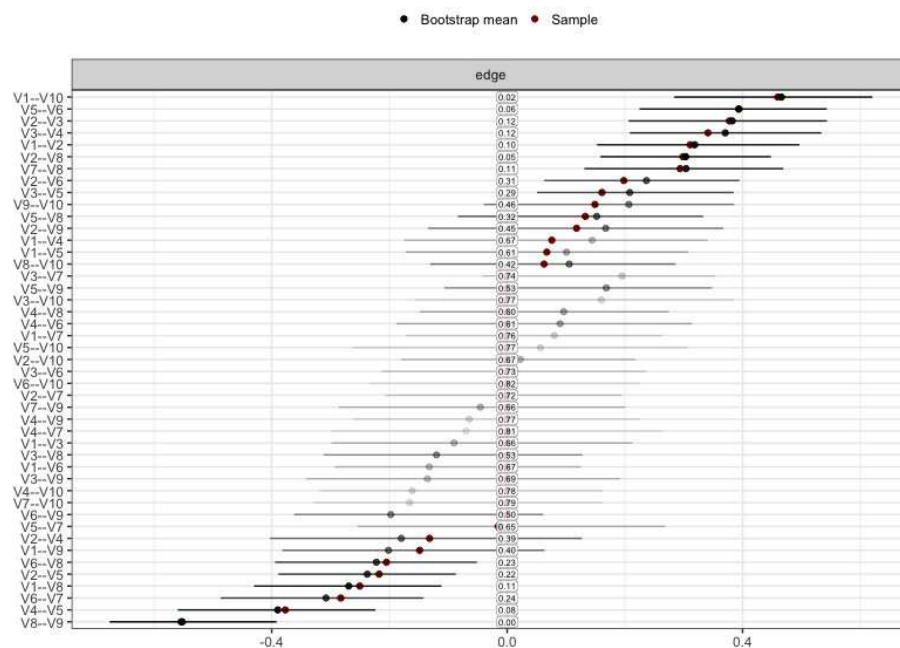
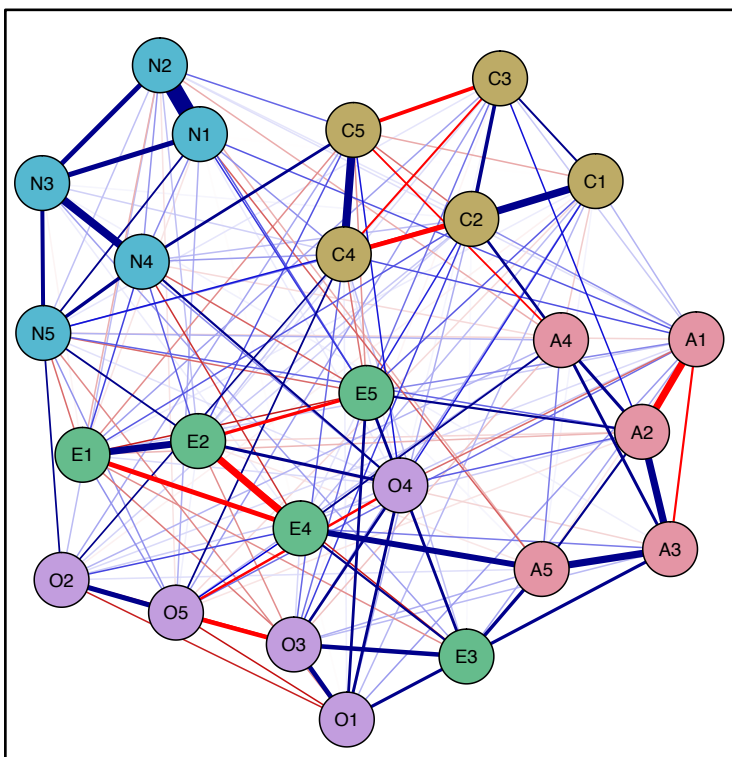
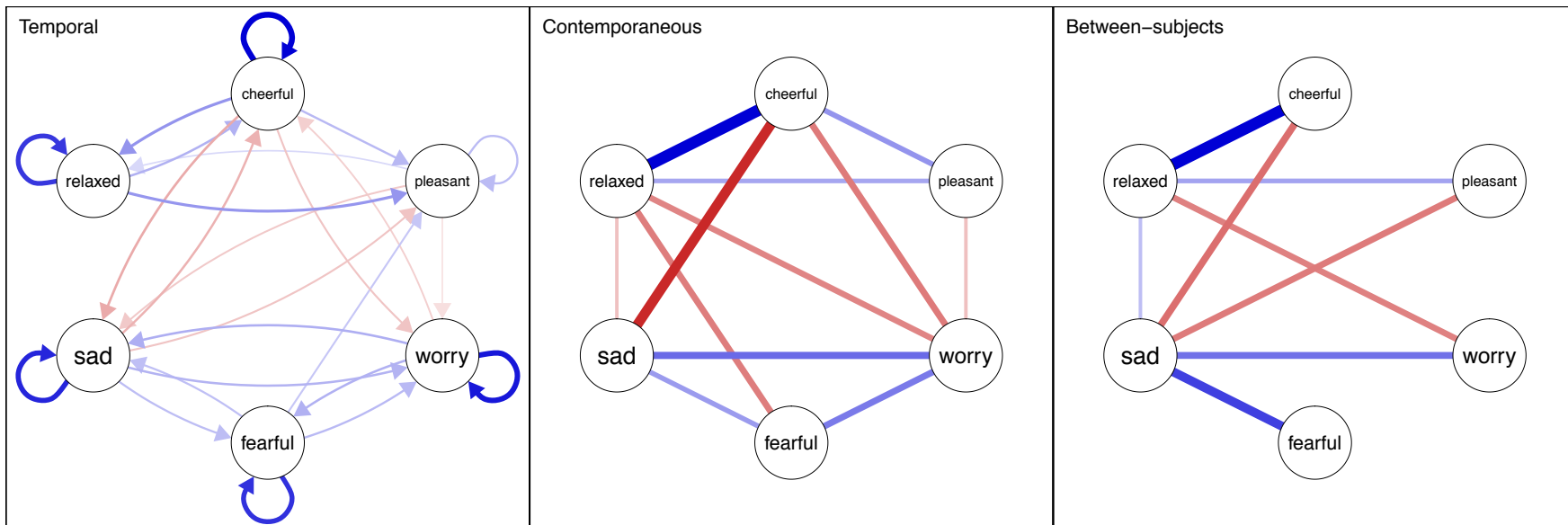


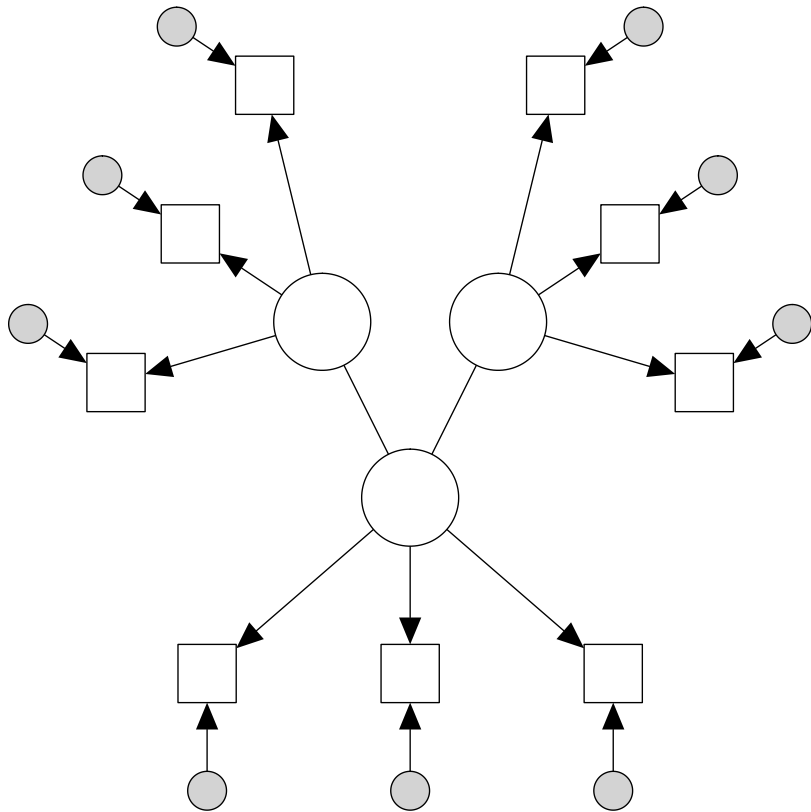
NETWORK PSYCHOMETRICS

PHASE 2

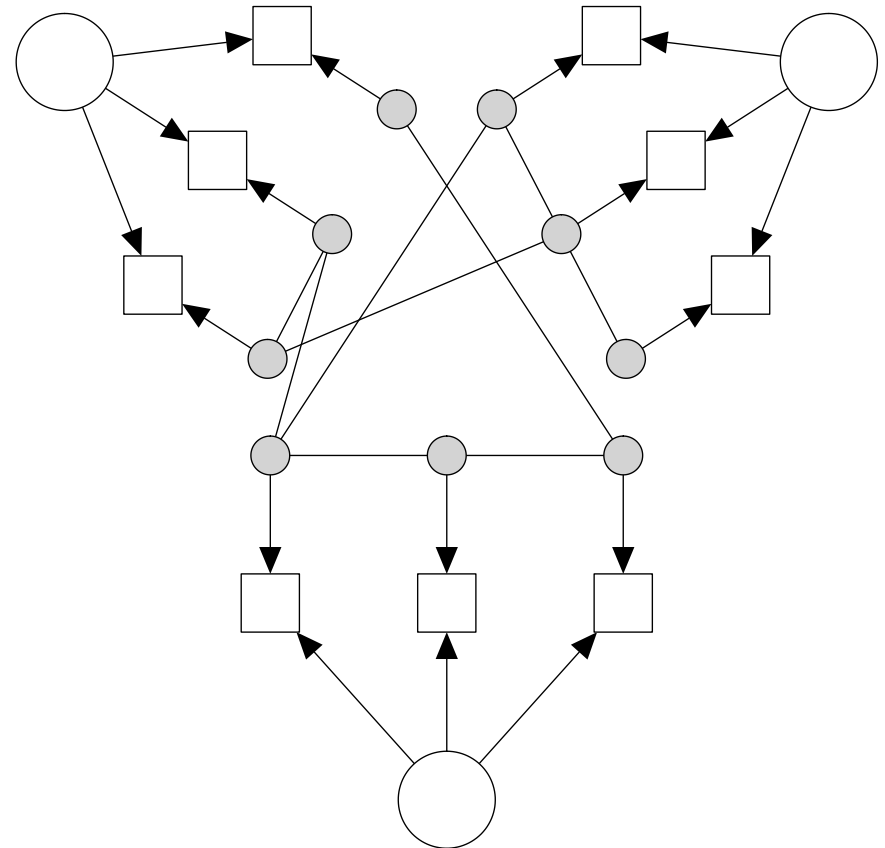
Sacha Epskamp – ICPS 2019



Latent network model



Residual network model



Epskamp, S., Rhemtulla, M. T., & Borsboom, D. (2017). Generalized Network Psychometrics: Combining Network and Latent Variable Models. *Psychometrika*, 82(4), 904–927.

Model fit & Multi-group analysis

TABLE 1.

Fit measures for three models estimated on the BFI dataset in the psych R package. CFA is the correlated five-factor model.

	df	chisq	AIC	BIC	EBIC	RMSEA	TLI	CFI
CFA	265	4715.62	230,250.58	230,606.82	231,559.30	0.08	0.75	0.78
RNM	163	688.74	226,427.69	227,389.55	229,961.26	0.03	0.95	0.97
RNM+LNM	168	723.89	226,452.85	227,385.01	229,877.35	0.03	0.95	0.97

RNM is the same model as the CFA model with a residual network. RNM+LNM denotes the same model as the RNM model in which edges of the latent network have been removed.

Epskamp, S., Rhemtulla, M., & Borsboom, D. (2017). Generalized network psychometrics: Combining network and latent variable models. *Psychometrika*, 82(4), 904-927.

Table 2

Showing the fit statistics of obtained in Application 1 (analysis of the Wechsler Adult Intelligence Scale – Fourth Edition).

Model	-2LL	χ^2	df	<i>P</i>	AIC	BIC	SABIC	CFI	NNFI	RMSEA	CI95 _l	CI95 _u	<i>P</i> _{RMSEA}
Saturated model	11,568.16	0	0	1.00	240.00	899.47	518.23	1.00	1.00	0.00	–	–	–
Measurement model	12,464.85	896.70	99	< 0.01	968.70	1.166.54	1.052.17	0.95	0.93	0.07	0.068	0.079	0.00
Second order <i>g</i> -model	12,490.71	922.56	101	< 0.01	990.56	1.177.41	1.069.39	0.95	0.93	0.07	0.068	0.079	0.00
Network	11,698.10	129.94	71	< 0.01	257.94	609.65	406.33	1.00	0.99	0.02	0.014	0.028	1.00

Note. Abbreviations: -2LL: minus 2 times the log-likelihood, df: degrees of freedom, CI95_l and CI95_u: lower and upper boundaries of the 95% confidence interval of the RMSEA value; *P*_{RMSEA}: the *P*-value associated with this interval. Preferred model bold faced and underlined.

Kan, K. J., van der Maas, H. L., & Levine, S. Z. (2019). Extending psychometric network analysis: Empirical evidence against *g* in favor of mutualism?. *Intelligence*, 73, 52-62.

A comprehensive overview of research on missing data analysis in network psychometrics:

[illegible]

psychonetrics

Models

- ✓ Cholesky decomposition
- ✓ Covariance matrix
- ✓ Gaussian graphical model
- ✓ Latent network model
 - (CFA)
- ✓ Residual Network model
 - (SEM)
- ✓ Graphical VAR for time-series
- Graphical VAR for panel data
- Structural VAR
- Ising model
- Fused latent and graphical IRT

Output

- ✓ Fit indices
- ✓ Modification indices
- ✓ Parameter estimates
- ✓ Standard errors
- ✓ Model comparison
 - Markdown document
 - Logbook / graph

Techniques

- ✓ MI model search
- ✓ Significance pruning
- ✓ Multi-group models
- ✓ Equality constraints
- GIMME-like model search
- Meta-analysis

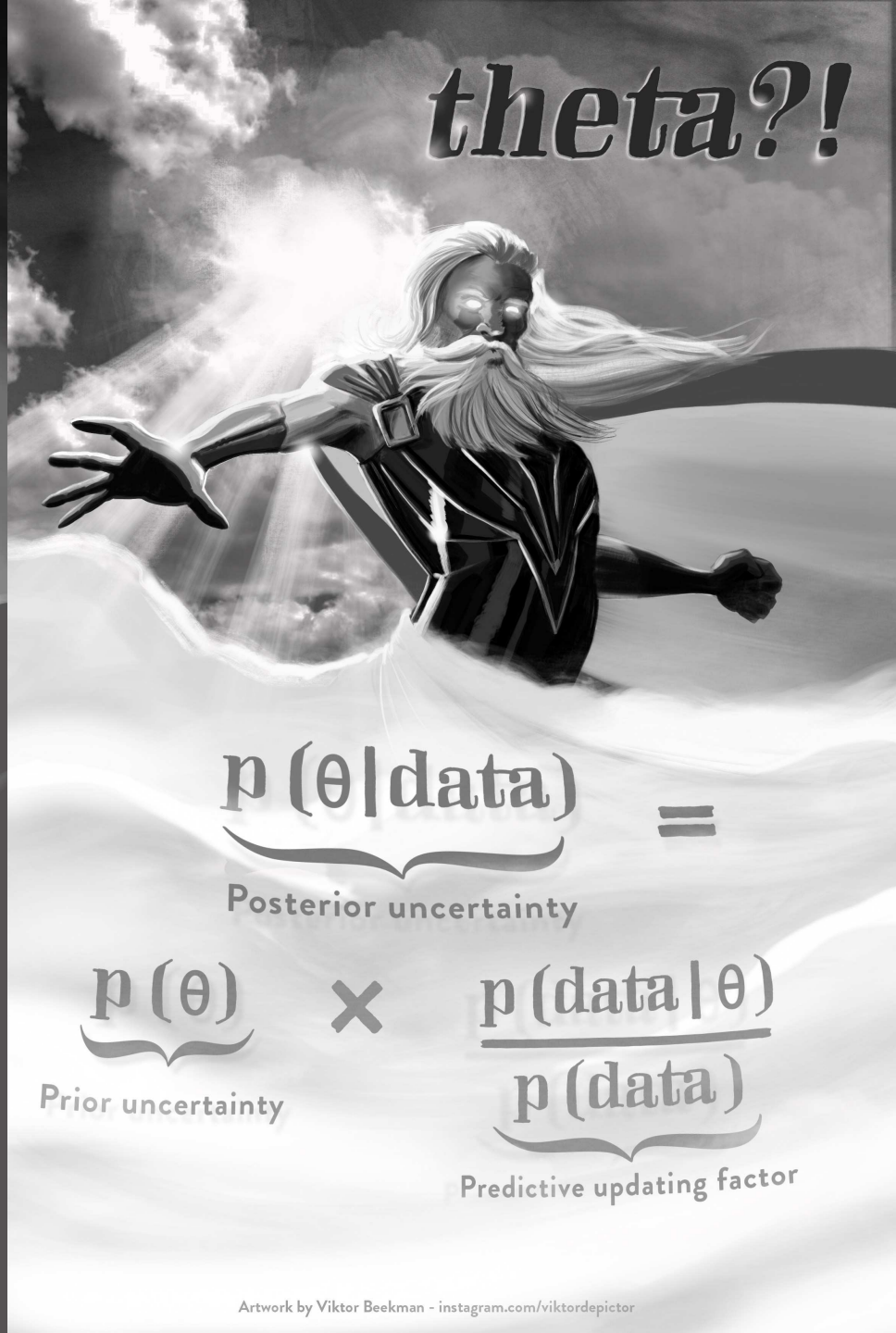
Estimators

- ✓ Maximum likelihood (summary statistics)
- ✓ Full-information maximum likelihood
 - Toeplitz for GVAR
- Raw time-series GVAR
- ✓ Least-squares
 - (diagonally) weighted least squares
- Robust ML estimation

Unstable alpha version:
github.com/SachaEpskamp/psychonetrics



Artwork by Viktor Beekman
[instagram.com/viktordepictor](https://www.instagram.com/viktordepictor)



theta?!

$$\underbrace{p(\theta | \text{data})}_{\text{Posterior uncertainty}} =$$

$$\underbrace{p(\theta)}_{\text{Prior uncertainty}} \times \frac{p(\text{data} | \theta)}{\underbrace{p(\text{data})}_{\text{Predictive updating factor}}}$$

Artwork by Viktor Beekman - [instagram.com/viktordepictor](https://www.instagram.com/viktordepictor)

Frequentism versus Bayes

- Disclaimer: Artwork might not accurately represent frequentism or Bayesianism
 - Source: <https://www.bayesianspectacles.org/>, powered by <https://jasp-stats.org/>
- psychometrics will be purely frequentist, implementing many maximum likelihood estimators
- There is also promising Bayesian work in this area
 - BGGM package by Donald Willaims (<https://psyarxiv.com/x8dpr/>)
 - Bdgraph package by Reza Mohammadi

Confirmatory fit of GGMs

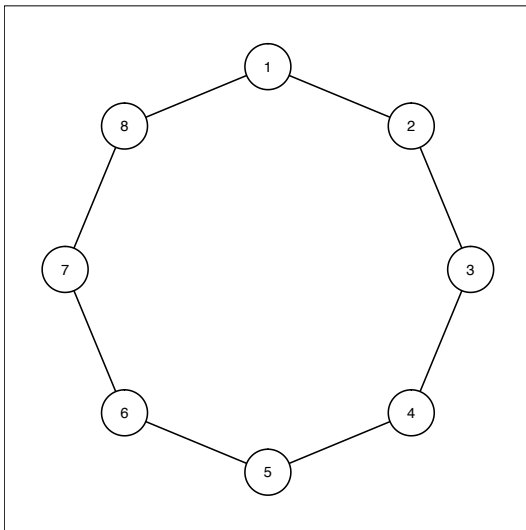
Simulation study:

- 100 repetitions in each condition
- Sample size 100, 250, 1000 & 2500
- Randomness 0, 0.1, 0.25, 0.5, 1
- Chi-square test and RMSEA

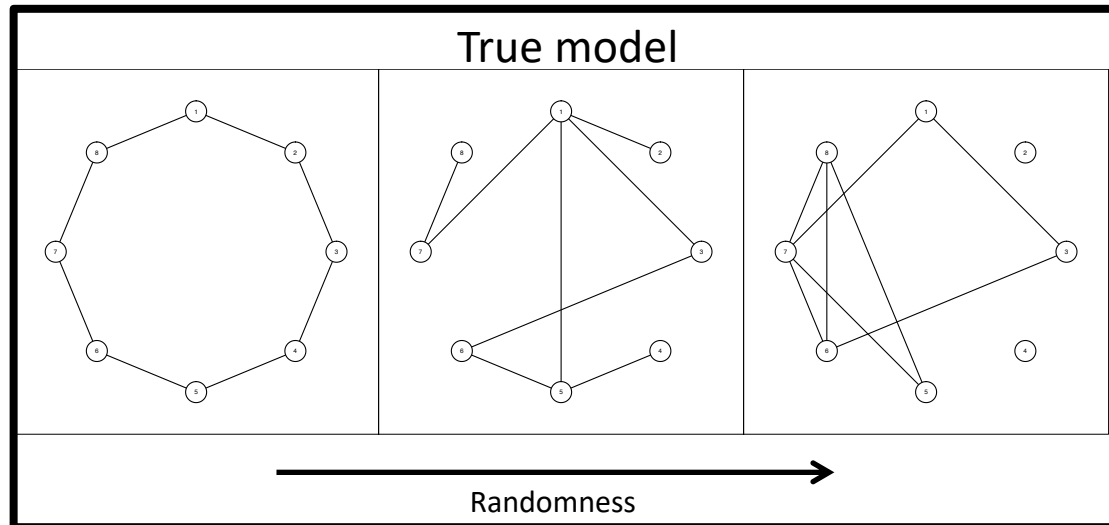
Code

```
library("parSim")
sims <- parSim(
  nSample = c(100,250,1000,2500),
  randomness = c(0,0.1,0.25,0.5,1),
  nNode = 8,
  reps = 100,
  nCores = 8,
  expression = {
    library("bootnet")
    library("psychometrics")
    library("dplyr")
    # Simulate true model:
    trueNet <- genGGM(nNode,p = randomness)
    # Simulate data:
    Data <- ggmGenerator()(nSample,trueNet)
    # Model to fit (chain):
    adj <- 1 * (genGGM(nNode) != 0)
    # Form psychometrics model:
    mod <- ggm(Data, omega = adj)
    # Run model:
    mod <- mod %>%
      runmodel(verbose=FALSE, addMIs=FALSE)
    # Return fit indices:
    mod@fitmeasures
  }
)
```

Fitted model

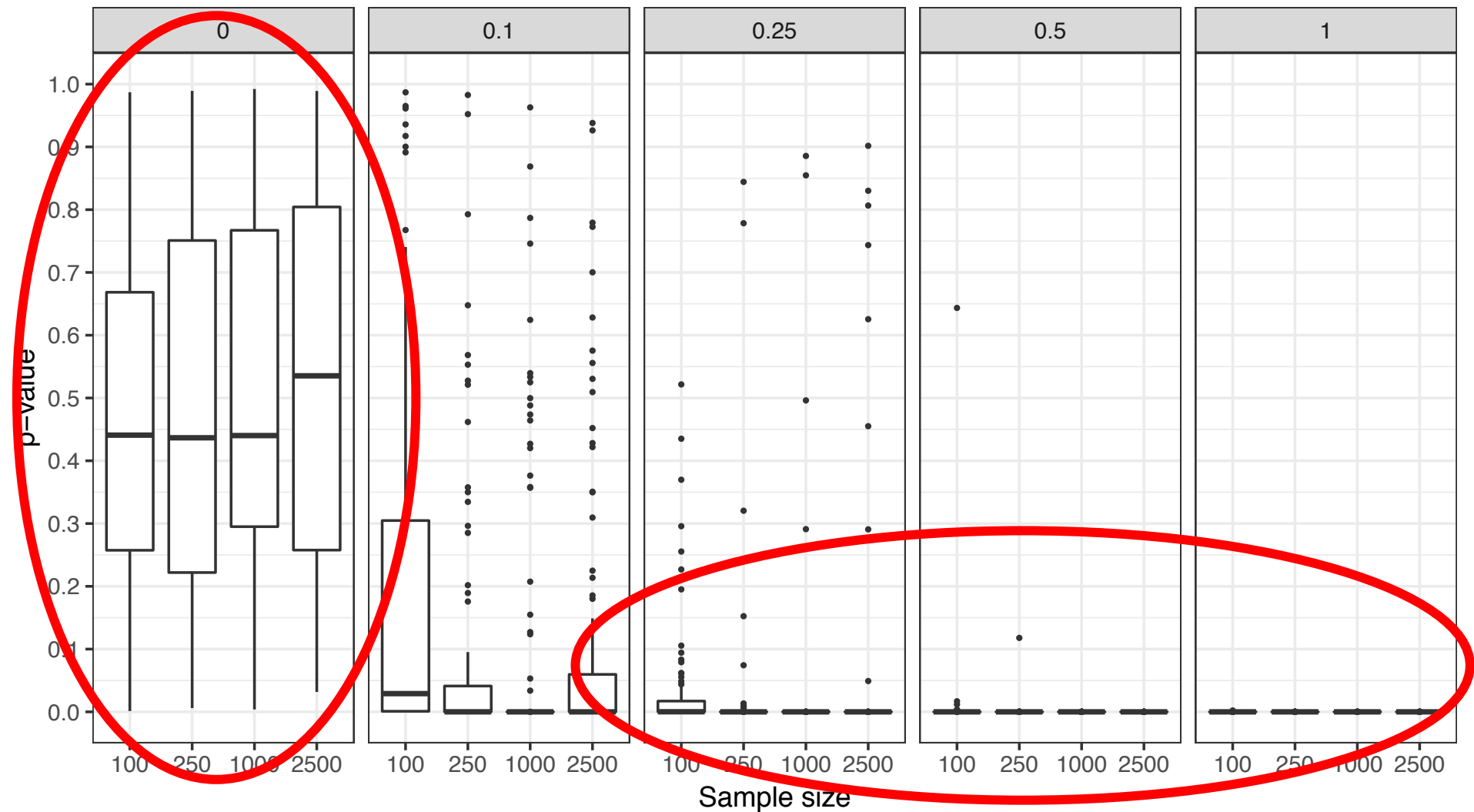


True model



chi-square test p-values

Varying randomness from 0 (true model) to 1 (random model)

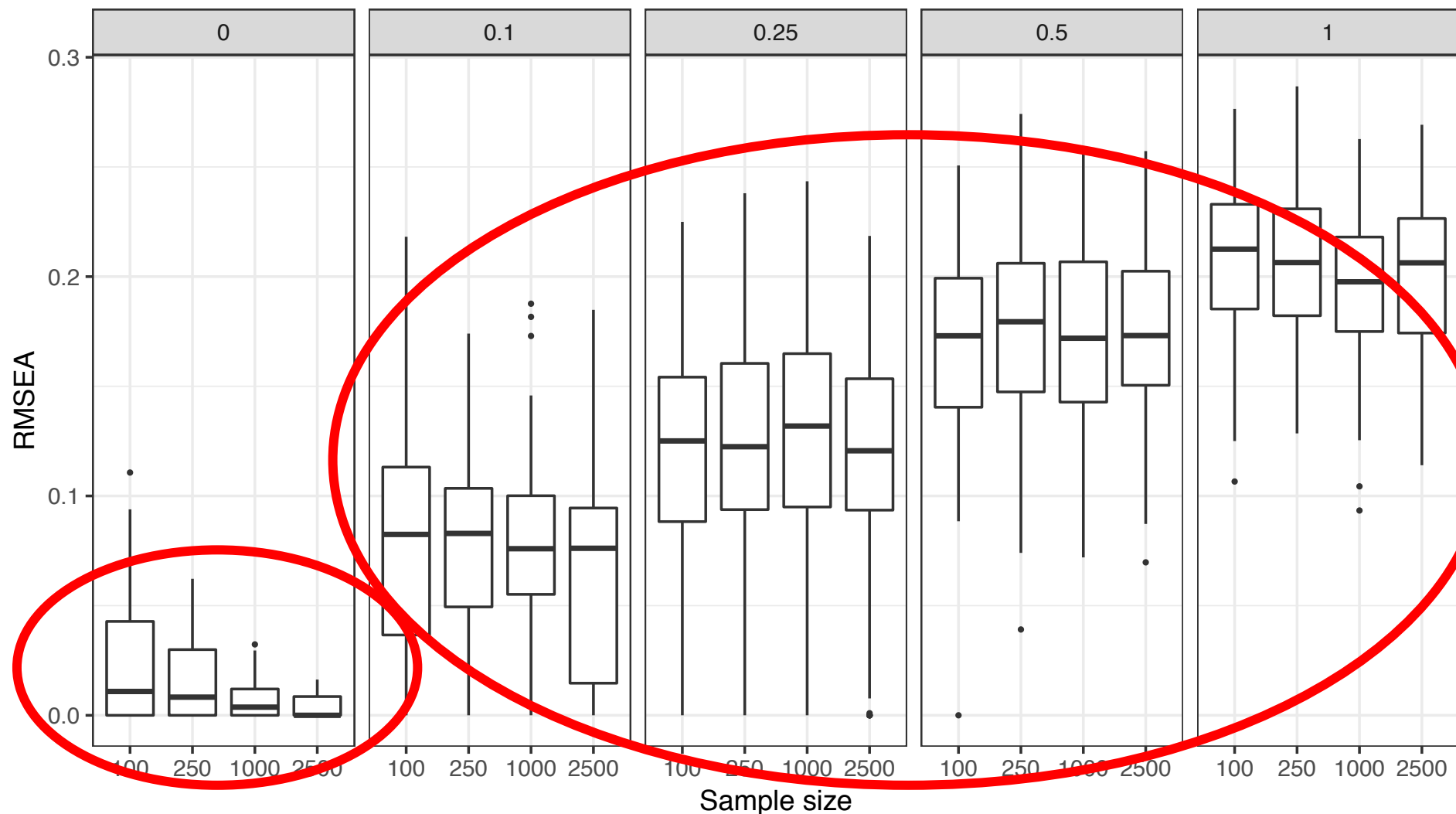


Uniform p -values for true model

High power to reject false model

Root mean square error of approximation

Varying randomness from 0 (true model) to 1 (random model).



RMSEA < 0.05 for true model

RMSEA > 0.05 for false model

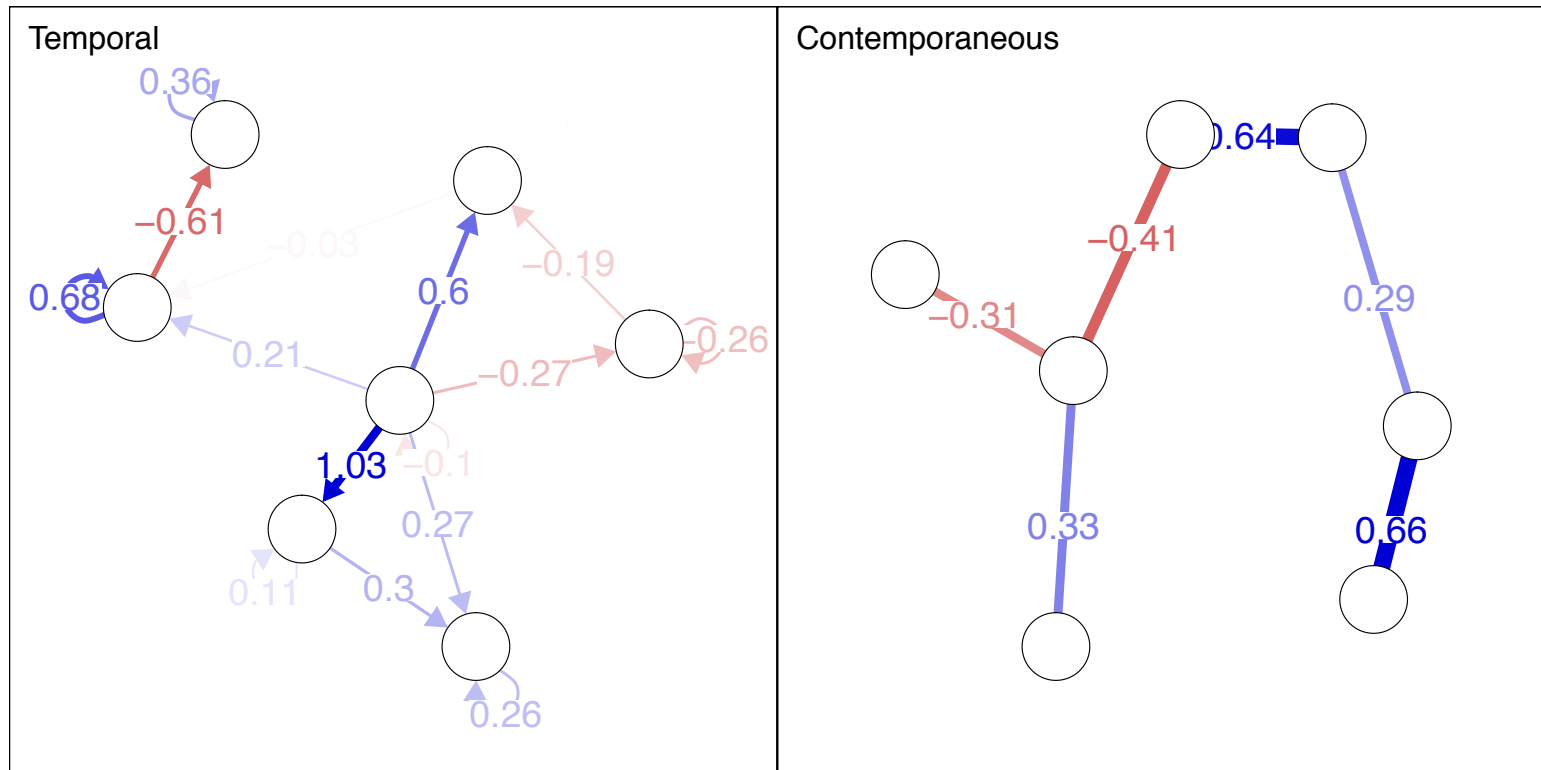
Missing data in graphical VAR models

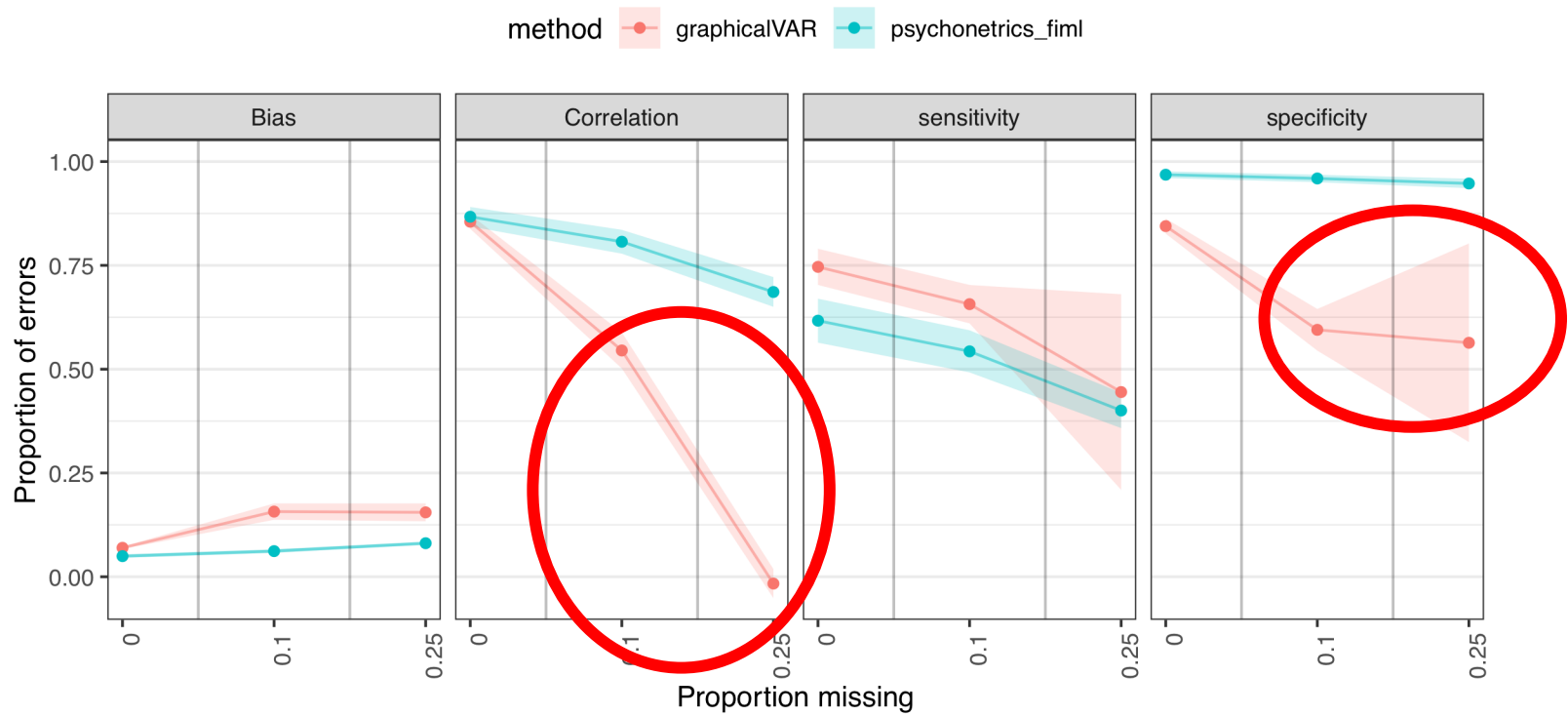
Simulation setup:

- 100 repetitions in each condition
- 75 time points
- 0%, 10% or 25% missingness (at random)

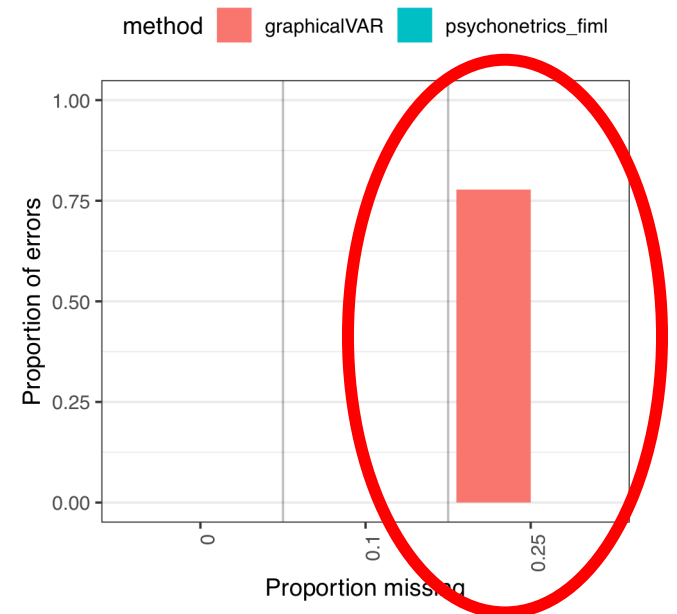
Estimation

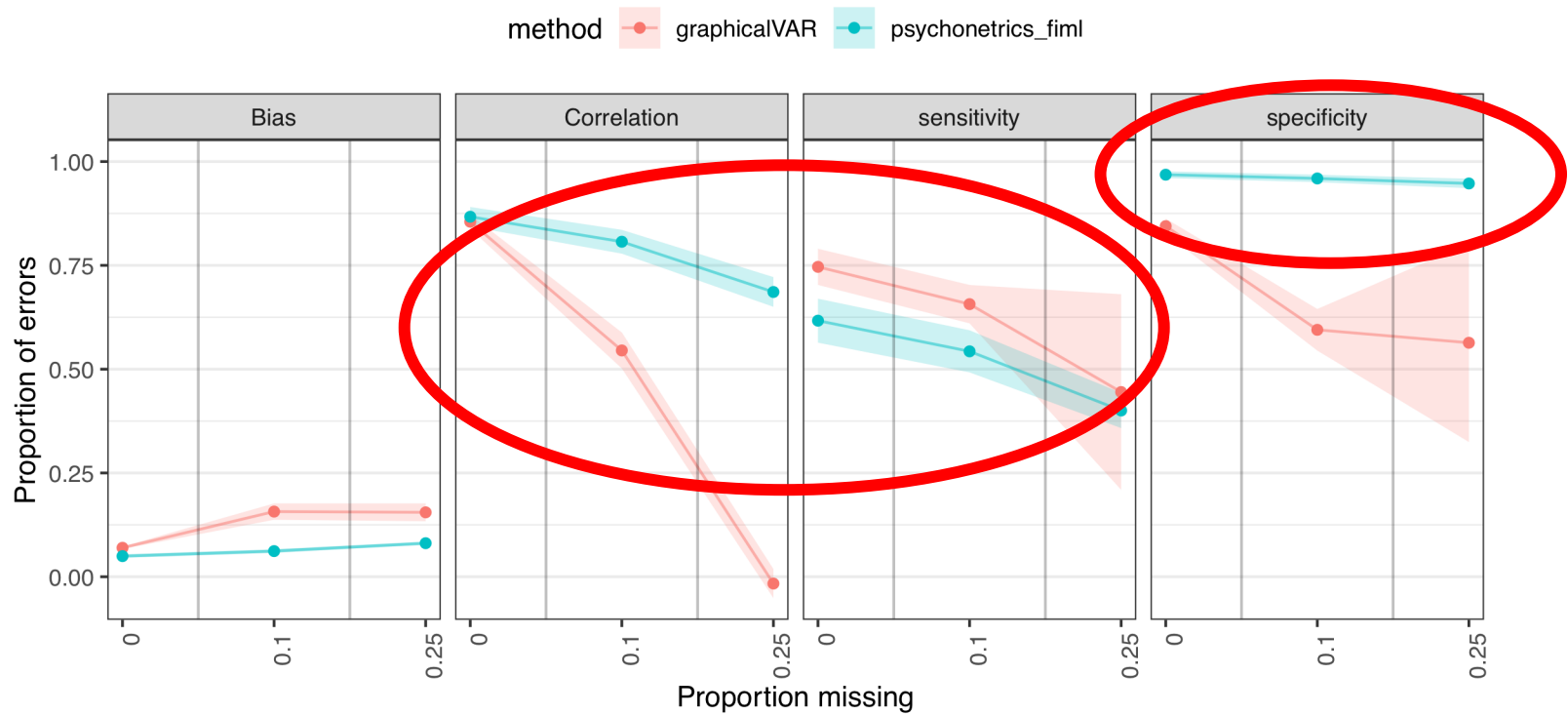
- graphicalVAR (LASSO) with BIC selection
- Psychometrics FIML
 - Stepup via MIs -> prune nonsig



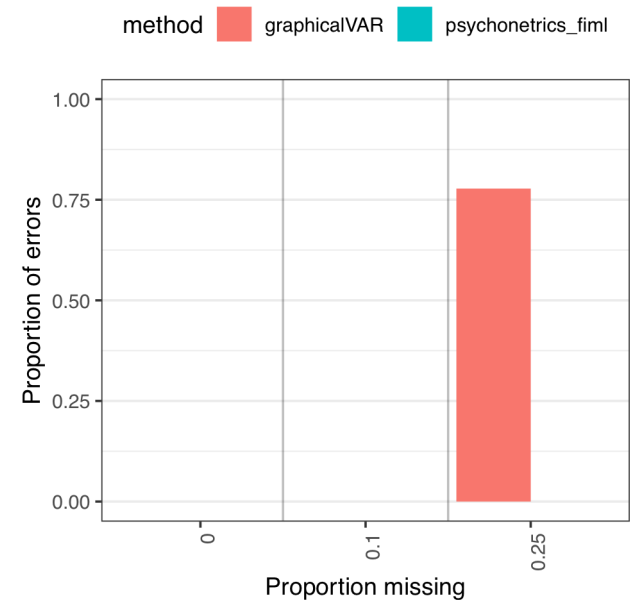


- graphicalVAR completely breaks down with missing data

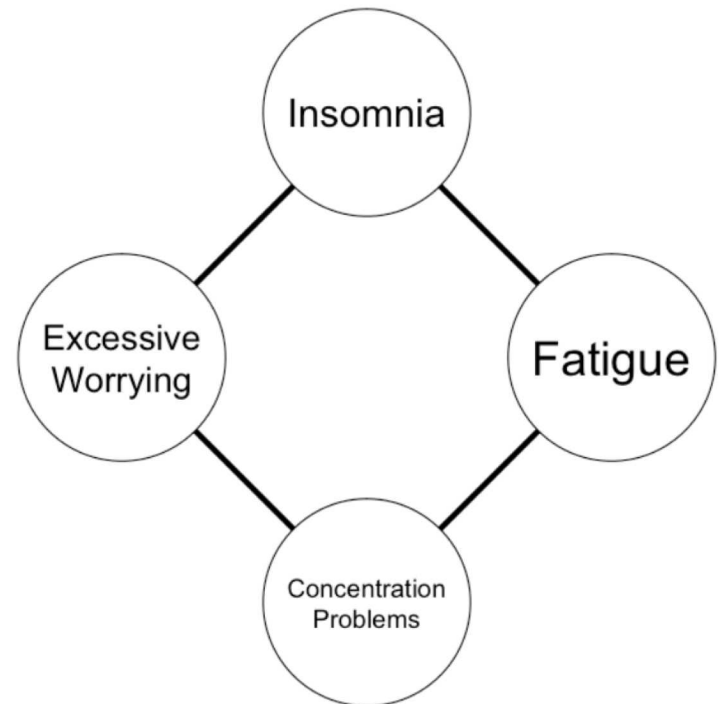
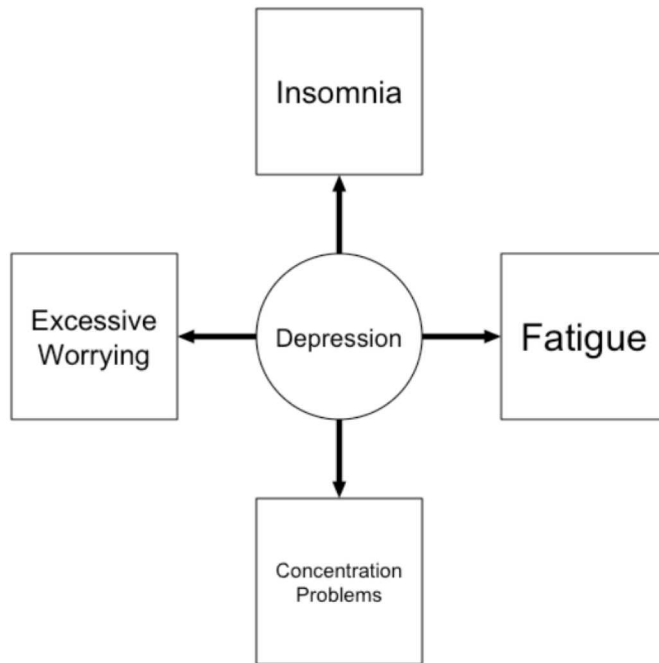


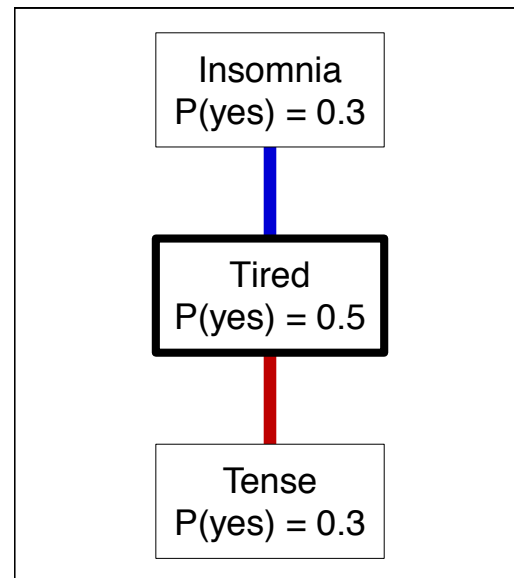
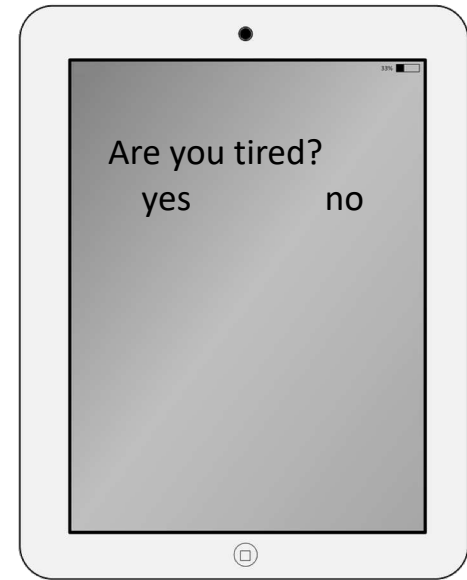
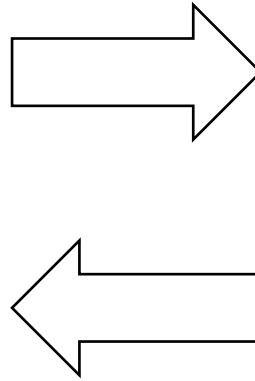
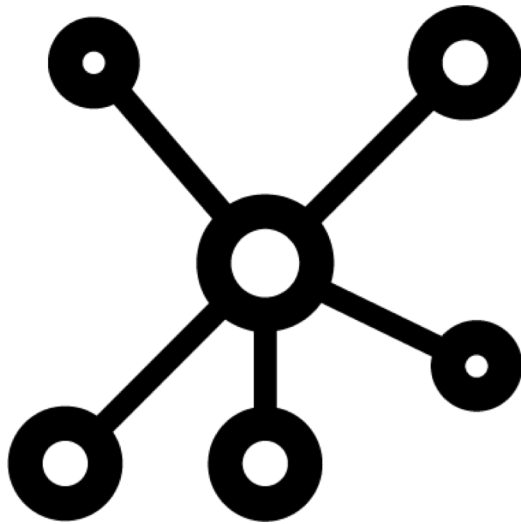


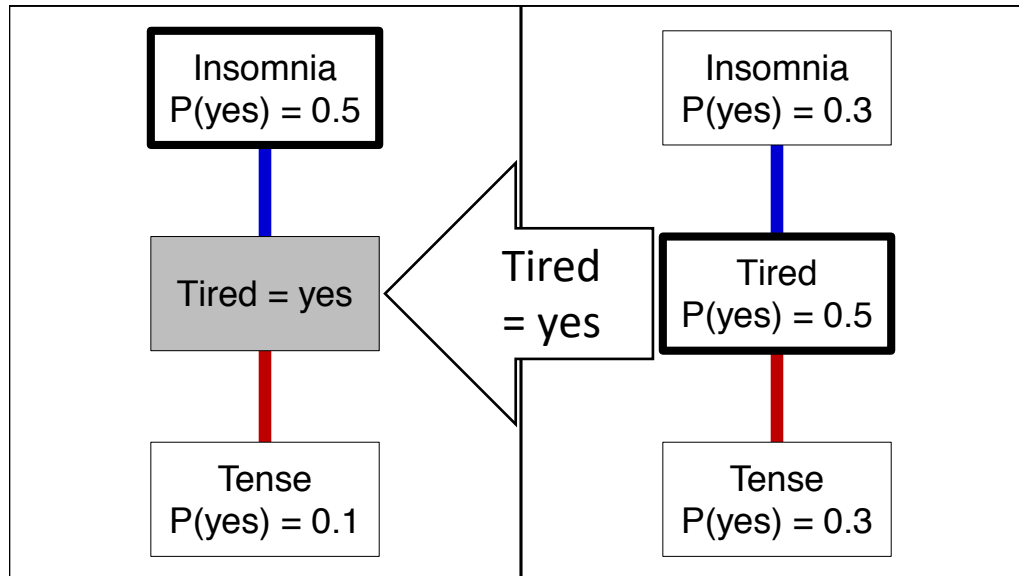
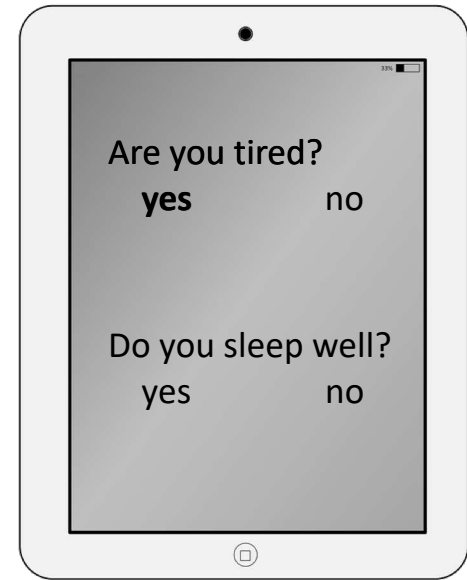
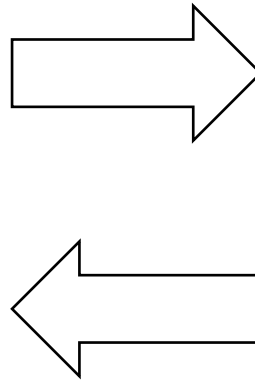
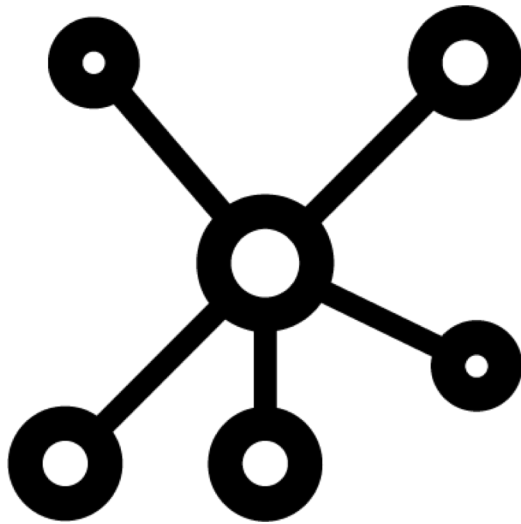
- graphicalVAR completely breaks down with missing data
- FIML stepup estimation using psychometrics:
 - Remains conservative
 - Has decent performance still with high missingness

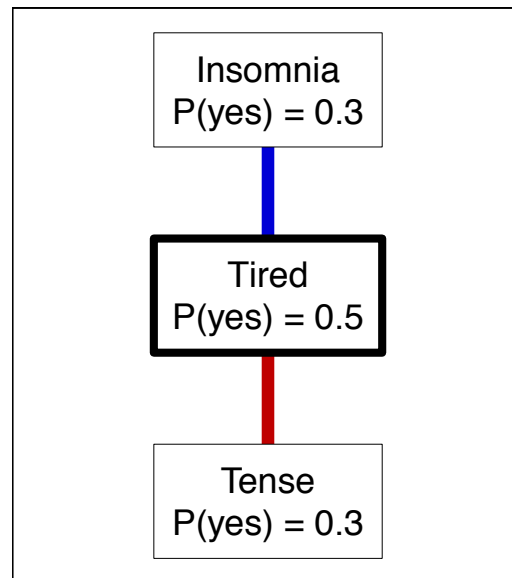
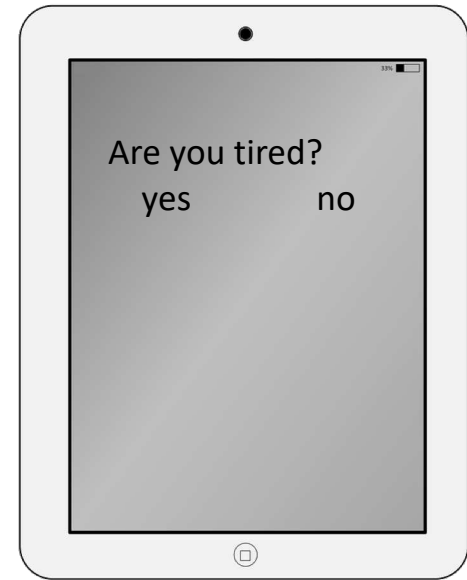
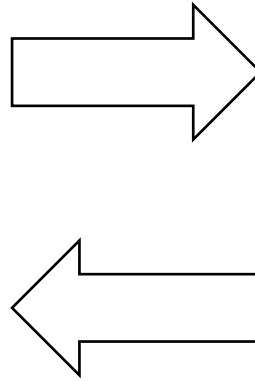
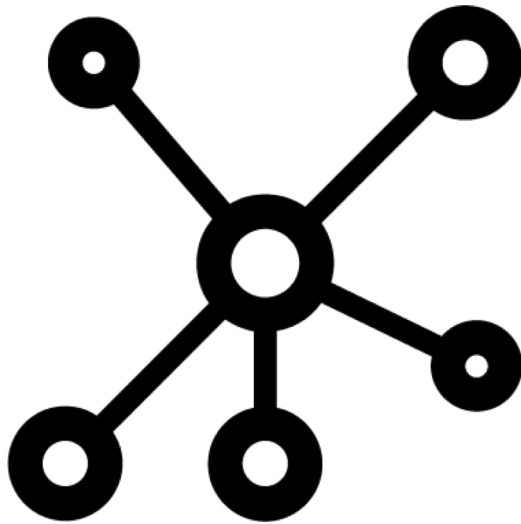


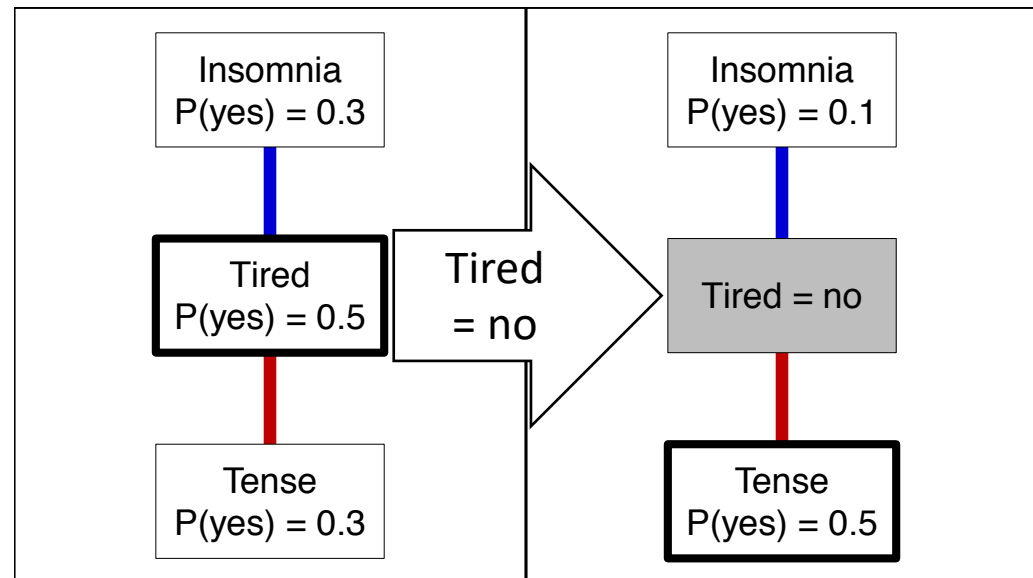
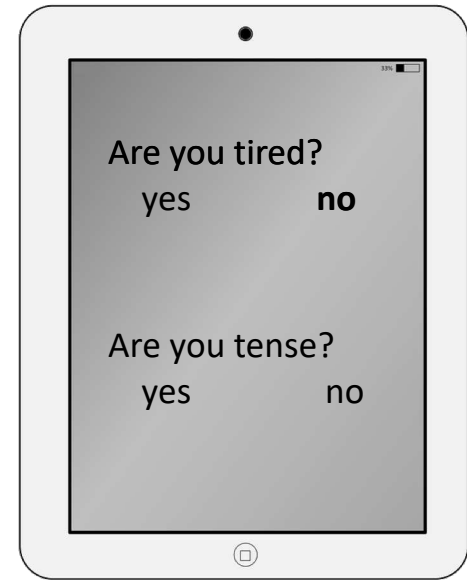
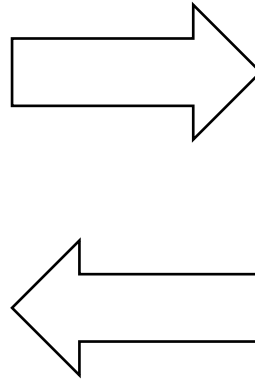
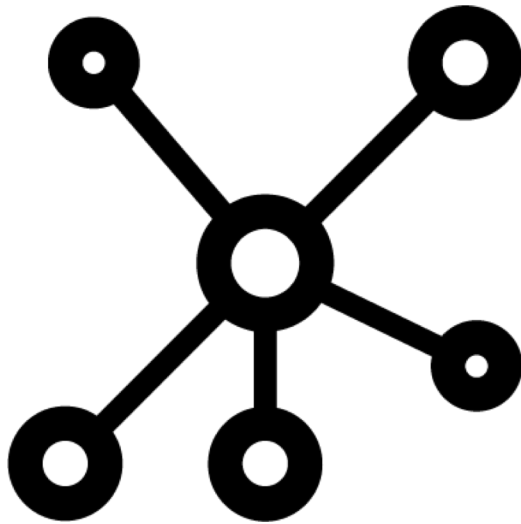
Measurement from a network perspective





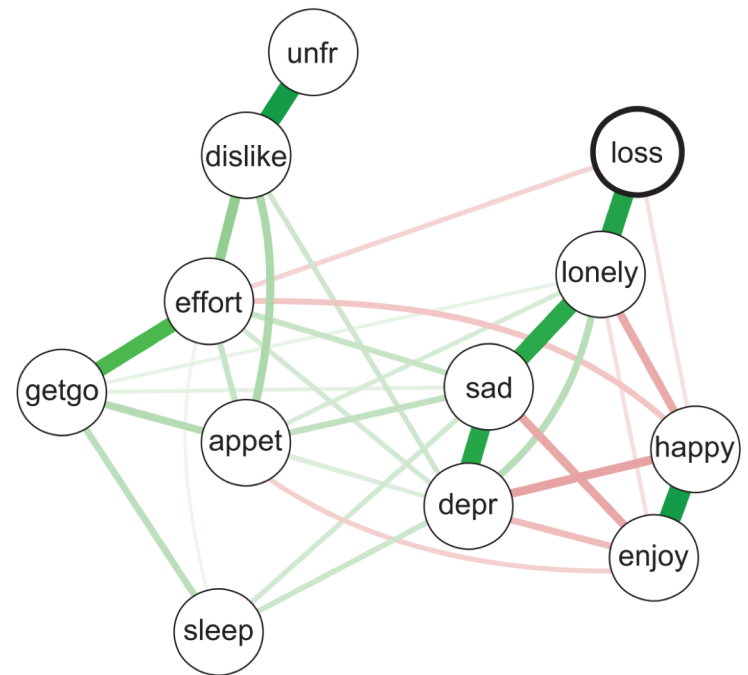


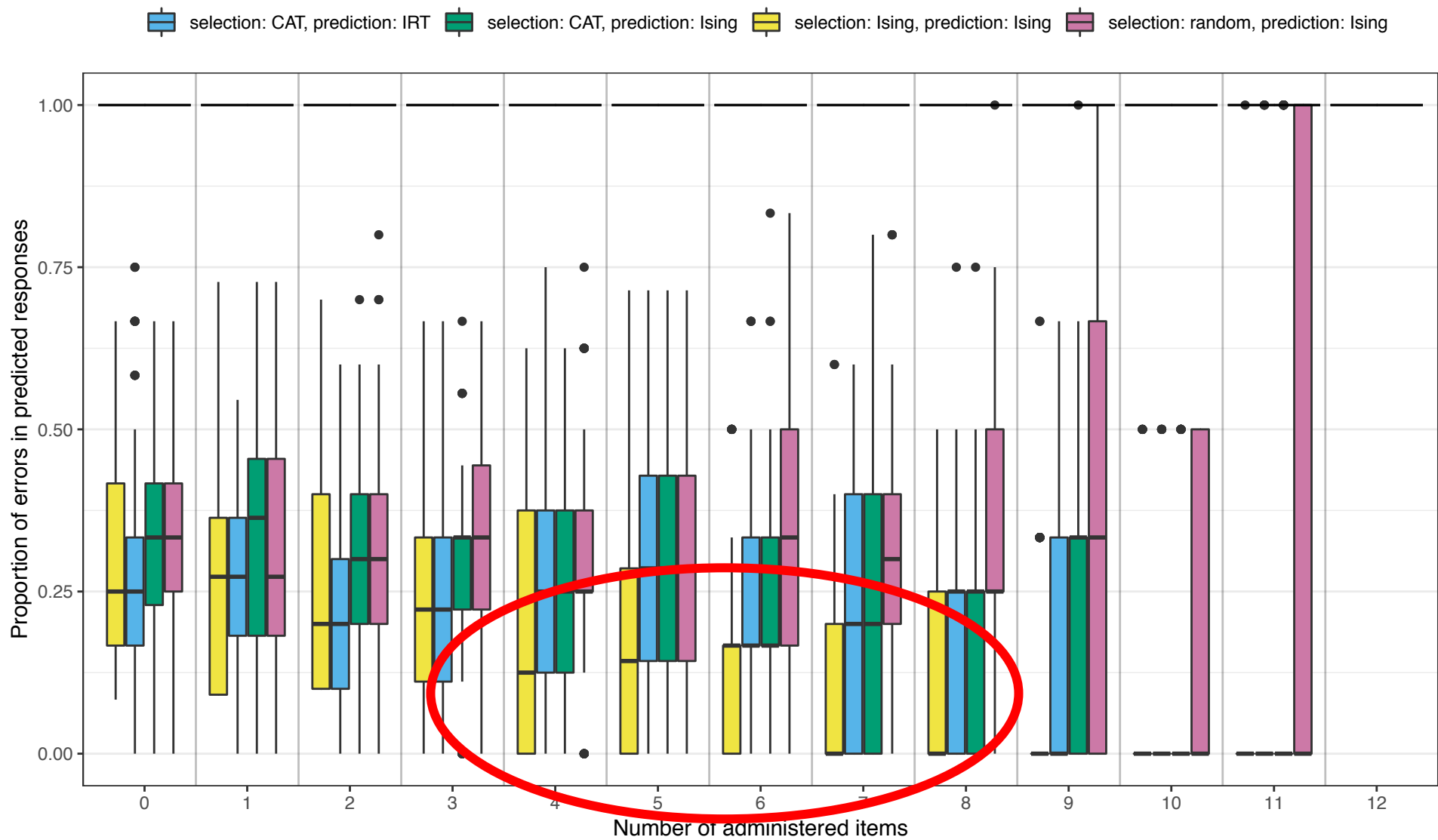




Simulation Study

- Empirical Ising model used as true structure
 - Fried, E. I., Bockting, C., Arjadi, R., Borsboom, D., Tuerlinckx, F., Cramer, A., Epskamp, S., Amshoff, M., Carr, D., & Stroebe, M. (2015). From loss to loneliness: The relationship between bereavement and depressive symptoms. *Journal of Abnormal Psychology*, 124, 256-265.
- Generate 1 case from true model
- Simulate adaptive assessment, using the true model, or IRT model based on N = 100,000 databank
- Each condition replicated 100 times





Better predictive power for network based adaptive testing

NETWORK PSYCHOMETRICS

PHASE 2

- From exploratory expedition to confirmatory methodology
- Move towards fine-grained analysis
 - Which edge can be added or removed?
 - Does edge A – B differ between two groups?
 - Does a theoretical model fit the data?
- Proper handling if missingness & nonnormality
- Network meta-analysis
- Network-based adaptive assessment

Thank you for your attention!

Publications & presentations:

www.sachaepskamp.com

Facebook group:

facebook.com/groups/PsychologicalDynamics