraceptive effectiveness	1 in 100 women using this product get pregnant in a 12 mth period	<input type="radio"/>	<input type="radio"/>
Cost	\$1 per month	<input type="radio"/>	<input type="radio"/>
Effect on Periods	Most women using this method experience light periods with less pain	<input type="radio"/>	<input type="radio"/>

Would you consider using this contraceptive product with the features described above?

☐ Very unlikely ☐ Somewhat likely ☐ Very likely

## The design

- Find an orthogonal array for all attributes except product.
- This has 32 level descriptors.
- Each of these 32 is linked with each of the 8 products to get  $8 \times 32 = 256$  descriptions in total.
- These are then subdivided into 16 versions of 16 descriptions, with two descriptions for each product in each version and 16 different level descriptors.
- Each woman completes one version.
- Ability to recapture "known" prior values confirmed by a simulation study.

## Simulation study

- Choose values for  $\beta_q$  and  $\beta_{q,x_q}$  (or for  $\beta_q + \beta_{q,x_q}$ ).
- Calculate the value of  $\gamma_{(x_{q1}, x_{q2})}$  for each pair in the implied choice set.
- Add a random error term of extreme value type 1.
- Choose the pair with the largest value.
- Analyse the results using the MNL.
- Repeat 100 times.
- Compare estimated and assumed terms.

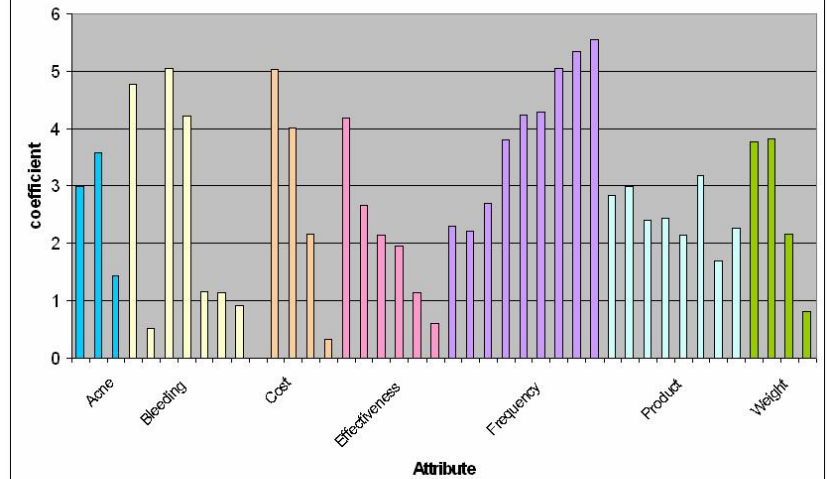
## Results of the simulation study

Level	Prior $\beta$	Mean $\beta$	Std Devn	Level	Prior $\beta$	Mean $\beta$	Std Devn
prod1	1.00	1.00	0.15	freq1	4.00	4.01	0.13
prod2	2.50	2.54	0.16	freq2	1.00	0.99	0.14
prod3	1.50	1.51	0.15	freq3	0.30	0.32	0.12
prod4	1.80	1.78	0.19	effect1	2.00	2.01	0.13
prod5	2.20	2.21	0.16	effect2	0.80	0.81	0.13
prod6	2.00	1.99	0.15	effect3	0.40	0.40	0.13
prod7	2.50	2.51	0.16	bleed1	0.20	0.21	0.15
prod8	2.00	2.04	0.18	bleed2	3.20	3.19	0.17
cost1	3.00	3.01	0.14	bleed3	1.50	1.50	0.15
cost2	2.50	2.51	0.15	bleed4	1.00	0.99	0.18
cost3	0.80	0.80	0.13	bleed5	0.30	0.31	0.15
cost4	0.50	0.50	0.13	bleed6	0.20	0.20	0.16
weight1	0.80	0.80	0.13	bleed7	0.10	0.10	0.15
weight2	1.25	1.25	0.14	acne1	0.50	0.50	0.12
weight3	0.50	0.50	0.14	acne2	1.50	1.50	0.15
weight4	1.00	1.02	0.12	acne3	1.00	1.00	0.15

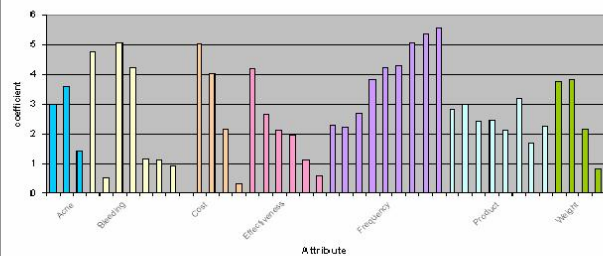
### Ranking levels best to worst: women's sample

Rank	Level	Level description
1	freq9	Once every 5 years
2	freq8	Once every 3 years
3	bleed3	Most women experience light periods with less pain
4	freq7	Once a year
5	cost1	\$1 per month
6	bleed1	Most women experience no periods
7	freq6	Once every 6 months
8	freq5	Once every 3 months
9	bleed4	Most women experience light periods with no change in pain
10	effect1	1 in 1000 women get pregnant in a 12 mth period
11	cost2	\$7 per month
12	Weight12	Some women may lose up to 1 kg in weight
13	freq4	Once a month
14	Weight1	This method has no effect on weight
15	acne2	Improves acne symptoms
16	prod6	Patch
17	prod2	Mini Pill
18	acne1	Has no effect on acne symptoms
19	prod1	Combined Pill
20	freq1	1 per day
21	effect2	1 in 500 women get pregnant in a 12 mth period
22	prod4	Implant
23	prod3	Injection
24	freq2	1 per day within interval
25	prod8	IUD
26	freq3	1 per day at the same time
27	cost3	\$20 per month
28	Weight3	Some women may gain up to 1 kg in weight
29	prod5	Intra-uterine Hormonal Device
30	effect3	1 in 100 women get pregnant in a 12 mth period
31	effect4	1 in 100 women get pregnant in a 12 mth period
32	prod7	Vaginal Ring
33	acne3	In some women worsens acne symptoms
34	bleed5	Most women experience light periods with increased pain
35	effect5	5 in 100 women get pregnant in a 12 mth period
36	bleed6	Most women experience heavy periods with less pain
37	bleed7	Most women experience heavy periods with no change in pain
38	Weight4	Some women may gain up to 3 kg in weight
39	effect6	10 in 100 women get pregnant in a 12 mth period
40	bleed2	Most women experience irregular bleeding
41	cost4	\$60 per month
42	bleed8	Most women experience heavy periods with increased pain

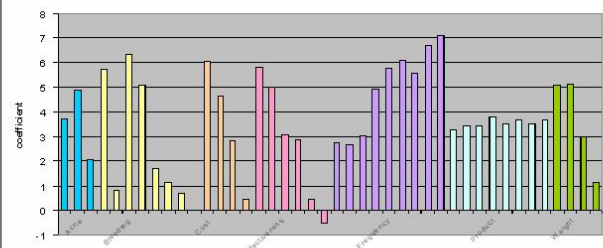
### Estimates for attribute levels: women's Best-Worst



### Estimates for attribute levels: women's Best-Worst



### Estimates for attribute levels: O-Ps' Best-Worst



## Open Questions

Make a systematic general comparison of the performance of designs under alternative hypotheses.

We have been talking about the max-diff model. What are good designs for the *weighted* max-diff model?

## References

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