Psychological Networks Summer School

Day 4, part 2: Discovering Psychological Dynamics in Time-series Data

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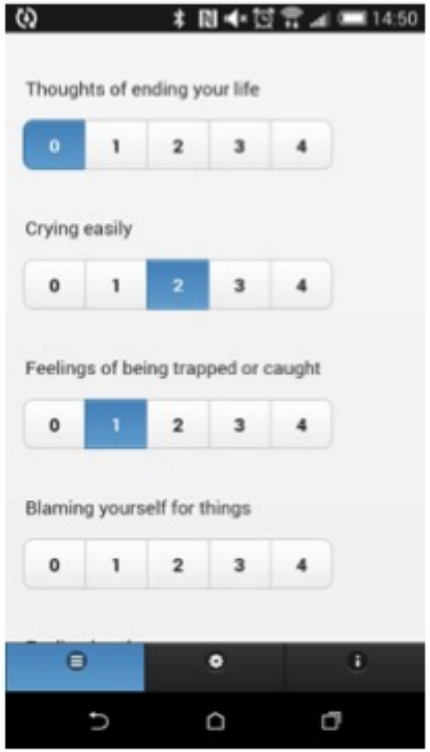
Goal

- Up to *three* network structures can be obtained in time-series data:
  - Contemporaneous networks
  - Temporal networks
  - Between-subjects networks
- All three structures can be interpreted in several ways:
  - Highlighting potential causal pathways
  - Showing predictive effects and mediation
  - Under very strict assumptions: a causal model

Outline

- When cases are independent
  - Cross-sectional data
  - The Gaussian Graphical model
  - Interpreting network structures
- When cases are not independent: $N = 1$
  - The VAR model
  - Temporal and contemporaneous networks and causation
- When cases are not independent: $N > 1$
  - The multi-level VAR model
  - Between-subjects networks and causation
- Conclusion

Experience Sampling Method



Subject	Measurement	Item 1	Item 2	Item 3
1	1	1	1	0
1	2	1	3	1
1	3	2	1	2
1	4	2	2	2
1	5	2	0	3
2	1	0	1	0
2	2	1	0	2
2	3	1	1	1
2	4	1	1	2
2	5	2	1	1
3	1	1	1	1
3	2	2	0	2
3	3	2	0	0
3	4	1	1	1
3	5	1	0	1

- Rows are termed the *cases*

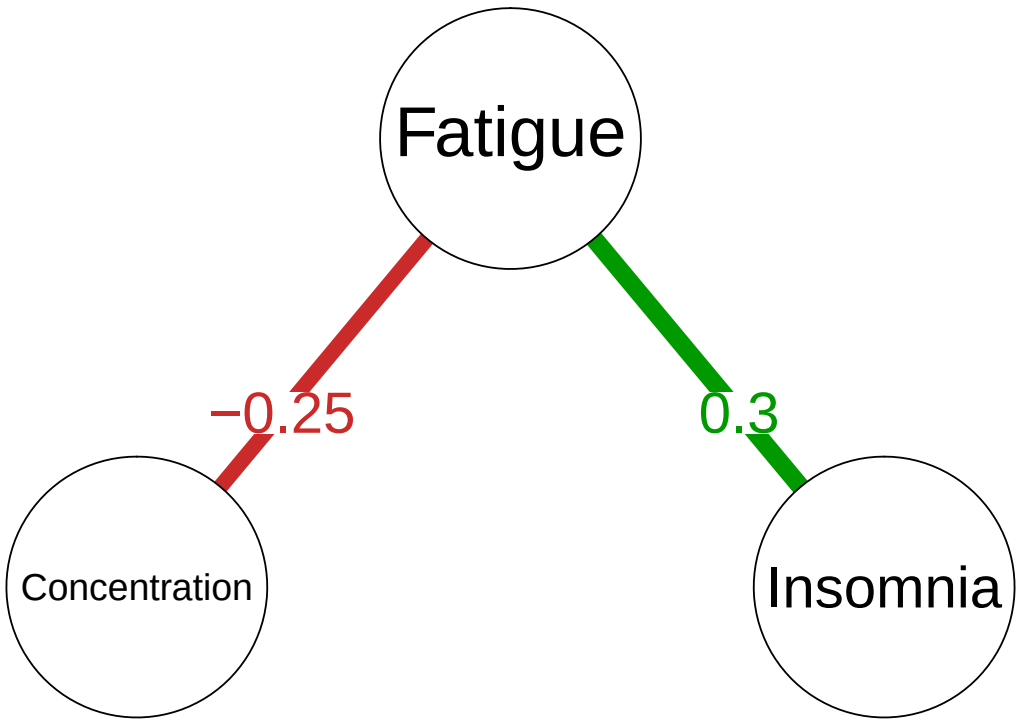
Cross-sectional Data

Cross-sectional Data

- Every person measured only *once*
- Cases can reasonably be assumed to be *independent*
  - Given IQ has a mean of 100 and SD of 15, does knowing that Peter has an IQ of 90 help us predict better that Sarah had an IQ of 110?
- Because of this assumption, likelihood reduces to a *product*
  - $\boldsymbol{Y} \sim N(\boldsymbol{\mu}, \boldsymbol{\Sigma})$
  - $f(\boldsymbol{y} \mid \boldsymbol{\mu}, \boldsymbol{\Sigma}) = \prod_{p=1}^{N} f\left(\boldsymbol{y}^{(p)} \mid \boldsymbol{\mu}, \boldsymbol{\Sigma}\right)$

The Gaussian Graphical Model

- $\boldsymbol{\Sigma}$, the variance-covariance matrix, encodes *all* information how variables relate to one-another
- Because of the Schur complement, it also encodes *all* conditional relationships
- We will focus on its *inverse*, $\boldsymbol{K}$:
  - $\boldsymbol{K} = \boldsymbol{\Sigma}^{-1}$
- The inverse variance-covariance matrix is called a Gaussian graphical model (GGM)
  - Encodes an undirected network



- GGM is a 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:

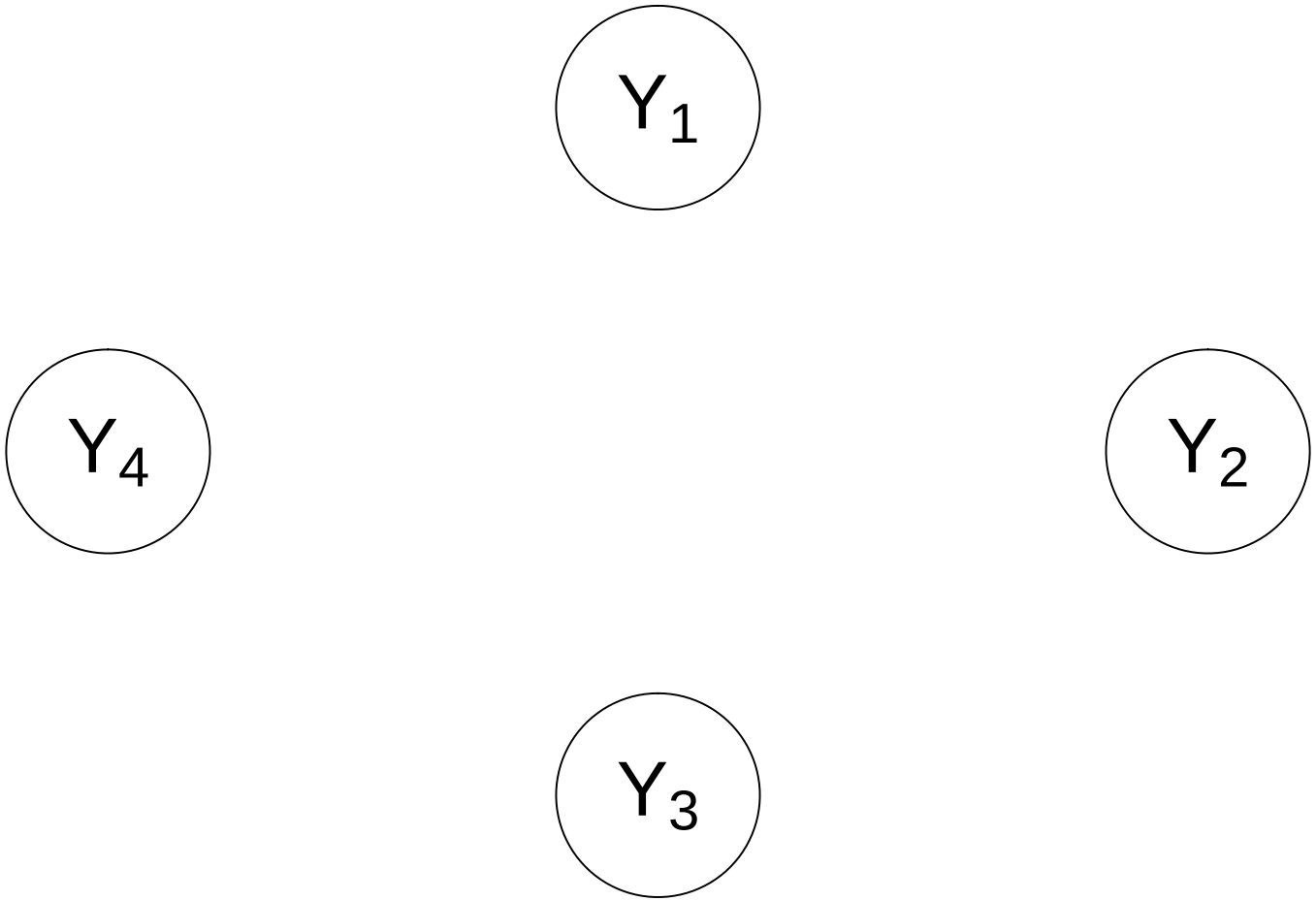
- Concentration – Fatigue – Insomnia

Is equivalent to three causal structures:

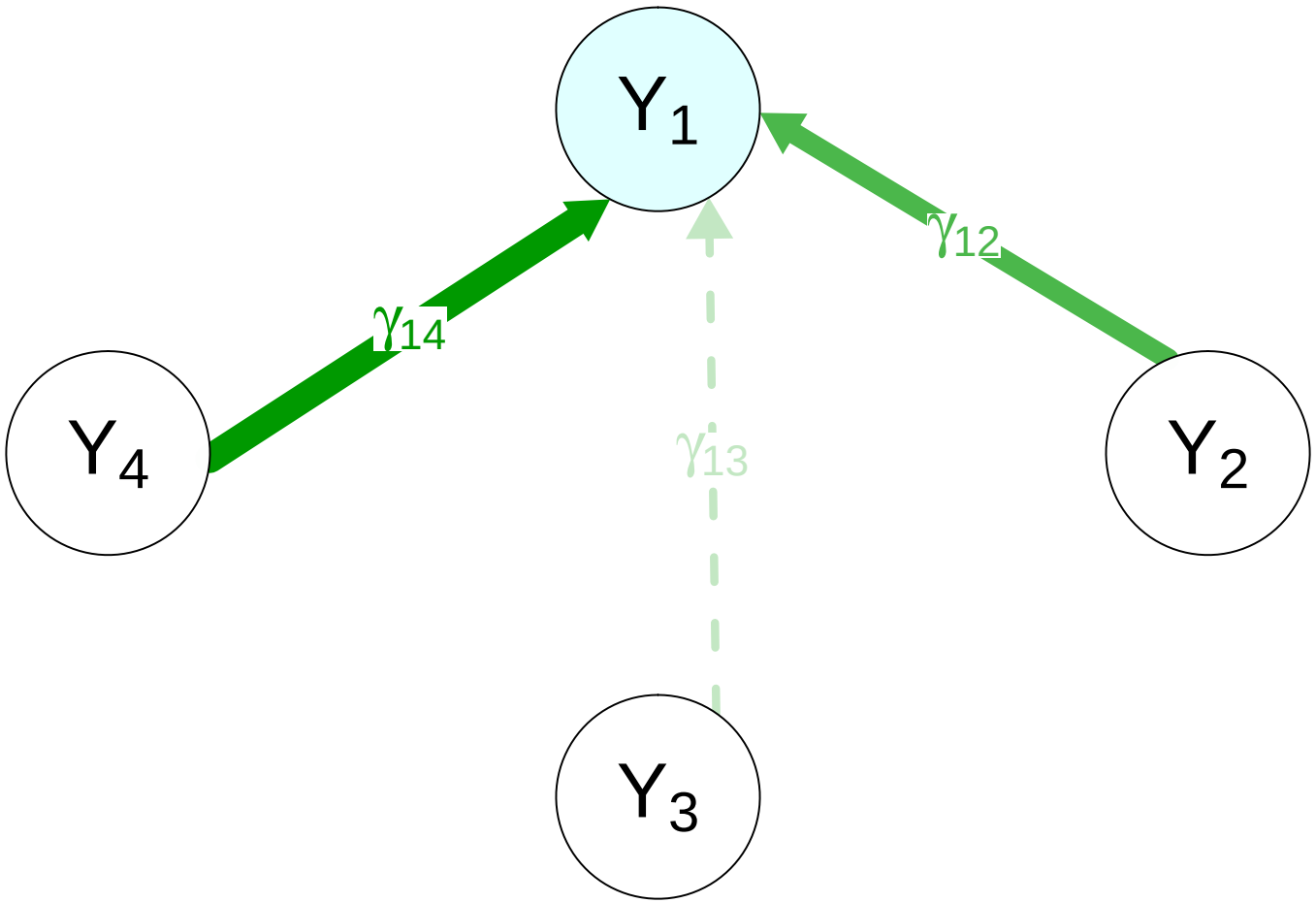
1. Concentration $\rightarrow$ Fatigue $\rightarrow$ Insomnia
2. Concentration $\leftarrow$ Fatigue $\rightarrow$ Insomnia
3. Concentration $\leftarrow$ Fatigue $\leftarrow$ Insomnia

Thus, the GGM highlights potential causal pathways

GGM and Multiple Regressions

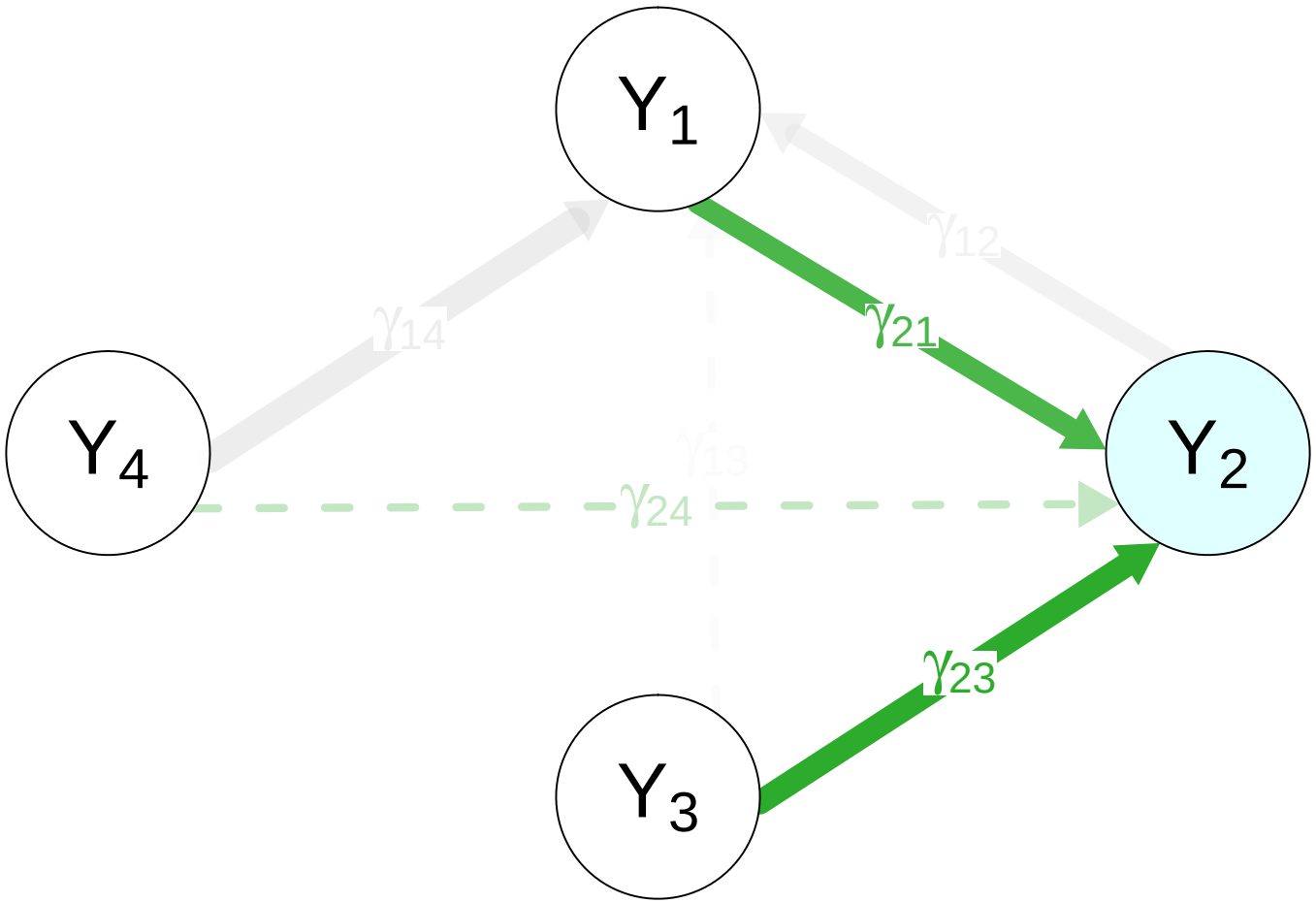


GGM and Multiple Regressions



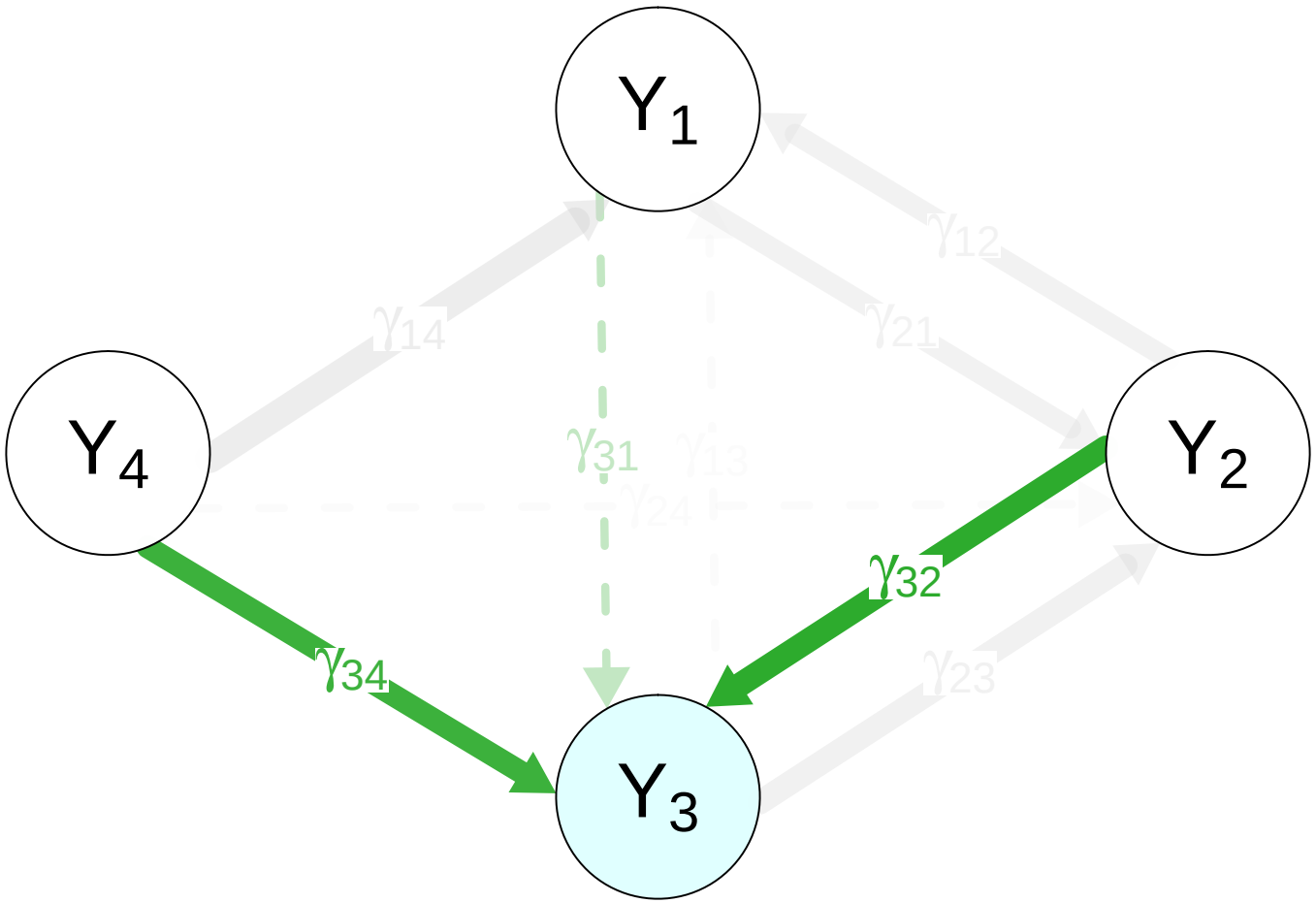
$$y_1 = \tau_1 + \gamma_{12} y_2 + \gamma_{13} y_3 + \gamma_{14} y_4 + \varepsilon_1$$

GGM and Multiple Regressions



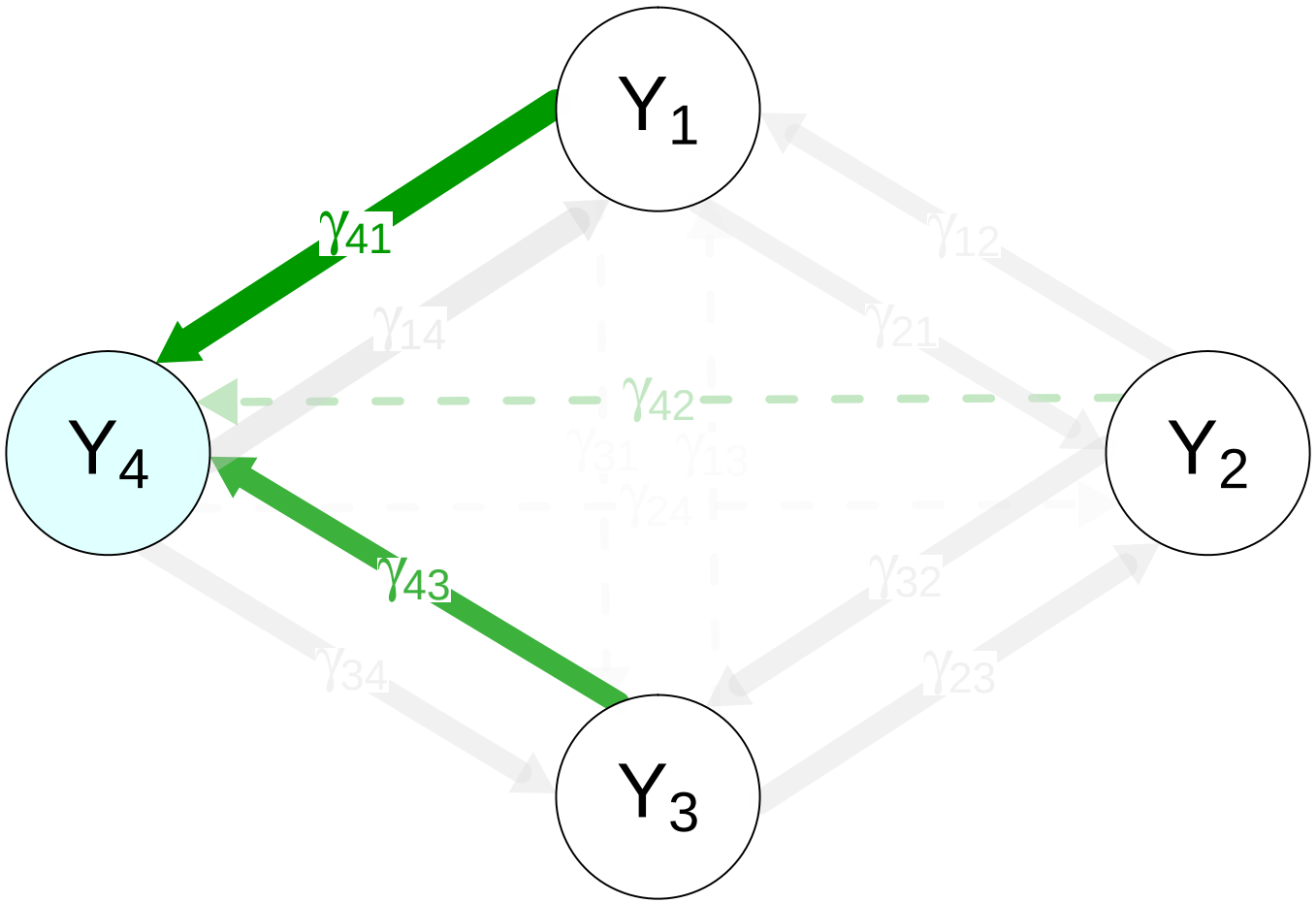
$$y_2 = \tau_2 + \gamma_{21} y_1 + \gamma_{23} y_3 + \gamma_{24} y_4 + \varepsilon_2$$

GGM and Multiple Regressions



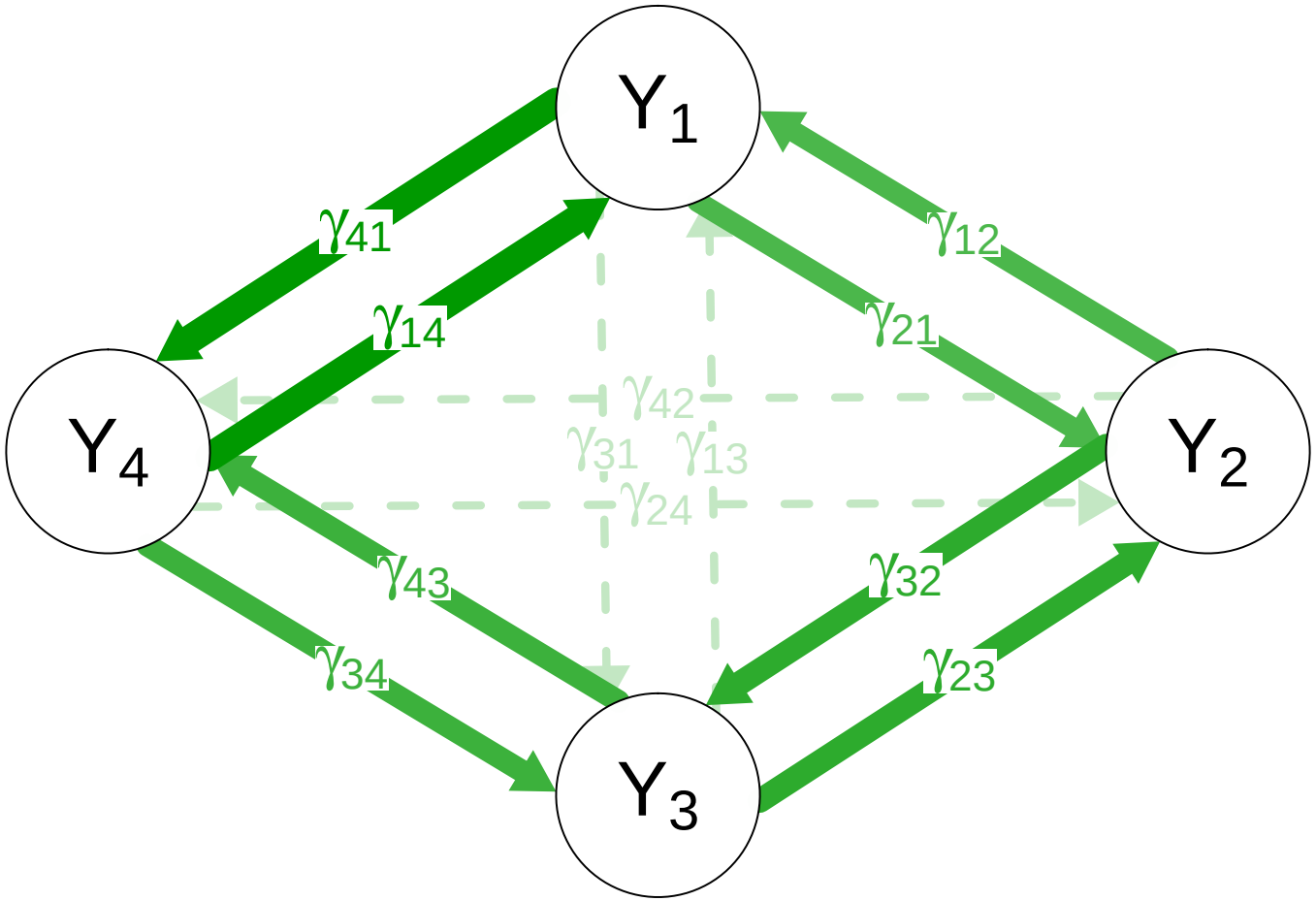
$$y_3 = \tau_3 + \gamma_{31} y_1 + \gamma_{32} y_2 + \gamma_{34} y_4 + \varepsilon_3$$

GGM and Multiple Regressions

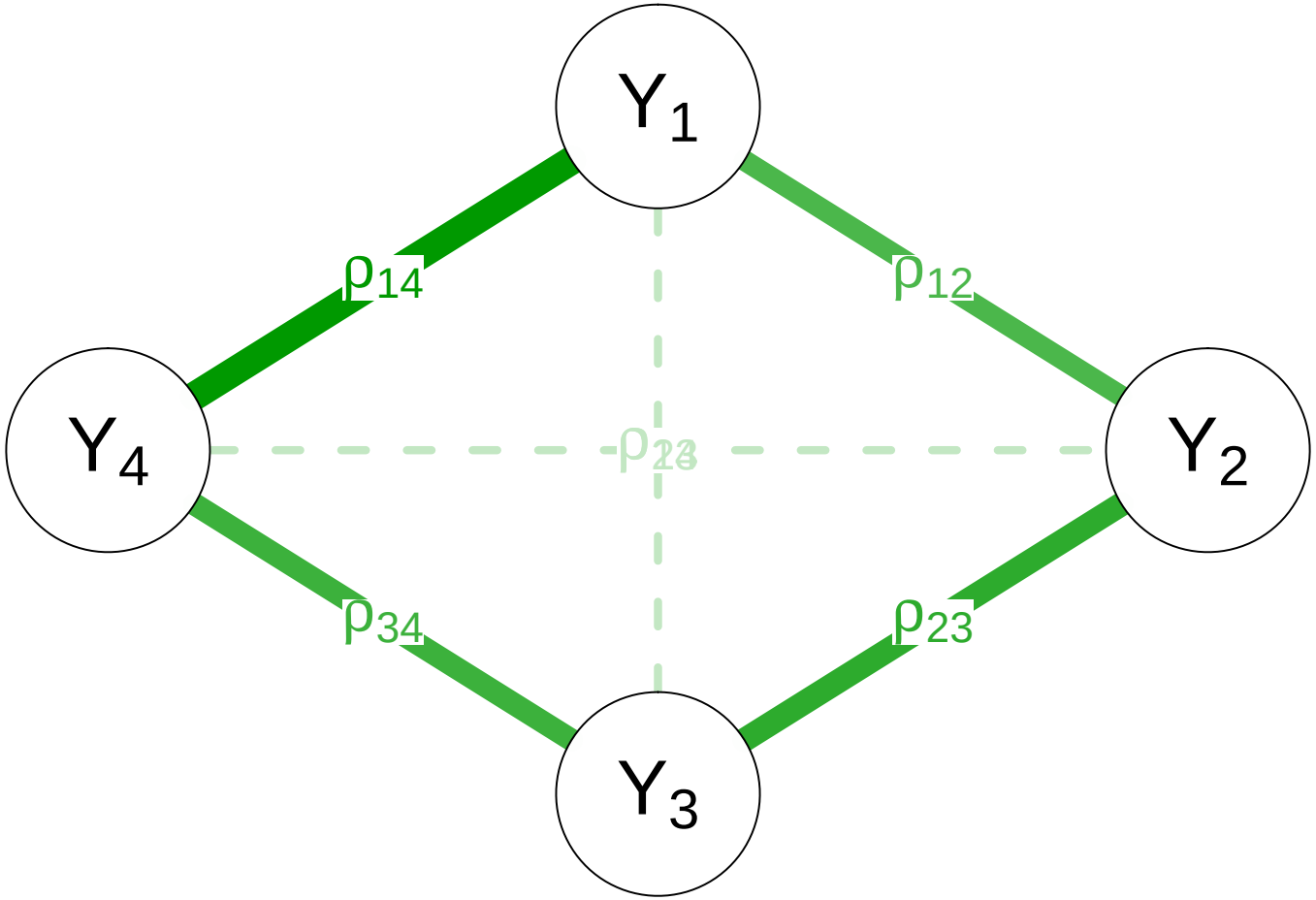


$$y_4 = \tau_4 + \gamma_{41} y_1 + \gamma_{42} y_2 + \gamma_{43} y_3 + \varepsilon_4$$

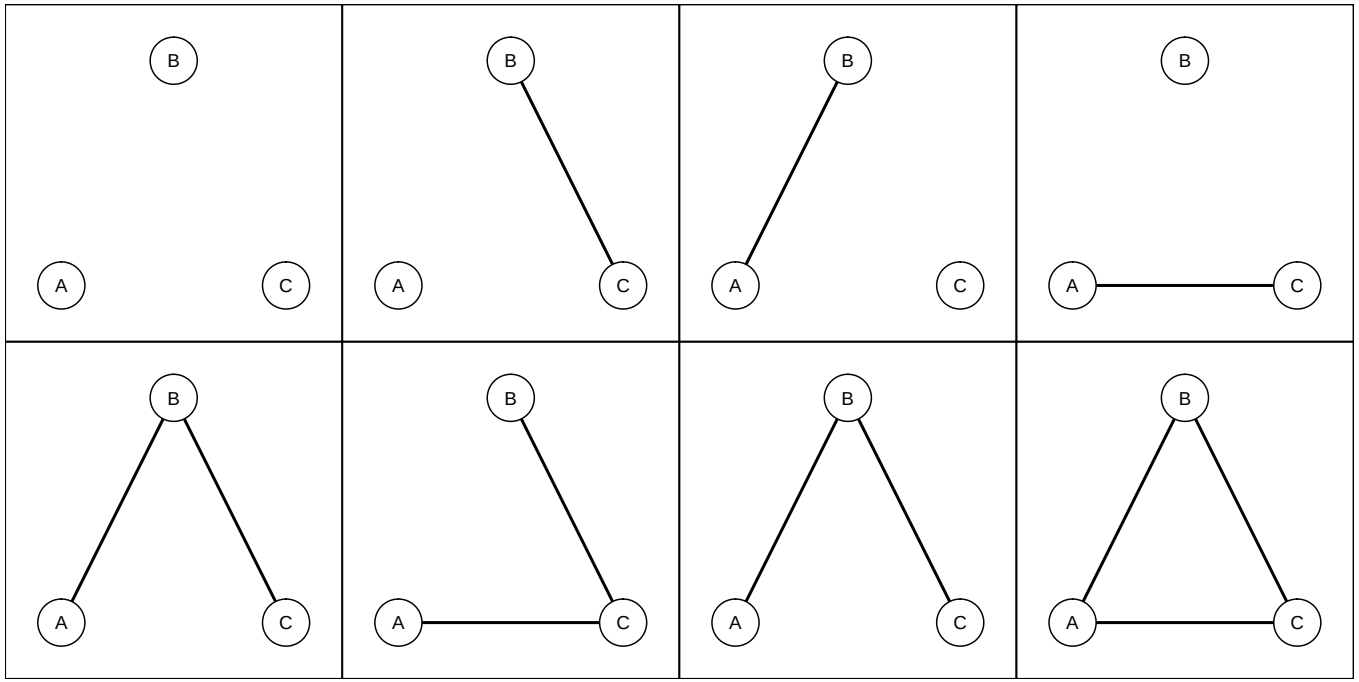
GGM and Multiple Regressions



GGM and Multiple Regressions



$$\rho_{ij} = \frac{\gamma_{ij}\mathrm{Var}\left(\varepsilon_j\right)}{\mathrm{Var}\left(\varepsilon_i\right)} = \frac{\gamma_{ji}\mathrm{Var}\left(\varepsilon_i\right)}{\mathrm{Var}\left(\varepsilon_j\right)}$$



- LASSO model selection using Extended Bayesian information criterion (EBIC)
- Epskamp & Fried. A Primer on Estimating Regularized Psychological Networks. Preprint on `http://arxiv.org/abs/1607.01367`.

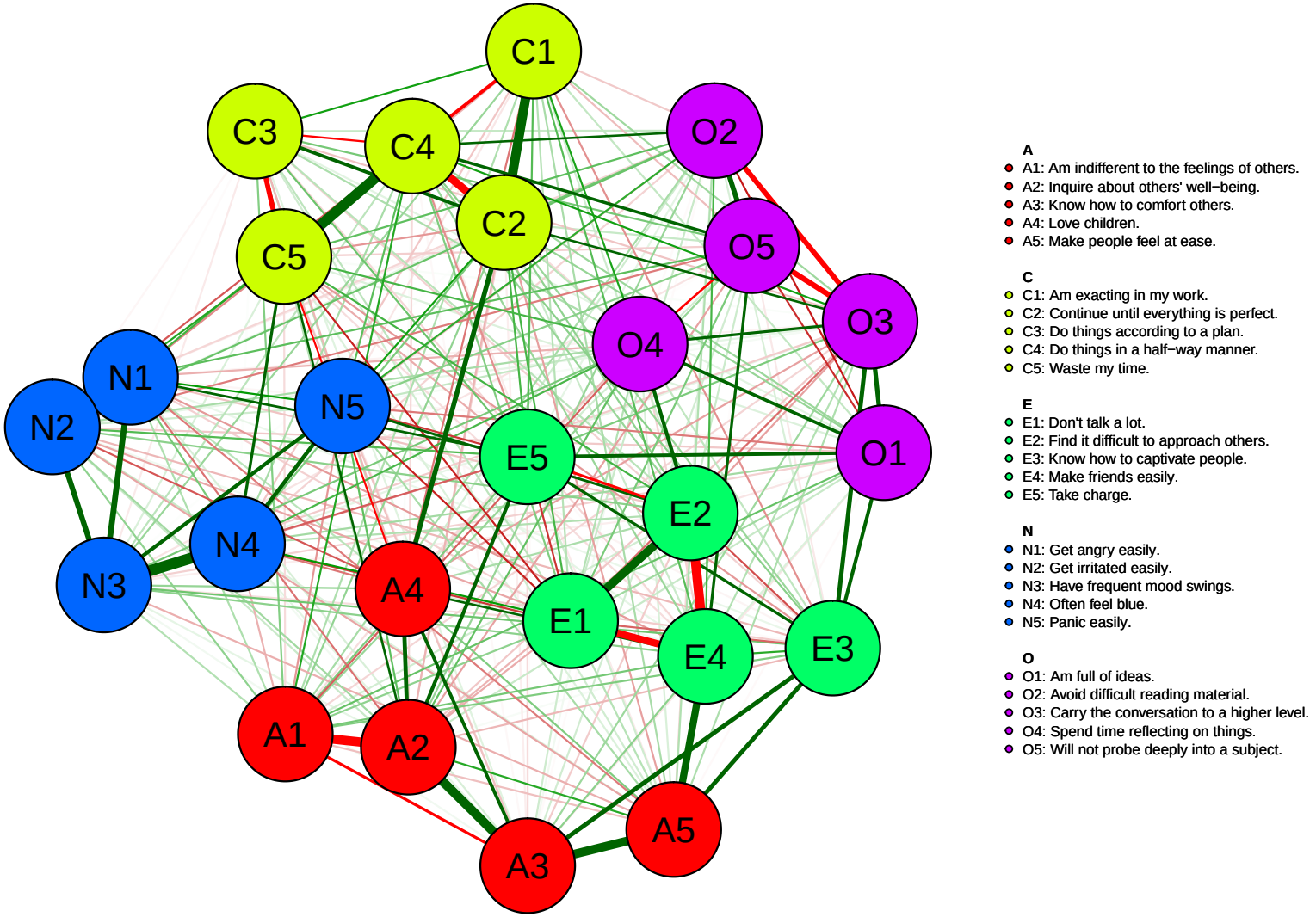
Emperical Example: Personality

I will analyze the BFI dataset from the pych package:

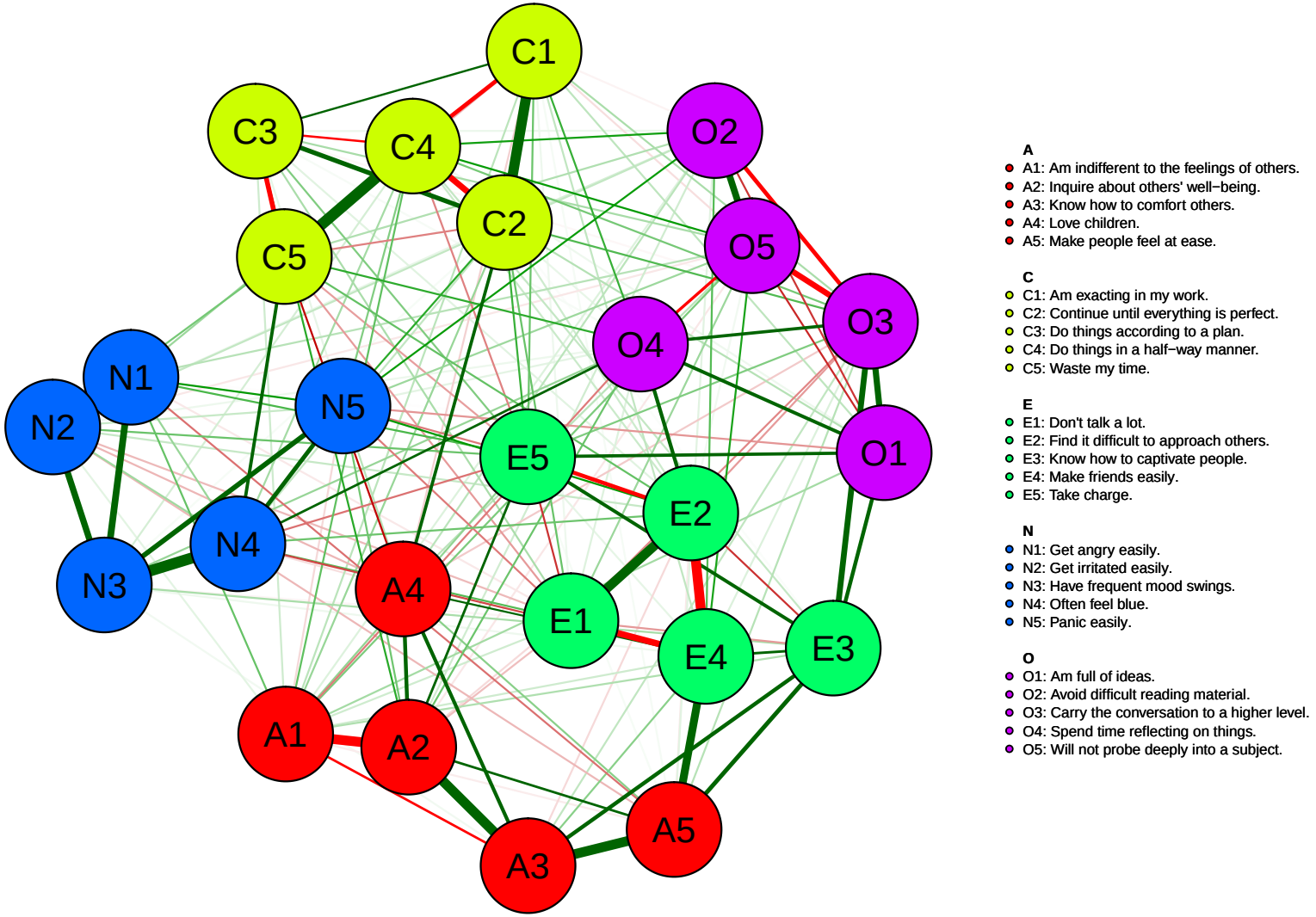
- 25 items
- 2800 subjects
- Five items for each of the five central personality traits

```
library("psych")
?bfi
```

Partial Correlation Network



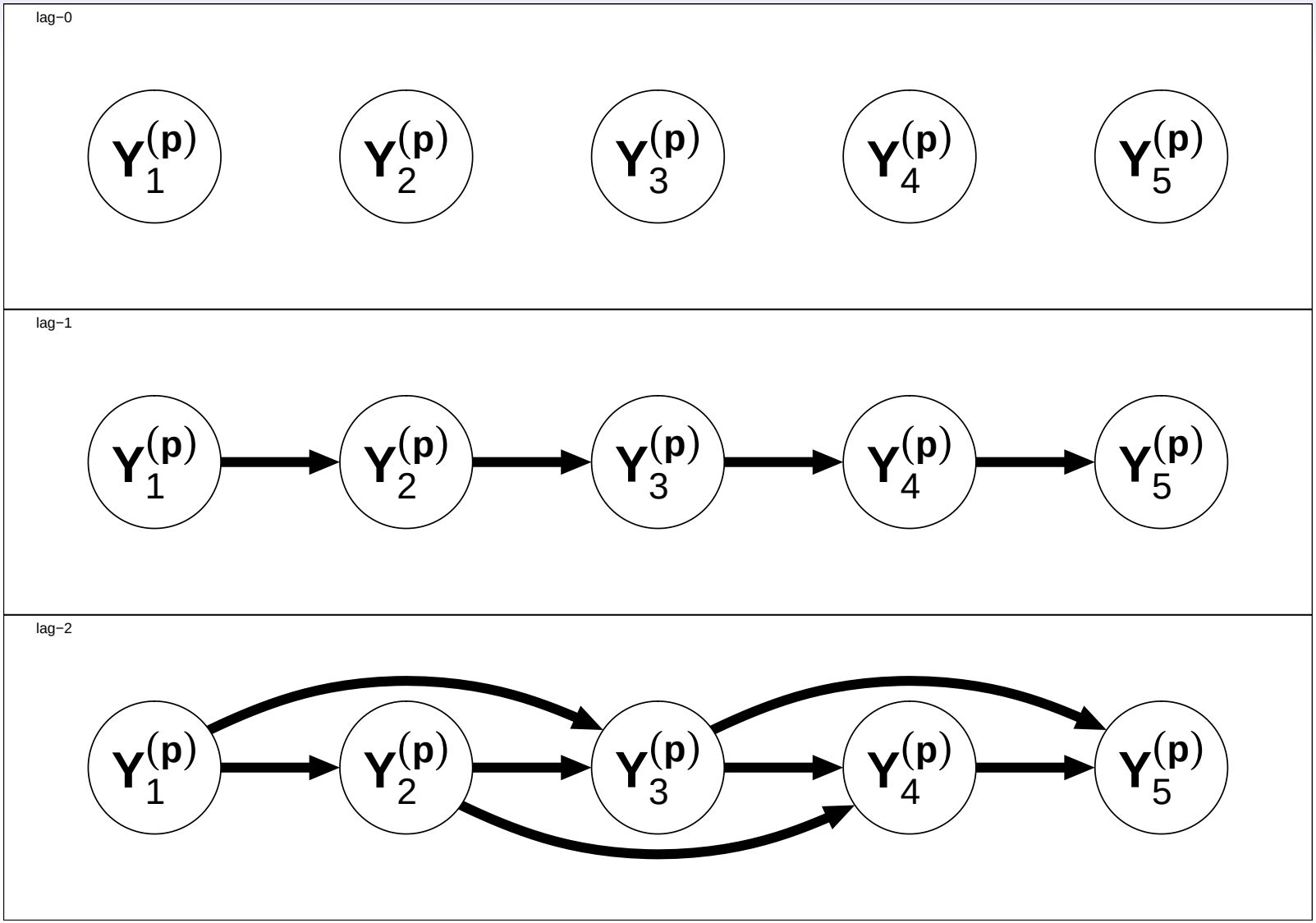
glasso network



Time-series: $n = 1$

Time-series Data

- One person measured several times in a short period
- Cases can **not** reasonably be assumed to be *independent*
  - Knowing someone's level of fatigue at a time point helps predict his or her level of fatigue at the next time point.
- Likelihood not easy to compute without three assumptions:
  - The time-series factorize according to a graph
  - The model does not change over time
  - The first measurement is exogenous

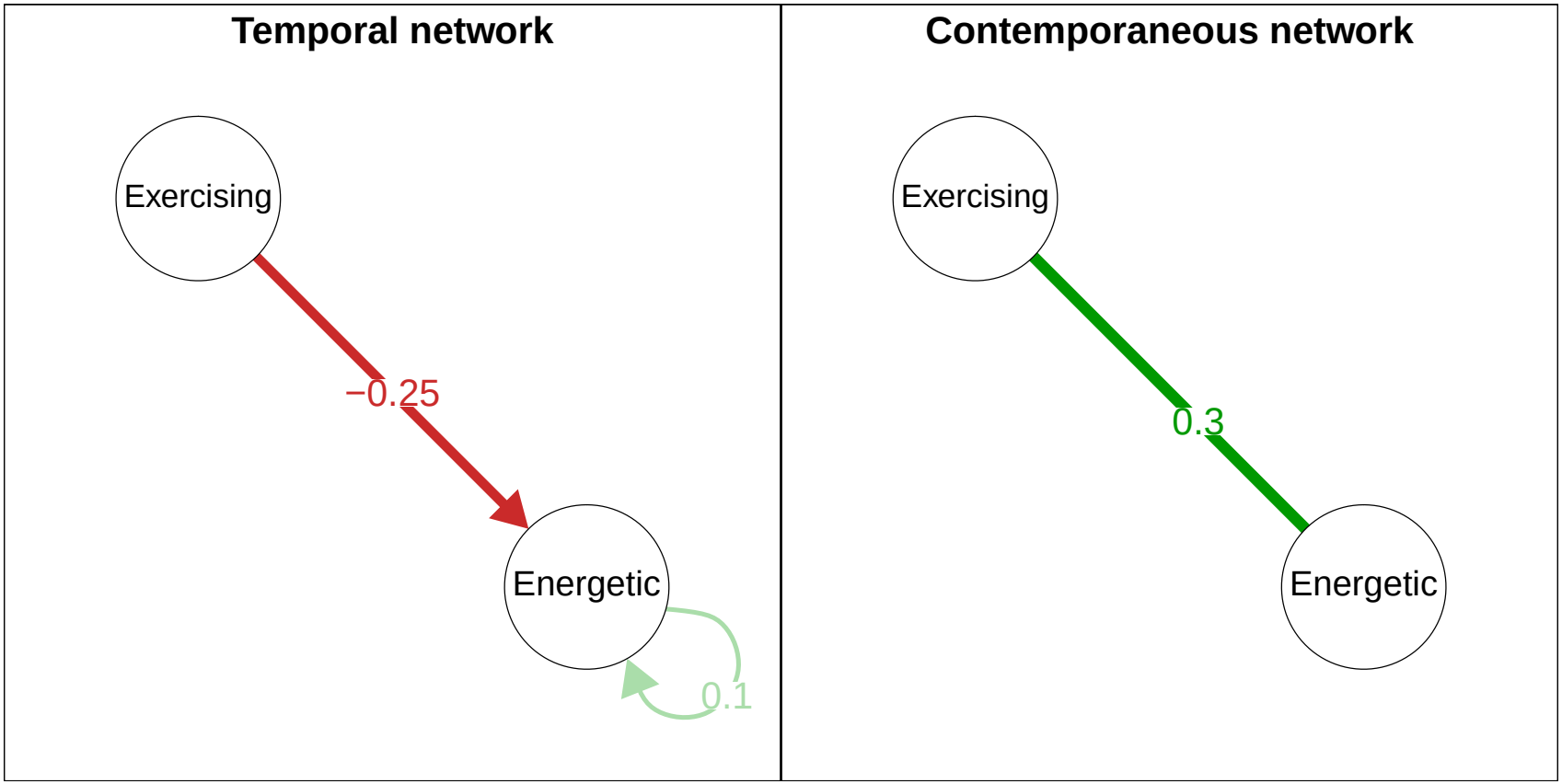


- We will use the lag-1 factorization

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
Exercising
−0.25
Energetic
0.1
Contemporaneous network
Exercising
0.3
Energetic

Contemporaneous Causation

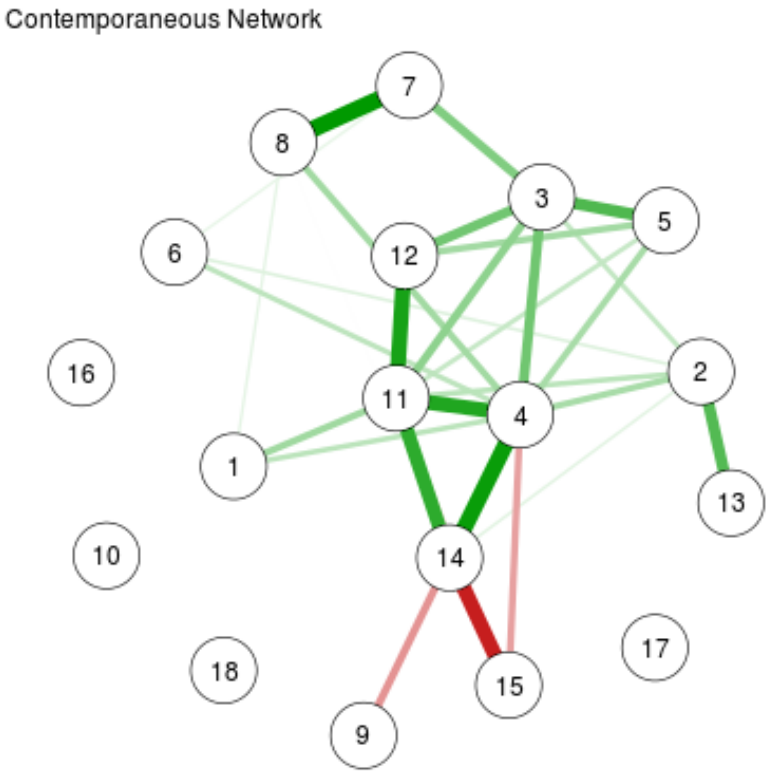
- Many causal effects likely faster than the time-window of measurement
  - Somatic arousal $\rightarrow$ anticipation of panic attack $\rightarrow$ anxiety
- These can be caught in a contemporaneous network of **partial correlations**
- Thus, the contemporaneous network can also be seen to highlight 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

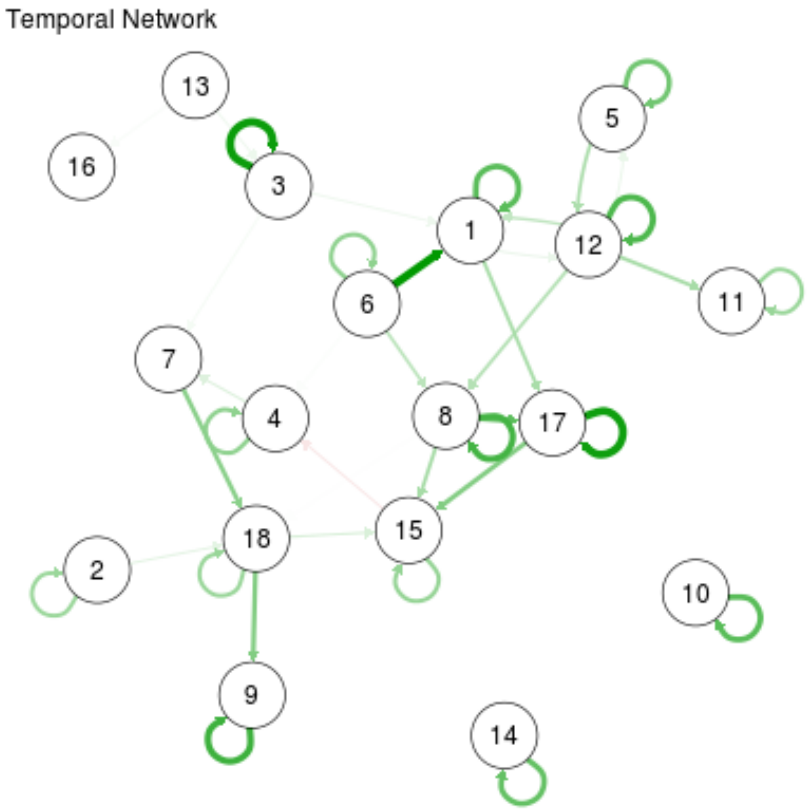
- Estimation straightforward using multiple regression
- For model selection, we use the graphical VAR model
  - Wild et al. (2010). A graphical vector autoregressive modelling approach to the analysis of electronic diary data. *BMC Medical Research Methodology 10 (1):* 28.
- Estimation via LASSO regularization, using EBIC to select optimal tuning parameter
  - Abegaz & Wit (2013). Sparse Time Series Chain Graphical Models for Reconstructing Genetic Networks. *Biostatistics*: kxt005.
  - Rothman, Elizaveta, & Zhu (2010). Sparse Multivariate Regression with Covariance Estimation. *Journal of Computational and Graphical Statistics 19 (4)*: 947–62.
- We implemented these methods in the R package `graphicalVAR`
- Also implemented in `sparseTSCGM`

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


Contemporaneous Network
7
8
3
5
6
12
16
11
4
2
1
13
10
14
17
18
15
9


Temporal Network
13
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15
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10
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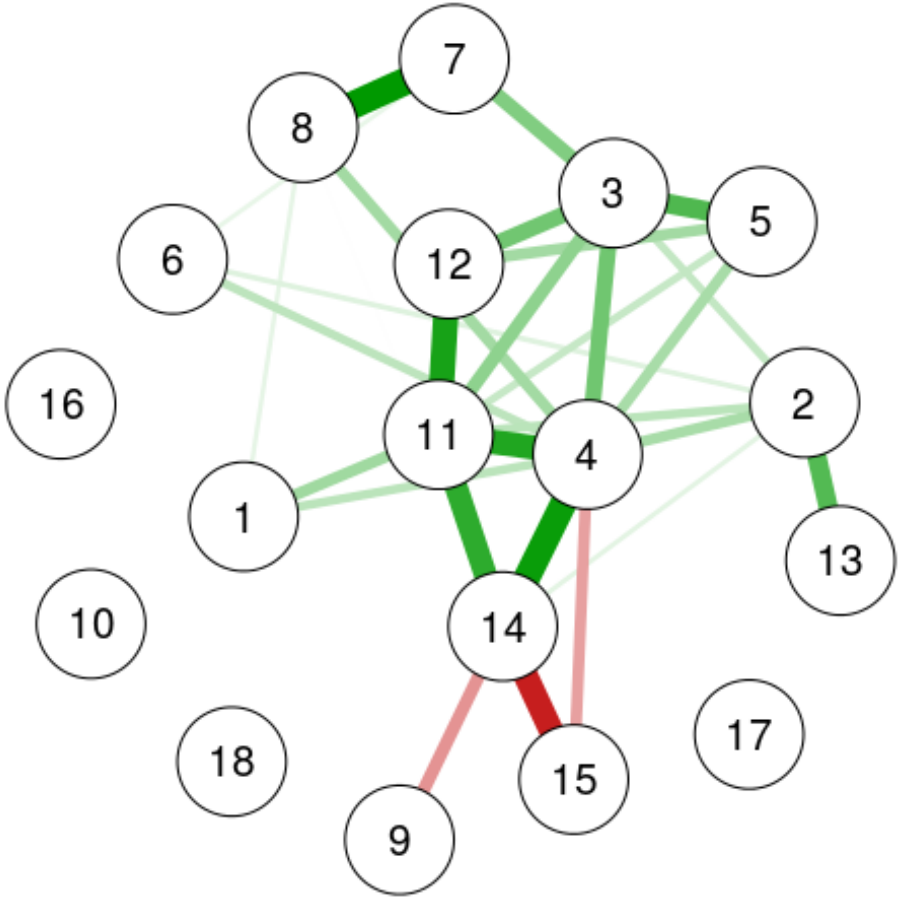
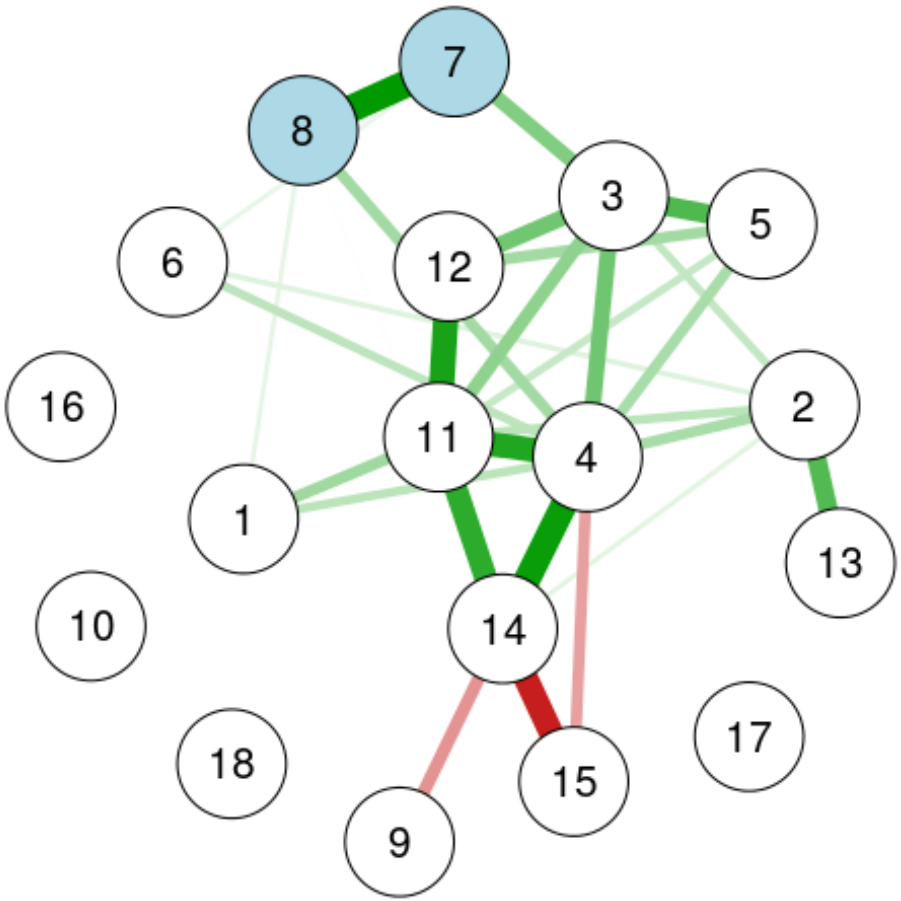
14



1: I feel anxious
2: I feel stressed
3: I feel angry
4: I feel sad
5: I feel guilty
6: I feel weak
7: I feel worthless
8: I feel helpless
9: I feel full of Energy
10: I am afraid of a panic attack
11: I am afraid I am going to cry
12: I am afraid of appearing angry
13: I have 'had to do things'
14: I am experiencing bodily discomfort
15: I am enjoying myself
16: I let something pass I find important
17: I experienced my social environment as pleasurable
18: I was physically active



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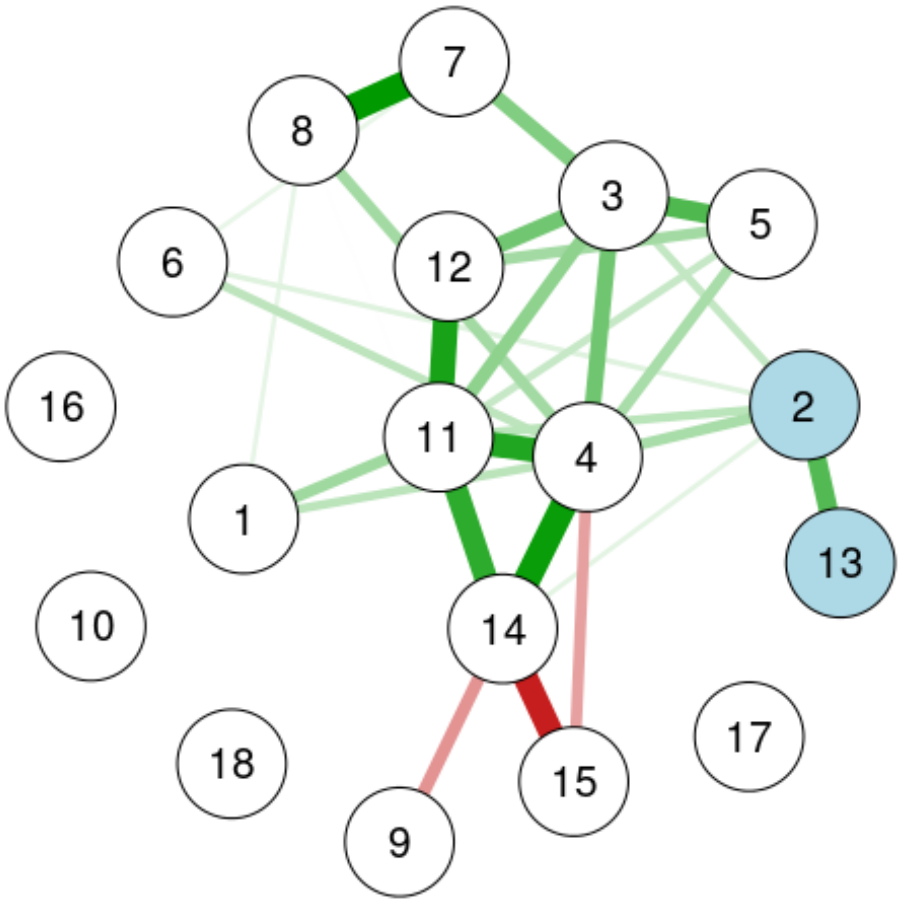
Feeling worthless interacts with feeling helpless



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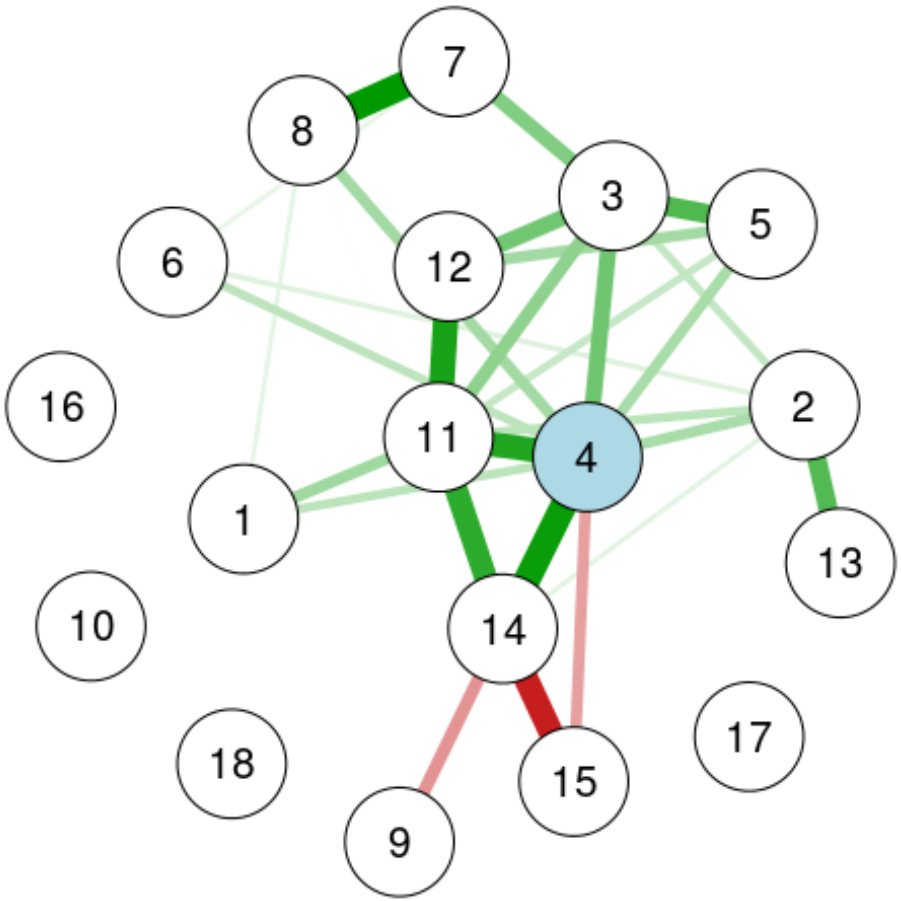
Feeling stressed interacts with feeling the need to do things



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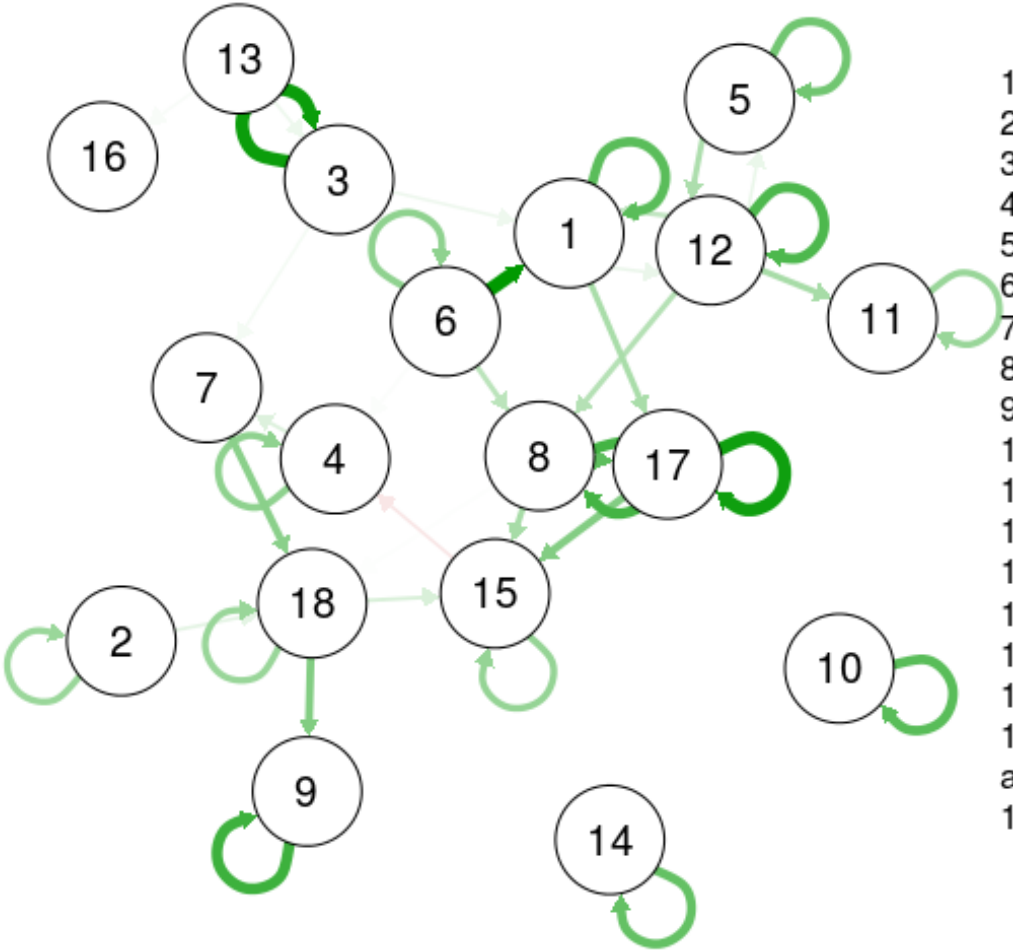
Central node: Feeling sad



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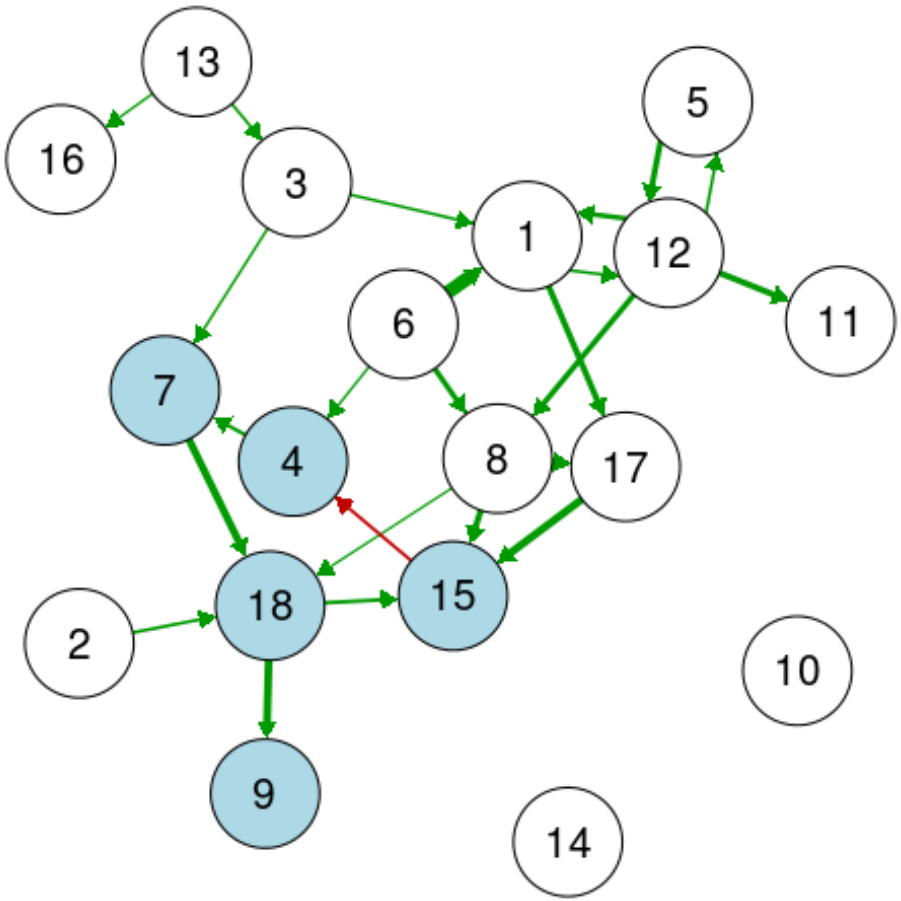

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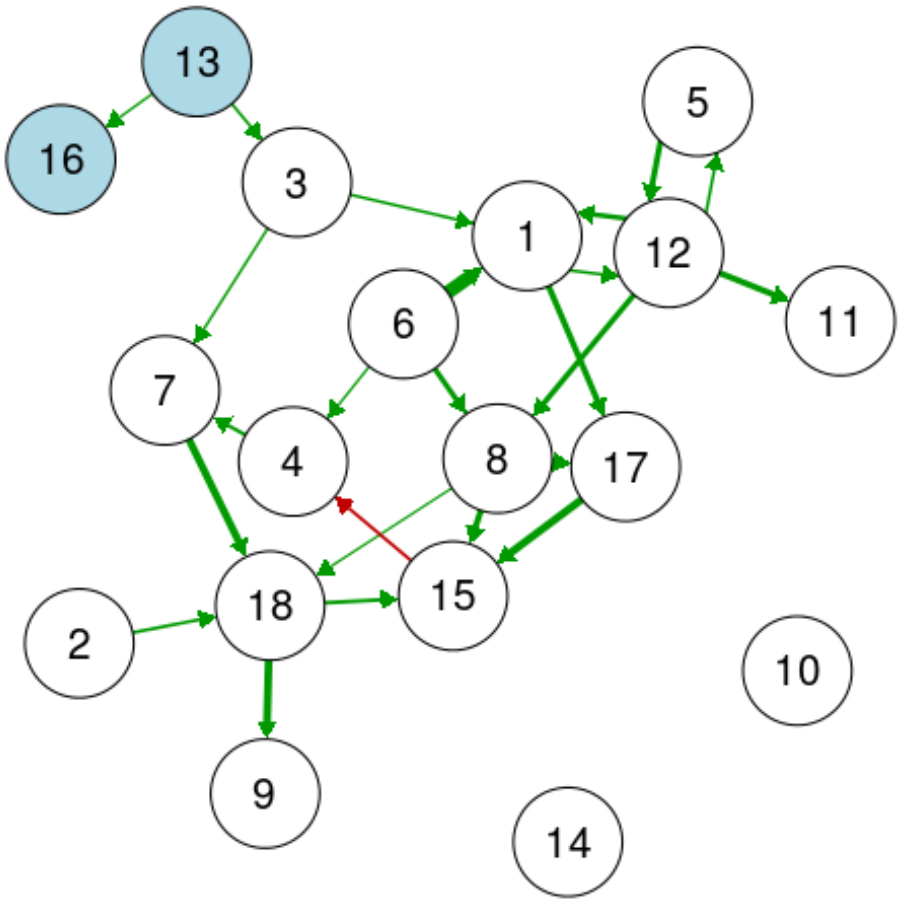
Cycle of enjoyment, feeling sad, feeling worthless and being active



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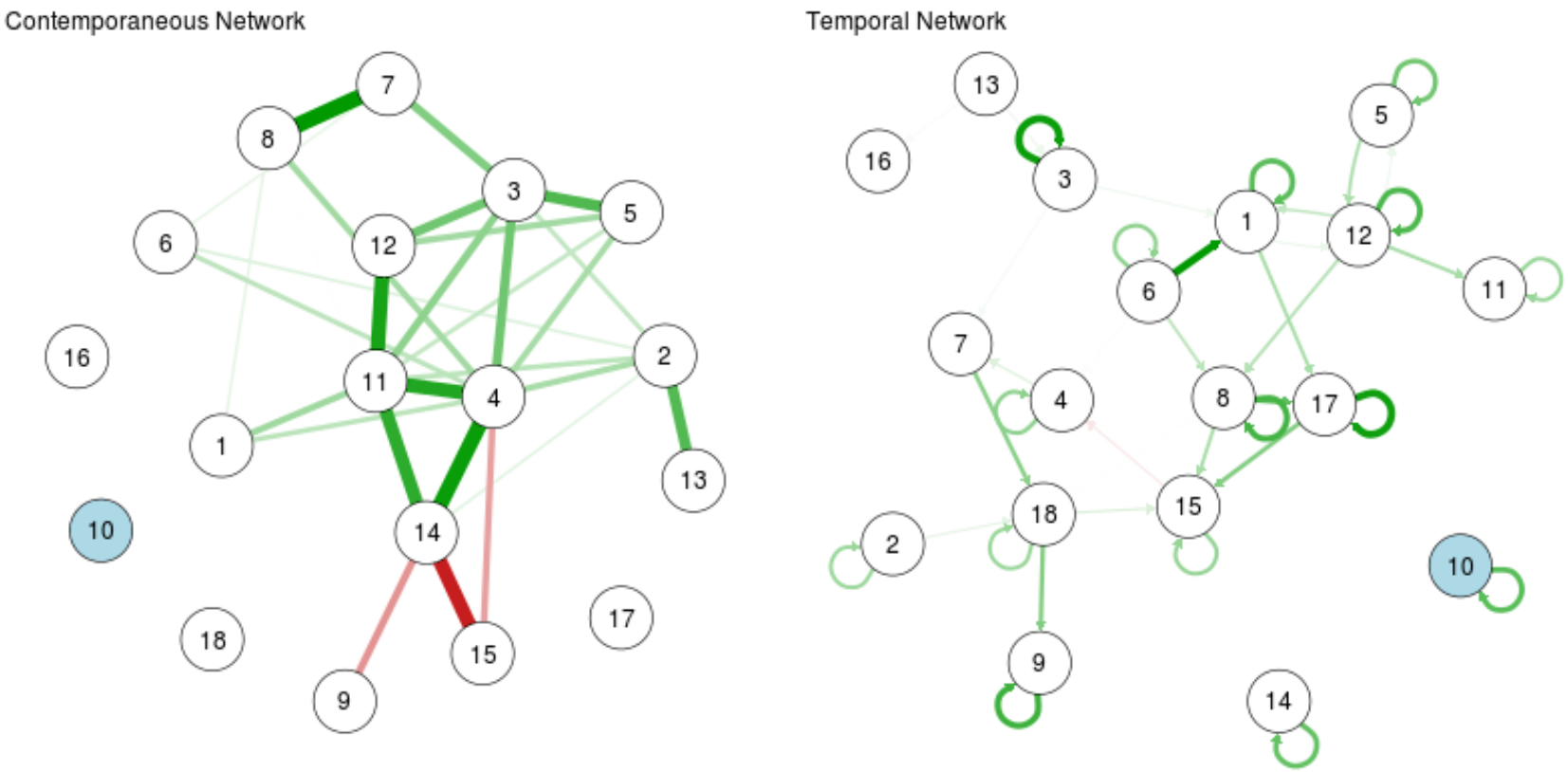
Having to had to do things leads to letting important things pass



Fear of panic attack is not connected

Time-series: $n > 1$

A Network Approach to Psychopathology: New Insights into Clinical Longitudinal Data

Laura F. Bringmann[1]*, Nathalie Vissers[1], Marieke Wichers[2], Nicole Geschwind[3], Peter Kuppens[1], Frenk Peeters[2], Denny Borsboom[4], Francis Tuerlinckx[1]

1 Department of Psychology, University of Leuven, Leuven, Belgium, **2** Department of Psychiatry and Neuropsychology, Maastricht University, Maastricht, The Netherlands, **3** Department of Clinical Psychological Science, Maastricht University, Maastricht, The Netherlands, **4** Department of Psychology, University of Amsterdam, Amsterdam, The Netherlands

Abstract

In the network approach to psychopathology, disorders are conceptualized as networks of mutually interacting symptoms (e.g., depressed mood) and transdiagnostic factors (e.g., rumination). This suggests that it is necessary to study how symptoms dynamically interact over time in a network architecture. In the present paper, we show how such an architecture can be constructed on the basis of time-series data obtained through Experience Sampling Methodology (ESM). The proposed methodology determines the parameters for the interaction between nodes in the network by estimating a multilevel vector autoregression (VAR) model on the data. The methodology allows combining between-subject and within-subject information in a multilevel framework. The resulting network architecture can subsequently be analyzed through network analysis techniques. In the present study, we apply the method to a set of items that assess mood-related factors. We show that the analysis generates a plausible and replicable network architecture, the structure of which is related to variables such as neuroticism; that is, for subjects who score high on neuroticism, worrying plays a more central role in the network. Implications and extensions of the methodology are discussed.

Citation: Bringmann LF, Vissers N, Wichers M, Geschwind N, Kuppens P, et al. (2013) A Network Approach to Psychopathology: New Insights into Clinical Longitudinal Data. PLoS ONE 8(4): e60188. doi:10.1371/journal.pone.0060188

Multi-level VAR

- Each subject is assumed to have their own temporal and contemporaneous VAR model
- VAR parameters come from distribution
  - Fixed effect
  - Random effect

Multi-level VAR

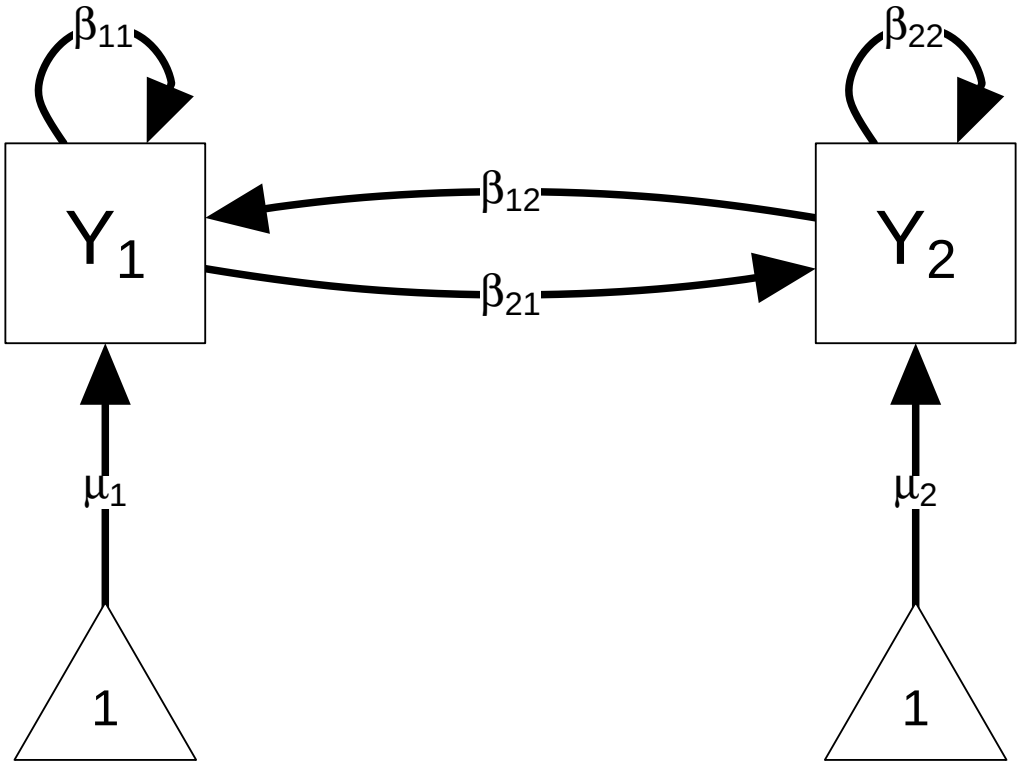
Adding superscript p for subject. Level 1 model:

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

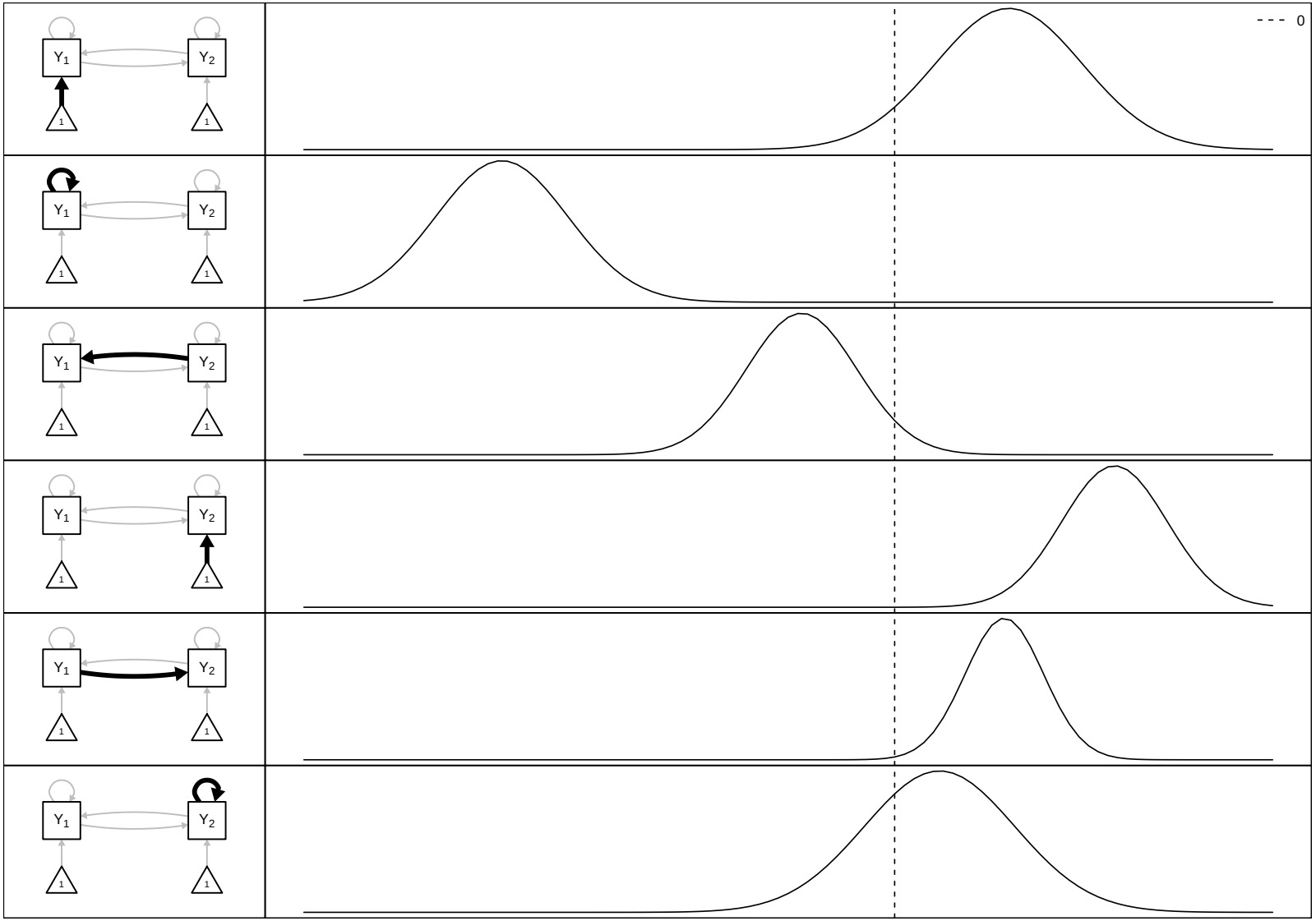
Level 2 model:

$$\begin{bmatrix} \boldsymbol{\mu}^{(p)} \\ \mathrm{Vec}\left(\boldsymbol{B}^{(p)}\right) \end{bmatrix} \sim N\left(\boldsymbol{f}, \boldsymbol{\Omega}\right).$$

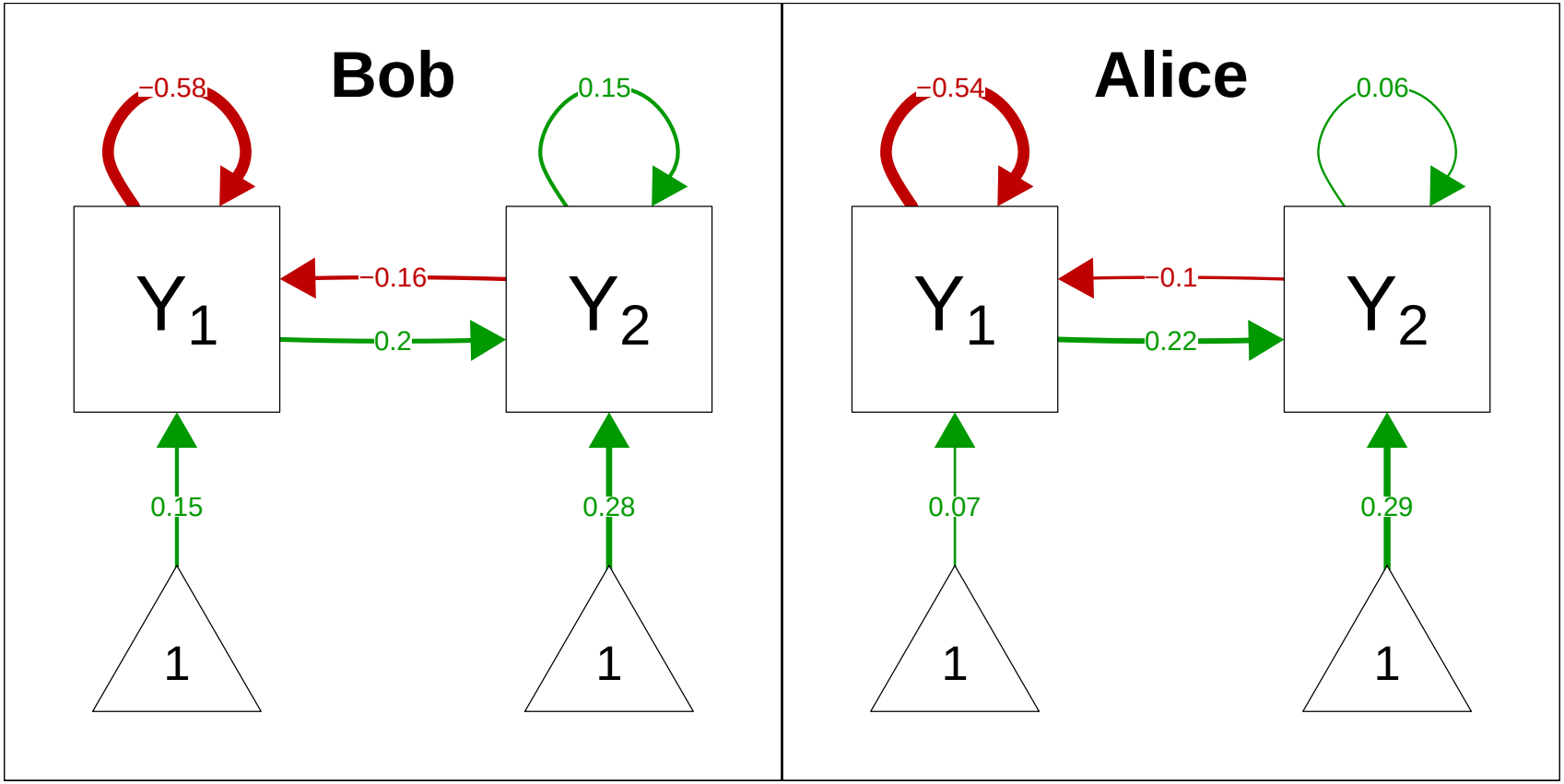
$\boldsymbol{f}$ encodes fixed effects and $\boldsymbol{\Omega}$ the distribution of random effects.


β11
β22
Y1
Y2
β12
β21
μ1
μ2
1
1

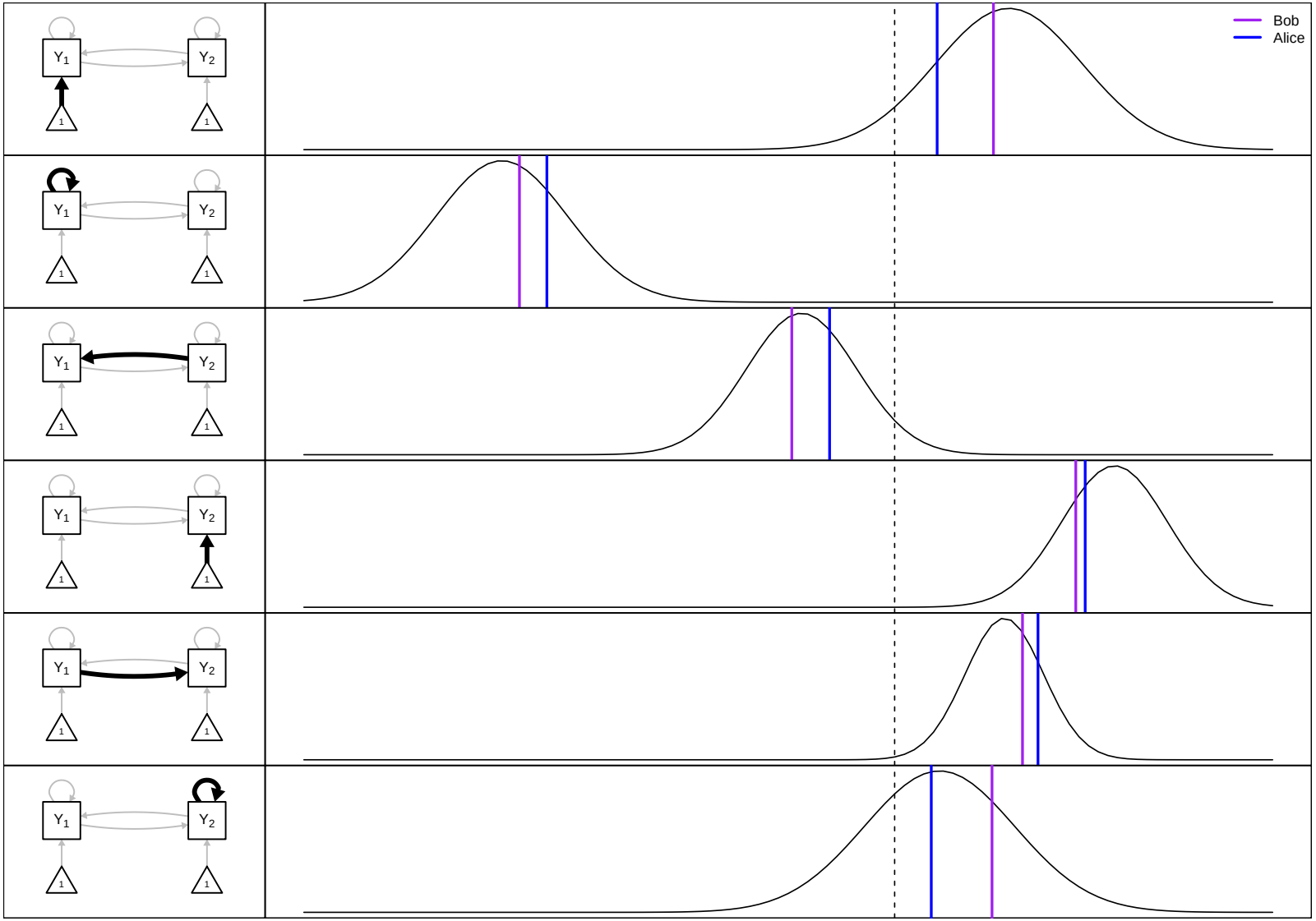
Each Parameter has a Distribution



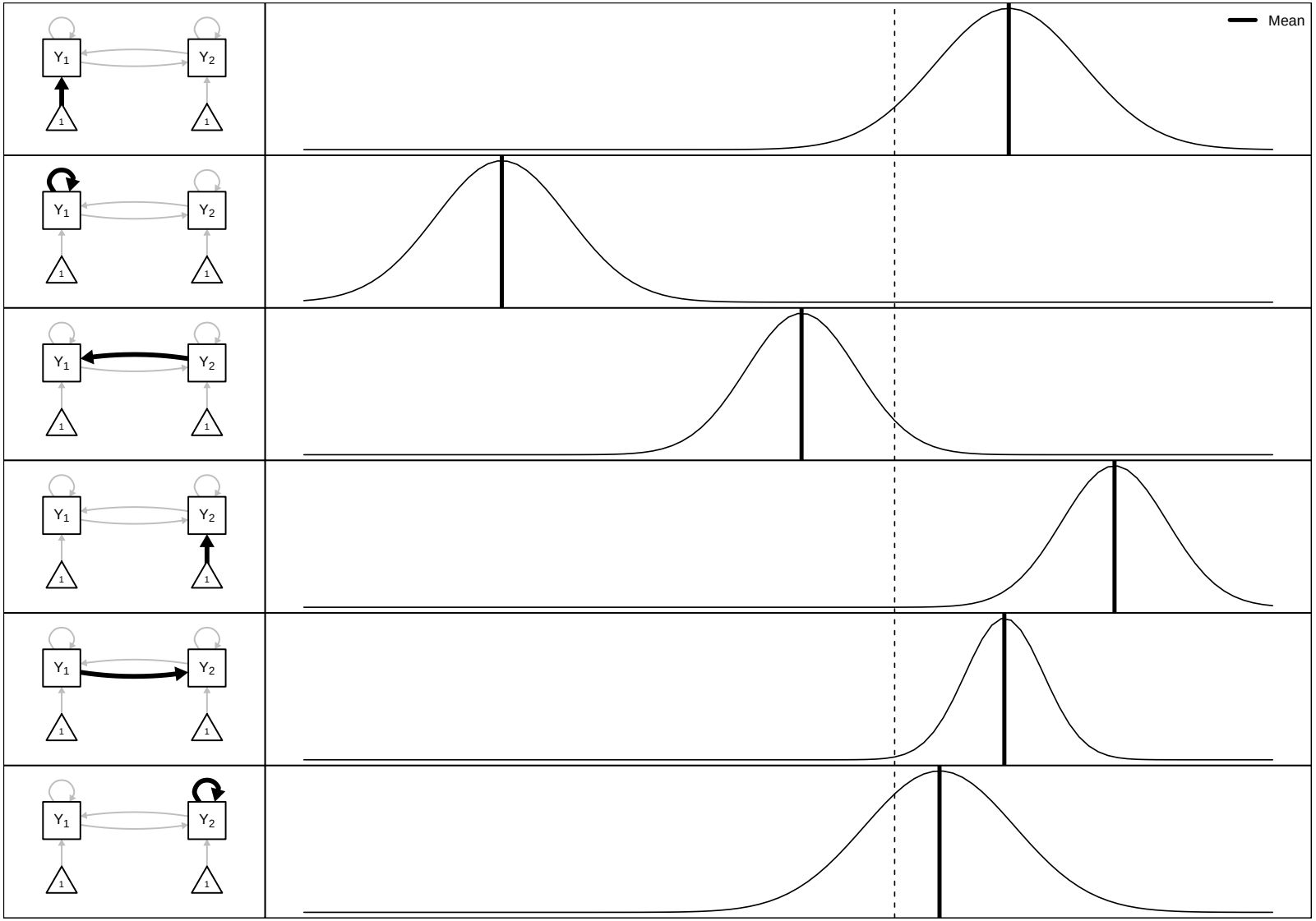
Individual Networks



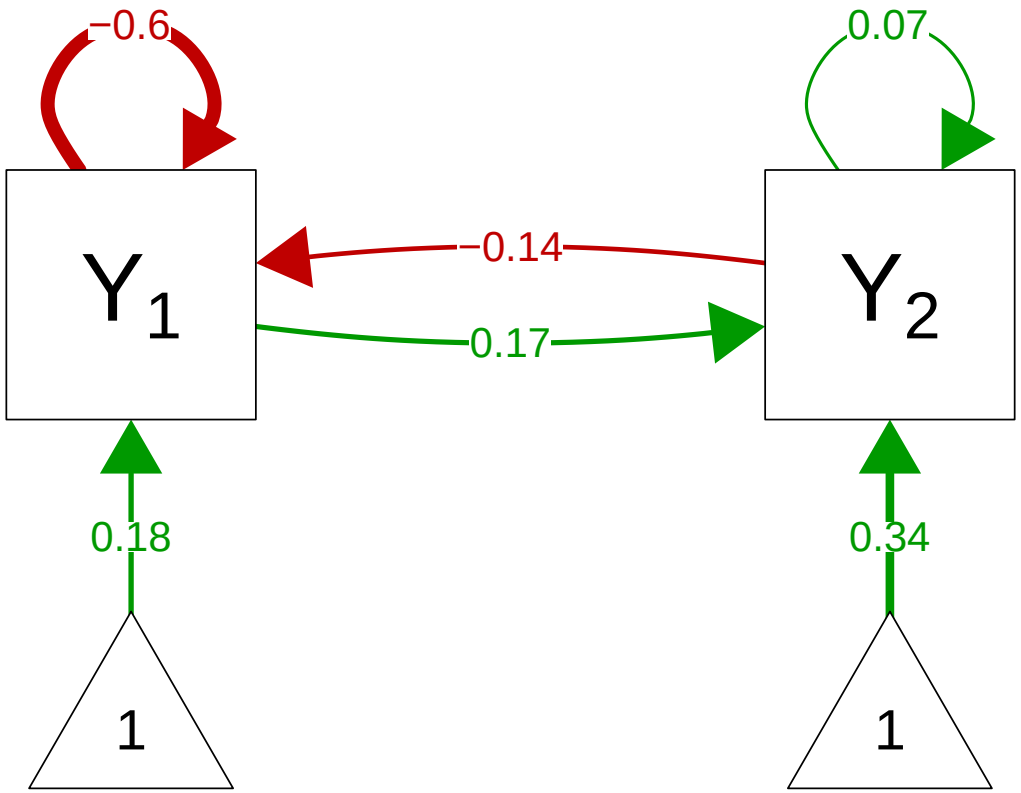
Random Effects



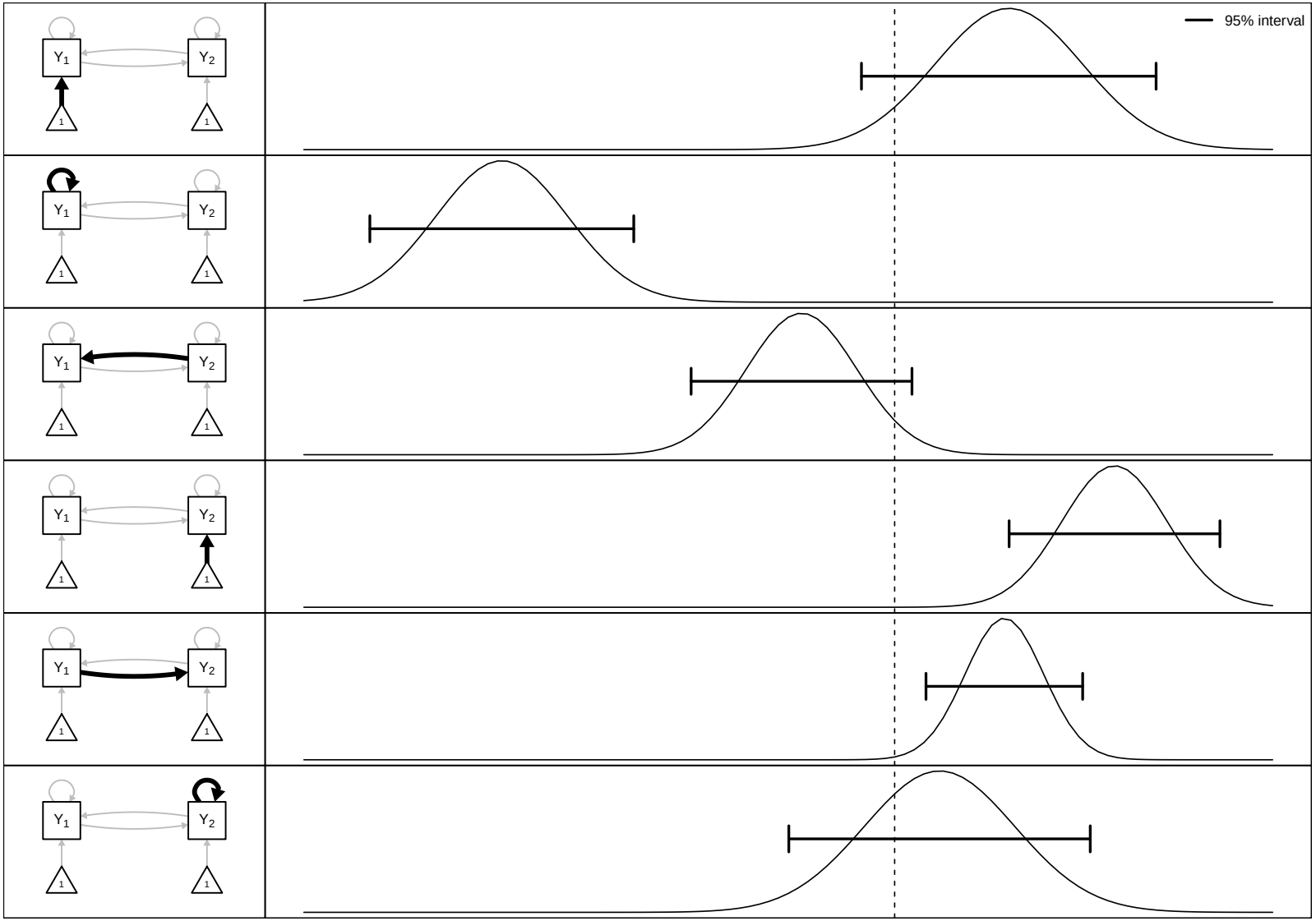
Fixed Effects



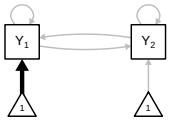
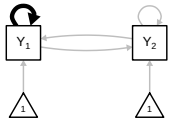
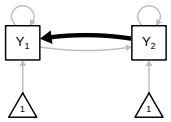
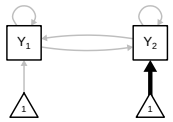
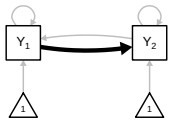
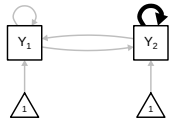
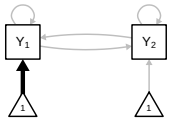
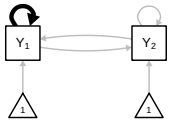
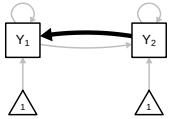
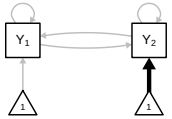
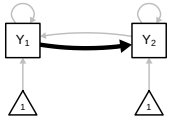
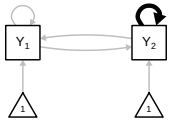
Fixed Effects



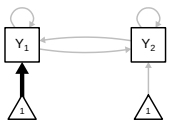
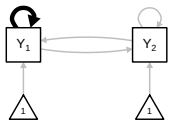
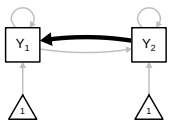
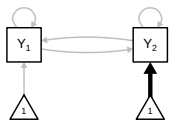
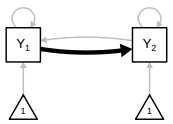
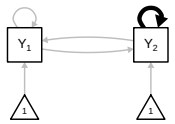
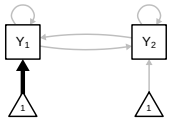
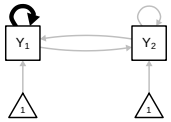
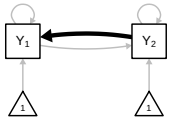
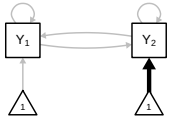
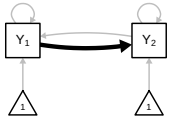
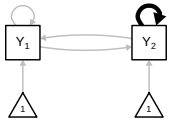
Individual Differences



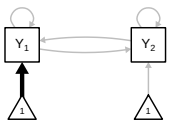
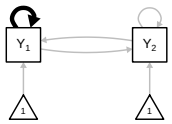
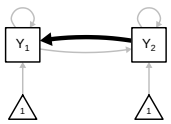
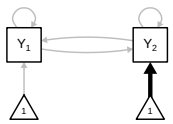
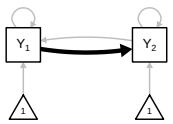
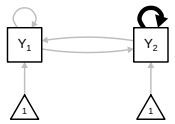
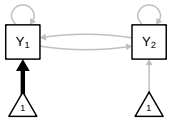
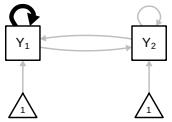
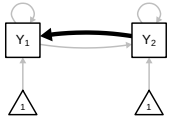
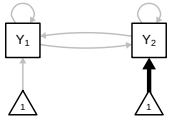
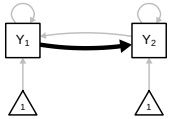
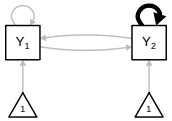
Parameter correlation Matrix

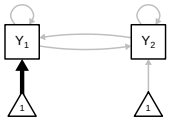
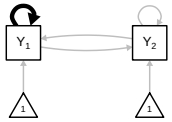
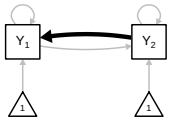
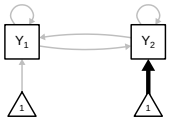
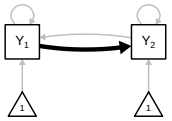
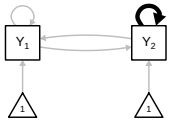
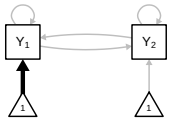
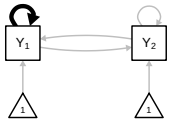
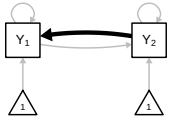
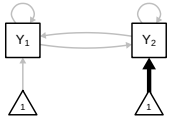
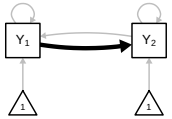
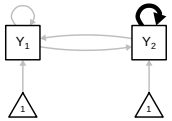
Parameter Correlation Matrix

						
	1	0.01	−0.54	0.21	−0.18	0.46
	0.01	1	−0.24	−0.66	0.77	0.06
	−0.54	−0.24	1	−0.12	0.34	−0.75
	0.21	−0.66	−0.12	1	−0.76	0.1
	−0.18	0.77	0.34	−0.76	1	−0.18
	0.46	0.06	−0.75	0.1	−0.18	1

Stability

						
	1	0.01	−0.54	0.21	−0.18	0.46
	0.01	1	−0.24	−0.66	0.77	0.06
	−0.54	−0.24	1	−0.12	0.34	−0.75
	0.21	−0.66	−0.12	1	−0.76	0.1
	−0.18	0.77	0.34	−0.76	1	−0.18
	0.46	0.06	−0.75	0.1	−0.18	1

Connectivity

						
	1	0.01	−0.54	0.21	−0.18	0.46
	0.01	1	−0.24	−0.66	0.77	0.06
	−0.54	−0.24	1	−0.12	0.34	−0.75
	0.21	−0.66	−0.12	1	−0.76	0.1
	−0.18	0.77	0.34	−0.76	1	−0.18
	0.46	0.06	−0.75	0.1	−0.18	1

Brief Empirical Report

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Emotion-Network Density in Major Depressive Disorder

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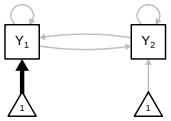
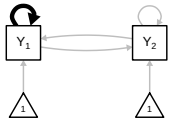
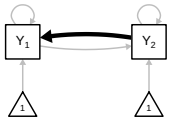
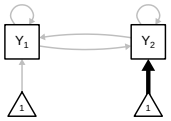
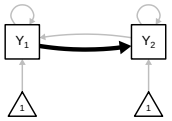
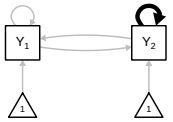
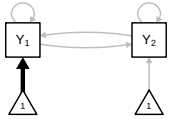
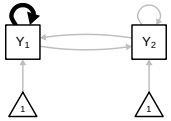
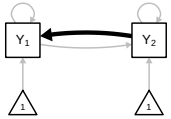
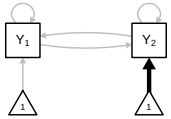
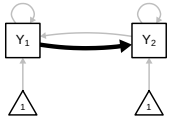
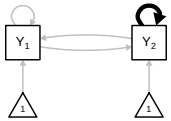
[1]Department of Psychology, KU Leuven; [2]Department of Psychology, Stanford University; [3]Department of Psychology, Washington University in St. Louis; [4]Max Planck Institute for Human Development; [5]School of Education, University of California, Irvine; [6]MIND Research Institute, Irvine, California; and [7]Department of Psychology, University of Michigan, Ann Arbor

Between-subject Effects

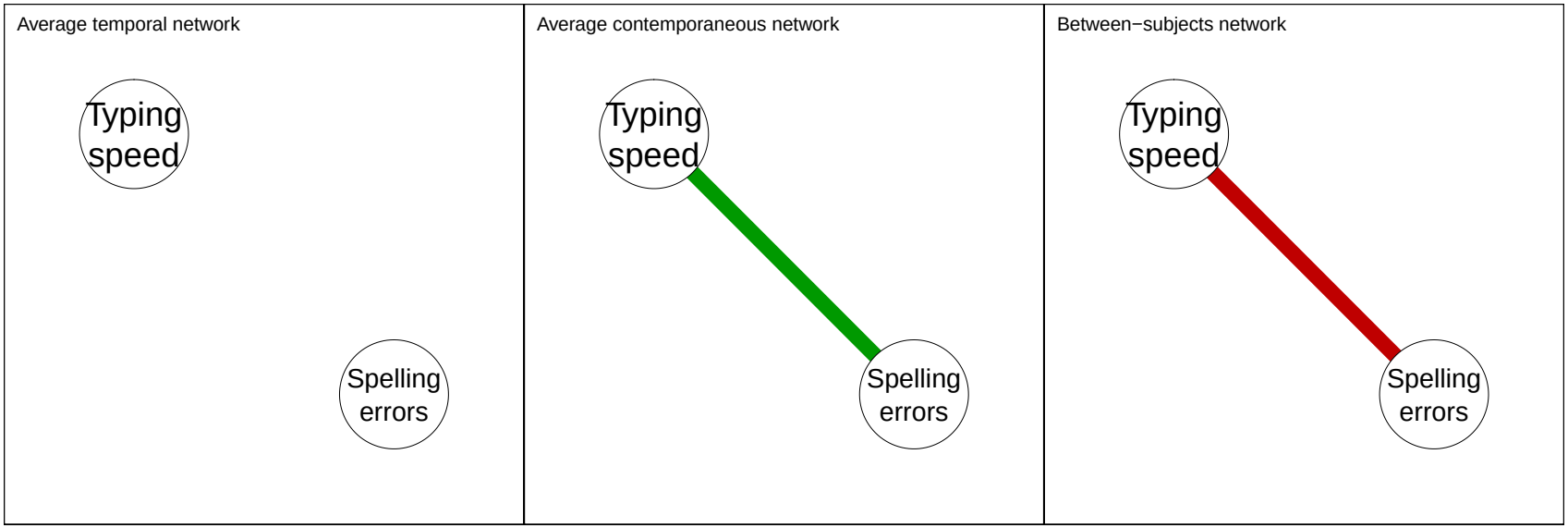
						
	1	0.01	−0.54	0.21	−0.18	0.46
	0.01	1	−0.24	−0.66	0.77	0.06
	−0.54	−0.24	1	−0.12	0.34	−0.75
	0.21	−0.66	−0.12	1	−0.76	0.1
	−0.18	0.77	0.34	−0.76	1	−0.18
	0.46	0.06	−0.75	0.1	−0.18	1

Between-subjects Network

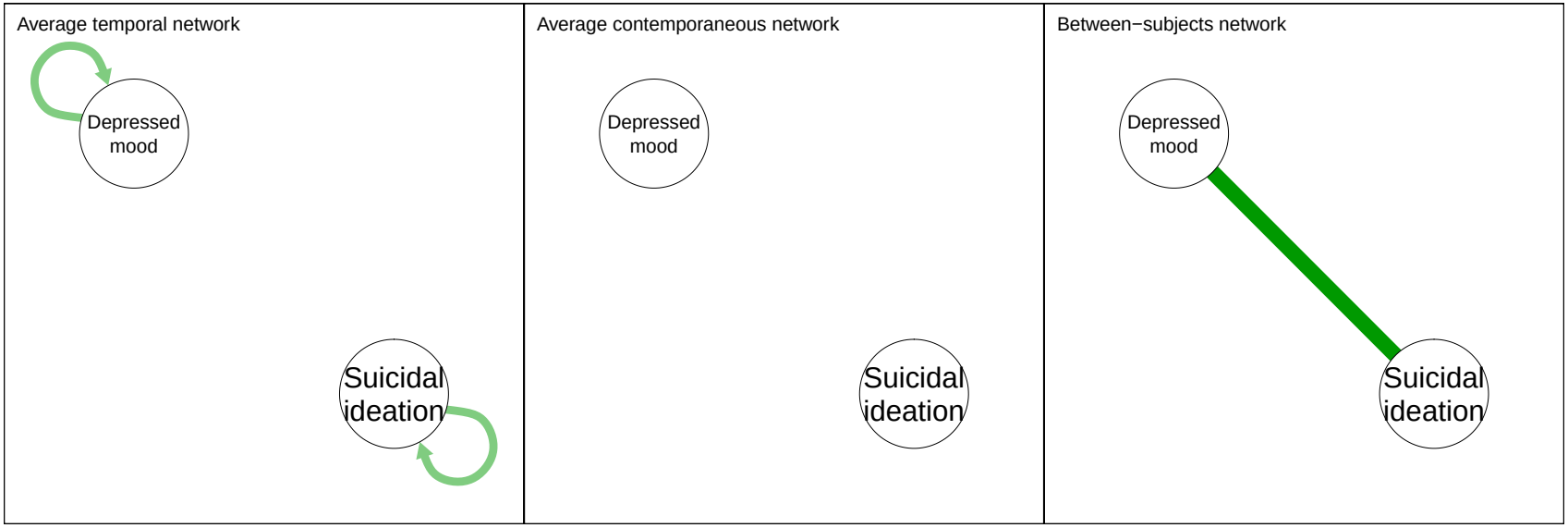
The random effects variance-covariance matrix can be divided in four blocks:

$$\begin{bmatrix} \boldsymbol{R_\mu} \\ \boldsymbol{R_B} \end{bmatrix} \sim N\left(\mathbf{0}, \begin{bmatrix} \boldsymbol{\Omega_\mu} & \boldsymbol{\Omega_{\mu B}} \\ \boldsymbol{\Omega_{B\mu}} & \boldsymbol{\Omega_B} \end{bmatrix}\right).$$

- Block $\boldsymbol{\Omega_\mu}$ 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.

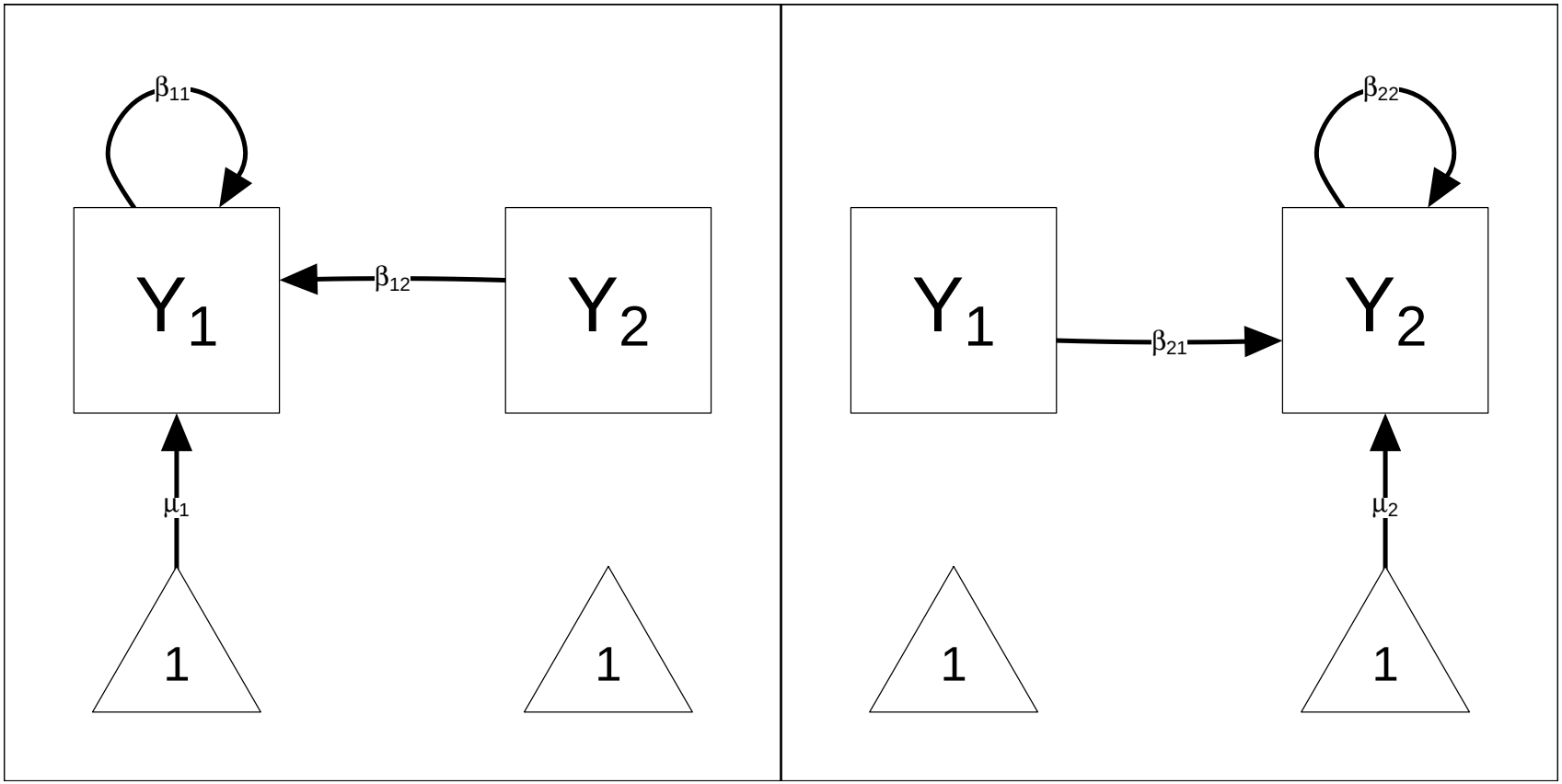


Hypothetical example of networks based on two persons:

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

Temporal Estimation

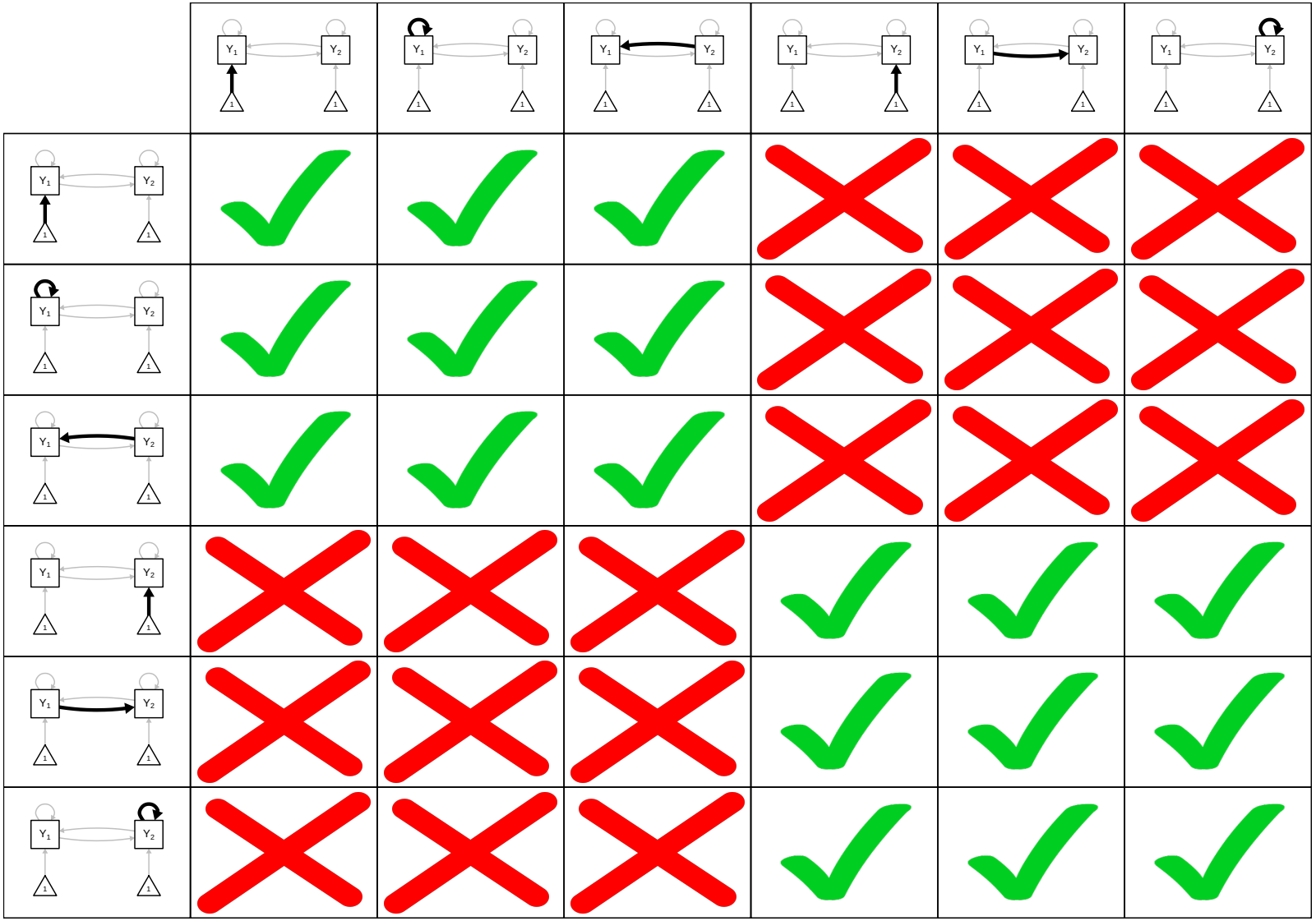
- Multi-variate multi-level MLE regression estimation is complicated and not yet well implemented in open source software
- `lme4` packages implements univariate multi-level regression
  - Douglas Bates, Martin Maechler, Ben Bolker, Steve Walker (2015). Fitting Linear Mixed-Effects Models Using lme4. Journal of Statistical Software, 67(1), 1-48. `doi:10.18637/jss.v067.i01`
  - `lmer` function
- A multi-level VAR model can be estimated by sequentially estimating univariate models
  - Estimate all incoming edges per node
  - Bringmann et al. (2013). A network approach to psychopathology: new insights into clinical time-series data. PloS one, 8(4), e60188.


β11
Y1
β12
Y2
μ1
1
1
β22
Y1
β21
Y2
μ2
1
1

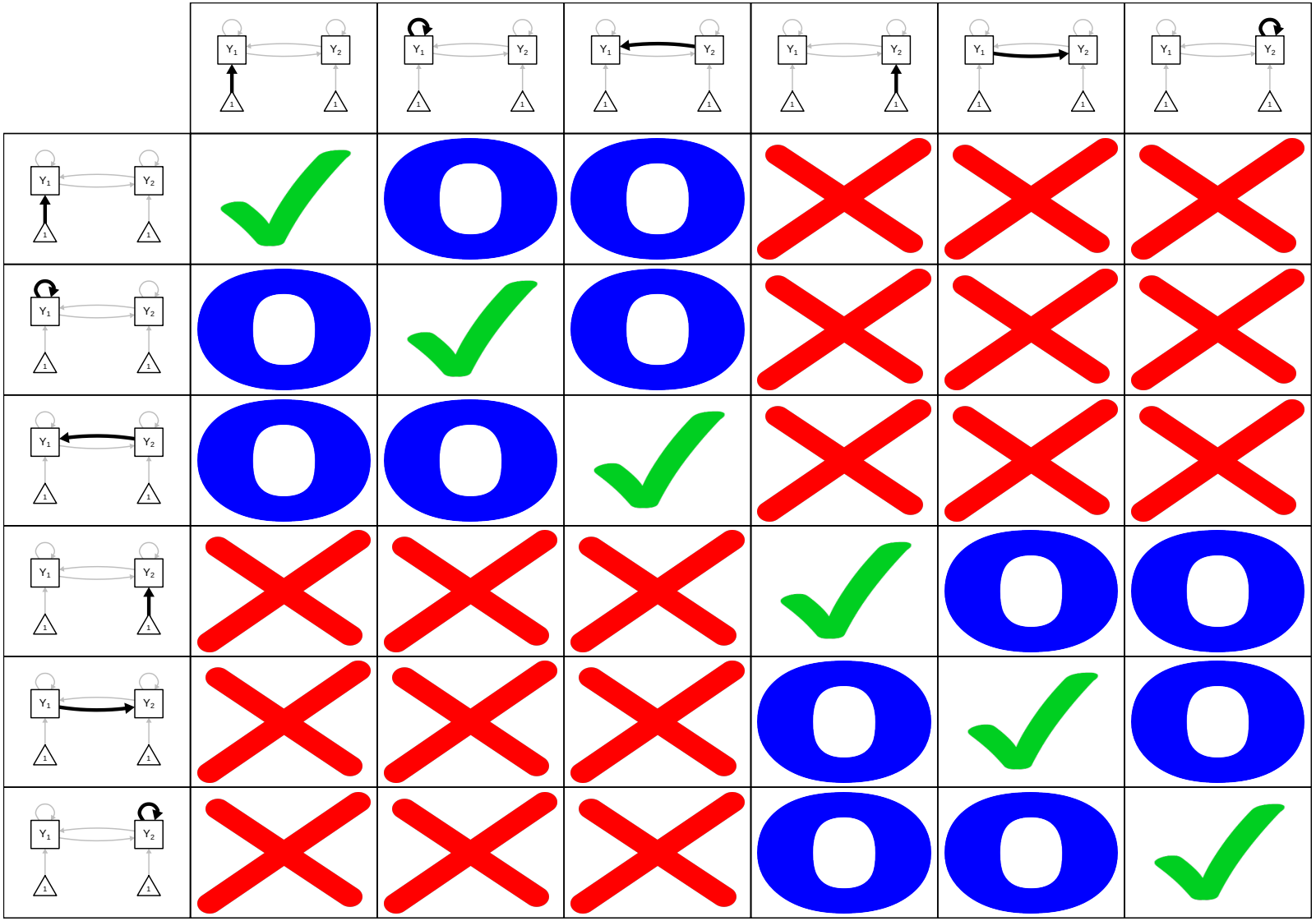
Temporal Estimation

- Correlated estimation:
  - Needs to integrate out a high-dimensional distribution over parameters
  - Only feasible for up to ~6 nodes
  - Does not estimate all parameter covariances
    - Not all parameters together in the same model
- Orthogonal estimation
  - Alternatively, parameter covariances can be fixed to zero
  - Fast, and works for high dimensions (e.g., 20 nodes)
  - But, does not return *any* parameter correlation

Correlated Estimation



Orthogonal Estimation



Between-subject Estimation

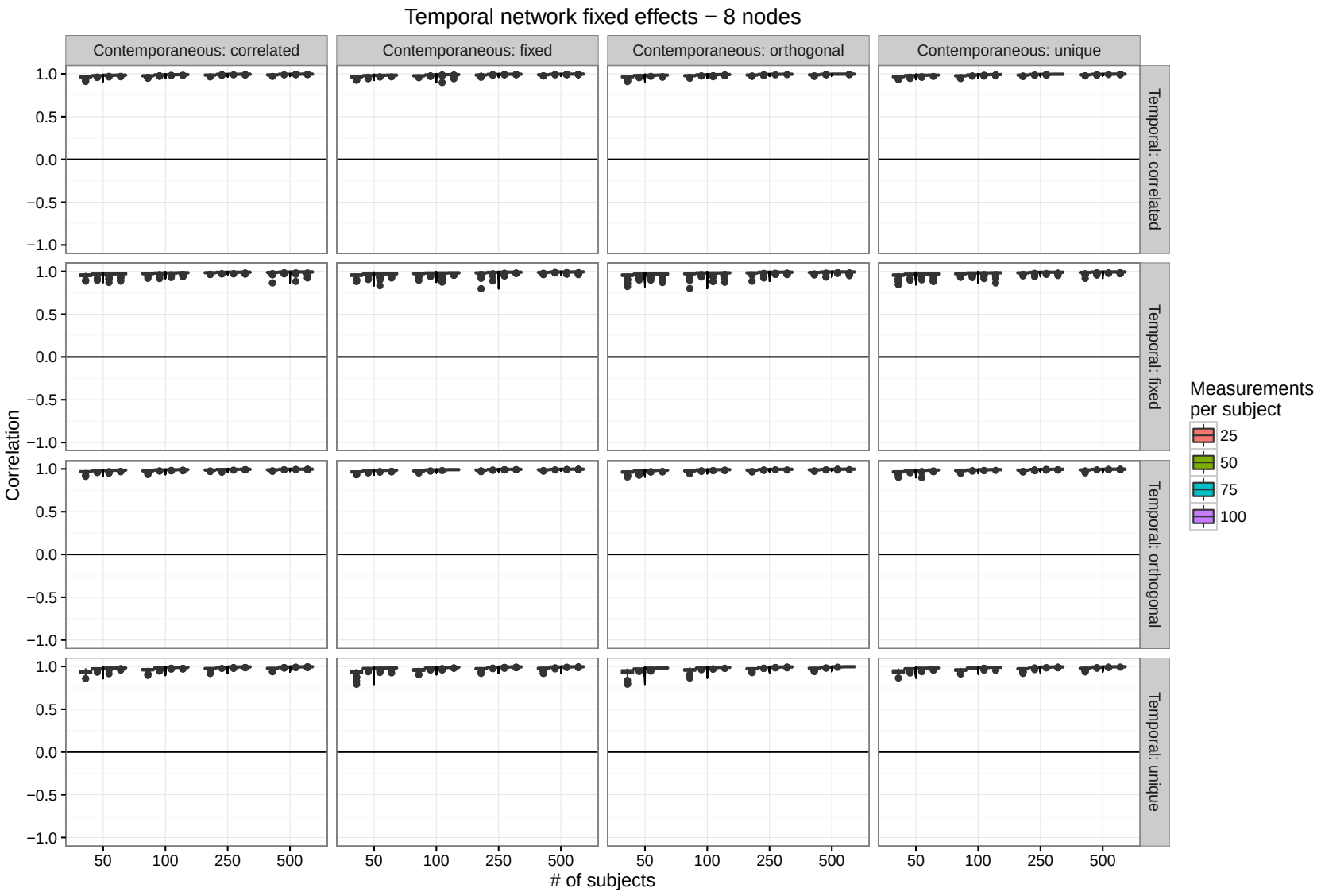
- Between subject effects can be obtained by centering predictors and adding the person-means as level 2 predictors
  - Hamaker, E. L., & Grasman, R. P. (2015). To center or not to center? Investigating inertia with a multilevel autoregressive model. Frontiers in psychology, 5, 1492.
- This can be seen 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

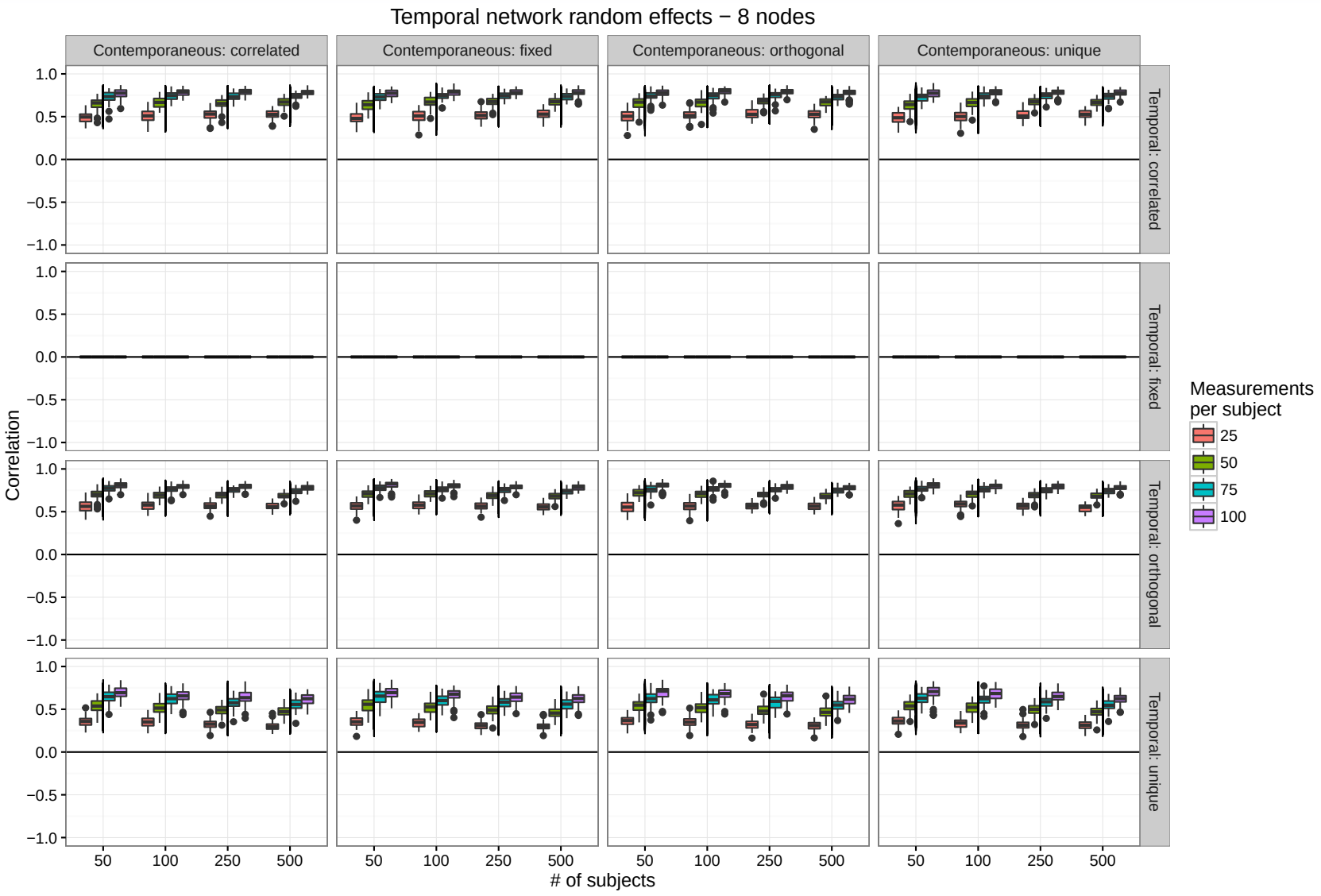
Contemporaneous Estimation

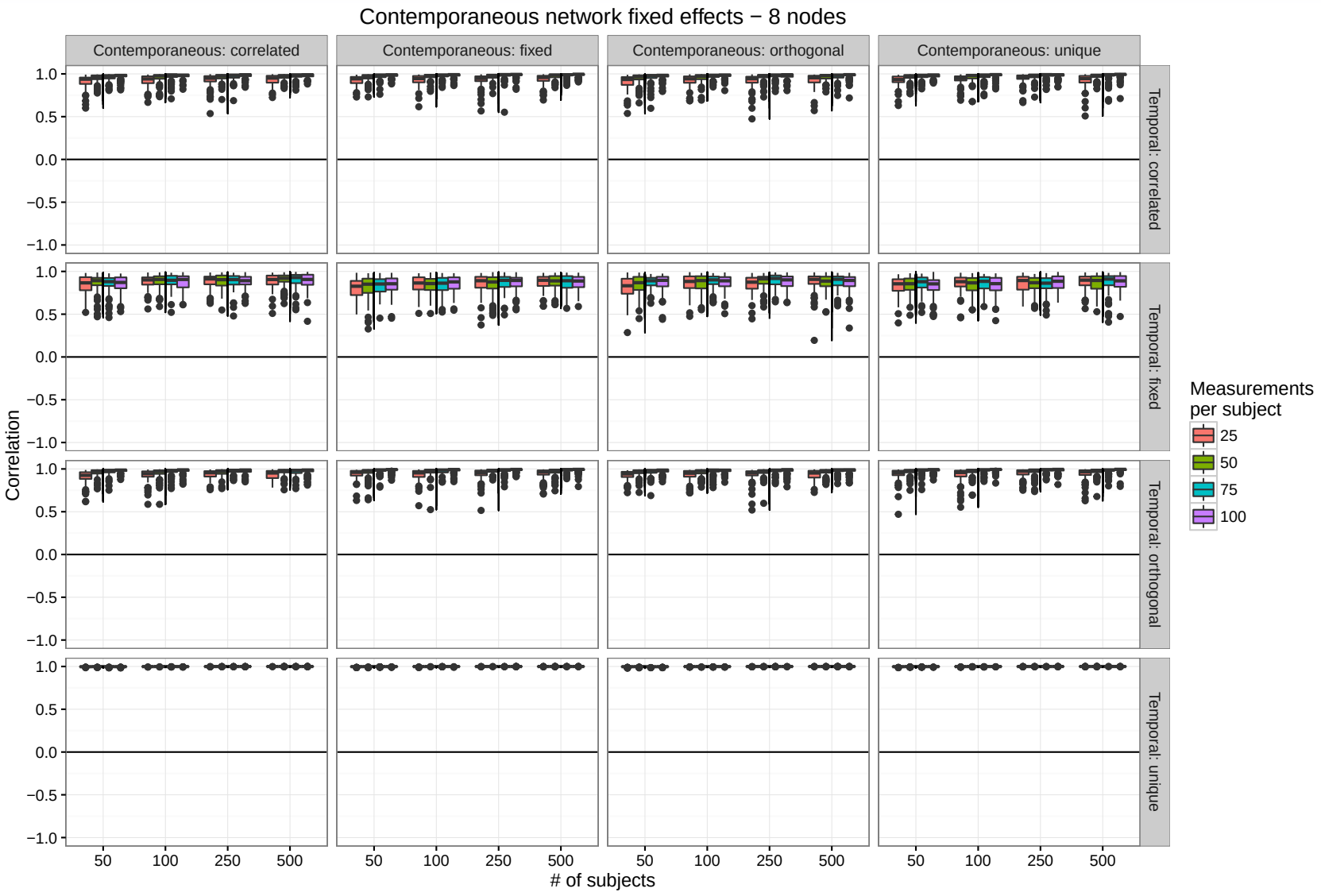
- Contemporaneous networks need to be estimated post-hoc by investigating the residuals
- Either inverting the sample variance-covariance matrix of residuals:
  - Fixed
  - Unique
- Or as a second multi-level model using nodewise estimation of a GGM:
  - Correlated
  - Orthogonal

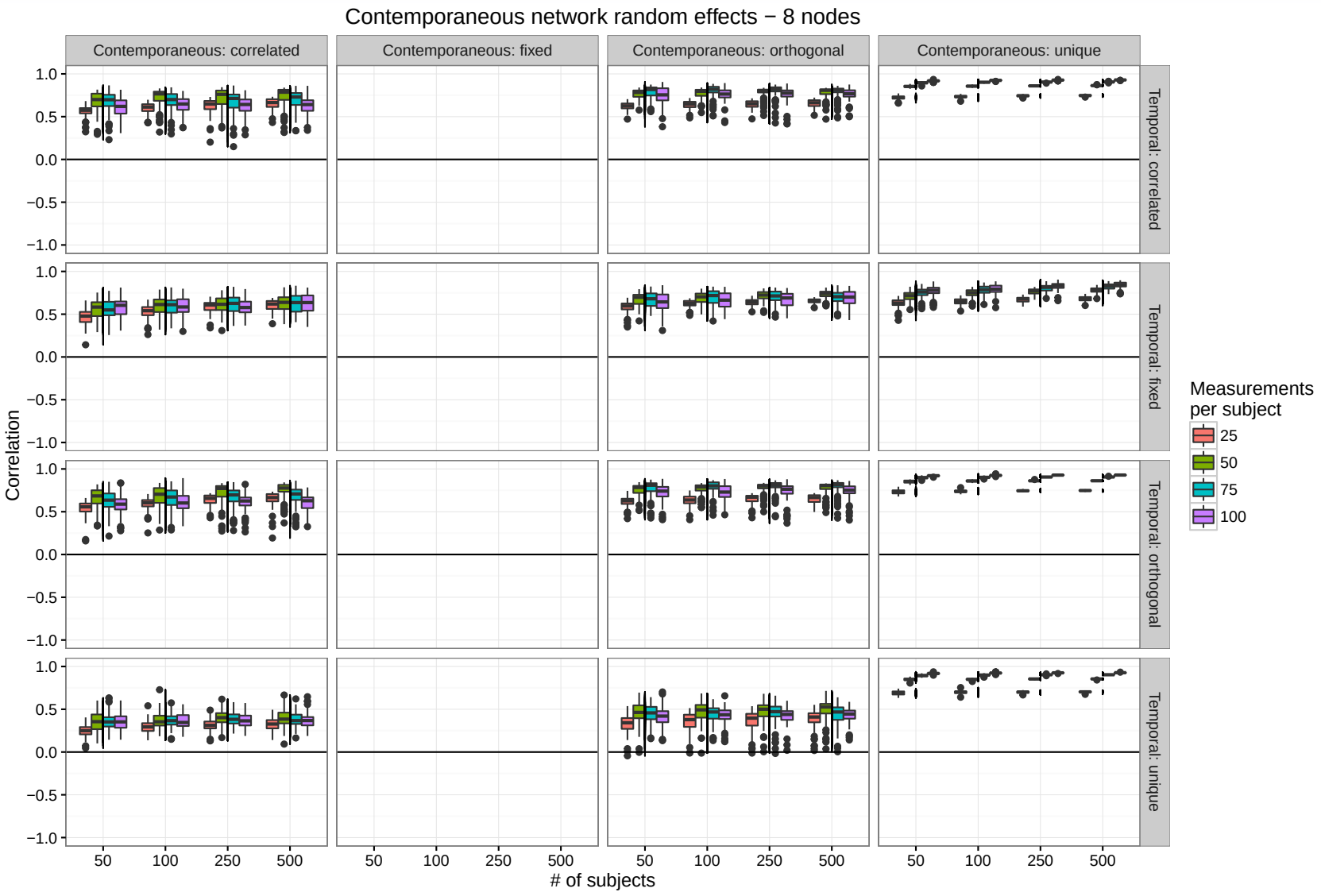
Simulation Studies

- 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

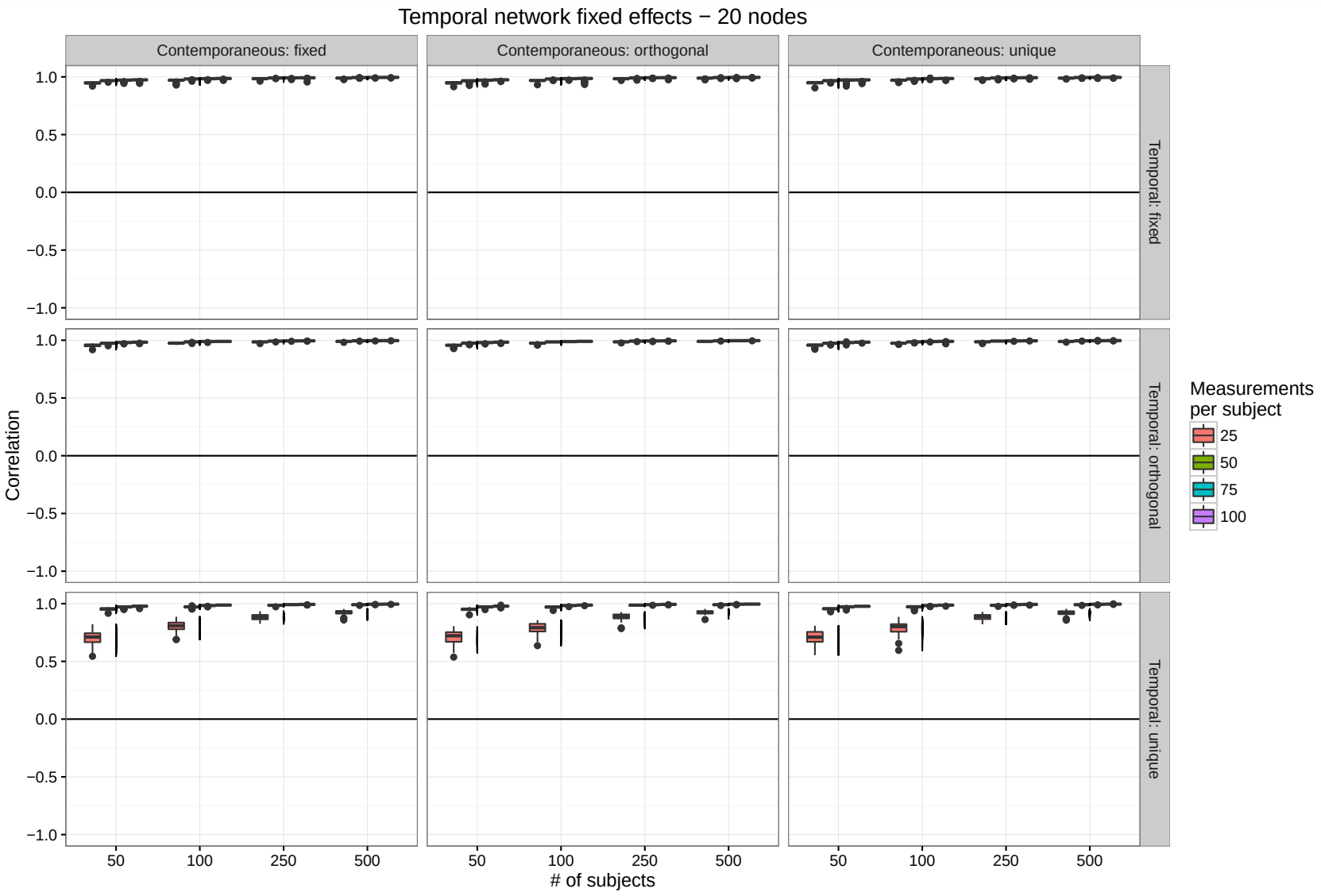

Temporal network fixed effects − 8 nodes
Contemporaneous: correlated
Contemporaneous: fixed
Contemporaneous: orthogonal
Contemporaneous: unique
Temporal: correlated
Temporal: fixed
Temporal: orthogonal
Temporal: unique
Correlation
1.0
0.5
0.0
−0.5
−1.0
50
100
250
500
# of subjects
Measurements per subject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

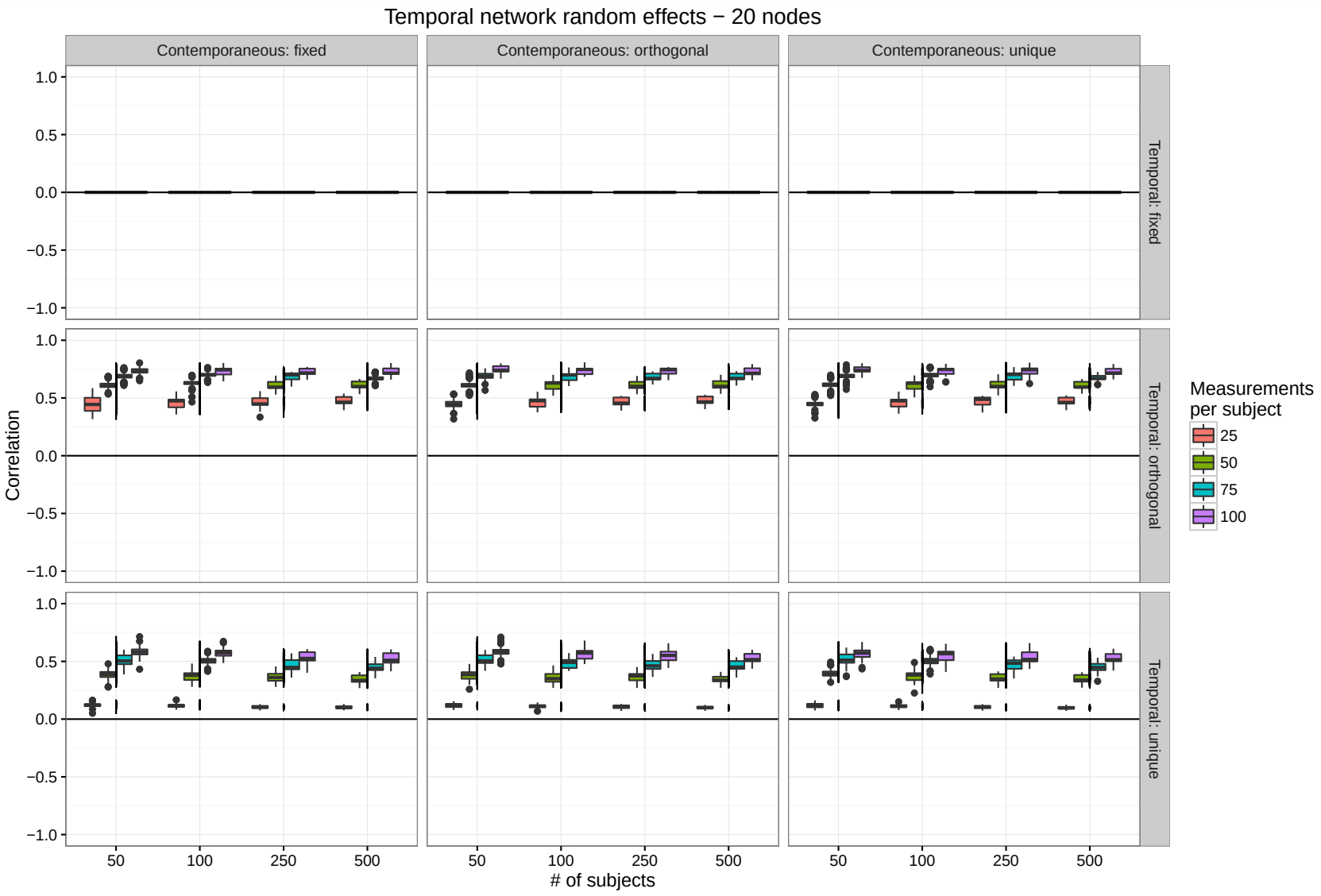

Temporal network random effects − 8 nodes
Contemporaneous: correlated
Contemporaneous: fixed
Contemporaneous: orthogonal
Contemporaneous: unique
Temporal: correlated
Temporal: fixed
Temporal: orthogonal
Temporal: unique
Correlation
1.0
0.5
0.0
−0.5
−1.0
50
100
250
500
# of subjects
Measurements per subject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

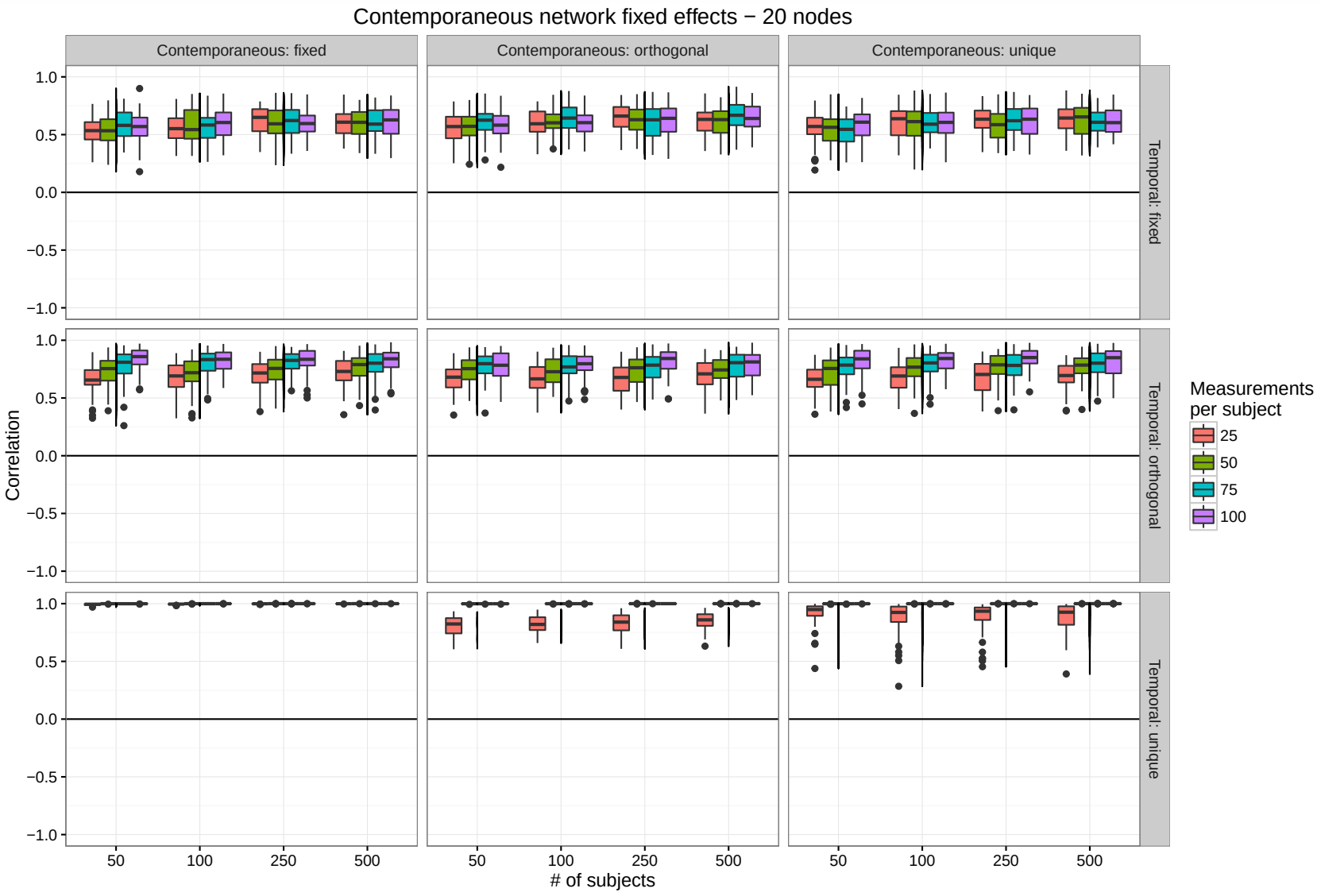

Contemporaneous network fixed effects − 8 nodes
Contemporaneous: correlated
Contemporaneous: fixed
Contemporaneous: orthogonal
Contemporaneous: unique
Temporal: correlated
Temporal: fixed
Temporal: orthogonal
Temporal: unique
Correlation
1.0
0.5
0.0
−0.5
−1.0
50
100
250
500
# of subjects
Measurements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

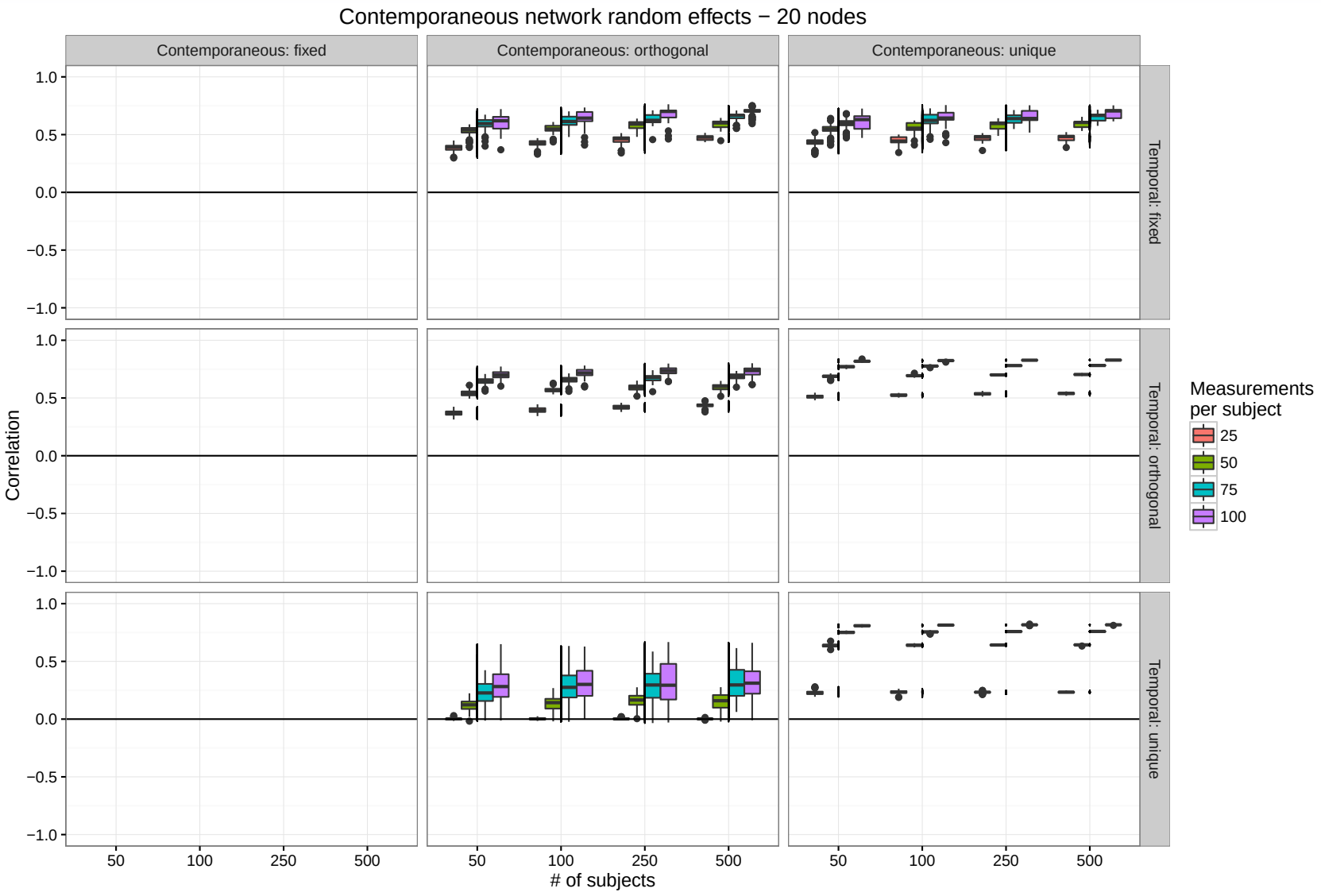

Contemporaneous network random effects − 8 nodes
Contemporaneous: correlated
Contemporaneous: fixed
Contemporaneous: orthogonal
Contemporaneous: unique
Temporal: correlated
Temporal: fixed
Temporal: orthogonal
Temporal: unique
Correlation
1.0
0.5
0.0
−0.5
−1.0
50
100
250
500
# of subjects
Measurements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

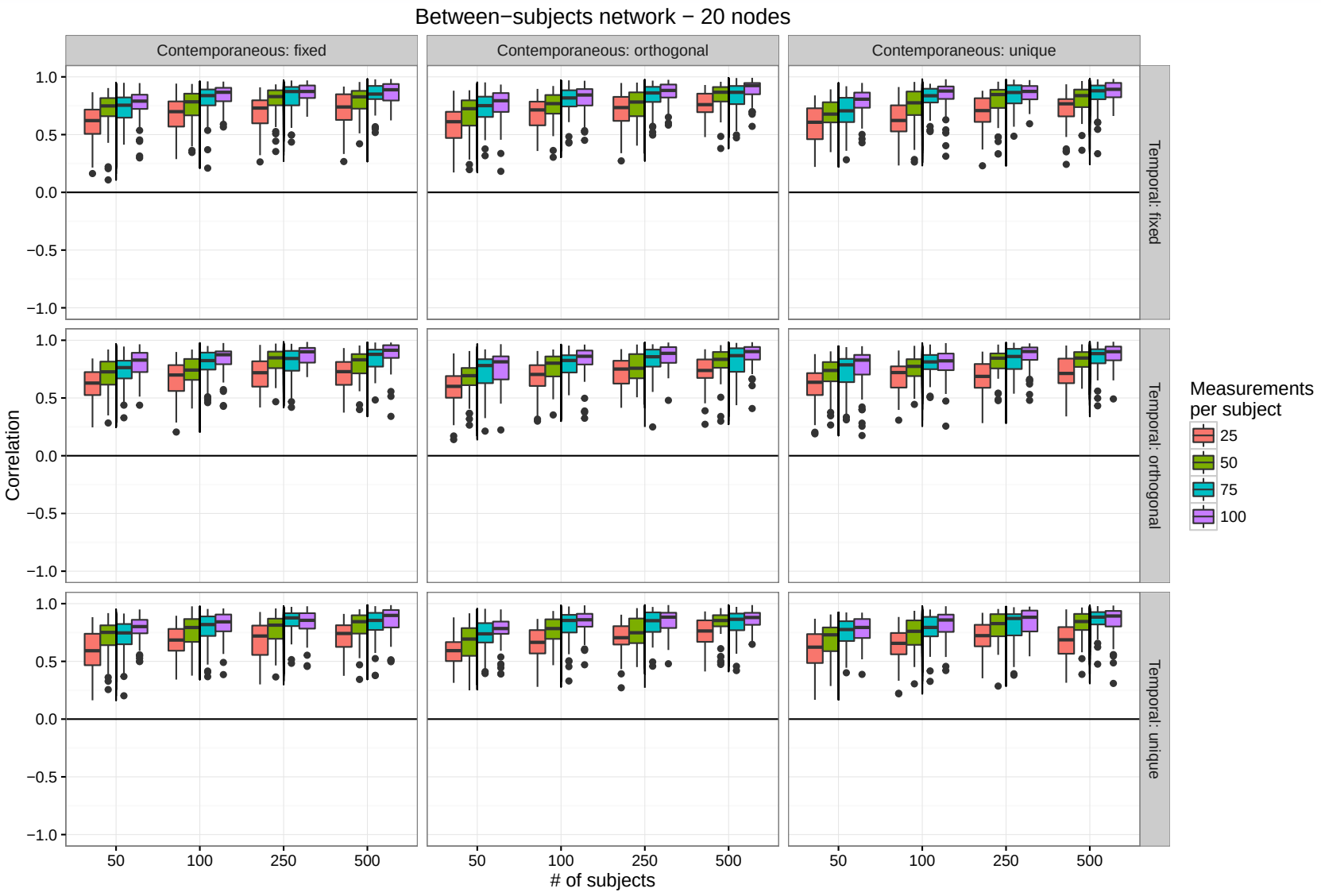

Between−subjects network − 8 nodes
Contemporaneous: correlated
Contemporaneous: fixed
Contemporaneous: orthogonal
Contemporaneous: unique
Temporal: correlated
Temporal: fixed
Temporal: orthogonal
Temporal: unique
Correlation
1.0
0.5
0.0
−0.5
−1.0
50
100
250
500
# of subjects
Measurements per subject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


Temporal network fixed effects − 20 nodes
Contemporaneous: fixed
Contemporaneous: orthogonal
Contemporaneous: unique
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


Temporal network random effects − 20 nodes
Contemporaneous: fixed
Contemporaneous: orthogonal
Contemporaneous: unique
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

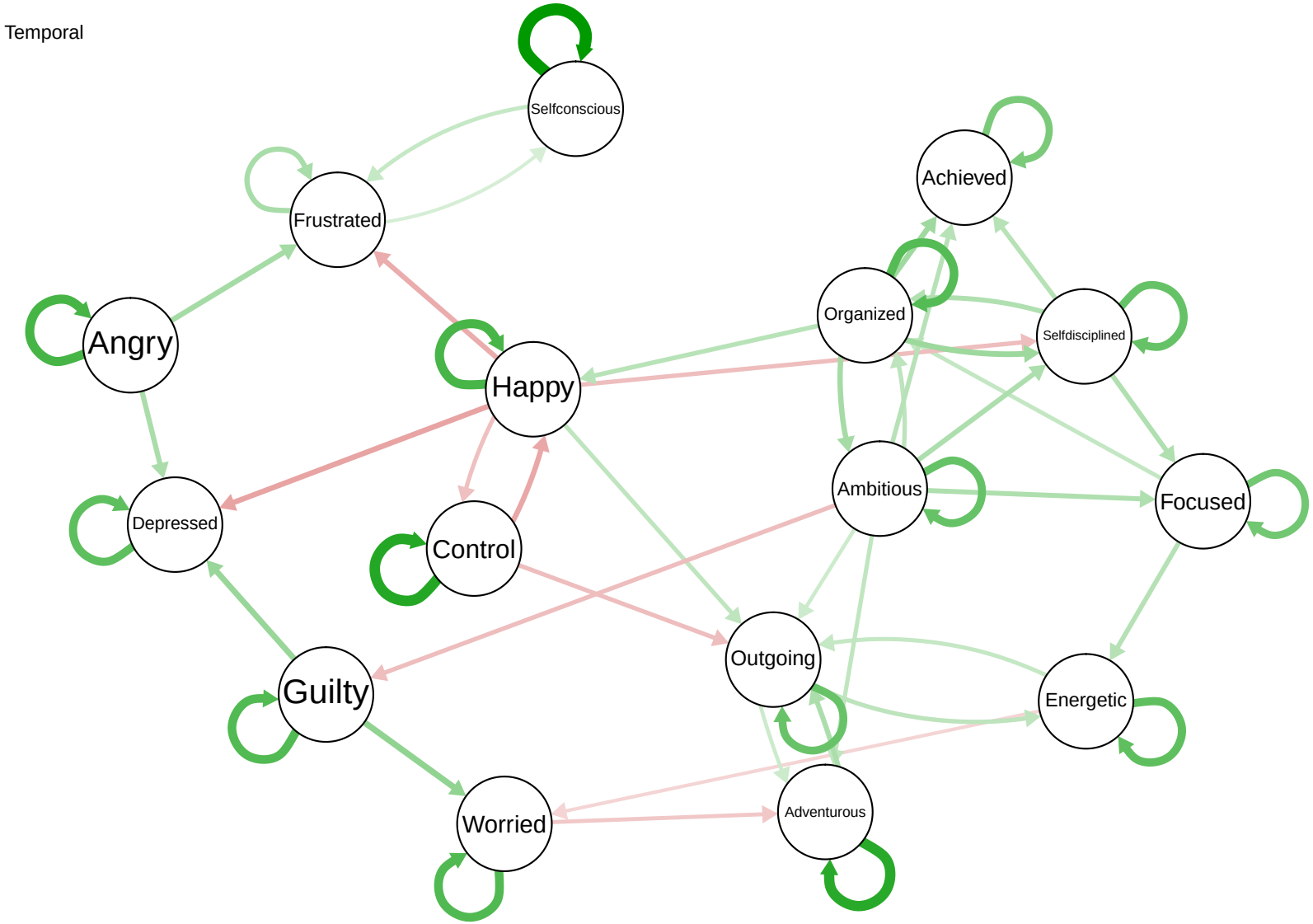

Contemporaneous network fixed effects − 20 nodes
Contemporaneous: fixed
Contemporaneous: orthogonal
Contemporaneous: unique
Temporal: fixed
Temporal: orthogonal
Temporal: unique
Correlation
1.0
0.5
0.0
−0.5
−1.0
50
100
250
500
# of subjects
Measurements per subject
25
50
75
100


Contemporaneous network random effects − 20 nodes
Contemporaneous: fixed
Contemporaneous: orthogonal
Contemporaneous: unique
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

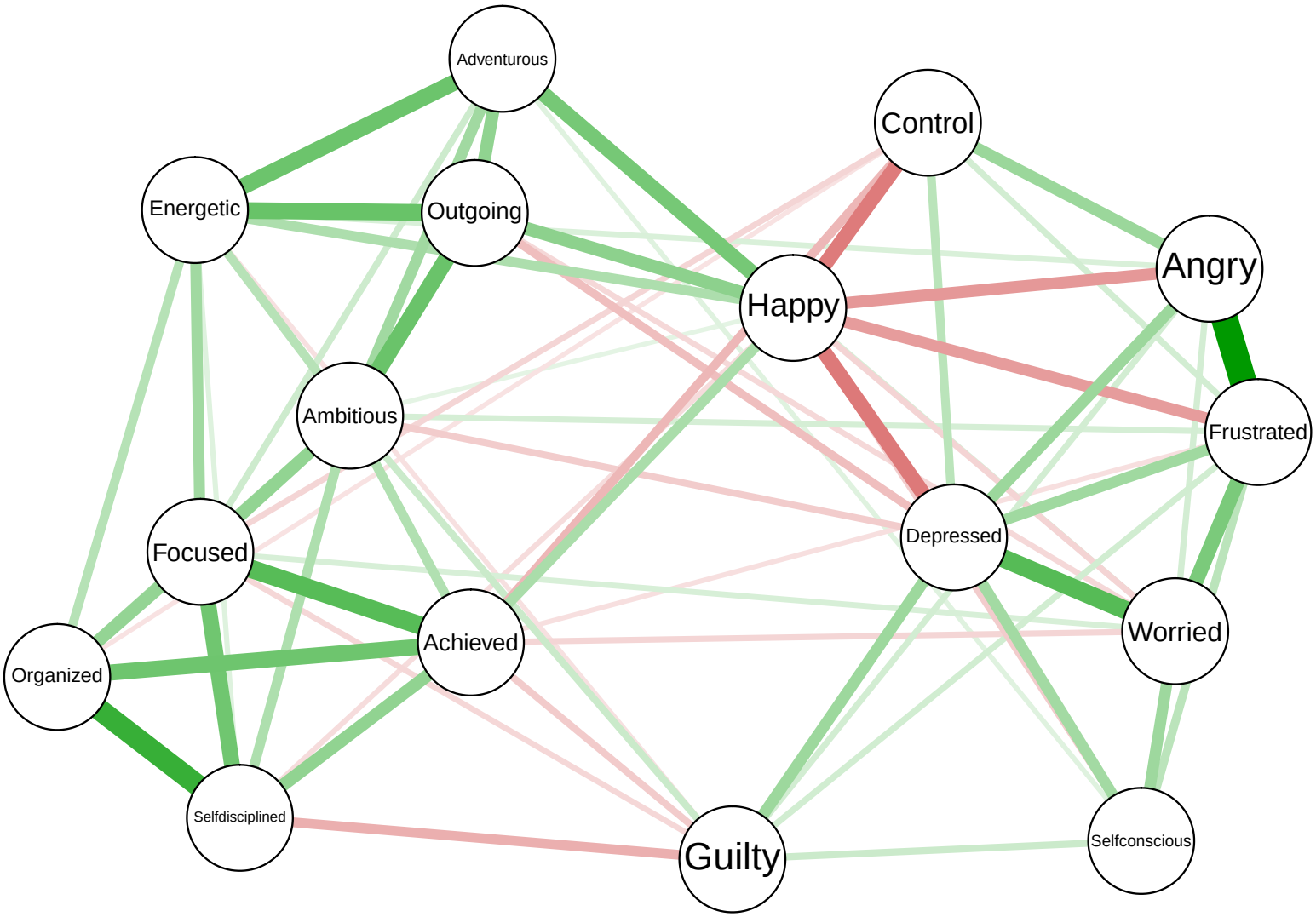

Between−subjects network − 20 nodes
Contemporaneous: fixed
Contemporaneous: orthogonal
Contemporaneous: unique
Temporal: fixed
Temporal: orthogonal
Temporal: unique
Correlation
1.0
0.5
0.0
−0.5
−1.0
50
100
250
500
# of subjects
Measurements per subject
25
50
75
100

Empirical Example

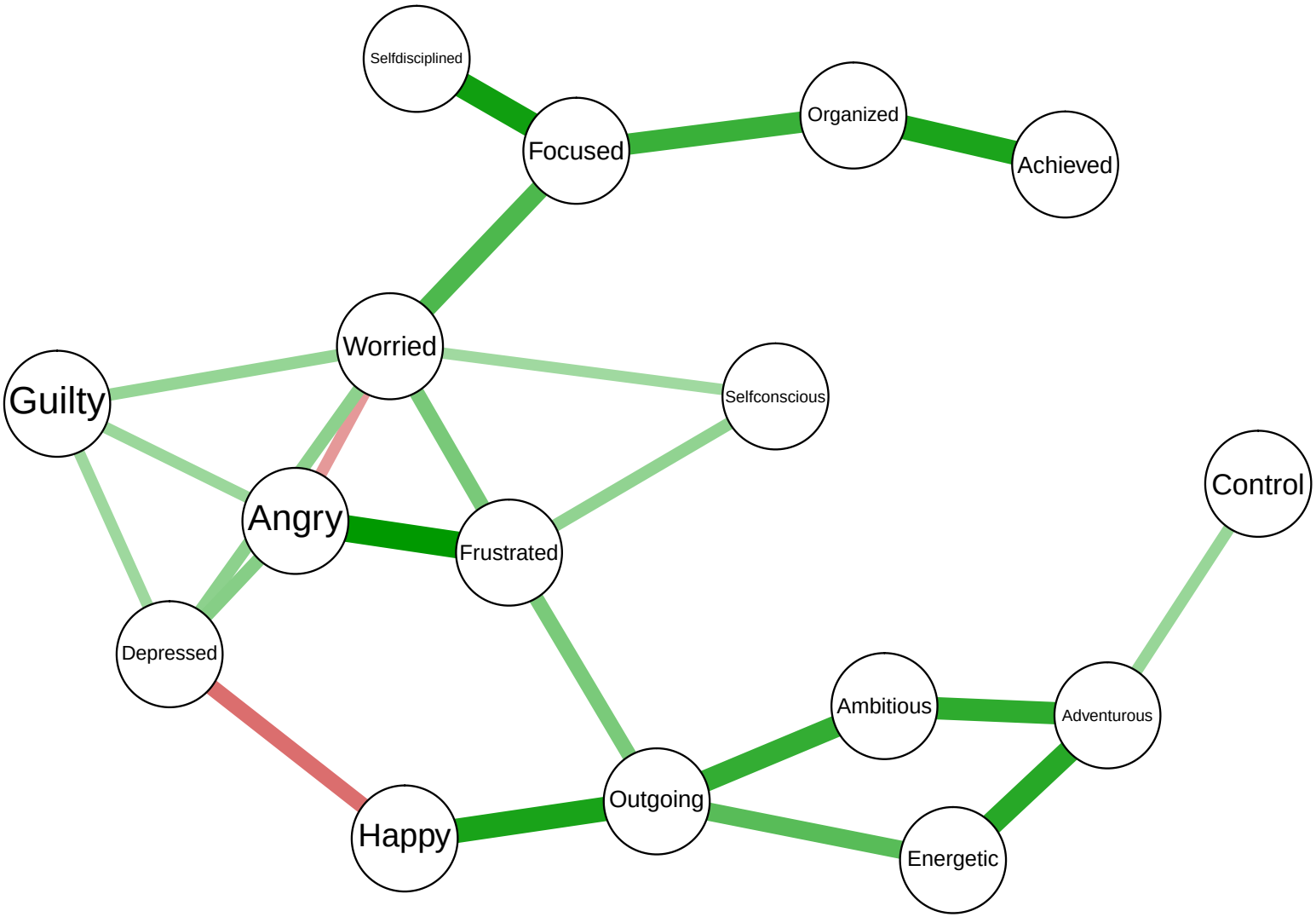
- Two datasets
  - Original: 26 subjects, 51 measurements on average, 1323 total observations
  - Replication: 65 subjects, 35.5 measurements on average, 2309 total observations
- 16 indicators of neuroticism, extroversion, conscientiousness
- Orthogonal estimation of temporal and contemporaneous effects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

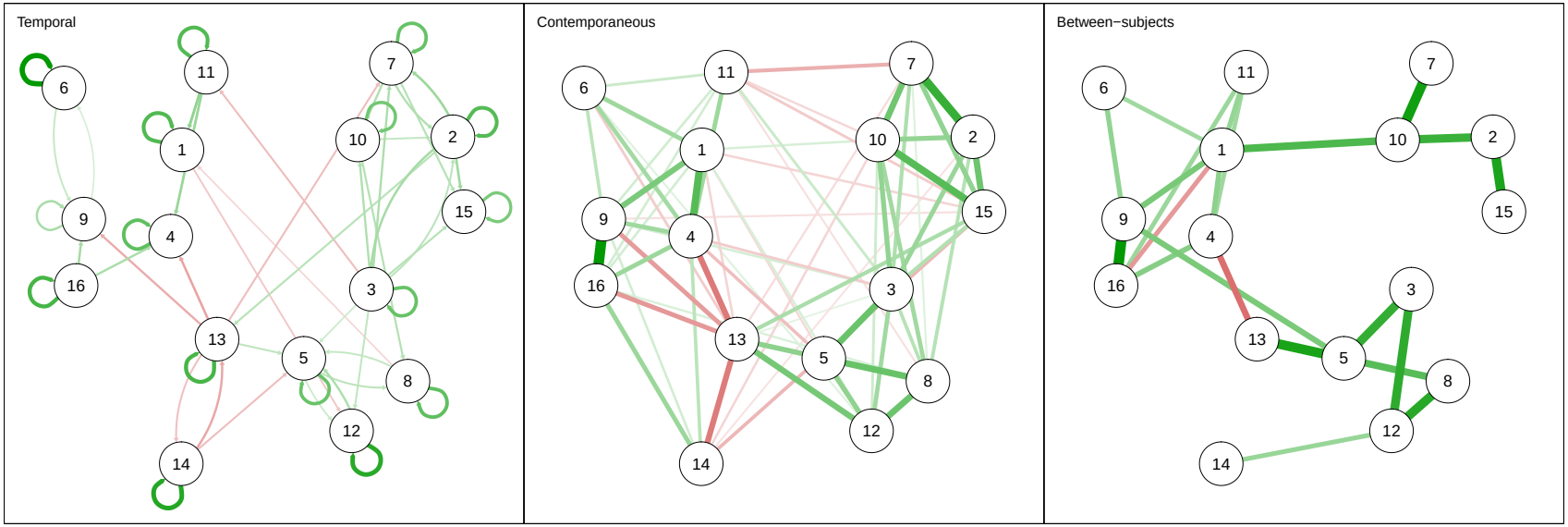

Temporal
Selfconscious
Frustrated
Angry
Happy
Depressed
Control
Guilty
Worried
Achieved
Organized
Selfdisciplined
Ambitious
Focused
Outgoing
Energetic
Adventurous

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)
- Time-series 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

Thank you for your attention!