Supplement B for

Measurement of Target Engagement and Network Analysis of Change Mechanisms in Web-Based Interpretation Bias Training for Anxiety

Jeremy W. Eberle

BS, BA, Tulane University, 2008

MA, University of Virginia, 2019

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Department of Psychology

University of Virginia

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Committee:

Bethany A. Teachman, PhD (Chair)

Steven M. Boker, PhD

Teague R. Henry, PhD

Laura E. Barnes, PhD

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Section SB1: Preregistration Deviations for Study 2

1.1 Estimation Methods for Network Intervention Analyses

We preregistered three estimation methods, which each have pros and cons regarding sensitivity and specificity (Blanken et al., 2022). First, we planned to use least absolute shrinkage and selection operator (LASSO) regularization with tuning parameter λ selected via 10-fold cross-validation (per Blanken et al., 2019; Blanken et al., 2021) and with `mgm`'s additional default beta-min threshold `LW` (i.e., Loh & Wainwright, 2013). Second, we planned to use LASSO regularization with a λ value that minimizes the extended Bayesian Information Criterion (EBIC) at `mgm`'s default hyperparameter γ value of 0.25 (per Blanken et al., 2019) and with the `LW` threshold. Third, given that LASSO may perform worse when the population network is dense and when the number of observations exceeds the number of variables, as is common in psychology research (vs. other fields in which this method was developed; Williams et al., 2019; Williams & Rast, 2020), we planned to estimate a nonregularized model (i.e., λ set to 0) that uses only the `LW` threshold to constrain smaller edges to 0 (per Fried et al., 2020). We planned to use these three estimation methods to test how robust edges are to different methods given that no one method is high in both sensitivity and specificity. We also preregistered to visualize the stability of parameter estimates in light of sampling variability using `mgm`'s `resample` function to fit each model in 500 bootstrap samples.

However, after estimating the networks with these three methods, we realized that they do not provide estimates of parameter uncertainty that would enable inference about the significance of specific edges. More specifically, the bootstrapping procedure to obtain plots of network stability cannot be used to generate confidence intervals (CIs) because the accuracy of the distribution of edge weights across the bootstrap samples is compromised by regularization (Williams, 2021), which affects our first and second proposed estimation methods. The distribution's accuracy is also compromised by constraining smaller edges to 0, which affects our third proposed method. (Constraining edges smaller than a given value to 0 and re-estimating the model based only on the retained edges is called *pruning*, whereas visualizing only edges larger than a given value, without re-estimating the model based only on those edges, is called *thresholding* [Blanken et al., 2022]. Although `LW` is called a threshold, the `mgm` package does not provide estimates for all of the edges, including those smaller than the `LW` threshold; estimates smaller than the `LW` threshold are outputted as 0. To obtain estimates for all edges in a saturated model, which are needed for bootstrapping to yield a distribution suitable for generating CIs, both the LASSO penalty and the `LW` threshold must be removed.) In general, performing statistical inference after applying model selection methods (e.g., regularization, pruning) results in model selection bias (Williams). Thus, we removed the LASSO penalty and the `LW` threshold to estimate saturated networks. We then bootstrapped the saturated networks to form CIs that we used to identify significant edges and to threshold edges (i.e., hide nonsignificant edges, without re-estimating the model) in our plots.

1.2 Time Points for Temporal Network Analyses

Although we preregistered to include anxiety items at all seven waves (baseline through Session 6), we obtained an error when using a design matrix that specified anxiety nodes at all waves and bias nodes at only three (baseline, Session 3, Session 6). Thus, we revised the model to include only the three waves containing all of these measures.

1.3 Estimation Method for Temporal Network Analyses

We preregistered Epskamp's (2020) procedure, in which after estimating a saturated model with all edges, we would use the `prune` function to remove all edges nonsignificant at an alpha level of .01, refit the model, and then use the `modelsearch` function to apply a stepwise model search algorithm. This algorithm considers removing edges that are nonsignificant at .01 and adding edges with modification indices that are significant at .01 and retains the model that locally minimizes BIC. We planned to then compare the original and pruned models and retain the model that showed better fit across multiple indices (chi-square, RMSEA, CFI, TLI, AIC, BIC). However, given that such model selection procedures result in model selection bias (see Section SB1.1 above), we decided to estimate saturated models and use thresholding in our plots.

1.4 Connectivity Metrics

Although we had preregistered to compute global strength and global expected influence as sums rather than means, we decided to compute them as means given that we are computing them based on saturated networks (in which case the number of edges in each permutation sample in our future preregistered permutation tests of condition differences will be the same). As a result, we will be able to more easily interpret the different kinds of connectivity (e.g., inter-node, intra-node, overall) all as unit rates.

Table SB1

Zero-Order Pearson Correlations Among Nodes for Intent-To-Treat Sample at Baseline

	1	2	3	4	5	6	7
1. Anx. Frequency	—						
2. Anx. Severity	.59	—					
3. Situational Avoidance	.42	.41	—				
4. Work Impairment	.51	.51	.57	—			
5. Social Impairment	.41	.37	.58	.52	—		
6. Negative Bias	.16	.19	.25	.19	.16	—	
7. Lack of Positive Bias [a]	.14	.10	.21	.13	.16	.21	—

[a] Reverse-scored positive bias.

Table SB2

All Cross-Sectional Mixed Graphical Model Effects for Each Condition Contrast at Each Time Point for Intent-To-Treat Sample

	Positive CBM-I vs. 50-50 CBM-I								Positive CBM-I vs. No-Training							
	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8
	Baseline (*n* = 469)								Baseline (*n* = 439)							
1. Pos. CBM-I	—								—							
2. Anx. Freq.	.07	—							.10	—						
3. Anx. Sev.	-.08	.40	—						-.04	.45	—					
4. Sit. Avoid	-.15	.09	.02	—					-.11	.03	.11	—				
5. Work Imp.	.00	.15	.24	.32	—				-.01	.22	.22	.27	—			
6. Soc. Imp.	.16	.18	.01	.38	.18	—			.13	.07	.03	.38	.23	—		
7. Neg. Bias	-.07	.00	.05	.12	.02	.01	—		-.11	.04	.07	.14	.05	-.09	—	
8. Lack Pos. Bias	-.02	.06	-.03	.08	.00	.05	.13	—	.02	.00	.01	.10	-.07	.10	.21	—
	Session 3 (*n* = 102)								Session 3 (*n* = 113)							
1. Pos. CBM-I	—								—							
2. Anx. Freq.	-.04	—							-.38	—						
3. Anx. Sev.	.09	.50	—						.15	.38	—					
4. Sit. Avoid	.02	.10	-.10	—					.00	.08	.04	—				
5. Work Imp.	-.13	.12	.28	.44	—				.14	.30	.21	.31	—			
6. Soc. Imp.	.19	.14	.10	.36	.20	—			.16	.08	.15	.39	.21	—		
7. Neg. Bias	-.44	.20	.03	.06	.06	-.12	—		-.21	.13	.01	.13	.03	-.04	—	
8. Lack Pos. Bias	-.21	-.20	.01	.23	-.01	-.02	.37	—	-.43	-.12	.13	.25	-.07	-.13	.33	—
	Session 6 (*n* = 58)								Session 6 (*n* = 58)							
1. Pos. CBM-I	—								—							
2. Anx. Freq.	.06	—							-.14	—						
3. Anx. Sev.	-.27	.71	—						-.19	.55	—					
4. Sit. Avoid	.19	-.47	.36	—					-.23	-.05	.17	—				
5. Work Imp.	.05	.20	.20	.40	—				.11	.30	.05	.25	—			
6. Soc. Imp.	.09	.63	-.32	.60	-.08	—			.47	.21	.07	.48	.23	—		
7. Neg. Bias	-.60	.41	-.34	.34	.03	-.26	—		-.28	.06	-.01	.07	.18	-.09	—	
8. Lack Pos. Bias	-.14	.00	-.04	.18	-.09	-.07	.31	—	-.21	.01	-.03	.00	-.15	.16	.58	—

Note. Pos. CBM-I = positive CBM-I (vs. reference group; coded 1 and 0, respectively). Anx. Freq. = anxiety frequency; Anx. Sev. = anxiety severity; Sit. Avoid = situational avoidance; Work Imp. = work impairment; Soc. Imp. = social impairment; Neg. Bias = negative bias; Lack Pos. Bias = lack of positive bias (i.e., reverse-scored positive bias).

Table SB3

All Cross-Sectional Mixed Graphical Model Effects for Each Contrast at Each Time Point for Participants With Complete Data

	Positive CBM-I vs. 50-50 CBM-I								Positive CBM-I vs. No-Training							
	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8
	Baseline (*n* = 57)								Baseline (*n* = 55)							
1. Pos. CBM-I	—								—							
2. Anx. Freq.	.21	—							.50	—						
3. Anx. Sev.	-.33	.48	—						-.47	.59	—					
4. Sit. Avoid	.04	.02	-.06	—					.16	.06	-.14	—				
5. Work Imp.	-.10	.04	.39	.37	—				-.39	.34	.12	.31	—			
6. Soc. Imp.	.45	.13	-.03	.33	.13	—			.41	-.16	.19	.52	.22	—		
7. Neg. Bias	-.01	-.12	.20	.11	-.17	.05	—		-.16	-.28	.25	.27	.00	-.25	—	
8. Lack Pos. Bias	-.11	.00	.01	.11	.03	.10	-.20	—	-.36	.12	-.21	.12	-.13	.13	.14	—
	Session 3 (*n* = 57)								Session 3 (*n* = 55)							
1. Pos. CBM-I	—								—							
2. Anx. Freq.	-.26	—							-.63	—						
3. Anx. Sev.	.10	.55	—						.08	.40	—					
4. Sit. Avoid	.24	.19	-.15	—					.02	.01	.07	—				
5. Work Imp.	-.40	.14	.17	.42	—				-.08	.29	.05	.34	—			
6. Soc. Imp.	.44	.18	.11	.24	.16	—			.57	.30	.15	.30	.25	—		
7. Neg. Bias	-.54	.04	.14	.03	.01	-.05	—		-.27	.11	.13	.01	-.09	.03	—	
8. Lack Pos. Bias	-.28	-.23	.00	.37	-.07	-.01	.35	—	-.37	-.17	-.02	.27	.01	-.08	.53	—
	Session 6 (*n* = 57)								Session 6 (*n* = 55)							
1. Pos. CBM-I	—								—							
2. Anx. Freq.	.03	—							-.14	—						
3. Anx. Sev.	-.35	.69	—						-.29	.53	—					
4. Sit. Avoid	.10	-.48	.31	—					-.37	-.05	.10	—				
5. Work Imp.	.12	.21	.23	.42	—				.27	.23	.11	.31	—			
6. Soc. Imp.	.13	.63	-.29	.60	-.10	—			.49	.26	.08	.46	.24	—		
7. Neg. Bias	-.66	.38	-.36	.29	.06	-.24	—		-.36	.08	-.06	.01	.23	-.09	—	
8. Lack Pos. Bias	-.09	.01	-.02	.19	-.11	-.08	.32	—	-.14	.01	.00	.03	-.17	.14	.60	—

Note. Pos. CBM-I = positive CBM-I (vs. reference group; coded 1 and 0, respectively). Anx. Freq. = anxiety frequency; Anx. Sev. = anxiety severity; Sit. Avoid = situational avoidance; Work Imp. = work impairment; Soc. Imp. = social impairment; Neg. Bias = negative bias; Lack Pos. Bias = lack of positive bias (i.e., reverse-scored positive bias).

Table SB4

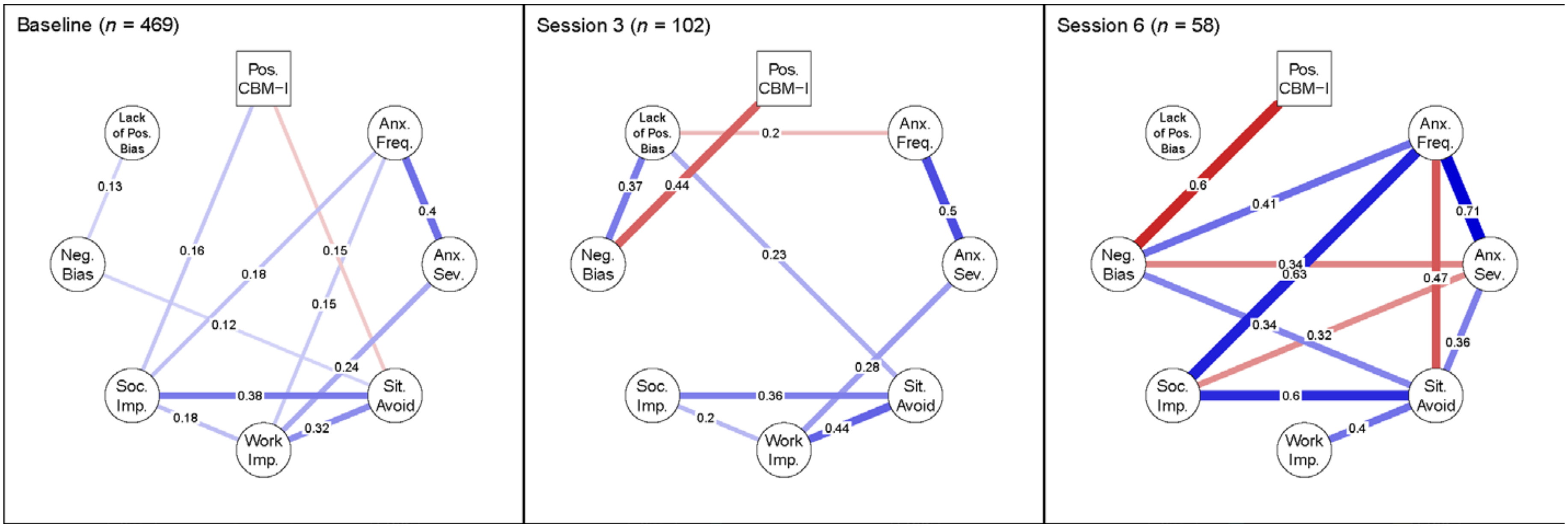
All Within-Person Effects by Condition for Multigroup GVAR Model for Intent-To-Treat Sample

	Temporal Effects (Partial Directed Correlations: Cross-Lagged From Row to Column; Autoregressive on Diagonal)							Contemporaneous Effects (Marginal Correlations in Upper; Partial Correlations in Lower)						
	1	2	3	4	5	6	7	1	2	3	4	5	6	7
Positive CBM-I														
1. Anxiety Frequency	.07	-.01	-.28	-.01	-.22	-.12	-.21	—	.31	.25	.12	.38	.28	-.28
2. Anxiety Severity	-.06	-.18	.12	.02	-.02	.01	-.14	.16	—	.31	.19	.20	.02	-.34
3. Situational Avoidance	-.13	.01	.24	.16	.26	-.05	-.08	.06	.20	—	.42	.44	.09	-.05
4. Work Impairment	-.20	-.21	-.09	-.25	.09	.10	-.11	-.13	.12	.25	—	.43	.24	.12
5. Social Impairment	-.08	-.05	-.01	-.03	.03	.02	-.30	.34	-.03	.26	.33	—	.08	-.03
6. Negative Bias	.23	.31	-.01	.47	-.03	.18	-.02	.36	-.01	-.02	.22	-.14	—	.23
7. Lack of Positive Bias	-.16	-.08	.01	.05	-.04	.08	.10	-.30	-.29	.01	.10	.06	.29	—
50-50 CBM-I														
1. Anxiety Frequency	-.14	-.31	.06	-.06	-.15	-.20	-.18	—	.46	.48	.34	.30	.02	-.19
2. Anxiety Severity	.37	.26	.00	.35	.27	-.21	.13	.31	—	.37	.65	.23	-.04	-.05
3. Situational Avoidance	.30	.08	.03	.10	.05	-.03	.14	.45	.02	—	.33	.35	-.03	.27
4. Work Impairment	.01	.24	.23	.16	.27	.42	.04	-.09	.58	.15	—	.35	.01	-.15
5. Social Impairment	-.13	-.07	.12	.01	-.15	.21	-.05	.02	-.04	.31	.19	—	.30	-.09
6. Negative Bias	.16	.06	.11	.05	.33	.21	-.18	.15	-.08	-.29	.04	.39	—	.25
7. Lack of Positive Bias	-.11	-.13	.22	.22	-.20	.25	.40	-.37	.12	.51	-.20	-.23	.38	—
No-Training														
1. Anxiety Frequency	.14	.02	.03	.11	.19	-.02	.15	—	.55	.28	.67	.57	.07	.04
2. Anxiety Severity	-.08	-.07	.06	.16	.17	.18	.00	.38	—	.40	.46	.47	-.04	-.14
3. Situational Avoidance	-.07	.03	.04	.08	.09	-.11	.21	-.50	.28	—	.65	.56	.19	.22
4. Work Impairment	-.06	-.06	.11	.03	.06	-.18	-.24	.63	-.10	.64	—	.57	-.03	.10
5. Social Impairment	.22	.11	.17	-.15	.00	.25	-.13	.36	.08	.37	-.03	—	.14	.13
6. Negative Bias	.10	-.09	-.06	-.25	-.17	-.10	.20	.22	-.06	.25	-.32	.02	—	.52
7. Lack of Positive Bias	-.10	.14	.05	.39	.20	.60	.32	.00	-.22	.09	.09	.02	.48	—

Note. Plots of contemporaneous networks show partial correlations. Between-person effects were not interpreted due to estimation issues.

Figure SB1

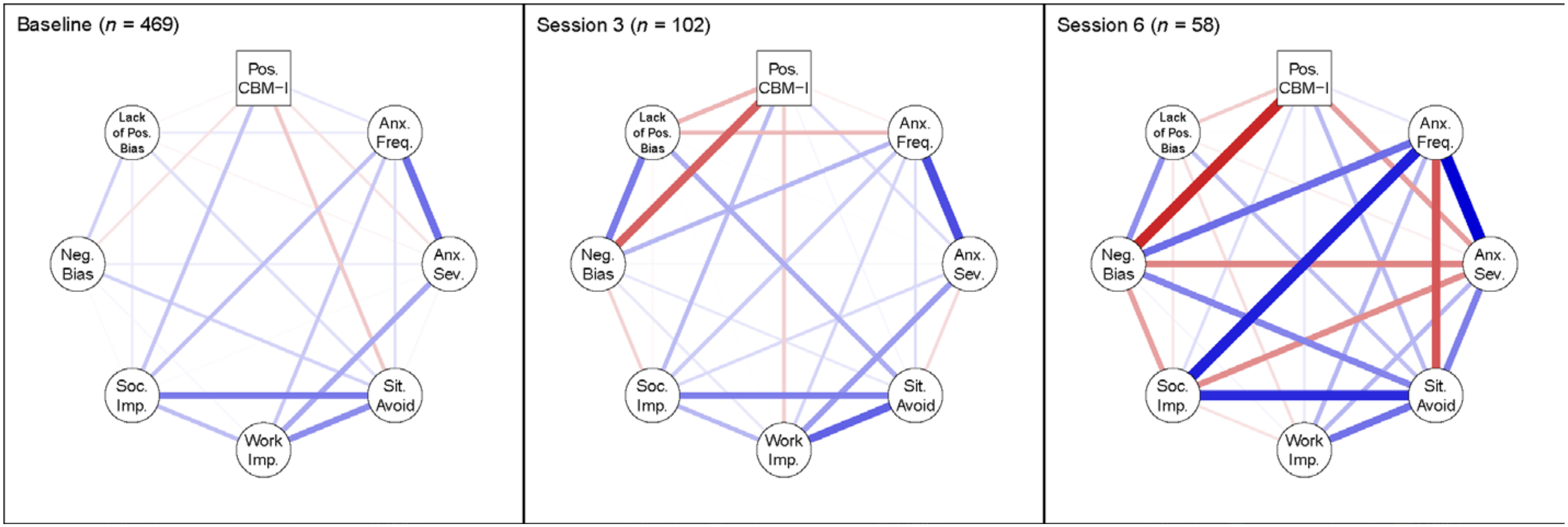
*Cross-Sectional Mixed Graphical Models at Each Time Point With Node Contrasting Positive CBM-I and 50-50 CBM-I for Intent-To-Treat Sample, Showing Thresholded Edges (*p *< .05)*



Note. Only edges significant at $p < .05$ threshold are shown. Sign of edge weight is mapped to edge color, with positive weights in blue and negative weights in red. Magnitude of edge weight is mapped to edge width and color saturation, with maximum width and saturation mapped to maximum edge magnitude (.71) across all mixed graphical models. All nodes were modeled as manifest. Plots were generated in `qgraph` using a circle layout. Pos. CBM-I = positive CBM-I (vs. 50-50 CBM-I; coded 1 and 0, respectively). Anx. Freq. = anxiety frequency; Anx. Sev. = anxiety severity; Sit. Avoid = situational avoidance; Work Imp. = work impairment; Soc. Imp. = social impairment; Neg. Bias = negative bias; Lack of Pos. Bias = lack of positive bias (i.e., reverse-scored positive bias).

Figure SB2

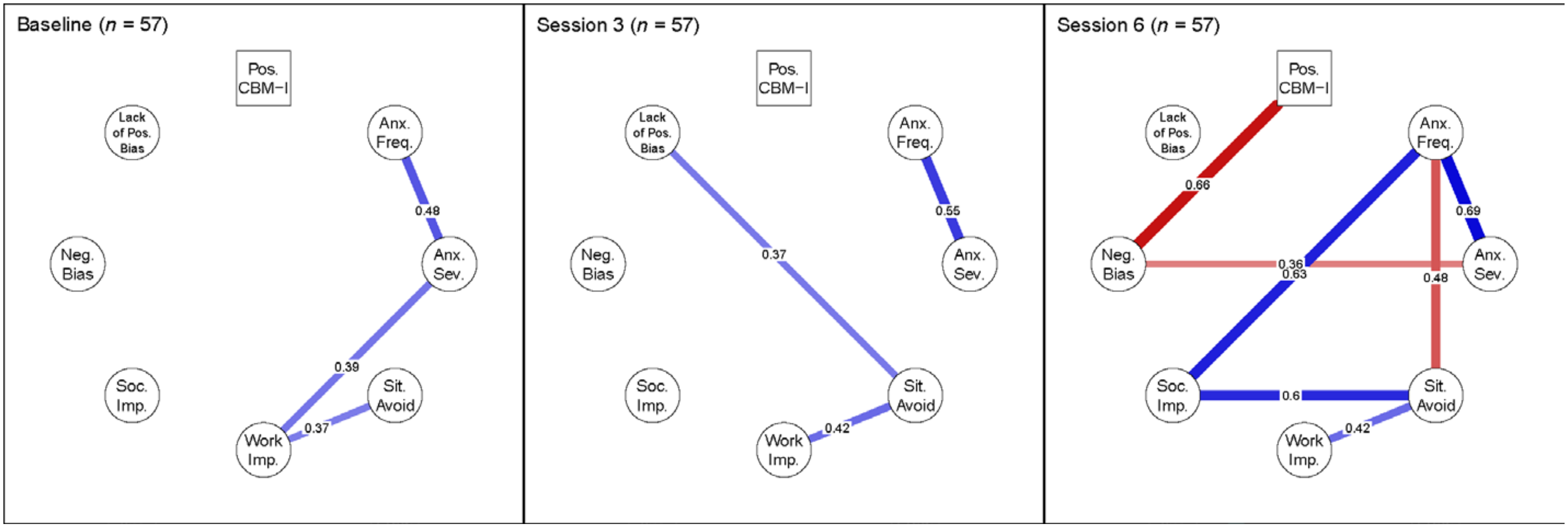
Cross-Sectional Mixed Graphical Models at Each Time Point With Node Contrasting Positive CBM-I and 50-50 CBM-I for Intent-To-Treat Sample, Showing All Edges



Note. All edges in saturated networks are shown. Sign of edge weight is mapped to edge color, with positive weights in blue and negative weights in red. Magnitude of edge weight is mapped to edge width and color saturation, with maximum width and saturation mapped to maximum edge magnitude (.71) across all mixed graphical models. All nodes were modeled as manifest. Plots were generated in `qgraph` using a circle layout. Pos. CBM-I = positive CBM-I (vs. 50-50 CBM-I; coded 1 and 0, respectively). Anx. Freq. = anxiety frequency; Anx. Sev. = anxiety severity; Sit. Avoid = situational avoidance; Work Imp. = work impairment; Soc. Imp. = social impairment; Neg. Bias = negative bias; Lack of Pos. Bias = lack of positive bias (i.e., reverse-scored positive bias).

Figure SB3

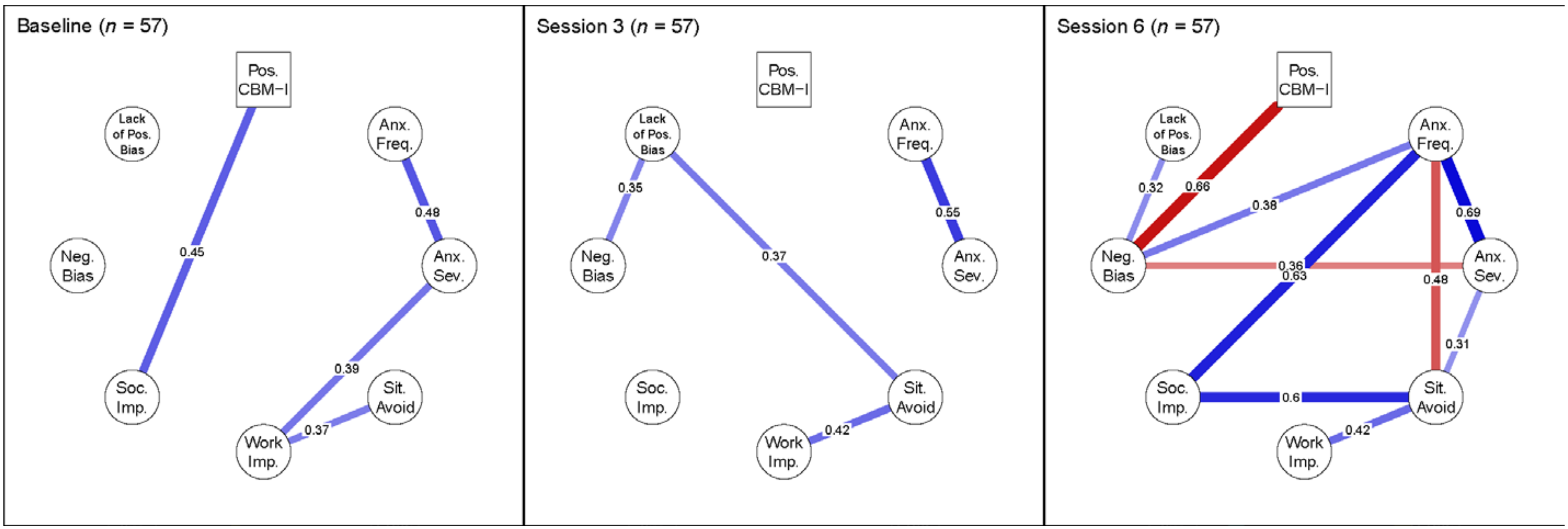
*Cross-Sectional Mixed Graphical Models at Each Time Point With Node Contrasting Positive CBM-I and 50-50 CBM-I for Participants With Complete Data, Showing Thresholded Edges (*p *< .01)*



Note. Only edges significant at $p < .01$ threshold are shown. Sign of edge weight is mapped to edge color, with positive weights in blue and negative weights in red. Magnitude of edge weight is mapped to edge width and color saturation, with maximum width and saturation mapped to maximum edge magnitude (.71) across all mixed graphical models. All nodes were modeled as manifest. Plots were generated in `qgraph` using a circle layout. Pos. CBM-I = positive CBM-I (vs. 50-50 CBM-I; coded 1 and 0, respectively). Anx. Freq. = anxiety frequency; Anx. Sev. = anxiety severity; Sit. Avoid = situational avoidance; Work Imp. = work impairment; Soc. Imp. = social impairment; Neg. Bias = negative bias; Lack of Pos. Bias = lack of positive bias (i.e., reverse-scored positive bias).

Figure SB4

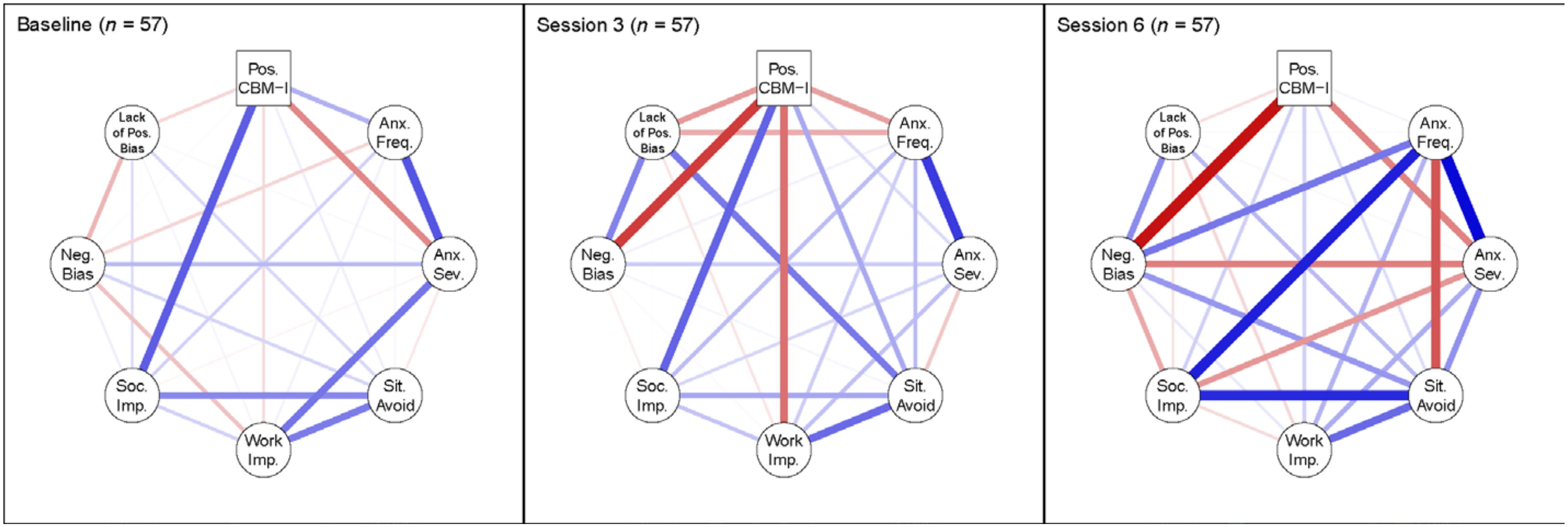
*Cross-Sectional Mixed Graphical Models at Each Time Point With Node Contrasting Positive CBM-I and 50-50 CBM-I for Participants With Complete Data, Showing Thresholded Edges (*p *< .05)*



Note. Only edges significant at $p < .05$ threshold are shown. Sign of edge weight is mapped to edge color, with positive weights in blue and negative weights in red. Magnitude of edge weight is mapped to edge width and color saturation, with maximum width and saturation mapped to maximum edge magnitude (.71) across all mixed graphical models. All nodes were modeled as manifest. Plots were generated in `qgraph` using a circle layout. Pos. CBM-I = positive CBM-I (vs. 50-50 CBM-I; coded 1 and 0, respectively). Anx. Freq. = anxiety frequency; Anx. Sev. = anxiety severity; Sit. Avoid = situational avoidance; Work Imp. = work impairment; Soc. Imp. = social impairment; Neg. Bias = negative bias; Lack of Pos. Bias = lack of positive bias (i.e., reverse-scored positive bias).

Figure SB5

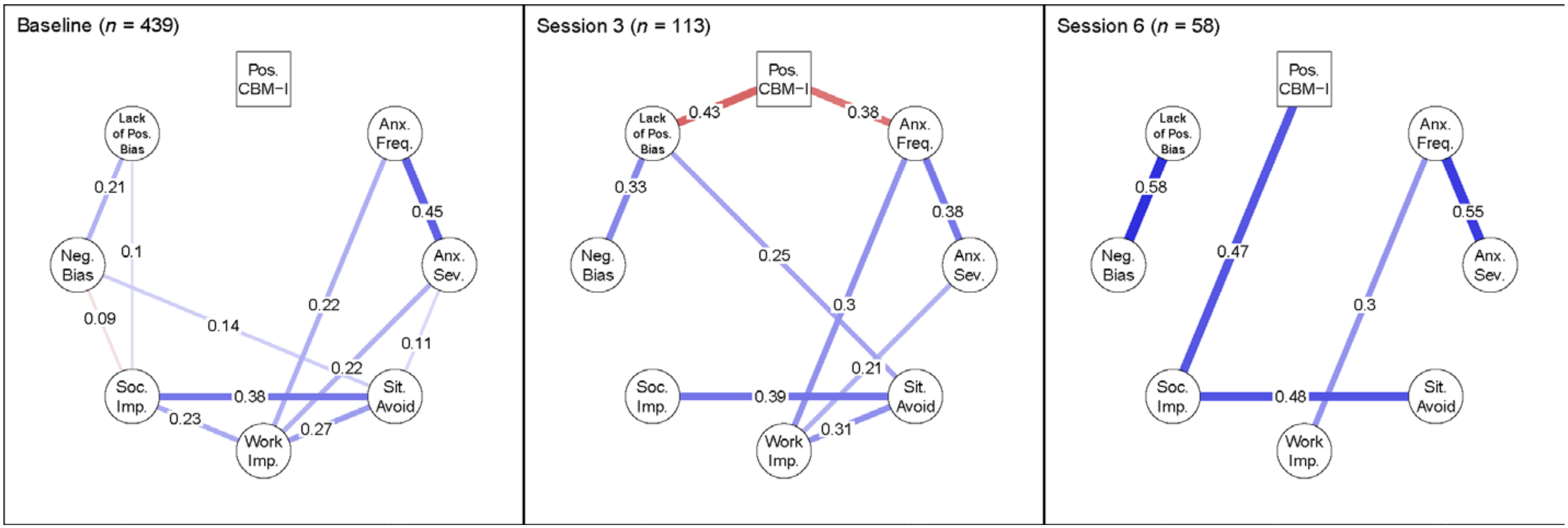
Cross-Sectional Mixed Graphical Models at Each Time Point With Node Contrasting Positive CBM-I and 50-50 CBM-I for Participants With Complete Data, Showing All Edges



Note. All edges in saturated networks are shown. Sign of edge weight is mapped to edge color, with positive weights in blue and negative weights in red. Magnitude of edge weight is mapped to edge width and color saturation, with maximum width and saturation mapped to maximum edge magnitude (.71) across all mixed graphical models. All nodes were modeled as manifest. Plots were generated in `qgraph` using a circle layout. Pos. CBM-I = positive CBM-I (vs. 50-50 CBM-I; coded 1 and 0, respectively). Anx. Freq. = anxiety frequency; Anx. Sev. = anxiety severity; Sit. Avoid = situational avoidance; Work Imp. = work impairment; Soc. Imp. = social impairment; Neg. Bias = negative bias; Lack of Pos. Bias = lack of positive bias (i.e., reverse-scored positive bias).

Figure SB6

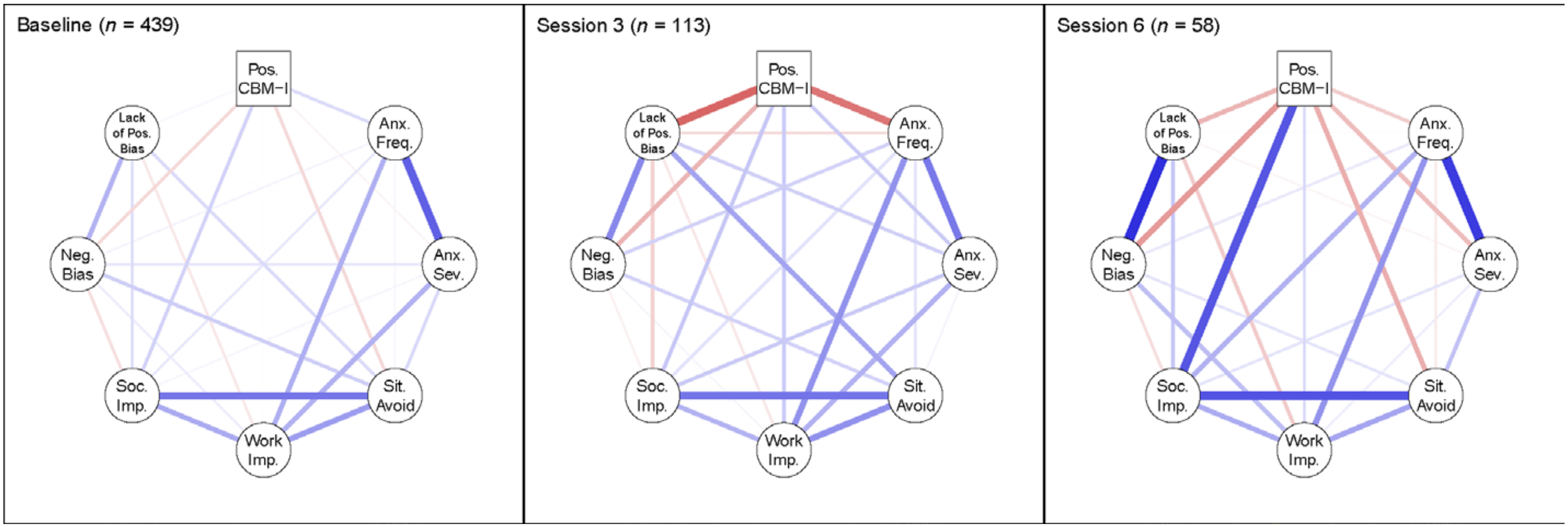
*Cross-Sectional Mixed Graphical Models at Each Time Point With Node Contrasting Positive CBM-I and No-Training for Intent-To-Treat Sample, Showing Thresholded Edges (*p *< .05)*



Note. Only edges significant at $p < .05$ threshold are shown. Sign of edge weight is mapped to edge color, with positive weights in blue and negative weights in red. Magnitude of edge weight is mapped to edge width and color saturation, with maximum width and saturation mapped to maximum edge magnitude (.71) across all mixed graphical models. All nodes were modeled as manifest. Plots were generated in `qgraph` using a circle layout. Pos. CBM-I = positive CBM-I (vs. no-training; coded 1 and 0, respectively). Anx. Freq. = anxiety frequency; Anx. Sev. = anxiety severity; Sit. Avoid = situational avoidance; Work Imp. = work impairment; Soc. Imp. = social impairment; Neg. Bias = negative bias; Lack of Pos. Bias = lack of positive bias (i.e., reverse-scored positive bias).

Figure SB7

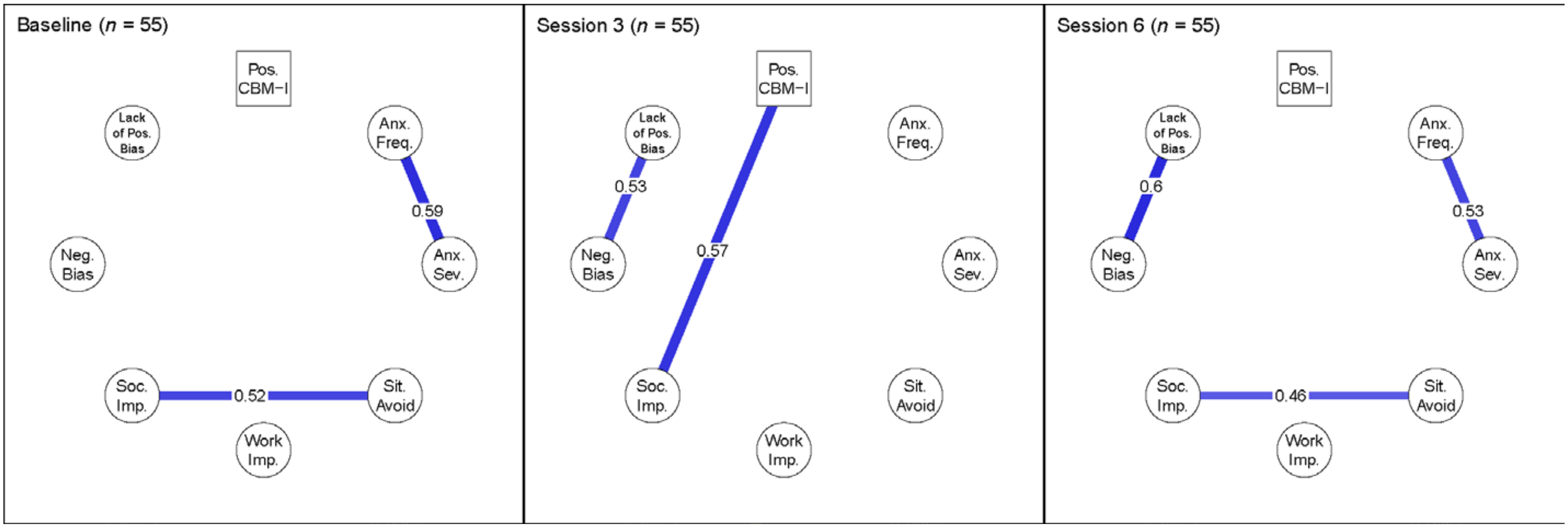
Cross-Sectional Mixed Graphical Models at Each Time Point With Node Contrasting Positive CBM-I and No-Training for Intent-To-Treat Sample, Showing All Edges



Note. All edges in saturated networks are shown. Sign of edge weight is mapped to edge color, with positive weights in blue and negative weights in red. Magnitude of edge weight is mapped to edge width and color saturation, with maximum width and saturation mapped to maximum edge magnitude (.71) across all mixed graphical models. All nodes were modeled as manifest. Plots were generated in `qgraph` using a circle layout. Pos. CBM-I = positive CBM-I (vs. no-training; coded 1 and 0, respectively). Anx. Freq. = anxiety frequency; Anx. Sev. = anxiety severity; Sit. Avoid = situational avoidance; Work Imp. = work impairment; Soc. Imp. = social impairment; Neg. Bias = negative bias; Lack of Pos. Bias = lack of positive bias (i.e., reverse-scored positive bias).

Figure SB8

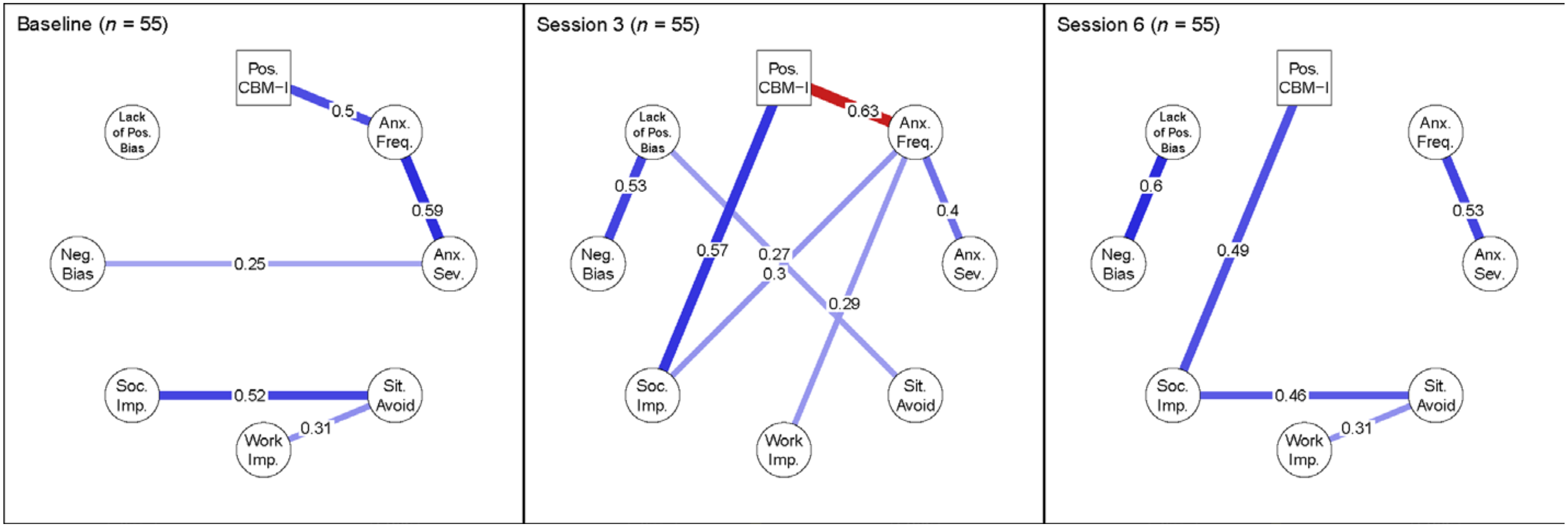
*Cross-Sectional Mixed Graphical Models at Each Time Point With Node Contrasting Positive CBM-I and No-Training for Participants With Complete Data, Showing Thresholded Edges (*p *< .01)*



Note. Only edges significant at $p < .01$ threshold are shown. Sign of edge weight is mapped to edge color, with positive weights in blue and negative weights in red. Magnitude of edge weight is mapped to edge width and color saturation, with maximum width and saturation mapped to maximum edge magnitude (.71) across all mixed graphical models. All nodes were modeled as manifest. Plots were generated in `qgraph` using a circle layout. Pos. CBM-I = positive CBM-I (vs. no-training; coded 1 and 0, respectively). Anx. Freq. = anxiety frequency; Anx. Sev. = anxiety severity; Sit. Avoid = situational avoidance; Work Imp. = work impairment; Soc. Imp. = social impairment; Neg. Bias = negative bias; Lack of Pos. Bias = lack of positive bias (i.e., reverse-scored positive bias).

Figure SB9

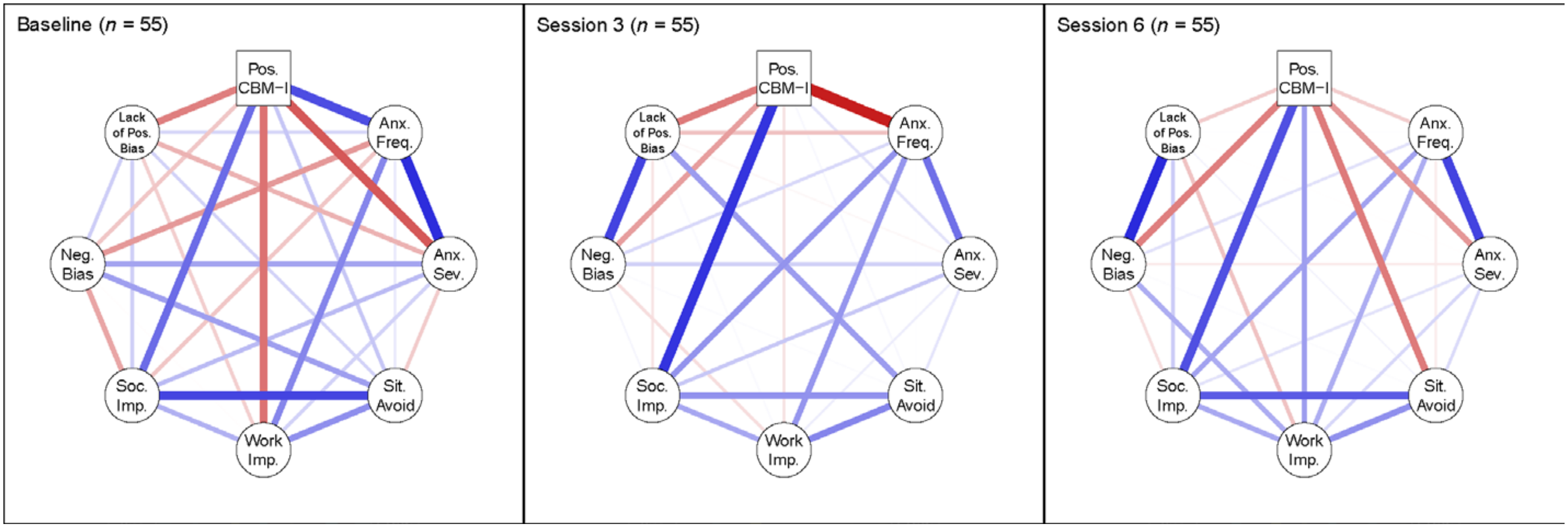
*Cross-Sectional Mixed Graphical Models at Each Time Point With Node Contrasting Positive CBM-I and No-Training for Participants With Complete Data, Showing Thresholded Edges (*p *< .05)*



Note. Only edges significant at *p* < .05 threshold are shown. Sign of edge weight is mapped to edge color, with positive weights in blue and negative weights in red. Magnitude of edge weight is mapped to edge width and color saturation, with maximum width and saturation mapped to maximum edge magnitude (.71) across all mixed graphical models. All nodes were modeled as manifest. Plots were generated in `qgraph` using a circle layout. Pos. CBM-I = positive CBM-I (vs. no-training; coded 1 and 0, respectively). Anx. Freq. = anxiety frequency; Anx. Sev. = anxiety severity; Sit. Avoid = situational avoidance; Work Imp. = work impairment; Soc. Imp. = social impairment; Neg. Bias = negative bias; Lack of Pos. Bias = lack of positive bias (i.e., reverse-scored positive bias).

Figure SB10

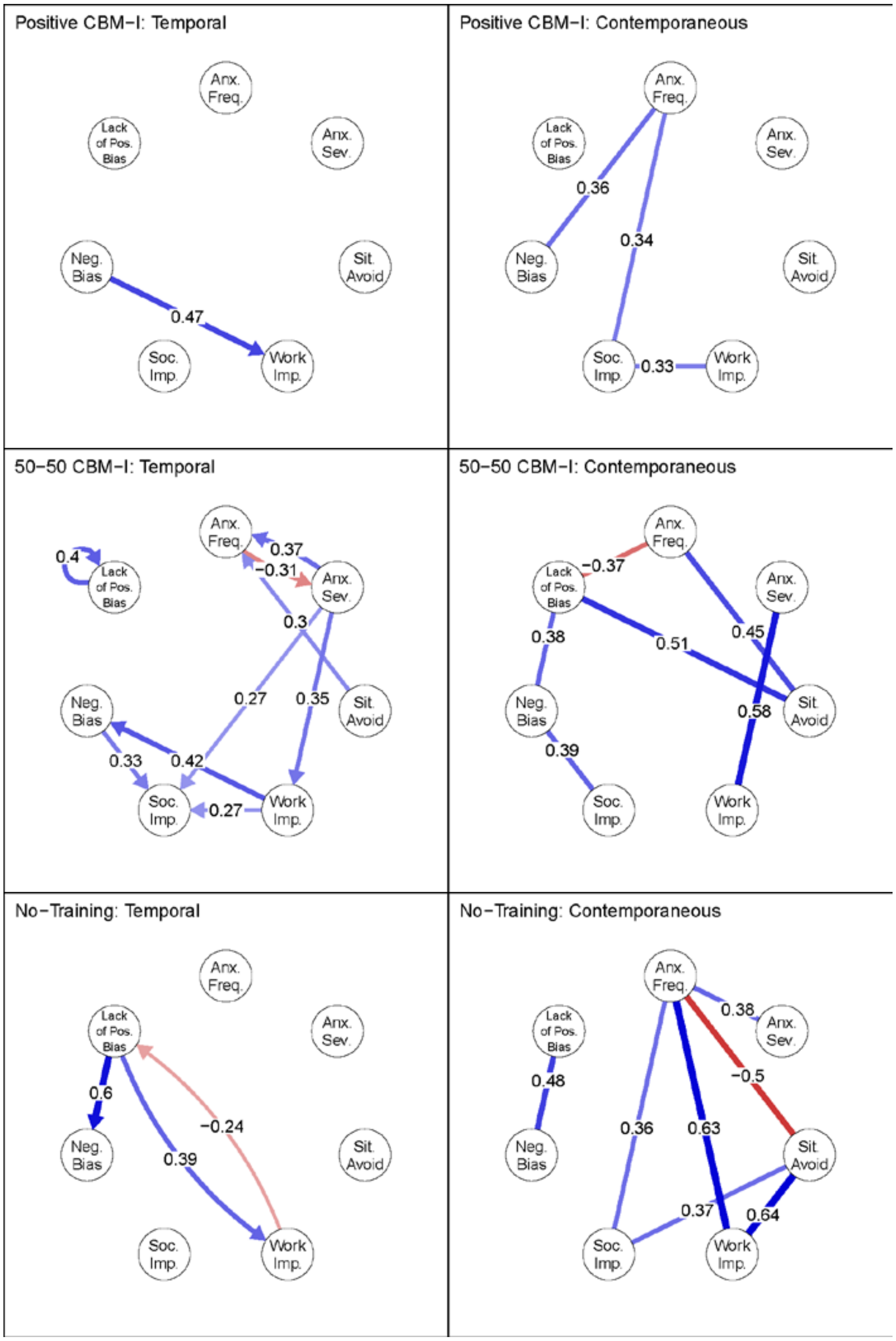
Cross-Sectional Mixed Graphical Models at Each Time Point With Node Contrasting Positive CBM-I and No-Training for Participants With Complete Data, Showing All Edges



Note. All edges in saturated networks are shown. Sign of edge weight is mapped to edge color, with positive weights in blue and negative weights in red. Magnitude of edge weight is mapped to edge width and color saturation, with maximum width and saturation mapped to maximum edge magnitude (.71) across all mixed graphical models. All nodes were modeled as manifest. Plots were generated in `qgraph` using a circle layout. Pos. CBM-I = positive CBM-I (vs. no-training; coded 1 and 0, respectively). Anx. Freq. = anxiety frequency; Anx. Sev. = anxiety severity; Sit. Avoid = situational avoidance; Work Imp. = work impairment; Soc. Imp. = social impairment; Neg. Bias = negative bias; Lack of Pos. Bias = lack of positive bias (i.e., reverse-scored positive bias).

Figure SB11

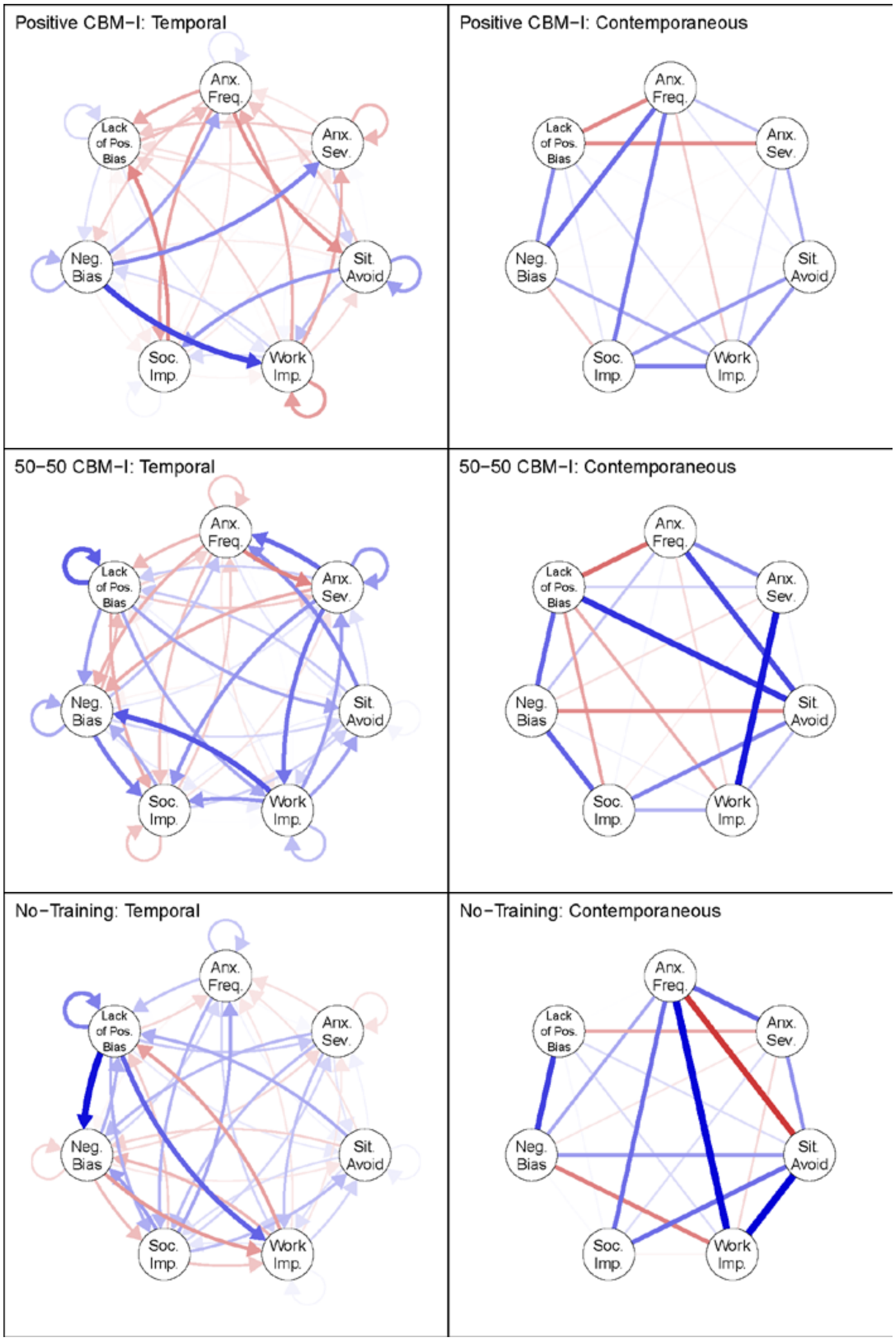
*Multigroup GVAR Model for Intent-To-Treat Sample, Showing Thresholded Edges (*p *< .05)*



Note. Only edges significant at $p < .05$ are shown. Edge weight (positive in blue, negative in red) is mapped to edge width and color saturation, with maximum width and saturation mapped to maximum edge magnitude (.64) across conditions. All nodes were modeled as manifest. Plot uses `qgraph`'s circle layout. Anx. Freq. = anxiety frequency; Anx. Sev. = anxiety severity; Sit. Avoid = situational avoidance; Work Imp. = work impairment; Soc. Imp. = social impairment; Neg. Bias = negative bias; Lack of Pos. Bias = lack of positive bias (i.e., reverse-scored positive bias).

Figure SB12

Multigroup GVAR Model for Intent-To-Treat Sample, Showing All Edges



Note. All edges in saturated networks are shown. Edge weight (positive in blue, negative in red) is mapped to edge width and color saturation, with maximum width and saturation mapped to maximum edge magnitude (.64) across conditions. All nodes were modeled as manifest. Plot uses `qgraph`'s circle layout. Anx. Freq. = anxiety frequency; Anx. Sev. = anxiety severity; Sit. Avoid = situational avoidance; Work Imp. = work impairment; Soc. Imp. = social impairment; Neg. Bias = negative bias; Lack of Pos. Bias = lack of positive bias (i.e., reverse-scored positive bias).