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Designing Efficient Data for Stated Choice Experiments: Accounting for Socio-demographic and contextual effects in designing stated choice experiments

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ITLS and Delft University

Presentation Overview

- What are stated choice experiments
- Experimental designs
- Generating experimental designs
- Efficient designs
- Rationale
- Current State of Practice
- Covariates and Experimental Design
- Testing of Efficient Experimental Designs
- Sample Optimisation
- How can you do this?

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What are Stated Choice experiments?

Paper and Pencil Surveys

CAPI Surveys

Internet Surveys

Card Number **L02A**

Your Trip:	CAR TOLL ROAD	CAR NO TOLL
Travel time to work	45 min.	70 min.
Time variability	± 1 min.	± 1 min.
Toll (one way)	$6.00	free
Pay toll if you leave between these times (otherwise free)	6:30-9:00 am	—
Fuel cost (per day)	$6.00	$12.00
Parking cost (per day)	$20.00	$10.00

Your Trip:	BUSWAY	TRAIN
Total time in the vehicle (one way)	30 min.	30 min.
Time from home to your closest stop	Walk 25 min. Car/Bus 8 min.	Walk 5 min. Car/Bus 4 min.
Time to your workplace from the closest stop	Walk 25 min. Bus 8 min.	Walk 5 min. Bus 4 min.
Frequency of service	Every 25 min.	Every 5 min.
Return fare (per day)	$3.00	$3.00

What are Stated Choice experiments?

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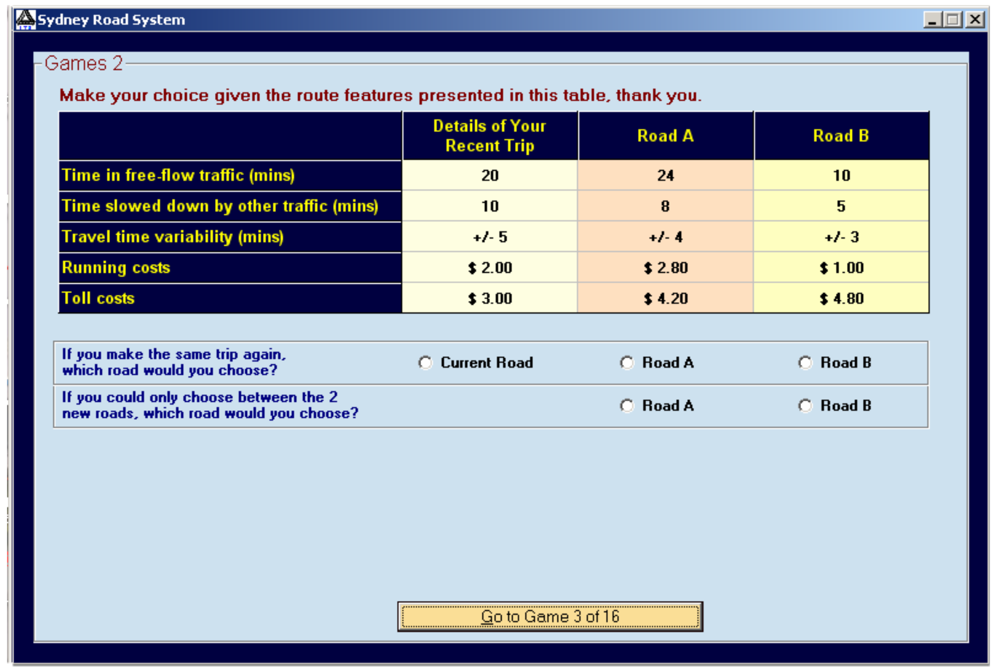
Paper and Pencil Surveys

CAPI Surveys

Internet Surveys



Sydney Road System

Games 2

Make your choice given the route features presented in this table, thank you.

	Details of Your Recent Trip	Road A	Road B
Time in free-flow traffic (mins)	20	24	10
Time slowed down by other traffic (mins)	10	8	5
Travel time variability (mins)	+/- 5	+/- 4	+/- 3
Running costs	$ 2.00	$ 2.80	$ 1.00
Toll costs	$ 3.00	$ 4.20	$ 4.80

If you make the same trip again, which road would you choose? ○ Current Road ○ Road A ○ Road B

If you could only choose between the 2 new roads, which road would you choose? ○ Road A ○ Road B

Go to Game 3 of 16

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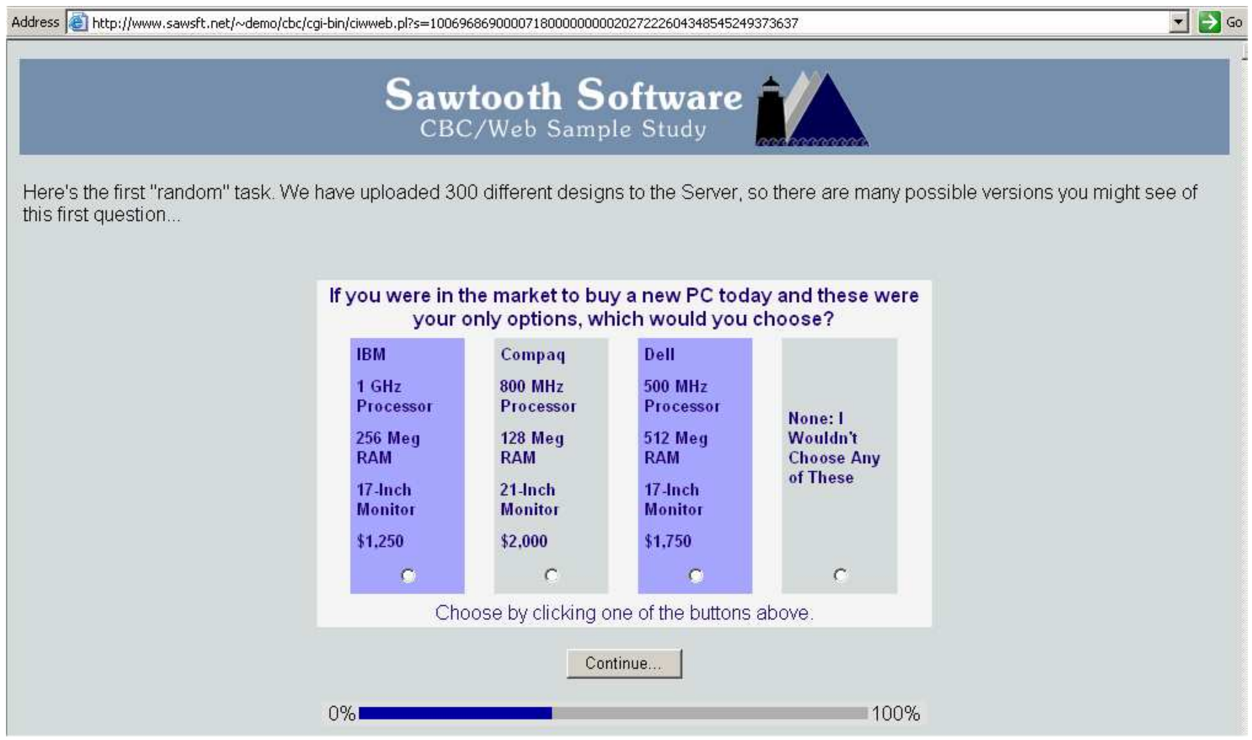
What are Stated Choice experiments?

Paper and Pencil Surveys

CAPI Surveys

Internet Surveys



Experimental Designs

Game 1	Car	Bus
Travel time (mins)	**10**	**20**
Fuel costs / fare	**$2**	**$1**
Your choice:	☐	☐

Game 2	Car	Bus
Travel time (mins)	**15**	**10**
Fuel costs / fare	**$1**	**$1**
Your choice:	☐	☐

Game 3	Car	Bus
Travel time (mins)	**20**	**10**
Fuel costs / fare	**$1**	**$2**
Your choice:	☐	☐

Experimental Designs

Game 1	Car	Bus
TT	10	20
C/F	$2	$1

Game 2	Car	Bus
TT	15	10
C/F	$1	$1

Game 3	Car	Bus
TT	20	10
C/F	$1	$2

Experimental design:

Car	Car	Bus	Bus
TT	C/F	TT	C/F

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

Experimental Designs

Experimental design:

Q: why should this be 10 here and 15 here?

Q: How do I determine what values go where?

Car	Car	Bus	Bus
TT	C/F	TT	C/F
10	$2	20	$1
15	$1	10	$1
20	$1	10	$2

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

Generating Experimental Designs

- Step 1: Specify the (final) model
  - Tie the design (data) to the model
  - Determine:
    - How many and what alternatives?
    - How many and what attributes?
    - How many and what attribute levels?
    - What type of parameters (generic vs alt specific)?

$$U^{car} = \beta_0 + \beta_1 \cdot Time^{car} + \beta_2 \cdot Cost^{car}$$

$$U^{bus} = \beta_3 \cdot Fare^{bus} + \beta_2 \cdot Fare^{bus}$$

alternative-specific parameters

generic parameter

Generating Experimental Designs

- Step 2: Generating experimental designs
  - Determine whether there is a no choice alternative
  - Determine number of choice situations
  - Determine type of design
    - Orthogonal
    - Optimal (orthogonal)
    - Efficient

Generating Experimental Designs

- Step 3: Construct the questionnaire

Game 1	Car	Bus
Travel time (mins)	10	20
Fuel costs / fare	$2	$1
Your choice:	☐	☐

Game 2	Car	Bus
Travel time (mins)	15	10
Fuel costs / fare	$1	$1
Your choice:	☐	☐

Efficient designs

Efficiency can be determined using the true parameter values.

Problem: true parameter values are unknown.

Solution: use prior parameter values as an indication.

Prior parameter values can be obtained from, e.g., literature and pilot studies.

Note:
Using prior parameter values equal to zero (i.e. no information, not even the sign) has a close correspondence with using an orthogonal design.

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Efficient designs

$\Omega_N(X, \tilde{\beta})$ = (asymptotic) variance-covariance matrix of the parameter estimates using experimental design X, prior parameters $\tilde{\beta}$, and a sample size of N respondents
[Note: the standard errors are the roots of the diagonals]

D-error = $\det(\Omega_N)^{1/K}$

A-error = $\mathrm{tr}(\Omega_N)/K$

The lower the D-error,
the higher the efficiency of the experimental design.

Aim: Determine experimental design X that generates the lowest D-error.

Efficient designs

Interesting observation:

If all respondents face the same choice situations, then

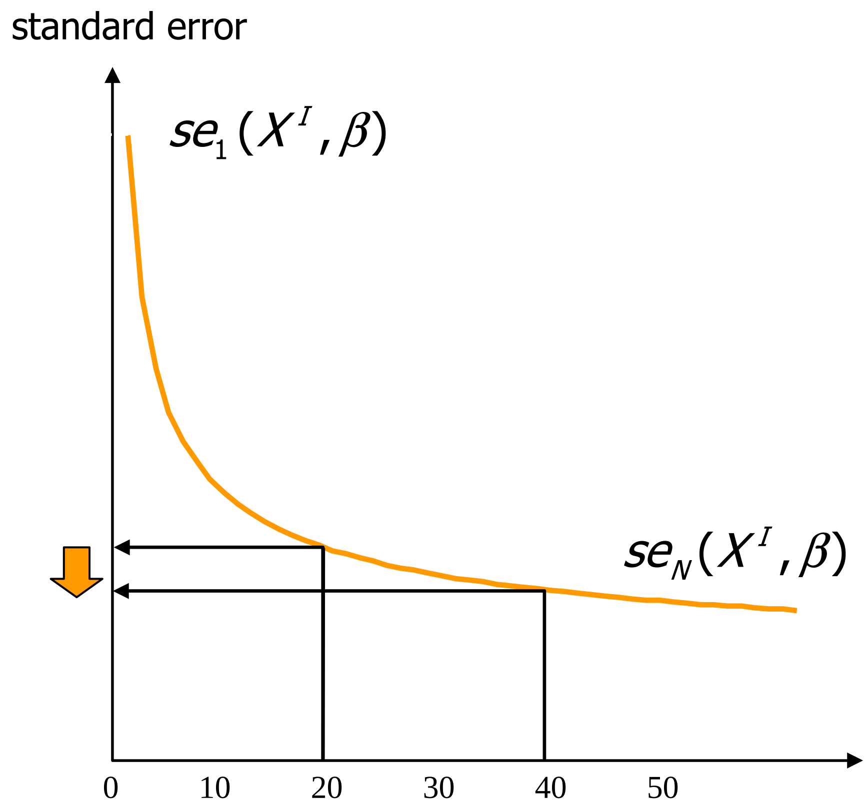
Hence, we can derive the asymptotic variance-covariance (AVC) matrix with *N* respondents from the AVC matrix from a single respondent.

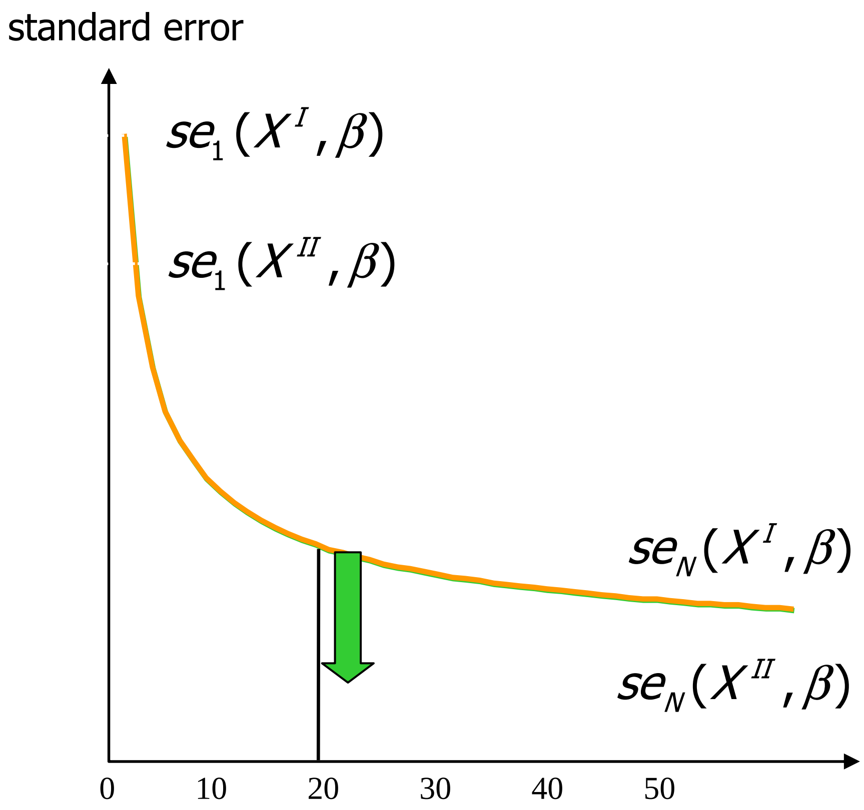
Furthermore:

$$se_N(X,\tilde{\beta}) = \frac{1}{\sqrt{N}} se_1(X,\tilde{\beta})$$

Efficient designs

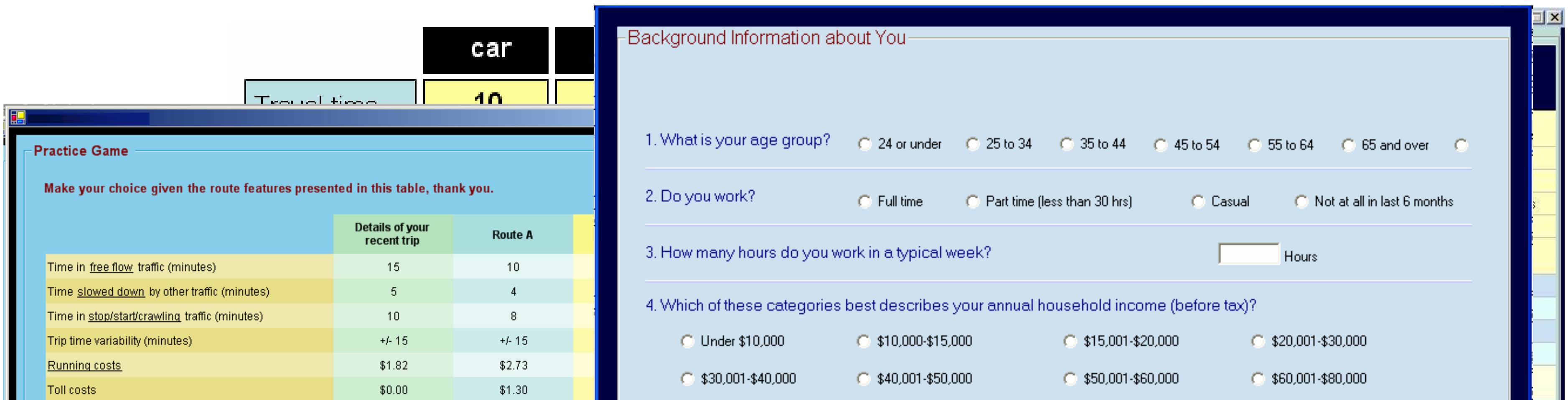
Investing in more respondents	Investing in better design





Rationale for including covariates

- One of the major problems with the experimental design literature dealing with stated choice is the emphasis on 'experimental designs'.



- Generally, very little effort or thought is given to other questions in the survey, and the impact that these may have on the outcome of the experiment.

Current State of Practice (1)

Consider an experiment with two alternatives, described by five attributes. The attribute levels for the experiment are:

Attribute / Level	A1	A2	A3	A4	A5
1	22	17	1	1	0.5
2	24	19	0	0	1.0
3	26	21	-	-	1.5
4	28	23	-	-	2.0

The utility specifications are:

$$V_1 = -0.5 - 0.5A_1 - 0.4A_2 + 0.9A_3 - 0.7A_4 + 0.8A_5$$

$$V_2 = -0.5A_1 - 0.4A_2 + 0.9A_3 - 0.7A_4 + 0.8A_5$$

Current State of Practice (2)

Experimental Design

	Alternative A						Alternative B				
#	Con	A1	A2	A3	A4	A5	B1	B2	B3	B4	B5
1	1	24	21	1	0	1	28	19	0	1	1.5
2	1	26	17	1	1	0.5	26	23	0	0	2
3	1	26	19	1	0	0.5	28	21	0	1	2
4	1	22	19	0	1	2	26	21	1	0	1
5	1	24	23	1	1	2	22	17	1	0	0.5
6	1	28	21	0	0	1.5	22	19	1	1	1
7	1	22	17	0	0	1.5	24	23	0	1	0.5
8	1	28	23	0	1	1	24	17	1	0	1.5

$$V_1 = -0.5 - 0.5A_1 - 0.4A_2 + 0.9A_3 - 0.7A_4 + 0.8A_5$$
$$V_2 = -0.5A_1 - 0.4A_2 + 0.9A_3 - 0.7A_4 + 0.8A_5$$

Pa	Pb
0.846	0.154
0.574	0.426
0.786	0.214
0.711	0.289
0.069	0.931
0.036	0.964
0.973	0.027
0.003	0.997

Asymptotic Variance-Covariance

	a0	a1	a2	a3	a4	a5
a0	**2.213**	0.312	0.162	-1.343	-0.361	-0.644
a1	0.312	**0.210**	-0.069	0.140	-0.203	0.310
a2	0.162	-0.069	**0.265**	-0.718	0.424	-1.012
a3	-1.343	0.140	-0.718	**8.377**	-0.251	6.706
a4	-0.361	-0.203	0.424	-0.251	**2.111**	-1.382
a5	-0.644	0.310	-1.012	6.706	-1.382	**7.225**

D-error
0.854

D_p-efficiency: D_p-error = $\det\left(\Omega_1^*(\hat{\beta} \mid X)\right)^{1/K}$

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Current State of Practice (3)

Experimental Design

#	Con	A1	A2	A3	A4	A5	B1	B2	B3	B4	B5
	Alternative A						Alternative B				
1	1	24	21	1	0	1	28	19	0	1	1
2	1	26	17	1	1	0.5	26	23	0	0	2
3	1	26	19	1	0	0.5	28	21	0	1	2
4	1	22	19	0	1	2	26	21	1	0	1.5
5	1	24	23	1	1	2	22	17	1	0	0.5
6	1	28	21	0	0	1.5	22	19	1	1	1
7	1	22	17	0	0	1.5	24	23	0	1	0.5
8	1	28	23	0	1	1	24	17	1	0	1.5

Pa	Pb
0.891	0.109
0.574	0.426
0.786	0.214
0.622	0.378
0.069	0.931
0.036	0.964
0.973	0.027
0.003	0.997

$$V_1 = -0.5 - 0.5A_1 - 0.4A_2 + 0.9A_3 - 0.7A_4 + 0.8A_5$$
$$V_2 = -0.5A_1 - 0.4A_2 + 0.9A_3 - 0.7A_4 + 0.8A_5$$

D-error
0.854

Asymptotic Variance-Covariance

	a0	a1	a2	a3	a4	a5
a0	**2.158**	0.330	0.112	-0.775	-0.481	-0.163
a1	0.330	**0.207**	-0.062	-0.086	-0.155	0.161
a2	0.112	-0.062	**0.289**	-0.383	0.348	-0.936
a3	-0.775	-0.086	-0.383	**4.630**	0.557	3.695
a4	-0.481	-0.155	0.348	0.557	**1.937**	-0.717
a5	-0.163	0.161	-0.936	3.695	-0.717	**5.525**

D-error
0.825

Dp-efficiency: Dp-error = $\det\left(\Omega_1^*(\hat{\beta} \mid X)\right)^{1/K}$

Current State of Practice (4)

Experimental Design

	Alt A						Alt B				
#	Con	A1	A2	A3	A4	A5	B1	B2	B3	B4	B5
1	1	24	23	1	0	1	28	19	0	1	1
2	1	26	17	1	1	0.5	26	23	0	0	2
3	1	26	19	1	0	0.5	28	21	0	1	2
4	1	22	19	0	1	2	26	21	1	0	1.5
5	1	24	21	1	1	2	22	17	1	0	0.5
6	1	28	21	0	0	1.5	22	19	1	1	1
7	1	22	17	0	0	1.5	24	23	0	1	0.5
8	1	28	23	0	1	1	24	17	1	0	1.5

Pa	Pb
0.818	0.182
0.574	0.426
0.786	0.214
0.622	0.378
0.119	0.881
0.036	0.964
0.973	0.027
0.003	0.997

$$V_1 = -0.5 - 0.5A_1 - 0.4A_2 + 0.9A_3 - 0.7A_4 + 0.8A_5$$
$$V_2 = -0.5A_1 - 0.4A_2 + 0.9A_3 - 0.7A_4 + 0.8A_5$$

Asymptotic Variance-Covariance

	a0	a1	a2	a3	a4	a5
a0	**1.986**	0.320	0.125	-1.166	-0.499	-0.570
a1	0.320	**0.172**	-0.007	-0.157	-0.132	-0.043
a2	0.125	-0.007	**0.275**	-0.490	0.425	-0.950
a3	-1.166	-0.157	-0.490	**4.281**	0.222	3.464
a4	-0.499	-0.132	0.425	0.222	**2.092**	-1.143
a5	-0.570	-0.043	-0.950	3.464	-1.143	**5.088**

D-error
0.854

D-error
0.825

D-error
0.732

Dp-efficiency: Dp-error = $\det\left(\Omega_1^*(\hat{\beta} \mid X)\right)^{1/K}$

What if the priors are unreliable?

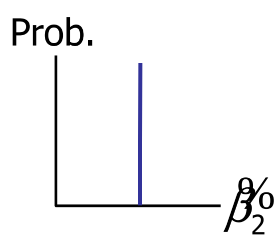
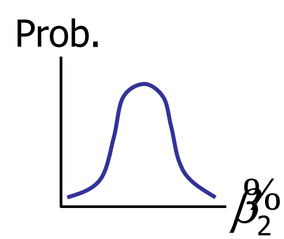
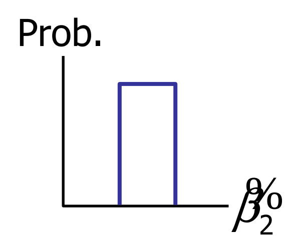
- Bayesian priors
  - In Bayesian efficient designs, we do not assume fixed prior parameter values, but we assume **random distributions** of prior parameter values

What if the priors are unreliable?

Instead of assumed fixed prior parameter values,
we can assume prior parameter distributions.

$$U^{car} = \beta_0 + \beta_1 \cdot Time^{car} + \beta_2 \cdot Cost^{car}$$

$$U^{bus} = \beta_3 \cdot Fare^{bus} + \beta_2 \cdot Fare^{bus}$$

Efficient designs	Bayesian efficient designs	
Fixed values	Probability distributions	
$\tilde{\beta}_2 = -0.1$	$\tilde{\beta}_2 : N(-0.1, 0.05)$	$\tilde{\beta}_2 : N(-0.2, 0)$
		

What if the priors are unreliable?

Efficient designs:

Minimize D-error = $\det\left(\Omega_N(X,\tilde{\beta})\right)^{1/K}$

Bayesian efficient designs:

Minimize Expected D-error = $\iiint\limits_{\tilde{\beta}} \det\left(\Omega_N(X,\tilde{\beta})\right)^{1/K} f(\tilde{\beta} \mid \omega)\, d\tilde{\beta}$

This integral can be approximated by
- pseudo-Monte Carlo simulation
- Modified Latin Hybercube sampling
- quasi-Monte Carlo simulation (e.g., Halton, Sobol draws)
- Guassian quadrature

A Bayesian efficient design is a more “stable” design that will be relatively efficient over a range of prior parameter values.

Testing of Efficient Experimental Designs

- Efficient experimental designs are only efficient if the assumptions under which they were generated hold.
  - Researchers can use Bayesian priors to account for uncertainty in the exact prior values;
  - Researchers can also fix the design and apply different priors to test what would happen under misspecification of the prior parameter estimates;
  - Researchers can fix the design and test using different model forms (e.g., MNL, NL, RPL)

Covariates and efficient designs (1)

- Many stated choice studies also include covariates as part of the utility specification.
- The impact that these covariates have on the efficiency of the experiment however, has until now, never been considered.

Covariates and efficient designs (2)

- Consider the same experiment, only now, let us attach a gender dummy (male = 1) to the utility of the second alternative, such that:

$$V_1 = -0.5 - 0.5A_1 - 0.4A_2 + 0.9A_3 - 0.7A_4 + 0.8A_5$$
$$V_2 = -0.5A_1 - 0.4A_2 + 0.9A_3 - 0.7A_4 + 0.8A_5 - 0.6Gender$$

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Covariates and efficient designs (3)

Experimental Design with Gender Dummy

	Alternative A						Alternative B					
#	Con	A1	A2	A3	A4	A5	B1	B2	B3	B4	B5	gend
1	1	24	23	1	0	1	28	19	0	1	1	1
2	1	26	17	1	1	0.5	26	23	0	0	2	1
3	1	26	19	1	0	0.5	28	21	0	1	2	1
4	1	22	19	0	1	2	26	21	1	0	1.5	1
5	1	24	21	1	1	2	22	17	1	0	0.5	1
6	1	28	21	0	0	1.5	22	19	1	1	1	1
7	1	22	17	0	0	1.5	24	23	0	1	0.5	1
8	1	28	23	0	1	1	24	17	1	0	1.5	1
1	1	24	23	1	0	1	28	19	0	1	1	0
2	1	26	17	1	1	0.5	26	23	0	0	2	0
3	1	26	19	1	0	0.5	28	21	0	1	2	0
4	1	22	19	0	1	2	26	21	1	0	1.5	0
5	1	24	21	1	1	2	22	17	1	0	0.5	0
6	1	28	21	0	0	1.5	22	19	1	1	1	0
7	1	22	17	0	0	1.5	24	23	0	1	0.5	0
8	1	28	23	0	1	1	24	17	1	0	1.5	0

Pa	Pb
0.998	0.002
0.198	0.802
0.978	0.022
0.168	0.832
0.182	0.818
0.083	0.917
0.973	0.027
0.002	0.998
0.997	0.003
0.119	0.881
0.961	0.039
0.100	0.900
0.109	0.891
0.047	0.953
0.953	0.047
0.001	0.999

The same design without the gender covariate

Asymptotic Variance-Covariance

	a0	a1	a2	a3	a4	a5
a0	**1.986**	0.320	0.125	-1.166	-0.499	-0.570
a1	0.320	**0.172**	-0.007	-0.157	-0.132	-0.043
a2	0.125	-0.007	**0.275**	-0.490	0.425	-0.950
a3	-1.166	-0.157	-0.490	**4.281**	0.222	3.464
a4	-0.499	-0.132	0.425	0.222	**2.092**	-1.143
a5	-0.570	-0.043	-0.950	3.464	-1.143	**5.088**

D-error
0.732

Adjusted for sample size $N = 2$

Asymptotic Variance-Covariance

	a0	a1	a2	a3	a4	a5	gend
a0	**6.861**	-0.570	0.912	0.166	-1.612	-2.166	4.470
a1	-0.570	**0.411**	-0.271	-0.385	0.501	0.334	0.172
a2	0.912	-0.271	**0.480**	0.114	-0.283	-1.056	-0.012
a3	0.166	-0.385	0.114	**5.855**	-1.172	2.557	-0.685
a4	-1.612	0.501	-0.283	-1.172	**3.354**	0.006	0.772
a5	-2.166	0.334	-1.056	2.557	0.006	**5.132**	-0.287
gend	4.470	0.172	-0.012	-0.685	0.772	-0.287	**8.426**

D-error
1.856

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Covariates and efficient designs (4)

Experimental Design with Gender Dummy

	Alternative A						Alternative B					
#	Con	A1	A2	A3	A4	A5	B1	B2	B3	B4	B5	gend
1	1	24	23	1	0	1	28	19	0	1	1	1
2	1	26	17	1	1	0.5	26	23	0	1	2	1
3	1	26	19	1	0	0.5	28	21	0	0	2	1
4	1	22	19	0	1	2	26	21	1	0	1.5	1
5	1	24	21	1	1	2	22	17	1	0	0.5	1
6	1	28	21	0	0	1.5	22	19	1	1	1	1
7	1	22	17	0	0	1.5	24	23	0	1	0.5	1
8	1	28	23	0	1	1	24	17	1	0	1.5	1
1	1	24	23	1	0	1	28	19	0	1	1	0
2	1	26	17	1	1	0.5	26	23	0	1	2	0
3	1	26	19	1	0	0.5	28	21	0	0	2	0
4	1	22	19	0	1	2	26	21	1	0	1.5	0
5	1	24	21	1	1	2	22	17	1	0	0.5	0
6	1	28	21	0	0	1.5	22	19	1	1	1	0
7	1	22	17	0	0	1.5	24	23	0	1	0.5	0
8	1	28	23	0	1	1	24	17	1	0	1.5	0

Pa	Pb
0.998	0.002
0.646	0.354
0.858	0.142
0.168	0.832
0.182	0.818
0.083	0.917
0.973	0.027
0.002	0.998
0.997	0.003
0.500	0.500
0.769	0.231
0.100	0.900
0.109	0.891
0.047	0.953
0.953	0.047
0.001	0.999

If we use this design, without considering gender

The same design without the gender covariate

Asymptotic Variance-Covariance

	a0	a1	a2	a3	a4	a5
a0	**2.054**	0.303	0.154	-1.461	-0.845	-0.673
a1	0.303	**0.166**	0.015	-0.142	-0.018	-0.114
a2	0.154	0.015	**0.200**	-0.460	0.164	-0.695
a3	-1.461	-0.142	-0.460	**5.118**	1.661	3.440
a4	-0.845	-0.018	0.164	1.661	**3.288**	-0.143
a5	-0.673	-0.114	-0.695	3.440	-0.143	**4.217**

D-error
0.732

D-error
0.789

Adjusted for sample size N = 2

Asymptotic Variance-Covariance

	a0	a1	a2	a3	a4	a5	gend
a0	**4.265**	-0.367	0.527	-0.507	-1.966	-0.342	2.901
a1	-0.367	**0.398**	-0.185	-0.317	0.989	-0.168	0.129
a2	0.527	-0.185	**0.314**	0.016	-0.579	-0.467	-0.025
a3	-0.507	-0.317	0.016	**5.437**	-1.110	3.178	-0.518
a4	-1.966	0.989	-0.579	-1.110	**6.331**	-1.100	0.541
a5	-0.342	-0.168	-0.467	3.178	-1.100	**3.885**	-0.107
gend	2.901	0.129	-0.025	-0.518	0.541	-0.107	**5.677**

D-error
1.512

D-error
1.856

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Sample Optimisation (1)

- To date, we have assumed a sample size equal to one (or one male, one female).
- However, it is possible to weight the asymptotic (co)variance matrix by each type of respondent.

Sample Optimisation (2)

- Taking the same experimental design, let us assume a sample size of ten.
- Assuming we must have at least one male and one female, would we be best to sample more or less males or females?

Sample Optimisation (3)

	Male = 9 / Female = 1						
	Asymptotic Variance-Covariance						
	a0	a1	a2	a3	a4	a5	gend
a0	**15.554**	-0.454	0.563	-0.286	-2.129	-0.268	14.121
a1	-0.454	**0.436**	-0.217	-0.411	1.222	-0.226	0.147
a2	0.563	-0.217	**0.354**	0.023	-0.613	-0.562	-0.039
a3	-0.286	-0.411	0.023	**4.987**	-1.701	3.143	-0.519
a4	-2.129	1.222	-0.613	-1.701	**7.047**	-1.728	0.624
a5	-0.268	-0.226	-0.562	3.143	-1.728	**4.338**	-0.130
gend	14.121	0.147	-0.039	-0.519	0.624	-0.130	**15.752**

D-error
1.772

	Male = 5 / Female = 5						
	Asymptotic Variance-Covariance						
	a0	a1	a2	a3	a4	a5	gend
a0	**4.265**	-0.367	0.527	-0.507	-1.966	-0.342	2.901
a1	-0.367	**0.398**	-0.185	-0.317	0.989	-0.168	0.129
a2	0.527	-0.185	**0.314**	0.016	-0.579	-0.467	-0.025
a3	-0.507	-0.317	0.016	**5.437**	-1.110	3.178	-0.518
a4	-1.966	0.989	-0.579	-1.110	**6.331**	-1.100	0.541
a5	-0.342	-0.168	-0.467	3.178	-1.100	**3.885**	-0.107
gend	2.901	0.129	-0.025	-0.518	0.541	-0.107	**5.677**

	Male = 1 / Female = 9						
	Asymptotic Variance-Covariance						
	a0	a1	a2	a3	a4	a5	gend
a0	**3.046**	-0.287	0.507	-0.761	-1.911	-0.439	1.697
a1	-0.287	**0.377**	-0.155	-0.242	0.790	-0.133	0.116
a2	0.507	-0.155	**0.286**	0.001	-0.557	-0.404	-0.012
a3	-0.761	-0.242	0.001	**6.213**	-0.539	3.445	-0.534
a4	-1.911	0.790	-0.557	-0.539	**5.967**	-0.571	0.476
a5	-0.439	-0.133	-0.404	3.445	-0.571	**3.710**	-0.098
gend	1.697	0.116	-0.012	-0.534	0.476	-0.098	**15.156**

D-error
1.852

D-error
1.512

Sample Optimisation (4)

- We have assumed a single design assigned to both males and females.
- Greater efficiency may be achieved if we allow for heterogeneous designs based on socio-demographic characteristics.

Sample Optimisation (5)

Experimental Design with Gender Dummy

	Alternative A						Alternative B					
#	Con	A1	A2	A3	A4	A5	B1	B2	B3	B4	B5	gend
1	1	24	23	1	0	1	28	19	0	1	1	1
2	1	26	17	1	1	0.5	26	23	0	1	2	1
3	1	26	19	1	0	0.5	28	21	0	0	2	1
4	1	22	19	0	1	2	26	21	1	0	1.5	1
5	1	24	21	1	1	2	22	17	1	0	0.5	1
6	1	28	21	0	0	1.5	22	19	1	1	1	1
7	1	22	17	0	0	1.5	24	23	0	1	0.5	1
8	1	28	23	0	1	1	24	17	1	0	1.5	1
1	1	28	23	1	0	1	26	19	1	1	1	0
2	1	26	17	1	1	2	26	23	0	0	2	0
3	1	26	23	1	1	0.5	28	21	0	1	2	0
4	1	22	19	0	0	0.5	28	21	1	0	1.5	0
5	1	24	21	1	1	2	22	17	1	0	0.5	0
6	1	28	19	0	0	1.5	22	19	0	1	0.5	0
7	1	22	17	0	0	1.5	24	23	0	0	1	0
8	1	24	21	0	1	1	24	17	1	1	1.5	0

Male = 1 / Female = 9

Asymptotic Variance-Covariance

	a0	a1	a2	a3	a4	a5	gend
a0	**1.507**	0.101	0.049	-0.298	0.524	-0.336	1.564
a1	0.101	**0.339**	-0.070	-0.846	0.846	-0.799	0.420
a2	0.049	-0.070	**0.088**	0.248	-0.085	0.093	-0.091
a3	-0.298	-0.846	0.248	**4.094**	-2.318	2.424	-1.013
a4	0.524	0.846	-0.085	-2.318	**4.127**	-2.317	1.708
a5	-0.336	-0.799	0.093	2.424	-2.317	**2.978**	-1.216
gend	1.564	0.420	-0.091	-1.013	1.708	-1.216	**4.871**

D-error
0.813

D-error
1.512

How Can You Do This?

- Program yourself
  - Excel
- Use Existing Software
  - Ngene

Future Research

- Expand to continuous covariates.
  - Work currently being conducted on generating samples of respondents with continuous and non-continuous covariates
- Test designs generated using different specifications in real world applications.
  - Compare designs with, orthogonal, and optimal designs
- Move away from SC to RP design generation.
  - Methods outlined here can be extended to RP data generation