Discovering Psychological Dynamics

In cross-sectional and time-series data

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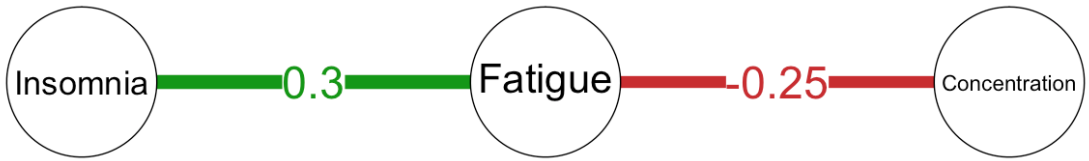
Goal

- Out-of-the-box methodology applicable to experience sampling method (ESM) data
  - Multiple people measured multiple times in relatively short time span (several weeks)
- Up to *three* network structures can be obtained in ESM data:
  - Contemporaneous networks
  - Temporal networks
  - Between-subjects networks



- The Gausian graphical models the inverse variance-covariance matrix
  - $\boldsymbol{K} = \boldsymbol{\Sigma}^{-1}$
- Network of *partial correlation coefficients*:
  - $\mathrm{Cor}\left(Y_i, Y_j \mid \boldsymbol{Y}^{-(i,j)}\right) = -\frac{\kappa_{ij}}{\sqrt{\kappa_{ii}}\sqrt{\kappa_{jj}}}$

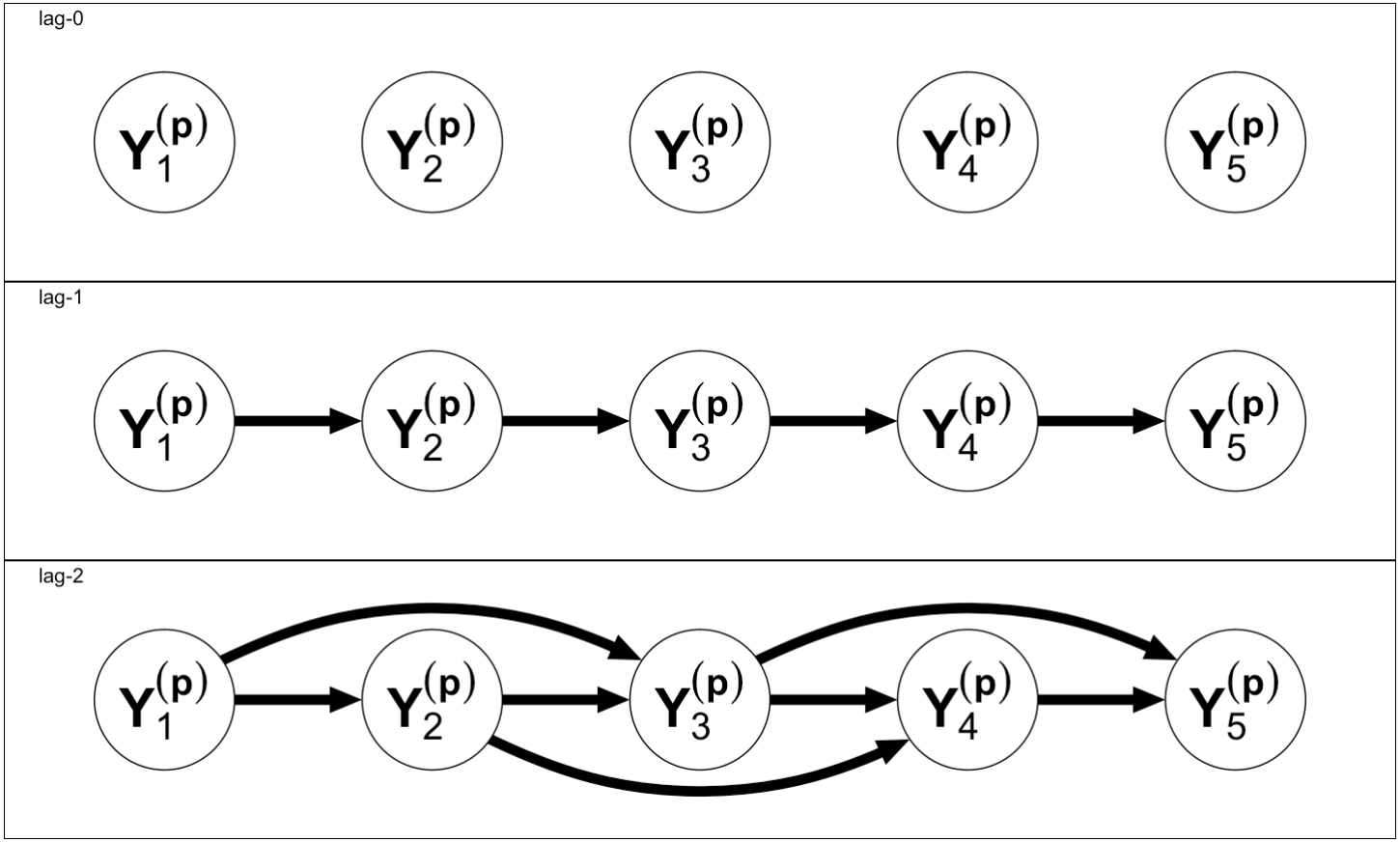
The GGM model:

- Concentration – Fatigue – Insomnia

Is equivalent to three causal structures:

1. Concentration → Fatigue → Insomnia
2. Concentration ← Fatigue → Insomnia
3. Concentration ← Fatigue ← Insomnia

Thus, the GGM highlights potential causal pathways. In addition, the partial correlations are *proportional* to multiple regression coefficients.



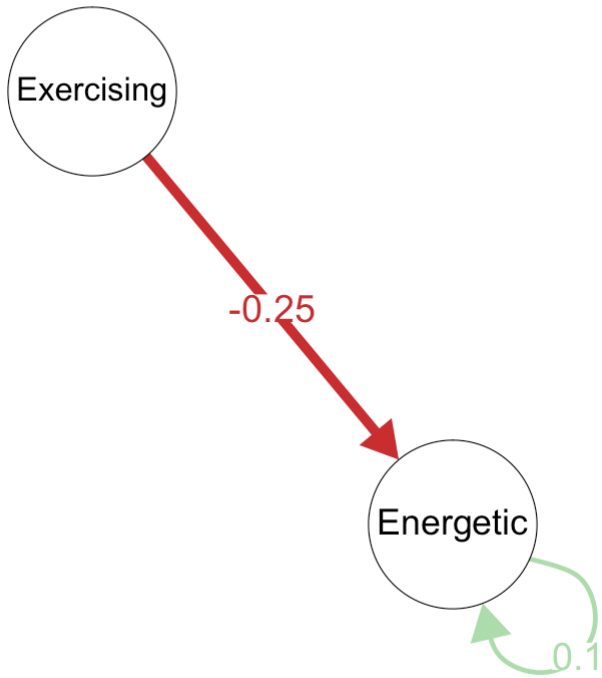
- We will use the lag-1 factorization

Vector Auto-regression

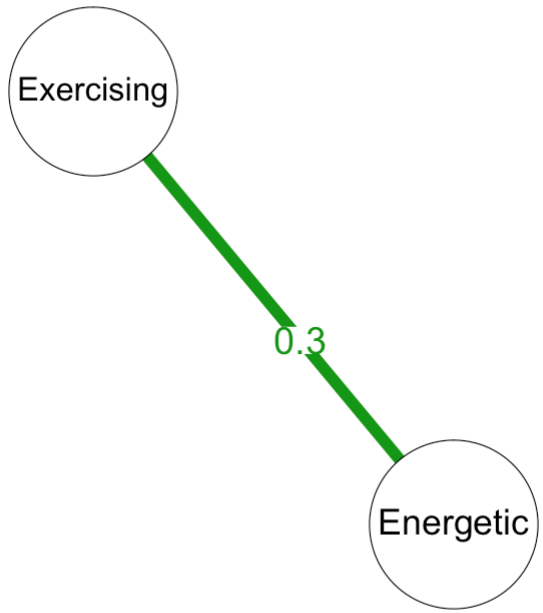
$$\boldsymbol{Y}_t \mid \boldsymbol{y}_{t-1} \sim N\left(\boldsymbol{\mu} + \boldsymbol{B}\left(\boldsymbol{y}_{t-1} - \boldsymbol{\mu}\right), \boldsymbol{\Theta}\right)$$

- $\boldsymbol{B}$ encodes the *temporal network*
  - Granger causality
- $\boldsymbol{\Theta}^{-1}$ encodes the *contemporaneous network*
  - GGM
- The sample means can be used as plugin to center the predictors

Temporal network



Contemporaneous network



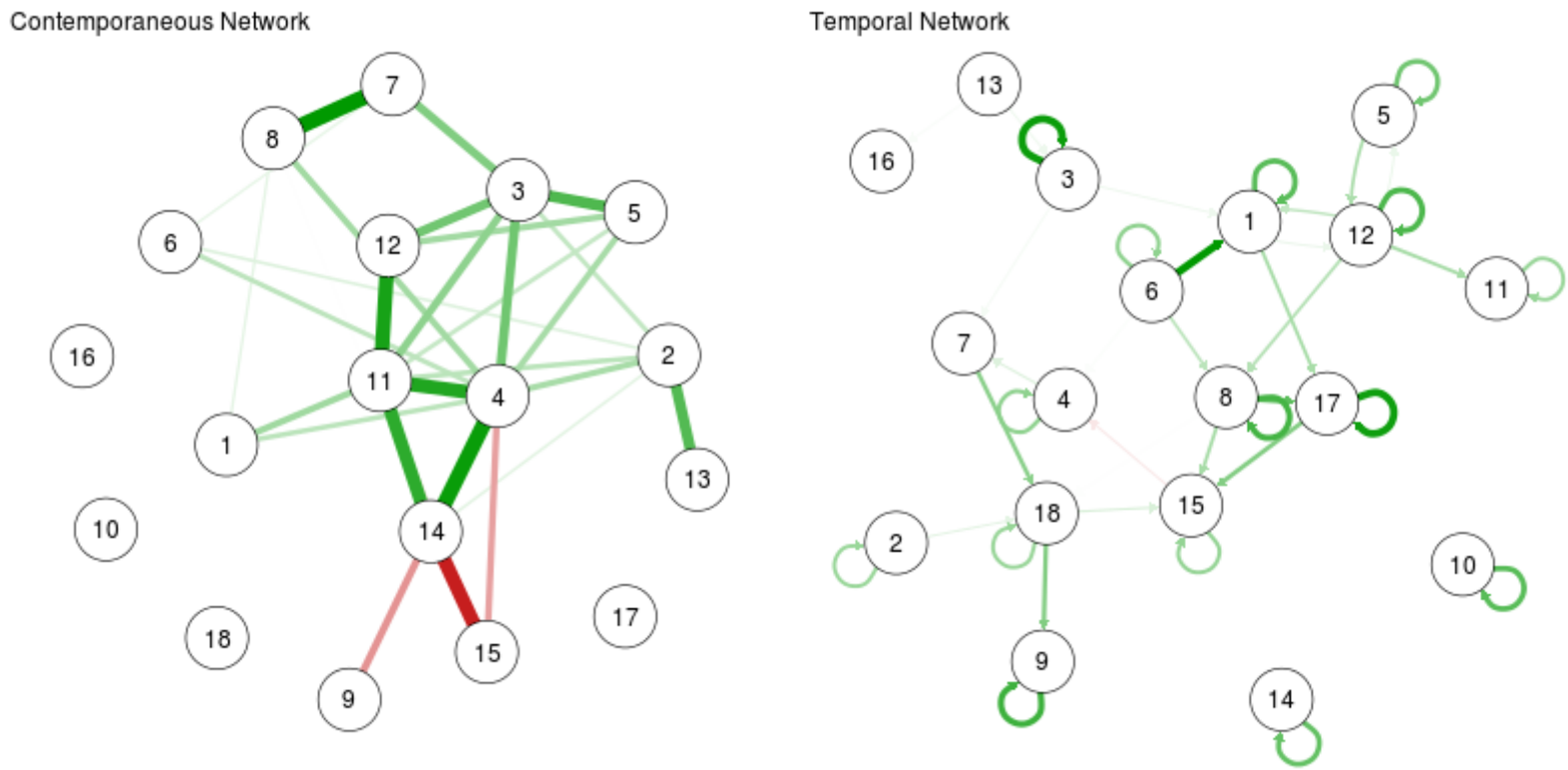
Contemporaneous Causation

- Many causal effects likely faster than the time-window of measurement
  - Somatic arousal → anticipation of panic attack → anxiety
- These can be caught in a contemporaneous network of **partial correlations**
- Thus, the contemporaneous network can also be seen to highlight potential causal relationships
- As the contemporaneous network is the GGM, the temporal network can be seen as a correction for dependent measurements in estimating the GGM

Empirical Example

Data collected by Date C. Van der Veen, in collaboration with Harriette Riese en Renske Kroeze.

- Patient suffering from panic disorder and depressive symptoms
  - Perfectionist
- Measured over a period of two weeks
- Five times per day
- Items were chosen after intake together with therapist



1: anxious, 2: stressed, 3: angry, 4: sad, 5: guilty, 6: weak, 7: worthless, 8: helpless, 9: full of energy, 10: fear panic attack, 11: fear to cry, 12: fear to appear angry, 13: 'had to do things', 14: bodily discomfort, 15: enjoying, 16: let something pass, 17: social env pleasurable, 18: physically active

Multi-level VAR

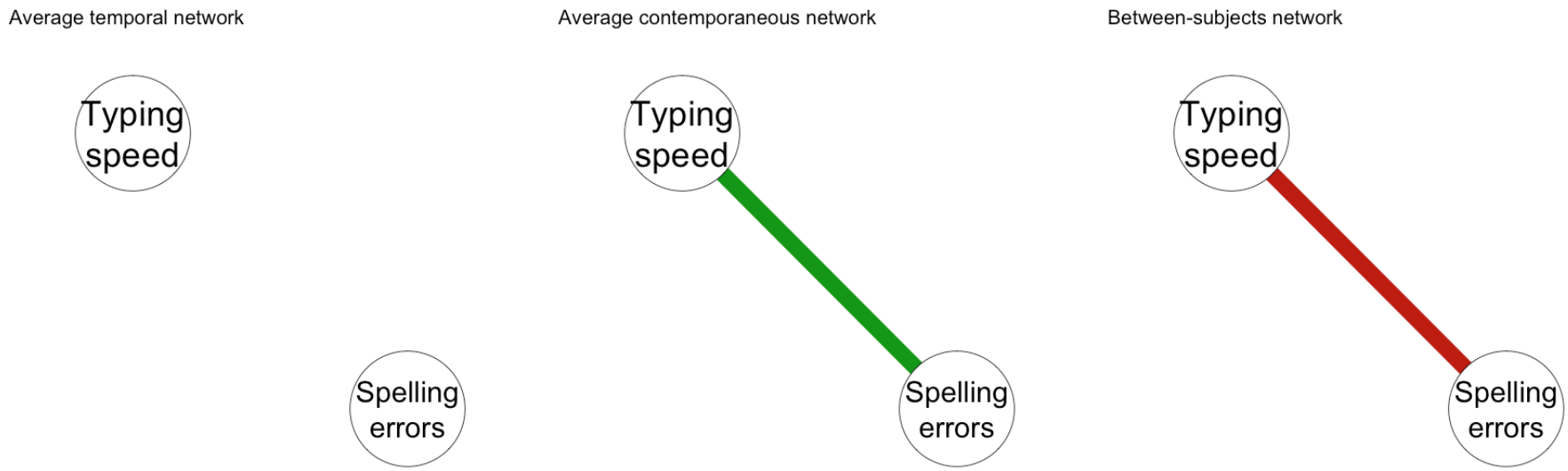
Adding superscript p for subject. Level 1 model:

$$\boldsymbol{Y}_t^{(p)} \mid \boldsymbol{y}_t^{(p)} = N\left(\boldsymbol{\mu}^{(p)} + \boldsymbol{B}^{(p)}\left(\boldsymbol{y}_{t-1}^{(p)} - \boldsymbol{\mu}^{(p)}\right), \boldsymbol{\Theta}^{(p)}\right)$$

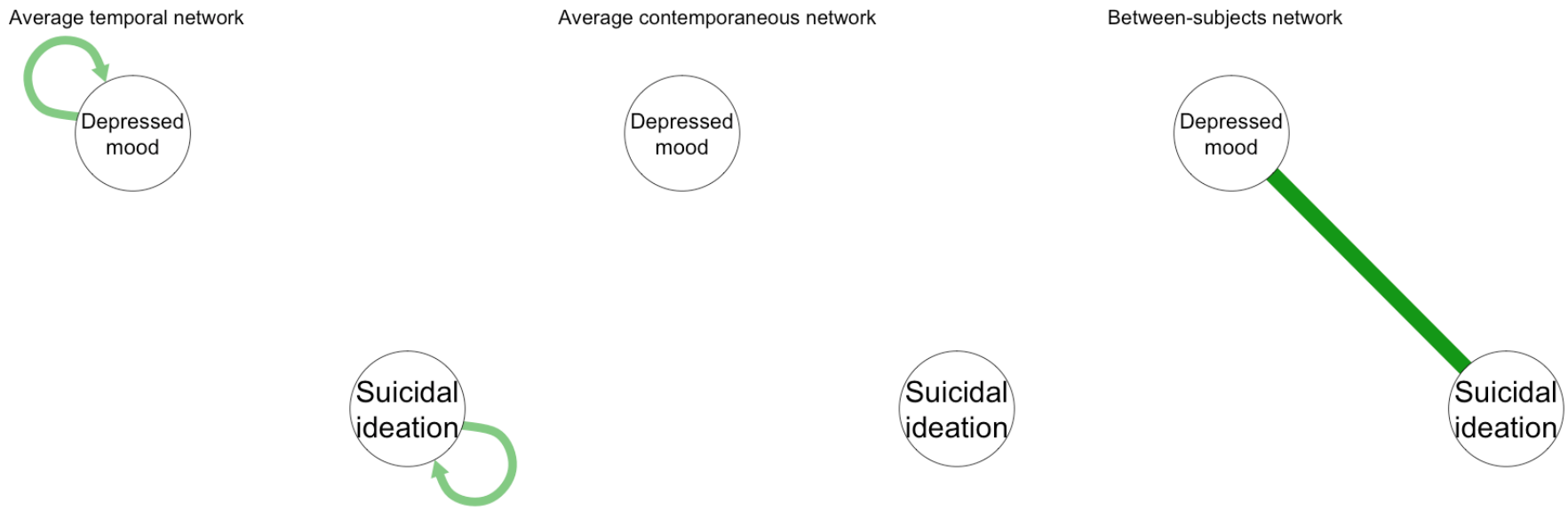
Level 2 model:

$$\begin{bmatrix} \boldsymbol{R}_{\boldsymbol{\mu}} \\ \boldsymbol{R}_{\boldsymbol{B}} \end{bmatrix} \sim N\left(\boldsymbol{0}, \begin{bmatrix} \boldsymbol{\Omega}_{\boldsymbol{\mu}} & \boldsymbol{\Omega}_{\boldsymbol{\mu B}} \\ \boldsymbol{\Omega}_{\boldsymbol{B\mu}} & \boldsymbol{\Omega}_{\boldsymbol{B}} \end{bmatrix}\right).$$

- Block $\boldsymbol{\Omega}_{\boldsymbol{\mu}}$ encodes the between-subject relationships between *means*
- These can be used to estimate a GGM
  - Between-subjects network of **partial correlations**



Example based on Hamaker, E. L. (2012). Why Researchers Should Think 'Within-Person': A Paradigmatic Rationale. *Handbook of Research Methods for Studying Daily Life*. The Guilford Press New York, NY, 43–61.



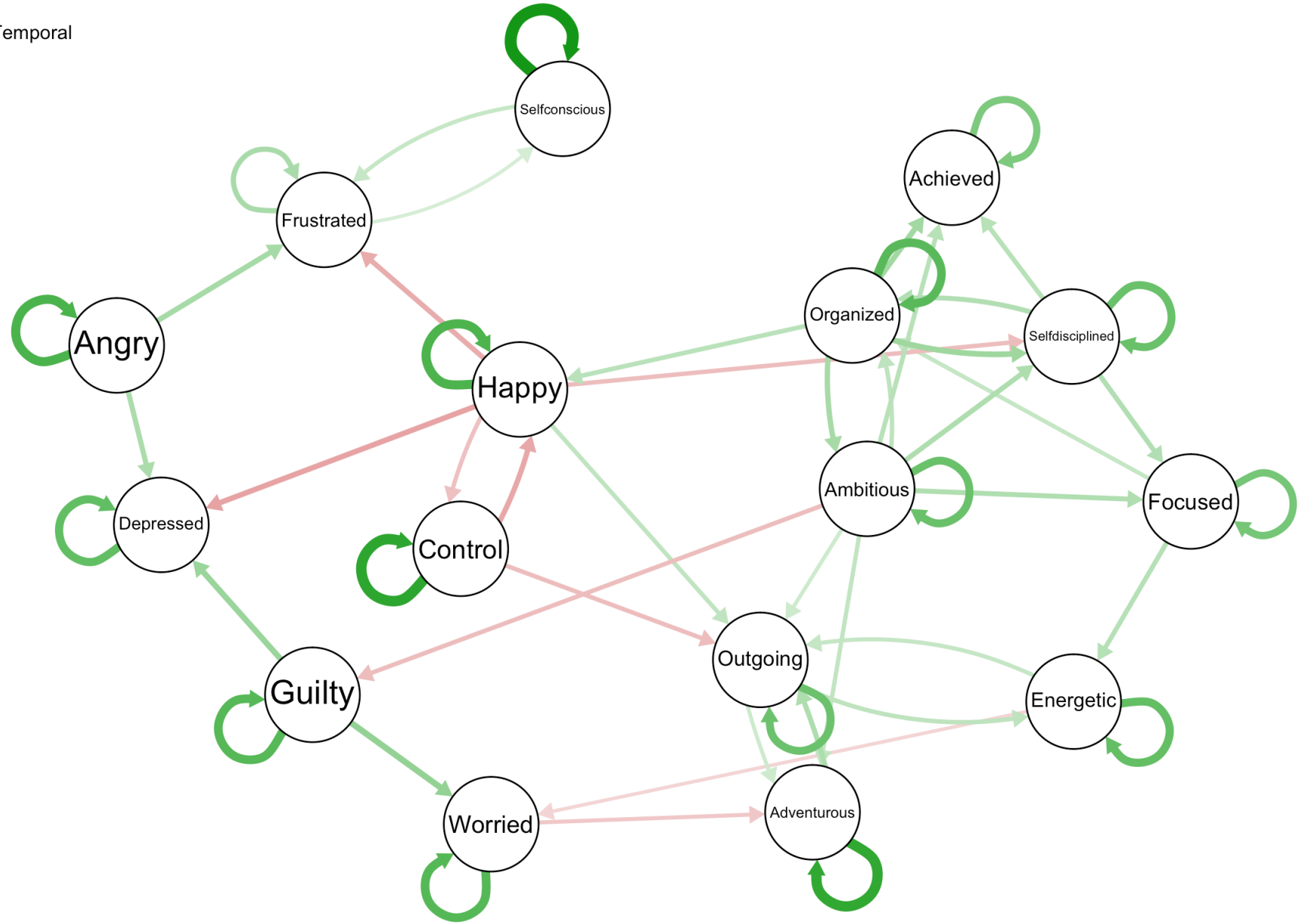
Hypothetical example of networks based on two persons:

- Clinically depressed person constantly scoring high on both
- Healthy person constantly scoring low on both

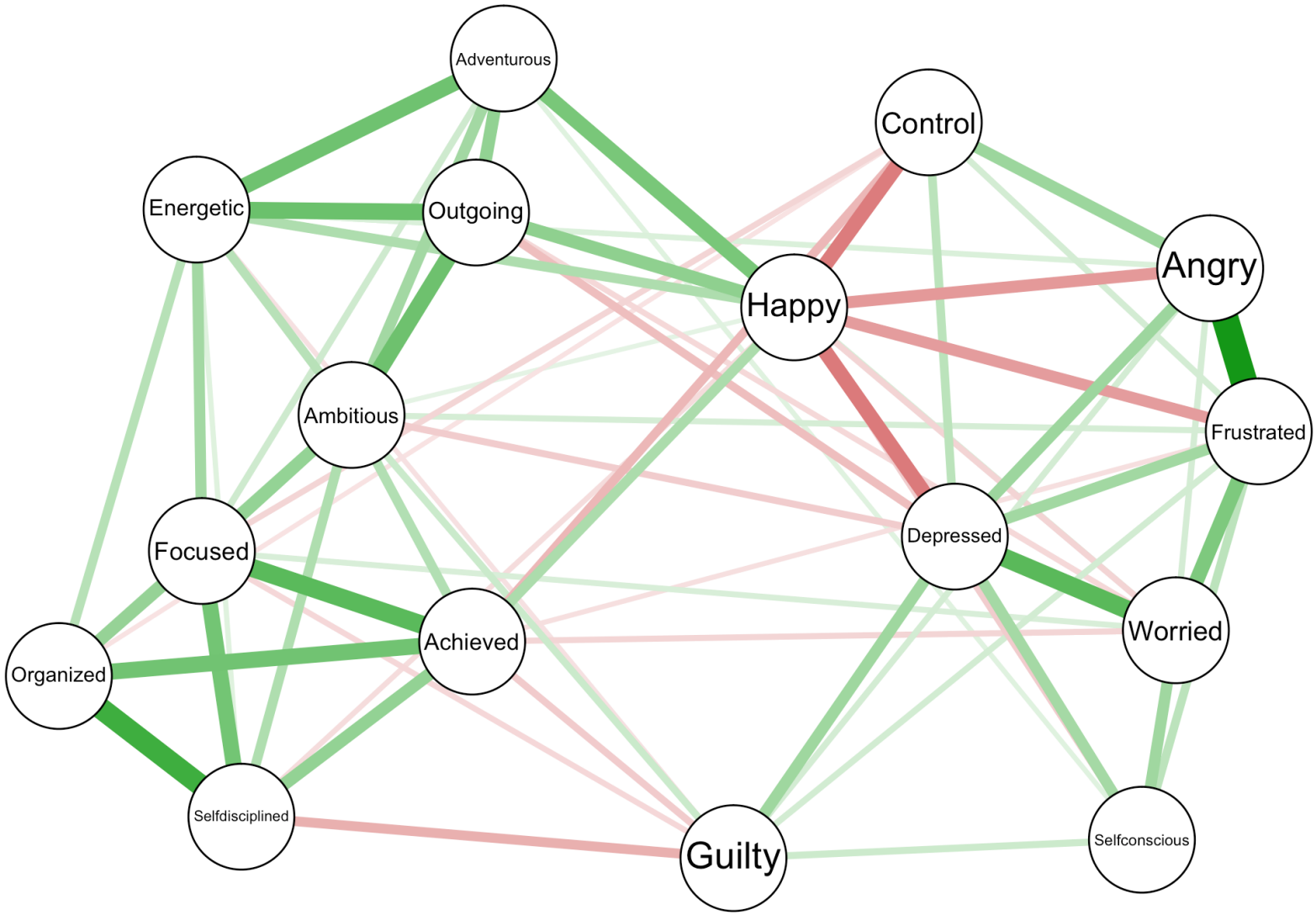
Empirical Example

- Two datasets
  - Original: 26 subjects, 51 measurements on average, 1323 total observations
  - Replication: 65 subjects, 35.5 measurements on average, 2309 total observations
- 16 indicators of neuroticism, extroversion, conscientiousness
- Orthogonal estimation of temporal and contemporaneous effects
- Only significant effects shown
  - Alpha = 0.05 and using the "or" rule
- *Very* preliminary results
  - I ran the analysis two days ago!

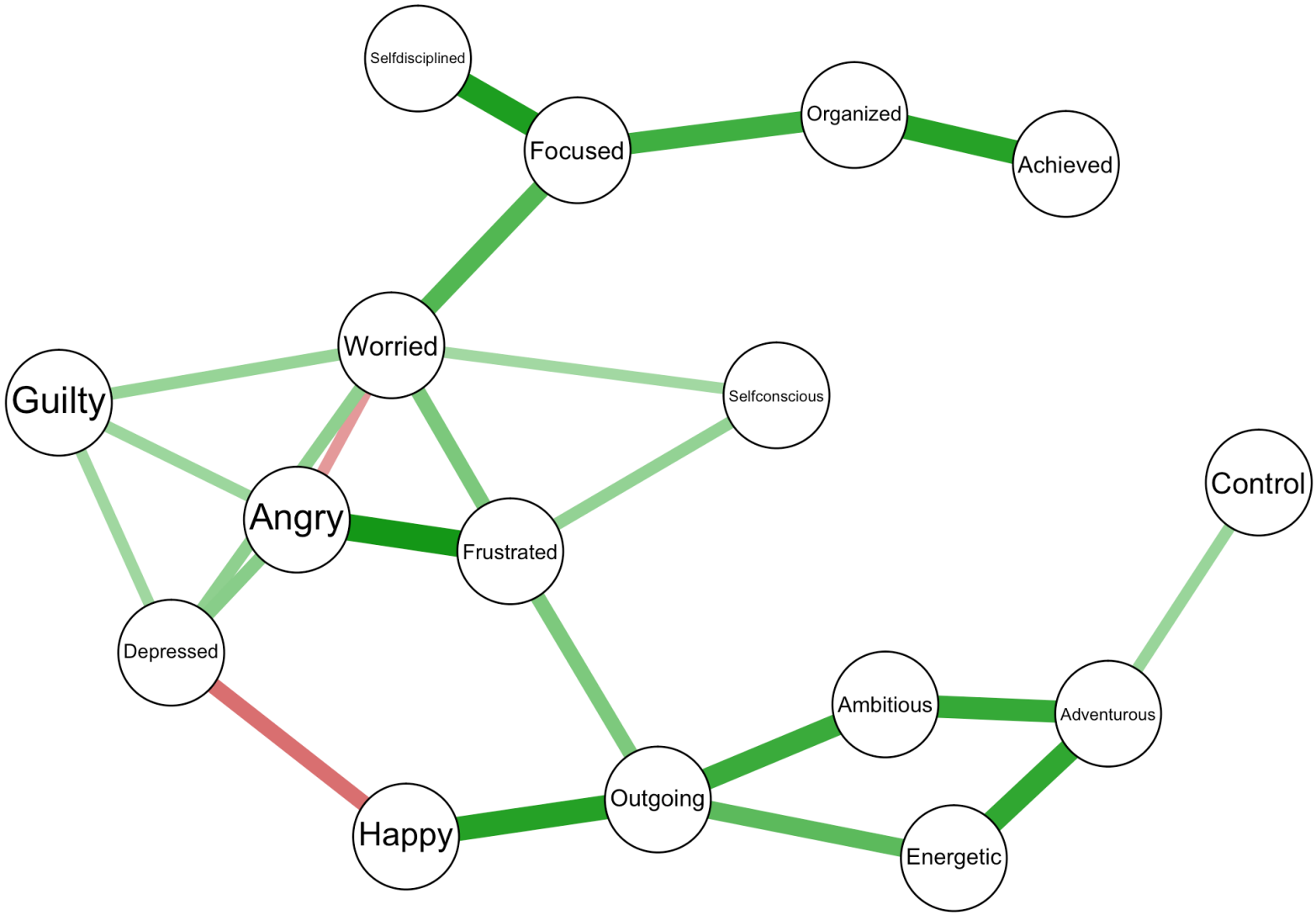
Temporal

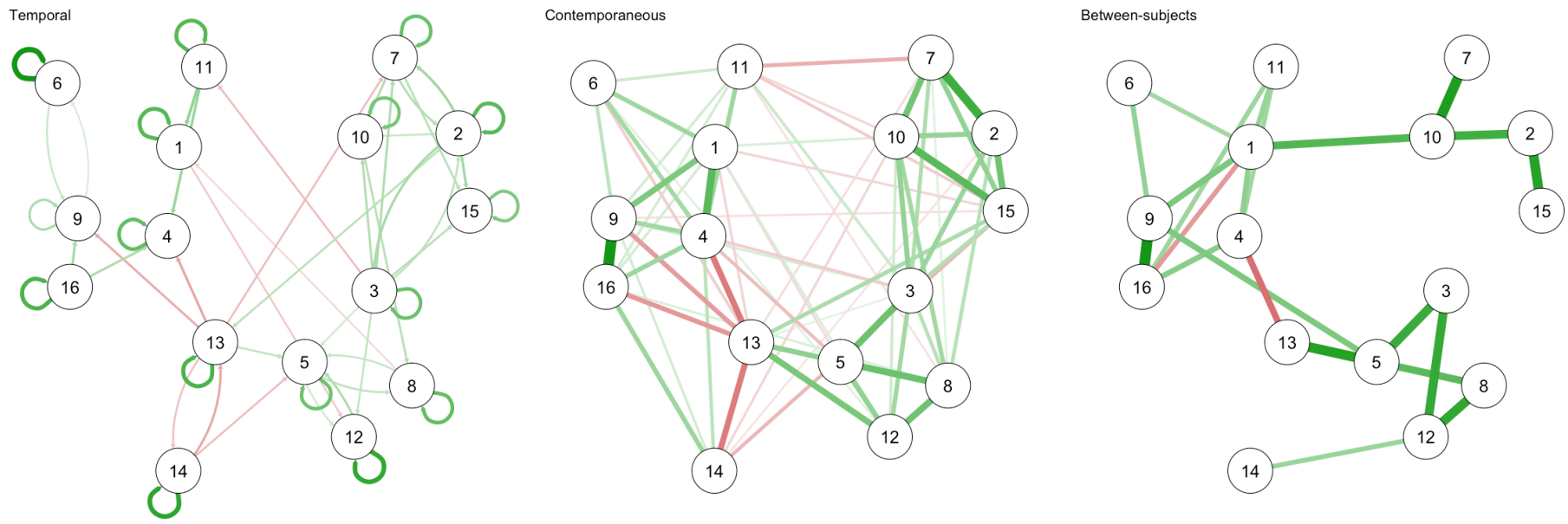

Selfconscious
Frustrated
Angry
Happy
Depressed
Control
Guilty
Worried
Achieved
Organized
Selfdisciplined
Ambitious
Focused
Outgoing
Energetic
Adventurous

Contemporaneous



Between-subjects





1: Worried, 2: Organized, 3: Ambitious, 4: Depressed, 5: Outgoing, 6: Selfconscious, 7: Selfdisciplined, 8: Energetic, 9: Frustrated, 10: Focused, 11: Guilty, 12: Adventurous, 13: Happy, 14: Control, 15: Achieved, 16: Angry

Conclusion

Conclusion

- Network structures are useful in discovering potential causal relationships
- Cross-sectional data:
  - Gaussian graphical model (GGM)
- ESM data:
  - Contemporaneous network (GGM)
  - Temporal network (VAR)
  - Between-subjects network (GGM)

Limitations and Future Directions

- A lot of potential problems with multi-level estimation
  - Multivariate estimation
  - Modeling random contemporaneous effects
  - Parameter variance-covariances
  - Model selection
- Possibly move away from multi-level
  - LASSO variants?
- Lag-interval

The Limit of Observational Data

- Network structures are only hypothesis generating
  - Highlighting potential causal pathways
- Observational data can *never* confirm causality
  - Mixture of experimental and observational data needed
- We need to completely rethink the modeling framework to do so

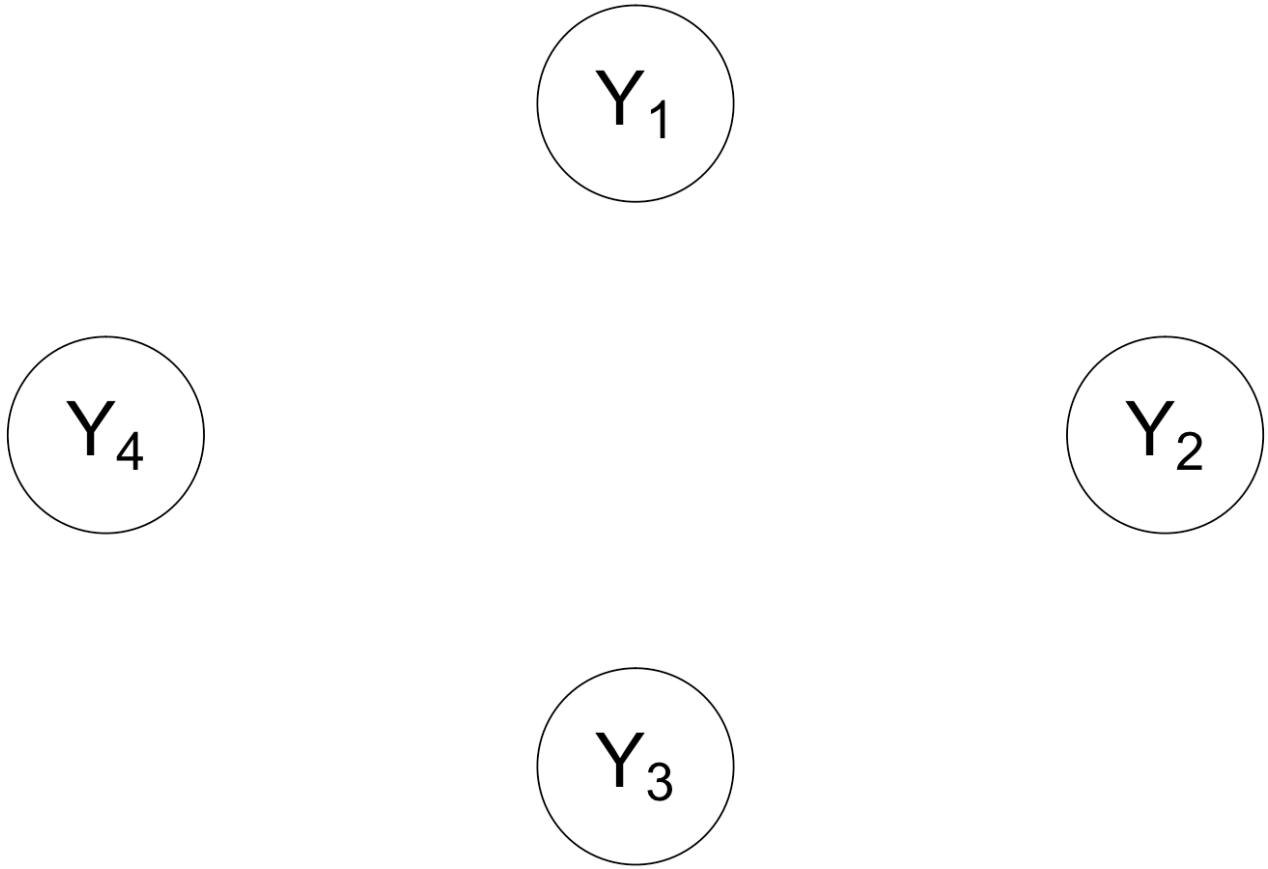
Also Included in Slides

- Estimation methods
  - Sequential estimation using lme4
  - Between-subject effects as level 2 predictors
  - Contemporaneous effects estimated post-hoc
- Simulation studies
  - 8 nodes
  - 20 nodes

Thank you for your attention!

Estimation

GGM and Multiple Regressions



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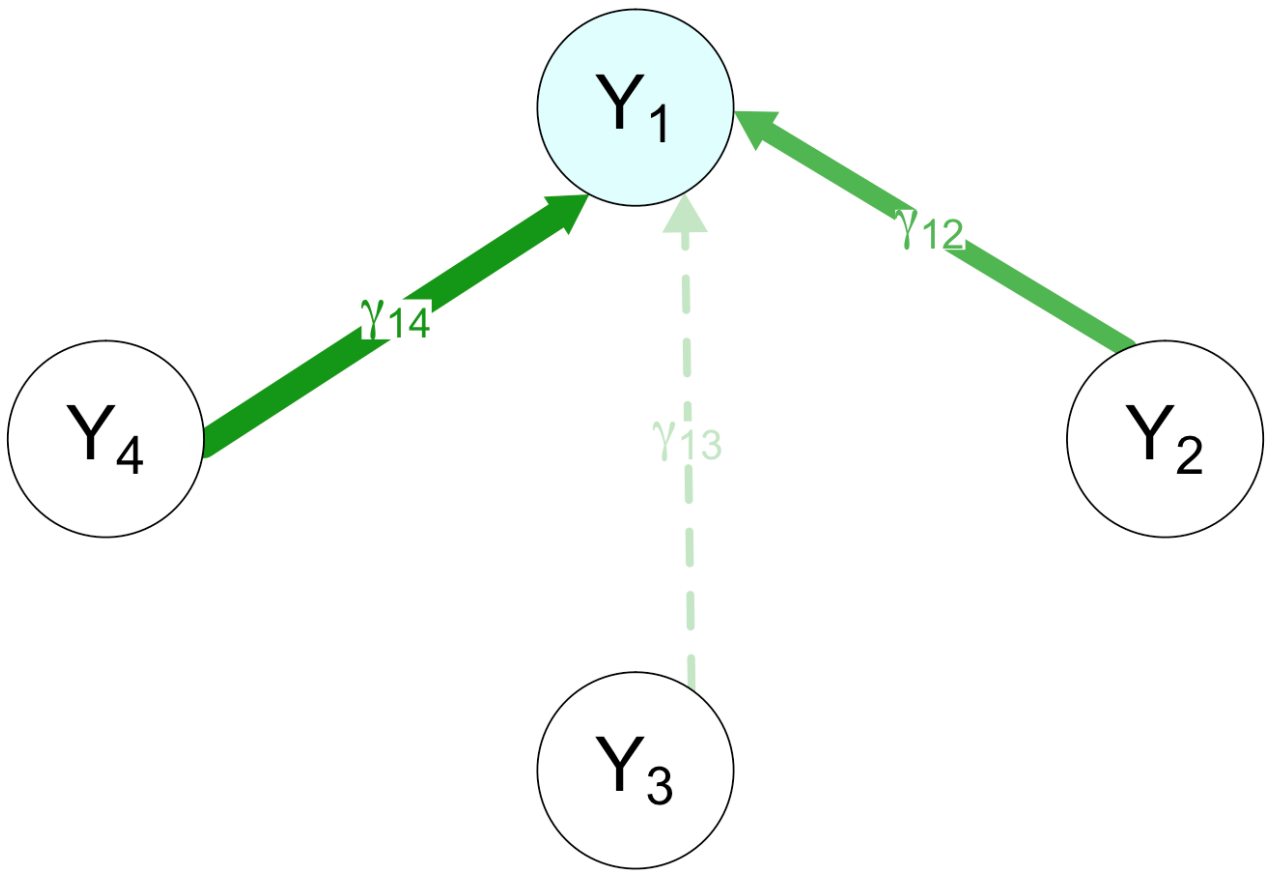
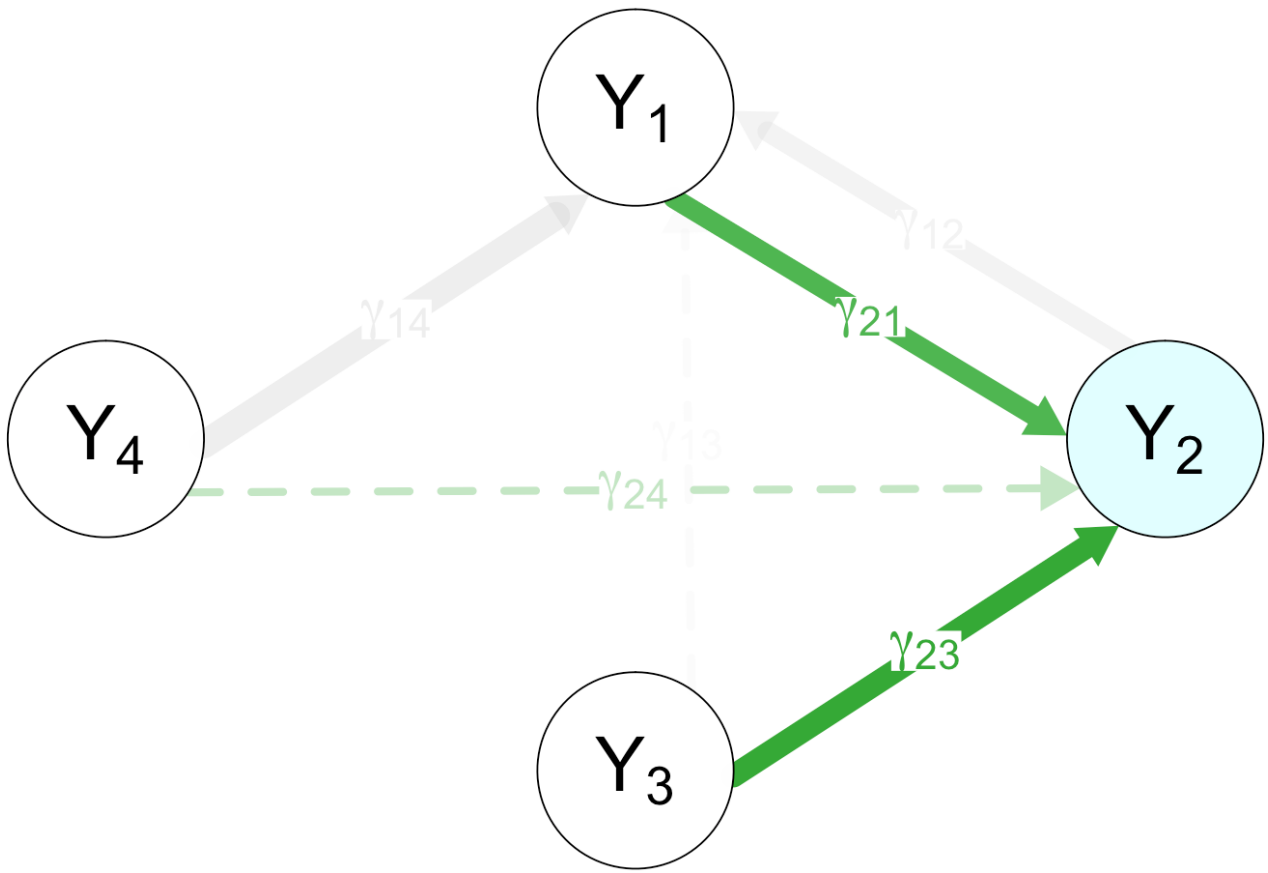


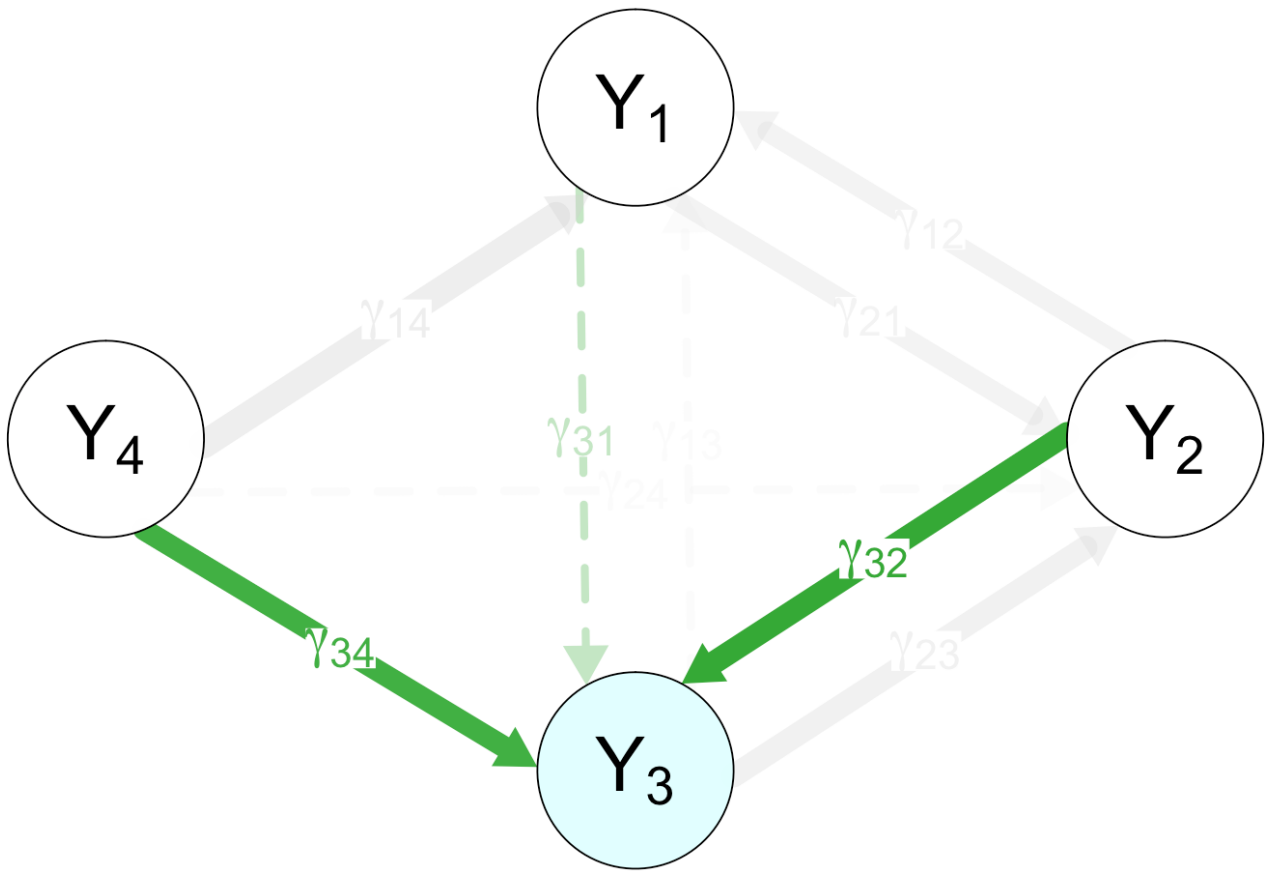
$$y_1 = \tau_1 + \gamma_{12} y_2 + \gamma_{13} y_3 + \gamma_{14} y_4 + \varepsilon_1$$

GGM and Multiple Regressions



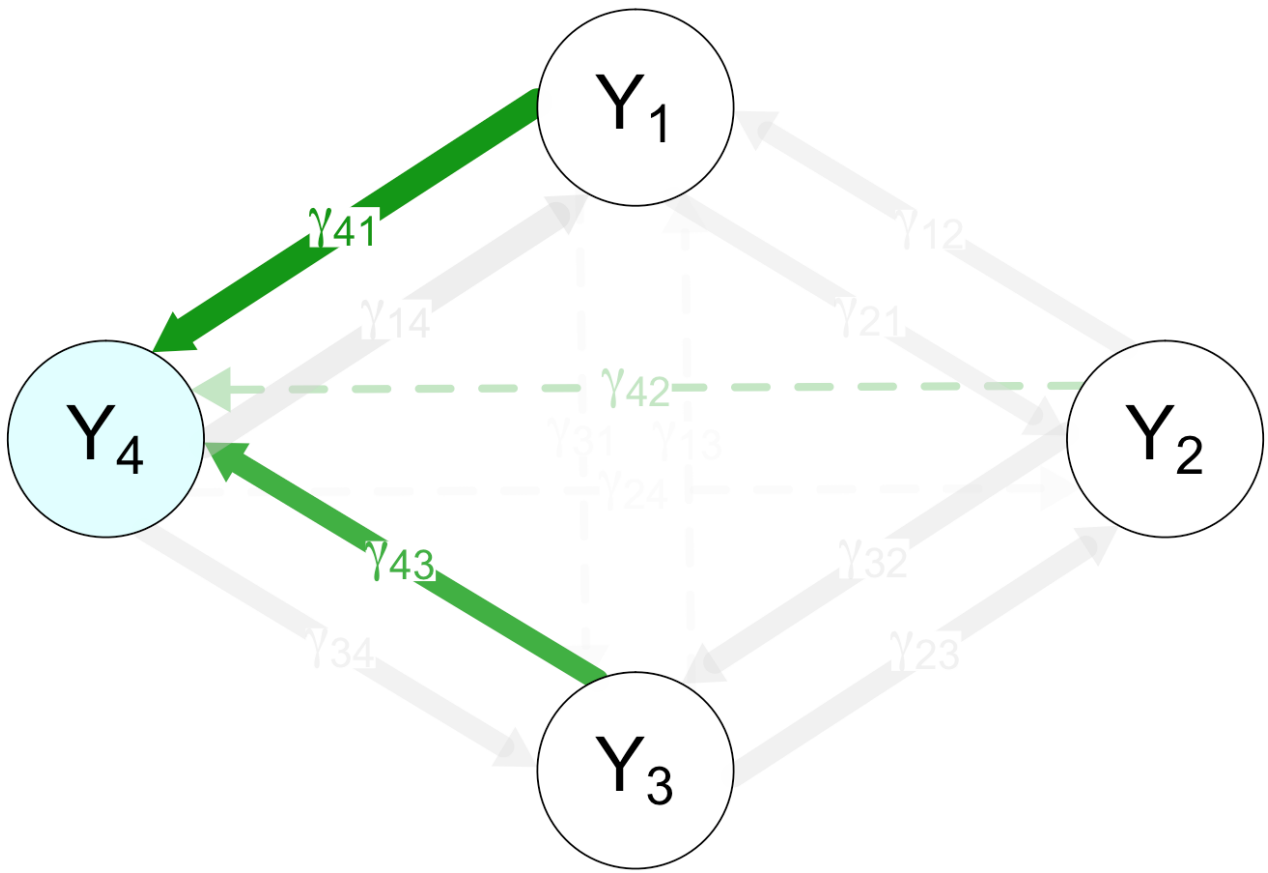
$$y_2 = \tau_2 + \gamma_{21} y_1 + \gamma_{23} y_3 + \gamma_{24} y_4 + \varepsilon_2$$

GGM and Multiple Regressions



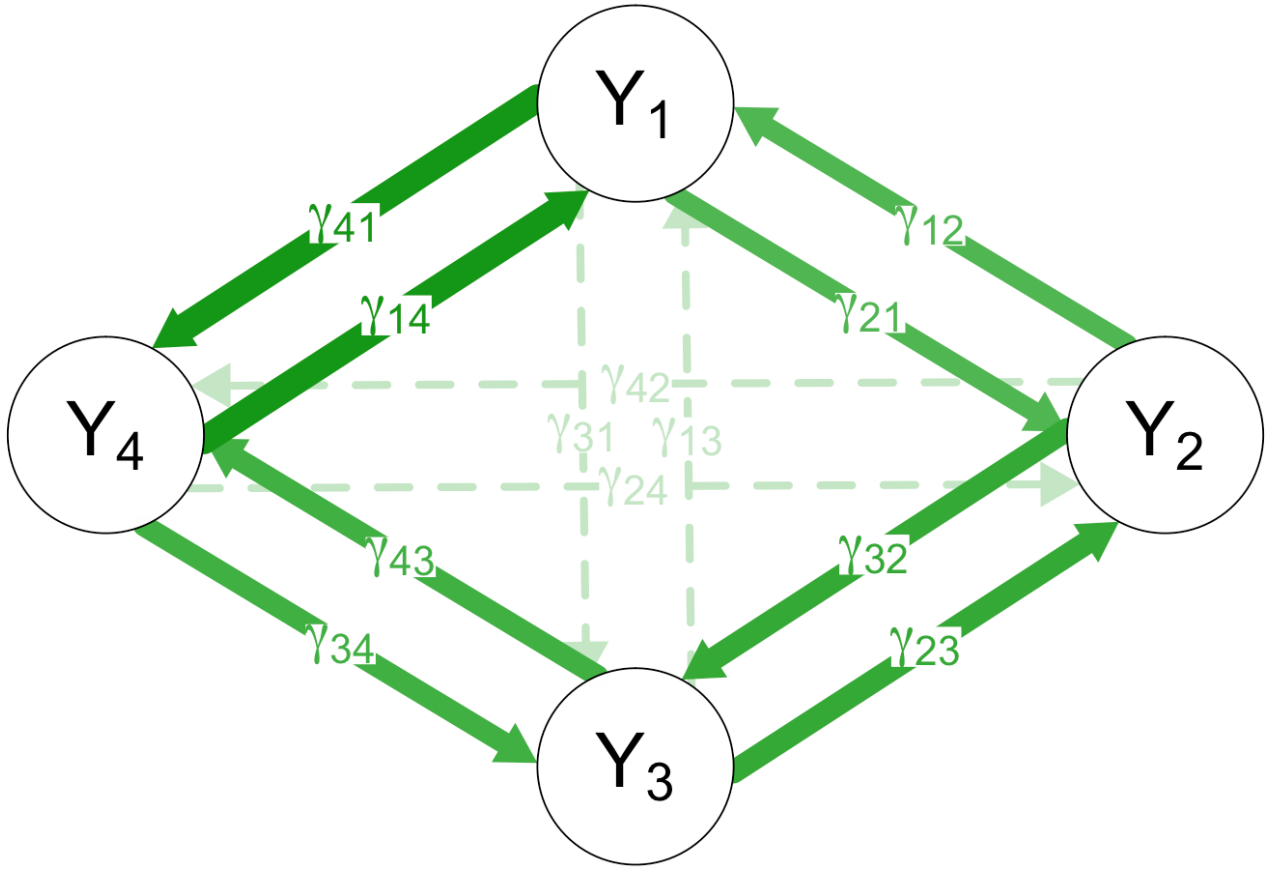
$$y_3 = \tau_3 + \gamma_{31} y_1 + \gamma_{32} y_2 + \gamma_{34} y_4 + \varepsilon_3$$

GGM and Multiple Regressions



$$y_4 = \tau_4 + \gamma_{41} y_1 + \gamma_{42} y_2 + \gamma_{43} y_3 + \varepsilon_4$$

GGM and Multiple Regressions



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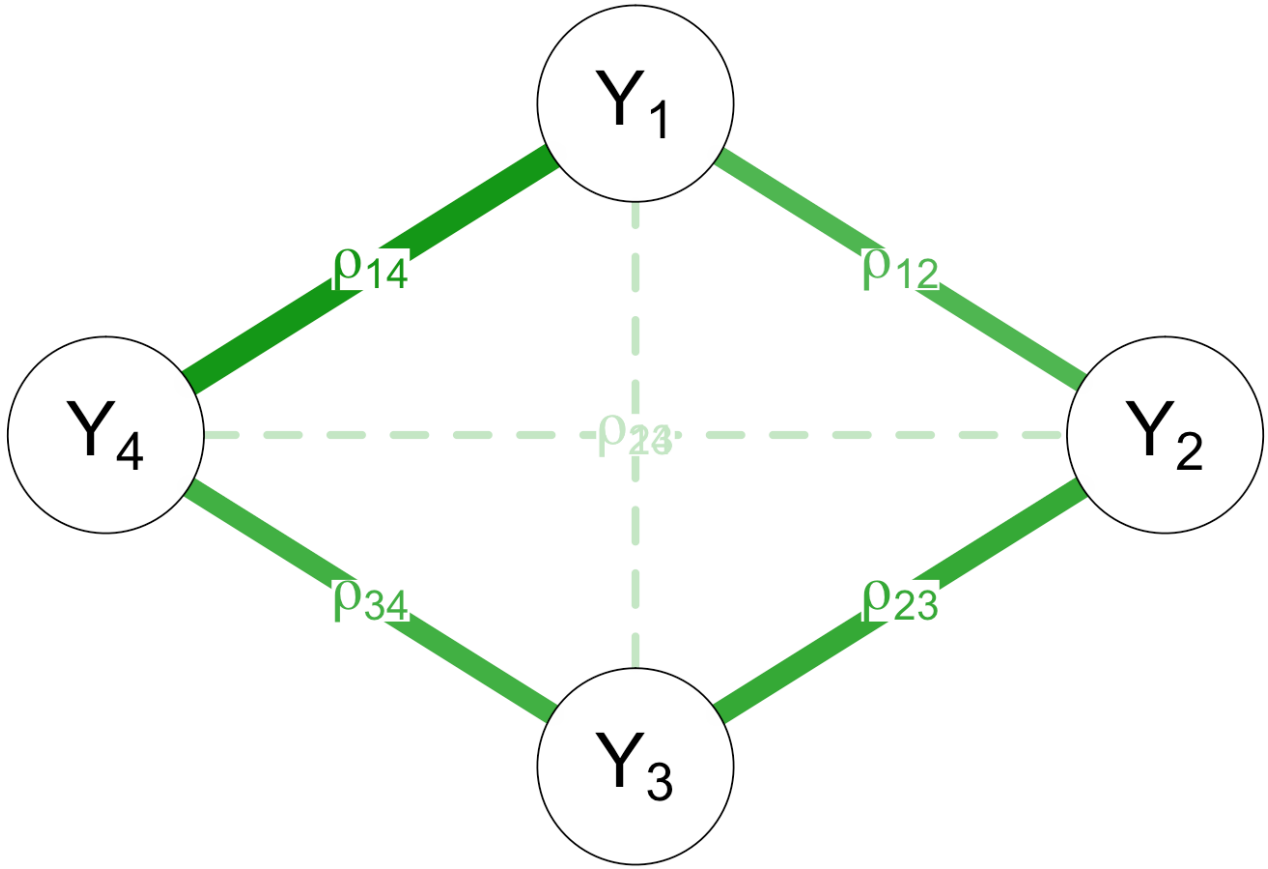
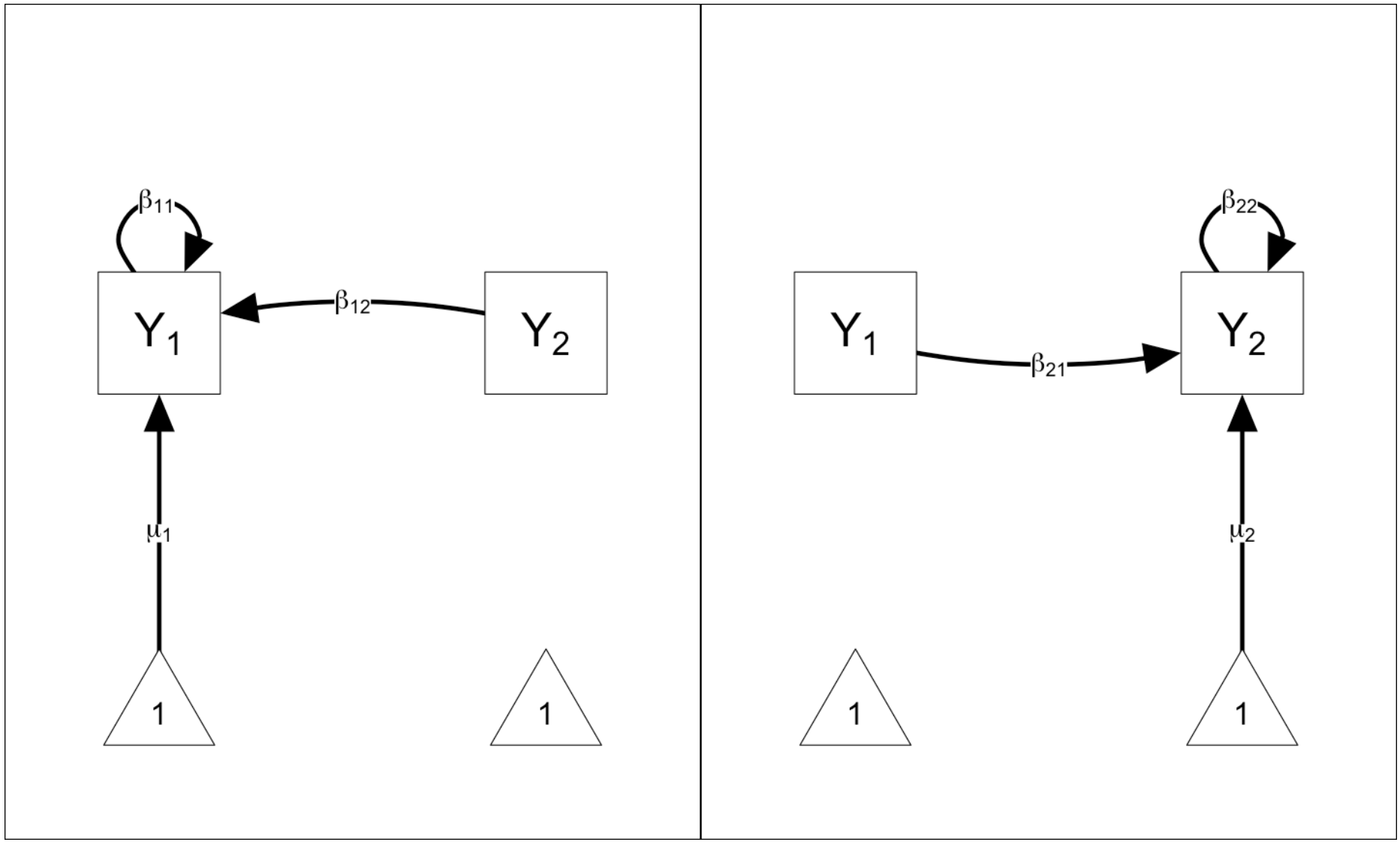
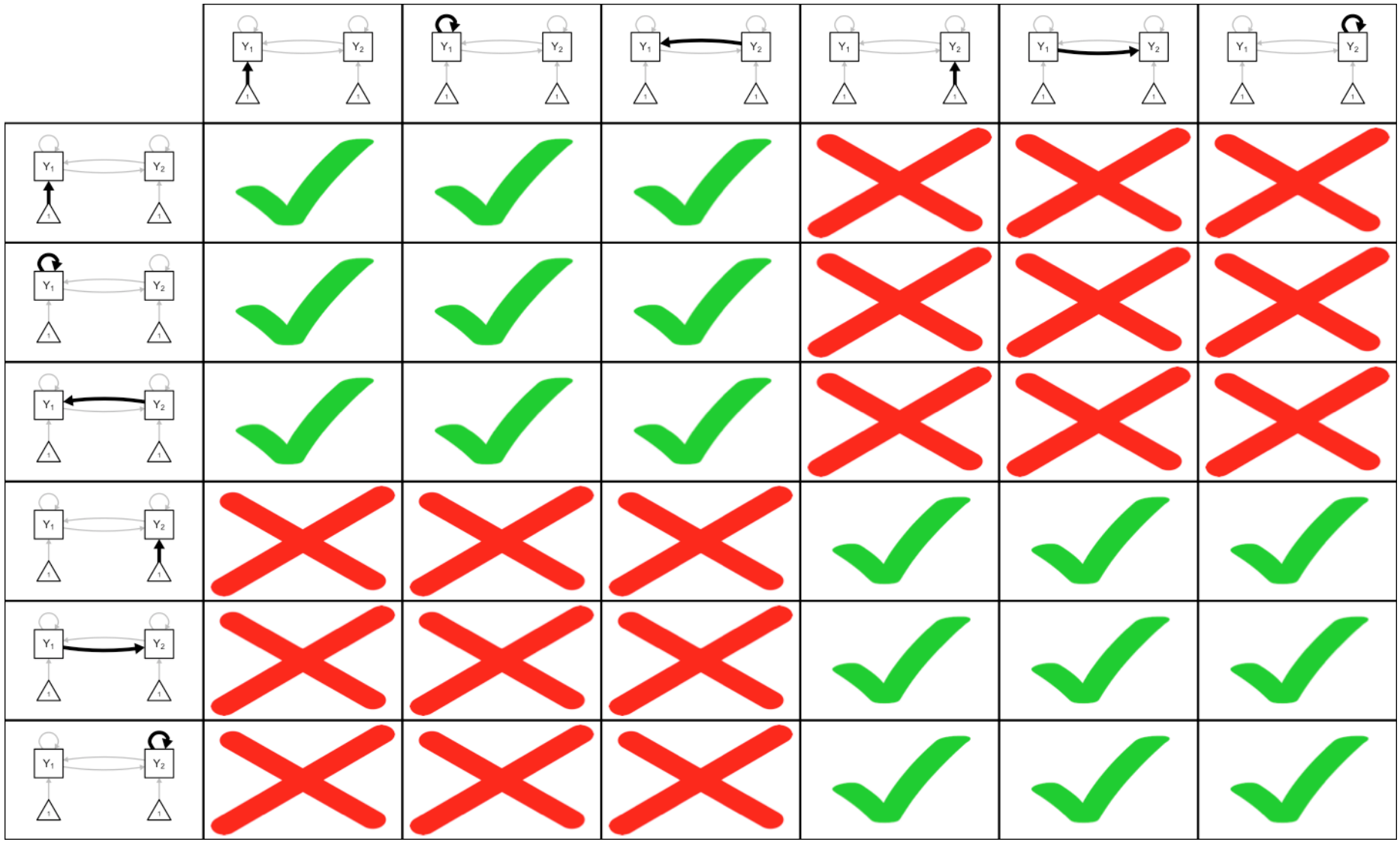


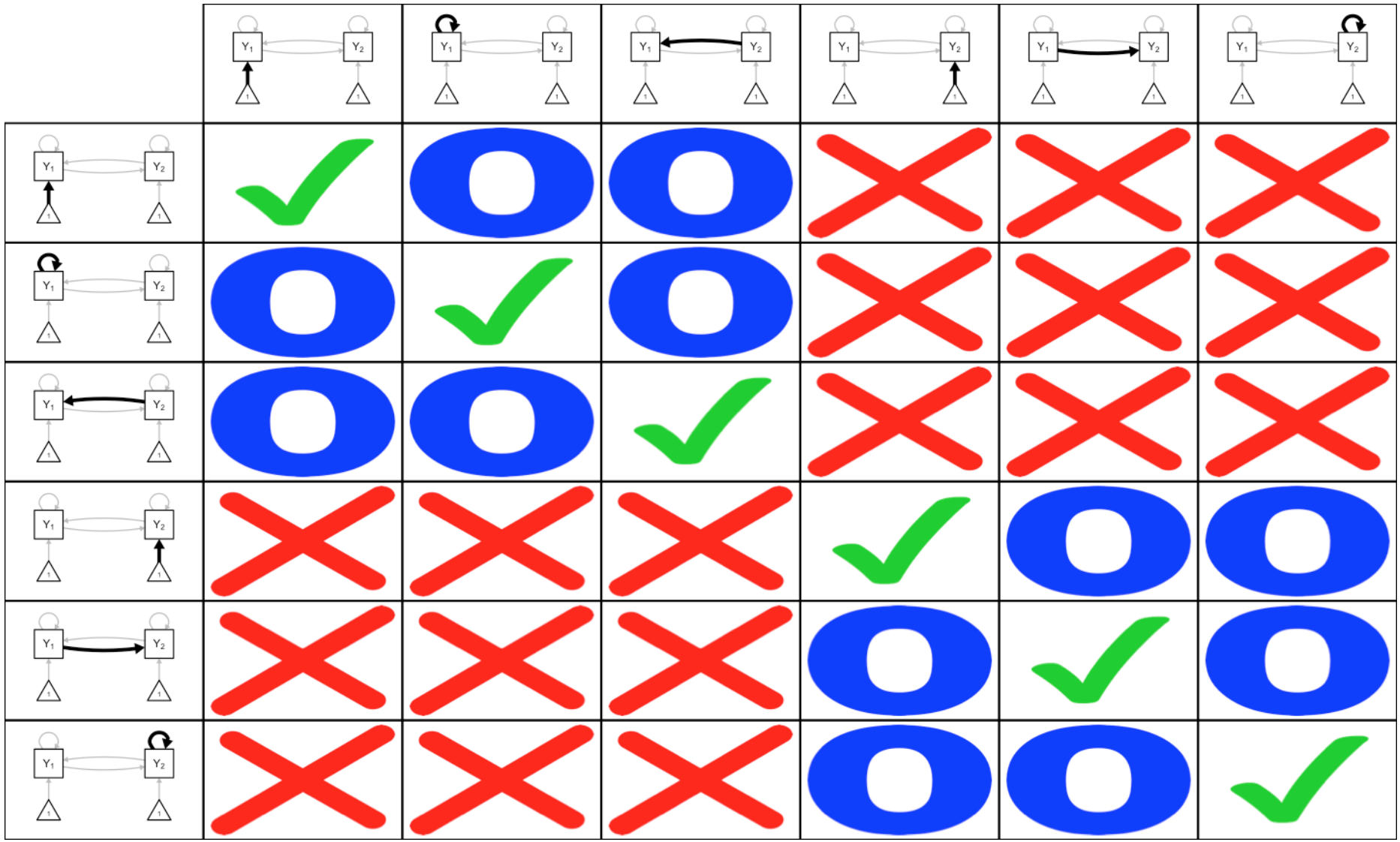
Temporal Estimation



Correlated Estimation



Orthogonal Estimation



Between-subject Estimation

- Between subject effects can be obtained by centering predictors and adding the person-means as level 2 predictors
  - Hamaker, E. L., & Grasman, R. P. (2015). To center or not to center? Investigating inertia with a multilevel autoregressive model. Frontiers in psychology, 5, 1492.
- This can be seen as node-wise estimation of a GGM
- Thus, an estimate for the between-subjects GGM can be obtained by averaging the level-2 predictive effects standardized with the residual variances

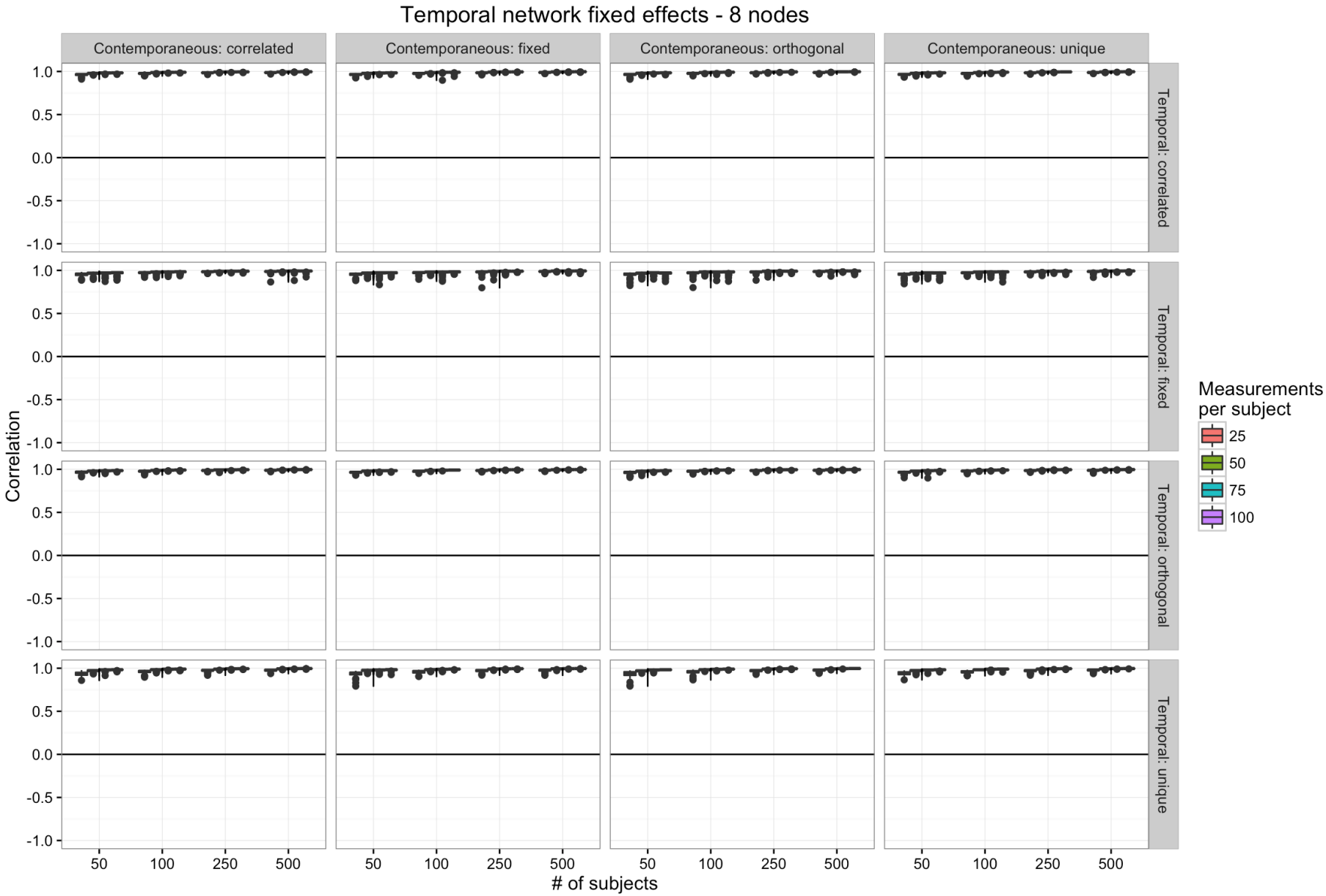
Contemporaneous Estimation

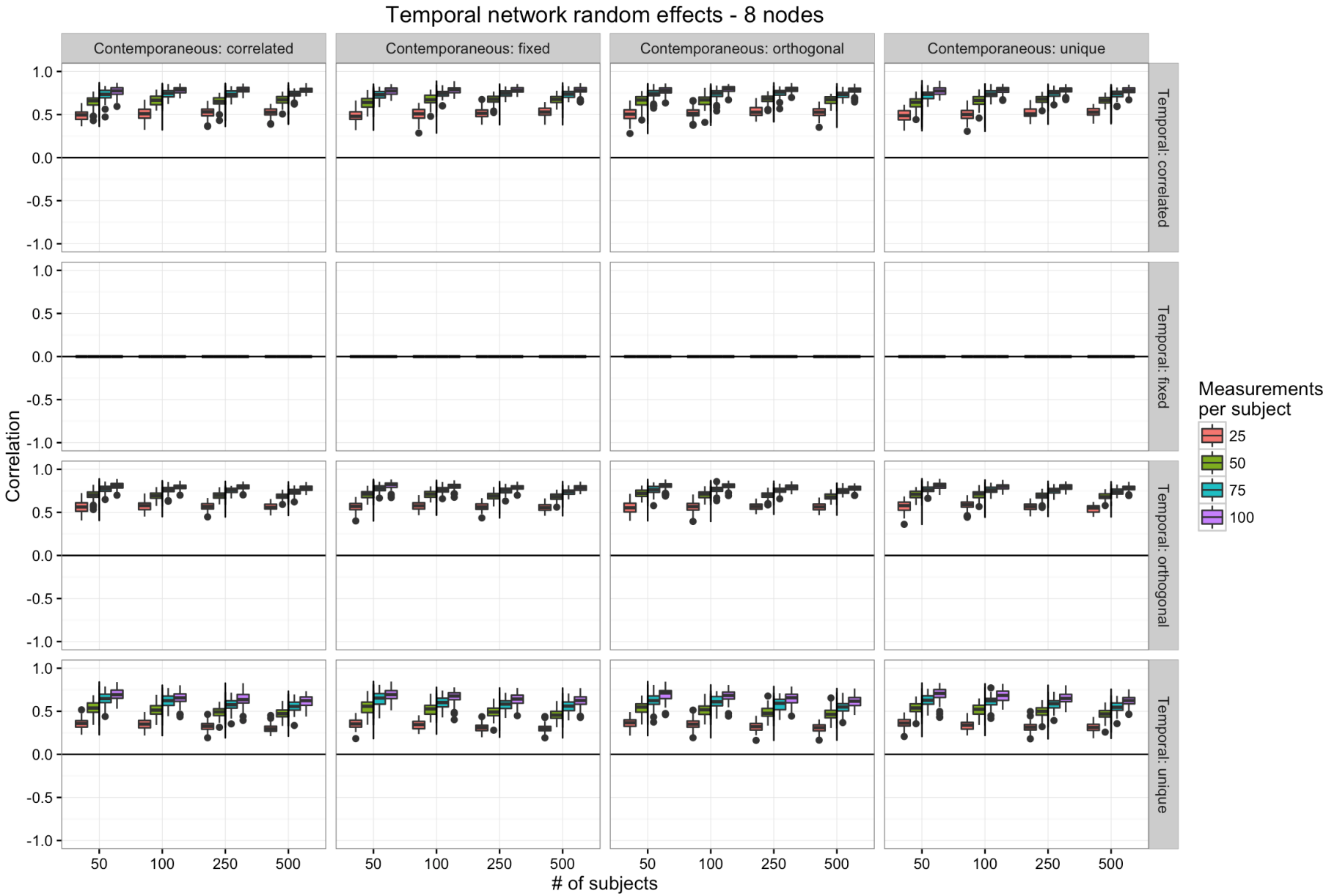
- Contemporaneous networks need to be estimated post-hoc by investigating the residuals
- Either inverting the sample variance-covariance matrix of residuals:
  - Fixed
  - Unique
- Or as a second multi-level model using nodewise estimation of a GGM:
  - Correlated
  - Orthogonal

Simulations

Simulation Studies

- 8 and 20 nodes
- Random between-subjects covariance matrix for means and temporal effects
  - `clusterGeneration` R package with "onion" method
  - No correlations between means and temporal effects
- Temporal effects scaled to enforce stationarity
- Random fixed contemporaneous covariance matrix
- Contemporaneous person-specific covariances drawn from Wishart distribution with *2P* DF
- Performance checked with temporal effects and **partial** correlations
- Each condition (# persons, # time, temporal estimation method and contemporaneous estimation method) replicated 100 times


Temporal network fixed effects - 8 nodes
Contemporaneous: correlated
Contemporaneous: fixed
Contemporaneous: orthogonal
Contemporaneous: unique
Temporal: correlated
Temporal: fixed
Temporal: orthogonal
Temporal: unique
Correlation
1.0
0.5
0.0
-0.5
-1.0
50
100
250
500
# of subjects
Measurements per subject
25
50
75
100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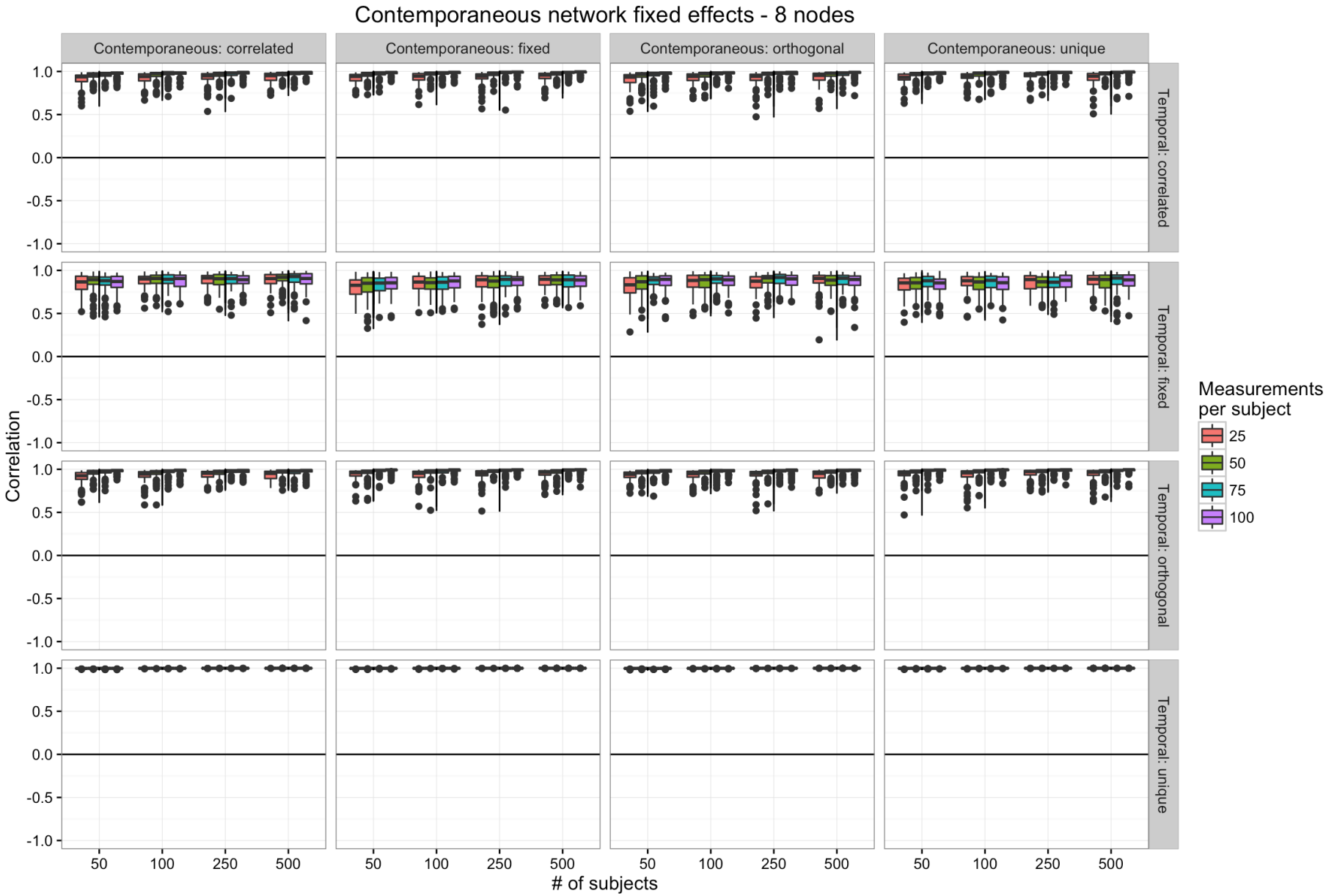
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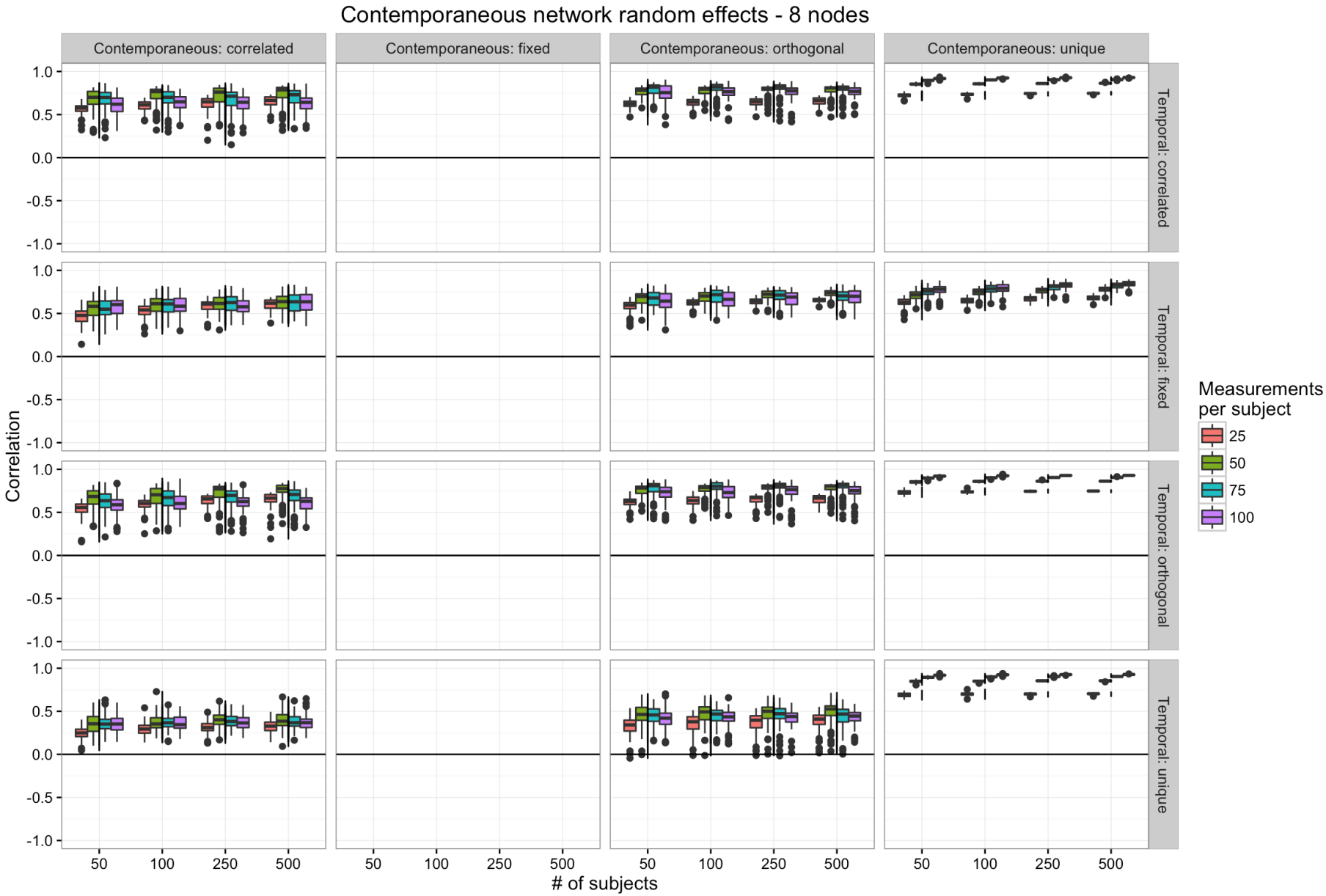
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Between-subjects network - 8 nodes
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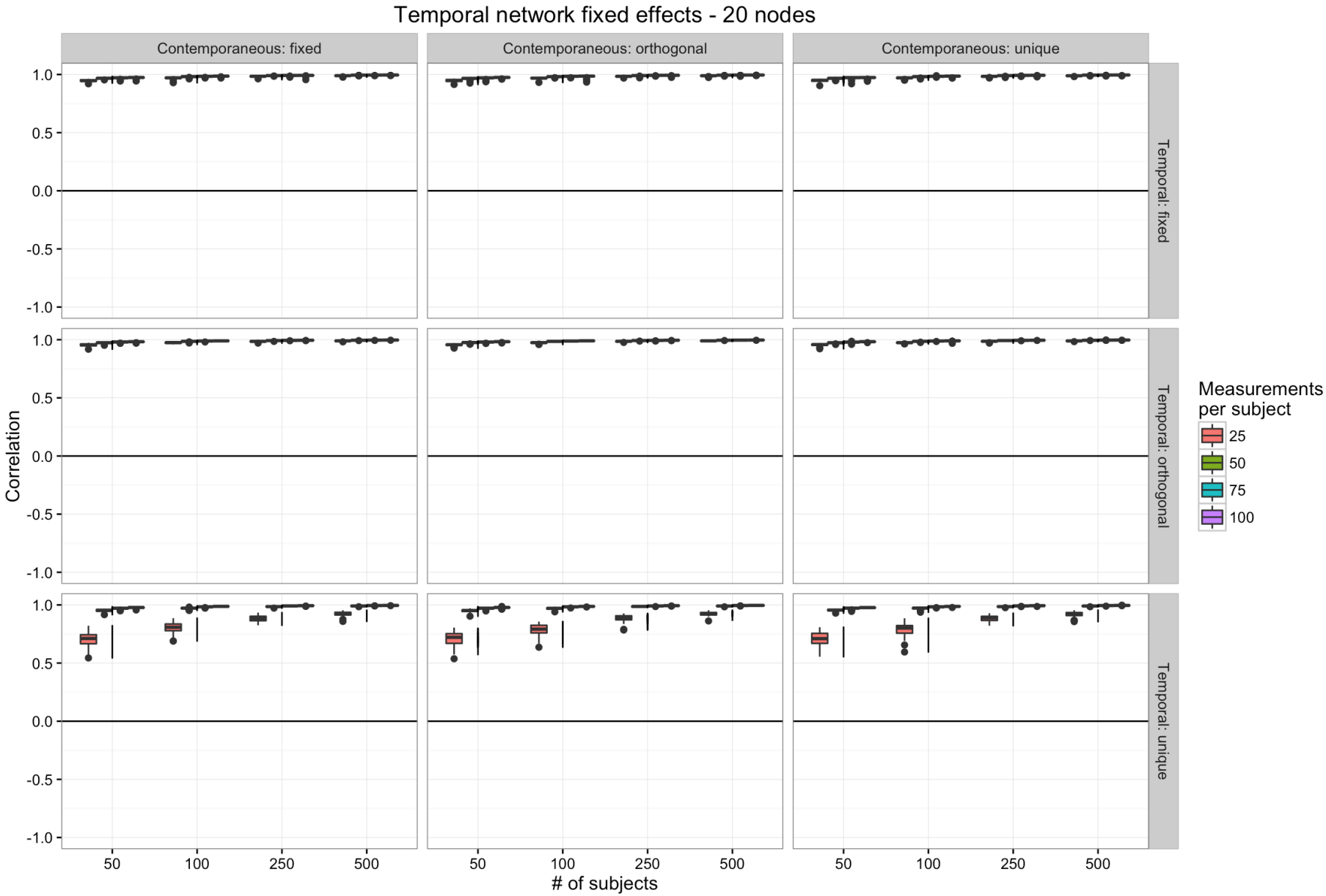
Temporal network fixed effects - 20 nodes
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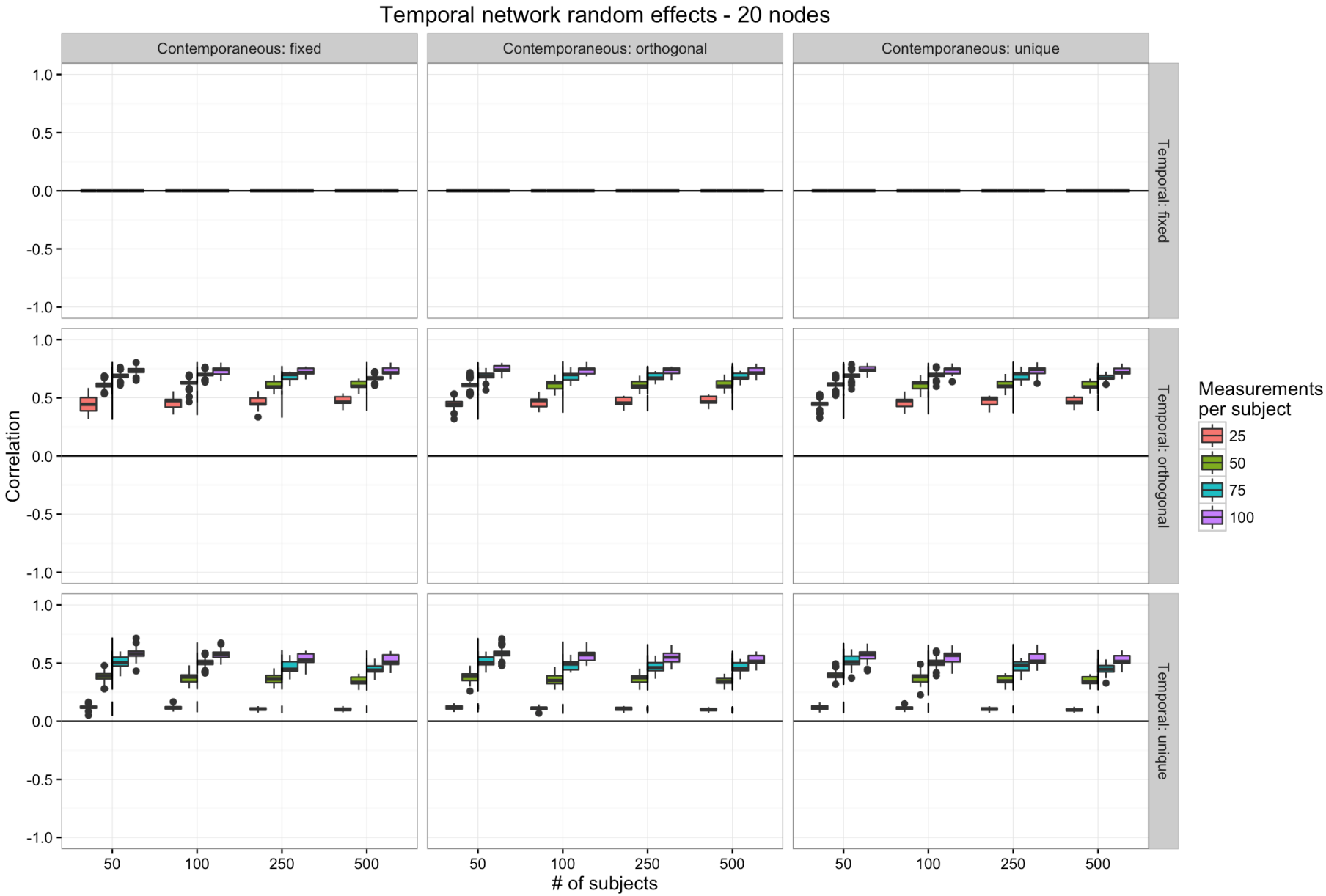
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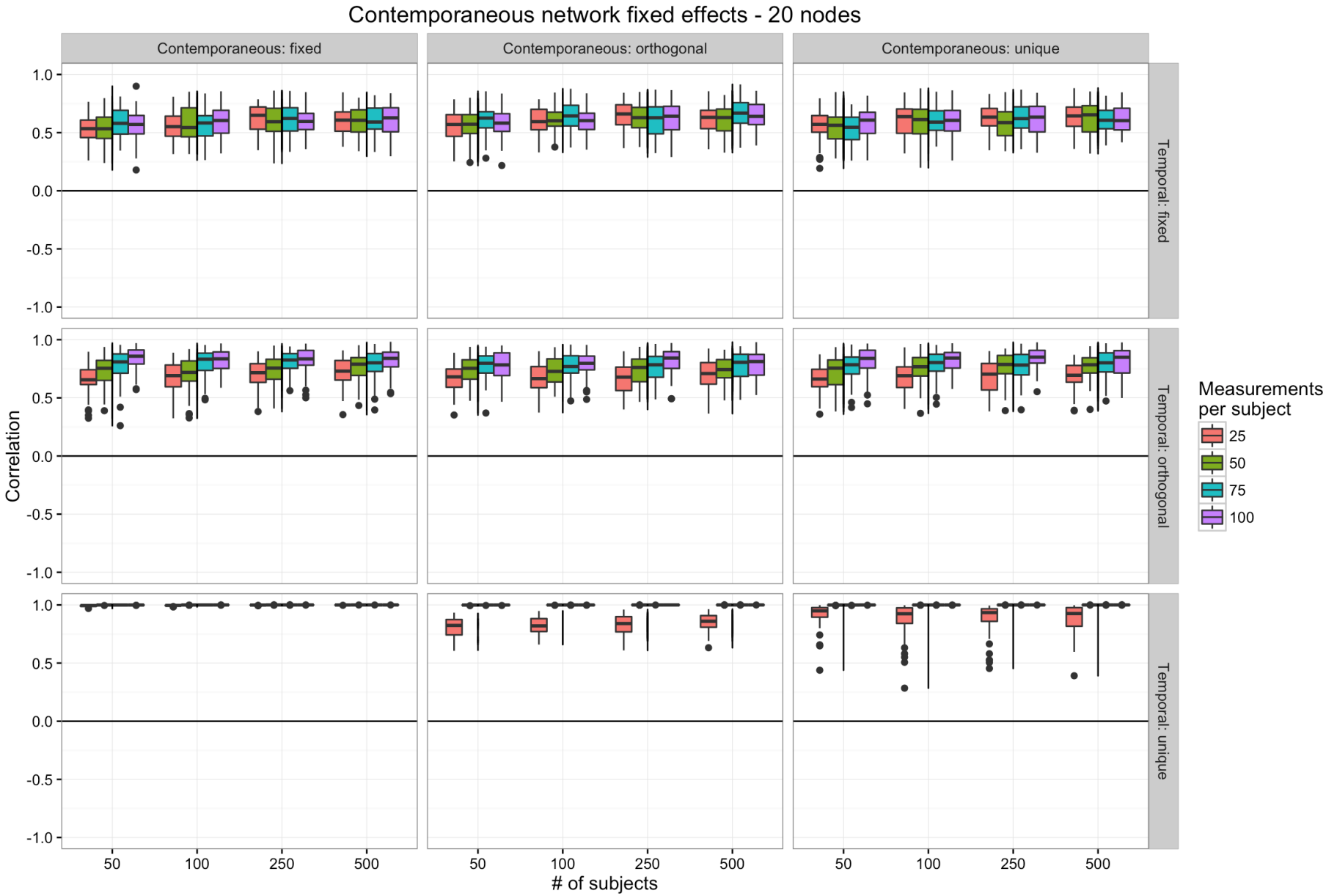
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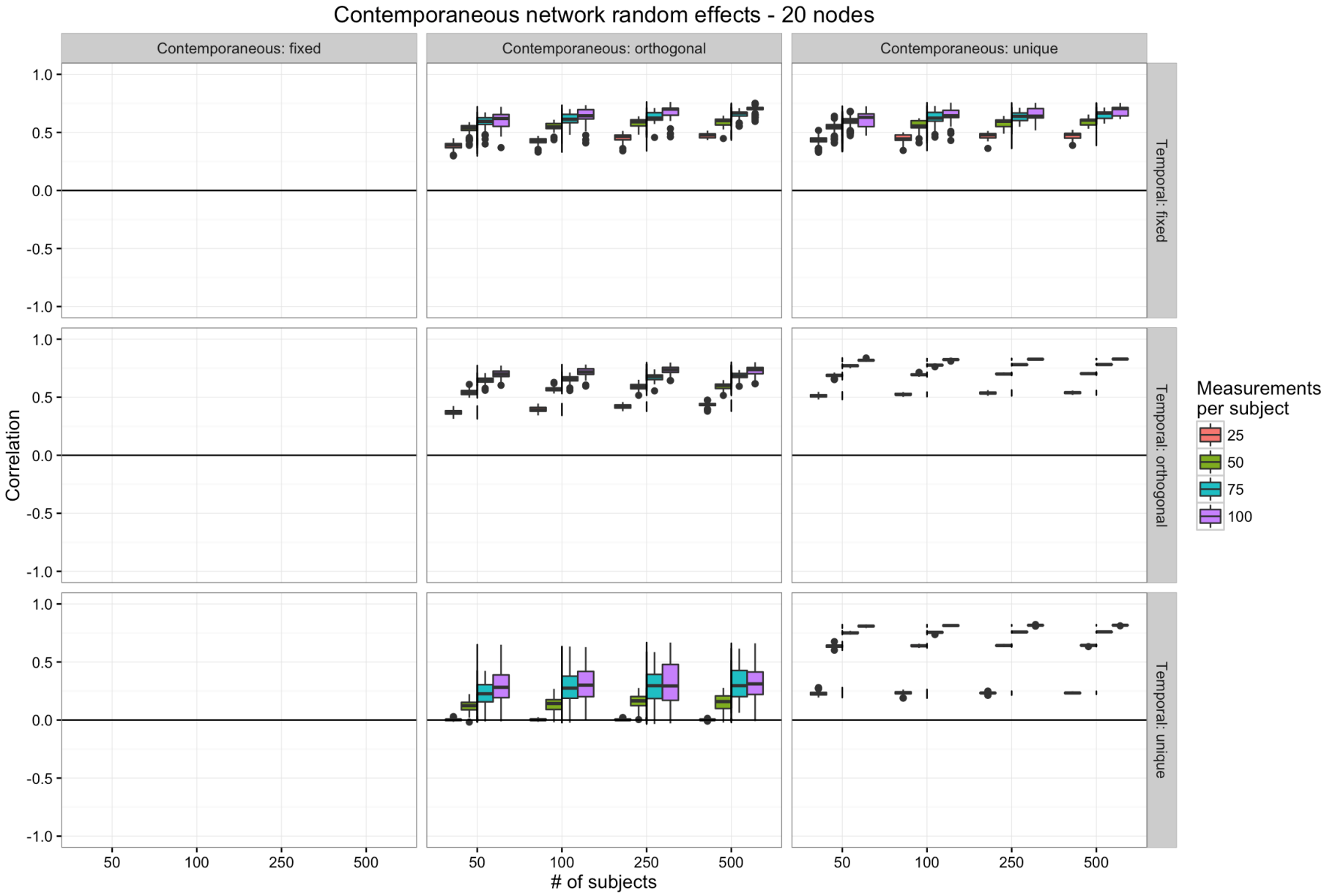
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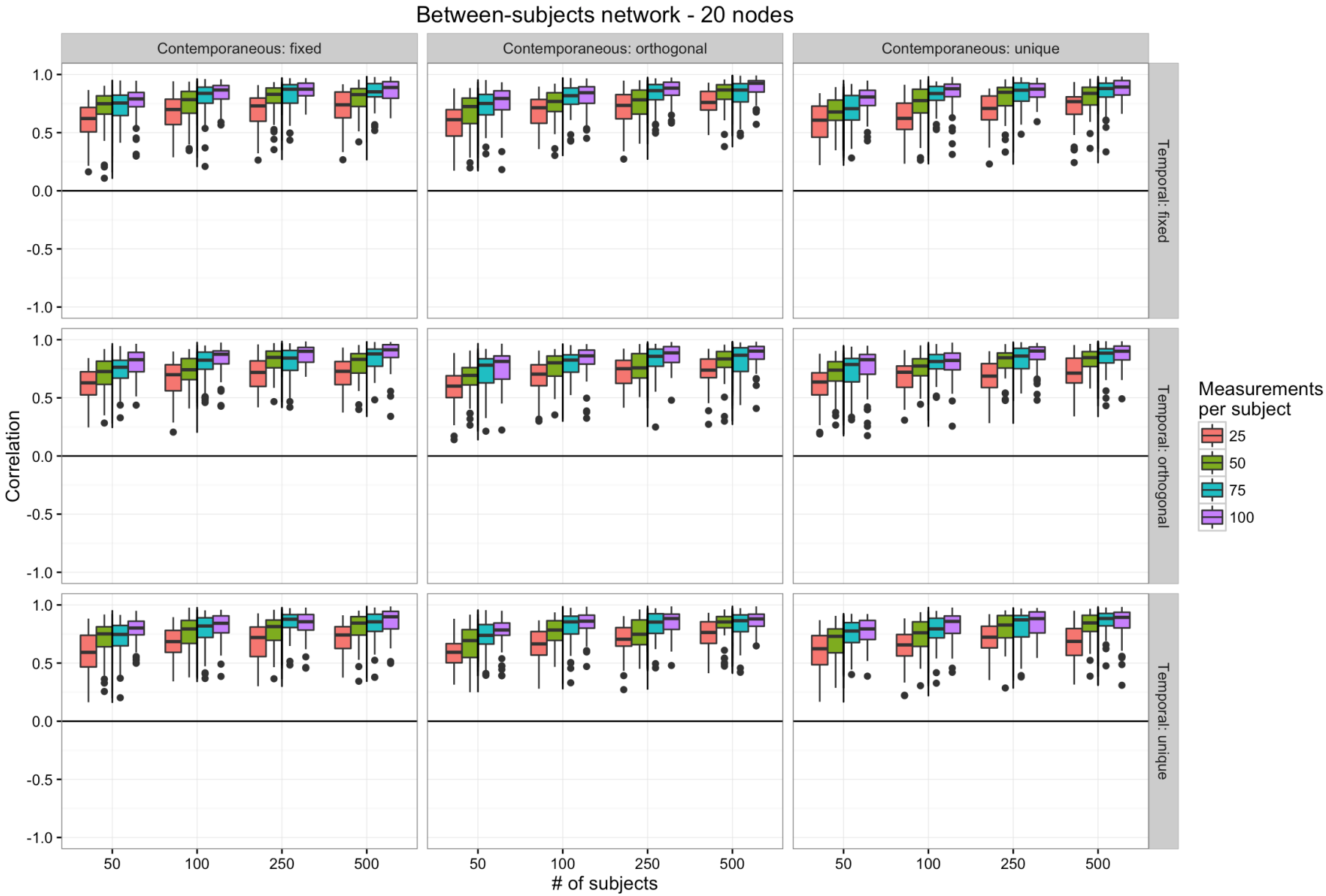
Between-subjects network - 20 nodes
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