connections at each time point, $E^{+}(t)$ and $E^{-}(t)$, respectively, which we refer to as *excursions*. We also counted the total number of excursions of both types at each time t as $E(t) = E^{+}(t) + E^{-}(t)$. To contextualize the number of excursions at any time point, we compared the observed counts to those obtained from an additional sample of 1000 surrogate datasets generated as described before. This allowed us to assign each excursion count score to a percentile and to focus on time points at which the number of excursions was greater than expected (greater than or equal to the 97.5th percentile).This process of contextualizing dynamic functional connections can be seen from a statistical point of view as an assessment of whether there is enough evidence to reject the null hypothesis that a dynamic functional connection is neither significantly stronger or weaker than its corresponding static connection.

It should be noted that the characterization of a dynamic functional connections as stronger or weaker than expected is always made with respect to a connection's static weight and never in an absolute sense. In other words, "stronger" refers to "more positive than expected" and "weaker" means "more negative than expected." This can lead to confusion when dealing with static connections whose weights are < 0. In such cases, weaker-than-expected actually means a more negative correlation (i.e. close to -1) while stronger-than-expected means a more positive correlation (i.e. closer to $+1$). As a consequence of adopting this convention a stronger-than-expected dynamic functional connection may actually approach a value of 0.

An alternative, and admittedly simpler, method for contextualizing excursion counts would be to randomly permute the order of time points, repeat this process many times, and compare the observed excursion counts to the distribution generated from the permutations. We believe that this approach, though simpler, is not appropriate, because dynamic functional networks are not in-