Sample size requirements to compare development between unbalanced subgroups in latent growth models

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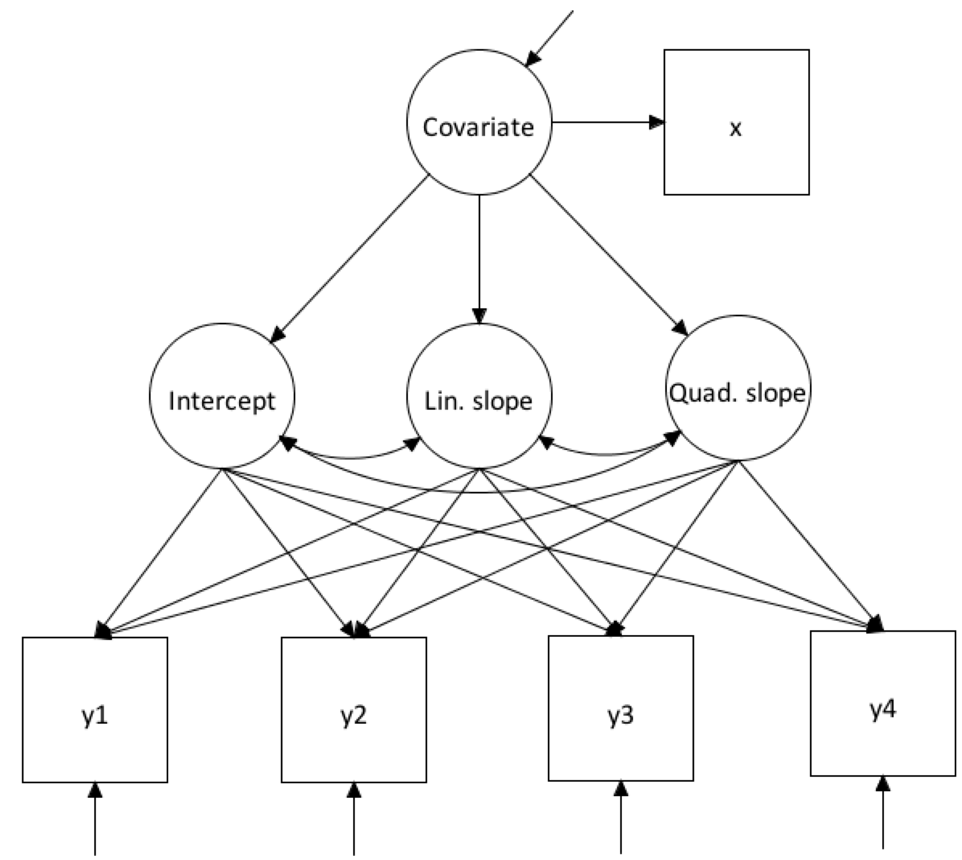
[3]North-West University, Optentia Research Focus Area

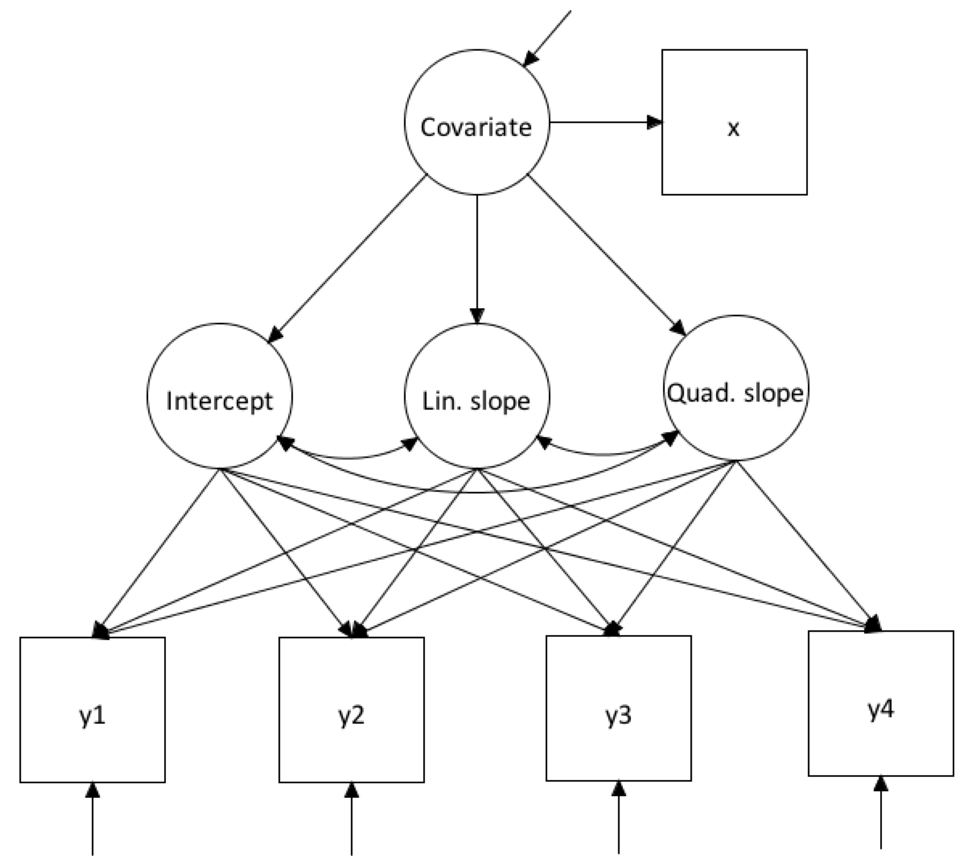
Outline

1. Introduction
2. What do we know?
3. Model
4. Simulation design
5. Syntax
6. Results
7. Conclusion
8. To be continued


Covariate
x
Intercept
Lin. slope
Quad. slope
y1
y2
y3
y4

exceptional group

group of interest

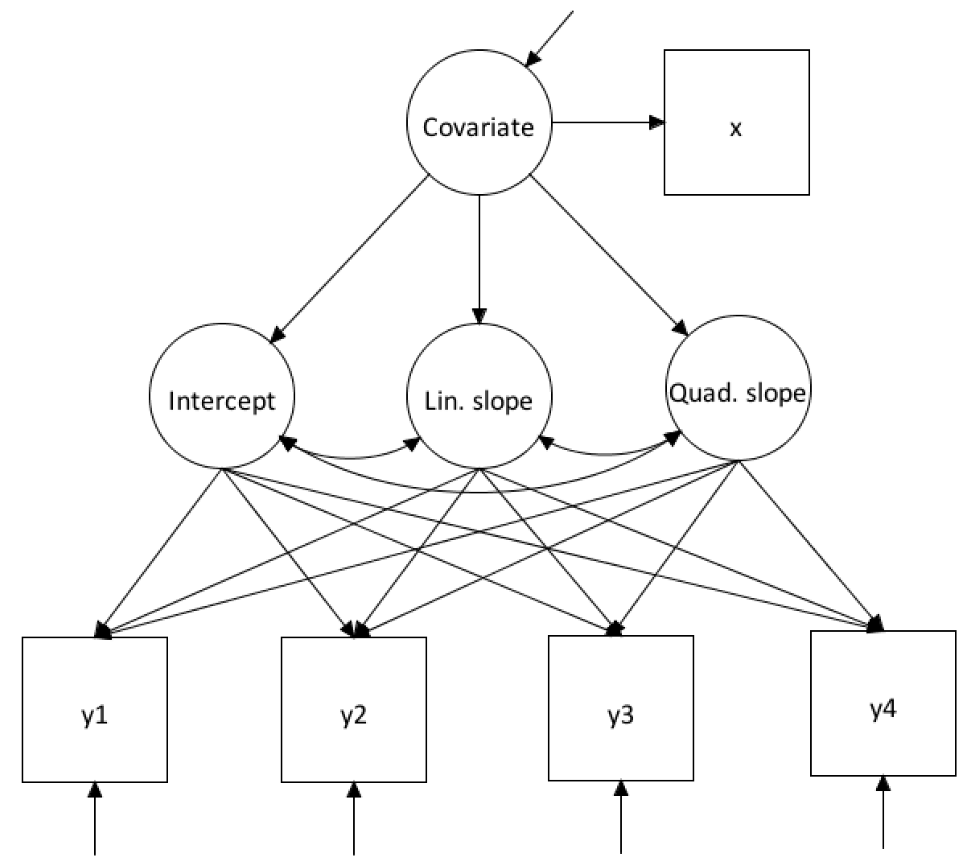


typically developing group

reference group

exceptional group

group of interest



What do we know?

- Maximum Likelihood (ML) estimation
- Bayesian estimation (default settings)
- Bayesian estimation with informative priors

What do we know?

- Maximum Likelihood (ML) estimation

small sample: +- 50 participants = little bias, but low power[1], Type I error > .05[2,3]

unbalanced samples: keeping everything else constant: balanced is better for power[4]

- Bayesian estimation (default prior settings)

- Bayesian estimation with informative priors

[1]Tolvanen (2000), [2]Meuleman & Billiet (2009), [3]Maas & Hox (2001), [4]Muthén & Curran (1997)

What do we know?

- Maximum Likelihood (ML) estimation

small sample:	+- 50 participants = little bias, but low power[1], Type I error > .05[2,3]
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- Bayesian estimation (default prior settings)

small sample:	+- 20 participants = little bias, but low power[5]
unbalanced samples:	?

- Bayesian estimation with informative priors

[1]Tolvanen (2000), [2]Meuleman & Billiet (2009), [3]Maas & Hox (2001), [4]Muthén & Curran (1997),
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What do we know?

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- Bayesian estimation (default prior settings)

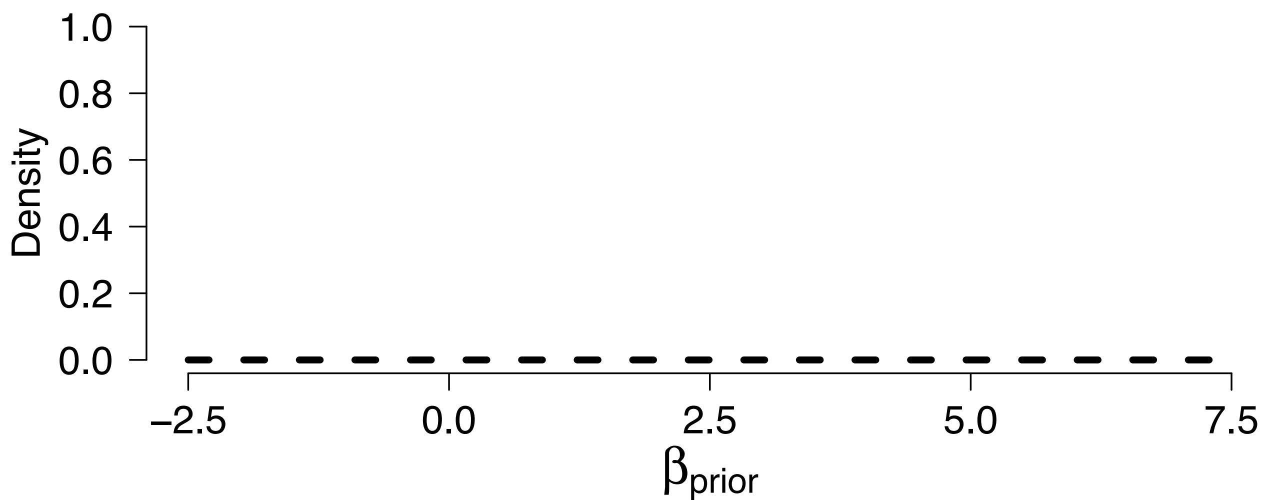
small sample:	+- 20 participants = little bias, but low power[5]
unbalanced samples:	?

- Bayesian estimation with informative priors

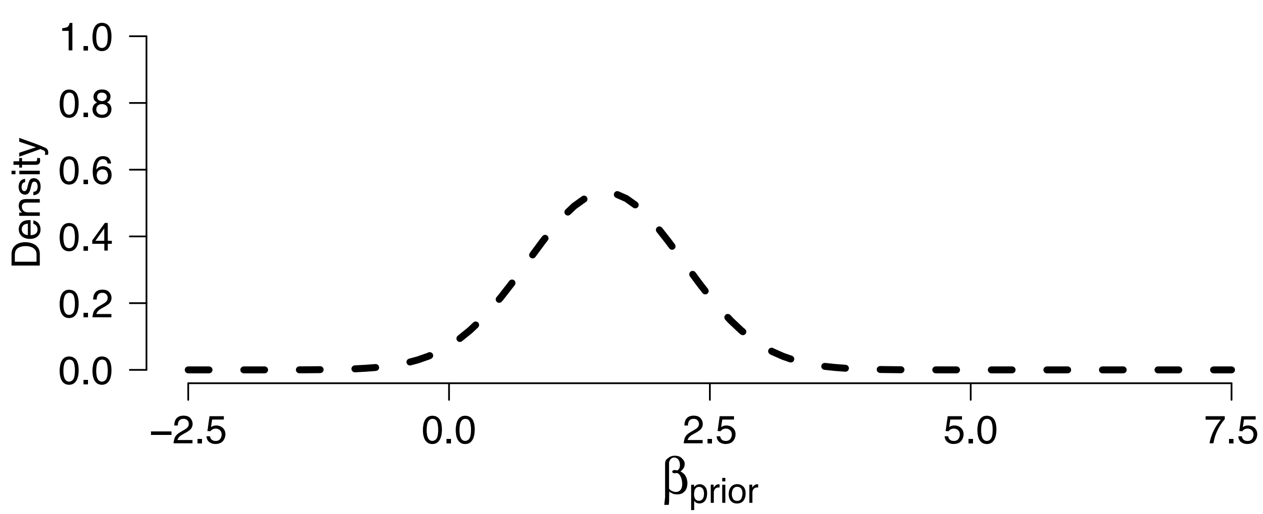
small sample:	+- ? participants ➜ expectation: fewer participants required[6,7]
unbalanced samples:	?

[1]Tolvanen (2000), [2]Meuleman & Billiet (2009), [3]Maas & Hox (2001), [4]Muthén & Curran (1997),
[5]Hox, Van de Schoot, & Matthijsse (2012), [6]Lee & Song (2004), [7]Depaoli (2013)

Prior information

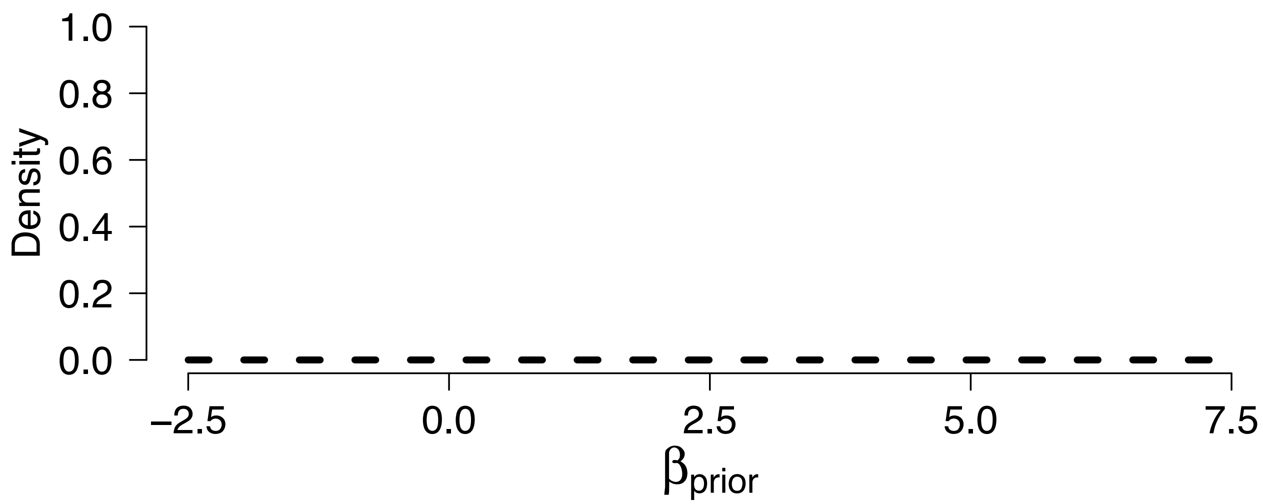


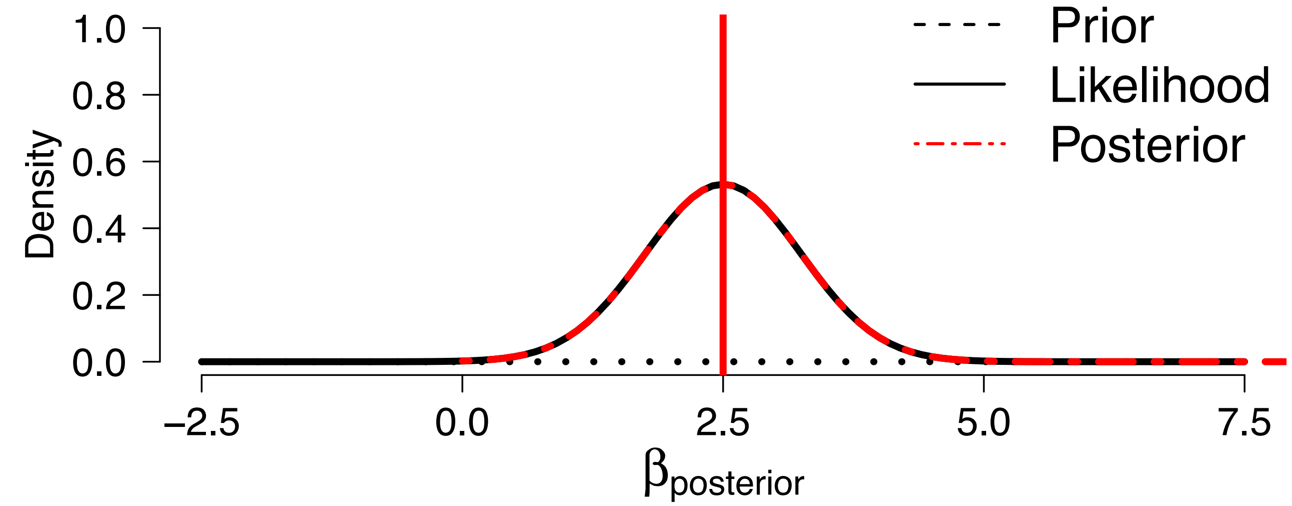
uninformative



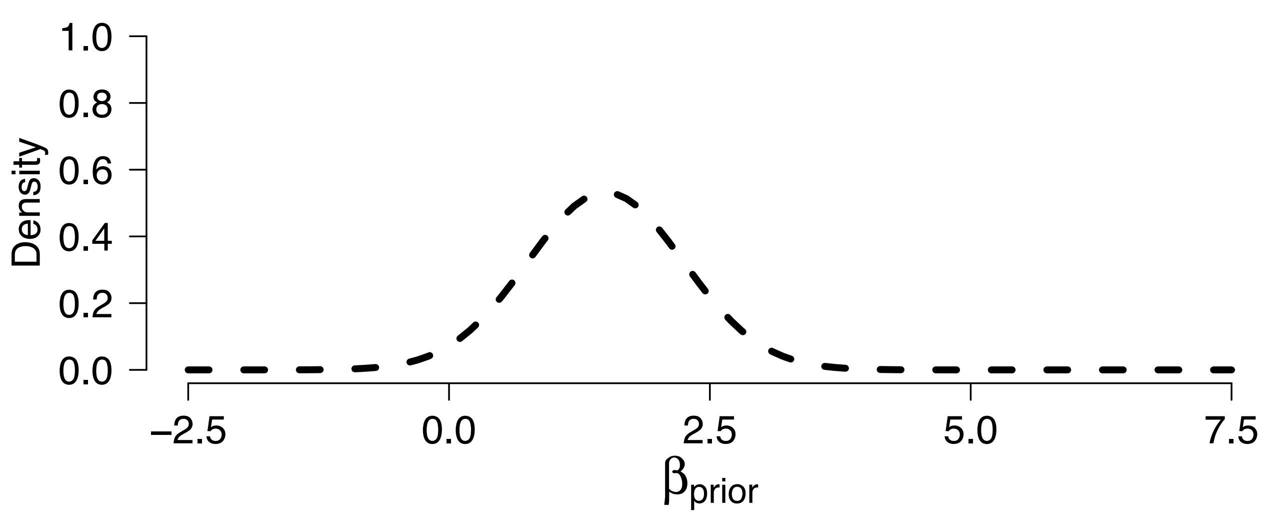
informative

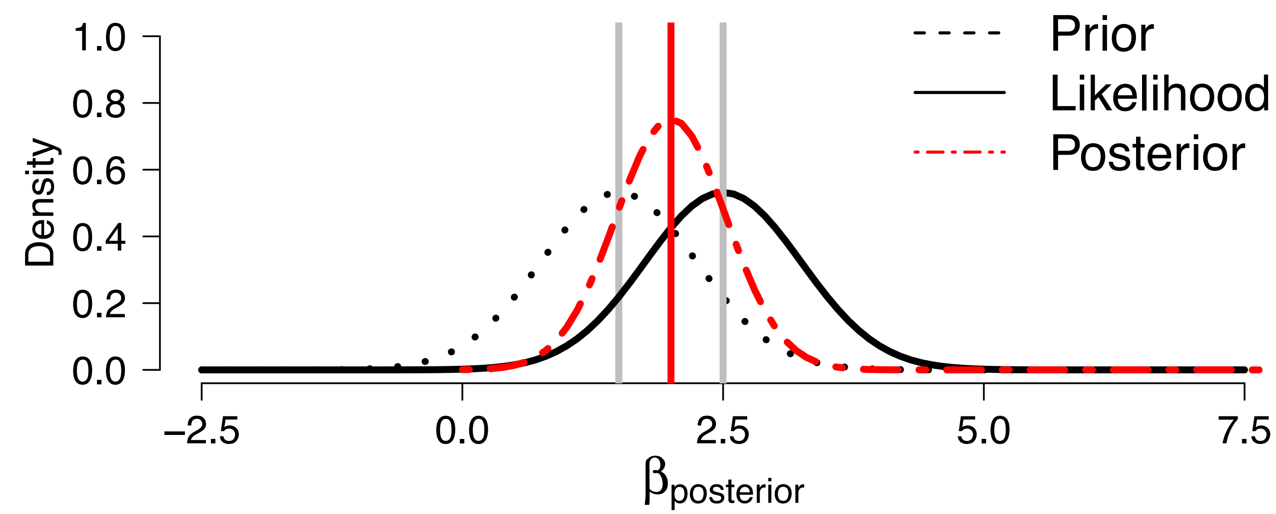
Prior information





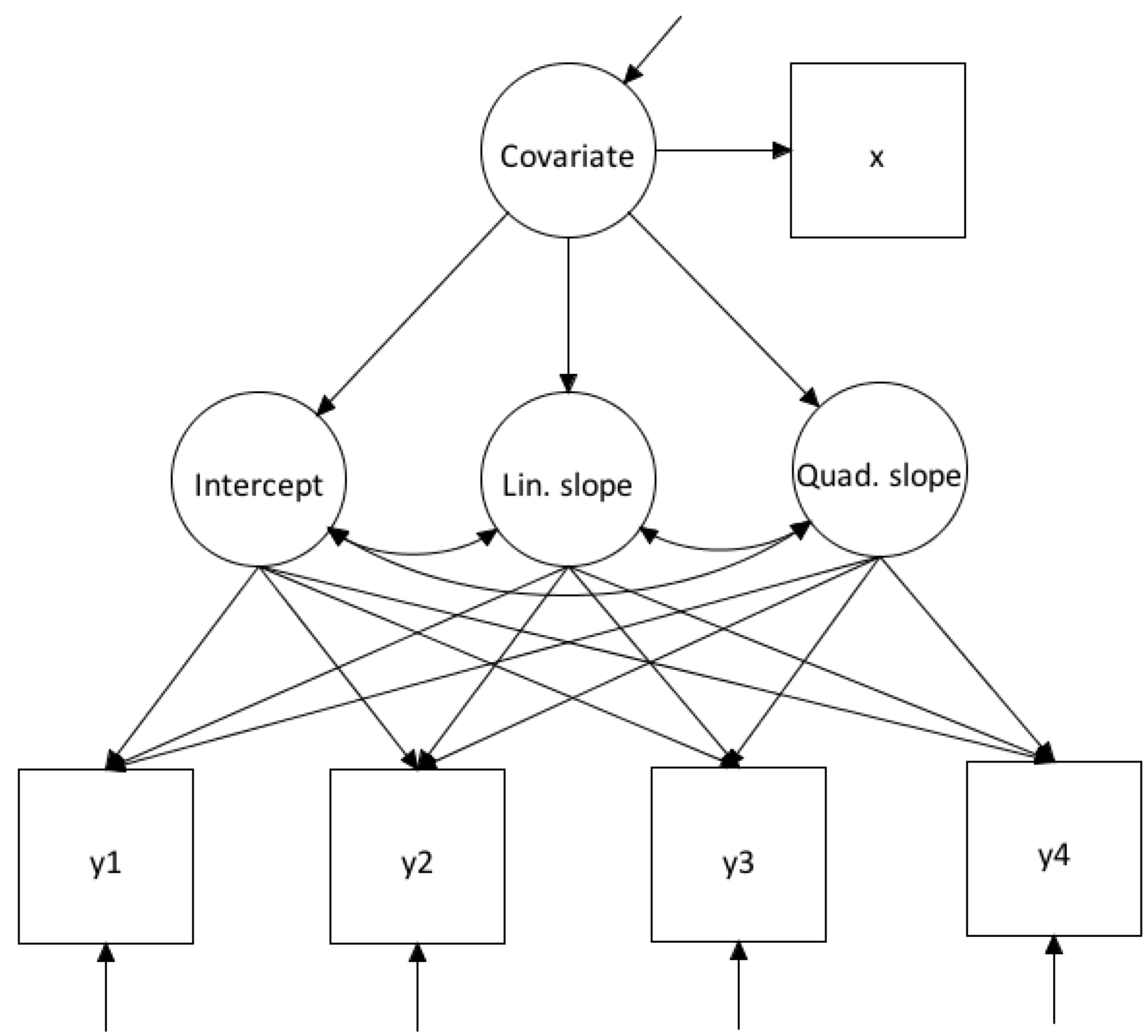
uninformative



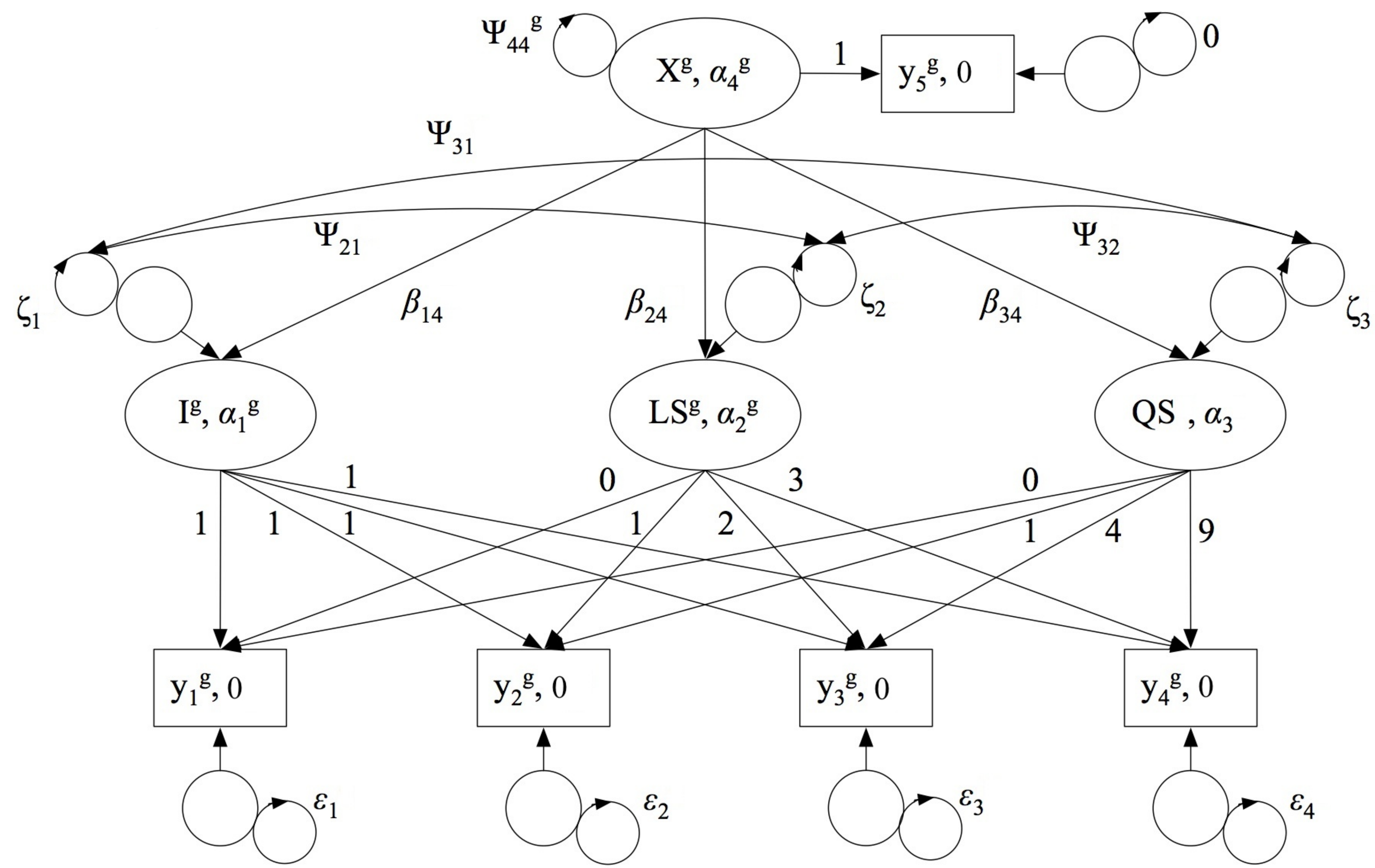


informative

The latent growth model in the Mplus Diagrammer



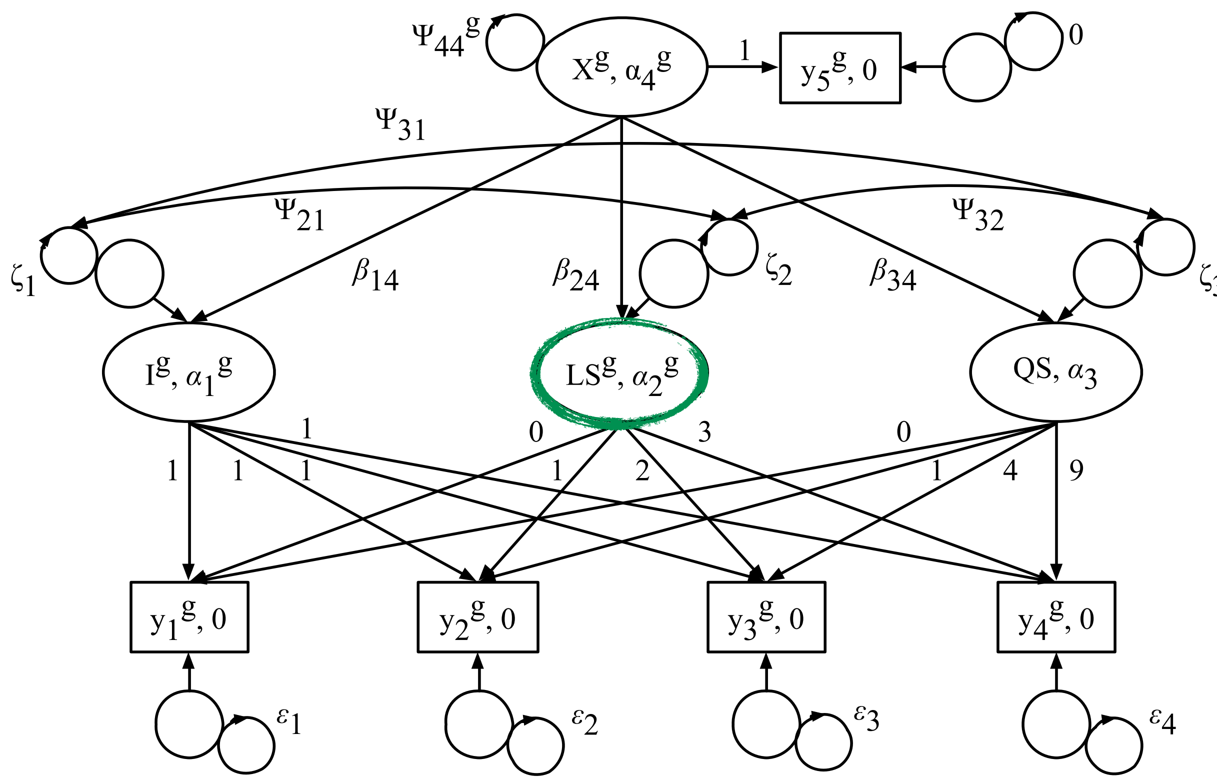
The multiple group latent growth model in Mplus



Simulation design (1)

Focus

$\alpha_2^1 - \alpha_2^2 = \Delta\alpha_2$

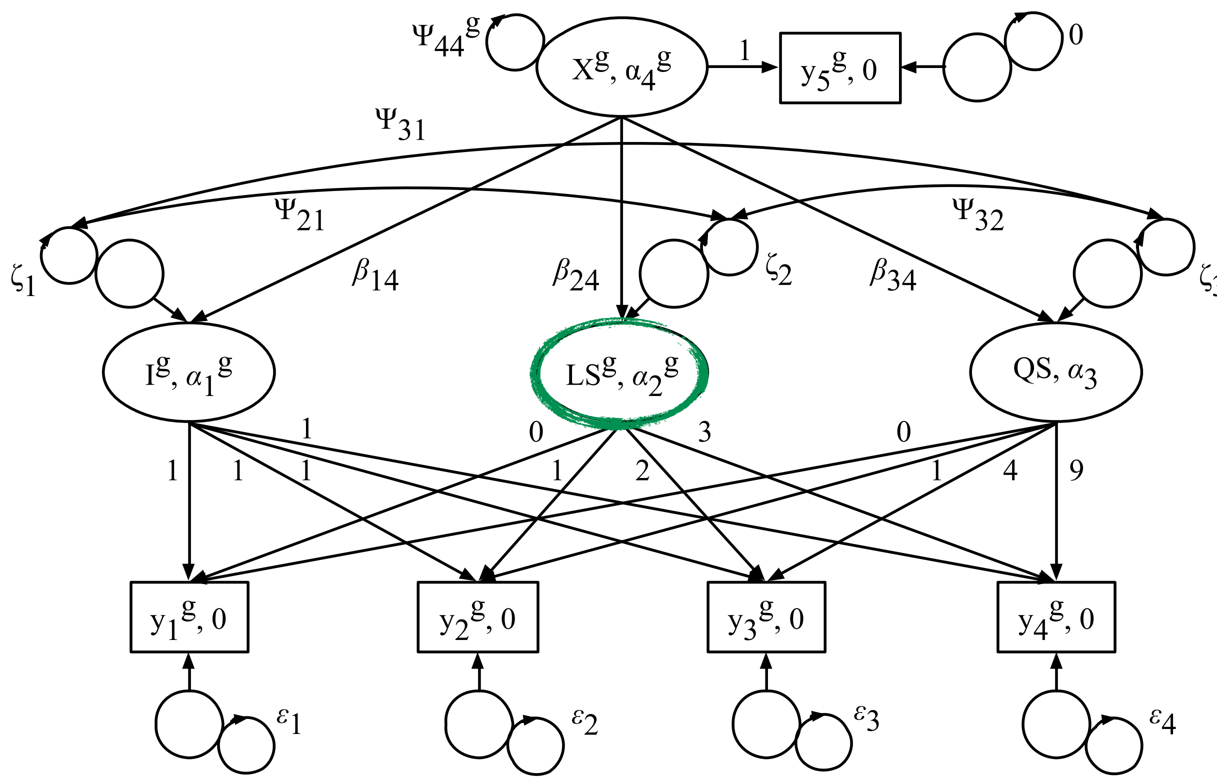


Simulation design (1)

Focus

$\alpha_2^1 - \alpha_2^2 = \Delta\alpha_2$

Factors



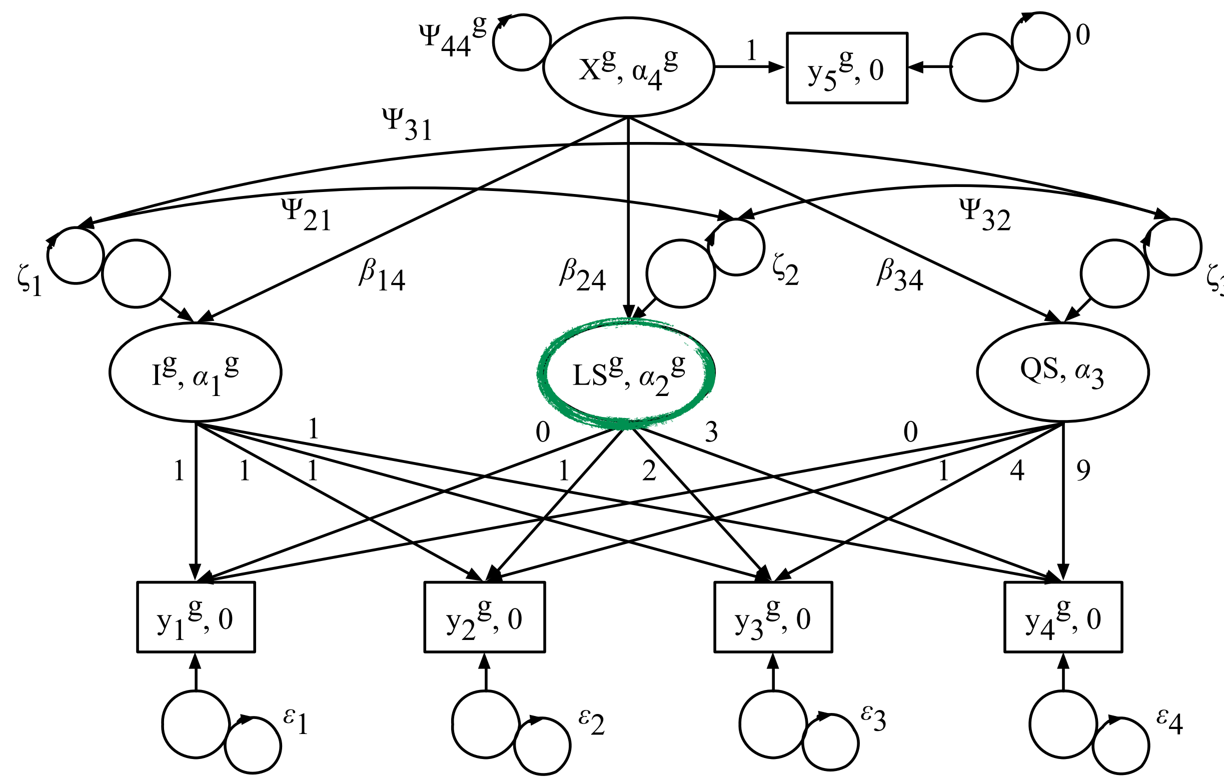
Simulation design (1)

Focus

$\alpha_2^1 - \alpha_2^2 = \Delta\alpha_2$

Factors

- *n* exceptional group



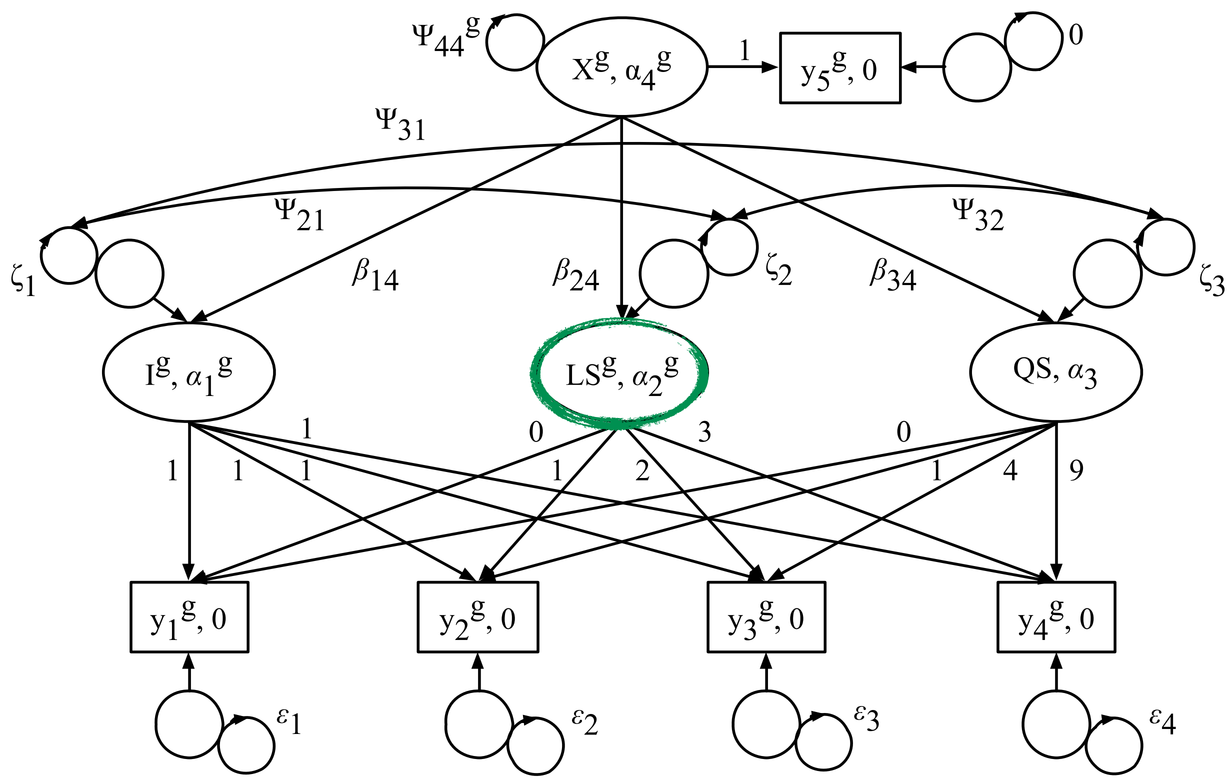
Simulation design (1)

Focus

$\alpha_2^{1} - \alpha_2^{2} = \Delta\alpha_2$

Factors

- *n* exceptional group
- *n* reference group



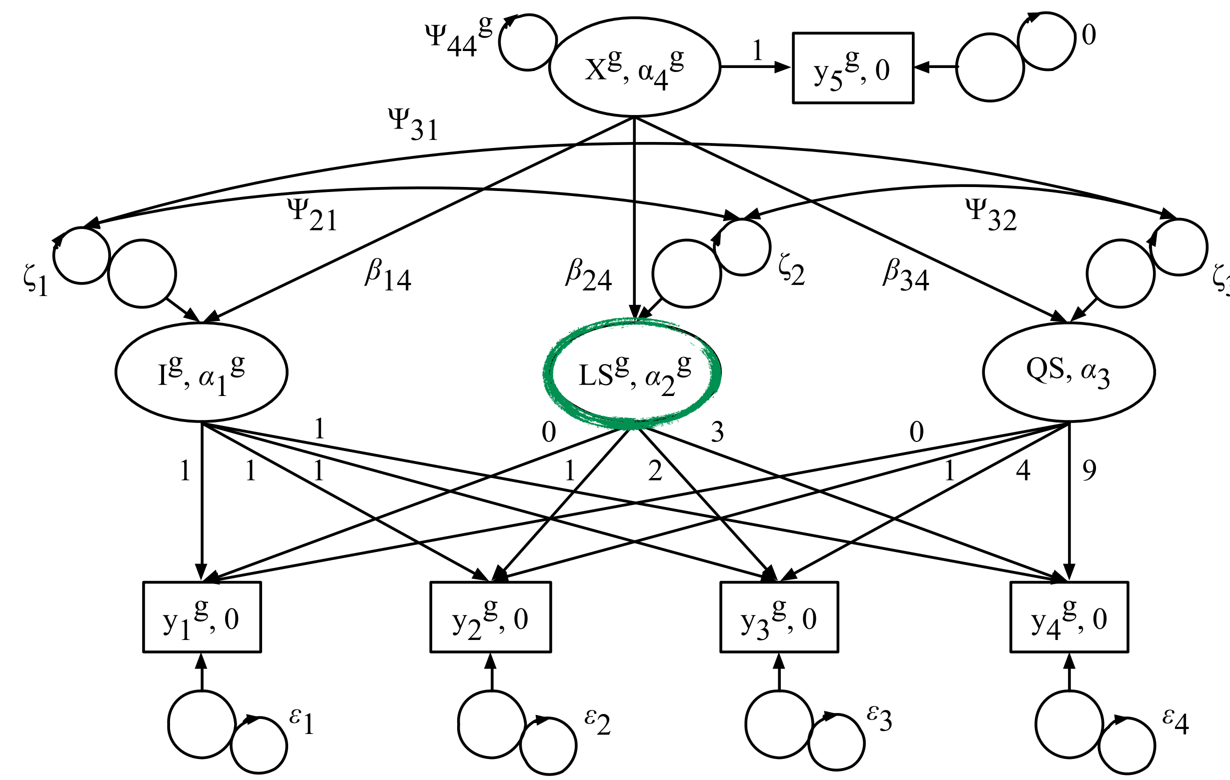
Simulation design (1)

Focus

$\alpha_2^1 - \alpha_2^2 = \Delta\alpha_2$

Factors

- *n* exceptional group
- *n* reference group
- (ratio exceptional:reference)



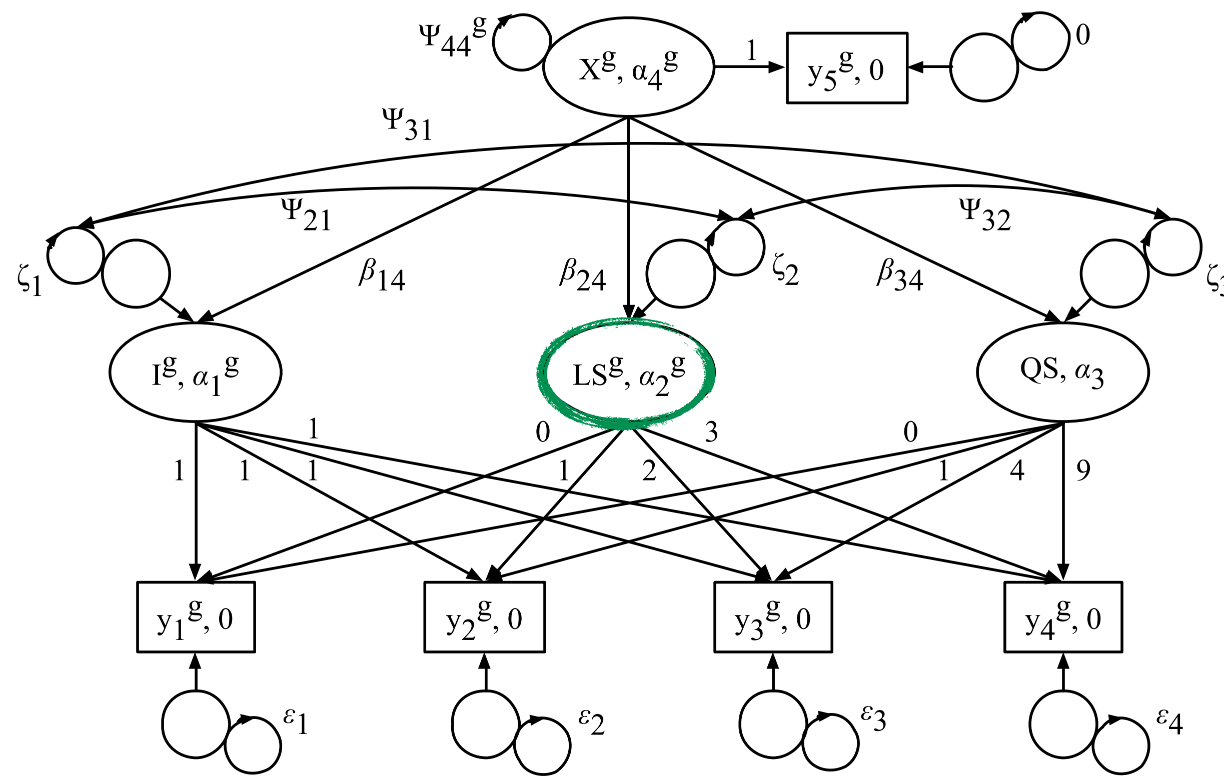
Simulation design (1)

Focus

$\alpha_2^1 - \alpha_2^2 = \Delta\alpha_2$

Factors

- *n* exceptional group
- *n* reference group
- (ratio exceptional:reference)
- estimation method & settings



Simulation design (1)

Focus

$\alpha_2^1 - \alpha_2^2 = \Delta\alpha_2$

Factors

- *n* exceptional group
- *n* reference group
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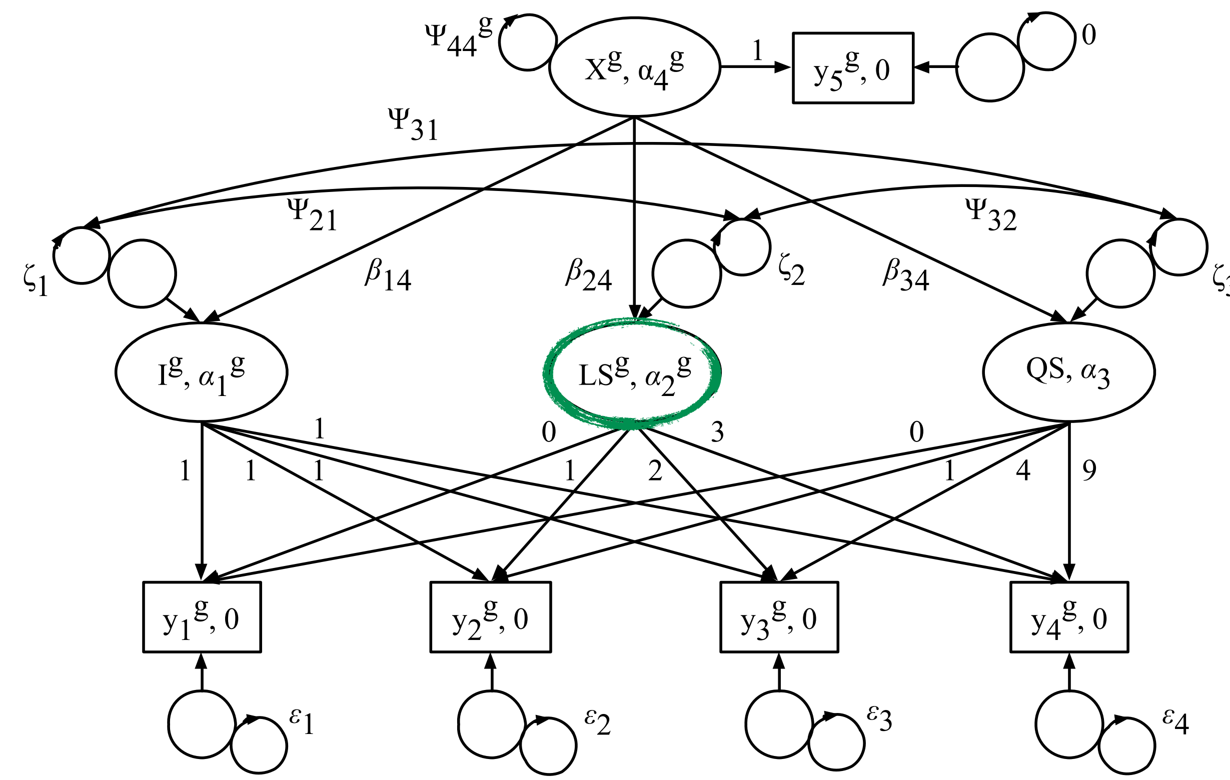
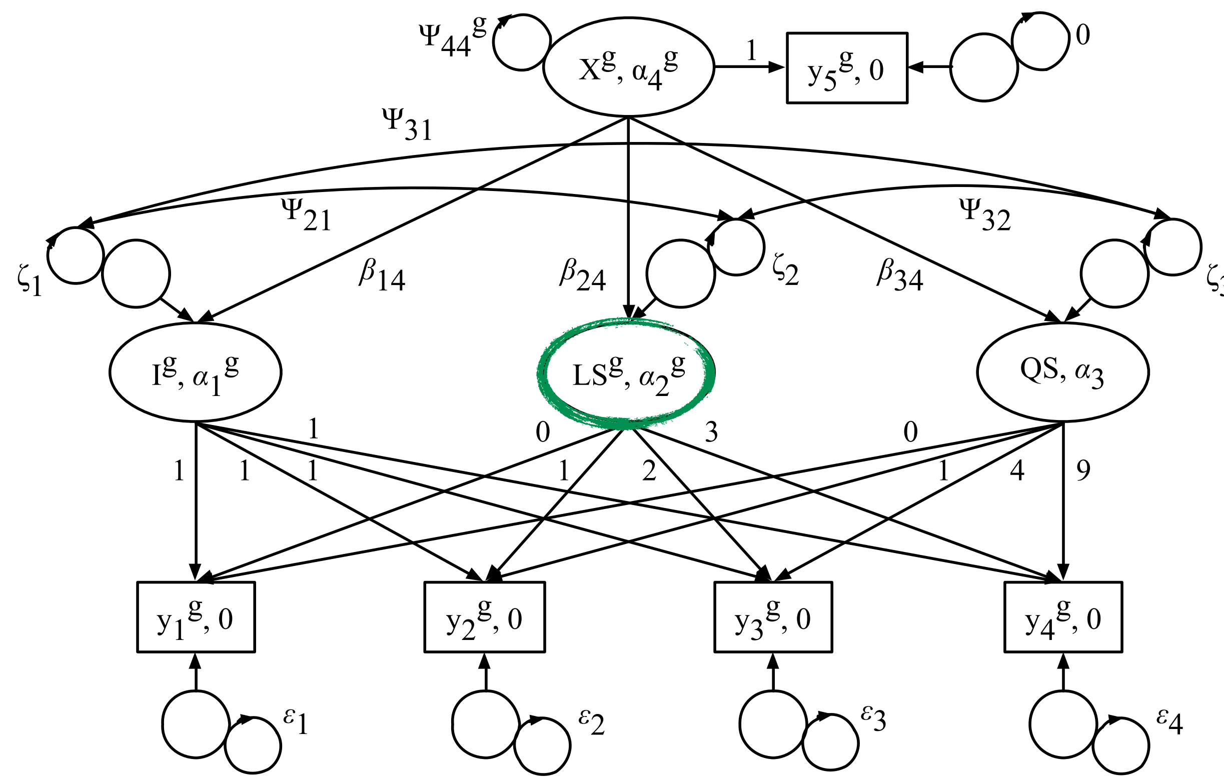


n exceptional group = 5, 10, 25, 50

Simulation design (1)

Focus

$\alpha_2^1 - \alpha_2^2 = \Delta\alpha_2$



Factors

- *n* exceptional group
- *n* reference group
- (ratio exceptional:reference)
- estimation method & settings

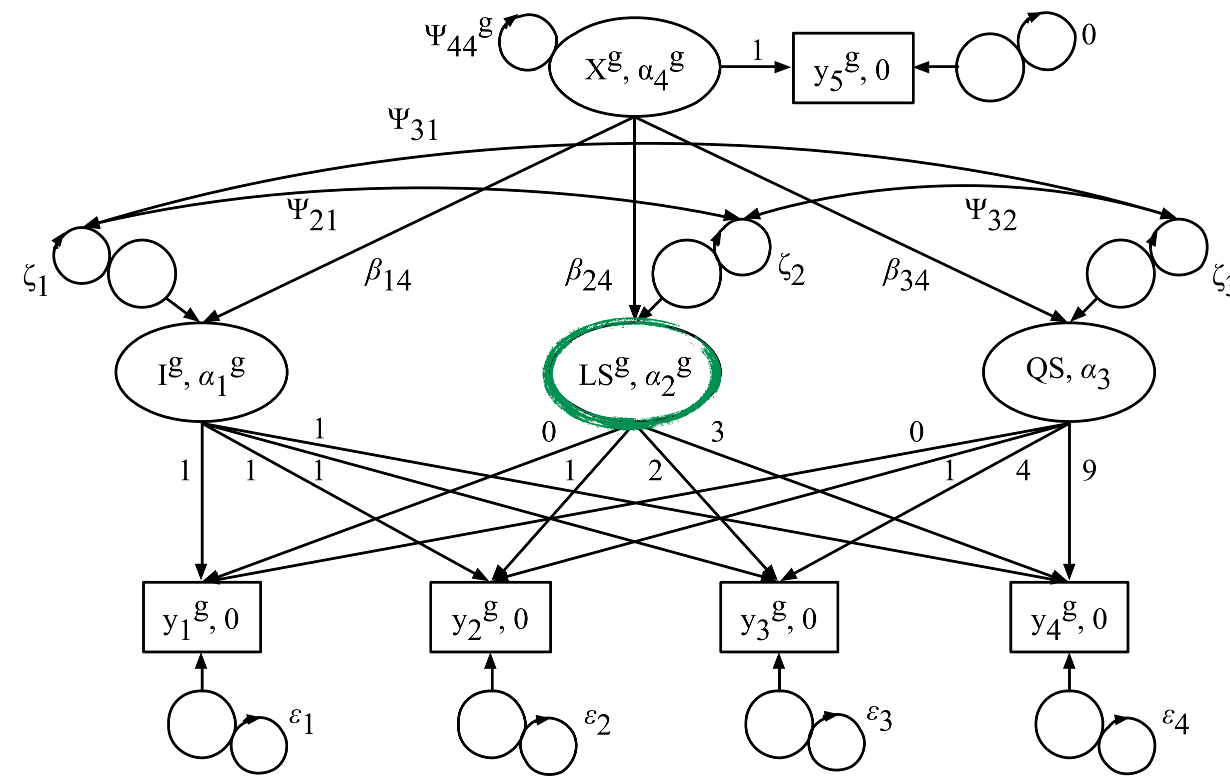
n exceptional group = 5, 10, 25, 50

n reference group = 50, 100, 200, 500, 1,000, 2,000, 5,000, 10,000

Simulation design (1)

Focus

$\alpha_2^1 - \alpha_2^2 = \Delta\alpha_2$



Factors

- *n* exceptional group
- *n* reference group
- (ratio exceptional:reference)
- estimation method & settings

n exceptional group	= 5, 10, 25, 50
n reference group	= 50, 100, 200, 500, 1,000, 2,000, 5,000, 10,000
ratio	= 1:1 - 1:2,000

Simulation design (2)

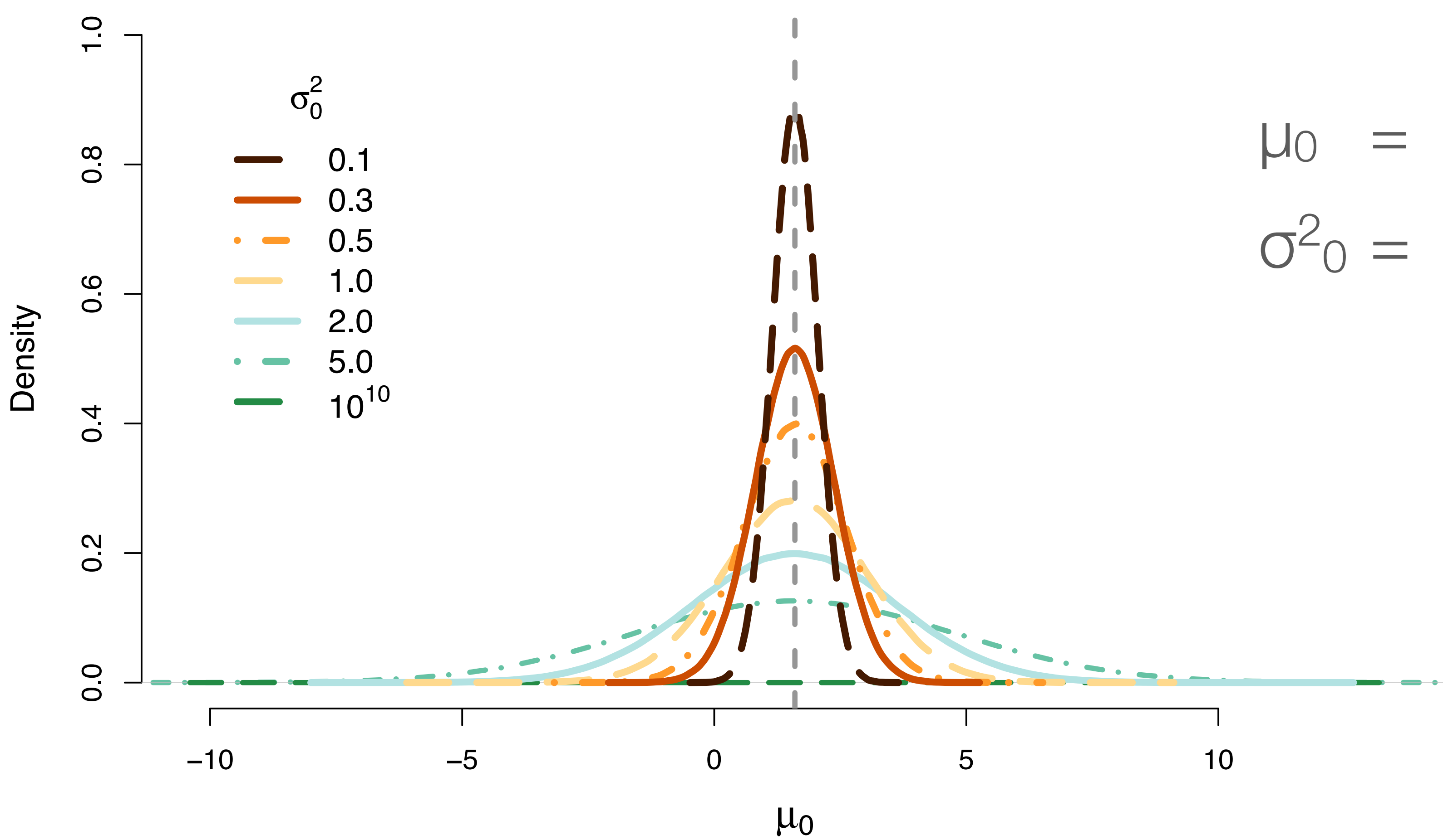
Estimation method and settings

- ML(R) estimation
- Bayes with default priors
- Bayes with informative priors on α_1^g, α_2^g, $\alpha_3 \sim N(\mu_0, \sigma^2_0)$

Simulation design (2)

Estimation method and settings

- ML(R) estimation
- Bayes with default priors
- Bayes with informative priors on α_1^g, α_2^g, $\alpha_3 \sim N(\mu_0, \sigma^2_0)$



μ_0 = population value

σ^2_0 = (10^{10}), 5, 2, 1, 0.5, 0.3, 0.1

Simulation design (3)

Cells

4 (exceptional group sample sizes)

x8 (reference group sample sizes) = 32 sample size settings

x8 (estimation settings) = 256 cells

- Mplus 7.11 (Muthén & Muthén, 1998-2012)
- R-package MplusAutomation (Hallquist, 2013)

Syntax data generation (32,000 data files)

```
[[init]]
iterators = nobsmin nobsmax;

nobsmin = 5 10 25 50;
nobsmax = 50 100 200 500 1000 2000 5000 10000;
filename = "[[nobsmin]]-[[nobsmax]].inp";

outputDirectory = "C:/Sim/S[[nobsmin]]/data";
[[/init]]
```

```
TITLE: Linear Growth MC

MONTECARLO:
NAMES = y1-y4 qft;
!y1-y4 = cognition, qft = alcohol use
count = qft;
generate = qft(c);
ngroups = 2;
nobs = [[nobsmax]] [[nobsmin]];

nreps = 1000;
seed = 4533;
repsave = all;
save = mc_[[nobsmin]]_[[nobsmax]]_*.dat;

ANALYSIS:
type = mixture;
algorithm = integration;

processors = 2;
```

```
MODEL POPULATION:
%OVERALL%

i s q | y1@0 y2@1 y3@2 y4@3;
i ON qft*-0.101;
s ON qft*-0.228;
q ON qft*0.131;

i with s*-53.669 q*12.342;
s with q*-14.052;

[qft*0.313];

[i*73.050 s*8.125 q*-2.161];
i*67.887; s*64 q*3.958;
y1*52.956 y2*64.049 y3*55.481 y4*19.390;

%g#1%

i s q | y1@0 y2@1 y3@2 y4@3;
i with s*-53.669 q*12.342;
s with q*-14.052;

[qft*0.313];

[i*73.050 s*8.125 q*-2.161];

%g#2%

i s q | y1@0 y2@1 y3@2 y4@3;
i with s*-53.669 q*12.342;
s with q*-14.052;

[qft*2.704];

[i*71.541 s*6.525 q*-2.161];

OUTPUT: TECH9;
```

Syntax data generation (32,000 data files)

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```

```
ATION:

0 y2@1 y3@2 y4@3;
.101;
.228;
131;

3.669 q*12.342;
4.052;

;

*8.125 q*-2.161];
*64 q*3.958;
y1*52.956 y2*64.049 y3*55.481 y4*19.390;

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g#1%

 s q | y1@0 y2@1 y3@2 y4@3;
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i*73.050 s*8.125 q*-2.161];

g#2%

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i with s*-53.669 q*12.342;
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```

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%g#1%

i s q | y1@0 y2@1 y3@2 y4@3;
i with s*-53.669 q*12.342;
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[qft*0.313];

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%g#2%

i s q | y1@0 y2@1 y3@2 y4@3;
i with s*-53.669 q*12.342;
s with q*-14.052;

[qft*2.704];

[i*71.541 s*6.525 q*-2.161];

OUTPUT: TECH9;
```

Syntax Bayesian analysis (224 input files)

```
[[init]]
iterators = nobsmin nobsmax prior;
nobsmin = 5 10 25 50;
nobsmax = 50 100 200 500 1000 2000 5000 10000;

prior = 10000000000 5 2 1 0.4 0.5 0.3 0.1;
filename = "bayes[[nobsmin]]prior[[prior]]-
[[nobsmax]].inp";

outputDirectory = "C:/Sim/S[[nobsmin]]/Bayes S/
bayesS[[nobsmin]]prior[[prior]]";
[[/init]]



TITLE: Linear Growth MC

DATA:
FILE = "C:/Sim/S[[nobsmin]]/Data/
mc_[[nobsmin]]_[[nobsmax]]_list.dat";
TYPE = MONTECARLO;
VARIABLE:
names = QFT Y1 Y2 Y3 Y4 G;
classes = cg(2);
knownclass is cg(g=1 g=2)

ANALYSIS: type = mixture;
ESTIMATOR = BAYES;
BCONVERGENCE = .05;
Chains=22;
Processors=22;

Biterations=(5000) 100000;
```

```
MODEL:
%OVERALL%
i s q | y1@0 y2@1 y3@2 y4@3;
i ON qft*-0.101;
s ON qft*-0.228;
q ON qft*0.131;

i with s*-53.669 q*12.342;
s with q*-14.052;

[qft*0.313]; qft;

[i*73.050 s*8.125 q*-2.161];
i*67.887; s*64 q*3.958;

y1*52.956 y2*64.049 y3*55.481 y4*19.390;

%cg#1%
i s q | y1@0 y2@1 y3@2 y4@3;
[qft*0.313]; qft;
[i*73.050 s*8.125 q*-2.161] (I1 S1 Qg);

%cg#2%
i s q | y1@0 y2@1 y3@2 y4@3;
[qft*2.704]; qft;
[i*71.541 s*6.525 q*-2.161] (I2 S2 Qg);

MODEL PRIORS:
I1~N(73.050,[[prior]]);
S1~N(8.125,[[prior]]);
I2~N(71.541,[[prior]]);
S2~N(6.525,[[prior]]);
Qg~N(-2.161,[[prior]]);

MODEL CONSTRAINT:
NEW(diff_s)*1.6;
diff_S = S1 - S2;
```

Syntax Bayesian analysis (224 input files)

```
[[init]]
iterators = nobsmin nobsmax prior;
nobsmin = 5 10 25 50;
nobsmax = 50 100 200 500 1000 2000 5000 10000;

prior = 10000000000 5 2 1 0.4 0.5 0.3 0.1;
filename = "bayes[[nobsmin]]prior[[prior]]-[[nobsmax]].inp";

outputDirectory = "C:/Sim/S[[nobsmin]]/Bayes S/bayesS[[nobsmin]]prior[[prior]]";
[[/init]]
```

```
DATA:
FILE = "C:/Sim/S[[nobsmin]]/Data/
mc_[[nobsmin]]_[[nobsmax]]_list.dat";
TYPE = MONTECARLO;
VARIABLE:
names = QFT Y1 Y2 Y3 Y4 G;
classes = cg(2);
knownclass is cg(g=1 g=2)

ANALYSIS: type = mixture;
ESTIMATOR = BAYES;
BCONVERGENCE = .05;
Chains=22;
Processors=22;

Biterations=(5000) 100000;
```

```
%cg#1%
i s q | y1@0 y2@1 y3@2 y4@3;
[qft*0.313]; qft;
[i*73.050 s*8.125 q*-2.161] (I1 S1 Qg);

%cg#2%
i s q | y1@0 y2@1 y3@2 y4@3;
[qft*2.704]; qft;
[i*71.541 s*6.525 q*-2.161] (I2 S2 Qg);

MODEL PRIORS:
I1~N(73.050,[[prior]]);
S1~N(8.125,[[prior]]);
I2~N(71.541,[[prior]]);
S2~N(6.525,[[prior]]);
Qg~N(-2.161,[[prior]]);

MODEL CONSTRAINT:
NEW(diff_s)*1.6;
diff_S = S1 - S2;
```

Syntax Bayesian analysis (224 input files)

```
[[init]]
iterators = nobsmin nobsmax prior;
nobsmin = 5 10 25 50;
nobsmax = 50 100 200 500 1000 2000 5000 10000;

prior = 10000000000 5 2 1 0.4 0.5 0.3 0.1;
filename = "bayes[[nobsmin]]prior[[prior]]-
[[nobsmax]].inp";

outputDirectory = "C:/Sim/S[[nobsmin]]/Bayes S/
bayesS[[nobsmin]]prior[[prior]]";
[[/init]]


TITLE: Linear Growth MC

DATA:
FILE = "C:/Sim/S[[nobsmin]]/Data/
mc_[[nobsmin]]_[[nobsmax]]_list.dat";
TYPE = MONTECARLO;
VARIABLE:
names = QFT Y1 Y2 Y3 Y4 G;
classes = cg(2);
knownclass is cg(g=1 g=2)

ANALYSIS: type = mixture;
ESTIMATOR = BAYES;
BCONVERGENCE = .05;
Chains=22;
Processors=22;

Biterations=(5000) 100000;
```

```
MODEL:
%OVERALL%
i s q | y1@0 y2@1 y3@2 y4@3;
i ON qft*-0.101;
s ON qft*-0.228;
q ON qft*0.131;

i with s*-53.669 q*12.342;
s with q*-14.052;

[qft*0.313]; qft;

[i*73.050 s*8.125 q*-2.161];
i*67.887; s*64 q*3.958;

y1*52.956 y2*64.049 y3*55.481 y4*19.390;

%cg#1%
i s q | y1@0 y2@1 y3@2 y4@3;
[qft*0.313]; qft;
[i*73.050 s*8.125 q*-2.161] (I1 S1 Qg);

%cg#2%
i s q | y1@0 y2@1 y3@2 y4@3;
[qft*2.704]; qft;
[i*71.541 s*6.525 q*-2.161] (I2 S2 Qg);

MODEL PRIORS:
I1~N(73.050,[[prior]]);
S1~N(8.125,[[prior]]);
I2~N(71.541,[[prior]]);
S2~N(6.525,[[prior]]);
Qg~N(-2.161,[[prior]]);

MODEL CONSTRAINT:
NEW(diff_s)*1.6;
diff_S = S1 - S2;
```

Syntax Bayesian analysis (224 input files)

```
[[init]]
iterators = nobsmin nobsmax prior;
nobsmin = 5 10 25 50;
nobsmax = 50 100 200 500 1000 2000 5000 10000;

prior = 10000000000 5 2 1 0.4 0.5 0.3 0.1;
filename = "bayes[[nobsmin]]prior[[prior]]-
[[nobsmax]].inp";

outputDirectory = "C:/Sim/S[[nobsmin]]/Bayes S/
bayesS[[nobsmin]]prior[[prior]]";
[[/init]]
TITLE: Linear Growth MC

DATA:
FILE = "C:/Sim/S[[nobsmin]]/Data/mc_[[nobsmin]]_[[nobsmax]]_list.dat";
TYPE = MONTECARLO;
VARIABLE:
names = QFT Y1 Y2 Y3 Y4 G;
classes = cg(2);
knownclass is cg(g=1 g=2)

ANALYSIS: type = mixture;

ESTIMATOR = BAYES;
BCONVERGENCE = .05;
Chains=22;
Processors=22;
Biterations=(5000) 100000;
```

```
MODEL:
%OVERALL%
i s q | y1@0 y2@1 y3@2 y4@3;
i ON qft*-0.101;
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q ON qft*0.131;

i with s*-53.669 q*12.342;
s with q*-14.052;

[qft*0.313]; qft;
```

Syntax Bayesian analysis (224 input files)

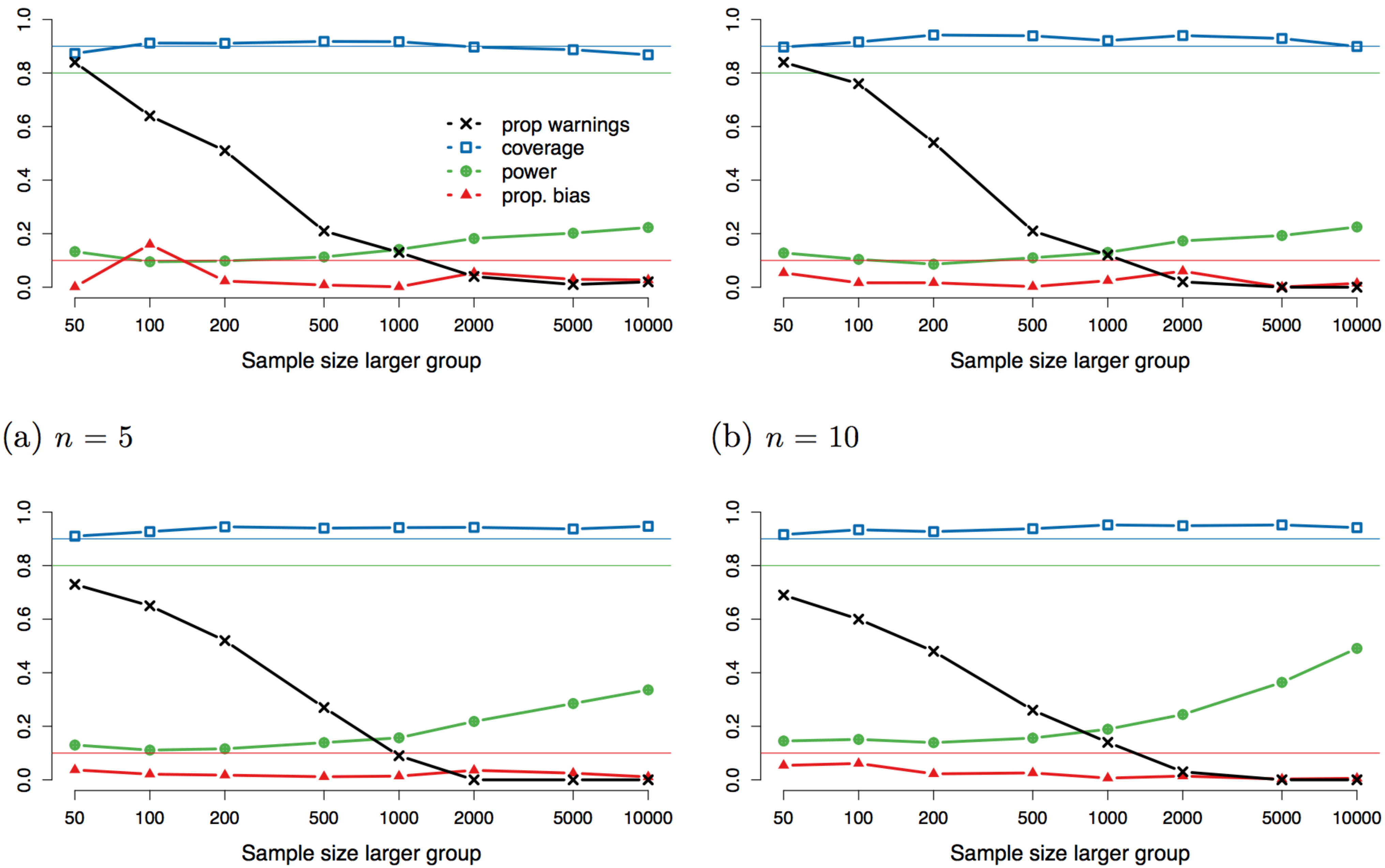
```
MODEL:
%OVERALL%
i s q | y1@0 y2@1 y3@2 y4@3;
i ON qft*-0.101;
s ON qft*-0.228;
q ON qft*0.131;

i with s*-53.669 q*12.342;
s with q*-14.052;

[qft*0.313]; qft;

[i*73.050 s*8.125 q*-2.161];
i*67.887; s*64 q*3.958;

y1*52.956 y2*64.049 y3*55.481 y4*19.390;


%cg#1%
i s q | y1@0 y2@1 y3@2 y4@3;
[qft*0.313]; qft;
[i*73.050 s*8.125 q*-2.161] (I1 S1 Qg);
```

```
%cg#2%
i s q | y1@0 y2@1 y3@2 y4@3;
[qft*2.704]; qft;
[i*71.541 s*6.525 q*-2.161] (I2 S2 Qg);


MODEL PRIORS:
I1~N(73.050,[[prior]]);
S1~N(8.125,[[prior]]);
I2~N(71.541,[[prior]]);
S2~N(6.525,[[prior]]);
Qg~N(-2.161,[[prior]]);


MODEL CONSTRAINT:
NEW(diff_s)*1.6;
diff_S = S1 - S2;
```

Simulation evaluation

- Relative bias (≤ .10)
  ($\Delta\alpha_{2\_pop}$ - $\Delta\alpha_{2\_est}$) / $\Delta\alpha_{2\_pop}$
- Coverage (≥ .90)
  % $\Delta\alpha_{2\_pop}$ in 95% interval of $\Delta\alpha_{2\_est}$
- Power to detect a small effect (≥ .80)
  % statistically sign. $\Delta\alpha_{2\_est}$
- Estimation problems (≈ 0)
  proportion of warnings, problems with convergence

Results ML estimation



(a) $n = 5$

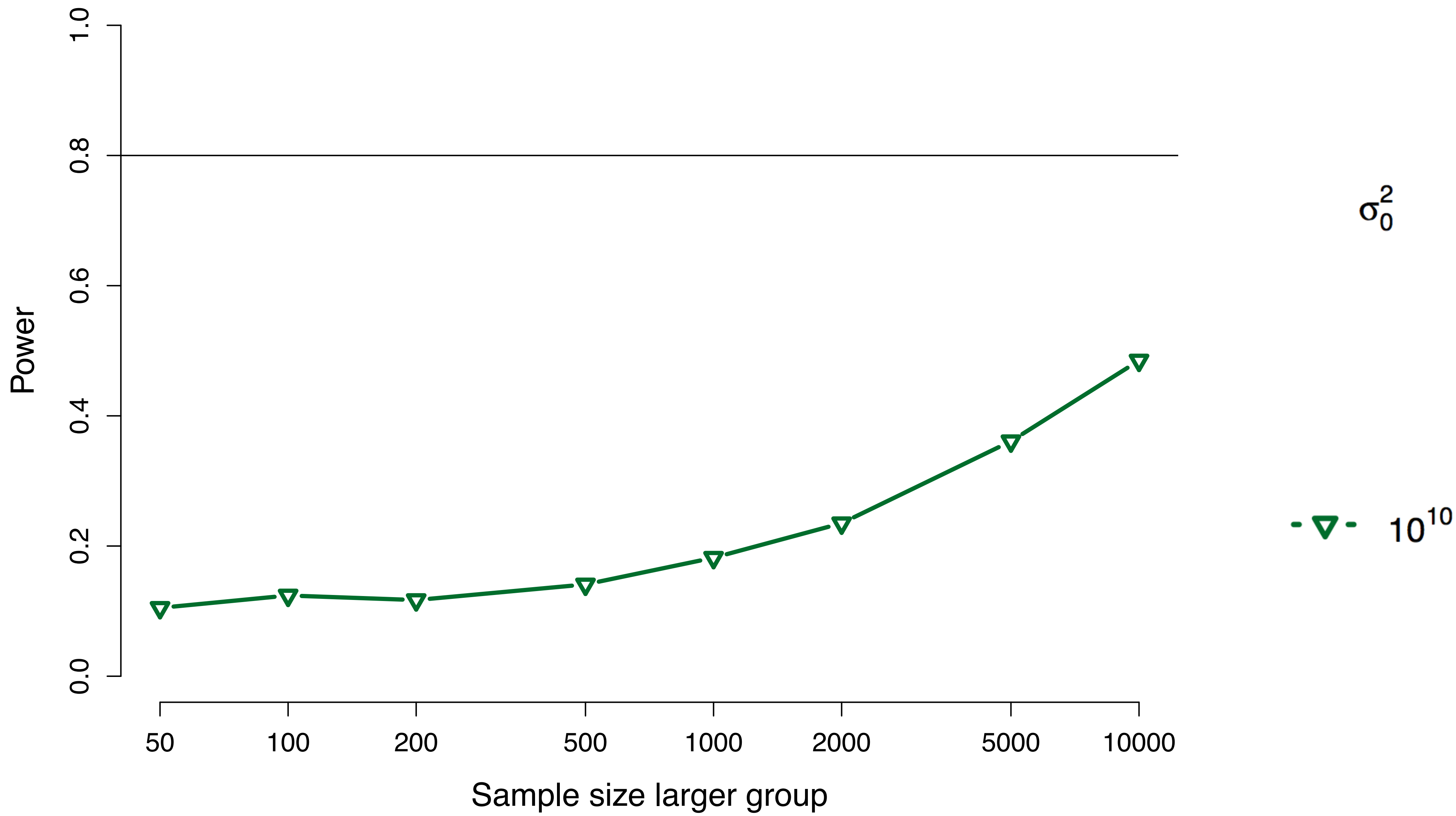
(b) $n = 10$

(c) $n = 25$

(d) $n = 50$

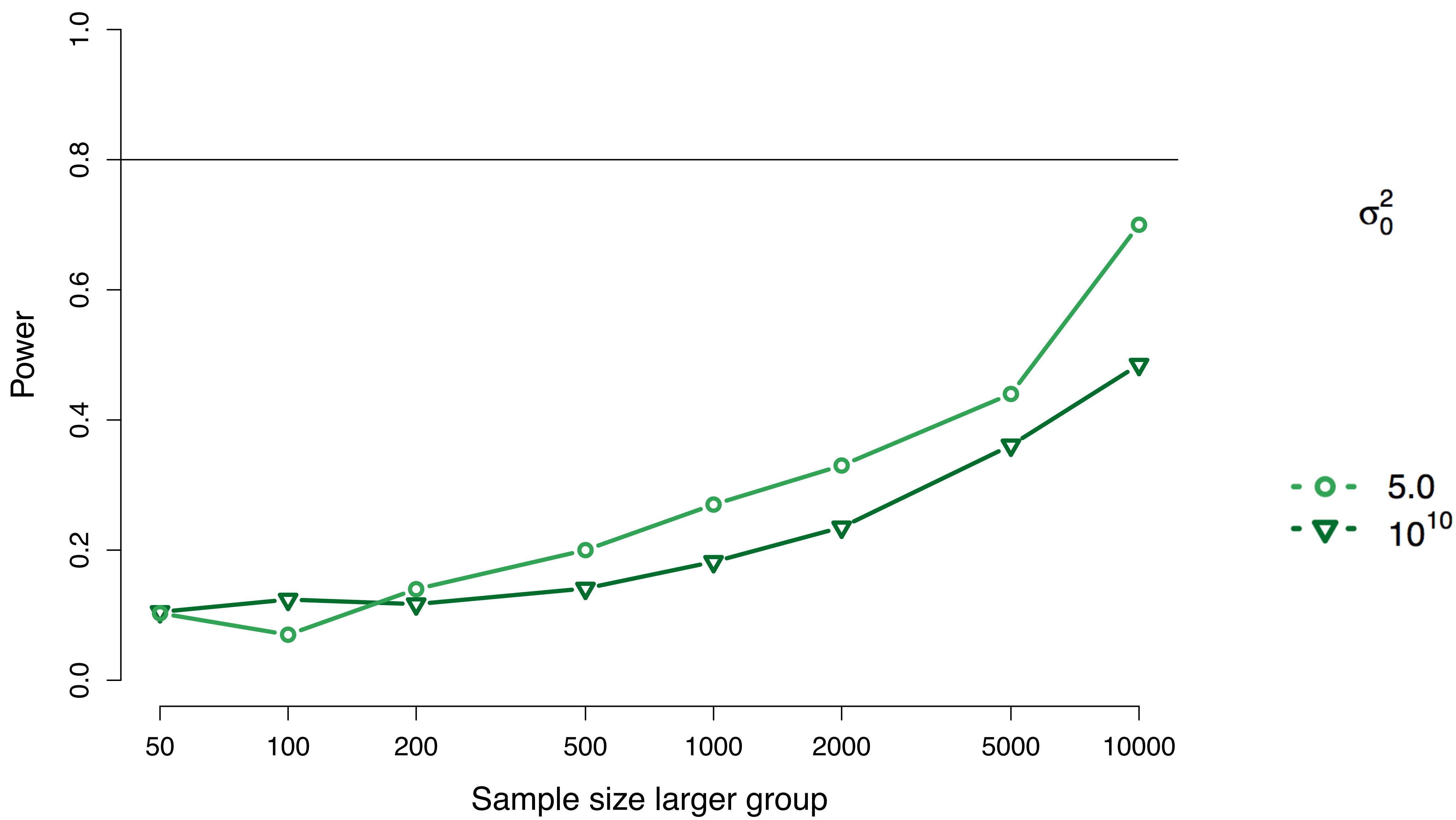
Figure 1. Results for ML estimation by exceptional group sample size.

Results Bayesian estimation



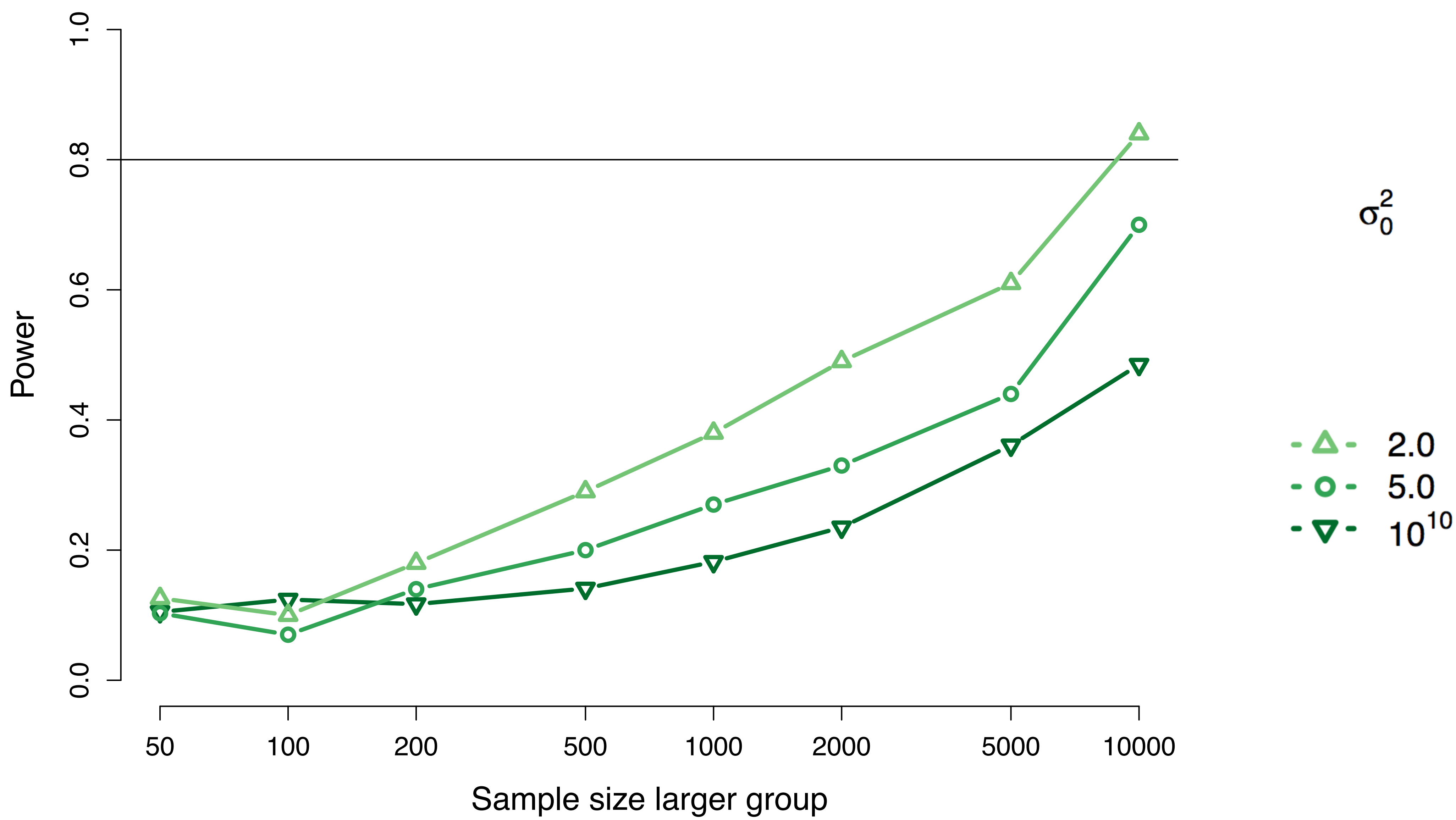
(d) $n = 50$

Results Bayesian estimation



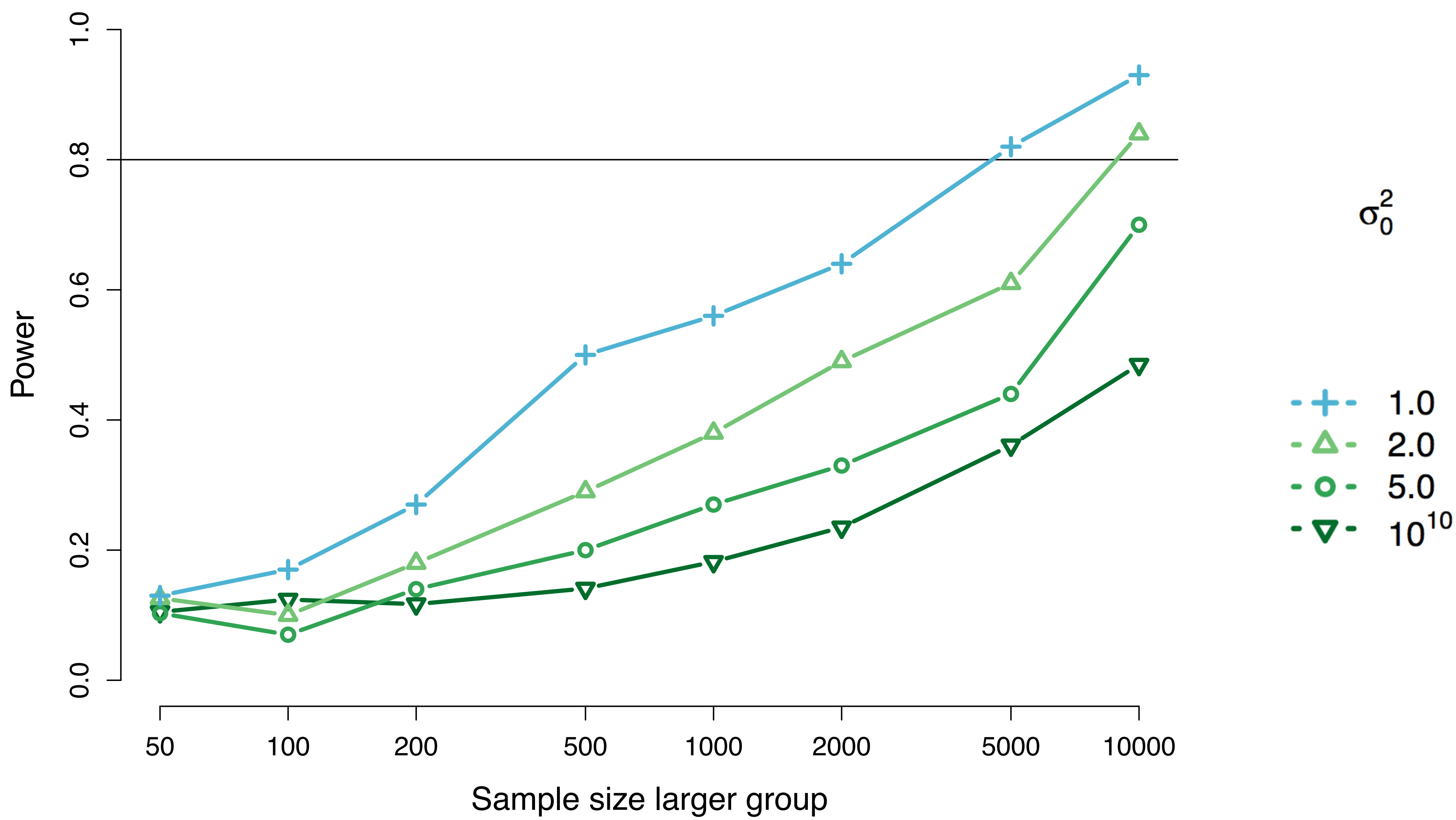
(d) $n = 50$

Results Bayesian estimation



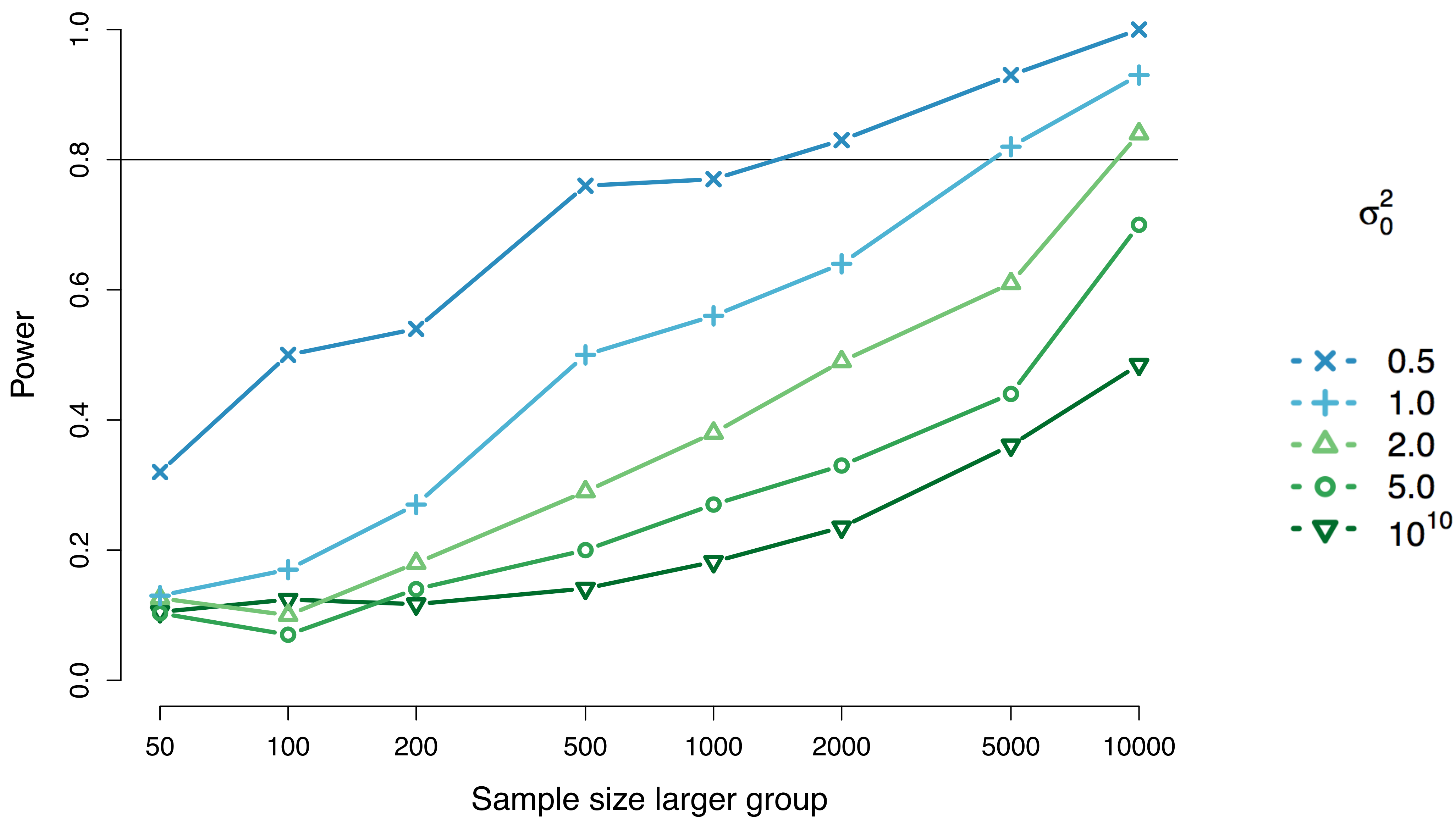
(d) $n = 50$

Results Bayesian estimation



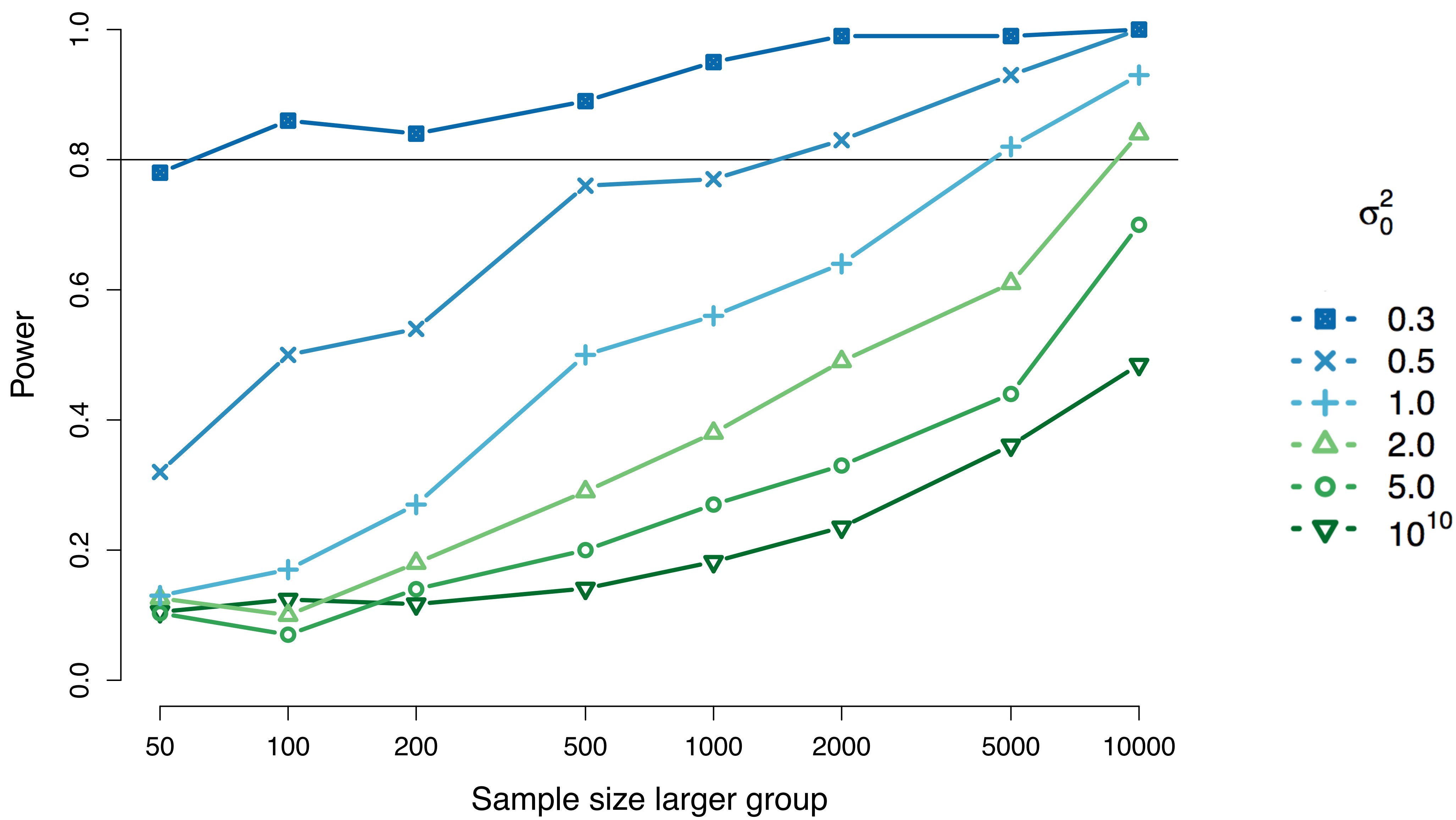
(d) $n = 50$

Results Bayesian estimation



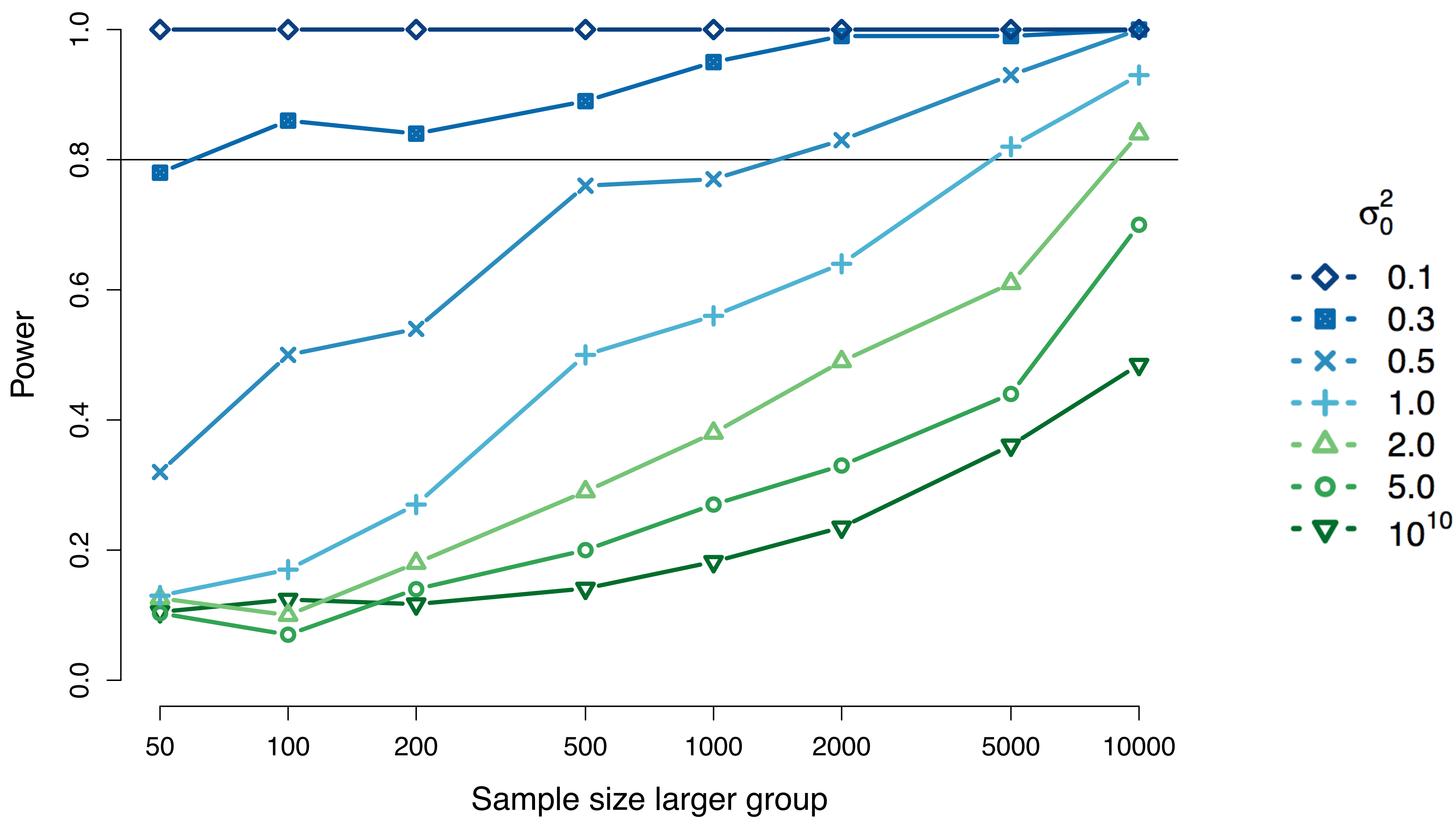
(d) $n = 50$

Results Bayesian estimation



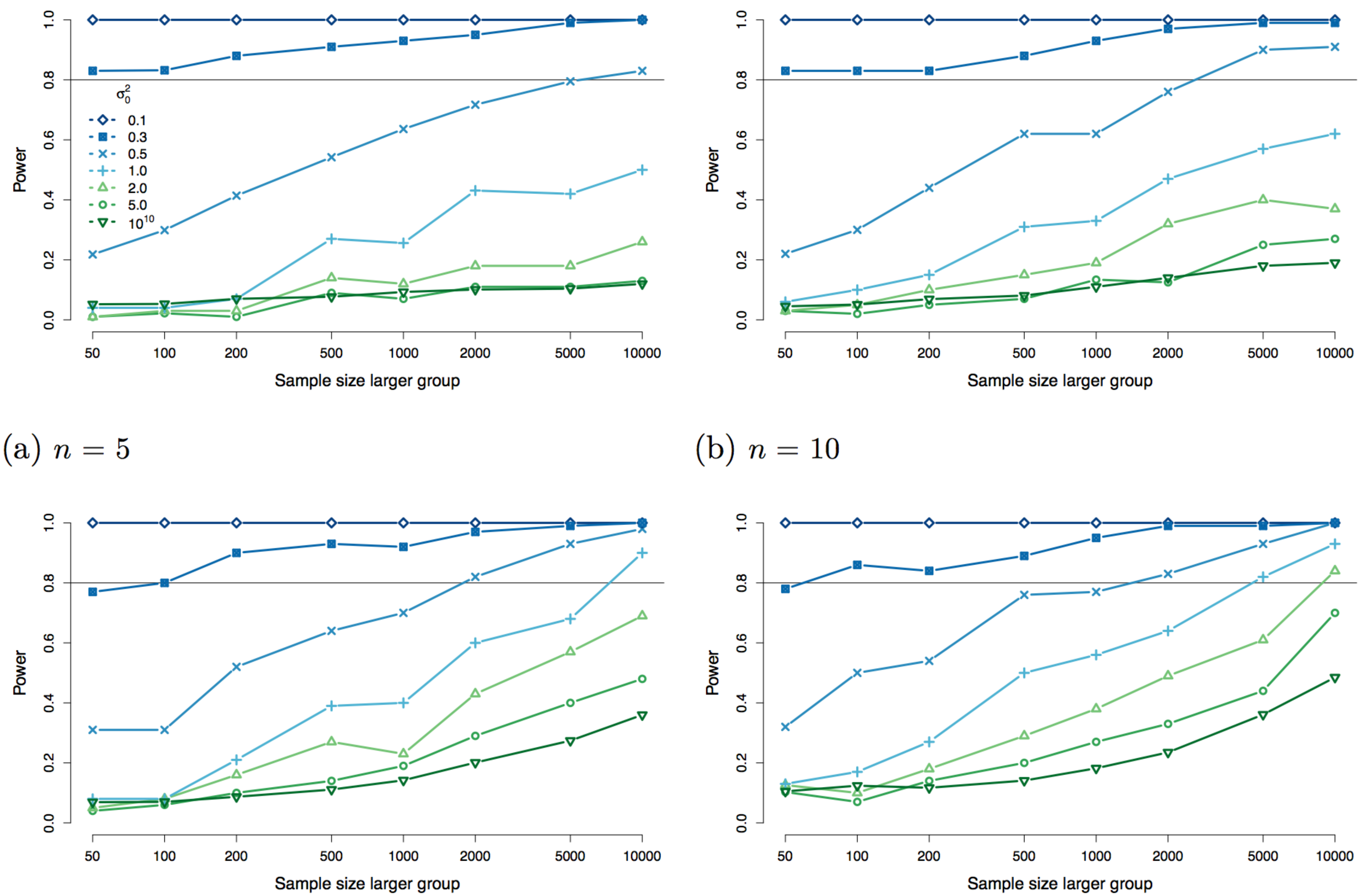
(d) $n = 50$

Results Bayesian estimation



(d) $n = 50$

Results Bayesian estimation



(a) $n = 5$ (b) $n = 10$

(c) $n = 25$ (d) $n = 50$

Figure 2. Power for Bayesian estimation by exceptional group sample size.

Overview & Conclusion

- ML
  bias: ✓, coverage: ✓, estimation issues: ✗, power: ✗

Overview & Conclusion

- ML
  bias: ✓, coverage: ✓, estimation issues: ✗, power: ✗

- Bayes default
  bias: ✓, coverage: ✓, estimation issues: ✓, power: ✗

Overview & Conclusion

- ML
  bias: ✓, coverage: ✓, estimation issues: ✗, power: ✗
- Bayes default
  bias: ✓, coverage: ✓, estimation issues: ✓, power: ✗
- Bayes informative
  bias: ✓, coverage: ✓, estimation issues: ✓, power: ✓

To be continued

Is it that easy?

Reference
Zondervan-Zwijnenburg, M. A. J., Peeters, M., Vollebergh, W. A. M., Van de Schoot, R. (2014). Pushing the limits: Sample size requirements with unbalanced subgroups in latent growth models. Unpublished master's thesis. Utrecht University, The Netherlands.

To be continued

Is it that easy?

➜ Friday 12:05 am, Ruppert Rood

Reference
Zondervan-Zwijnenburg, M. A. J., Peeters, M., Vollebergh, W. A. M., Van de Schoot, R. (2014). Pushing the limits: Sample size requirements with unbalanced subgroups in latent growth models. Unpublished master's thesis. Utrecht University, The Netherlands.

To be continued

Is it that easy?

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Questions

Reference
Zondervan-Zwijnenburg, M. A. J., Peeters, M., Vollebergh, W. A. M., Van de Schoot, R. (2014). Pushing the limits: Sample size requirements with unbalanced subgroups in latent growth models. Unpublished master's thesis. Utrecht University, The Netherlands.