

on multiple time series, the random phase is added uniformly across all channels to the same frequency bin. Next, the data are transformed back into time series via an inverse Fourier transform. Finally, the original time series amplitudes are rank-matched to the phase-randomized time series. The resulting surrogate time series preserve the same amplitude distribution of the original data and approximate the same power spectrum.

For each realization of surrogate data, we generate a dynamic functional connectivity matrix, from which we collect observations of dynamic fluctuations. Repeating this procedure many times allows us to approximate the distribution of dynamic fluctuations for each functional connection (Figure 2). We return to the original data and assign each dynamic functional connection a percentile based on where that dynamic fluctuation falls with respect to the distribution of expected fluctuations.

It should be noted that there are alternative methods for estimating this null distribution. For example, instead of estimating this distribution using phase-randomized surrogates, one could follow the approach of Zalesky et al. (2014) and estimate the parameters of a bi-variate time series model (e.g. autoregressive moving average - ARMA) for a dynamic functional connection. The ARMA model and its parameters could then be used to generate surrogate time series and dynamic functional connectivity matrices, and from these matrices one could approximate the distribution of expected fluctuations.

Characterizing conditional dynamic functional connectivity

We made several measurements based on the conditional dynamic functional connectivity matrices. First, we applied a threshold to each matrix, retaining only those connections that were unexpectedly strong or weak (greater than the 97.5th percentile or less than the 2.5th percentile; see Figure 3). From these thresholded matrices, we calculated the number of unexpectedly strong/weak