Workshop on experimental designs

Danish Choice Modelling Day 2012

John Rose | Prof.
Experimental Designs| **Dec 4th-5th**

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Experimental design

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Allocation task

- Exactly how analysts distribute the levels of the design attributes over the course of an experiment (which typically is via the underlying experimental design), may play a big part in whether or not an independent assessment of each attribute's contribution to the choices observed to have been made by sampled respondents can be determined.
- The allocation of the attribute levels within the experimental design may also impact upon the statistical power of the experiment insofar as its ability to detect statistical relationships that may exist within the data.

Stated choice experimental designs

	Oyster Bay	Casa del Cerro	Fazi Battaglia	None
Cost (per bottle)	€14	€10	€8	
Grape	M	Riesling	Verdicchio	
Year bottled	2009	2008	2009	
Country of Origin	New Zealand	Italy	Chile	
I would choose:	○	○	○	○

Stated choice experimental designs

	Wine A	Wine B	None
Cost (per bottle)	€14	€10	
Grape	Muscat	Riesling	
Year bottled	2009	2008	
Country of Origin	New Zealand	Italy	
I would choose:	○	○	○

Stated choice experimental designs

- Conceptually, an experimental design may be viewed as nothing more than a matrix of values that is used to determine what goes where in a SC survey.
- The values that populate the matrix represent the attribute levels that will be used in the SC survey, whereas the columns and rows of the matrix represent the choice situations, attributes and alternatives of the experiment.

Stated choice experimental designs

	Wine A	Wine B	None
Cost (per bottle)	€14	€10	
Grape	Muscat	Riesling	
Year bottled	2009	2008	
Country of Origin	New Zealand	Italy	

Experimental Designs

Stated choice experimental designs

	Wine A	Wine B	None
Cost (per bottle)	€14	€10	
Grape	Muscat	Riesling	
Year bottled	2009	2008	
Country of Origin	New Zealand	Italy	
	Wine A	**Wine B**	**None**
Cost (per bottle)	€12	€14	
Grape	Pinot Blanc	Semillon	
Year bottled	2007	2009	
Country of Origin	France	Australia	
	Wine A	**Wine B**	**None**
Cost (per bottle)	€10	€10	
Grape	Sav. Blanc	Riesling	
Year bottled	2008	2008	
Country of Origin	France	Italy	

Choice task

Alternative

Attribute

Attribute level

Terminology

› Different literature use different terminology to describe components of an experimental design

Literature	Source				
Transport	**Bliemer and Rose (2010)**	Attribute	Attribute level	Alternatives	Choice task /choice set/ choice situation
Experimental design literature	**Hicks and Turner (1999)**	Factor	Factor level	Treatment combination	Run
Marketing	**Huber and Zwerina (1996) and Sandor and Wedel (2002)**	Attribute	Attribute level	Alternative/Profile	Choice set
Environmental Economics	**Ferrini and Scarpa (2007)**	Attribute	Attribute level	Alternative profile	Choice set/choice task
Health Economics	**Carlsson and Martisson (2003)**	Attribute	Attribute level	Alternative	Choice set

Stated choice experimental designs

	Wine A	Wine B	None
Cost (per bottle)	€14	€10	
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Year bottled	2009	2008	
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Year bottled	2007	2009	
Country of Origin	France	Australia	
	Wine A	Wine B	None
Cost (per bottle)	€10	€10	
Grape	Sav. Blanc	Riesling	
Year bottled	2008	2008	
Country of Origin	France	Italy	

'None' or status quo alternatives, whilst important for the design later, have no attribute levels.

Stated choice experimental designs

	Wine A	Wine B
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Cost (per bottle)	€10	€10
Grape	Sav. Blanc	Riesling
Year bottled	2008	2008
Country of Origin	France	Italy

Experimental Design (*X*)

Wine A				Wine B			
Cost	Grape	Year	C.O.O	Cost	Grape	Year	C.O.O
…	…	…	…	…	…	…	…
…	…	…	…	…	…	…	…
…	…	…	…	…	…	…	…
…	…	…	…	…	…	…	…

Each column represents an attribute.
Each row represents a choice task.

Discrete choice modelling process

2

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Discrete choice modelling process

Typical modelling steps in discrete choice studies

Experimental design

1	30	3	15	4
2	30	1	35	4
3	30	1	20	4
4	20	1	25	4
5	25	5	30	2
6	20	3	35	2
7	20	1	20	4
8	25	3	40	2
9	25	5	25	2
10	20	5	15	2
11	30	5	30	2
12	25	3	40	4

→

Survey

Please look at each of the following scenarios and choose the alternative you most prefer in each

Task 1 of 3

	Oyster Bay	Casa del Cerro	Fazi Battaglia	None
Cost (per bottle)	€14	€10	€8	
Grape	M	Riesling	Verdicchio	
Year bottled	2009	2008	2009	
Country of Origin	New Zealand	Italy	Chile	
I would choose:	○	○	○	○

Task 2 of 3

	Oyster Bay	Casa del Cerro	Fazi Battaglia	None
Cost (per bottle)	€14	€10	€8	
Grape	M	Riesling	Verdicchio	
Year bottled	2009	2008	2009	
Country of Origin	New Zealand	Italy	Chile	
I would choose:	○	○	○	○

Task 3 of 3

	Oyster Bay	Casa del Cerro	Fazi Battaglia	None
Cost (per bottle)	€14	€10	€8	
Grape	M	Riesling	Verdicchio	
Year bottled	2009	2008	2009	
Country of Origin	New Zealand	Italy	Chile	
I would choose:	○	○	○	○

→

Respondents

→

Data

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

→

Estimation

Specification of:
1. Model type
2. Utility functions

$$V_1 = \sum_{k=1}^{K} \beta_{1k} x_{1k}$$

$$V_2 = \sum_{k=1}^{K} \beta_{2k} x_{2k}$$

$$\vdots$$

$$V_j = \sum_{k=1}^{K} \beta_{jk} x_{jk}$$

←

$$\hat{\beta}$$

$$se(\hat{\beta})$$

Results

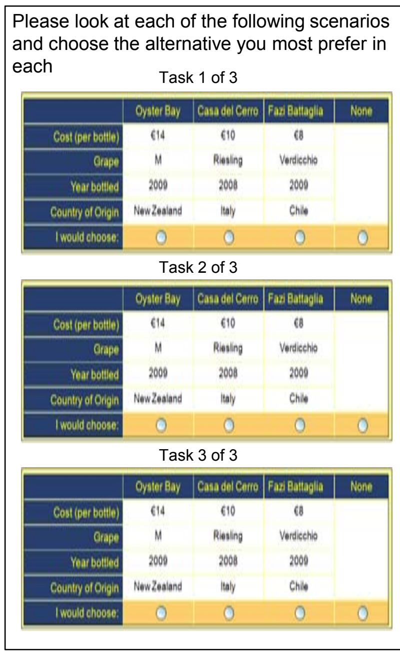
Discrete choice modelling process

How do we determine the efficiency of a design without conducting the survey?

Experimental design

1	30	3	15	4
2	30	1	35	4
3	30	1	20	4
4	20	1	25	4
5	25	5	30	2
6	20	3	35	2
7	20	1	20	4
8	25	3	40	2
9	25	5	25	2
10	20	5	15	2
11	30	5	30	2
12	25	3	40	4

Survey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Task 3 of 3

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I would choose:	○	○	○	○

Respondents

Data

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

Estimation

Specification of:
1. Model type
2. Utility functions

$$V_1 = \sum_{k=1}^{K} \beta_{1k} x_{1k}$$

$$V_2 = \sum_{k=1}^{K} \beta_{2k} x_{2k}$$

$$\vdots$$

$$V_j = \sum_{k=1}^{K} \beta_{jk} x_{jk}$$

$$\hat{\beta}$$

$$se(\hat{\beta})$$

Results

The question is what is the relationship between the results and the experimental design?

Discrete choice modelling process

To progress....

› How do we determine the efficiency of a design without conducting the survey?

- First, assume prior parameter estimates (best guesses for the true parameter values)
- Second, approximate the variance-covariance matrix for the parameter estimates - **This can be done without conducting any surveys!**

Experimental design

1	30	3	15	4
2	30	1	35	4
3	30	1	20	4
4	20	1	25	4
5	25	5	30	2
6	20	3	35	2
7	20	1	20	4
8	25	3	40	2
9	25	5	25	2
10	20	5	15	2
11	30	5	30	2
12	25	3	40	4

$$\Rightarrow \hat{\beta} \Rightarrow se(\hat{\beta})$$

Asymptotic variance covariance matrix

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Asymptotic variance covariance matrix

The A in AVC

- The asymptotic variance-covariance (AVC) matrix is an approximation of the true variance-covariance matrix
- “Asymptotic” means
  - assuming a very large sample; or
  - assuming a large number of repetitions using a small sample
- The roots of the diagonals of the variance-covariance matrix denote the standard errors

variance-covariance matrix $= \begin{pmatrix} se(\beta_1)^2 & \cdots & \\ \vdots & \ddots & \\ & & se(\beta_K)^2 \end{pmatrix}$, where $se(\beta_k)$ is the standard error of parameter β_k

Asymptotic variance covariance matrix

Step 1: Log-likelihood function

› First, determine the loglikelihood function:

$$L_N(\beta \mid X, y) = \sum_{n=1}^{N} \sum_{s=1}^{S} \sum_{j=1}^{J} y_{jsn} \log P_{jsn}(X \mid \beta)$$

› Note that:

› In estimation, given the (design) data *X* and the observations *y*, one aims to determine estimates β such that $L_N(\beta \mid X, y)$ is maximised [maximum likelihood estimation]

› When generating an experimental design, these parameter estimates are unknown β

› The values of $P_{jsn}(X \mid \beta)$ depend on the model used (MNL, NL, ML)

Asymptotic variance covariance matrix

Step 2: Determine the Fisher Information Matrix

› Secondly, determine the Fisher information matrix:

$$I_N(\beta \mid X, y) = -E_y\left(\frac{\partial^2 L_N(\beta \mid X, y)}{\partial\beta\partial\beta'}\right)$$

[expected negative Hessian matrix of second derivatives]

Asymptotic variance covariance matrix

Step 3: Determine the AVC Matrix

$$\Omega_N(\beta \mid X, y) = I_N^{-1}(\beta \mid X, y)$$ [inverse matrix]

› Note that:

- The AVC matrix depends on the design, X
- The AVC matrix depends on the choice observations, y !
- The AVC matrix depends on the parameters, β !
- The AVC matrix depends on the number of respondents, N

› Both y and β are unknown when generating a design

Asymptotic variance covariance matrix

MNL model AVC

› Example: MNL model with generic parameters (McFadden, 1974)

$$I_N(\beta \mid X) = -\sum_{n=1}^{N}\sum_{s=1}^{S}\sum_{j=1}^{J} X_{jk_1sn} P_{jsn}(X \mid \beta)\left(X_{jk_2sn} - \sum_{i=1}^{J} X_{ik_2sn} P_{isn}(X \mid \beta) \right)$$

Assuming that all responds observe the same choice situations,

$$\begin{aligned} I_N(\beta \mid X) &= -N \cdot \sum_{s=1}^{S}\sum_{j=1}^{J} X_{jk_1s} P_{js}(X \mid \beta)\left(X_{jk_2s} - \sum_{i=1}^{J} X_{ik_2s} P_{is}(X \mid \beta) \right) \\ &= N \cdot I_1(\beta \mid X) \end{aligned}$$

Therefore, the AVC matrix becomes:

$$\begin{aligned} \Omega_N(\beta \mid X) &= I_N^{-1}(\beta \mid X) \\ &= \tfrac{1}{N} \cdot I_1^{-1}(\beta \mid X) \end{aligned}$$

Measuring Efficiency

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Its all about the AVC matrix

› Numerical Example

MNL model: $U_A = \beta_1 + \beta_2 A_1 + \beta_3 A_2$

$U_B = \beta_2 B_1 + \beta_4 B_2$

Priors: $\beta_1 = -0.2$

$\beta_2 = 0.3$

$\beta_3 = 0.4$

$\beta_4 = 0.5$

Design:

	A1	A2	B1	B2
1	2	1	2	1
2	4	3	6	2
3	6	5	4	3
4	2	5	4	1
5	4	3	2	2
6	6	1	6	3

$$I_1(\beta \mid X) = \begin{array}{c} \\ \beta_1 \\ \beta_2 \\ \beta_3 \\ \beta_4 \end{array} \begin{array}{c} \begin{array}{cccc} \beta_1 & \beta_2 & \beta_3 & \beta_4 \end{array} \\ \begin{pmatrix} -1.30 & 0.03 & -3.92 & 2.50 \\ 0.03 & -3.54 & 0.16 & 0.79 \\ -3.92 & 0.16 & -15.21 & 7.69 \\ 2.50 & 0.79 & 7.69 & -5.66 \end{pmatrix} \end{array}$$

$$\Omega_{10}(\beta \mid X) = \begin{array}{c} \\ \beta_1 \\ \beta_2 \\ \beta_3 \\ \beta_4 \end{array} \begin{array}{c} \begin{array}{cccc} \beta_1 & \beta_2 & \beta_3 & \beta_4 \end{array} \\ \begin{pmatrix} \boxed{0.88} & 0.07 & -0.08 & 0.29 \\ 0.07 & \boxed{0.04} & 0.00 & 0.04 \\ -0.08 & 0.00 & \boxed{0.03} & 0.01 \\ 0.29 & 0.04 & 0.01 & \boxed{0.16} \end{pmatrix} \end{array}$$

Comparing AVC matrices

› Numerical Example

Design 1:

	A1	A2	B1	B2
1	2	1	2	1
2	4	3	6	2
3	6	5	4	3
4	2	5	4	1
5	4	3	2	2
6	6	1	6	3

$$\Omega_1 = \begin{pmatrix} 8.76 & 0.69 & -0.78 & 2.91 \\ 0.69 & 0.38 & 0.02 & 0.39 \\ -0.78 & 0.02 & 0.30 & 0.07 \\ 2.91 & 0.39 & 0.07 & 1.61 \end{pmatrix}$$

Design 2:

	A1	A2	B1	B2
1	6	3	2	2
2	4	1	6	1
3	2	5	4	3
4	2	5	4	1
5	6	1	2	2
6	4	3	6	3

$$\Omega_1 = \begin{pmatrix} 6.97 & -0.22 & -0.77 & 1.92 \\ -0.22 & 0.13 & 0.12 & 0.06 \\ -0.77 & 0.12 & 0.39 & 0.21 \\ 1.92 & 0.06 & 0.21 & 1.27 \end{pmatrix}$$

Which design is more efficient?

Its all about the AVC matrix

- In order to assess the efficiency of different designs, several efficiency measures have been proposed
- The most widely used ones are:
  - *D*-error $= \det\left(\Omega_1\right)^{1/K}$ [determinant of AVC matrix]
  - *A*-error $= \dfrac{\mathrm{tr}\left(\Omega_1\right)}{K}$ [trace of AVC matrix]

  $K =$ number of parameters (size of the matrix), used as a scaling factor for the efficiency measure
- The lower the *D*-error or *A*-error, the more efficient the design

Measuring efficiency

Comparing AVC matrices...

Design 1:

	A1	A2	B1	B2
1	2	1	2	1
2	4	3	6	2
3	6	5	4	3
4	2	5	4	1
5	4	3	2	2
6	6	1	6	3

$$\Omega_1 = \begin{pmatrix} 8.76 & 0.69 & -0.78 & 2.91 \\ 0.69 & 0.38 & 0.02 & 0.39 \\ -0.78 & 0.02 & 0.30 & 0.07 \\ 2.91 & 0.39 & 0.07 & 1.61 \end{pmatrix}$$

D-error = 0.568
A-error = 2.761

Design 2:

	A1	A2	B1	B2
1	6	3	2	2
2	4	1	6	1
3	2	5	4	3
4	2	5	4	1
5	6	1	2	2
6	4	3	6	3

$$\Omega_1 = \begin{pmatrix} 6.97 & -0.22 & -0.77 & 1.92 \\ -0.22 & 0.13 & 0.12 & 0.06 \\ -0.77 & 0.12 & 0.39 & 0.21 \\ 1.92 & 0.06 & 0.21 & 1.27 \end{pmatrix}$$

D-error = 0.434
A-error = 2.194

Design 2 is more efficient

Optimising sample sizes

› So, if we know β_k and $se_1(\beta_k)$, then we can compute the t-ratio for any sample size.

› Suppose that a t-ratio of t^* is requested for parameter β_k

› Then the required sample size for this parameter is $N_k = \left(\frac{se_1(\beta_k)t^*}{\beta_k} \right)^2$

› The required overall sample size (for all parameters) is $N = \max_k \{N_k\}$

Utility balance I

› The property of utility balance is sometimes seen as a requirement for efficiency (Huber and Zwerina, 1996)

- A design is more utility balanced if there are no dominating alternatives in the choice situations

	A1	A2	B1	B2	UA	UB	PA	PB	B
1	2	1	2	1	0.8	1.1	0.43	0.57	98%
2	4	3	6	2	2.2	2.8	0.35	0.65	92%
3	6	5	4	3	3.6	2.7	0.71	0.29	82%
4	2	5	4	1	2.4	1.7	0.67	0.33	89%
5	4	3	2	2	2.2	1.6	0.65	0.35	92%
6	6	1	6	3	2.0	3.3	0.21	0.79	67%
									87%

$$U_A = \beta_1 + \beta_2 A_1 + \beta_3 A_2$$
$$U_B = \beta_2 B_1 + \beta_4 B_2$$

$$\beta_1 = -0.2$$
$$\beta_2 = 0.3$$
$$\beta_3 = 0.4$$
$$\beta_4 = 0.5$$

- compute U_A and U_B
- compute P_A and P_B
- compute utility balance factor B

$$U_A = -0.2 + 0.3 \cdot 2 + 0.4 \cdot 1 = 0.8$$
$$U_B = 0.3 \cdot 2 + 0.5 \cdot 1 = 1.1$$

$$P_A = \exp(0.8) / \left(\exp(0.8) + \exp(1.1)\right) = 0.43$$
$$P_B = \exp(1.1) / \left(\exp(0.8) + \exp(1.1)\right) = 0.57$$

$$B = \left(\frac{0.43}{0.50}\right)\left(\frac{0.57}{0.50}\right) \times 100\% = 98\%$$

Utility balance II

› Numerical Example

› General formulation of the utility balance is measure:

› Utility balance per choice situation: $B_s = \prod_{j=1}^{J} \left(\frac{P_{js}}{1/J} \right) \times 100\%$

P = (½, ½) gives 100%, P = (1,0) gives 0%

P = (⅓, ⅓, ⅓) gives 100%, P = (1,0,0) and P = (½, ½,0) give 0%

› Average utility balance for whole design: $\bar{B} = \frac{1}{S} \sum_{s=1}^{S} B_s$

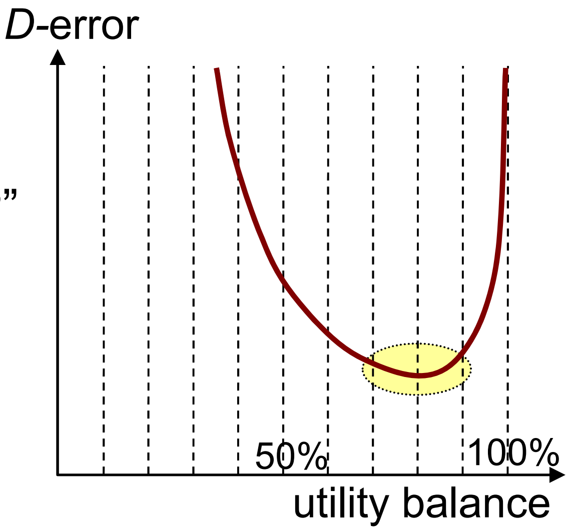
PA	PB	PC	B
0.23	0.17	0.60	63%
0.57	0.38	0.05	29%
0.17	0.43	0.40	79%
0.30	0.31	0.39	98%
0.26	0.37	0.37	96%
0.93	0.03	0.04	3%
			61%

$$\longrightarrow B_1 = \left(\frac{0.23}{0.33} \right) \left(\frac{0.17}{0.33} \right) \left(\frac{0.60}{0.33} \right) \times 100\% = 63\%$$

$$\longrightarrow \bar{B} = \frac{63\% + 29\% + 79\% + 98\% + 96\% + 3\%}{6} = 61\%$$

Utility balance III

- The higher utility balance, the better? No!
- A 100% utility balanced design will be very *in*efficient (why?)
- A design with a very low utility balance is *in*efficient too (why?)
- What is a good level of utility balance?
  - Indication for a design with 2 alternatives: utility balance of 70% – 90%
  - This corresponds with probabilities (0.25,0.75) – (0.35,0.65)
  - These probabilities are confirmed by so-called "Magic P" values (discussed later)
  - More research on this topic needed (especially with respect to designs with more than 2 alternatives)



Willingness to pay

- WTP is calculated as the ratio of the change in marginal utility of *attribute k* to the change in marginal utility for a cost attribute

$$\frac{\Delta x_k}{\Delta Cost} = \frac{\frac{d}{dx_k}\beta_k x_k}{\frac{d}{dx_c}\beta_c x_c} = \frac{\beta_k}{\beta_c}$$

- Both parameters have standard errors and covariances (which come from the AVC matrix)
- Using the delta method

$$s.e._{\left(\frac{\beta_k}{\beta_c}\right)} \cong \sqrt{\frac{1}{\beta_c^2}\left[Var(\beta_k) - \frac{2\beta_k}{\beta_c}.Cov(\beta_k,\beta_c) + \left(\frac{\beta_k}{\beta_c}\right)^2 Var(\beta_c)\right]}$$

Willingness to pay

- It is therefore possible to minimise the standard errors of the ratios of two parameters (WTP)
- We call this *C*-error (or WTP-error)

$$C-error = \min_{k}\left\{\max\left[s.e._{\left(\frac{\beta_k}{\beta_c}\right)}\right]\right\}$$

The prior parameters

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The prior parameters

Where can I get my priors?

› Prior parameter estimates can be obtained from:

- the literature
- pilot studies
- focus groups
- expert judgement

› If no prior information is available, what to do?

1. Create a design using zero priors or use an orthogonal design
2. Give design to 100% of respondents

1. Create a design using zero priors or use an orthogonal design
2. Give design to 10% of respondents
3. Estimate parameters, use as priors
4. Create efficient design
5. Give design to 90% of respondents

Parameter prior misspecification I

- What if the priors have been wrongly specified?
  - For example, what if β_1 is 0.6 instead of 0.4 ?
  - The AVC matrices and *D*-errors for the *D*-efficient design are:

$\beta_1 = 0.4$

D-error = 0.1775

	b1	b2	b3	b4	b5	b6	b7
b1	0.110	0.065	0.059	0.133	-0.124	0.065	0.141
b2	0.065	0.079	0.065	0.097	-0.144	0.056	0.116
b3	0.059	0.065	0.605	0.044	1.166	0.040	0.125
b4	0.133	0.097	0.044	0.334	0.332	0.076	0.250
b5	-0.124	-0.144	1.166	0.332	22.034	-2.564	-0.982
b6	0.065	0.056	0.040	0.076	-2.564	0.586	0.133
b7	0.141	0.116	0.125	0.250	-0.982	0.133	0.387

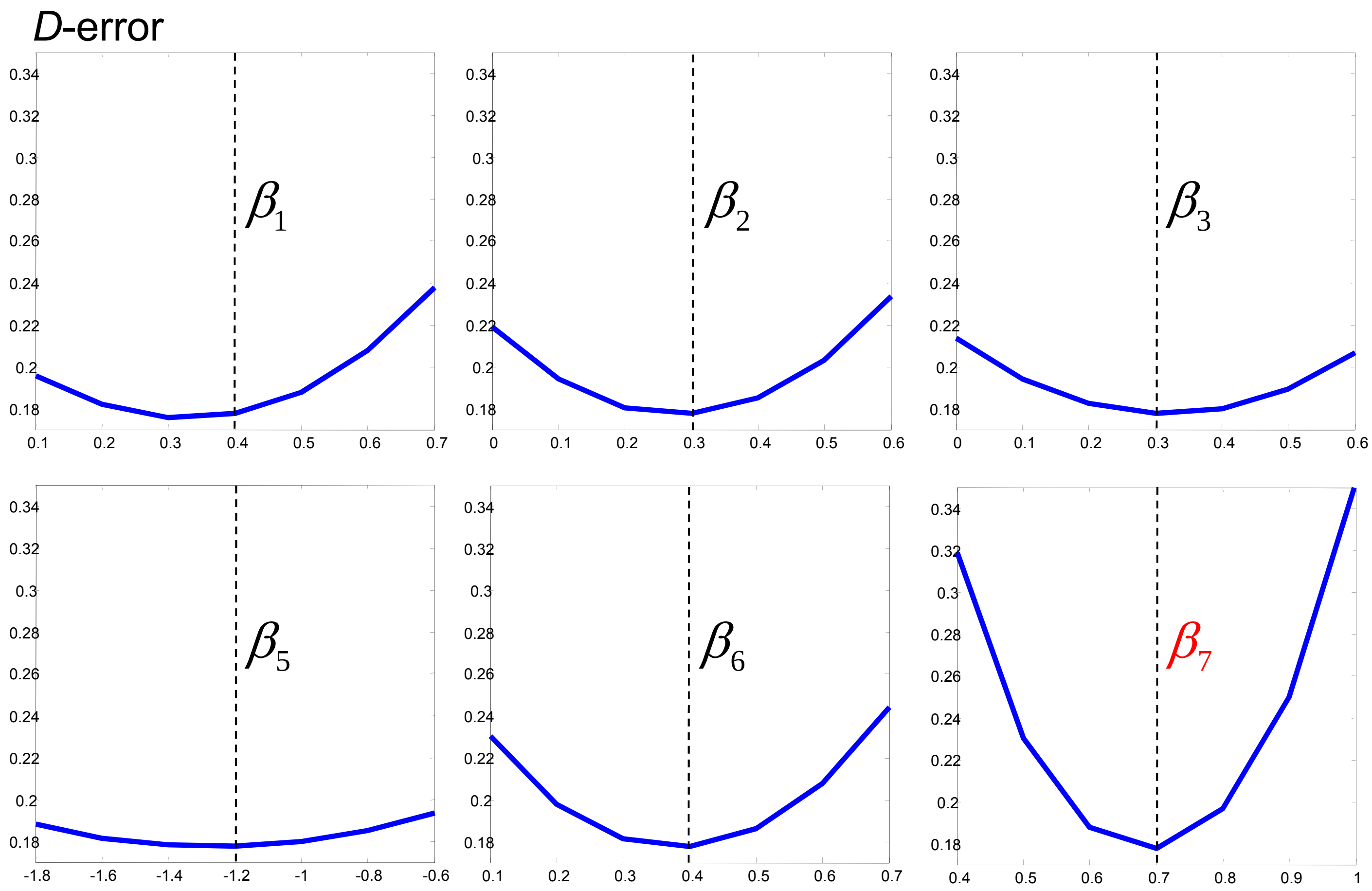
$\beta_1 = 0.6$

D-error = 0.2074

	b1	b2	b3	b4	b5	b6	b7
b1	0.142	0.083	0.074	0.170	-0.186	0.087	0.183
b2	0.083	0.094	0.079	0.115	-0.202	0.070	0.142
b3	0.074	0.079	0.706	0.054	1.431	0.020	0.155
b4	0.170	0.115	0.054	0.402	0.332	0.098	0.312
b5	-0.186	-0.202	1.431	0.332	25.911	-3.081	-1.134
b6	0.087	0.070	0.020	0.098	-3.081	0.686	0.165
b7	0.183	0.142	0.155	0.312	-1.134	0.165	0.471

Designs are efficient under the assumption of true parameter values. Wrongly specified priors typically lead to a loss in efficiency.

Parameter prior misspecification II



It is possible to already check beforehand to which parameters the design is most sensitive to.

One can put more effort in finding good priors for these parameters.

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Ngene is designed to be the single source of stated choice (SC) experimental designs. As such, it has an extensive range of features and outputs.

With Ngene you can:

Specify designs with great flexibility:

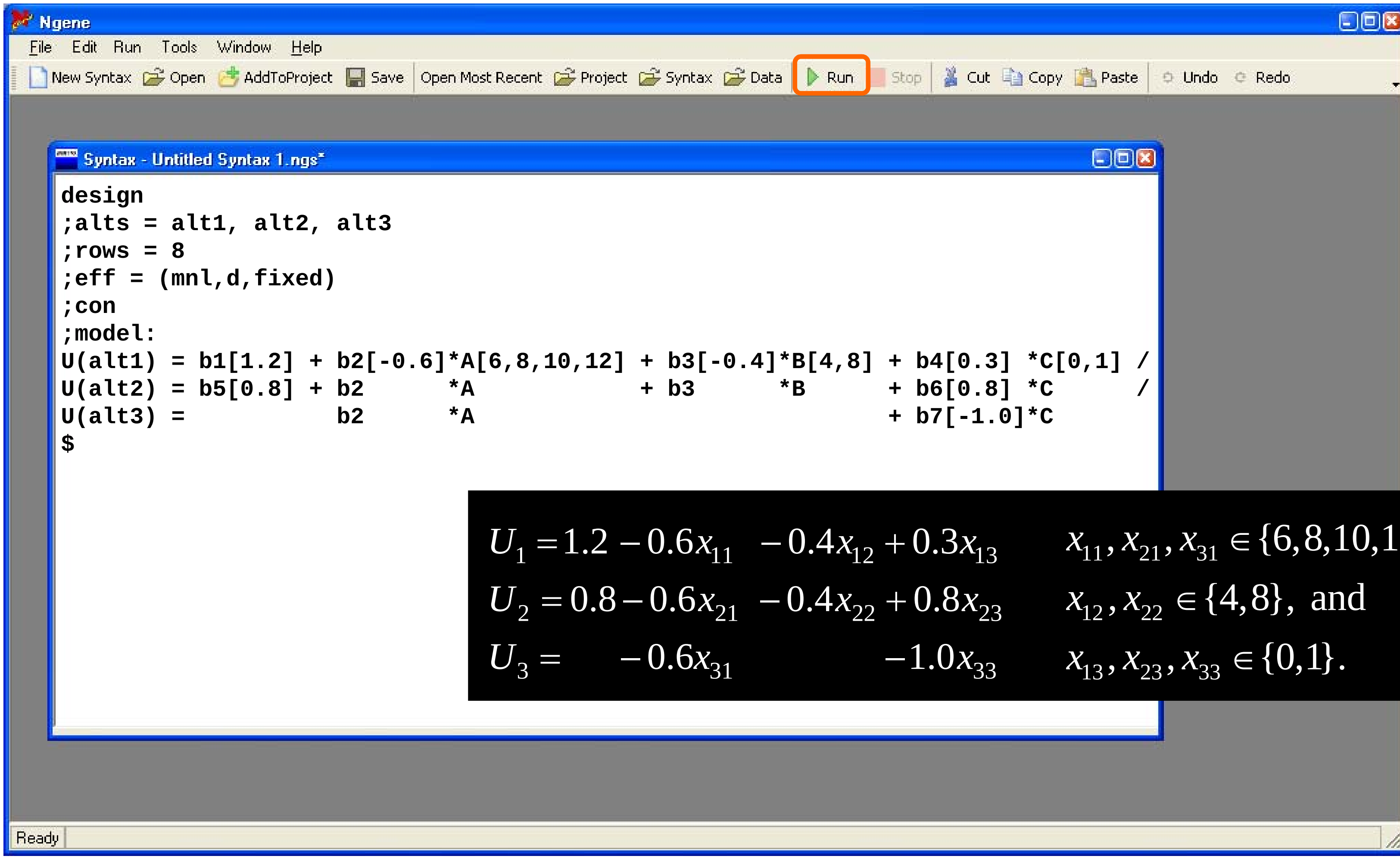
- Generate designs with any number of choice situations, alternatives, attributes and attribute levels.
- Maintain attribute level balance, or specify that an attribute must occur an exact number of times or between a minimum and maximum number of times.
- Dummy and effects code attributes.
- Specify logical rules to limit what attribute levels can coexist in a choice situation.
- Interrogate design level correlations as calculated using a range of correlation formulas (Pearson product moment, G index, J index, Spearman rank, Point biserial, CP coefficient, H index).

Generate full and fractional factorial designs.

Generate orthogonal designs:

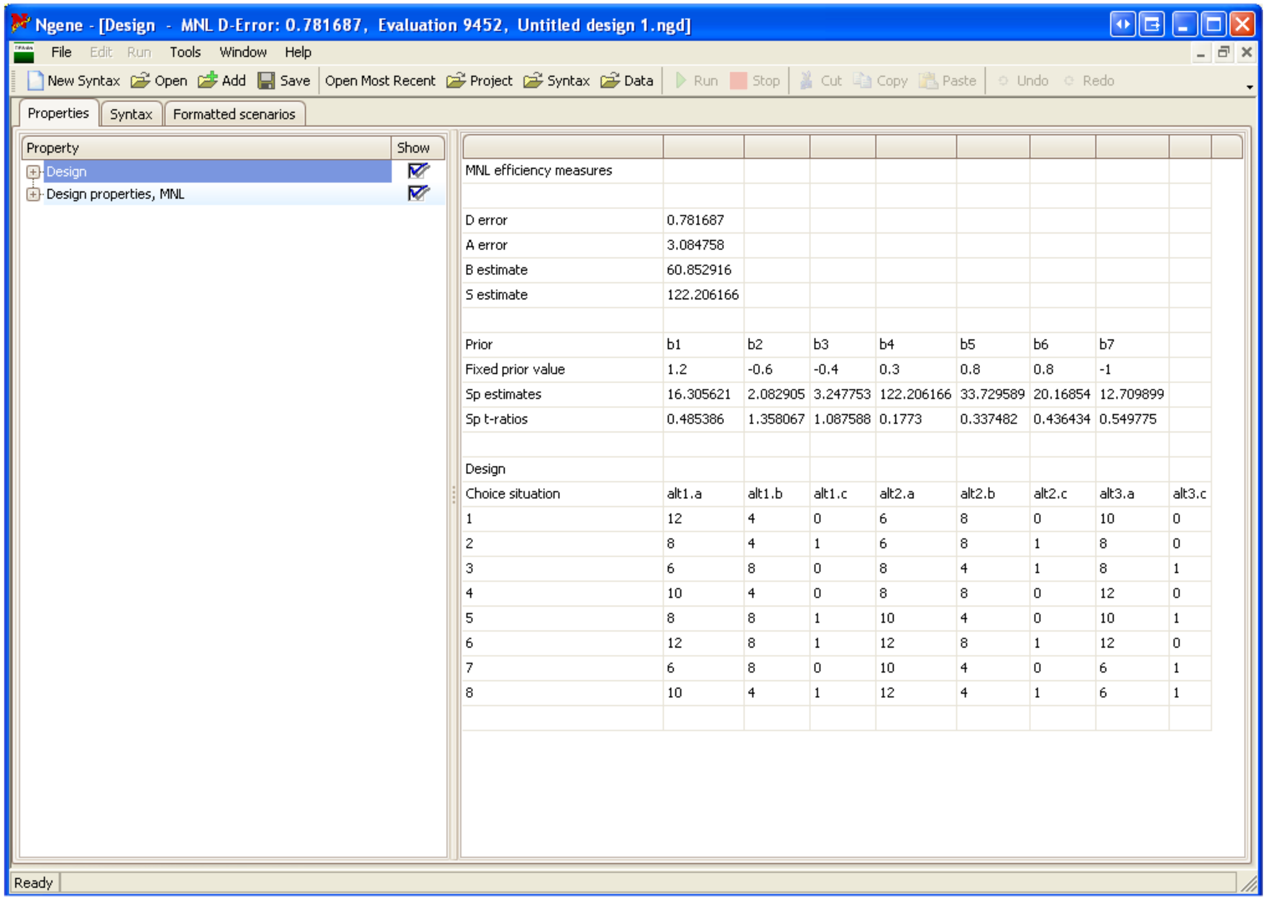
- Maintain orthogonality either across or within alternatives.
- Obtain orthogonal designs for a very large range of design dimensions.
- Add blocking and foldover columns.
- Generate optimal orthogonal in the differences designs.
- Find the most efficient orthogonal design.

Example syntax



$$
\begin{aligned}
U_1 &= 1.2 - 0.6x_{11} - 0.4x_{12} + 0.3x_{13} \qquad & x_{11}, x_{21}, x_{31} &\in \{6,8,10,12\}, \\
U_2 &= 0.8 - 0.6x_{21} - 0.4x_{22} + 0.8x_{23} \qquad & x_{12}, x_{22} &\in \{4,8\},\ \text{and} \\
U_3 &= - 0.6x_{31} \phantom{- 0.4x_{22}} - 1.0x_{33} \qquad & x_{13}, x_{23}, x_{33} &\in \{0,1\}.
\end{aligned}
$$

Design Output I



MNL efficiency measures								
D error	0.781687							
A error	3.084758							
B estimate	60.852916							
S estimate	122.206166							
Prior	b1	b2	b3	b4	b5	b6	b7	
Fixed prior value	1.2	-0.6	-0.4	0.3	0.8	0.8	-1	
Sp estimates	16.305621	2.082905	3.247753	122.206166	33.729589	20.16854	12.709899	
Sp t-ratios	0.485386	1.358067	1.087588	0.1773	0.337482	0.436434	0.549775	
Design								
Choice situation	alt1.a	alt1.b	alt1.c	alt2.a	alt2.b	alt2.c	alt3.a	alt3.c
1	12	4	0	6	8	0	10	0
2	8	4	1	6	8	1	8	0
3	6	8	0	8	4	1	8	1
4	10	4	0	8	8	0	12	0
5	8	8	1	10	4	0	10	1
6	12	8	1	12	8	1	12	0
7	6	8	0	10	4	0	6	1
8	10	4	1	12	4	1	6	1

Bayesian prior parameter distributions

7

Bayesian prior parameter distributions

Background

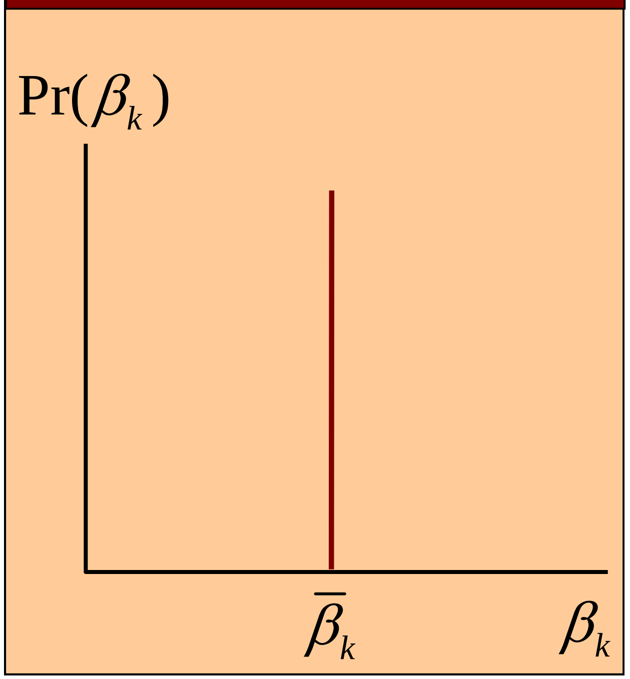
- Efficient design
  - Example:
  - Find *D*-efficient design based on priors β_k
- Bayesian efficient design
  - Example:
  - Find Bayesian *D*-efficient design based on priors $\beta_k \sim N(\mu_k, \sigma_k^2)$

Bayesian prior parameter distributions

Prior parameter distributions

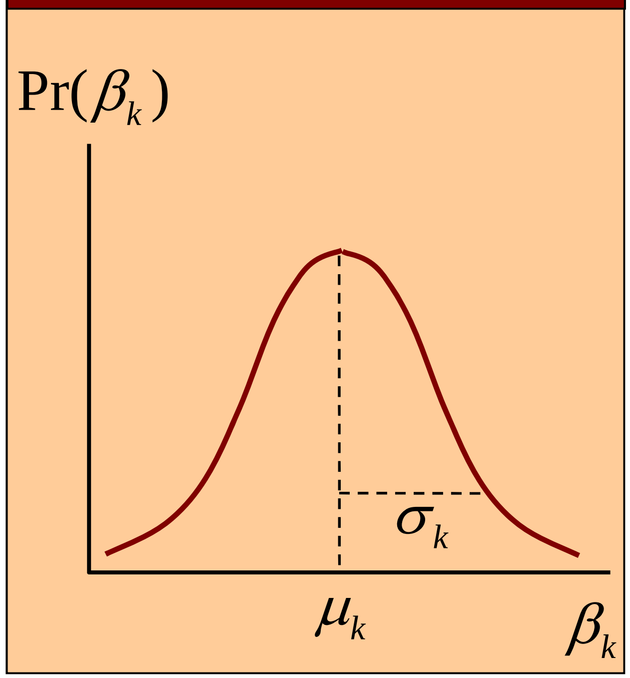
Fixed

$$\beta_k = \bar{\beta}_k$$



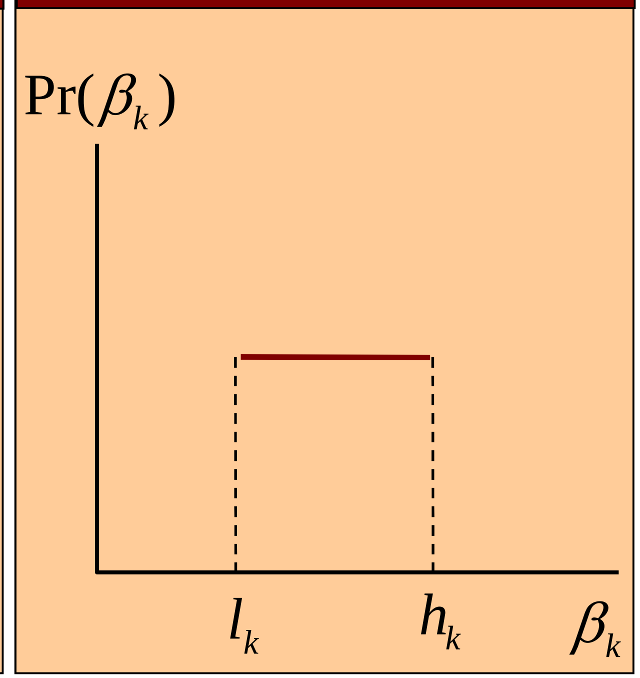
Normal

$$\beta_k \sim N(\mu_k, \sigma_k^2)$$



Uniform

$$\beta_k \sim U(l_k, h_k)$$



Bayesian measures I

- Each efficiency measure (***D*-error, *A*-error, etc.)** has a Bayesian counterpart (**Bayesian *D*-error, Bayesian *A*-error, etc.**)
- Since the priors are random parameters, the efficiency measures will be random too
- Bayesian efficiency measures the expected efficiency

Example:
Using *D*-efficiency as efficiency measure and assuming $\beta \sim N(\mu, \sigma^2)$

D-error = $\det\left(\Omega(\beta \mid X)\right)^{1/K}$

Bayesian *D*-error = $\int_{\beta} \det\left(\Omega(\beta \mid X)\right)^{1/K} f(\beta \mid \mu, \sigma^2) d\beta$

Normal probability density function

Bayesian measures II

› Bayesian efficiency is difficult to compute, it needs to evaluate a complex (multi-dimensional) integral

$$\text{Bayesian } D\text{-error} = \int_{\beta} \det\left(\Omega(\beta \mid X)\right)^{1/K} f(\beta \mid \theta) d\beta$$

› However, it is nothing more than a simple average of *D*-errors:

$$\text{Bayesian } D\text{-error} \approx \frac{1}{R}\sum_{r=1}^{R} \det\left(\Omega(\beta^{(r)} \mid X)\right)^{1/K}$$

where $\beta^{(r)}$ are random draws from the distribution function (we take $r = 1,\ldots,R$ draws)

Bayesian prior parameter distributions

Bayesian versus locally optimal designs I

$$U_A = \beta_1 A_1 + \beta_2 A_2$$
$$U_B = \beta_1 B_1 + \beta_2 B_2$$

D-efficient design

	A1	A2	C1	C2
1	10	4	35	0
2	20	2	35	2
3	30	4	50	0
4	40	4	65	0
5	40	4	65	1
6	20	3	35	2
7	30	2	50	2
8	40	3	65	1
9	20	3	20	1
10	30	2	50	1
11	10	2	20	2
12	10	3	20	0

$$\beta_1 = 0.20$$
$$\beta_2 = 1.10$$

D-error = 0.0276
Bayesian *D*-error = 0.0488

Bayesian *D*-efficient design

	A1	A2	C1	C2
1	20	4	20	1
2	30	3	50	1
3	40	4	65	0
4	20	4	35	0
5	40	4	50	0
6	10	2	65	2
7	20	3	35	0
8	30	2	20	2
9	10	2	20	2
10	10	3	35	1
11	30	3	65	1
12	40	2	50	2

$$\beta_1 \sim N(0.20, 0.08^2)$$
$$\beta_2 \sim N(1.10, 0.5^2)$$

D-error = 0.0330
Bayesian *D*-error = 0.0440

What if: $\beta_1 = 0.30$, $\beta_2 = 0.60$?

D-error = 0.1188 (*D*-efficient design)

D-error = 0.0691 (Bayesian *D*-efficient design)

Bayesian versus locally optimal designs II

› Efficient designs are more efficient than Bayesian efficient designs if the prior parameters are correct

› However, if the priors are wrong, an efficient design can become quite *in*efficient

› The efficiency of a Bayesian *D*-efficient design is less sensitive to misspecification of the priors, and therefore called more robust

Generating Bayesian efficient designs

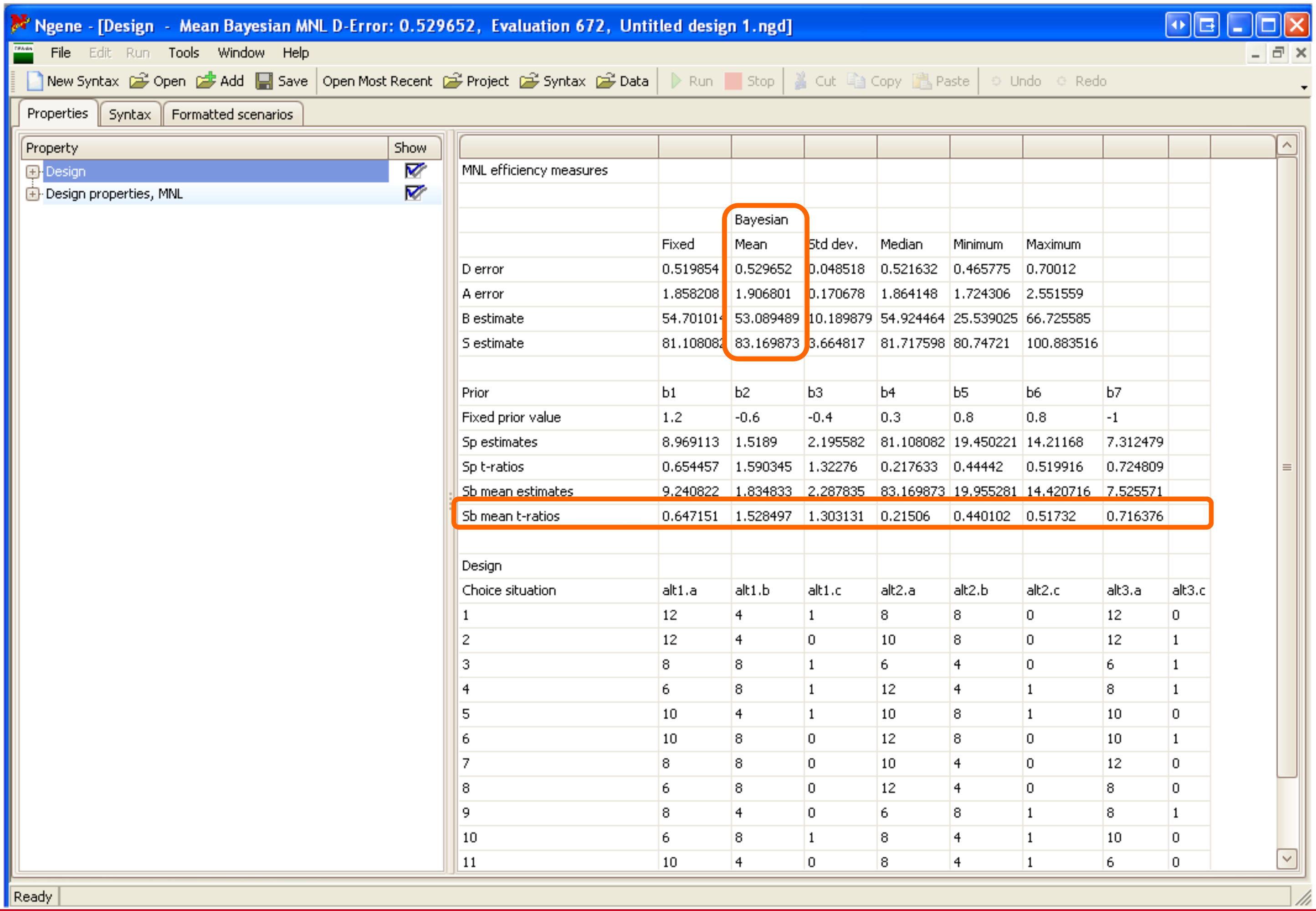
- The same algorithms for determining an efficient design can be used for generating a Bayesian efficient design
- If *R* random draws (e.g., 100) are used for computing the Bayesian efficiency, finding a Bayesian efficient design may take *R* times longer
- It is recommended to always use ‘smart draws’ (e.g., Halton draws) instead of random draws

Example Syntax

```
design
;alts = alt1, alt2, alt3
;rows = 12
;eff = (mnl,d,mean)
;bdraws = halton(100)
;con
;model:
U(alt1) = b1[1.2] + b2[(n,-0.6,0.2)]*A[6,8,10,12] + b3[-0.4]*B[4,8] + b4[0.3] *C[0,1] /
U(alt2) = b5[0.8] + b2                *A              + b3      *B      + b6[0.8] *C      /
U(alt3) =           b2                *A                                + b7[-1.0]*C
$
```

$$\beta_2 \sim N(-0.6, 0.2)$$

Interpreting Bayesian output



MNL efficiency measures

	Fixed	Bayesian Mean	Std dev.	Median	Minimum	Maximum
D error	0.519854	0.529652	0.048518	0.521632	0.465775	0.70012
A error	1.858208	1.906801	0.170678	1.864148	1.724306	2.551559
B estimate	54.70101	53.089489	10.189879	54.924464	25.539025	66.725585
S estimate	81.10808	83.169873	3.664817	81.717598	80.74721	100.883516

Prior	b1	b2	b3	b4	b5	b6	b7
Fixed prior value	1.2	-0.6	-0.4	0.3	0.8	0.8	-1
Sp estimates	8.969113	1.5189	2.195582	81.108082	19.450221	14.21168	7.312479
Sp t-ratios	0.654457	1.590345	1.32276	0.217633	0.44442	0.519916	0.724809
Sb mean estimates	9.240822	1.834833	2.287835	83.169873	19.955281	14.420716	7.525571
Sb mean t-ratios	0.647151	1.528497	1.303131	0.21506	0.440102	0.51732	0.716376

Design

Choice situation	alt1.a	alt1.b	alt1.c	alt2.a	alt2.b	alt2.c	alt3.a	alt3.c
1	12	4	1	8	8	0	12	0
2	12	4	0	10	8	0	12	1
3	8	8	1	6	4	0	6	1
4	6	8	1	12	4	1	8	1
5	10	4	1	10	8	1	10	0
6	10	8	0	12	8	0	10	1
7	8	8	0	10	4	0	12	0
8	6	8	0	12	4	0	8	0
9	8	4	0	6	8	1	8	1
10	6	8	1	8	4	1	10	0
11	10	4	0	8	4	1	6	0

The AVC matrix and advanced models

8

Bliemer, M.C.J. and Rose, J.M. (2010) Construction of Experimental Designs for Mixed Logit Models Allowing for Correlation Across Choice Observations, *Transportation Research Part B*, 44, 720-734

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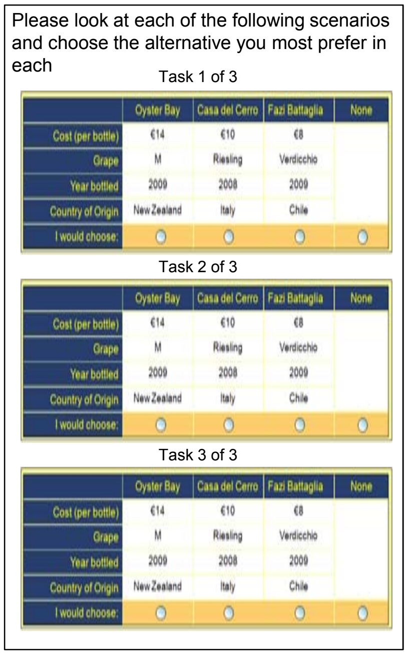
Typical modelling steps in discrete choice studies

Experimental design

1	30	3	15	4
2	30	1	35	4
3	30	1	20	4
4	20	1	25	4
5	25	5	30	2
6	20	3	35	2
7	20	1	20	4
8	25	3	40	2
9	25	5	25	2
10	20	5	15	2
11	30	5	30	2
12	25	3	40	4

Survey



Please look at each of the following scenarios and choose the alternative you most prefer in each

Task 1 of 3

	Oyster Bay	Casa del Cerro	Fazi Battaglia	None
Cost (per bottle)	€14	€10	€8	
Grape	M	Riesling	Verdicchio	
Year bottled	2009	2008	2009	
Country of Origin	New Zealand	Italy	Chile	
I would choose:				

Task 2 of 3

	Oyster Bay	Casa del Cerro	Fazi Battaglia	None
Cost (per bottle)	€14	€10	€8	
Grape	M	Riesling	Verdicchio	
Year bottled	2009	2008	2009	
Country of Origin	New Zealand	Italy	Chile	
I would choose:				

Task 3 of 3

	Oyster Bay	Casa del Cerro	Fazi Battaglia	None
Cost (per bottle)	€14	€10	€8	
Grape	M	Riesling	Verdicchio	
Year bottled	2009	2008	2009	
Country of Origin	New Zealand	Italy	Chile	
I would choose:				

Respondents

Data

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

Estimation

Specification of:
1. Model type
2. Utility functions

$$V_1 = \sum_{k=1}^{K} \beta_{1k} x_{1k}$$

$$V_2 = \sum_{k=1}^{K} \beta_{2k} x_{2k}$$

$$\vdots$$

$$V_j = \sum_{k=1}^{K} \beta_{jk} x_{jk}$$

$$\hat{\beta}$$

$$se(\hat{\beta})$$

Results

The question is what is the relationship between the results and the experimental design?

Recall...

- The asymptotic variance-covariance (AVC) matrix is an approximation of the true variance-covariance matrix
- "Asymptotic" means
  - assuming a very large sample; or
  - assuming a large number of repetitions using a small sample
- The roots of the diagonals of the variance-covariance matrix denote the standard errors

$$\text{variance-covariance matrix} = \begin{pmatrix} se(\beta_1)^2 & \cdots & \\ \vdots & \ddots & \\ & & se(\beta_K)^2 \end{pmatrix},$$

where $se(\beta_k)$ is the standard error of parameter β_k

The MNL model

› First, determine the loglikelihood function:

$$LL = \sum_{n=1}^{N} \sum_{s \in S_n} \sum_{j \in J_{ns}} y_{nsj} \ln\left(P_{nsj}\right).$$

› Secondly, determine the Fisher information matrix:

$$\frac{\partial^2 LogL}{\partial \beta_{k_1}^* \partial \beta_{k_2}^*} = -\sum_{n=1}^{N} \sum_{s \in S_n} \sum_{j \in J_{ns}} x_{nsjk_1}^* P_{nsj} \left(x_{nsjk_2}^* - \sum_{i=1}^{J} P_{nsi} x_{nsik_2}^* \right)$$

$$\frac{\partial^2 LogL}{\partial \beta_{j_1 k_1} \partial \beta_{k_2}^*} = -\sum_{n=1}^{N} \sum_{s \in S_n} \sum_{j \in J_{ns}} x_{j_1 k_1 s} P_{j_1 s} \left(x_{j_1 k_2 s}^* - \sum_{i=1}^{J} x_{ik_2 s}^* P_{is} \right)$$

$$\frac{\partial^2 LogL}{\partial \beta_{j_1 k_1} \partial \beta_{j_2 k_2}} = \begin{cases} \sum_{n=1}^{N} \sum_{s \in S_n} \sum_{j \in J_{ns}} x_{j_1 k_1 s} x_{j_2 k_2 s} P_{j_1 s} P_{j_2 s}, & \text{if } j_1 \neq j_2; \\ -\sum_{n=1}^{N} \sum_{s \in S_n} \sum_{j \in J_{ns}} x_{j_1 k_1 s} x_{j_2 k_2 s} P_{j_1 s} \left(1 - P_{j_2 s}\right), & \text{if } j_1 = j_2. \end{cases}$$

The cross sectional MMNL model

› First, determine the loglikelihood function:

$$LL = \sum_{n=1}^{N} \sum_{s \in S_n} \sum_{j \in J_{ns}} y_{nsj} \ln\left[E\left(P_{nsj} \right) \right].$$

› Secondly, determine the Fisher information matrix:

$$\frac{\partial^2 \log E(L)}{\partial \theta_{k_1 m_1} \partial \theta_{k_2 m_2}} = \sum_{n=1}^{N} \sum_{s \in S_n} \sum_{j \in J_{ns}} P_{nsj} \left(\frac{1}{E\left(P_{nsj}\right)} E\left(\frac{\partial^2 P_{nsj}}{\partial \theta_{k_1 m_1} \partial \theta_{k_2 m_2}} \right) - \frac{1}{\left(E\left(P_{nsj}\right)\right)^2} E\left(\frac{\partial P_{nsj}}{\partial \theta_{k_1 m_1}} \right) E\left(\frac{\partial P_{nsj}}{\partial \theta_{k_2 m_2}} \right) \right).$$

The panel MMNL model

› First, determine the loglikelihood function:

$$LL = \sum_{n=1}^{N} \ln \int_{\beta} \prod_{s\in S_n} \prod_{j\in J_{ns}} \left(P_{nsj}\right)^{y_{nsj}} f\left(\beta \mid \theta\right) d\beta,$$

› Secondly, determine the Fisher information matrix:

$$\frac{\partial^2 \log E(L)}{\partial\theta_{k_1m_1}\partial\theta_{k_2m_2}} = \sum_{n=1}^{N}\left(\frac{1}{E\left(P_n^*\right)}\frac{\partial^2 E\left(P_n^*\right)}{\partial\theta_{k_1m_1}\partial\theta_{k_2m_2}} - \frac{1}{\left(E\left(P_n^*\right)\right)^2}\frac{\partial E\left(P_n^*\right)}{\partial\theta_{k_1m_1}}\frac{\partial E\left(P_n^*\right)}{\partial\theta_{k_2m_2}}\right)$$

$$= \sum_{n=1}^{N}\left(\frac{1}{E\left(P_n^*\right)}E\left(\frac{\partial^2 P_n^*}{\partial\theta_{k_1m_1}\partial\theta_{k_2m_2}}\right) - \frac{1}{\left(E\left(P_n^*\right)\right)^2}E\left(\frac{\partial P_n^*}{\partial\theta_{k_1m_1}}\right)E\left(\frac{\partial P_n^*}{\partial\theta_{k_2m_2}}\right)\right),$$

where $\frac{\partial P_n^*}{\partial\theta_{km}} = P_n^* \frac{\partial\beta_k}{\partial\theta_{km}} \sum_{s\in S_n}\sum_{j\in J_{ns}} \frac{y_{nsj}}{P_{nsj}}\frac{\partial P_{nsj}}{\partial\beta_k},$

$$\frac{\partial^2 P_n^*}{\partial\theta_{k_1m_1}\partial\theta_{k_2m_2}} = \frac{1}{P_n^*}\frac{\partial P_n^*}{\partial\theta_{k_1m_1}}\frac{\partial P_n^*}{\partial\theta_{k_2m_2}} - P_n^*\frac{\partial\beta_{k_1}}{\partial\theta_{k_1m_1}}\frac{\partial\beta_{k_1}}{\partial\theta_{k_2m_2}}\sum_{s\in S_n}\sum_{j\in J_{ns}}\frac{\partial P_{nsj}}{\partial\beta_{k_2}}x_{nsjk_1} + P_n^*\frac{\partial^2\beta_{k_1}}{\partial\theta_{k_1m_1}\partial\theta_{k_2m_2}}\sum_{s\in S_n}\sum_{j\in J_{ns}}\frac{y_{nsj}}{P_{nsj}}\frac{\partial P_{nsj}}{\partial\beta_{k_1}},$$

$$\frac{\partial P_{nsj}}{\partial\beta_k} = P_{nsj}\left(x_{nsjk} - \sum_{i\in J_{ns}} P_{nsi}x_{nsik}\right).$$

Error components models

› Error components models are a form of MMNL models

$$U_{nsj} = \beta x_{nsj} + \eta z_n d_h + \varepsilon_{nsj}$$

where $$d_h = \begin{cases} 1 & \text{if alt } i \text{ is in nest } h \\ 0 & \text{otherwise.} \end{cases}$$

and $Z_n \sim N(0, \sigma)$

› They can be therefore also be treated as cross sectional or panel models

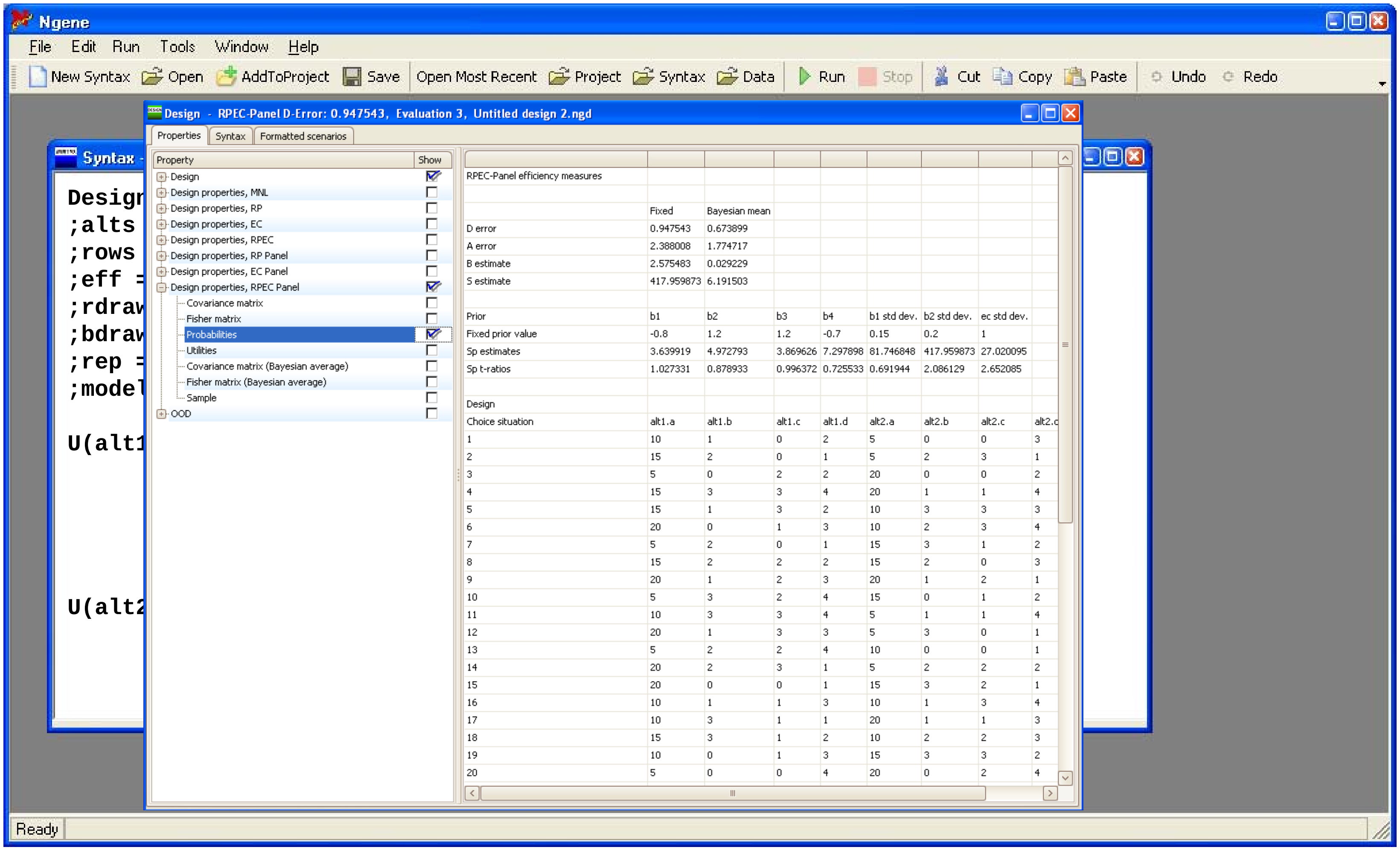
Bayesian random parameters…

```
Design
;alts = alt1, alt2, alt3
;rows = 20
;eff = (rpecpanel,d)
;rdraws = gauss(2)
;bdraws = gauss(2)
;rep = 250
;model:

U(alt1) = SP1[0.8] + b1[n,(n,-0.8,0.1),(u,0.1,0.2)] * A[5,10,15,20]
                   + b2[n,1.2,0.2]                  * B[0,1,2,3]
                   + b3[1.2]                        * C[0,1,2,3]
                   + b4[-0.7]                       * D[1,2,3,4]
                   + EC[EC,1] /

U(alt2) = SP2[0.6] + b1 * A + b2 * B + b3 * C + b4 * D + EC $
```

Bayesian random parameters…



RPEC-Panel efficiency measures								
	Fixed	Bayesian mean						
D error	0.947543	0.673899						
A error	2.388008	1.774717						
B estimate	2.575483	0.029229						
S estimate	417.959873	6.191503						
Prior	b1	b2	b3	b4	b1 std dev.	b2 std dev.	ec std dev.	
Fixed prior value	-0.8	1.2	1.2	-0.7	0.15	0.2	1	
Sp estimates	3.639919	4.972793	3.869626	7.297898	81.746848	417.959873	27.020095	
Sp t-ratios	1.027331	0.878933	0.996372	0.725533	0.691944	2.086129	2.652085	
Design								
Choice situation	alt1.a	alt1.b	alt1.c	alt1.d	alt2.a	alt2.b	alt2.c	alt2.d
1	10	1	0	2	5	0	0	3
2	15	2	0	1	5	2	3	1
3	5	0	2	2	20	0	0	2
4	15	3	3	4	20	1	1	4
5	15	1	3	2	10	3	3	3
6	20	0	1	3	10	2	3	4
7	5	2	0	1	15	3	1	2
8	15	2	2	2	15	2	0	3
9	20	1	2	3	20	1	2	1
10	5	3	2	4	15	0	1	2
11	10	3	3	4	5	1	1	4
12	20	1	3	3	5	3	0	1
13	5	2	2	4	10	0	0	1
14	20	2	3	1	5	2	2	2
15	20	0	0	1	15	3	2	1
16	10	1	1	3	10	1	3	4
17	10	3	1	1	20	1	1	3
18	15	3	1	2	10	2	2	3
19	10	0	1	3	15	3	3	2
20	5	0	0	4	20	0	2	4

Experimental design influences on stated choice outcomes

Case study 1: An empirical study in air travel choice

Bliemer, M.C.J. and Rose, J.M. (2011) Experimental design influences on stated choice outputs: an empirical study in air travel choice, *Transportation Research Part A*, 45(1), 63-79.

John Rose | Prof.
Experimental Designs| **Dec 4th-5th**

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Introduction

1

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Orthogonal vs. efficient designs

- **Orthogonal designs** have been widely used in stated choice experiments.

- **Efficient designs** have been proposed to yield smaller standard errors in model estimation.

- Until now, efficient designs have not been compared to orthogonal designs **in real life** with respect to their standard errors, only in hypothetical simulation studies.

- In this study we investigate whether the theoretical advantages of
- efficient designs (smaller standard errors at smaller sample sizes) indeed translate into practice.

Empirical studies

"More efficient designs lead to greater error variance (lower scale parameter)."
– Louviere et al. (2008)

"Efficient designs only lead to marginal improvements over orthogonal designs, design blocking seems more important."
– Hess et al. (2008)

"Efficient designs can lead to significantly lower standard errors and require smaller sample sizes than using an orthogonal design."
– Bliemer and Rose (2010)

Description case study

2

Description case study

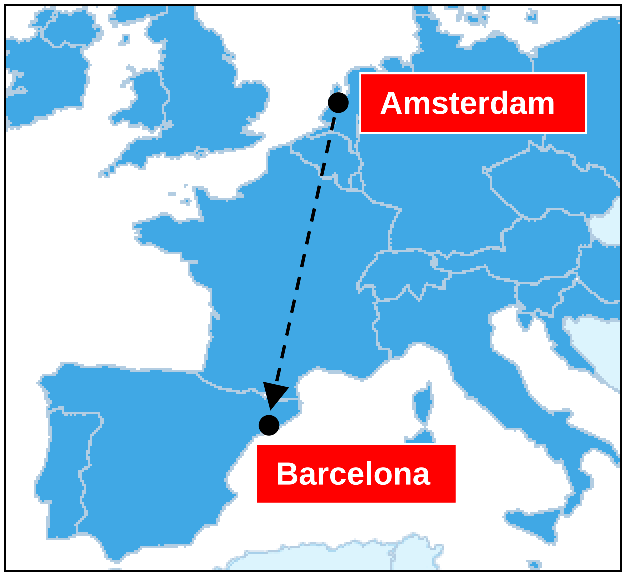
Air travel choice

› Investigate travel behavior of travelers, depending on:
  - Airline
  - ticket price
  - transfers
  - departure time
  - egress travel time
  - egress travel costs

using a web-based stated choice experiment for a trip from Amsterdam to Barcelona.

Description case study

Barcelona or Girona airport?



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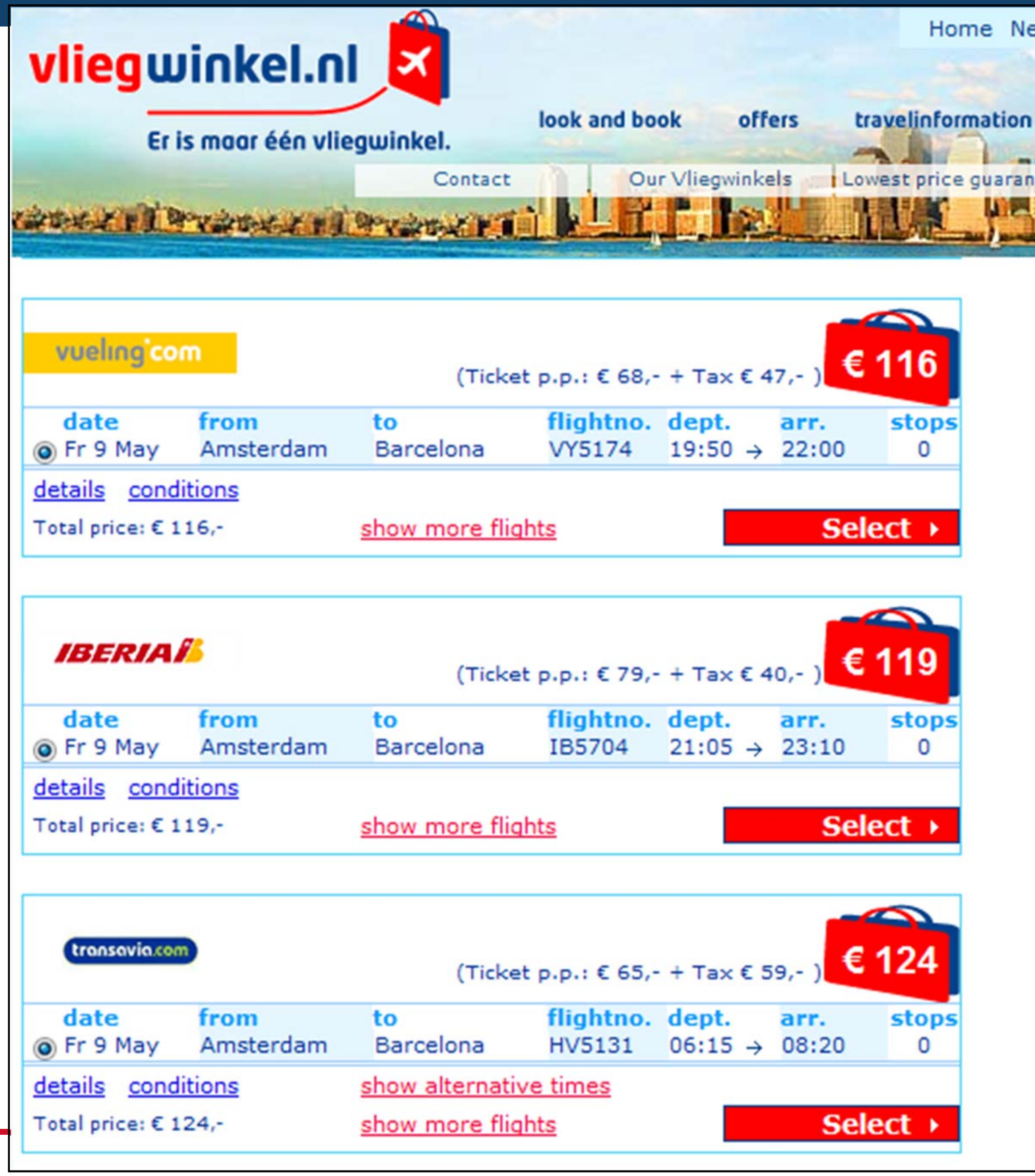
Description case study

Online booking



Online booking

Attribute	Show	Sort by	Information
Flight			
Airline	☑	○	
Departure Time	☑	○	
Arrival Time	☑	○	Depature time + inflight time + transfer time
Number of Stops / Transfer Time	☑	○	Time spent waiting at the stop(s)
Travel Time	☑	○	Travel time needed from Amsterdam to Barcelona airport or to Girona airport (including inflight time and transfer time)
Price	☑	◉	Ticket price (flight only) including fees and taxes
Ground transportation			
Travel Time	☑	○	Additional price for traveling from the arrival airport to the city centre
Price	☑	○	Additional time needed to travel from the arrival airport to the city centre
Total Travel Time	☑	○	Total travel time (including inflight time and ground transportation travel time) from Amsterdam airport to Barcelona City
Total Price	☑	○	Total price (including flight price and ground transportation price) from Amsterdam to Barcelona City

Iberia IBERIA	From	To	Departure	Arrival	Total Stops	3 hr 40 min Travel Time	€ 65 Price	
Flight	Amsterdam	Girona Airport	6:00	8:00	0	2 hr 00 min	€ 50	Choose this ticket
Ground Transportation	Girona Airport	Barcelona City				1 hr 40 min	€ 15	

Transavia transavia.com	From	To	Departure	Arrival	Total Stops	5 hr 00 min Travel Time	€ 65 Price	
Flight	Amsterdam	Girona Airport	12:00	16:00	1 - (2 hr 00)	4 hr 00 min	€ 50	Choose this ticket
Ground Transportation	Girona Airport	Barcelona City				1 hr 00 min	€ 15	

Vueling vueling.com	From	To	Departure	Arrival	Total Stops	4 hr 20 min Travel Time	€ 84 Price	
Flight	Amsterdam	Girona Airport	6:00	9:00	1 - (1 hr 00)	3 hr 00 min	€ 75	Choose this ticket
Ground Transportation	Girona Airport	Barcelona City				1 hr 20 min	€ 9	

Experimental design

3

Experimental design

Design dimensions

- Alternatives: 5
- Number of choice situations per respondent: 6
- Attributes and levels:
  - airline: Air France, KLM, Iberia, Vueling, Transavia, EasyJet
  - ticket price: €50, €75, €100
  - transfer time: none, 1 hour, 2 hours
  - departure time: 6am, noon, 6pm
  - egress travel time: 20min, 30min, 40min (Barcelona)
    60min, 80min, 100min (Girona)
  - egress travel costs: €1, €3, €5 (Barcelona)
    €9, €12, €15 (Girona)

Design generation (using Ngene)

› Three designs have been generated:

- **orthogonal design**

  Number of choice situations: 108

  Number of blocks: 18

- **Bayesian D-efficient design 1***

  Number of choice situations: 108

  Number of blocks: 18

- **Bayesian D-efficient design 2***

  Number of choice situations: 18

  Number of blocks: 3

* Using parameter priors from pilot study (36 respondents, orthogonal design)

Bayesian parameter priors

Attribute	Parameter	*t*-value	Prior (mean)	Prior (stdev)
Air France	-0.516	-1.596	0	0.323
KLM	0.194	0.661	0	0.293
Iberia	-0.218	-0.729	0	0.299
Vueling	0.125	0.426	0	0.293
Transavia	-0.547	-1.765	0	0.31
Ticket Price	-0.04	-8.444	-0.04	0.005
Departure Time (6am)	0.215	0.974	0	0.221
Departure Time (12pm)	0.614	2.883	0.614	0.213
Transfer Time	-0.006	-3.298	-0.006	0.002
Egress Price	-0.027	-0.904	0	0.03
Egress Time	-0.018	-3.265	-0.018	0.006

Experimental design

Efficient design *

s	j	A	PR	DT	TR	EP	ET	s	j	A	PR	DT	TR	EP	ET
1	1	2	100	12	60	3	30	10	1	0	100	6	120	9	80
1	2	1	50	18	0	15	60	10	2	3	100	18	0	3	20
1	3	2	100	18	60	1	40	10	3	1	50	18	60	12	80
1	4	4	75	12	120	1	30	10	4	0	50	6	120	9	60
1	5	0	50	6	60	1	30	10	5	5	75	12	0	3	40
2	1	5	75	12	60	5	20	11	1	1	50	18	120	1	20
2	2	2	100	18	60	3	40	11	2	0	100	12	120	5	30
2	3	4	75	18	0	12	60	11	3	5	100	6	0	5	30
2	4	3	100	6	60	3	40	11	4	2	75	6	60	5	40
2	5	3	50	6	120	9	100	11	5	3	50	12	0	9	80
3	1	0	75	12	0	9	100	12	1	4	50	6	120	15	60
3	2	4	75	6	0	5	40	12	2	2	100	6	60	12	60
3	3	3	75	12	120	9	60	12	3	0	100	12	0	1	30
3	4	5	75	6	60	12	80	12	4	5	50	18	0	12	100
3	5	2	50	18	120	12	60	12	5	1	100	18	60	3	30
4	1	2	100	18	60	12	100	13	1	3	75	6	0	12	60
4	2	3	50	18	120	5	20	13	2	5	75	18	120	1	30
4	3	1	50	6	0	9	100	13	3	0	50	12	60	12	100
4	4	5	50	6	120	9	80	13	4	1	100	6	60	3	30
4	5	4	75	12	0	15	60	13	5	2	100	18	0	3	20
5	1	1	50	6	0	1	30	14	1	2	75	12	120	5	40
5	2	4	50	12	120	15	100	14	2	5	50	6	0	15	80
5	3	5	50	18	60	15	60	14	3	4	100	12	120	3	20
5	4	0	50	18	120	15	80	14	4	3	50	18	0	9	100
5	5	4	100	18	0	1	20	14	5	1	100	18	60	12	80
6	1	3	50	6	60	15	80	15	1	5	100	12	60	9	60
6	2	0	50	12	60	9	60	15	2	3	75	6	0	9	80
6	3	5	75	12	120	3	30	15	3	4	50	18	0	15	100
6	4	2	100	18	0	5	30	15	4	1	100	12	60	1	20
6	5	2	50	6	120	5	40	15	5	0	75	6	120	5	30
7	1	4	50	18	120	1	40	16	1	4	75	6	0	3	40
7	2	0	100	6	60	3	30	16	2	1	75	18	0	12	80
7	3	1	75	6	60	15	80	16	3	2	75	18	60	1	20
7	4	2	100	12	0	3	20	16	4	3	50	12	120	5	20
7	5	5	100	12	60	12	100	16	5	5	75	6	60	1	40
8	1	1	100	18	0	3	20	17	1	3	100	12	60	15	100
8	2	2	50	12	120	9	100	17	2	1	75	12	120	1	40
8	3	3	100	6	120	5	20	17	3	2	50	6	0	9	80
8	4	0	100	12	0	15	60	17	4	4	75	18	60	12	60
8	5	3	100	18	120	5	20	17	5	0	75	12	60	15	100
9	1	5	50	18	120	12	80	18	1	0	75	18	0	5	30
9	2	4	100	6	60	1	20	18	2	5	75	12	60	12	100
9	3	0	75	12	120	5	40	18	3	3	100	6	120	3	40
9	4	4	75	18	0	1	40	18	4	1	75	12	120	15	100
9	5	1	75	12	0	15	80	18	5	4	50	6	120	9	60

Model Estimation

4

Pooled data results (using Nlogit)

Attribute	*parameter*	*t-ratio*	*lower 95%*	*upper 95%*
Air France	**0.377**	6.019	0.254	0.500
KLM	**-0.232**	-3.456	-0.364	-0.101
Iberia	**-0.535**	-7.629	-0.672	-0.398
Vueling	-0.008	-0.120	-0.132	0.117
Transavia	**-0.137**	-2.046	-0.268	-0.006
Ticket Price	**-0.028**	-25.115	-0.030	-0.026
Departure Time (6am)	**0.283**	6.221	0.194	0.372
Departure Time (12pm)	**0.460**	9.860	0.368	0.551
Transfer Time	**-0.015**	-32.228	-0.016	-0.014
Egress Price	**-0.035**	-5.956	-0.047	-0.024
Egress Time	**-0.009**	-8.459	-0.011	-0.007
		Model fits		
LL(ASC only model)				-5879.526
LL(β)				-4774.862
ρ^2				0.188
Respondents				618
Observations				3708

"Travellers are willing to pay 10 euros more for a ticket to Barcelona Airport (and save 40 minutes egress time)"

206 orthogonal design
208 efficient design 1
204 efficient design 2

Design-specific results

	Design 1: Orthogonal, S = 108				Design 2: Efficient, S = 108				Design 3: Efficient, S = 18			
Attribute	*par.*	*t-ratio*	*lower 95%*	*upper 95%*	*par.*	*t-ratio*	*lower 95%*	*upper 95%*	*par.*	*t-ratio*	*lower 95%*	*upper 95%*
Air France	**0.422**	3.423	0.180	0.664	**0.319**	2.994	0.110	0.527	**0.457**	4.401	0.253	0.660
KLM	-0.231	-1.883	-0.471	0.010	**-0.402**	-3.265	-0.643	-0.161	-0.112	-1.017	-0.328	0.104
Iberia	**-0.488**	-3.756	-0.742	-0.233	**-0.650**	-5.445	-0.884	-0.416	**-0.417**	-3.523	-0.649	-0.185
Vueling	**0.285**	2.345	0.047	0.524	-0.141	-1.324	-0.349	0.068	-0.131	-1.173	-0.351	0.088
Transavia	0.024	0.190	-0.227	0.276	**-0.301**	-2.635	-0.524	-0.077	-0.052	-0.469	-0.270	0.166
Ticket Price	**-0.035**	-17.780	-0.038	-0.031	**-0.023**	-10.808	-0.027	-0.019	**-0.021**	-9.649	-0.026	-0.017
Departure Time (6am)	**0.300**	3.311	0.123	0.478	**0.410**	5.387	0.261	0.560	**0.171**	2.285	0.024	0.318
Departure Time (12pm)	**0.627**	7.181	0.456	0.798	**0.348**	4.181	0.185	0.511	**0.303**	3.786	0.146	0.460
Transfer Time	**-0.011**	-13.999	-0.012	-0.009	**-0.015**	-19.410	-0.017	-0.014	**-0.018**	-22.350	-0.020	-0.017
Egress Price	**-0.041**	-3.311	-0.065	-0.017	**-0.038**	-3.894	-0.057	-0.019	**-0.032**	-3.330	-0.051	-0.013
Egress Time	**-0.012**	-5.205	-0.016	-0.007	**-0.006**	-3.102	-0.010	-0.002	**-0.006**	-3.342	-0.01	-0.003
					Model fits							
LL(ASC only model)	-1953.577				-1940.001				-1983.633			
LL(β)	-1557.904				-1607.444				-1550.317			
ρ^2	0.203				0.171				0.218			
Respondents	206				204				208			
Observations	1236				1248				1224			

Design comparison

5

Efficient 1 (S=108) vs. Efficient 2 (S=18)

	Design 1: Orthogonal, S = 108				Design 2: Efficient, S = 108				Design 3: Efficient, S = 18			
Attribute	*par.*	*t-ratio*	*lower 95%*	*upper 95%*	*par.*	*t-ratio*	*lower 95%*	*upper 95%*	*par.*	*t-ratio*	*lower 95%*	*upper 95%*
Air France	**0.422**	3.423	0.180	0.664	**0.319**	2.994	0.110	0.527	**0.457**	4.401	0.253	0.660
KLM	-0.231	-1.883	-0.471	0.010	**-0.402**	-3.265	-0.643	-0.161	-0.112	-1.017	-0.328	0.104
Iberia	**-0.488**	-3.756	-0.742	-0.233	**-0.650**	-5.445	-0.884	-0.416	**-0.417**	-3.523	-0.649	-0.185
Vueling	**0.285**	2.345	0.047	0.524	-0.141	-1.324	-0.349	0.068	-0.131	-1.173	-0.351	0.088
Transavia	0.024	0.190	-0.227	0.276	**-0.301**	-2.635	-0.524	-0.077	-0.052	-0.469	-0.270	0.166
Ticket Price	**-0.035**	-17.780	-0.038	-0.031	**-0.023**	-10.808	-0.027	-0.019	**-0.021**	-9.649	-0.026	-0.017
Departure Time (6am)	**0.300**	3.311	0.123	0.478	**0.410**	5.387	0.261	0.560	**0.171**	2.285	0.024	0.318
Departure Time (12pm)	**0.627**	7.181	0.456	0.798	**0.348**	4.181	0.185	0.511	**0.303**	3.786	0.146	0.460
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Egress Price	**-0.041**	-3.311	-0.065	-0.017	**-0.038**	-3.894	-0.057	-0.019	**-0.032**	-3.330	-0.051	-0.013
Egress Time	**-0.012**	-5.205	-0.016	-0.007	**-0.006**	-3.102	-0.010	-0.002	**-0.006**	-3.342	-0.01	-0.003
												Model fits
LL(ASC only model)	-1953.577				-1940.001				-1983.633			
LL(β)	-1557.904				-1607.444				-1550.317			
ρ^2	0.203				0.171				0.218			
Respondents	206				204				208			
Observations	1236				1248				1224			

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Design comparison

Orthogonal (S=108) vs. Efficient 1 (S=108)

	Design 1: Orthogonal, S = 108				Design 2: Efficient, S = 108				Design 3: Efficient, S = 18			
Attribute	*par.*	*t-ratio*	*lower 95%*	*upper 95%*	*par.*	*t-ratio*	*lower 95%*	*upper 95%*	*par.*	*t-ratio*	*lower 95%*	*upper 95%*
Air France	**0.422**	3.423	0.180	0.664	**0.319**	2.994	0.110	0.527	**0.457**	4.401	0.253	0.660
KLM	-0.231	-1.883	-0.471	0.010	**-0.402**	-3.265	-0.643	-0.161	-0.112	-1.017	-0.328	0.104
Iberia	**-0.488**	-3.756	-0.742	-0.233	**-0.650**	-5.445	-0.884	-0.416	**-0.417**	-3.523	-0.649	-0.185
Vueling	**0.285**	2.345	0.047	0.524	-0.141	-1.324	-0.349	0.068	-0.131	-1.173	-0.351	0.088
Transavia	0.024	0.190	-0.227	0.276	**-0.301**	-2.635	-0.524	-0.077	-0.052	-0.469	-0.270	0.166
Ticket Price	**-0.035**	-17.780	-0.038	-0.031	**-0.023**	-10.808	-0.027	-0.019	**-0.021**	-9.649	-0.026	-0.017
Departure Time (6am)	**0.300**	3.311	0.123	0.478	**0.410**	5.387	0.261	0.560	**0.171**	2.285	0.024	0.318
Departure Time (12pm)	**0.627**	7.181	0.456	0.798	**0.348**	4.181	0.185	0.511	**0.303**	3.786	0.146	0.460
Transfer Time	**-0.011**	-13.999	-0.012	-0.009	**-0.015**	-19.410	-0.017	-0.014	**-0.018**	-22.350	-0.020	-0.017
Egress Price	**-0.041**	-3.311	-0.065	-0.017	**-0.038**	-3.894	-0.057	-0.019	**-0.032**	-3.330	-0.051	-0.013
Egress Time	**-0.012**	-5.205	-0.016	-0.007	**-0.006**	-3.102	-0.010	-0.002	**-0.006**	-3.342	-0.01	-0.003
												Model fits
LL(ASC only model)	-1953.577				-1940.001				-1983.633			
LL(β)	-1557.904				-1607.444				-1550.317			
ρ^2	0.203				0.171				0.218			
Respondents	206				204				208			
Observations	1236				1248				1224			

Design comparison

D-errors of the data sets

	Orthogonal design (S=108)	*D-efficient design 1 (S=108)*	*D-efficient design 2 (S=18)*
D-error	0.1253	0.1035	0.1017

- **Efficient designs are in practice indeed more efficient;**

  Shows that theoretical efficiency indeed translates into practical efficiency.

- **Size of the design does not influence efficiency;**

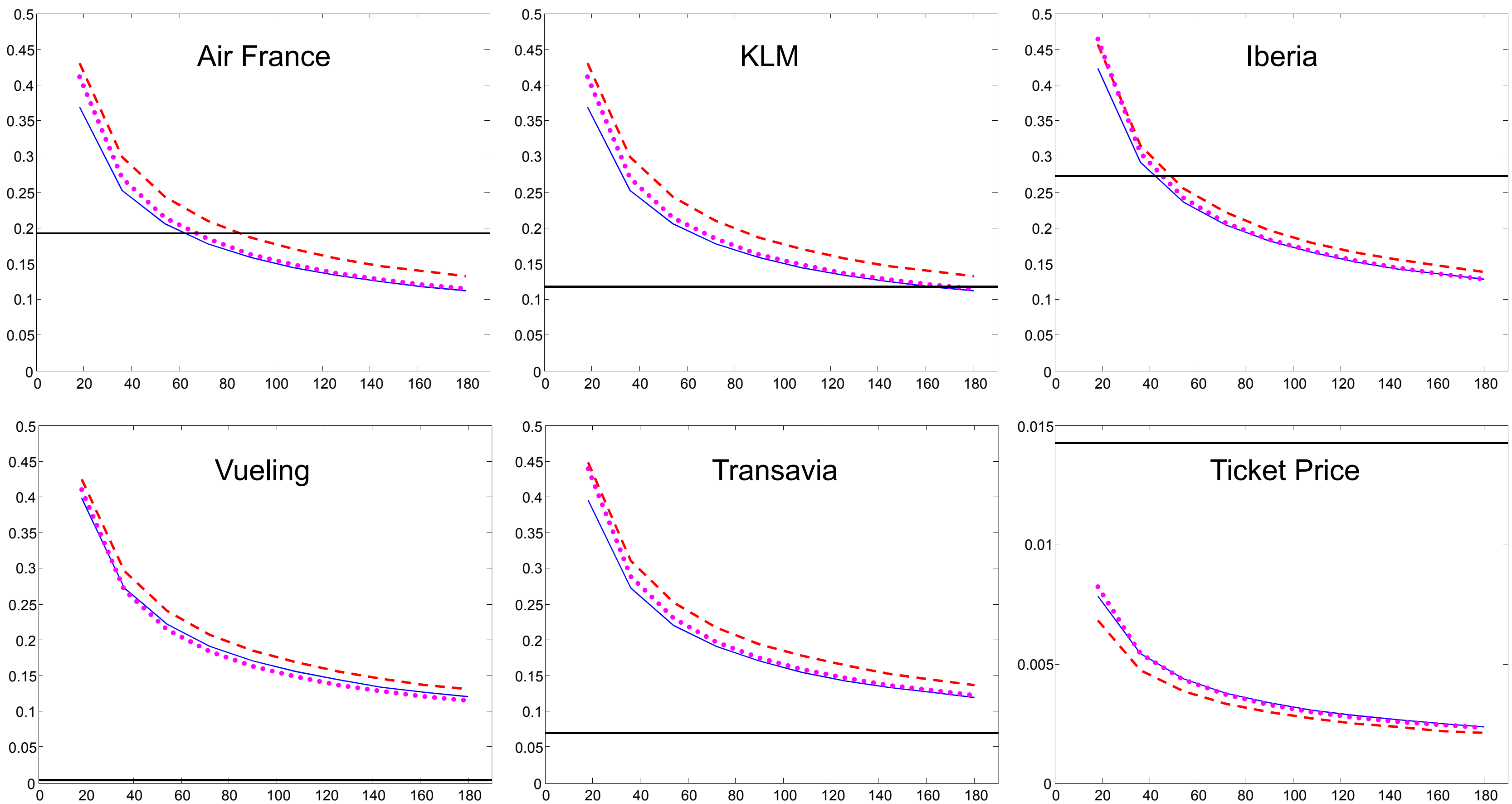
  Shows that small designs are sufficient.

  Note: there exists no orthogonal design with S<108.

Design comparison

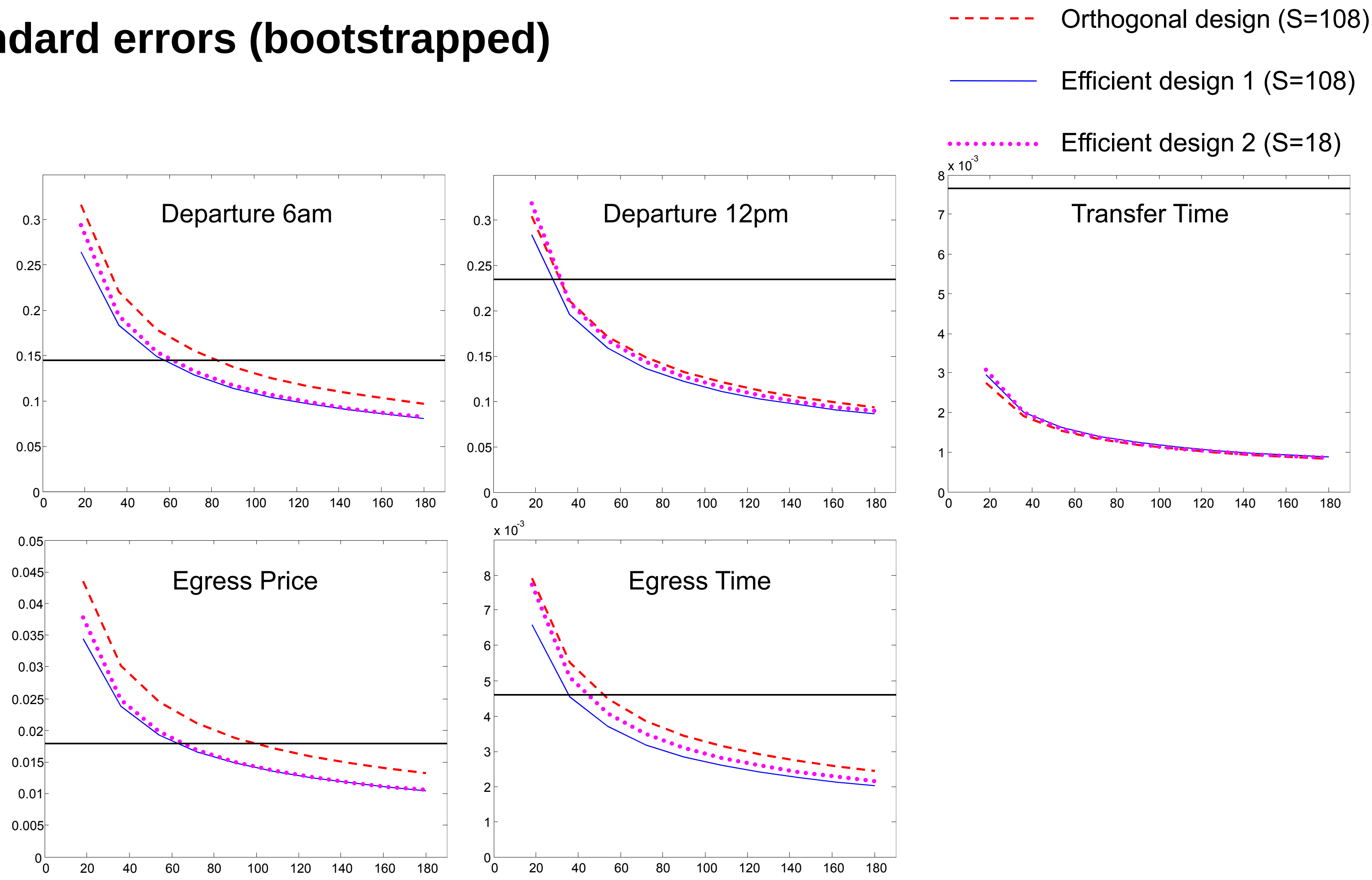
Standard errors (bootstrapped)

Orthogonal design (S=108)
Efficient design 1 (S=108)
Efficient design 2 (S=18)



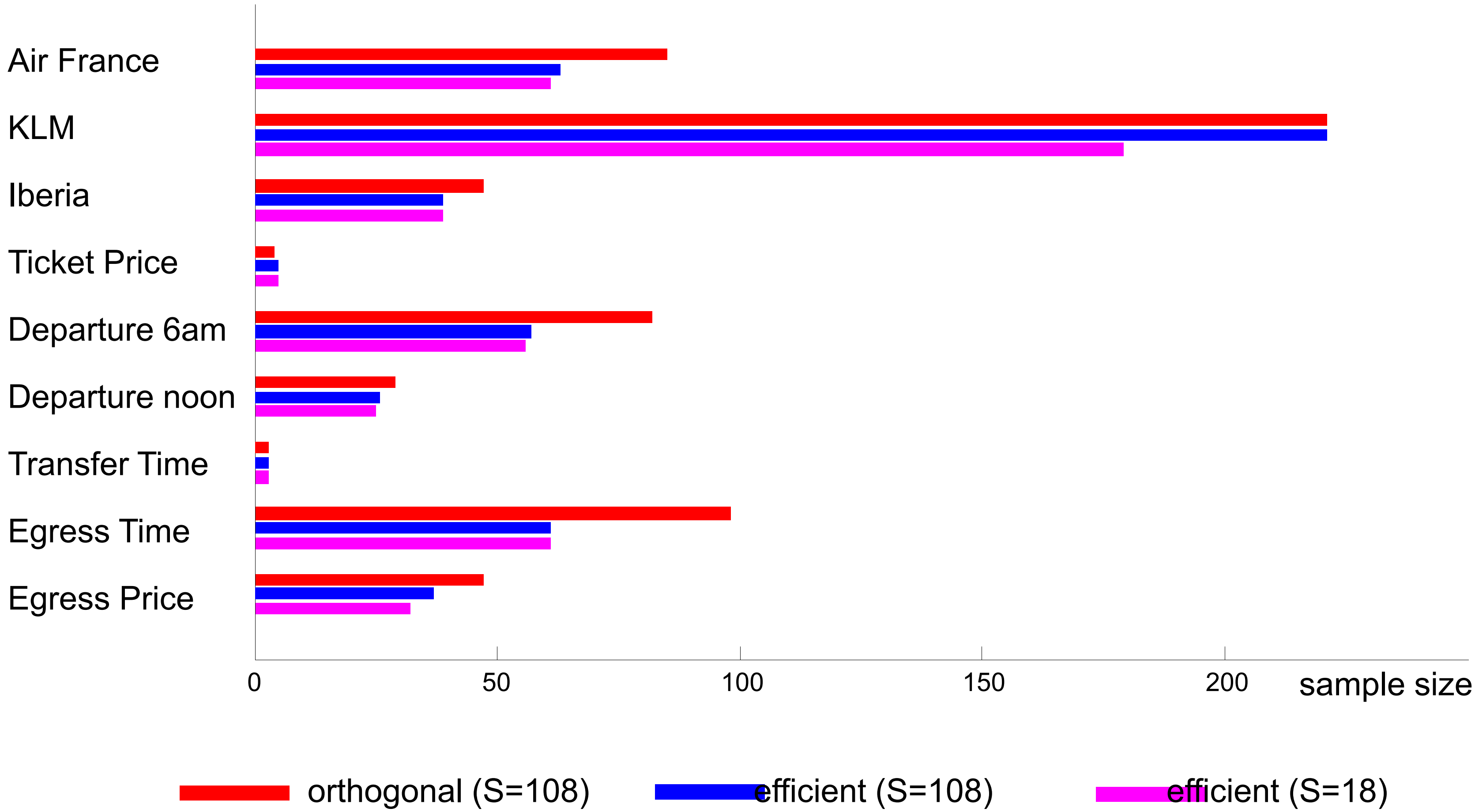
Design comparison

Standard errors (bootstrapped)

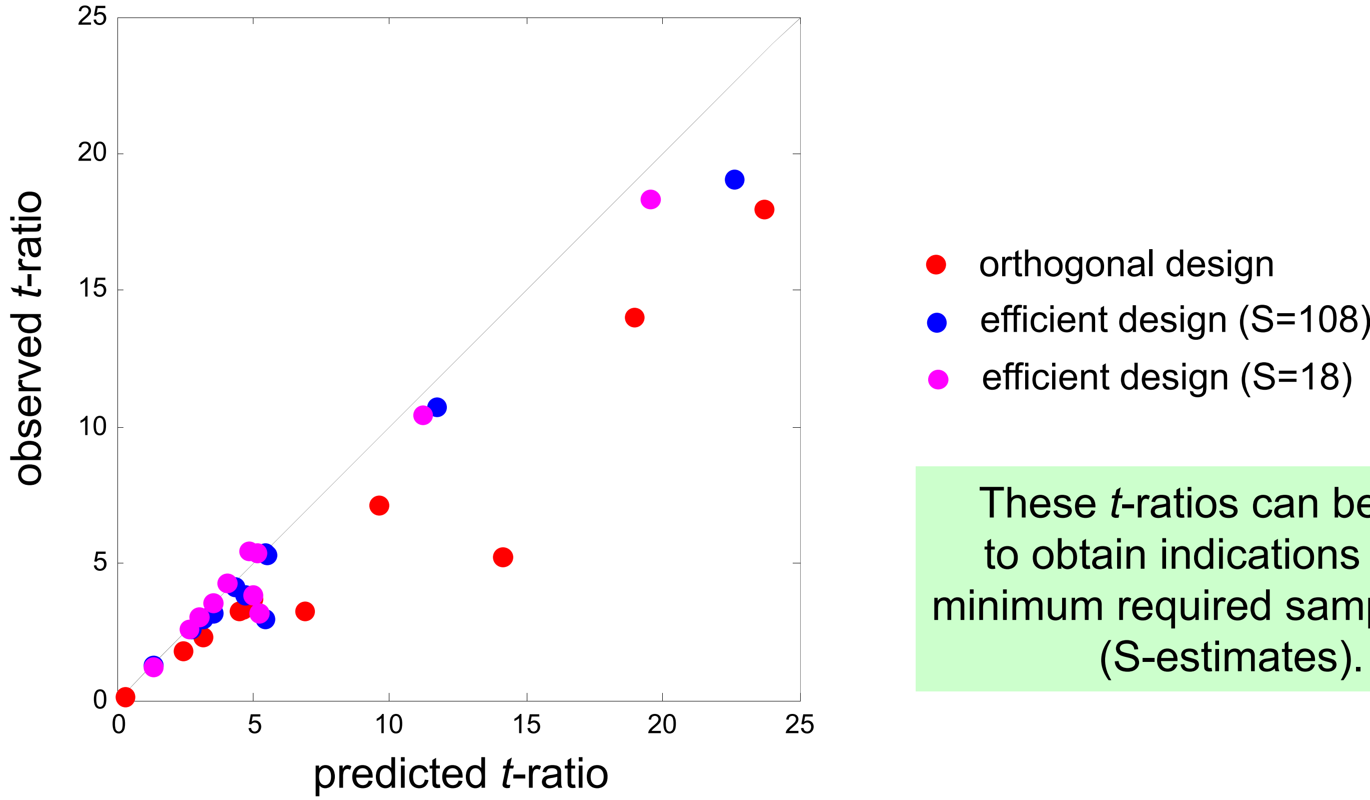


Design comparison

Required sample sizes (bootstrapped)



Prediction power of *t*-ratios



These *t*-ratios can be used to obtain indications about minimum required sample sizes (S-estimates).

Conclusions and discussion

6

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Conclusions and discussion

Take away 1 and 2

› 1. Efficient designs lead in practice to smaller standard errors, as predicted by the theory, thereby outperforming orthogonal designs.

› 2. The size (number of choice situations) of the design has no influence on the efficiency. Hence, there is no need to use large designs. Small orthogonal designs in general do not exist, however efficient designs can be kept very small.

Conclusions and discussion

Take away 3 and 4

› 3. The S-estimates introduced by Bliemer and Rose (2005,2009) & Rose and Bliemer (2005) seem indeed to offer a good prediction for the required sample sizes for statistically significant parameter estimates.

› 4. Accurate parameter priors used for generating efficient designs are important, efficiency is quickly lost with incorrect priors. Bayesian priors are therefore recommended.

Conclusions and discussion

Take away 5 and 6

- 5. As also found by Louviere et al. (2008), highly efficient designs yield larger error variance (smaller scale). Less efficient designs (e.g., orthogonal designs) seem to have smaller error variance (larger scale) due to the existence of more dominant alternatives in a choice situation. Therefore, the design can have an influence on the exact parameters due to this scale factor.

- 6. Although in this case study the MNL model was used, the same arguments can be used for other model types (e.g., MMNL).

What's next?

What are we currently working on?

John Rose | Prof.
Experimental Designs| **Dec 4th-5th**

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What's next

What are we working on…

› Availability designs

- To date, all work in efficient designs has assumed all alternatives are available in all choice tasks
- Here we allow variable choice set sizes (varying the number of alternatives) either at the discretion of the user or as a variable to optimize on

› Best worst designs

- Best worst cases 1,2 and 3 can be set up to be modeled using logit models
- The difference is the data structure
- We are working on optimizing for the unique data structures associated with these question mechanisms

What are we working on…

› **Designs accounting for information processing strategies (IPS)**

- In generating designs, it is assumed that all attributes will be fully attended to
- A zero prior is not the same as assuming that an attribute will be ignored given that in modeling we would remove an attribute with an insignificant parameter estimate

$$\frac{\partial^2 L_N(\beta \mid X)}{\partial \beta_{k_1} \partial \beta_{k_2}} = \sum_{n=1}^{N} \sum_{s=1}^{S} \sum_{j=1}^{J} X_{jk_1sn} P_{jsn}(X \mid \beta) \left(X_{jk_2sn} - \sum_{i=1}^{J} X_{ik_2sn} P_{isn}(X \mid \beta) \right)$$

- Here we add an additional Bayesian which will remove an attribute from the utility function up to a probability

› **Designs allowing for non-linear utility functions**

› **New model types including designs for WTP space, latent class**

Serial Choice Conjoint Analysis for Estimating Discrete Choice Models

Case study 2: The future????

Bliemer, M.C.J. and Rose, J.M. (2010) Serial Choice Conjoint Analysis for Estimating Discrete Choice Models in Hess, S. and Daly, A. (ed.) Choice Modelling: State-of-the-Art and the State-of Practice: *Proceedings from the Inaugural International Choice Modelling Conference*, Emerald Press, Bingley, United Kingdom, 139-61.

John Rose | Prof.

What is a good design?

1

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What is a good design?

A good experimental design

- yields parameter estimates with **high accuracy**

  unbiased, close to true values

- yields parameter estimates with **high precision**

  high reliability, low standard errors

What is a good design?

A good experimental design

Observation 1:

Any experimental design can be used to find the true parameters

[all designs yield accurate parameter estimates… in the limit!]

Observation 2:

A ‘good’ experimental design will find these true parameters at (much) smaller sample sizes than ‘bad’ designs;

[a good design yields more precise parameter estimates]

So, how to find these ‘good’ (efficient) experimental designs?

Building good designs

2

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Different design types

Efficient? \ Orthogonal?	Yes	No
No	Orthogonal designs	Other designs
Yes	D-optimal (efficient) designs based on $\beta = 0$ **no parameter priors needed (assumed zero)**	D-optimal (efficient) designs based on $\beta \neq 0$ **parameter priors needed**

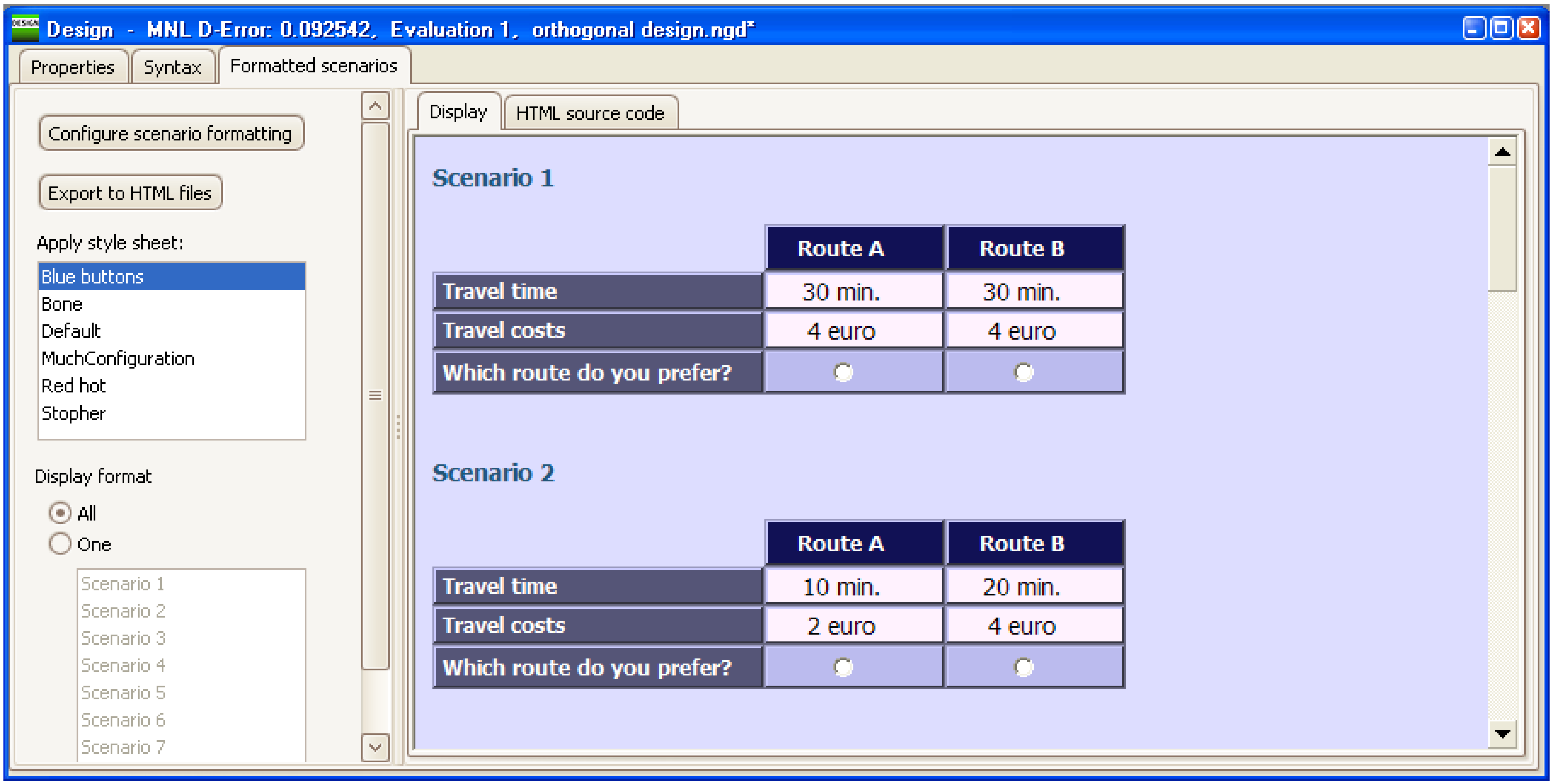
Parameter priors

› **Priors** are **best guesses** for the unknown parameter values.

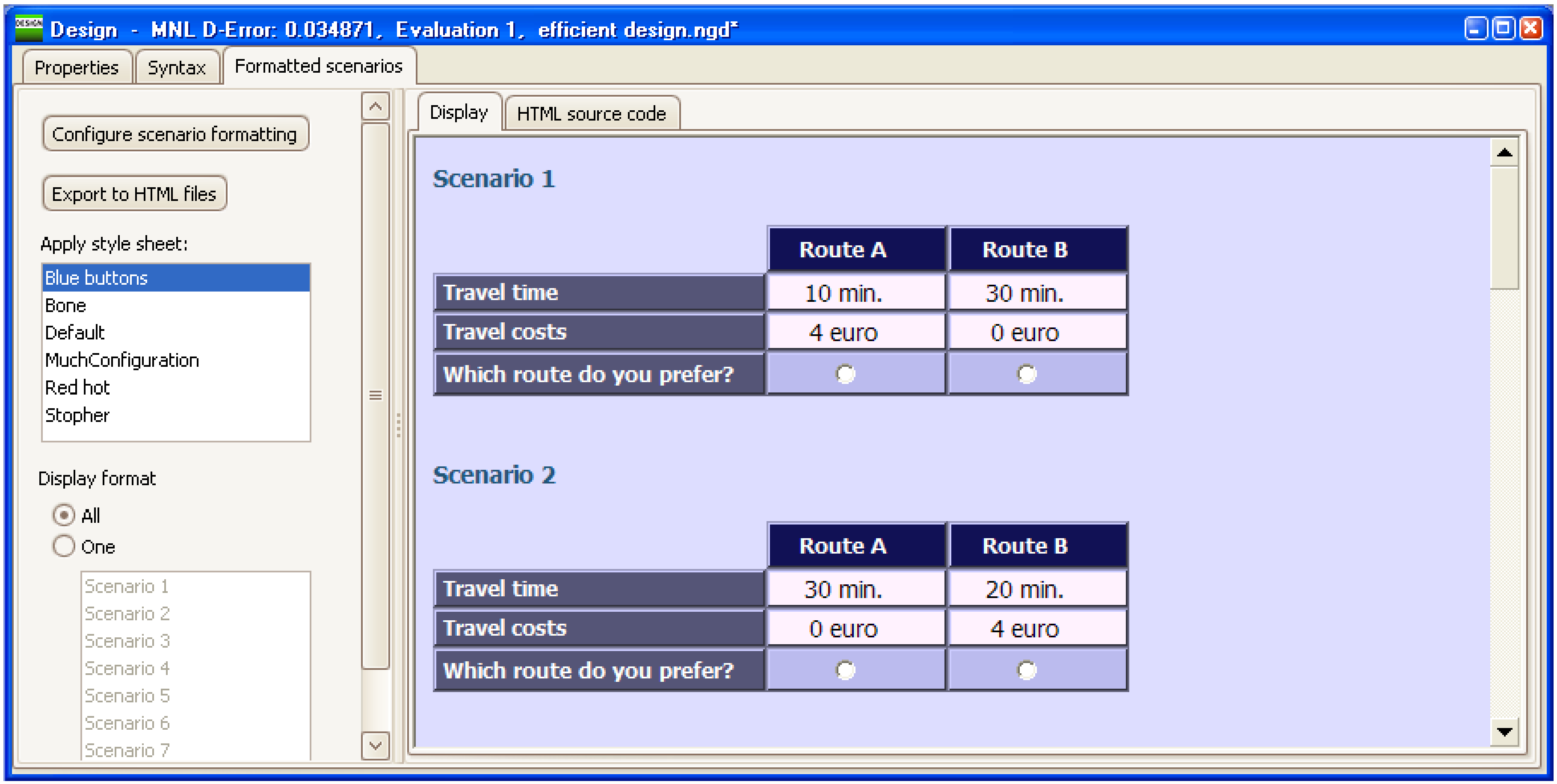
› Usually obtained from:

- literature studies
- expert judgment
- pilot studies

Example orthogonal design (zero priors)



Example orthogonal design (non-zero priors)



Parameter priors

- Experimental designs are only efficient under the assumption that the **assumed priors are accurate**.

- Orthogonal designs assume zero-valued priors.
  - If the parameters are all zero, why doing the estimation?
  - Therefore, **orthogonal designs will always loose efficiency**.

- D-optimal designs assume non-zero valued priors.
  - If the parameters priors are all accurate, why doing the estimation?
  - Therefore, **D-optimal designs will always loose efficiency.**

- How much efficiency is lost?
  - Depends on how much the actual values deviate from assumed priors.
  - *Approach: create designs in a serial fashion based on current estimates.*

Adapt or die…

3

Adaptive designs

- Adaptive designs (such as serial/sequential designs) may be subject to **endogeneity bias** (Toubia et al., 2003):

  "To understand this result we first recognize that any adaptive question-design method is potentially subject to endogeneity bias. Specifically, the *q*th question depends upon the answers to the first $q-1$ questions. This means that the *q*th question depends, in part, on any response errors in the first $q-1$ questions. This is a classical problem, which often leads to bias (see, for example, Judge et al. 1985, p. 571). Thus, adaptivity represents a tradeoff: We get better estimates more quickly, but with the risk of endogeneity bias."

- Adaptations in the design can happen within-respondent (higher risk of bias)

  Johnson (1987, 1991), Green et al. (1991)

- across respondents (lower risk of bias)

  This presentation

Parameter priors

› **1. Initialization**

- Set n = 1.
- Set priors $\bar{\beta}^{(n)} = 0.$

› **2. Generate D-optimal design**

- Find experimental design X_n that minimizes the determinant of the asymptotic variance-covariance matrix, assuming priors $\bar{\beta}^{(n)}$.
- Give design to respondent *n.*
- Observe choices Y_n.

› **3. Estimate parameters**

- Use data (X_n, Y_n) to obtain maximum likelihood parameter estimates $\hat{\beta}^{(n)}$.

› **4. Update priors**

- Set $\bar{\beta}_k^{(n)} = \begin{cases} \hat{\beta}_k^{(n)}, & \text{if parameter is statistically significant;} \\ 0, & \text{otherwise.} \end{cases}$

Set *n*:=*n*+1,
return to Step 2.

Adapt or die…

Disadvantages serial design process

- Designs need to be generated during the survey, requiring a more complex survey process

- Mainly suitable for
  - CAPI (computer aided personal interviewing)
  - Internet-based surveys

- Respondents have to be interviewed in a serial manner,
- or alternatively (as proposed by Kanninen and others):
  - interview 10% of respondents
  - estimate parameters
  - generate new efficient design
  - interview next 10% of respondents
  - etc.

Case Study

4

Background

› In the case study, we use simulation to generate choice observations. We repeat this process 100 times in a Monte Carlo setting.

› <u>Three experimental designs are considered:</u>

- Orthogonal design *
- Fixed D-optimal design (based on true parameters) *
- Serial D-optimal design (based on parameter estimates) **

* Generated using Ngene 1.0

** Generated using Matlab implementation

Priors

MNL model with following utility functions:

$$
\begin{aligned}
V_1 &= \beta_1 \qquad + \beta_3 X_{1,1} + \beta_4 X_{2,1} + \beta_5 X_{3,1} \\
V_2 &= \qquad \beta_2 + \beta_3 X_{1,2} + \beta_4 X_{2,2} + \beta_6 X_{3,2} \\
V_3 &= \qquad\qquad \beta_3 X_{1,3} \qquad\qquad + \beta_7 X_{3,3}
\end{aligned}
$$

Attribute levels:

$$X_{1,j} \in \{6,8,10,12\}, \quad X_{2,j} \in \{4,8\}, \quad X_{3,j} \in \{0,1\}$$

Parameter priors:

$$\bar{\beta} = (1.2,\, 0.8 - 0.6, -0.4,\, 0.3,\, 0.8, -1.0)$$

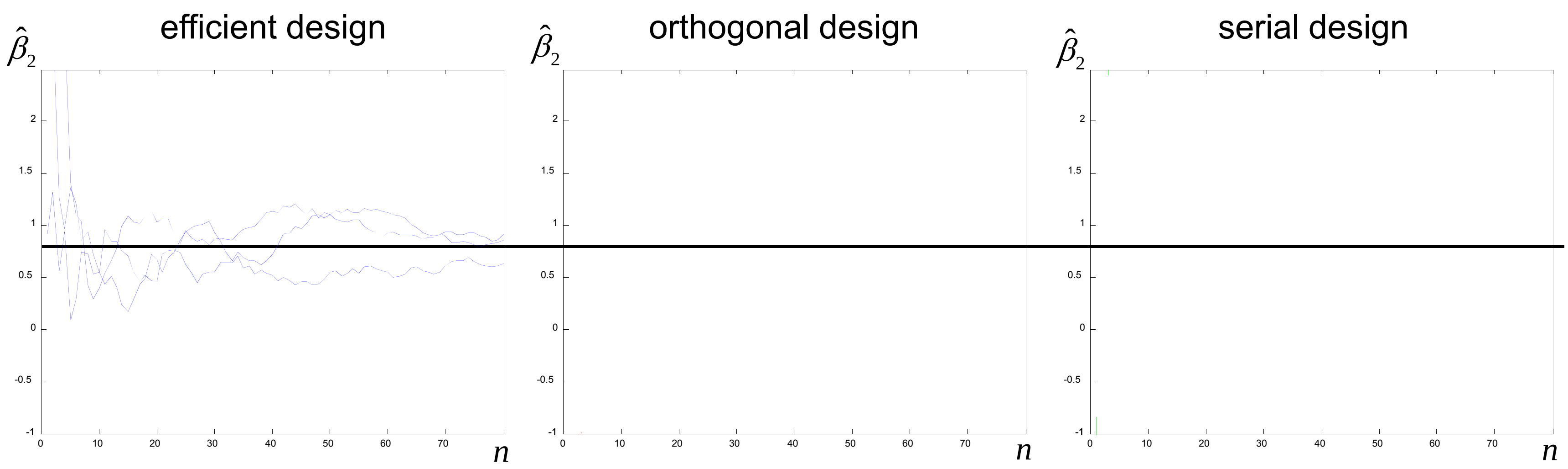
Number of choice situations per respondent: 12

What was done

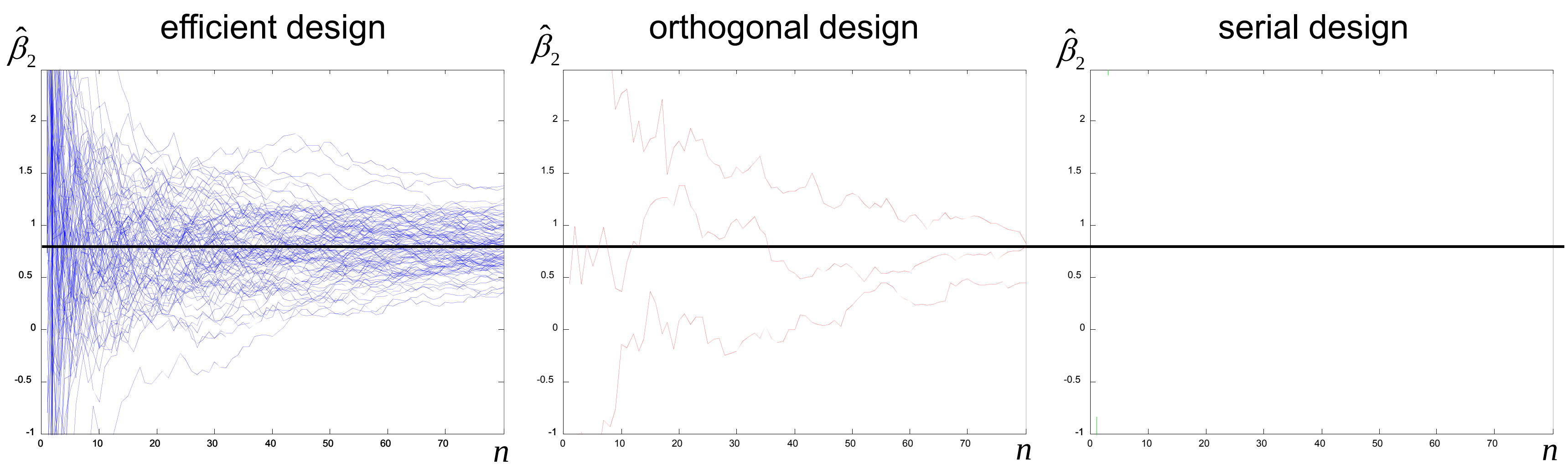
› Compare the following experimental designs:

1. Orthogonal design (no priors needed)
   orthogonal design, see Louviere et al. (2000)
2. Locally D-optimal design, assuming $\beta = \overline{\beta}$
   efficient design, see Huber and Zwerina (1996)
3. Locally D-optimal design, assuming $\beta = \hat{\beta}^{(i)}$
   serial design, this presentation

Results I

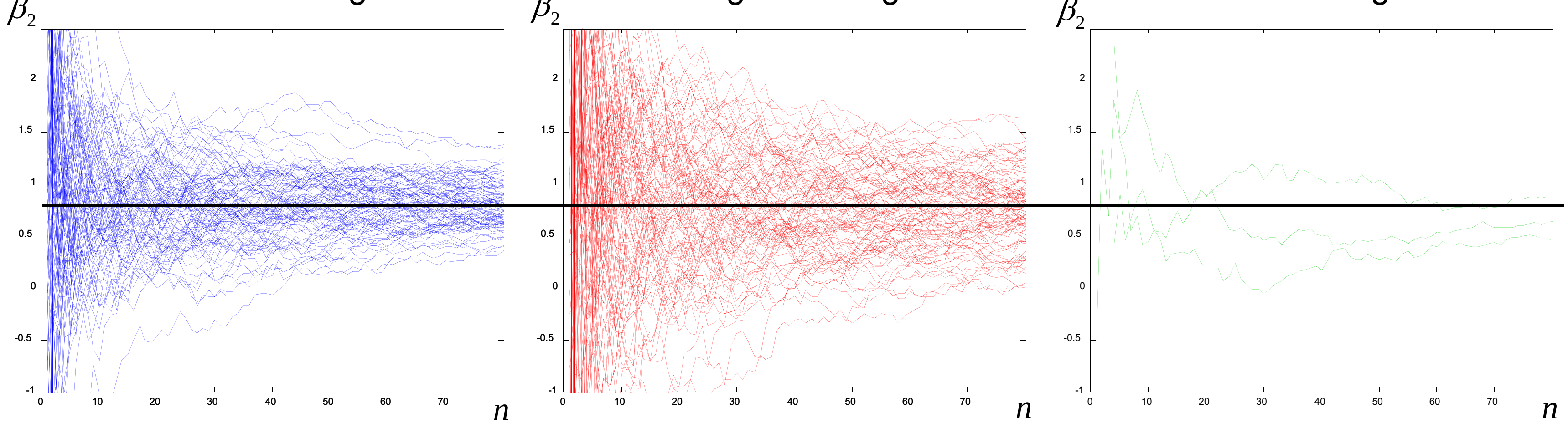

efficient design
orthogonal design
serial design
$\hat{\beta}_2$
n
2
1.5
1
0.5
0
-0.5
-1
0
10
20
30
40
50
60
70

Results I

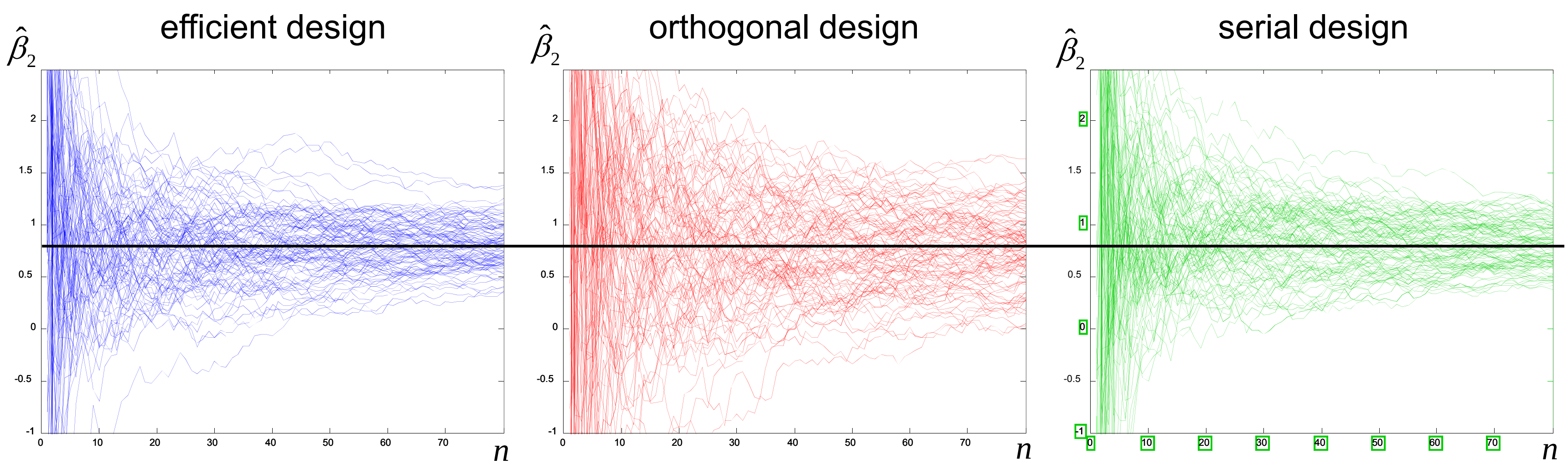

efficient design
orthogonal design
serial design
$\hat{\beta}_2$
n
2
1.5
1
0.5
0
-0.5
-1
0
10
20
30
40
50
60
70

Results I

efficient design orthogonal design serial design

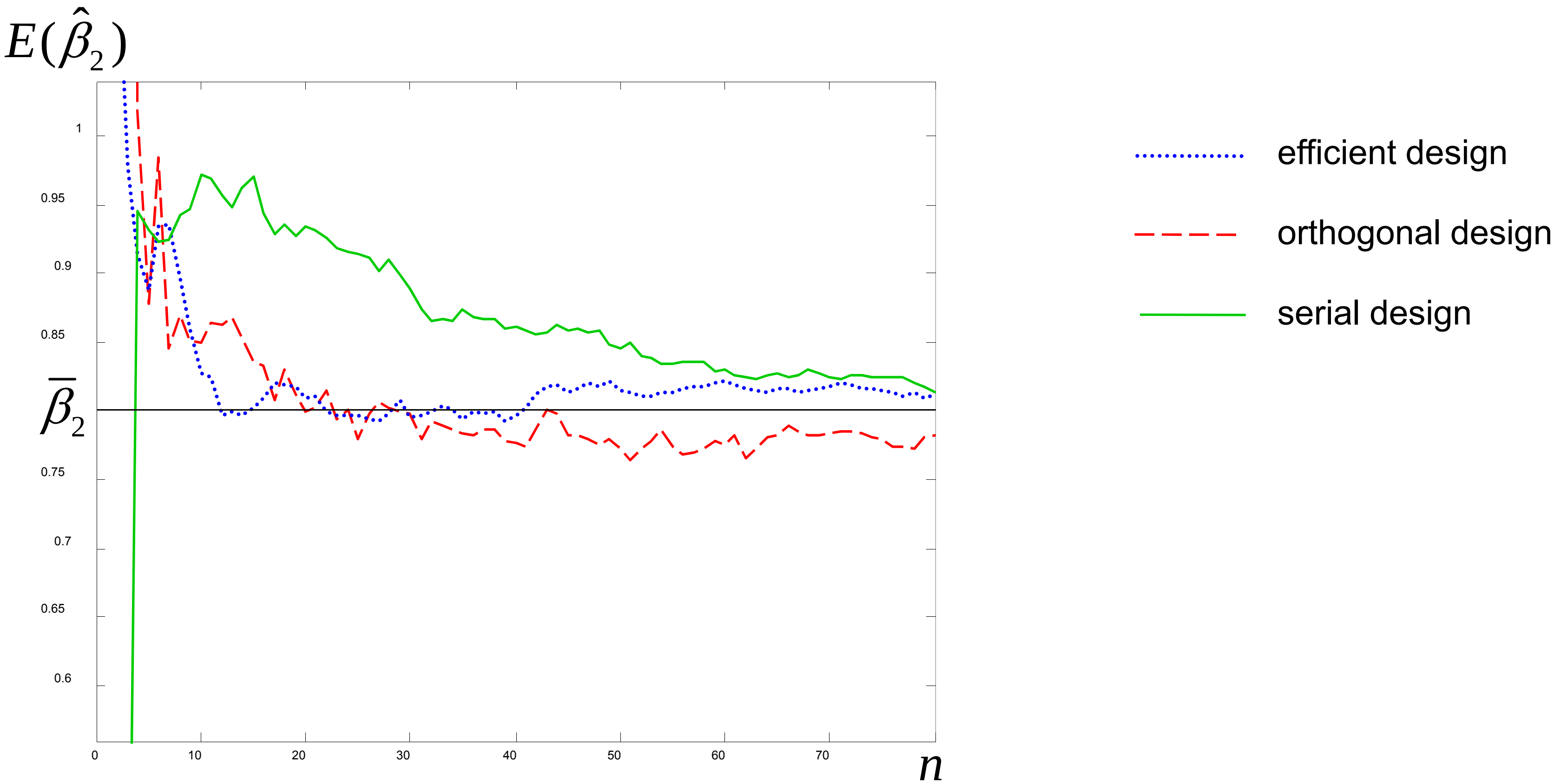


Results I

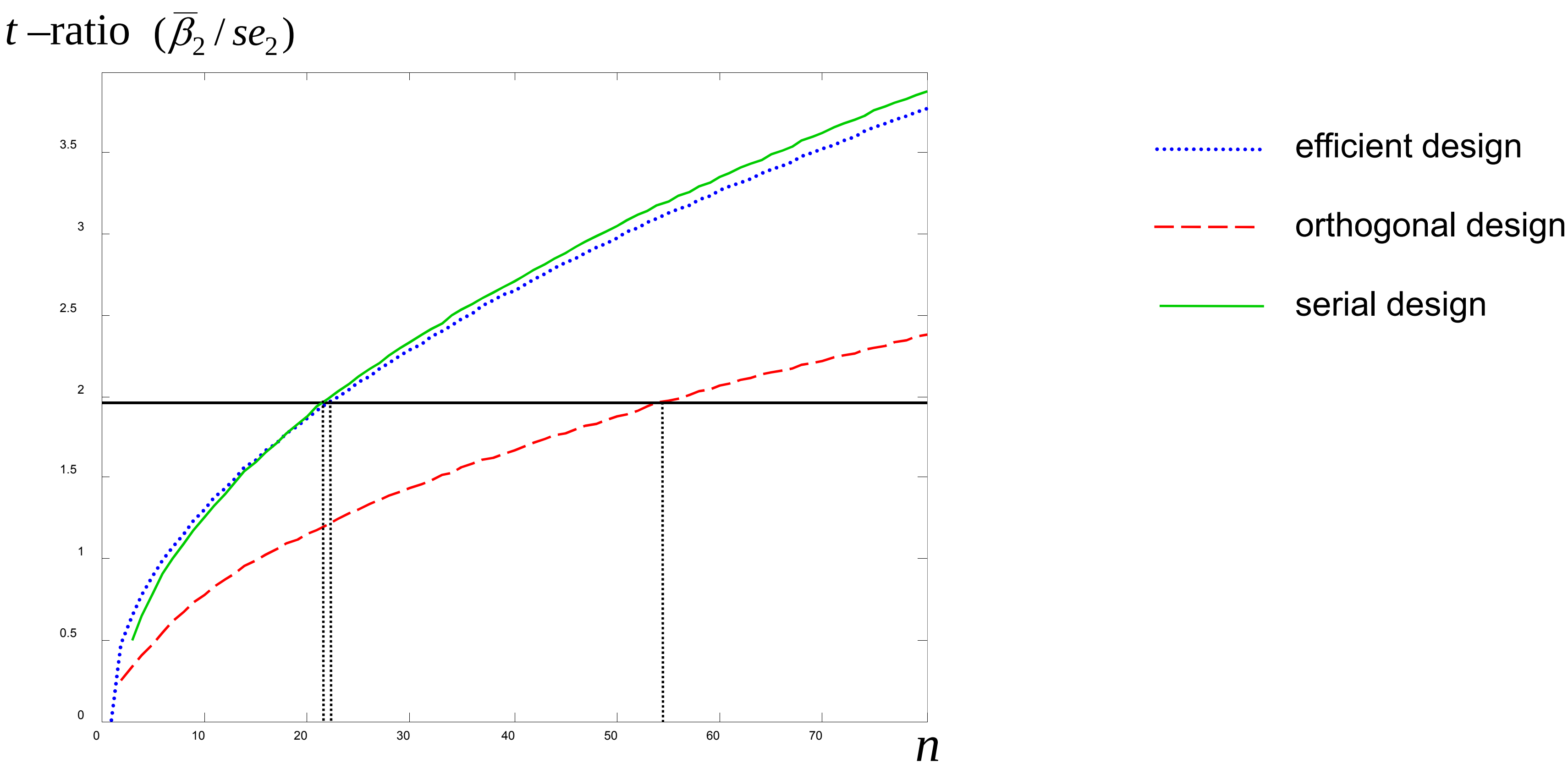


efficient design
orthogonal design
serial design
$\hat{\beta}_2$
n
2
1.5
1
0.5
0
-0.5
-1
0
10
20
30
40
50
60
70

Results II

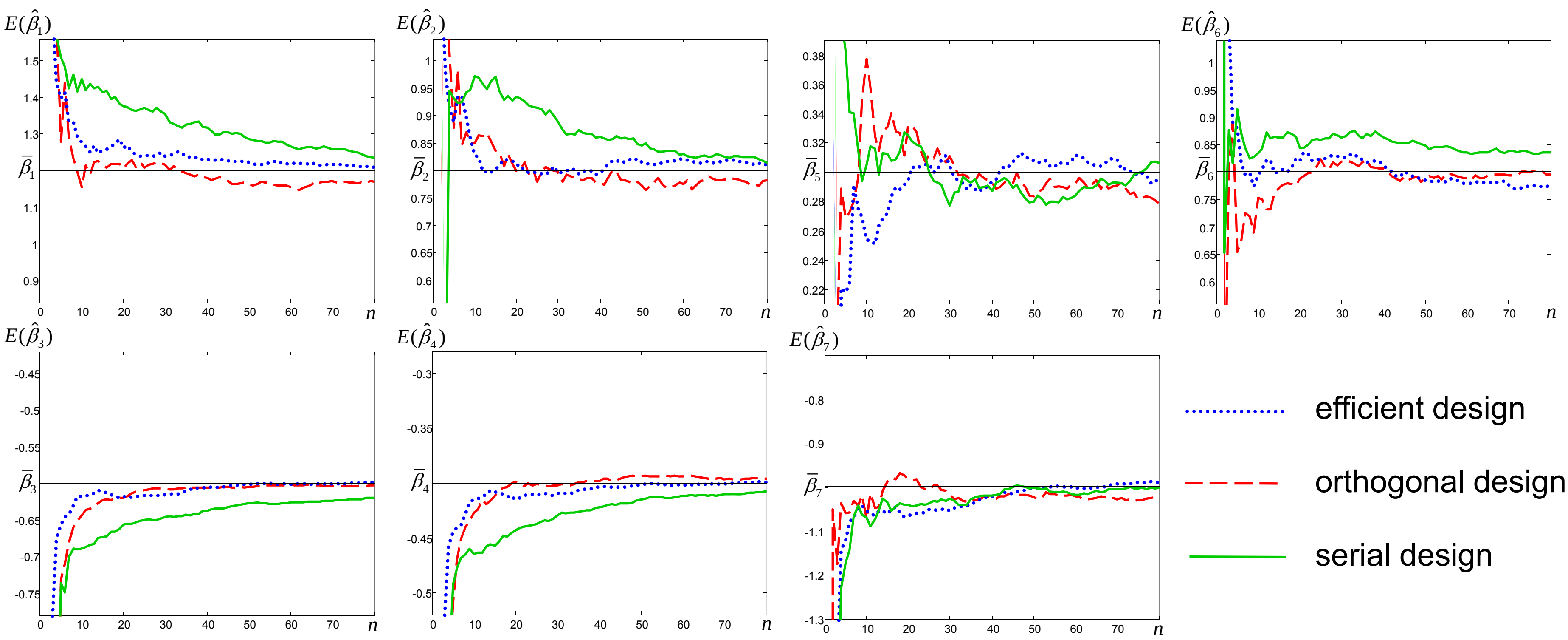

$E(\hat{\beta}_2)$
1
0.95
0.9
0.85
$\overline{\beta}_2$
0.75
0.7
0.65
0.6
0
10
20
30
40
50
60
70
n
efficient design
orthogonal design
serial design

Results II

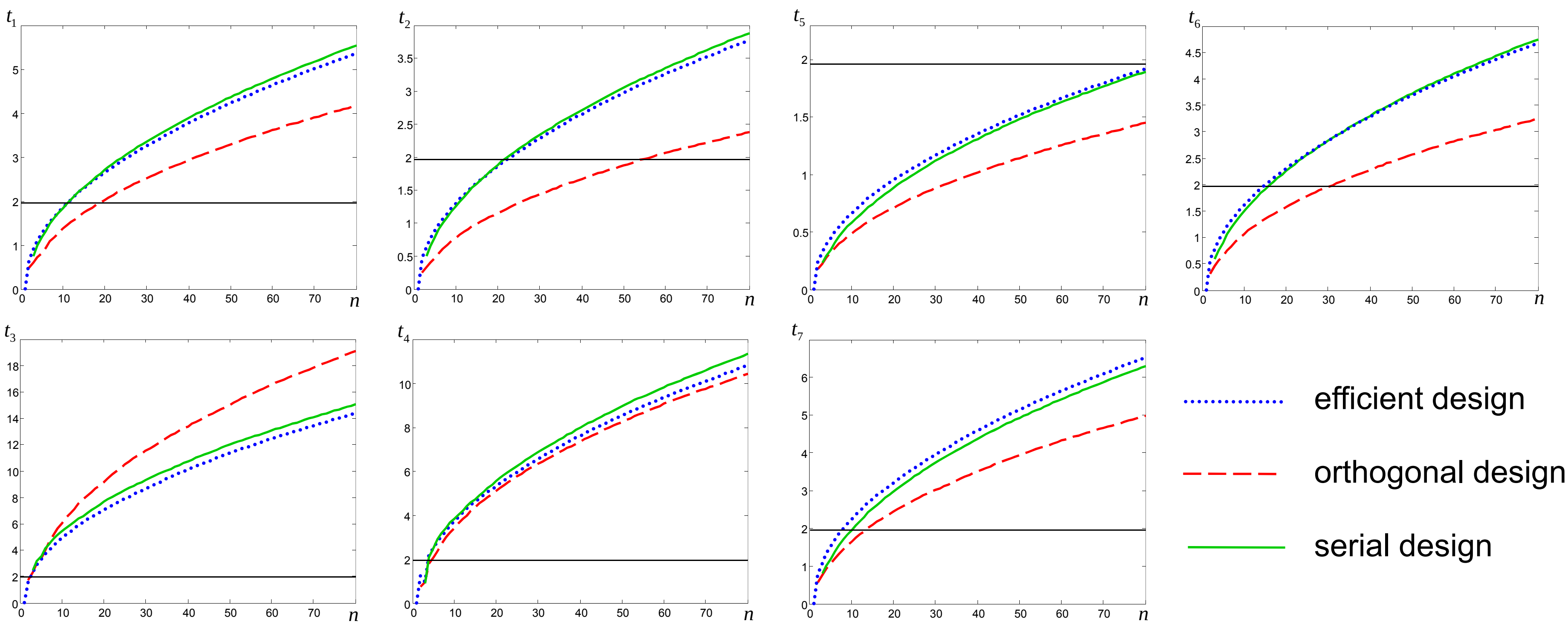


t –ratio $(\bar{\beta}_2 / se_2)$
3.5
3
2.5
2
1.5
1
0.5
0
0
10
20
30
40
50
60
70
n
efficient design
orthogonal design
serial design

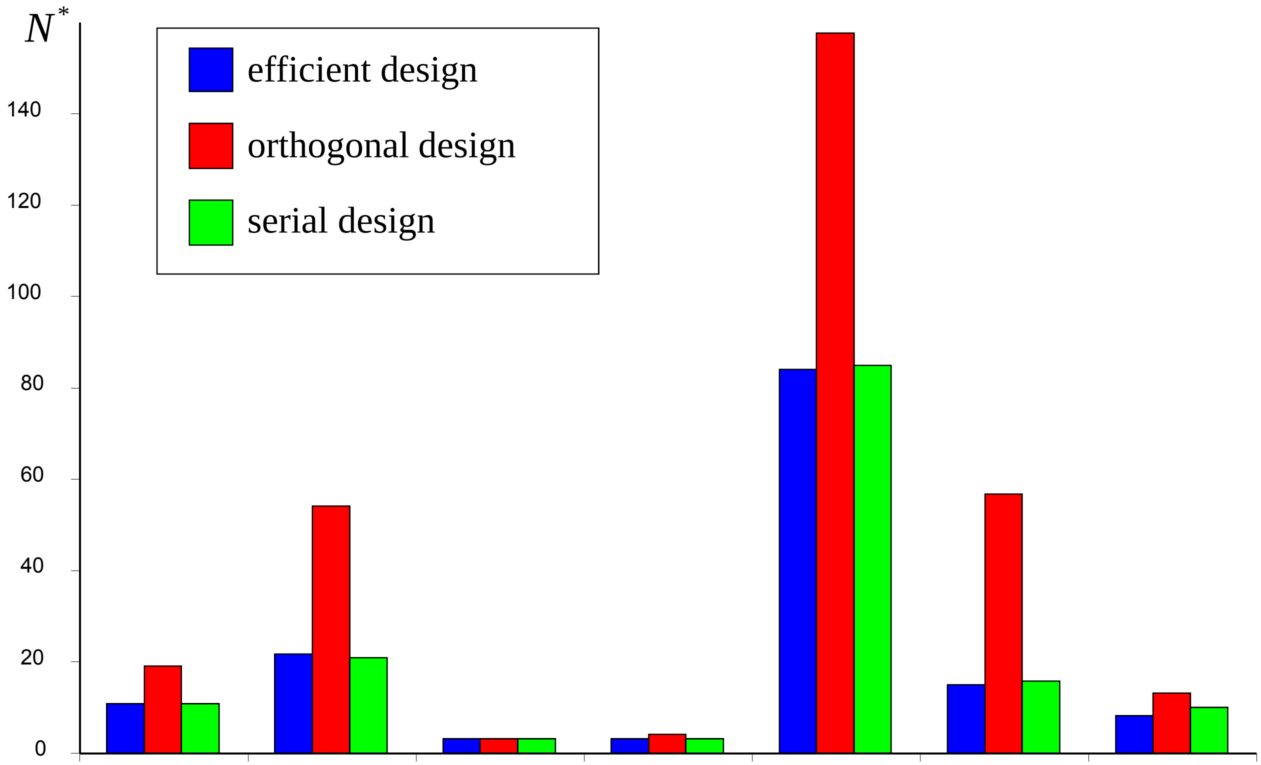
Results: Expected parameter estimates for different sample sizes



Results: Expected t -ratios for different sample sizes



Results: Required sample size for parameter estimation*



*for statistical significance $(\alpha = 0.05)$

Potential problem?

5

Potential problem?

Biases?

› Serial designs may lead to **biased parameter estimates** in **small sample sizes**

› However, serial designs enable **small standard errors** (high *t*-ratios)

› Parameters seem biased in small sample sizes due to (very) bad priors used to generate serial designs for the first few respondents

› Solution: Use **orthogonal design for first few respondents**, and then generate serial efficient designs

Potential problem?

Case study revisited

› Compare the following experimental designs:

1. Orthogonal design (no priors needed)

   orthogonal design, see Louviere et al. (2000)

2. Locally D-optimal design, assuming $\beta = \bar{\beta}$

   efficient design, see Huber and Zwerina (1996)

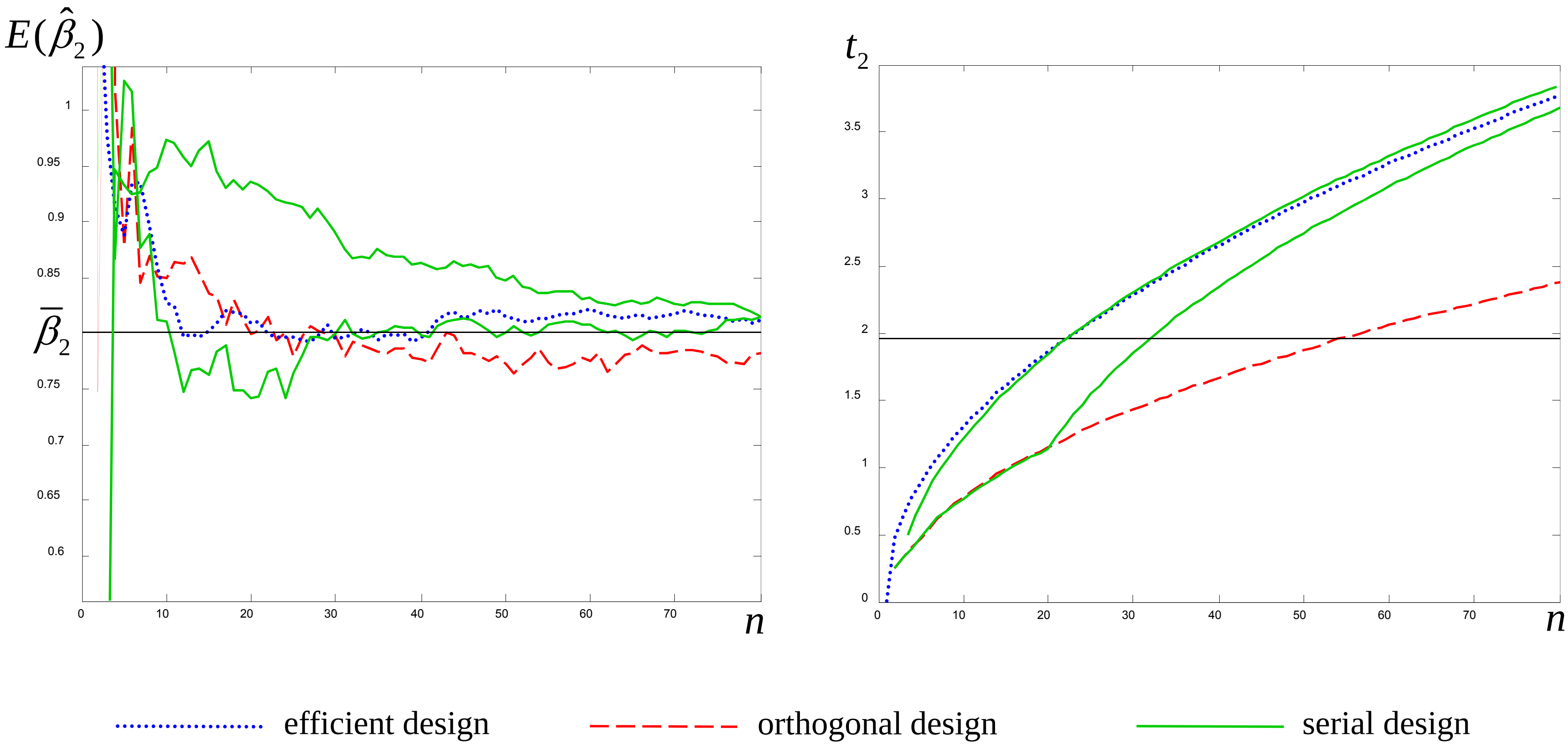
3. a) For first 20 respondents: orthogonal design

   b) For next respondents: locally D-optimal design, assuming $\beta = \hat{\beta}^{(i)}$

   serial design, see this presentation

Potential problem?

New results



Conclusions

5

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Conclusions

Summary

- With a serial design, no predefined priors are required (zero-valued parameter values are assumed), therefore one need not worry about priors misspecification.
- With a serial design, approx. the same level of efficiency can be achieved as with a D-optimal design based on accurate priors.
- Since parameters are estimated continuously, data collection can automatically stop if sufficient respondents have been interviewed.
- Endogeneity bias in small sample sizes can be avoided by using an orthogonal design for the first few respondents.
- Respondents need not be interviewed in a completely serial manner, but can be interviewed in batches.