

Common and Unique Latent Transition Analysis (CULTA) as a Way to Examine the Trait-State Dynamics of Alcohol Intoxication (Supplementary Materials)

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ADD YOUR GRANTS HERE...

Computations for this research were performed on the Pennsylvania State University's Institute for Computational and Data Sciences' Roar supercomputer using SLURM for job scheduling (Yoo et al., 2003), GNU Parallel to run the simulations in parallel (Tange, 2021), and Apptainer to ensure a reproducible software stack (Kurtzer et al., 2017, 2021).

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Links

Research Compendium

The data and materials for this study are available on OSF (<https://osf.io/gtdmr>) and GitHub (<https://github.com/jeksterslab/manCULTA>, <https://jeksterslab.github.io/manCULTA/index.html>).

Data Simulation and Model Fitting

<https://jeksterslab.github.io/manCULTA/articles/sim-culta-2-profiles.html>

Comparison of Misspecified and Correctly Specified Models

- One-Profile CULTA vs. Two-Profile CULTA:

<https://jeksterslab.github.io/manCULTA/articles/sim-culta-1-profile.html>

- Two-Profile LTA vs. Two-Profile CULTA:

<https://jeksterslab.github.io/manCULTA/articles/sim-lta-2-profiles.html>

- Two-Profile RI-LTA vs. Two-Profile CULTA:

<https://jeksterslab.github.io/manCULTA/articles/sim-ri-lta-2-profiles.html>

Generating Mplus Input Files

<https://jeksterslab.github.io/manCULTA/articles/sim-input.html>

Containers for Reproducibility

<https://jeksterslab.github.io/manCULTA/articles/containers.html>

Mplus Input File for the Empirical Data Analysis**Final Model**

TITLE:

2-Profile CULTA with Covariate (Final);

DATA:

FILE = __DATA__;

VARIABLE:

NAMES =

id x
y1t0 y2t0 y3t0 y4t0 y1t1 y2t1 y3t1 y4t1
y1t2 y2t2 y3t2 y4t2 y1t3 y2t3 y3t3 y4t3
y1t4 y2t4 y3t4 y4t4 y1t5 y2t5 y3t5 y4t5

;

USEVARIABLES =

x
y1t0 y2t0 y3t0 y4t0 y1t1 y2t1 y3t1 y4t1
y1t2 y2t2 y3t2 y4t2 y1t3 y2t3 y3t3 y4t3
y1t4 y2t4 y3t4 y4t4 y1t5 y2t5 y3t5 y4t5

;

IDVARIABLE = id;

CLASSES = c0(2) c1(2) c2(2) c3(2) c4(2) c5(2);

MISSING = .;

DEFINE:

STANDARDIZE

y1t0 y2t0 y3t0 y4t0 y1t1 y2t1 y3t1 y4t1
y1t2 y2t2 y3t2 y4t2 y1t3 y2t3 y3t3 y4t3
y1t4 y2t4 y3t4 y4t4 y1t5 y2t5 y3t5 y4t5
;

ANALYSIS:

```
TYPE = MIXTURE;
STARTS = 1000 500;
STSCALE = 2;
STITERATIONS = 200;
PROCESS = __CORES__;
MODEL = NOCOV;
```

MODEL:

```
%OVERALL%
! unique traits -----
!! factor loadings
!!! k = 3
u3 BY y3t0@1;
u3 BY y3t1@1;
u3 BY y3t2@1;
u3 BY y3t3@1;
u3 BY y3t4@1;
u3 BY y3t5@1;
!!! k = 4
u4 BY y4t0@1;
u4 BY y4t1@1;
u4 BY y4t2@1;
u4 BY y4t3@1;
u4 BY y4t4@1;
u4 BY y4t5@1;

!! latent means
[ u3@0 ];
[ u4@0 ];
```

```
!! latent variances
u3 (psip3);
u4 (psip4);

! common states -----
!! factor loadings
!!! t = 0
s0 BY y1t0@1;
s0 BY y2t0 (lambdas2);
s0 BY y3t0 (lambdas3);
s0 BY y4t0 (lambdas4);

!!! t = 1
s1 BY y1t1@1;
s1 BY y2t1 (lambdas2);
s1 BY y3t1 (lambdas3);
s1 BY y4t1 (lambdas4);

!!! t = 2
s2 BY y1t2@1;
s2 BY y2t2 (lambdas2);
s2 BY y3t2 (lambdas3);
s2 BY y4t2 (lambdas4);

!!! t = 3
s3 BY y1t3@1;
s3 BY y2t3 (lambdas2);
s3 BY y3t3 (lambdas3);
s3 BY y4t3 (lambdas4);

!!! t = 4
s4 BY y1t4@1;
s4 BY y2t4 (lambdas2);
s4 BY y3t4 (lambdas3);
s4 BY y4t4 (lambdas4);
```

```
!!! t = 5
s5 BY y1t5@1;
s5 BY y2t5 (lambdas2);
s5 BY y3t5 (lambdas3);
s5 BY y4t5 (lambdas4);

!! latent means
[ s0@0 ];
[ s1@0 ];
[ s2@0 ];
[ s3@0 ];
[ s4@0 ];
[ s5@0 ];

!! latent variance of s0
s0 (psis0);

!! variance of the process noise
s1 (psis);
s2 (psis);
s3 (psis);
s4 (psis);
s5 (psis);

! unique states -----
!! variances
!!! t = 0
y1t0 (theta11);
y2t0 (theta22);
y3t0 (theta33);
y4t0 (theta44);
```

```
!!! t = 1
y1t1 (theta11);
y2t1 (theta22);
y3t1 (theta33);
y4t1 (theta44);

!!! t = 2
y1t2 (theta11);
y2t2 (theta22);
y3t2 (theta33);
y4t2 (theta44);

!!! t = 3
y1t3 (theta11);
y2t3 (theta22);
y3t3 (theta33);
y4t3 (theta44);

!!! t = 4
y1t4 (theta11);
y2t4 (theta22);
y3t4 (theta33);
y4t4 (theta44);

!!! t = 5
y1t5 (theta11);
y2t5 (theta22);
y3t5 (theta33);
y4t5 (theta44);

! constrained intercepts -----
!! t = 0
[ y1t0@0 ];
[ y2t0@0 ];
[ y3t0@0 ];
```

```
[ y4t000 ];
!! t = 1
[ y1t100 ];
[ y2t100 ];
[ y3t100 ];
[ y4t100 ];
!! t = 2
[ y1t200 ];
[ y2t200 ];
[ y3t200 ];
[ y4t200 ];
!! t = 3
[ y1t300 ];
[ y2t300 ];
[ y3t300 ];
[ y4t300 ];
!! t = 4
[ y1t400 ];
[ y2t400 ];
[ y3t400 ];
[ y4t400 ];
!! t = 5
[ y1t500 ];
[ y2t500 ];
[ y3t500 ];
[ y4t500 ];

! lta -----
!! initial profile membership
[ c0#1 ] (nu0);
c0#1 ON x (kappa0);
```

```
!! profile transitions
[ c1#1 ] (alpha0);
[ c2#1 ] (alpha0);
[ c3#1 ] (alpha0);
[ c4#1 ] (alpha0);
[ c5#1 ] (alpha0);
c1#1 ON c0#1 (beta00);
c2#1 ON c1#1 (beta00);
c3#1 ON c2#1 (beta00);
c4#1 ON c3#1 (beta00);
c5#1 ON c4#1 (beta00);

MODEL c0:
%c0#1%
    ! profile specific means
    [ y1t0 ] (mu10);
    [ y2t0 ] (mu20);
    [ y3t0 ] (mu30);
    [ y4t0 ] (mu40);

    ! covariate
    c1 ON x (gamma00);

%c0#2%
    ! profile specific means
    [ y1t0 ] (mu11);
    [ y2t0 ] (mu21);
    [ y3t0 ] (mu31);
    [ y4t0 ] (mu41);

    ! covariate
    c1 ON x (gamma10);
```

```
MODEL c1:  
%c1#1%  
  ! profile specific means  
  [ y1t1 ] (mu10);  
  [ y2t1 ] (mu20);  
  [ y3t1 ] (mu30);  
  [ y4t1 ] (mu40);
```

```
  ! covariate  
c2 ON x (gamma00);
```

```
  ! inertia  
s1 ON s0@0 (phi0);
```

```
%c1#2%  
  ! profile specific means  
  [ y1t1 ] (mu11);  
  [ y2t1 ] (mu21);  
  [ y3t1 ] (mu31);  
  [ y4t1 ] (mu41);
```

```
  ! covariate  
c2 ON x (gamma10);
```

```
  ! inertia  
s1 ON s0 (phi1);
```

```
MODEL c2:
```

```
%c2#1%  
  ! profile specific means  
  [ y1t2 ] (mu10);  
  [ y2t2 ] (mu20);
```

```
[ y3t2 ] (mu30);
[ y4t2 ] (mu40);

! covariate
c3 ON x (gamma00);

! inertia
s2 ON s1@0 (phi0);

%c2#2%
! profile specific means
[ y1t2 ] (mu11);
[ y2t2 ] (mu21);
[ y3t2 ] (mu31);
[ y4t2 ] (mu41);

! covariate
c3 ON x (gamma10);

! inertia
s2 ON s1 (phi1);

MODEL c3:
%c3#1%
! profile specific means
[ y1t3 ] (mu10);
[ y2t3 ] (mu20);
[ y3t3 ] (mu30);
[ y4t3 ] (mu40);

! covariate
c4 ON x (gamma00);
```

```
! inertia
s3 ON s2@0 (phi0);

%c3#2%
! profile specific means
[ y1t3 ] (mu11);
[ y2t3 ] (mu21);
[ y3t3 ] (mu31);
[ y4t3 ] (mu41);

! covariate
c4 ON x (gamma10);

! inertia
s3 ON s2 (phi1);

MODEL c4:
%c4#1%
! profile specific means
[ y1t4 ] (mu10);
[ y2t4 ] (mu20);
[ y3t4 ] (mu30);
[ y4t4 ] (mu40);

! covariate
c5 ON x (gamma00);

! inertia
s4 ON s3@0 (phi0);

%c4#2%
! profile specific means
```

```
[ y1t4 ] (mu11);
[ y2t4 ] (mu21);
[ y3t4 ] (mu31);
[ y4t4 ] (mu41);

! covariate
c5 ON x (gamma10);

! inertia
s4 ON s3 (phi1);

MODEL c5:
%c5#1%
  ! profile specific means
  [ y1t5 ] (mu10);
  [ y2t5 ] (mu20);
  [ y3t5 ] (mu30);
  [ y4t5 ] (mu40);

  ! inertia
  s5 ON s4@0 (phi0);

%c5#2%
  ! profile specific means
  [ y1t5 ] (mu11);
  [ y2t5 ] (mu21);
  [ y3t5 ] (mu31);
  [ y4t5 ] (mu41);

  ! inertia
  s5 ON s4 (phi1);
```

MODEL CONSTRAINT:

```
! means for the first profile are higher than the second  
mu10 > mu11;  
mu20 > mu21;  
mu30 > mu31;  
mu40 > mu41;  
  
! make sure variances are greater than zero  
psip3 > 0;  
psip4 > 0;  
psis0 > 0;  
psis > 0;  
theta11 > 0;  
theta22 > 0;  
theta33 > 0;  
theta44 > 0;
```

OUTPUT:

```
TECH1 TECH3 TECH4 TECH7 TECH8 TECH12 TECH15 ENTROPY;
```

SAVEDATA:

```
ESTIMATES = __ESTIMATES__;  
RESULTS = __RESULTS__;  
TECH3 = __TECH3__;  
TECH4 = __TECH4__;  
FILE = __CPROB__;  
SAVE = CPROBABILITIES;
```

Monte Carlo Simulation to Evaluate the CULTA Model

The Monte Carlo simulation evaluated the recovery of parameters from the Common and Unique Latent Transition Analysis (CULTA) model under five sample sizes: $N = 100, 200, 300, 400$, and 500 . The CULTA model was compared to two alternative models: standard Latent Transition Analysis (LTA) and Random-Intercept Latent Transition Analysis (RILTA). Model performance was assessed using several evaluation metrics. Figure 1 shows information criteria (AIC, BIC, and aBIC), while Figure 2 presents entropy values as indicators of classification quality. Parameter recovery was evaluated in terms of relative bias (Figure 3), root mean square error (RMSE; Figure 4), coverage probability of 95% confidence intervals (Figure 5), and statistical power (Figure 6). In addition, for parameters common across all models, we compared CULTA, LTA, and RILTA in terms of relative bias (Figure 7), RMSE (Figure 8), coverage (Figure 9), and power (Figure 10).

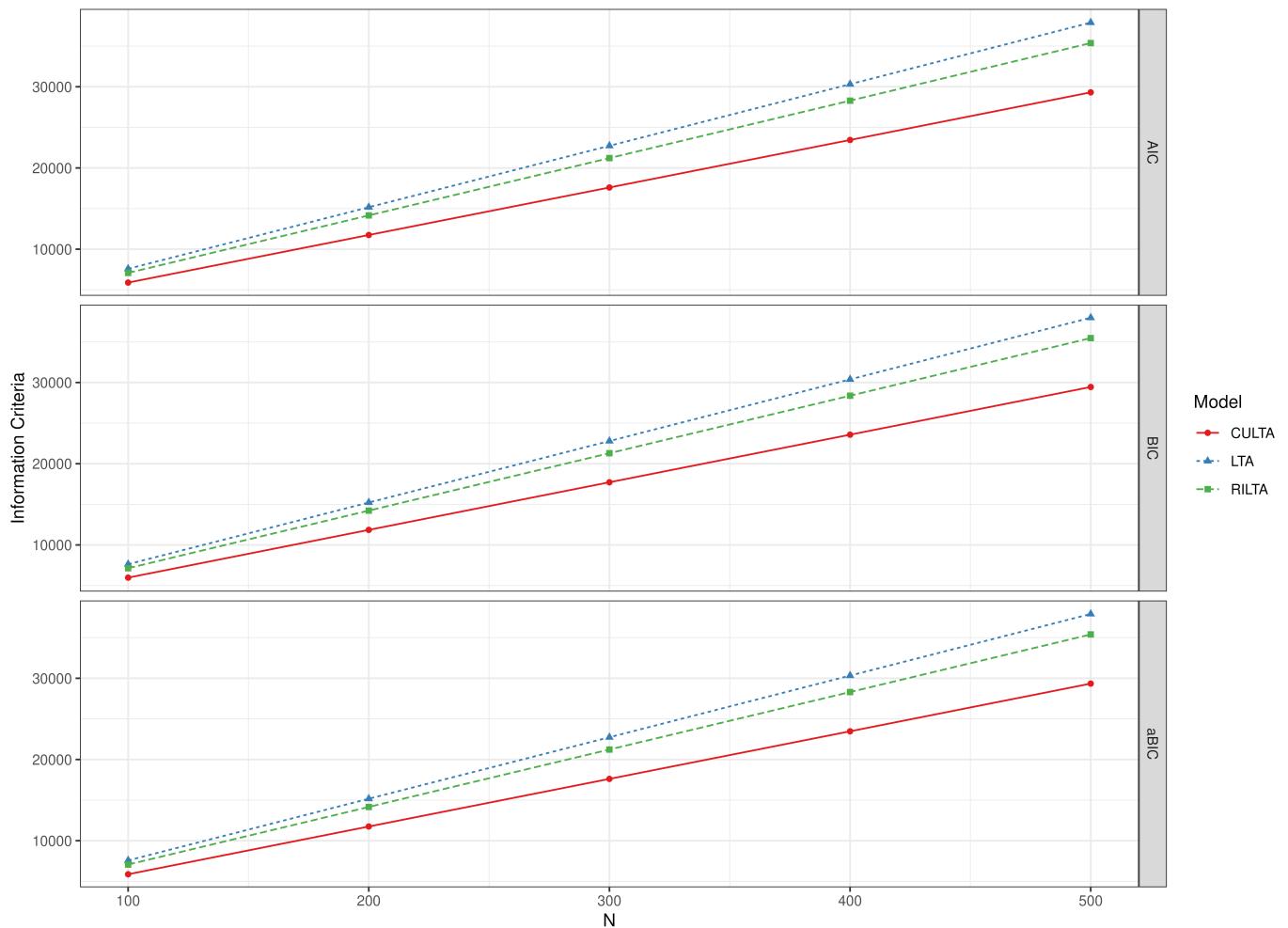
Table 1
CULTA Parameters

No.	Symbol	Description
1	ϕ_0	Autoregressive coefficient for profile 0.
2	ϕ_1	Autoregressive coefficient for profile 1.
3	ψ_T	Variance in the common trait; reflects stable between-person differences.
4	$\lambda_{T_{rise}}$	Factor loading for the common trait and item 2.
5	$\lambda_{T_{fall}}$	Factor loading for the common trait and item 3.
6	$\lambda_{T_{dura}}$	Factor loading for the common trait and item 4.
7	ψ_{peak}	Trait-specific item 1 variance.
8	ψ_{rise}	Trait-specific item 2 variance.
9	ψ_{fall}	Trait-specific item 3 variance.
10	ψ_{dura}	Trait-specific item 4 variance.
11	$\psi_{S_{t0}}$	Initial-day variance of the common state.
12	ψ_S	Residual state variance over days.
13	$\lambda_{S_{rise}}$	Factor loading for the common state and item 2.
14	$\lambda_{S_{fall}}$	Factor loading for the common state and item 3.
15	$\lambda_{S_{dura}}$	Factor loading for the common state and item 4.
16	θ_{peak}	Unique state variance for item 1.
17	θ_{rise}	Unique state variance for item 2.
18	θ_{fall}	Unique state variance for item 3.
19	θ_{dura}	Unique state variance for item 4.
20	ν_0	Intercept for initial log-odds of profile 0 (vs. profile 1) when $X = 0$.
21	κ_0	Covariate effect on initial profile membership; higher X increases odds of profile 0.
22	α_0	Baseline log-odds of being in profile 0 across days.
23	β_{00}	Increased odds of staying in profile 0 if previously in that profile; reflects persistence.
24	γ_{00}	Covariate effect on staying in profile 0; higher X increases persistence.
25	γ_{10}	Covariate effect on switching from state to profile 0; higher X increases transition odds.
26	μ_{peak_0}	Profile specific mean for profile 0 and item 1.
27	μ_{rise_0}	Profile specific mean for profile 0 and item 2.
28	μ_{fall_0}	Profile specific mean for profile 0 and item 3.
29	μ_{dura_0}	Profile specific mean for profile 0 and item 4.
30	μ_{peak_1}	Profile specific mean for profile 1 and item 1.
31	μ_{rise_1}	Profile specific mean for profile 1 and item 2.
32	μ_{fall_1}	Profile specific mean for profile 1 and item 3.
33	μ_{dura_1}	Profile specific mean for profile 1 and item 4.

Table 2
Parameters Common to CULTA, LTA, and RILTA

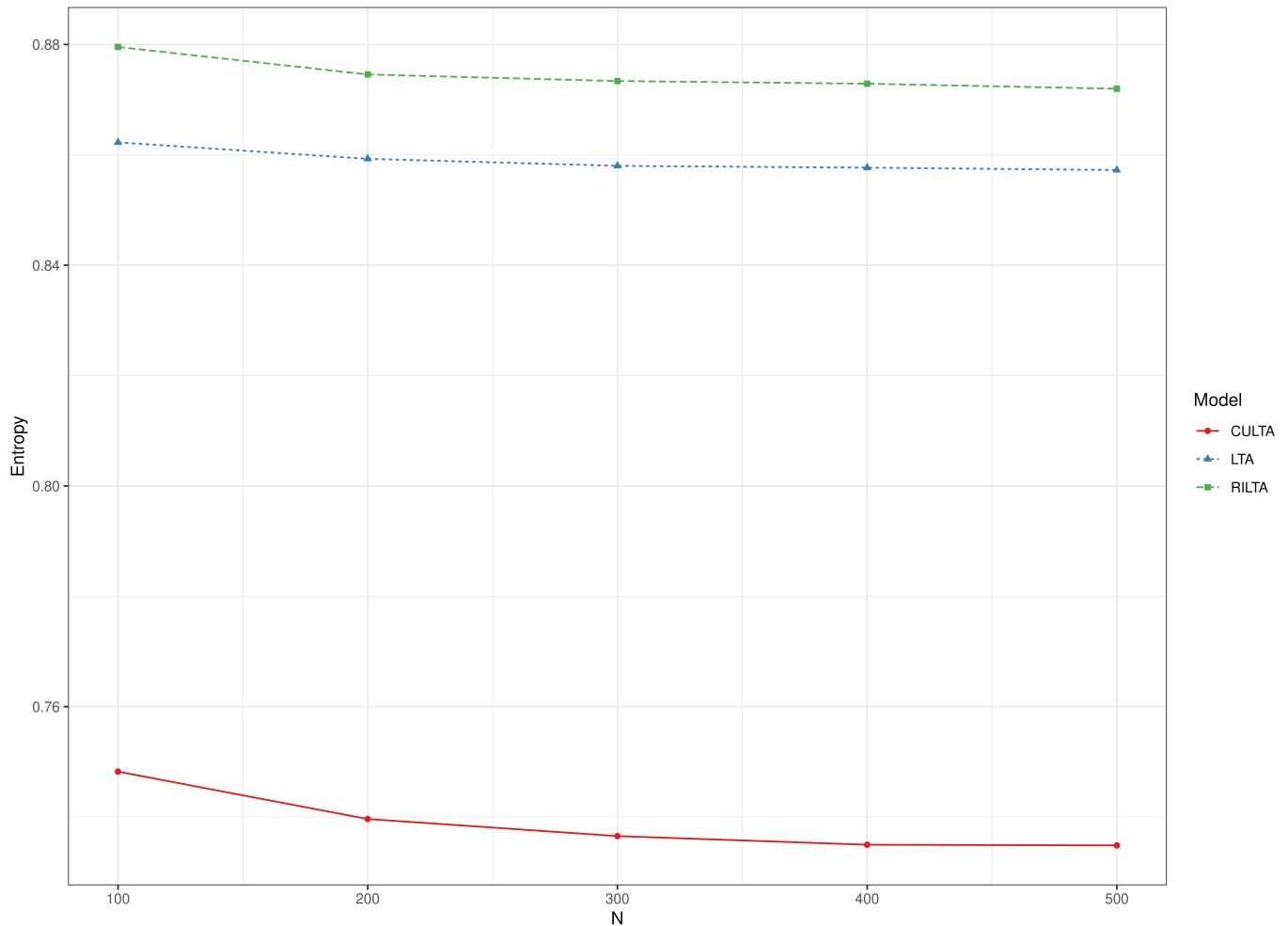
No.	Symbol	Description
1	θ_{peak}	Unique state variance for item 1.
2	θ_{rise}	Unique state variance for item 2.
3	θ_{fall}	Unique state variance for item 3.
4	θ_{dura}	Unique state variance for item 4.
5	ν_0	Intercept for initial log-odds of profile 0 (vs. profile 1) when $X = 0$.
6	κ_0	Covariate effect on initial profile membership; higher X increases odds of profile 0.
7	α_0	Baseline log-odds of being in profile 0 across days.
8	β_{00}	Increased odds of staying in profile 0 if previously in that profile; reflects persistence.
9	γ_{00}	Covariate effect on staying in profile 0; higher X increases persistence.
10	γ_{10}	Covariate effect on switching from state to profile 0; higher X increases transition odds.
11	μ_{peak_0}	Profile specific mean for profile 0 and item 1.
12	μ_{rise_0}	Profile specific mean for profile 0 and item 2.
13	μ_{fall_0}	Profile specific mean for profile 0 and item 3.
14	μ_{dura_0}	Profile specific mean for profile 0 and item 4.
15	μ_{peak_1}	Profile specific mean for profile 1 and item 1.
16	μ_{rise_1}	Profile specific mean for profile 1 and item 2.
17	μ_{fall_1}	Profile specific mean for profile 1 and item 3.
18	μ_{dura_1}	Profile specific mean for profile 1 and item 4.

Figure 1
Information Criteria



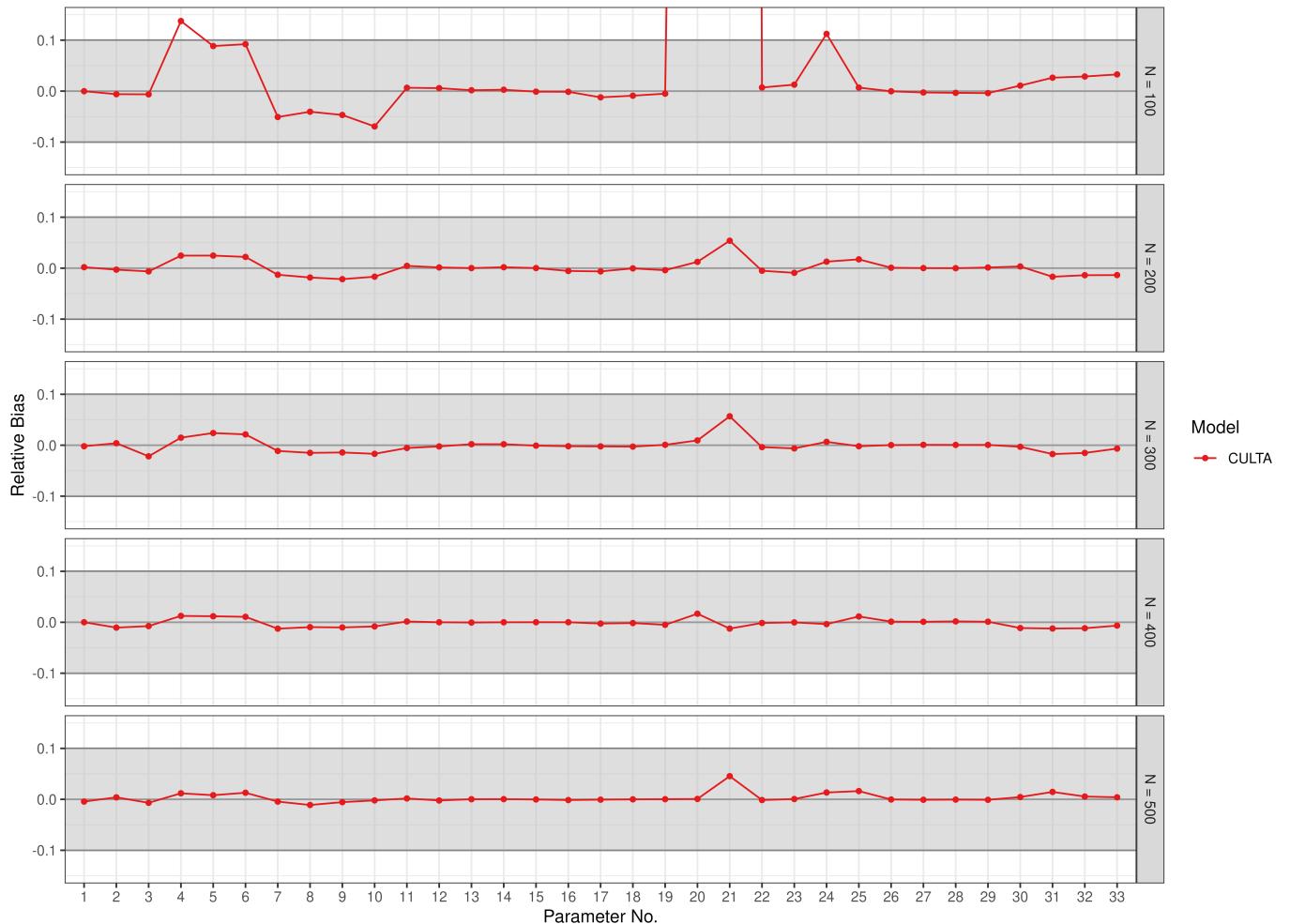
Note: CULTA = Common and Unique Latent Transition Analysis. LTA = Latent Transition Analysis. RILTA = Random-Intercept Latent Transition Analysis. AIC = Akaike Information Criteria. BIC = Bayesian Information Criteria. aBIC = sample size adjusted BIC.

Figure 2
Entropy



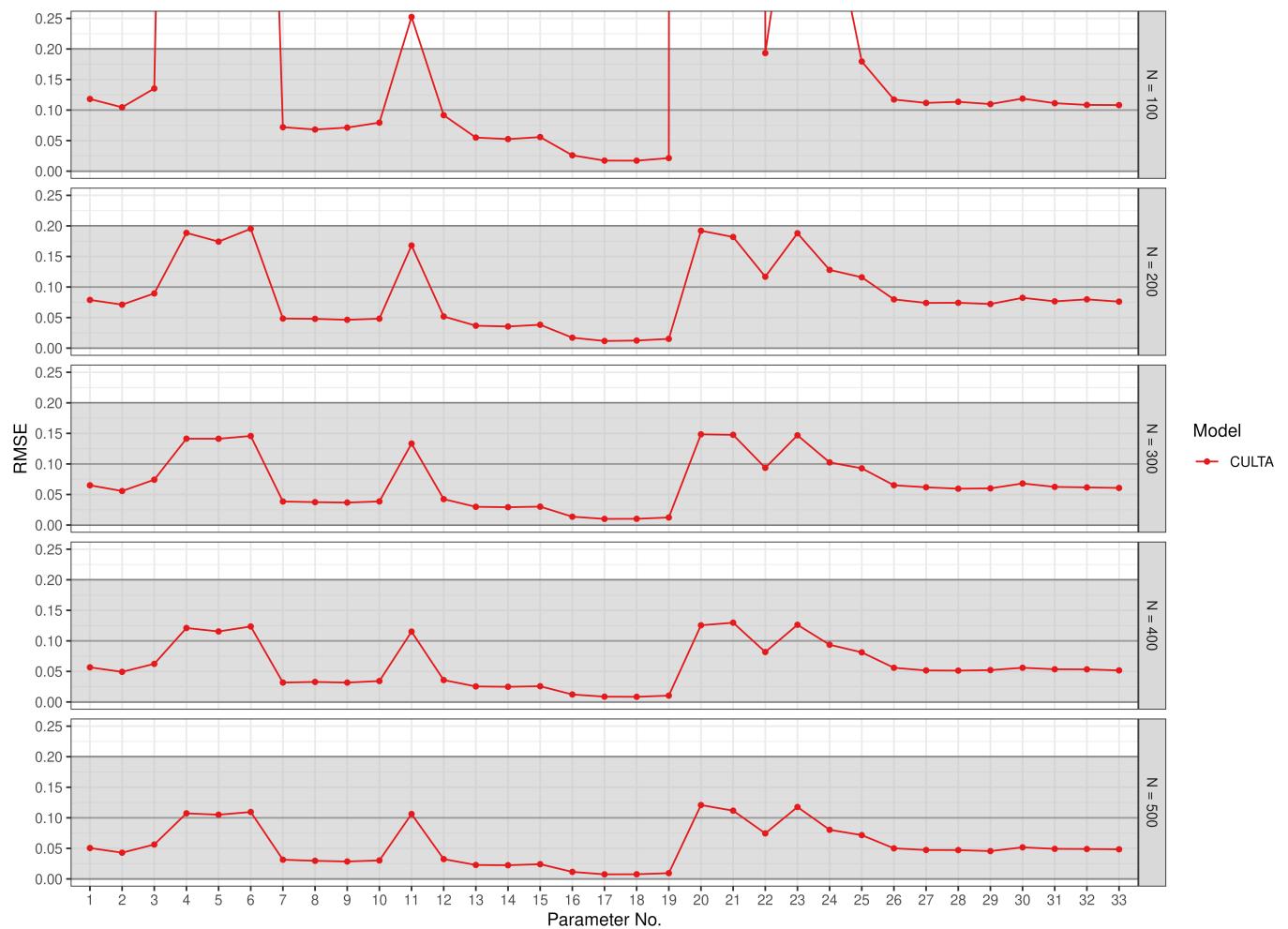
Note: CULTA = Common and Unique Latent Transition Analysis. LTA = Latent Transition Analysis. RILTA = Random-Intercept Latent Transition Analysis.

Figure 3
Relative Bias



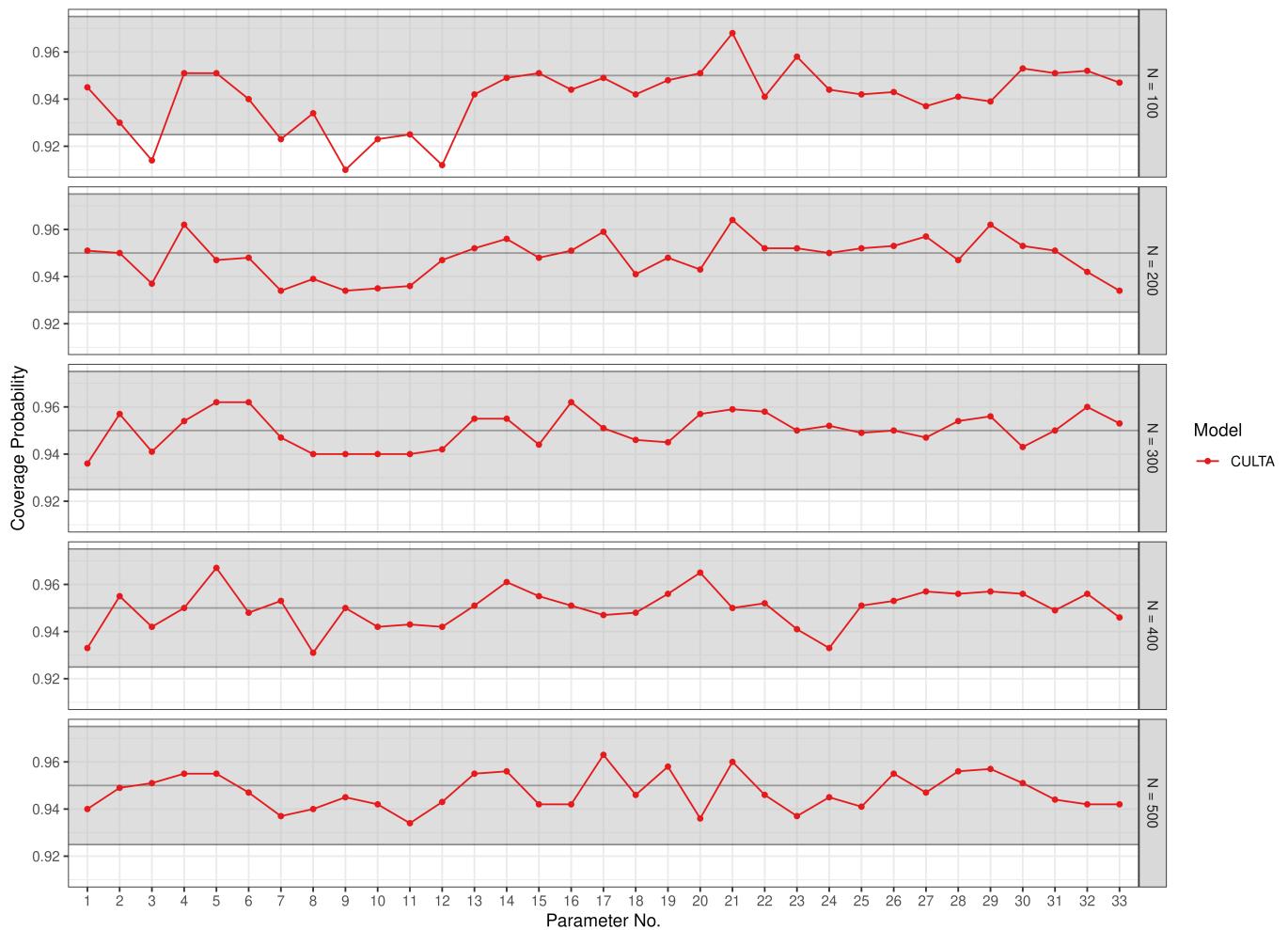
Note: CULTA = Common and Unique Latent Transition Analysis. For parameter 1 (ϕ_0), the mean absolute bias was reported in place of relative bias due to a population value of zero. See Table 1 for the parameters in the x-axis.

Figure 4
Root Mean Square Error



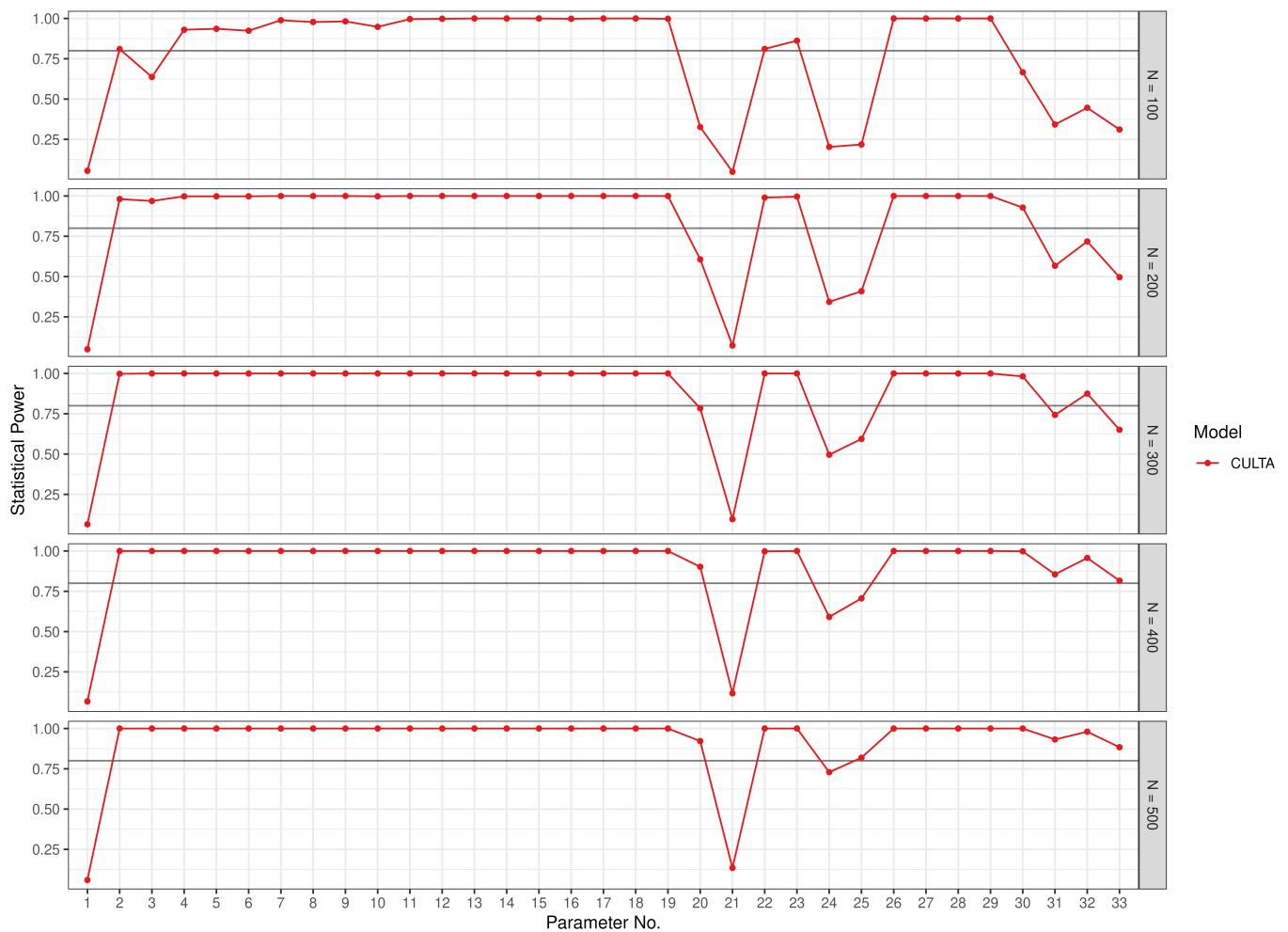
Note: CULTA = Common and Unique Latent Transition Analysis. See Table 1 for the parameters in the x-axis.

Figure 5
Coverage Probability



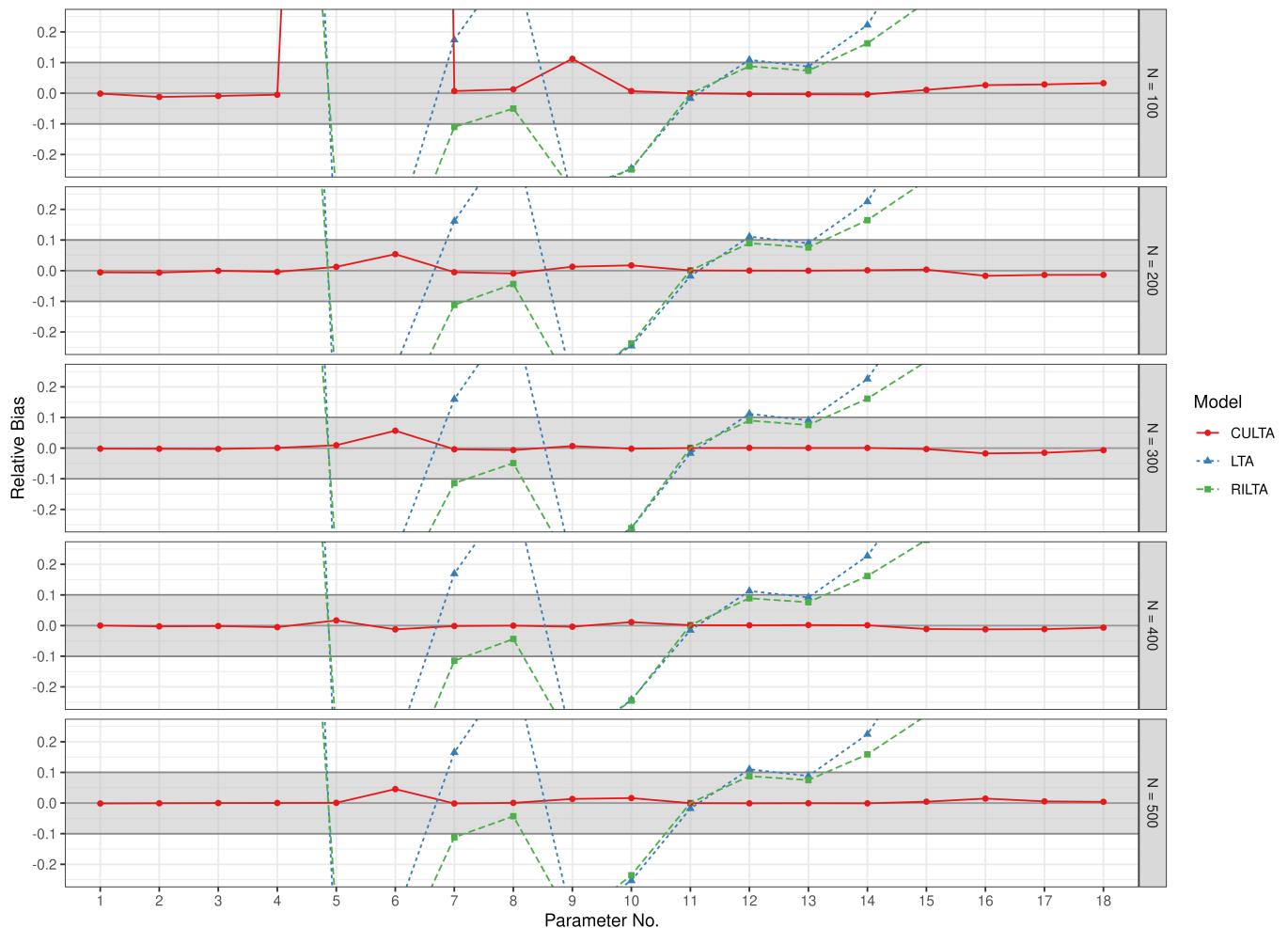
Note: CULTA = Common and Unique Latent Transition Analysis. See Table 1 for the parameters in the x-axis.

Figure 6
Statistical Power



Note: CULTA = Common and Unique Latent Transition Analysis. See Table 1 for the parameters in the x-axis.

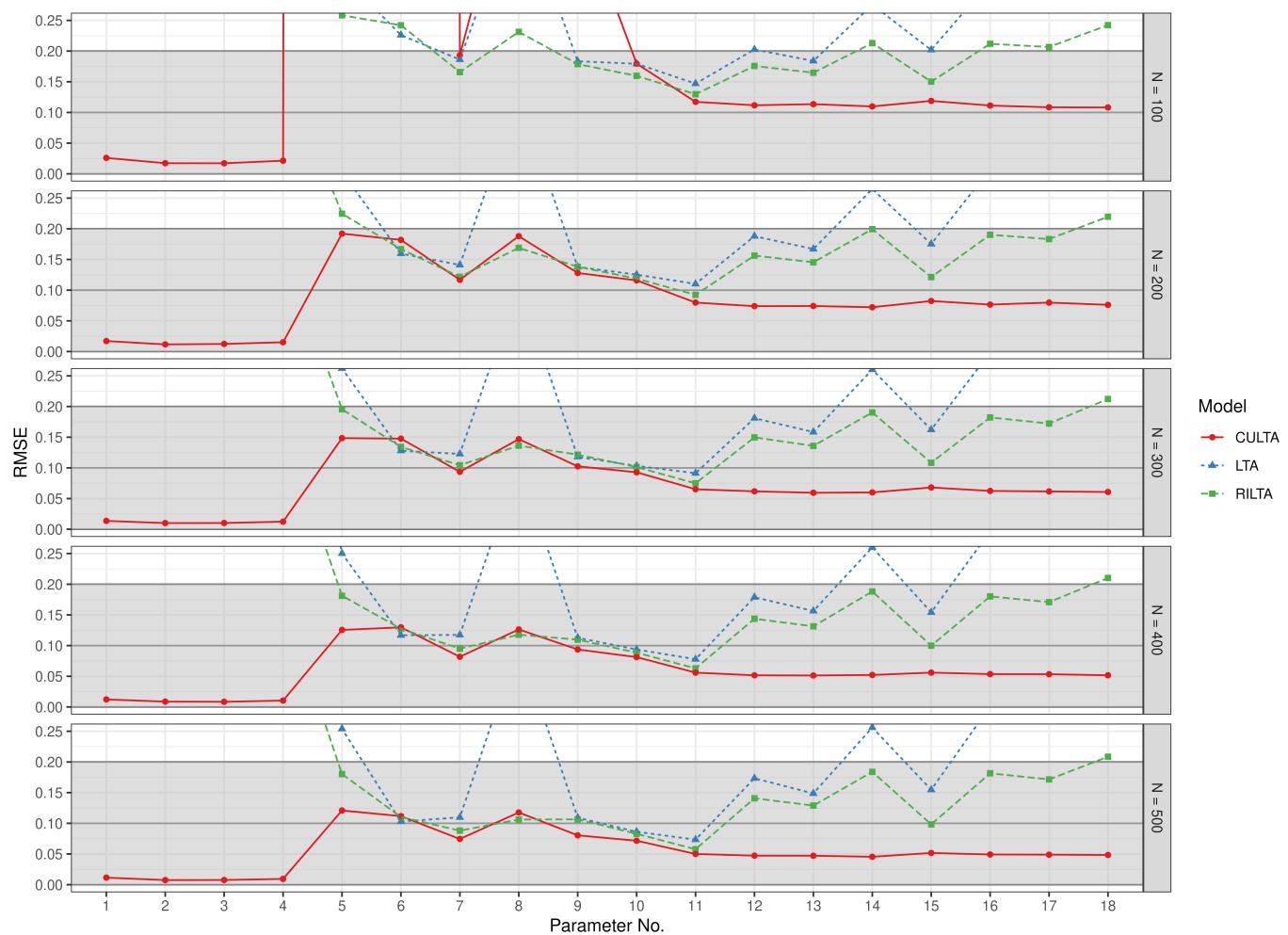
Figure 7
Relative Bias (Parameters Common to CULTA, LTA, and RILTA)



Note: CULTA = Common and Unique Latent Transition Analysis. LTA = Latent Transition Analysis. RILTA = Random-Intercept Latent Transition Analysis. See Table 2 for the parameters in the x-axis.

Figure 8

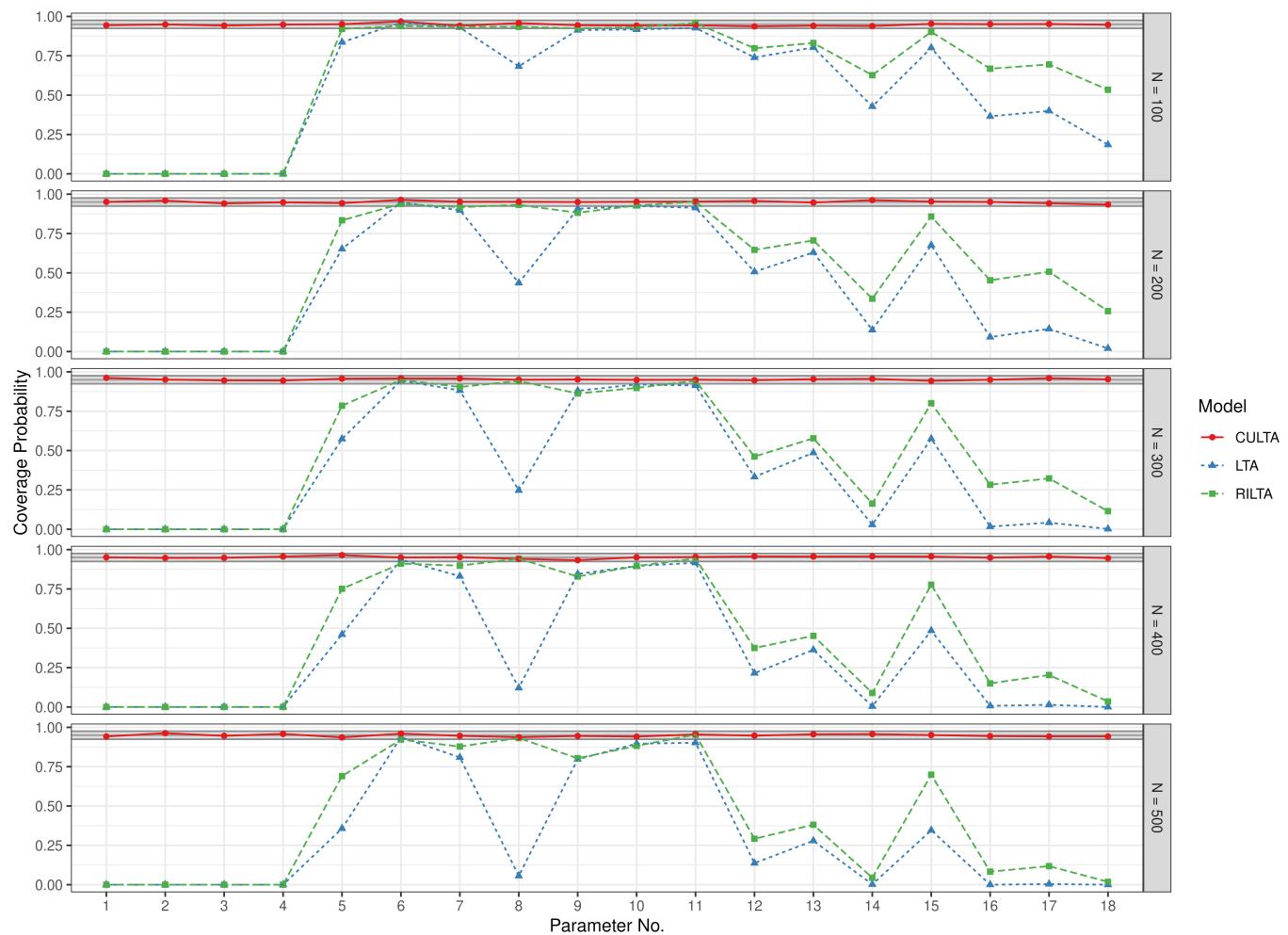
Root Mean Square Error (Parameters Common to CULTA, LTA, and RILTA)



Note: CULTA = Common and Unique Latent Transition Analysis. LTA = Latent Transition Analysis. RILTA = Random-Intercept Latent Transition Analysis. See Table 2 for the parameters in the x-axis.

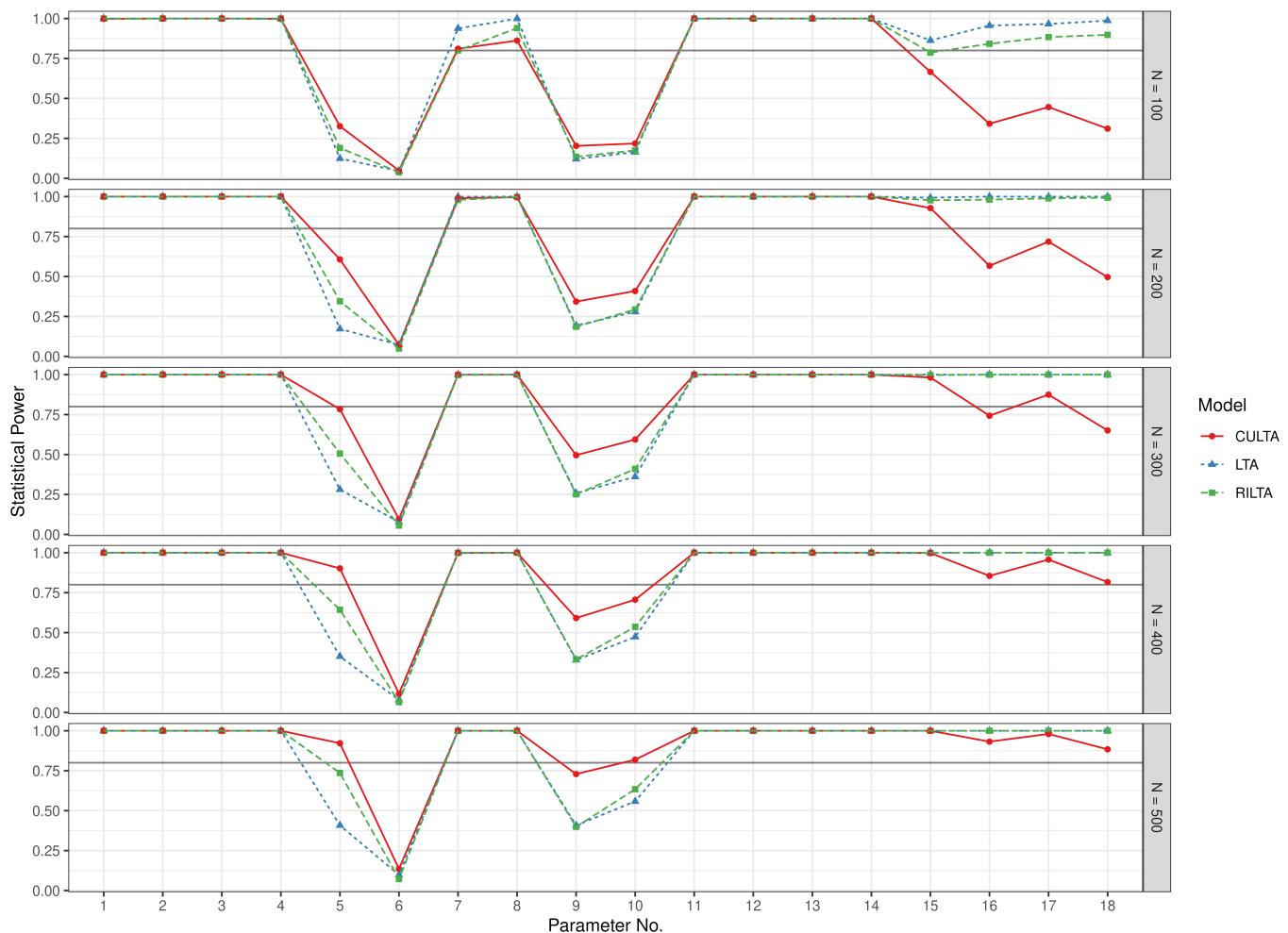
Figure 9

Coverage Probability (Parameters Common to CULTA, LTA, and RILTA)



Note: CULTA = Common and Unique Latent Transition Analysis. LTA = Latent Transition Analysis. RILTA = Random-Intercept Latent Transition Analysis. See Table 2 for the parameters in the x-axis.

Figure 10
Statistical Power (Parameters Common to CULTA, LTA, and RILTA)



Note: CULTA = Common and Unique Latent Transition Analysis. LTA = Latent Transition Analysis. RILTA = Random-Intercept Latent Transition Analysis. See Table 2 for the parameters in the x-axis.