

# Competitive and cooperative dynamics of large-scale brain functional networks supporting recollection

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**Analyses of functional interactions between large-scale brain networks have identified two broad systems that operate in apparent competition or antagonism with each other. One system, termed the default mode network (DMN), is thought to support internally oriented processing. The other system acts as a generic external attention system (EAS) and mediates attention to exogenous stimuli. Reports that the DMN and EAS show anticorrelated activity across a range of experimental paradigms suggest that competition between these systems supports adaptive behavior. Here, we used functional MRI to characterize functional interactions between the DMN and different EAS components during performance of a recollection task known to coactivate regions of both networks. Using methods to isolate task-related, context-dependent changes in functional connectivity between these systems, we show that increased cooperation between the DMN and a specific right-lateralized frontoparietal component of the EAS is associated with more rapid memory recollection. We also show that these cooperative dynamics are facilitated by a dynamic reconfiguration of the functional architecture of the DMN into core and transitional modules, with the latter serving to enhance integration with frontoparietal regions. In particular, the right posterior cingulate cortex may act as a critical information-processing hub that provokes these context-dependent reconfigurations from an intrinsic or default state of antagonism. Our findings highlight the dynamic, context-dependent nature of large-scale brain dynamics and shed light on their contribution to individual differences in behavior.**

complex | graph | modularity | rest | connectome

Increasing evidence points to a fundamental distinction between two large-scale functional systems in the brain (1–4). One system, comprising regions of lateral prefrontal and parietal cortex, dorsal anterior cingulate, and anterior insula/frontoopercular regions, typically shows increased activation during performance of challenging cognitive tasks and has been implicated in attentional and cognitive control functions (5, 6). It may thus be generally referred to as an external attention system (EAS), but it has also been labeled the task-positive and extrinsic network (3, 4). The other system, often called the default mode network (DMN), is localized primarily to midline posterior and anterior cortical regions, the angular gyri, and medial and lateral temporal cortices (7, 8). It often shows decreased activity during tasks requiring attention to external stimuli (9, 10) and increased activity during unconstrained thought, introspection, and self-related processing (7, 11). The apparent antagonism between these two systems is mirrored in their spontaneous dynamics, which are often strongly anticorrelated (2). These competitive interactions are thought to promote adaptive and efficient alternation between DMN-dominated introspective thought and EAS-mediated processing of external stimuli (1–4).

Several lines of evidence support this bipartite model of brain function. First, DMN activity reductions during cognitively demanding tasks, termed deactivations, often scale in accordance with attentional demands (12). Second, reduced deactivation in

such contexts has been associated with poorer task performance, putatively reflecting an interference of endogenous processes (e.g., mind wandering) with attention to the outside world (13, 14). Third, during memory task performance, greater DMN activity is associated with poor encoding (which requires attention to external stimuli) but successful memory retrieval (which requires attention to internal mental processes), whereas EAS regions show the opposite pattern (15). Fourth, activity in DMN and EAS regions is often anticorrelated (2), and individuals showing stronger anticorrelations display faster and less variable reaction times (RTs) during performance of cognitive control tasks (16, 17). Fifth, patients with psychiatric disorders associated with attentional disturbances show reduced anticorrelation between the DMN and EAS (18, 19). Finally, anticorrelated interactions emerge spontaneously in computational models of neural dynamics simulated on realistic anatomical architectures, suggesting that they reflect an intrinsic property of the brain's dynamical behavior (20).

Recent work, however, indicates that this bipartite model may be somewhat simplistic. First, the DMN and EAS do not always operate as functionally homogeneous entities, often splitting into distinct subnetworks depending on task demands (5, 7, 21, 22). This finding is particularly true for the EAS, which has been functionally dissociated into a number of distinct subsystems (5, 6, 22–26), although similar observations have been noted for the DMN (7, 10, 21). Second, local field potentials recorded from putative DMN and EAS regions in felines are more often positively than negatively correlated with each other, suggesting that these regions often interact cooperatively (27). Third, there are multiple human functional MRI (fMRI) reports of coactivation or cooperation (positively correlated activity) between DMN and EAS regions during recollection (28), perception of near-threshold acoustic stimuli (29), working memory and attention (30, 31), goal-directed introspective processing (23, 32), and unattended mind wandering (11). The emergence of these cooperative interactions seems critically dependent on the task being performed by participants at the time of scanning; i.e., they are context-specific (17, 22, 23, 33).

The above findings suggest that certain task conditions may provoke a departure from an intrinsic or default state of competition between the DMN and EAS to enable cooperative interactions between the two systems. It is unclear, however, whether greater cooperation between the DMN and EAS actually facilitates better performance in such contexts and how these

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large-scale systems dynamically reconfigure themselves to support these context-dependent collaborative interactions.

In this study, we used fMRI to distinguish task-related, context-dependent functional interactions between the DMN and EAS from task-unrelated, spontaneous network dynamics in individuals performing a recollection task previously shown to coactivate regions of both networks (28). Our aims were threefold. First, we aimed to test the hypothesis that greater context-dependent cooperation between DMN and EAS regions would facilitate better recollection performance. Second, we aimed to map how changing task conditions provoke a dynamic reconfiguration of brain functional organization from a default state of antagonism to one of greater functional integration of DMN and EAS processes. Third, we aimed to characterize the role that each individual brain region plays in facilitating these shifts in functional network architecture.

## Results

### Group-Level Interactions Between the DMN and EAS Are Competitive.

Sixteen adult participants performed a task requiring them to recollect the context in which well-learned word pairs (e.g., bacon and eggs) were previously encountered (the second word was perceived or imagined by the participant or read aloud by either the participant or the experimenter). Blocks of recollection trials alternated with blocks of nonrecollection trials requiring simple semantic judgments about probe stimuli matched for basic perceptual features (*SI Text, sections S.1 and S.2 and Fig. S1*).

Task-related functional networks corresponding to the DMN and EAS were identified in an unbiased, data-driven manner using spatial independent component analysis (ICA) (34) (*SI Text, section S.3*). The method is well-suited for characterizing the spatial anatomy and temporal dynamics of each network, while accounting for possible functional heterogeneity within either the DMN and/or EAS (5, 7, 21, 22, 24) (*SI Text, section S.3*). The DMN was identified as a single component with a characteristic functional anatomy consistent with prior work (7, 10). The EAS was split into four distinct components: (*i*) a dorsal attention network (DAN) commonly associated with focusing attention on external stimuli (2, 6); (*ii*) a cinguloopercular network (CON) implicated in interoceptive awareness (35), salience processing of external stimuli (25), and maintenance of response set during cognitive task performance (5); and (*iii* and *iv*) left and (4) right frontoparietal networks (LFPN and RFPN, respectively) often implicated in top-down executive control processes (5, 24). ICA commonly identifies these left and right components as separate networks, and prior work supports functional dissociations between the two components (26). Our findings below support this functional distinction. The spatial anatomy and representative time courses of each of these five networks is presented in Fig. 1 (*Table S1*).

Across participants, DMN activity was higher during the semantic baseline condition than recollection trials ( $t = -6.074$ ,  $P < 0.001$ ), whereas the opposite was true for the CON ( $t = 9.387$ ,  $P < 0.001$ ), DAN ( $t = 7.59$ ,  $P < 0.001$ ), LFPN ( $t = 11.618$ ,  $P < 0.001$ ), and RFPN ( $t = 9.661$ ,  $P < 0.001$ ) (Fig. 1). Accordingly, cross-correlation analysis of component time courses averaged across participants indicated that DMN activity was strongly anticorrelated with the CON ( $r = -0.78$ ,  $P < 0.001$ ), DAN ( $r = -0.79$ ,  $P < 0.001$ ), LFPN ( $r = -0.73$ ,  $P < 0.001$ ), and RFPN ( $r = -0.59$ ,  $P < 0.001$ ), whereas the activity of each of the four EAS networks was strongly positively correlated ( $0.70 < r < 0.88$ , all  $P < 0.001$ ).

**Context-Dependent Cooperation Between the DMN and RFPN Facilitates Rapid Recollection.** The group-level results indicate that, on average, the different EAS components showed strong cooperation with each other, while interacting competitively with the DMN. Analysis of individual differences suggested that there was

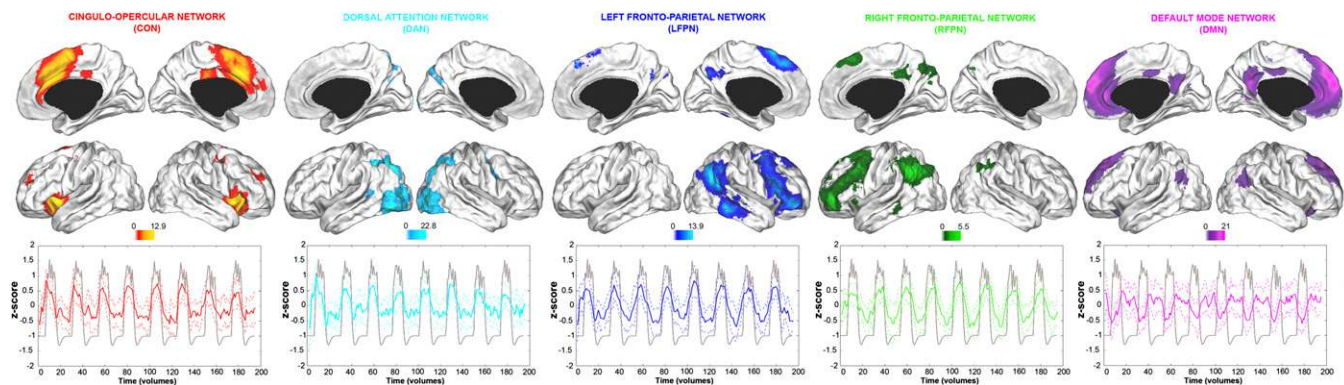
considerable variability around this group-averaged behavior. To analyze these differences, we extracted activity time courses for each network and each participant and computed subject-specific estimates of both task-related and task-unrelated functional interactions between the DMN and each EAS component. This distinction was critical, because it allowed us to separate context-dependent (task-related) network interactions from putative spontaneous or intrinsic (task-unrelated) functional dynamics.

Spontaneous or task-unrelated network interactions,  $ni_s$ , were estimated by band-pass filtering of each network time course ( $0.008 < f < 0.08$  Hz) and orthogonalizing it with respect to covariates modeling various noise sources and task-related variance in the data (36). Task-related network interactions ( $ni_t$ ) were estimated using a correlational psychophysiological interaction (cPPI) approach that used partial correlations to isolate covariations in task-related modulations of network activity as distinct from task-unrelated connectivity, noise, and coactivation effects. For both types of analysis, interactions between the DMN and each of the four EAS components were estimated after partialing covariance with the remaining EAS components to ensure that only temporal correlations specific to each network pair were being analyzed (*SI Text, section S.4* has additional details of these methods).

For both task-unrelated and task-related interactions, the degree to which cooperative or competitive functional interactions were expressed varied across individuals and network pairs (*SI Text, section S.7 and Figs. S2 and S3*). To determine whether these differences were associated with task performance, we correlated the subject-specific  $ni_s$  and  $ni_t$  estimates for each of the four DMN–EAS network pairs with measures of recollection accuracy and RT. We found a specific and significant negative correlation between recollection RT and task-related DMN–RFPN  $ni_t$  values ( $\rho = -0.671$ ,  $P = 0.005$ ) (Fig. S4B) but not task-unrelated  $ni_s$  values ( $\rho = -0.353$ ,  $P = 0.176$ ) (Fig. S4A). The former result survived Bonferroni correction for multiple comparisons. Moreover, the difference between the two correlations was significant ( $ZI^* = -1.718$ ,  $P = 0.043$ ) (*SI Text, section S.6*). No other associations with behavior approached significance.

The results were replicated when the analysis was repeated after partialing covariance with all other 19 components identified by the ICA as representing distinct sources of signal and noise in the data. The correlation between RT and DMN–RFPN  $ni_t$  remained significant ( $\rho = -0.621$ ,  $P = 0.008$ ) (Fig. S4D); the association between RT and  $ni_s$  values was not significant ( $\rho = -0.056$ ,  $P = 0.821$ ) (Fig. S4C); and the difference between the two correlations was also significant ( $ZI^* = -1.729$ ,  $P = 0.042$ ). This analysis provides a stringent test of the specificity of the association between RT and DMN–RFPN  $ni_t$  values and suggests that greater task-related cooperation between these two networks was associated with more rapid recollection.

**Context-Dependent Reconfiguration of the DMN Supports Cooperative Interactions with the RFPN.** The specific association between higher DMN–RFPN  $ni_t$  values and faster RT suggests that greater functional integration between the DMN and RFPN supports rapid recollection performance. This network-level integration must be facilitated by a dynamic reconfiguration of pairwise functional connectivity between the constituent regions of the DMN and RFPN. We mapped this reconfiguration using graph analysis. Specifically, we extracted activity time courses from each of 34 regions comprising the DMN and RFPN (20 DMN and 14 RFPN regions) (Fig. 24 and *Table S2*) and separately computed task-related and task-unrelated functional connectivity between each pair of regions to yield two  $34 \times 34$  functional connectivity matrices (one task-related and one task-unrelated) for each individual. These matrices were then decomposed into nonoverlapping sets of brain regions, termed modules, showing higher functional connectivity with each other than with other areas using a modularity



**Fig. 1.** Connectivity Z maps and sample mean network time courses of each of the five networks of interest. Dotted lines represent SD. Time courses are overlaid on a task regressor modeling activity associated with recollection blocks and indicating the onset of these trials relative to the baseline condition (gray line, arbitrary units). The spatial maps display voxels showing significant functional connectivity at  $P < 0.05$ , familywise error corrected (cluster extent  $> 10$  voxels). Left hemisphere presented on the right hand side of each panel.

decomposition algorithm suitable for unthresholded, weighted, and signed networks (37) (*SI Text, section S.5*).

To account for individual variability in the number and composition of modules identified across participants, we adapted previously described methods (38) to identify the optimal modular architecture for the entire sample for both task-related and task-unrelated networks. Briefly, a coclassification matrix representing the frequency with which each pair of nodes was assigned to the same module across participants was constructed separately for the task-related (Fig. 2*B*) and task-unrelated data (Fig. 2*F*). These matrices were then subjected to a second-level modular decomposition (Fig. 2*C* and *G*). By this procedure, two regions consistently coclassified in the same module across participants were assigned to the same module in the second-level partition (additional details in *SI Text, section S.5*).

For task-unrelated networks, the optimal decomposition identified two modules that almost perfectly replicated the ICA-based classification; i.e., all nodes derived from the RFPN component mapped onto a common module, whereas all DMN regions, except for the right angular gyrus, were also grouped together (Fig. 2*A–C*, RFPN is shown in green, and DMN is shown in magenta). Thus, the initial ICA-based separation of DMN and RFPN regions was recapitulated by a modular decomposition of their pairwise spontaneous interactions. This consistency is noteworthy given the different processing and analysis techniques used to derive these partitions, and it supports the hypothesis that the default or intrinsic state of these two systems is one of functional segregation or antagonism.

In contrast, the optimal modular decomposition for task-related interactions identified three modules. All but one of the regions in the RFPN module were consistent with the analysis of task-unrelated data, but the DMN split into two smaller subgroups: a larger module comprising 12 nodes (DMNa module; magenta in Fig. 2*E* and *G*) and a smaller group comprising seven regions (DMNb module; cyan in Fig. 2*E* and *G*).

To understand the functional roles played by each module and their constituent nodes, we examined the consistency and diversity with which different regions were coclassified into the same module across participants. Classification consistency was estimated by computing the within-module strength,  $z$ , of each node separately in the task-related and task-unrelated group coclassification matrices. Classification diversity was computed using the diversity coefficient  $h$  (37, 39) (formal definitions are provided in *SI Text, section S.5*). Applied in this context,  $z$  quantified the degree to which each region was classified in the same module across participants relative to other nodes in the same module. Brain regions with high  $z$  values represent core components of

their module and thus act as local connectivity hubs. The diversity coefficient,  $h$ , quantified the variability of each region's modular assignment across participants. Regions with high  $h$  have a relatively equal probability of being classified into different modules across participants, because their connectivity is dispersed between modules from individual to individual. These regions, therefore, represent transitional nodes that facilitate functional integration between modules (37, 39) (additional details in *SI Text, section S.5*).

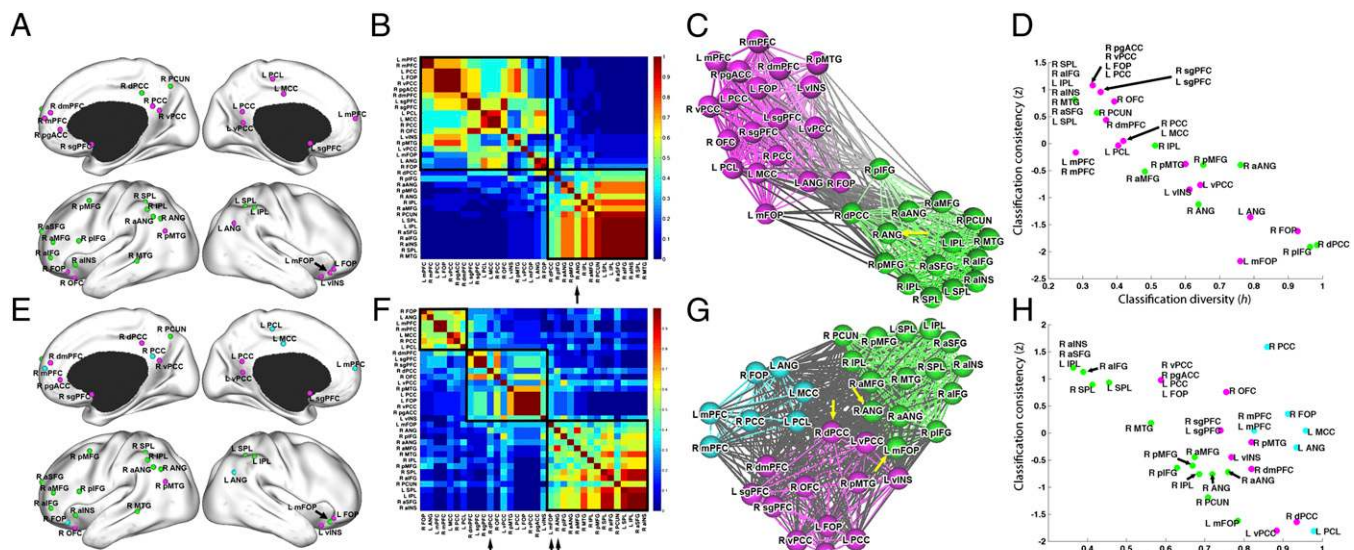
For task-unrelated networks, regional  $z$  and  $h$  were negatively correlated such that network nodes were characterized by either high classification consistency or high classification diversity (Fig. 2*D*). DMN regions with high  $z$ , representing core module elements, included known hubs such as posterior cingulate and dorsal and ventromedial prefrontal regions (7). Core RFPN elements included superior parietal and lateral prefrontal areas, consistent with prior work (24). Transitional nodes, characterized by high  $h$ , included areas that have previously been shown to promote functional integration between DMN and EAS regions in certain task contexts, such as dorsal posterior cingulate and right frontoopercular cortices (22, 30, 40).

A similar negative association between  $z$  and  $h$  values was evident for nodes in the DMNa and RFPN modules of task-related networks (magenta and green, respectively, in Fig. 2*E* and *G*). In contrast, nodes in the DMNb module (cyan in Fig. 2*E* and *G*) were primarily characterized by high  $h$ . This property suggests that these DMNb regions collectively formed a transitional module with connectivity dispersed across DMNa and RFPN regions. In other words, the DMNb module acted as a bridge facilitating functional integration within and between the DMN and RFPN. ANOVA confirmed that the mean diversity coefficient of DMNb regions ( $M = 0.90$ ,  $SD = 0.062$ ) was higher than for DMNa ( $M = 0.734$ ,  $SD = 0.12$ ) and RFPN ( $M = 0.569$ ,  $SD = 0.160$ ) regions [ $F(2, 31) = 15.512$ ,  $P < 0.001$ ]. Against this background, the right posterior cingulate cortex (PCC) stood out as a region showing both high  $h$  and high  $z$ , indicating that it was a core element of the transitional DMNb module that also retained diverse connectivity with DMNa and RFPN regions. This result suggests that the right PCC represents a putative information-processing bottleneck that acted as a connectivity hub within the transitional DMNb module, while concomitantly facilitating functional integration between DMNa and RFPN regions. Notably, however, individual differences in nodal connectivity measures did not correlate with recollection RT (*SI Text, section S.6*).

## Discussion

Replicated reports of competitive or anticorrelated dynamics between large-scale functional brain systems have been interpreted





**Fig. 2.** Illustration of node-specific functional roles mediating task-related and task-unrelated functional interactions between the DMN and RFPN. (A) Anatomical location of spherical regions of interest that comprise the DMN (magenta) and RFPN (green) modules, as identified by the modular decomposition of the task-unrelated functional connectivity data (maps colored according to the original assignments implied by the ICA can be seen in Fig. S5). (B) Task-unrelated group consistency coclassification matrices (*SI Text, section S.5*) reordered to emphasize the optimal modular structure for the sample. Solid black lines indicate boundary between modules. Arrows highlight regions with module assignment that differed from the assignment implied by the initial ICA. (C) Fruchterman–Reingold force-directed projections showing intra- and intermodular connectivity in the task-unrelated network. Strongly connected nodes are placed in closer proximity to each other. Intramodule connections are colored according to the module identity of the nodes that they interconnect. Intermodular connections are colored black. Yellow arrows highlight regions with module assignments that differ from the assignments implied by the initial ICA (Fig. S5). (D) Scatterplots of classification consistency,  $z$ , and classification diversity,  $h$ , of each region in the task-unrelated data. Colors indicate the module to which each region belongs. (E) Location of regions belonging to the RFPN (green), DMNa (magenta), and DMNb (cyan) modules identified in the task-related functional connectivity analysis. (F–H) Group coclassification matrix, force-directed projection, and consistency-diversity scatterplot, respectively, for the task-related data. Table S2 explains the abbreviated node labels. R, right hemisphere; L, left hemisphere.

as evidence for a fundamental distinction and antagonism between neural systems supporting introspective and extrospective processing (1, 2, 16). Our results suggest a revision of this view in light of (i) the diversity of interactions between the DMN and different components of the EAS; (ii) the context dependence of these interactions; and (iii) the substantial variability in the degree to which competitive or cooperative interactions between the DMN and different EAS components were expressed across individuals. In particular, our findings show that, under certain task conditions (such as the recollection paradigm studied here), greater cooperation between these systems is actually associated with better performance. This enhanced cooperation is facilitated by dynamic, context-dependent reconfiguration of the DMN into core and transitional modules, with the latter supporting greater functional integration between the DMN core and frontoparietal areas. In facilitating these dynamic shifts of functional network architecture, the right PCC seems to act as a critical information-processing bottleneck, representing a major hub of the transitional DMN module while also retaining high functional integration with other regions.

The association between faster recollection RT and stronger DMN–RFPN cooperation counters the hypothesis that greater antagonism between DMN and EAS regions invariably supports optimal task performance (1, 16). According to this view, the introspective processes mediated by the DMN can interfere with EAS-related processes that support attention to external stimuli. Consequently, greater separation of these functions, which are reflected in a stronger anticorrelation between their activation dynamics, should support adaptive and efficient behavior. This hypothesis has been supported by work using attentional or cognitive control tasks (14, 16, 17). Recent work using alternative experimental paradigms has, however, identified task contexts during which DMN and EAS regions coactivate or enhance

functional connectivity (11, 22, 23, 29, 31–33, 41). Such findings indicate that competitive large-scale brain network dynamics are not an invariant property of brain function.

In our analyses, the need to isolate context-dependent network interactions was highlighted by the different findings that we obtained when considering task-unrelated dynamics. Indeed, our results indicate that cooperative interactions between DMN and EAS regions emerge as a context-dependent shift from an intrinsic or default state of antagonism as functional segregation between the DMN and different EAS components was generally more pronounced in task-unrelated functional connectivity measures (the major exception was the DMN–LFPN pair) (Fig. 1 and Fig. S2). Thus, methods that isolate task-related, context-dependent network interactions will provide a more sensitive characterization of circumstances under which cooperation between the DMN and EAS arises. Accordingly, many of the studies reporting evidence for cooperation between these systems have used such techniques (23, 31, 32, 41). In our analyses, the importance of isolating these interactions was underscored by the 33–38% greater covariance observed between recollection RT and DMN–RFPN  $n_i$  values compared with  $n_i$  measures.

Functional diversity within the EAS may also contribute to inconsistent reports of competitive or cooperative interactions with the DMN across studies. The EAS is loosely defined as a collection of brain regions often showing increased activation during cognitively demanding tasks, and it has been labeled with a variety of names, including the task positive network (3, 15), extrinsic network (4), external awareness network (42), and cognitive control network (30). Part of this confusion stems from differences in the methods used to define the system, which have included activation patterns (5), seed-based correlation analyses (24), anticorrelation with the DMN (2), and ICA (3, 16, 30). Each of these methods can result in different network definitions.

For example, the work by Vincent et al. (24) used seed-based correlation analysis of resting-state fMRI data to identify a broad frontoparietal control system, comprising regions of the CON, LFPN, and RFPN as defined in our study. They argued that this control system was anatomically interposed between the DMN and anticorrelated DAN, and was thus well-positioned to facilitate functional integration between the two. Support for this view comes from evidence that regions of the frontoparietal control system flexibly couple with either the DMN or DAN, depending on the task at hand (23, 33). However, this view does not account for metaanalytic evidence supporting functional dissociations between cinguloopercular and frontoparietal components of the broader control system described by Vincent et al. (5, 24, 26) as well as evidence that the CON may initiate switches between competitive processing modes dominated by the DMN and frontoparietal regions (22).

Our results support a functional distinction between the CON and frontoparietal systems as well as between left- and right-lateralized components of the frontoparietal network. Specifically, we found that the CON, LFPN, and RFPN each showed diverse modes of interaction with the DMN (Fig. S2); that recollection RT correlated specifically RFPN–DMN interactions; and that it was the context-dependent interactions between these networks that most strongly dissociated the RFPN from other components of the EAS. The last conclusion is supported by our analyses of group-averaged and task-related data, which pointed to strong functional segregation between the DMN and all EAS components (Figs. 1 and 2). This result again highlights the importance of considering the context-dependent character of large-scale brain dynamics.

The identification of DMN–RFPN interactions as being specifically associated with recollection RT is notable given the proposed roles of these networks in recollection. The DMN is commonly activated during successful memory retrieval and less active during recollection errors (15). Accordingly, it is thought to play a critical role in the storage and/or recollection of contextual associations (43). In contrast, activation specifically of right-lateralized frontal and parietal regions has been associated with controlled memory retrieval (44) and heuristic evaluation processes (45), the monitoring of retrieved memoranda (46), and more general retrieval-related decision-making (47). Together, these findings indicate that the DMN supports rapid, effortless retrieval of contextual associations, whereas the RFPN may support more strategic searches through memory and/or the monitoring of retrieved information. Our findings indicate that cooperative interactions between these two networks, as reflected in greater positive functional connectivity, are associated with more rapid recollection performance. Thus, one hypothesis to emerge from these data is that enhanced functional coupling of DMN and right-lateralized frontoparietal regions reflects greater access of RFPN-related search and monitoring processes to well-learned contextual associations mediated by the DMN, resulting in relatively effortless and rapid retrieval. This view predicts that memory recalled with greater confidence should be associated with greater DMN–RFPN cooperation. To test this hypothesis, we ran secondary analyses testing for associations between DMN–RFPN  $n_i$  values and behavioral measures of recollection confidence acquired during our task (SI Text, section S.1). We found that strong positive functional connectivity between the DMN and RFPN was indeed associated with greater memory confidence ( $\rho = 0.544$ ,  $P = 0.027$ ). This result supports the hypothesis that enhanced RFPN–DMN coupling is associated with rapid, effortless recollection.

Greater cooperation between the DMN and RFPN was facilitated by a context-dependent reconfiguration of the DMN into two distinct components: a core DMNa module and a smaller DMNb transitional module. The high mean classification diversity of nodes in the transitional module indicated that it acted

as a bridge supporting functional integration between the DMNa and RFPN modules. In particular, the right PCC stood out as a putative information-processing bottleneck, representing a core hub of the transitional module while also retaining high connectivity with the other two modules. It may thus act as a catalyst that provokes context-dependent departures from a default state of DMN–RFPN antagonism to support greater functional integration during recollection. In this regard, although there was no significant correlation between recollection RT and individual differences in PCC function (or between RT and functional measures computed for any other area) (SI Text, section S.6), the region played a critical role in facilitating the context-dependent shifts of large-scale network organization that did support rapid recollection (i.e., greater task-related collaboration between DMN and RFPN regions). The centrality of the PCC to these network interactions is also supported by recent evidence that the region plays an important role in recollection (43), that it is a major connectivity hub in the brain (48) with functional properties that are under strong genetic influence (49, 50), and that it represents a core region that flexibly interacts with different DMN components depending on the task being performed at any given time (30).

In summary, our findings highlight the context dependence of large-scale functional network interactions in the brain. In particular, they indicate that competitive interactions between DMN and EAS regions are not an invariant property of adaptive behavior and that these systems can interact cooperatively in certain circumstances to support optimal task performance. A greater appreciation of the diversity of functional interactions in the brain, their context sensitivity, and the roles that individual brain regions play in facilitating these interactions will yield a more accurate characterization of the behavioral significance of large-scale brain network dynamics.

## Methods

**Experimental Design.** Sixteen healthy, right-handed participants (seven male; mean age = 24.3 y, range = 19–36 y) underwent five study and five test phases of a contextual recollection task in the scanner, although only test phases were scanned (additional details in SI Text, section S.1 and details on image acquisition, processing, and general linear model in SI Text, section S.2). All participants gave written, informed consent. The study was approved by the Cambridge Local Research Ethics Committee.

**Network Analyses.** We identified spatially independent, temporally coherent networks of voxels using spatial ICA, which was implemented in the Group ICA for fMRI Toolbox (GIFT; <http://mialab.mrn.org/software/gift/>) (SI Text, section S.3). Task-related and task-unrelated functional interactions between these large-scale networks were computed using partial correlation of representative component time courses. Task-related network interactions were estimated using a correlational psychophysiological interaction (cPPI) analysis developed specifically for this purpose using freely available code ([http://www.psychiatry.unimelb.edu.au/centres-units/mnc/research/connectivity\\_software.html](http://www.psychiatry.unimelb.edu.au/centres-units/mnc/research/connectivity_software.html)) (SI Text, section S.4). Task-unrelated functional interactions were estimated after task-related variance was removed from each network's time course using a Gramm–Schmidt orthogonalization procedure, consistent with previous studies (36) (SI Text, section S.4). We chose this method over a pure resting-state design, because we wanted to examine putative spontaneous processes during performance of the actual task and not during a completely different experimental context, which can influence estimates of spontaneous functional interactions (51–53) (SI Text, section S.4). Modularity analyses were performed using freely available software (<https://sites.google.com/a/brain-connectivity-toolbox.net/bct/>) (SI Text, section S.5). Associations with behavior were tested using Spearman's rank correlation coefficient combined with permutation testing and Bonferroni correction for multiple comparisons (SI Text, section S.6).

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1. Sonuga-Barke EJ, Castellanos FX (2007) Spontaneous attentional fluctuations in impaired states and pathological conditions: A neurobiological hypothesis. *Neurosci Biobehav Rev* 31:977–986.
2. Fox MD, et al. (2005) The human brain is intrinsically organized into dynamic, anti-correlated functional networks. *Proc Natl Acad Sci USA* 102:9673–9678.
3. Fransson P (2006) How default is the default mode of brain function? Further evidence from intrinsic BOLD signal fluctuations. *Neuropsychologia* 44:2836–2845.
4. Golland Y, Golland P, Bentin S, Malach R (2008) Data-driven clustering reveals a fundamental subdivision of the human cortex into two global systems. *Neuropsychologia* 46:540–553.
5. Dosenbach NU, et al. (2006) A core system for the implementation of task sets. *Neuron* 50:799–812.
6. Corbetta M, Patel G, Shulman GL (2008) The reorienting system of the human brain: From environment to theory of mind. *Neuron* 58:306–324.
7. Buckner RL, Andrews-Hanna JR, Schacter DL (2008) The brain's default network: Anatomy, function, and relevance to disease. *Ann N Y Acad Sci* 1124:1–38.
8. Gusnard DA, Raichle ME, Raichle ME (2001) Searching for a baseline: Functional imaging and the resting human brain. *Nat Rev Neurosci* 2:685–694.
9. Shulman GL, et al. (1997) Common blood flow changes across visual tasks: II. Decreases in cerebral cortex. *J Cogn Neurosci* 9:648–663.
10. Harrison BJ, et al. (2008) Consistency and functional specialization in the default mode brain network. *Proc Natl Acad Sci USA* 105:9781–9786.
11. Christoff K, Gordon AM, Smallwood J, Smith R, Schooler JW (2009) Experience sampling during fMRI reveals default network and executive system contributions to mind wandering. *Proc Natl Acad Sci USA* 106:8719–8724.
12. McKiernan KA, Kaufman JN, Kucera-Thompson J, Binder JR (2003) A parametric manipulation of factors affecting task-induced deactivation in functional neuroimaging. *J Cogn Neurosci* 15:394–408.
13. Weissman DH, Roberts KC, Visscher KM, Woldorff MG (2006) The neural bases of momentary lapses in attention. *Nat Neurosci* 9:971–978.
14. Eichele T, et al. (2008) Prediction of human errors by maladaptive changes in event-related brain networks. *Proc Natl Acad Sci USA* 105:6173–6178.
15. Kim H, Daselaar SM, Cabeza R (2010) Overlapping brain activity between episodic memory encoding and retrieval: Roles of the task-positive and task-negative networks. *Neuroimage* 49:1045–1054.
16. Kelly AM, Uddin LQ, Biswal BB, Castellanos FX, Milham MP (2008) Competition between functional brain networks mediates behavioral variability. *Neuroimage* 39:527–537.
17. De Pisapia N, Turatto M, Lin P, Jovicich J, Caramazza A (2012) Unconscious priming instructions modulate activity in default and executive networks of the human brain. *Cereb Cortex* 22:639–649.
18. Whitfield-Gabrieli S, et al. (2009) Hyperactivity and hyperconnectivity of the default network in schizophrenia and in first-degree relatives of persons with schizophrenia. *Proc Natl Acad Sci USA* 106:1279–1284.
19. Castellanos FX, et al. (2008) Cingulate-precuneus interactions: A new locus of dysfunction in adult attention-deficit/hyperactivity disorder. *Biol Psychiatry* 63:332–337.
20. Honey CJ, Kötter R, Breakspear M, Sporns O (2007) Network structure of cerebral cortex shapes functional connectivity on multiple time scales. *Proc Natl Acad Sci USA* 104:10240–10245.
21. Andrews-Hanna JR, Reidler JS, Sepulcre J, Poulin R, Buckner RL (2010) Functional-anatomic fractionation of the brain's default network. *Neuron* 65:550–562.
22. Sridharan D, Levitin DJ, Menon V (2008) A critical role for the right fronto-insular cortex in switching between central-executive and default-mode networks. *Proc Natl Acad Sci USA* 105:12569–12574.
23. Spreng RN, Stevens WD, Chamberlain JP, Gilmore AW, Schacter DL (2010) Default network activity, coupled with the frontoparietal control network, supports goal-directed cognition. *Neuroimage* 53:303–317.
24. Vincent JL, Kahn I, Snyder AZ, Raichle ME, Buckner RL (2008) Evidence for a frontoparietal control system revealed by intrinsic functional connectivity. *J Neurophysiol* 100:3328–3342.
25. Seeley WW, et al. (2007) Dissociable intrinsic connectivity networks for salience processing and executive control. *J Neurosci* 27:2349–2356.
26. Smith SM, et al. (2009) Correspondence of the brain's functional architecture during activation and rest. *Proc Natl Acad Sci USA* 106:13040–13045.
27. Popa D, Popescu AT, Paré D (2009) Contrasting activity profile of two distributed cortical networks as a function of attentional demands. *J Neurosci* 29:1191–1201.
28. Simons JS, Henson RN, Gilbert SJ, Fletcher PC (2008) Separable forms of reality monitoring supported by anterior prefrontal cortex. *J Cogn Neurosci* 20:447–457.
29. Sadaghiani S, Hesselmann G, Kleinschmidt A (2009) Distributed and antagonistic contributions of ongoing activity fluctuations to auditory stimulus detection. *J Neurosci* 29:13410–13417.
30. Leech R, Kamourieh S, Beckmann CF, Sharp DJ (2011) Fractionating the default mode network: Distinct contributions of the ventral and dorsal posterior cingulate cortex to cognitive control. *J Neurosci* 31:3217–3224.
31. Bluhm RL, et al. (2011) Default network connectivity during a working memory task. *Hum Brain Mapp* 32:1029–1035.
32. Gerlach KD, Spreng RN, Gilmore AW, Schacter DL (2011) Solving future problems: Default network and executive activity associated with goal-directed mental simulations. *Neuroimage* 55:1816–1824.
33. Gao W, Lin W (2012) Frontal parietal control network regulates the anti-correlated default and dorsal attention networks. *Hum Brain Mapp* 33:192–202.
34. Calhoun VD, Adali T, Pekar JJ (2004) A method for comparing group fMRI data using independent component analysis: Application to visual, motor and visuomotor tasks. *Magn Reson Imaging* 22:1181–1191.
35. Critchley HD, Wiens S, Rotshtein P, Ohman A, Dolan RJ (2004) Neural systems supporting interoceptive awareness. *Nat Neurosci* 7:189–195.
36. Fair DA, et al. (2007) A method for using blocked and event-related fMRI data to study "resting state" functional connectivity. *Neuroimage* 35:396–405.
37. Rubinov M, Sporns O (2011) Weight-conserving characterization of complex functional brain networks. *Neuroimage* 56:2068–2079.
38. van den Heuvel M, Mandl R, Hulshoff Pol H (2008) Normalized cut group clustering of resting-state fMRI data. *PLoS One* 3:e2001.
39. Guimera R, Nunes Amaral LA (2005) Functional cartography of complex metabolic networks. *Nature* 433:895–900.
40. Leech R, Braga R, Sharp DJ (2012) Echoes of the brain within the posterior cingulate cortex. *J Neurosci* 32:215–222.
41. Prado J, Weissman DH (2011) Heightened interactions between a key default-mode region and a key task-positive region are linked to suboptimal current performance but to enhanced future performance. *Neuroimage* 56:2276–2282.
42. Boly M, et al. (2008) Intrinsic brain activity in altered states of consciousness: How conscious is the default mode of brain function? *Ann N Y Acad Sci* 1129:119–129.
43. Bar M (2007) The proactive brain: Using analogies and associations to generate predictions. *Trends Cogn Sci* 11:280–289.
44. Velanova K, et al. (2003) Functional-anatomic correlates of sustained and transient processing components engaged during controlled retrieval. *J Neurosci* 23:8460–8470.
45. Dobbins IG, Simons JS, Schacter DL (2004) fMRI evidence for separable and lateralized prefrontal memory monitoring processes. *J Cogn Neurosci* 16:908–920.
46. Henson RN, Rugg MD, Shallice T, Dolan RJ (2000) Confidence in recognition memory for words: Dissociating right prefrontal roles in episodic retrieval. *J Cogn Neurosci* 12:913–923.
47. Hayama HR, Rugg MD (2009) Right dorsolateral prefrontal cortex is engaged during post-retrieval processing of both episodic and semantic information. *Neuropsychologia* 47:2409–2416.
48. Hagmann P, et al. (2008) Mapping the structural core of human cerebral cortex. *PLoS Biol* 6:e159.
49. Fornito A, et al. (2011) Genetic influences on cost-efficient organization of human cortical functional networks. *J Neurosci* 31:3261–3270.
50. Glahn DC, et al. (2010) Genetic control over the resting brain. *Proc Natl Acad Sci USA* 107:1223–1228.
51. Barnes A, Bullmore ET, Suckling J (2009) Endogenous human brain dynamics recover slowly following cognitive effort. *PLoS One* 4:e6626.
52. Harrison BJ, et al. (2008) Modulation of brain resting-state networks by sad mood induction. *PLoS One* 3:e1794.
53. Fornito A, Bullmore ET (2010) What can spontaneous fluctuations of the blood oxygenation-level-dependent signal tell us about psychiatric disorders? *Curr Opin Psychiatry* 23:239–249.



# Supporting Information

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## SI Text

**S.1. Experimental Paradigm.** The task comprised five study and five test phases. Only test phases were scanned. Each study phase comprised 32 trials, where participants were presented with a cue saying either SUBJECT or EXPERIMENTER. After 500 ms, either a word pair (e.g., bacon and eggs; perceive condition) or the first word of a pair and a question mark (bacon and ?; imagine condition) appeared. If the cue read SUBJECT, the participant had to either read the presented word pair aloud (perceive condition) or imagine the second word pair and say the word pair out loud (imagine condition). If the cue read EXPERIMENTER, the experimenter performed the task and read the word pair aloud over the scanner intercom. The subject/experimenter and perceive/imagine conditions were crossed in a  $2 \times 2$  factorial design.

Test phases, which were scanned, consisted of five sessions, comprising eight blocks of four trials each. Each block was preceded by an instruction presented for 2–8 s indicating the type of judgment required (Fig. S1). A single, centrally presented word was then shown, and participants were required to recollect the context in which the second word in the pair had been presented based on the instruction cue (i.e., did you perceive or imagine it or did you or the experimenter read it?). Participants had 4.5 s to make their response. The semantic baseline asked participants to judge whether a nonstudied word referred to a manmade or naturally occurring object. Blocks alternated between contextual memory and semantic baseline in an  $A_1A_2BBA_1A_2BB$  format, where  $A_1$  and  $A_2$  refer to the different types of recollection judgments (i.e., perceived/imagined or self/experimenter). The presentation order of the recollection blocks was counterbalanced across subjects. The intertrial interval was jittered between 500 and 1,400 ms according to an exponential distribution. Responses were made using a button box. When making a response, participants held down the button to indicate their confidence in the response. A confidence bar at the bottom of the screen increased in size to indicate their confidence level. Additional details can be found in ref. 1.

## S.2. Image Acquisition, Preprocessing, and General Linear Modeling.

Echo planar functional images were acquired using a 3T Siemens TIM Trio system (36 sequential 2-mm-thick axial slices with 1 mm interslice gap oriented  $\sim 10\text{--}20^\circ$  to the anterior commissure–posterior commissure (AC-PC) transverse plane and with a time-to-repetition (TR) = 2.25 s and time-to-echo (TE) = 30 ms) across five sessions (200 volumes per session). The first five volumes were discarded to allow for T1 equilibration.

Images were preprocessed and analyzed using SPM5 (<http://www.fil.ion.ucl.ac.uk/spm/software/>). Functional images were first corrected for head motion and slice-timing differences. The mean of these functional images was coregistered to each participant's T1-weighted image. These T1 images were also segmented into gray, white, and cerebrospinal fluid tissue compartments and spatially normalized to Montreal Neurological Institute stereotaxic space. The realigned, slice time-corrected functional volumes were then spatially realigned using the T1-weighted normalization parameters and resampled in  $3\text{-mm}^3$  voxels. The functional data were spatially smoothed with an 8-mm full-width, half-maximum isotropic Gaussian kernel, temporally filtered (high-pass cutoff of 1/128 Hz) and corrected for temporal autocorrelation using an autoregressive AR (1) model. All image processing and subsequent analyses were performed using Matlab 7.8 (Mathworks).

Task-evoked activity was characterized using a general linear model (GLM) in which the onsets of each event were modeled

with zero-duration  $\delta$ -functions convolved with a canonical hemodynamic response function. Unique covariates modeled the onsets of each correctly responded recollection trial (i.e., perceive/imagine and self/experimenter) and their corresponding baseline conditions and instruction periods. A separate regressor modeling incorrectly responded trials was included along with the time and dispersion derivatives of each covariate. Model parameter values were computed by restricted maximum likelihood estimation (additional details in ref. 1). Contrasts between these parameter estimates were used to isolate task-related interactions between networks and brain regions. Although self/experimenter and perceive/imagine recollection trials were modeled separately, the major task-related influence on network activity involved the distinction between semantic baseline and recollection (irrespective of the type of recollection) (Fig. 1). Thus, for simplicity, we focused our analysis on this contrast and collapsed across self/experimenter and perceive/imagine recollection judgments.

**S.3. Independent Component Analysis. Component identification.** We used spatial independent component analysis (ICA) to identify spatially independent, temporally coherent networks of voxels in the functional data. Spatial ICA is a widely used method for decomposing high-dimensional functional MRI (fMRI) data into distinct signal and noise components (2–4), and it has been applied to consistently identify the default mode network (DMN) and different external attention system (EAS) components across diverse experimental paradigms (5–8). A particular advantage of this method is that it makes no a priori assumptions concerning the nature of blood oxygenation level-dependent (BOLD) responses evoked by the task (i.e., it is completely data-driven). This property was desirable for present purposes given variability and contradictions concerning how the EAS should be best defined. For example, ICA consistently identifies the cinguloopercular network (CON) as distinct from the dorsal attention network (DAN) and frontoparietal systems (6, 9), whereas seed-based correlation approaches typically include these networks in one unitary system (10). The differences between the two techniques arise because seed-based techniques identify regions showing strong functional connectivity with the seed region alone, whereas ICA identifies regions making a strong contribution to the network as a whole, while also maximizing spatial independence between components. This property of ICA ensured that our network definitions were not biased by a priori selection of specific seed regions and allowed a finer-grained analysis of the specificity of interactions between the DMN and different EAS components. Examining this specificity is critical given metaanalytic evidence for functional dissociations between EAS components (6, 11). Functional dissociations between EAS components were also evident in our findings.

Spatial ICA was implemented using the Group ICA for fMRI Toolbox (<http://mialab.mrn.org/software/gift/>). Briefly, the analysis proceeded in three broad stages. The dimensionality of the data was reduced from 195 (the number of time points per session) to 21 components through a two-step principle components analysis and subjectwise data concatenation procedure. The dimensionality of the data (number of components) was determined by information theoretic criteria (12). A group spatial ICA was then performed on the concatenated and reduced data using the Infomax algorithm. Spatial maps and representative time courses of each component were subsequently estimated for each subject through back-reconstruction, allowing representation

of interindividual variation in component anatomy and temporal dynamics. The resulting output was a series of spatial maps and representative time courses for each subject, each session, and each of the 21 estimated components. Both spatial maps and time courses were calibrated using  $z$  scores. As such, voxel intensities in the spatial maps encoded the degree to which that voxel's activity time course was coherent with the overall component time course; the units in the time course reflected moment-to-moment fluctuations in component activity relative to the session mean. Detailed descriptions of the methods have been provided elsewhere (2).

**Spatial mapping.** The spatial anatomy of each component was characterized by entering the participant-specific spatial maps into a second-level, one-sample  $t$  test to identify voxels with group-averaged  $z$  scores that were significantly different from zero. The threshold for significance was set using a familywise error rate correction procedure as implemented in SPM5 ( $P < 0.05$ , cluster extent = 10 voxels). These spatial maps were in combination with the unthresholded component maps and time courses to identify the DMN, CON, DAN, left frontoparietal network (LFPN), and right frontoparietal network (RFPN) based on their known functional anatomy and comparisons with prior literature (10, 11, 13–15). These five networks could be clearly differentiated from other components reflecting signal and noise in the data.

**Task-related modulation of component time courses.** To understand how activity in the DMN, CON, DAN, LFPN, and RFPN was modulated by the task, each network's time course was regressed against covariates modeling condition-specific activity defined in the GLM activation analysis (*SI Text, section S.2*). The result was a series of  $\beta$ -coefficients quantifying the degree to which each network's activity covaried with each task condition. To isolate task-related modulations of network activity specific to contextual recollection, we compared the magnitude of these  $\beta$ -coefficients for recollection trials (collapsed across perceive/imagine and self/experimenter conditions) with the corresponding coefficients for semantic baseline trials using one-way ANOVA. As reported in the text, this analysis revealed that activity was significantly greater in recollection than baseline trials in the four EAS components, whereas DMN activity was greater for baseline compared with recollection trials.

**5.4. Network Interaction Analysis.** Functional interactions between the DMN, DAN, CON, LFPN, and RFPN were characterized using functional connectivity analysis. Functional connectivity refers to a statistical dependence between spatially distinct neurophysiological signals (16). In our analyses, this dependence was computed using partial correlations between network time courses, as described below. These analyses were performed separately to estimate task-unrelated and task-related functional interactions between networks. This distinction is critical, because correlations between raw time courses measured during task-based fMRI can arise for a number of reasons. Primary among these reasons are task-unrelated, spontaneous, or intrinsic functional dynamics; task-related, context-dependent modulations of functional coupling; physiological and/or scanner noise; and interregional coactivation induced by the task, which can arise from independent task-related regional activation in the absence of direct functional interaction. Our analyses aimed to separate task-related and task-unrelated components of functional interactions between networks, while controlling for noise-related effects and coactivation.

**Measuring task-unrelated network interactions.** Spontaneous fluctuations of the BOLD signal recorded in the absence of an explicit task are highly organized, showing temporal coherence across spatially distributed and well-characterized functional networks of brain regions (17). These correlations persist during task performance (18), account for a major source of variance in task-evoked activity (19–21), and are under strong genetic influence

(22, 23). Thus, these task-unrelated processes putatively reflect intrinsic interregional synchronization dynamics (17).

We used previously described and validated methods to isolate task-unrelated interactions between the DMN and the four EAS networks. Specifically, for each participant, each of the five network time courses of interest was band pass-filtered ( $0.008 < f < 0.08$ ) to remove very low-frequency confounds, high-frequency physiological noise and isolate the low-frequency fluctuations known to dominate spontaneous BOLD signals (24). These temporally filtered time courses were then orthogonalized with respect to the following variables: (i) six head motion parameters (three translation and three rotation parameters) estimated during motion correction of the functional volumes; (ii) signal time courses extracted from spherical seed regions placed in the cerebrospinal fluid (CSF) and white matter; (iii) a mean signal extracted from a mask of the entire cerebrum; and (iv) all task regressors (including time and dispersion derivatives) included in the GLM as well as additional regressors modeling sustained activity across each task block.

The temporal filtering and correction for head motion, white matter, CSF, and global signals emulate preprocessing strategies traditionally used in analyses of spontaneous BOLD signal correlations (25). These methods are routinely used to investigate anticorrelated interactions between large-scale brain networks (5, 26, 27). Orthogonalization with respect to the task design matrix removed as much task-related variance from the network time courses as possible. Functional connectivity measures derived from the residuals of this correction process have been shown to yield results comparable with those findings obtained using task-free, resting-state fMRI data (28), and the method has been used to link individual differences in task performance to putative anticorrelated spontaneous dynamics recorded during the task (5).

Network interactions were estimated as the partial correlation between each subject's noise- and task-corrected DMN time course,  $t_{DMN}$ , and each of the four noise- and task-corrected EAS network time courses,  $t_{EAS}$ , while controlling for the effects of the remaining three networks [i.e.,  $r_{t_{DMN} \setminus EAS, t_{EAS} \setminus \{EAS\}}$ , where  $t_{EAS} = \{t_{CON}, t_{DAN}, t_{LFPN}, t_{RFPN}\}$ ]. This procedure allowed us to isolate functional interactions that were specific to each DMN and EAS component pair.

Orthogonalizing fMRI time series with respect to task design matrices has often been used to approximate task-unrelated functional processes that putatively reflect intrinsic neural dynamics during task performance (5, 28). We preferred this method to using a pure resting-state design because we wanted to examine these processes during performance of the actual task and not during a completely different psychological context and experimental preparation. This choice is justified by recent evidence indicating that psychological context can indeed influence functional connectivity measures obtained during resting-state recordings (29–31). It is important to note that although the correction procedure described above is able to reproduce functional networks observed during resting-state designs with high fidelity, some differences can be apparent and possibly reflect residual, unmodeled task-related variance in the data (28). In our analyses, a failure to adequately remove task-related activity would increase the similarity between task-unrelated and task-related network interaction measures and reduce our power to detect differences between the two. As such, our findings may represent a conservative estimate of the true variation between task-related and task-unrelated functional dynamics.

**Measuring task-related, context-dependent network interactions.** Task-related functional connectivity describes interregional interactions that vary in accordance with changing task conditions (i.e., interactions that change from one task condition to the next). As such, they reflect interregional synchronization dynamics specifically associated with the cognitive operation(s) being probed



by the experimental task. It is important, however, to distinguish these context-dependent effects from task-unrelated, spontaneous processes and coactivation effects. The latter may arise simply because task stimulation drives activity in two different regions in a similar way, causing their time courses to be correlated even if the regions do not directly interact with each other (i.e., the two regions activate independently to the task).

To isolate task-related network interactions while controlling for such effects, we implemented a correlational technique based on the logic of psychophysiological interactions (PPI) (32). In a traditional PPI analysis, a representative activity time course of a seed region,  $t$ , is extracted and multiplied by a task regressor of interest,  $\psi$ , to generate a term reflecting the psychophysiological interaction between the seed region's activity and the specified experimental manipulation. Voxels showing significant covariations with the seed region's task-related activity are then identified using a GLM of the form (Eq. S1)

$$y_i = I_j \cdot \beta_i + [t_j \psi \mathcal{G}] \cdot \beta_G + e_i, \quad [\text{S1}]$$

where  $y_i$  denotes the activity in voxel  $i$ ,  $I_j = t_j \times \psi$  (the PPI term for seed time course  $t_j$ ),  $\mathcal{G}$  denotes a matrix with columns that contain covariates of no interest, and  $e_i$  represents experimental error. The coefficient  $\beta_i$  is the parameter estimate for the PPI term  $I_j$ , and  $\beta_G$  represents the parameter estimates for the main effects  $t_j$ ,  $\psi$ , and  $\mathcal{G}$ . Including the main effect of  $t_j$  in the model controls for task-unrelated covariance between  $t_j$  and  $y_i$  and/or any noise-related processes correlated with  $t_j$ . Including the main effect of  $\psi$  in the model controls for possible coactivation effects induced by the task waveform. Thus, the model isolates context-sensitive alterations in functional coupling, while controlling for task-unrelated functional connectivity, noise, and coactivation effects.

The model defined in Eq. S1 is inherently directional; i.e., for any given pair of time series, one must be designated as the predictor and the other must be designated the response variable. The analysis therefore provides a rudimentary model of effective connectivity (32) and works well when there are clear hypotheses about which region might be driving activity in other areas. However, in cases where no such predictions can be made, the assignment of one or the other time course to the left- or right-hand side of Eq. S1 can be arbitrary.

To avoid arbitrary directional assumptions and retain a focus on analysis of functional rather than effective connectivity between networks, we used a partial correlation framework to estimate task-related, pairwise interactions between the DMN and the four EAS networks. Specifically, for each pair of networks, we generated two PPI terms,  $I_{DMN}$  and  $I_{EAS_i}$ , by separately multiplying the task regressor  $\psi$  with the two network time courses  $t_{DMN}$  and  $t_{EAS_i}$ , respectively. We then computed the partial correlation  $r_{I_{DMN} I_{EAS_i} : Z}$ , where  $Z = \{t_{DMN}, t_{EAS_i}, \psi\}$ . This correlational PPI (cPPI) approach thus quantifies covariations in task-related activity modulations of the DMN and each EAS network (the PPI terms  $I_{DMN}$  and  $I_{EAS_i}$ ), while controlling for background fluctuations (and correlated noise processes) in the activity of the DMN and all four EAS networks ( $t_{DMN}$  and  $t_{EAS_i}$ ), as well as any coactivation effects induced by the task stimulation ( $\psi$ ). In our analyses, our task regressor modeled activity modulations that were greater during recollection than semantic baseline trials, consistent with our interest in this particular task manipulation.

When computing the interaction term  $I$  for each time series, we used the deconvolution approach advocated in ref. 33. Specifically, we used an empirical Bayesian method for hemodynamic deconvolution of the original BOLD time series,  $t$ , to estimate underlying neuronal activity. This estimated neural signal was then multiplied by the unconvolved task regressor and reconvolved to generate a BOLD-level measurement of the neural PPI term. Computing the PPI interaction term with signals already con-

involved with a hemodynamic response function is not equivalent to the hemodynamic convolution of an interaction computed at the neural level [i.e.,  $(H\psi)(Ht) \neq H(\psi t)$ , where  $H$  is the hemodynamic response function in Toeplitz matrix form]. The deconvolution step therefore provides a more direct estimate of interactions between neural activity and the task, because such interactions occur at the neural rather than hemodynamic level (additional details in ref. 30). Software for implementing cPPI analysis is freely downloadable at [http://www.psychiatry.unimelb.edu.au/centres-units/mnc/research/connectivity\\_software.html](http://www.psychiatry.unimelb.edu.au/centres-units/mnc/research/connectivity_software.html).

**Addressing motion and other confounds.** In our analyses, we accounted for the potential effects of head motion and other confounds by analyzing the residuals obtained after regressing our signals of interest against time courses representing these noise effects, consistent with widely used protocols (17). Recent work has suggested that such an approach may not be sufficient to remove all noise-related effects from the data (34, 35). Residual noise effects are unlikely to impact our findings for several reasons.

First, our main finding, that recollection reaction time (RT) is correlated with DMN-RFPN  $ni_i$  and not  $ni_s$  values, persisted after we corrected for time courses extracted from all other components identified in the ICA. These components represent a variety of sources of both neural signal and noise, including complex head motion and physiological artifacts (36). Thus, these effects cannot explain the observed brain-behavior associations.

Second, our analyses were focused on examining differences between task-related and task-unrelated components of network interactions within the same individual and dataset. Thus, any contributions of head motion or physiological noise to these data will be equivalent and subtract out in any comparisons.

Third, we reanalyzed the data after controlling for several additional parameters describing various head motion properties. Specifically, we computed the number of significant movements (defined as  $>0.10$  mm relative displacement between adjacent volumes), mean head displacement, maximum head displacement, and mean head rotation, as described in ref. 34. The association between DMN-RFPN  $ni_i$  and RT values actually strengthened ( $\rho = -0.771$ ,  $P = 0.005$ ), whereas the association between RT and  $ni_s$  was virtually unchanged ( $\rho = -0.353$ ,  $P = 0.26$ ).

**S.5. Modularity Analysis.** We used graph theoretic techniques (37, 38) and modularity analysis (39–41) to characterize, in more detail, the roles that individual brain regions played in facilitating functional interactions between the DMN and RFPN. For each participant, we modeled interactions between regions comprising the DMN and RFPN as a weighted, unthresholded graph of 34 nodes connected by all possible  $(34^2 - 34)/2 = 561$  edges. In all graphs, the nodes represented the different brain regions constituting each network (20 DMN and 14 RFPN regions), and they were defined by generating 4-mm-radius spheres centered on the stereotaxic coordinates of each significant cluster maximum and submaxima in the statistically thresholded component spatial maps (Fig. 2 A and E and Table S2). Two separate graphs were constructed for each participant, representing task-unrelated and task-related interactions between regions, as estimated using the methods described above.

**Participant-specific modular decomposition.** Modularity detection algorithms enable a data-driven partition of a graph-based representation of network connectivity into subgroups of nodes, termed modules, which show higher connectivity with each other than with other areas. Identifying the optimal modular decomposition of a graph is a rich field of inquiry within complex network science, and many alternative algorithms are available (reviewed in ref. 42). Typically, these algorithms attempt to maximize some quality function reflecting the goodness of the partition. Most commonly, this function reflects the difference between the degree of observed intramodular connectivity and the degree expected by chance (40). In our analysis, we used a

generalization of this definition applicable to unthresholded, weighted, and signed graphs (39), where the goodness of the partition was given by (Eq. S2)

$$Q^* = \frac{1}{v^+} \sum_{ij} (w_{ij}^+ - e_{ij}^+) \delta_{M_i M_j} - \frac{1}{v^+ + v^-} \sum_{ij} (w_{ij}^- - e_{ij}^-) \delta_{M_i M_j}. \quad [\text{S2}]$$

In this formulation,  $w_{ij}^+$  and  $w_{ij}^-$  reflect the positive and negative connection strengths between nodes  $i$  and  $j$ , respectively, and  $\delta_{M_i M_j} = 1$  if nodes  $i$  and  $j$  belong to the same module,  $M$  ( $\delta_{M_i M_j} = 0$  otherwise). The chance-expected positive connectivity between nodes  $i$  and  $j$  is given by  $e_{ij}^+ = \frac{s_i^+ s_j^+}{v^+}$ , where  $s^+$  reflects the sum of each node's positive weights and  $v^+$  reflects the sum total of positive weights in the graph. Similarly, the chance-expected negative connectivity between nodes  $i$  and  $j$  is given by  $e_{ij}^- = \frac{s_i^- s_j^-}{v^-}$ . The factor  $\frac{1}{v^+}$  rescales the contribution of positive within-module connectivity to the range  $[0, 1]$ . The factor  $\frac{1}{v^+ + v^-}$  rescales the contribution of negative within-module connectivity in the same range, while also down-weighting the contribution of negative relative to positive weights in the final estimation of network modularity,  $Q^*$ . This asymmetric weighting is applied, because positively weighted connectivity directly associates nodes with a given module (i.e., high positive connectivity between nodes implies that they serve similar functions and should be assigned to the same module), whereas negative connection weights indirectly associate nodes with modules by dissociating them from other nodes (i.e., high negative connectivity between nodes implies that they serve opposing functions and should be placed in distinct modules, although a specific modular identity is not necessarily assigned; additional details in ref. 39). By this formulation, a graph partition maximizing  $Q^*$  will be one with high positive and low negative intramodular connectivity between nodes. We used the Louvain method (43) to find partitions optimizing  $Q^*$ , as implemented in freely available software (<https://sites.google.com/a/brain-connectivity-toolbox.net/bct/>).

Determining the optimal modular decomposition of a graph is a nontrivial (nondeterministic, polynomial-time hard) problem, and heuristics are often used to estimate the optimum solution (42). As a result, severe degeneracies in the final solution can arise; i.e., the final decomposition may represent one example of a range of alternative partitions with comparable goodness-of-fit estimates (44). To account for any potential degeneracies in our data, we iterated the algorithm 10,000 times for each dataset. Across these iterations, the number of unique partitions found was generally very low. For the task-related connectivity networks, the mode percentage of degenerate partitions found across participants was  $<0.01\%$ , and the maximum was  $1.4\%$ ; for the task-unrelated connectivity networks, the mode was  $<0.01\%$ , and the maximum was  $1.5\%$ . For all datasets, the most frequently found partition was the partition with the maximal  $Q^*$  value. These data strongly suggest that this partition represented the optimum modular decomposition for each dataset.

**Group-level representation of modular architecture.** Due to intersubject variability in brain network organization, the brain's modular structure will vary from person to person. Identifying which nodes are consistently cclassified into the same module and which nodes show a more variable pattern of module membership, therefore, represents a critical step in understanding conservation and variability of brain functional organization across subjects. To this end, we adapted previously described methods (45) to derive a group-level characterization of modular architecture. Specifically, we took the optimal modular decomposition for each subject identified in the degeneracy analysis described above and constructed a  $34 \times 34$  cclassification matrix, such that  $C_{ij} = 1$  if nodes  $i$  and  $j$

belonged to the same module and  $C_{ij} = 0$  otherwise. We then summed these matrices across subjects to generate a group consistency matrix,  $G$ . The weights of this consistency matrix,  $G_{ij}$ , reflected the number of participants for whom nodes  $i$  and  $j$  were classified in the same module (Fig. 2 B and F).

The consistency matrix  $G$  was then subjected to a further modular decomposition. Thus, nodes that were frequently cclassified in the same module across participants were more likely to belong to the same module in the decomposition of  $G$ . We iterated the algorithm 10,000 times to test for degeneracies in the data, although these degeneracies were extremely low ( $<0.01\%$  for the task-related data and 0 for the task-unrelated data), providing confidence in the robustness of the findings. The resulting partition associated with the highest  $Q^*$  value was taken as the optimum modular architecture representative of the entire sample (Fig. 2 B, C, F, and G).

**Node roles.** We characterized the roles of each individual node using cartographic analysis of the modular decomposition of  $G$  (39, 41, 46). In such an analysis, the role that each node plays within the wider network can be characterized using two measures: the within-module strength,  $z$ , and the diversity coefficient,  $h$ . The within-module strength quantifies each node's intramodular connectivity. Formally (Eq. S3),

$$z = \frac{s_i(m_i) - \bar{s}(m_i)}{\sigma^{s(m_i)}}, \quad [\text{S3}]$$

where  $m_i$  is the module containing node  $i$ ,  $s_i(m_i)$  is the intramodular nodal strength of node  $i$ , defined as the sum of the within-module weights of node  $i$ , and  $\bar{s}(m_i)$  and  $\sigma^{s(m_i)}$  are the mean and SD of the intramodular strength of all nodes in module  $m_i$ , respectively.

The diversity coefficient can be used to characterize how each node's connectivity is distributed across different modules, and it is computed as (Eq. S4)

$$h_i = \frac{1}{\log m} \sum_{u \in M} p_i(u) \log p_i(u), \quad [\text{S4}]$$

where  $p_i(u) = \frac{s_i(u)}{s_i}$ ,  $s_i(u)$  is the strength of node  $i$  in module  $u$ , and  $m$  is the number of modules in the partition  $M$ .

In typical applications, nodes with high  $z$  are interpreted to represent local, intramodular information-processing hubs, whereas nodes with high  $h$  show a relatively even distribution of connectivity across all modules (i.e., they support functional integration between modules). In our analyses, we computed these measures using edge weights derived from the group consistency matrix,  $G$ . The weights in  $G$  do not reflect a direct measure of connectivity between nodes but rather, the frequency with which two nodes were cclassified into the same module across subjects. Thus, nodes with high  $z$  in our application showed high classification consistency (i.e., a high probability of being cclassified with other nodes in the same module relative to the other nodes). Regions with high  $z$  scores therefore represent a core element of the module to which they belong, showing a relatively conserved modular identity across subjects. Because of their conserved nature, these modules are also likely to represent connectivity hubs within their module. Nodes with high  $h$  showed high classification diversity; i.e., they showed a more equal probability of being cclassified with nodes assigned to different modules because their modular identity was variable from person to person. Thus, these regions retained high levels of connectivity with nodes assigned to diverse modules across participants, consistent with a role in facilitating functional integration between modules.

We focused our analysis of node roles on the group consistency matrix data rather than individual differences in participant-specific values, because the number of modules found from subject

to subject was variable. This variability can influence resulting network measures. The best way of accounting for such variability is unclear (preliminary work in this area is in ref. 47).

**5.6. Analysis of Brain–Behavior Correlations.** Associations between network interaction values and behavioral performance during recollection trials were computed using Spearman’s rank correlation. The significance of each observed association was tested against an empirical null distribution obtained by 5,000 permutations of the data. To control type I error rates, correlations were declared significant only if they survived a Bonferroni correction of  $\alpha = 0.05/4 = 0.013$ , because interaction values between four network pairs were tested for association with each behavioral measure. Differences between correlation coefficients were tested using the Dunn and Clark statistic,  $ZI^*$  (48).

To test for associations between recollection RT and node-specific connectivity measures, we computed, for each participant, the total nodal strength of each of the 34 nodes studied in the modularity analysis (Fig. 2 and Table S2). This measure is a commonly used index of the strength of each node’s connectivity with the rest of the network, and it is formally defined as (Eq. S5)

$$s_i = \frac{1}{N-1} \sum_{j \in N} w_{ij}, \quad \text{[S5]}$$

where  $w_{ij}$  represents the absolute connectivity weight between nodes  $i$  and  $j$ , and  $N$  represents the total number of nodes.

Individual differences in the connectivity strength of each node were correlated with recollection RT using the same procedure described above. No significant associations were found, even when using a relatively liberal threshold of  $P < 0.05$ , uncorrected. Similarly, no associations were found when using strength measures computed separately for positive and negative connectivity weights. These results suggest that task performance was specifically associated with the large-scale collective dynamics of the DMN and RFPN rather than the contributions of any individual brain region.

**5.7. Results. Behavioral analysis.** RTs were significantly slower during recollection ( $M = 1,730.8$  ms;  $SD = 209.44$  ms) than semantic baseline trials [ $M = 1,090.2$  ms;  $SD = 166.89$  ms;  $t(15) = -15.82$ ,  $P < 0.001$ ], consistent with the greater demand placed on memory retrieval processes during the former condition. The variance in accuracy measures (percentage correct) during baseline trials was not sufficient to allow statistical analysis, because all participants were at ceiling (median = 0.99, interquartile range = 0.02), although it was, on average, higher than in recollection trials (median = 0.83, interquartile range = 0.10).

**Individual differences in task-related and task-unrelated network interactions.** Fig. S2 illustrates the individual variability of task-unrelated and task-related network interaction estimates for each DMN–EAS component pair. Estimates derived using raw network time courses are presented for comparison (the only processing applied to these data was a high-pass filter with a cutoff at 0.008 Hz to remove low-frequency noise). As can be seen, functional interactions between the DMN and each EAS component varied considerably across individuals and in a network- and context-specific manner.

In general, a range of positive and negative network interactions were observed for functional connectivity between the DMN and CON and DMN and RFPN, indicating that these network pairs interacted competitively for some participants and cooperatively for others. In contrast, there was a strong trend for DMN–LFPN interactions to be cooperative and DMN–DAN interactions to be competitive for most participants. These general trends were, however, modulated by whether the task-unrelated or task-related component of network interactions was

being assessed. In particular, both DMN–DAN and DMN–RFPN task-related interaction values,  $ni_t$ , were significantly higher than task-unrelated interactions,  $ni_s$ . For the DMN–DAN pair, this finding reflected an attenuation of the average degree of anticorrelation apparent in task-unrelated interactions [e.g., median  $ni_s = -0.50$ ; median  $ni_t = -0.14$ ;  $t(15) = -9.61$ ,  $P < 0.001$ ]. For the DMN–RFPN pair, the sample average functional connectivity shifted from negatively to positively correlated when moving from task-unrelated to task-related estimates [median  $ni_s = -0.10$ ; median  $ni_t = 0.11$ ;  $t(15) = -5.87$ ,  $P < 0.001$ ]. Although a range of both positive and negative values was observed for both task-unrelated and task-related DMN–RFPN interactions, this shift to more positive  $ni_t$  values is consistent with our brain–behavior correlations, suggesting that cooperative, context-dependent interactions between these networks facilitate better task performance.

DMN–CON interactions were relatively constant across task-unrelated and task-related components, suggesting relatively little contextual modulation of functional interactions between these networks. On average, interactions between the DMN and LFPN were cooperative, and there was a trend for  $ni_s$  to be higher than  $ni_t$  values [ $t(15) = 2.07$ ,  $P = 0.06$ ]. This finding highlights substantial differences in the way in which the left- and right-lateralized aspects of the frontoparietal system interact with the DMN and how these interactions are modulated by task context. This result, combined with our finding of a specific association between DMN–RFPN  $ni_t$  values and recollection RT, supports our analysis of the LFPN and RFPN as distinct functional networks.

Collectively, these results highlight three important points: (i) there is substantial individual variability in terms of whether any given pair of networks interacts competitively or cooperatively; (ii) there is considerable diversity of interactions between the DMN and different components of the EAS; and (iii) complete characterization of this diversity requires a distinction between task-related and task-unrelated components of the functional interactions between networks. In particular, interactions between the DMN and DAN and DMN and RFPN showed significant differences in task-related and task-unrelated interaction values, suggesting that functional connectivity between these network pairs was particularly affected by task performance. Reanalysis of the data using nonparametric statistics (Wilcoxon’s signed rank test) generally yielded the same results (the only notable variation was that the difference between  $ni_s$  and  $ni_t$  for DMN–LFPN interactions changed from trend-level to barely significant; i.e., from  $P = 0.06$  to  $P = 0.049$ ), indicating that outliers or violations of parametric assumptions did not drive the findings.

One concern is that the above differences reflect the global signal correction procedure implemented when estimating task-unrelated network interactions. We used this step to emulate traditional preprocessing strategies in resting-state analyses, but the procedure is known to enhance the degree of anticorrelation between DMN and EAS regions (27, 49). We therefore repeated the analyses using measures of task-unrelated network interactions that were not corrected for the global mean signal (Fig. S3). The results for comparisons between task-related and task-unrelated network interactions were similar; the major variations were that the difference between DMN–RFPN  $ni_s$  and  $ni_t$  reached significance ( $P = 0.02$ ), whereas the differences between raw and task-unrelated network interactions for the DMN–DAN and DMN–RFPN pairs were no longer significant ( $P = 0.08$  and  $P = 0.12$ , respectively). The correlation between recollection RT and DMN–RFPN  $ni_s$  was still not significant when  $ni_s$  was estimated without global signal correction. This finding was the case after correcting for covariance with signals from the CON, LFPN, and DAN components ( $\rho = -0.42$ ,  $P = 0.11$ ) as well as after correcting for covariance with all other components identified in the ICA ( $\rho = -0.06$ ,  $P = 0.83$ ).



1. Simons JS, Henson RN, Gilbert SJ, Fletcher PC (2008) Separable forms of reality monitoring supported by anterior prefrontal cortex. *J Cogn Neurosci* 20: 447–457.
2. Calhoun VD, Adali T, Pekar JJ (2004) A method for comparing group fMRI data using independent component analysis: Application to visual, motor and visuomotor tasks. *Magn Reson Imaging* 22:1181–1191.
3. Calhoun VD, Kiehl KA, Pearlson GD (2008) Modulation of temporally coherent brain networks estimated using ICA at rest and during cognitive tasks. *Hum Brain Mapp* 29: 828–838.
4. Beckmann CF, Smith SM (2004) Probabilistic independent component analysis for functional magnetic resonance imaging. *IEEE Trans Med Imaging* 23:137–152.
5. Kelly AM, Uddin LQ, Biswal BB, Castellanos FX, Milham MP (2008) Competition between functional brain networks mediates behavioral variability. *Neuroimage* 39: 527–537.
6. Smith SM, et al. (2009) Correspondence of the brain's functional architecture during activation and rest. *Proc Natl Acad Sci USA* 106:13040–13045.
7. Eichele T, et al. (2008) Prediction of human errors by maladaptive changes in event-related brain networks. *Proc Natl Acad Sci USA* 105:6173–6178.
8. Leech R, Kamourieh S, Beckmann CF, Sharp DJ (2011) Fractionating the default mode network: Distinct contributions of the ventral and dorsal posterior cingulate cortex to cognitive control. *J Neurosci* 31:3217–3224.
9. Seeley WW, et al. (2007) Dissociable intrinsic connectivity networks for salience processing and executive control. *J Neurosci* 27:2349–2356.
10. Vincent JL, Kahn I, Snyder AZ, Raichle ME, Buckner RL (2008) Evidence for a frontoparietal control system revealed by intrinsic functional connectivity. *J Neurophysiol* 100:3328–3342.
11. Dosenbach NU, et al. (2006) A core system for the implementation of task sets. *Neuron* 50:799–812.
12. Li YO, Adali T, Calhoun VD (2007) Estimating the number of independent components for functional magnetic resonance imaging data. *Hum Brain Mapp* 28: 1251–1266.
13. Harrison BJ, et al. (2008) Consistency and functional specialization in the default mode brain network. *Proc Natl Acad Sci USA* 105:9781–9786.
14. Smith EE, Jonides J, Marshuetz C, Koeppel RA (1998) Components of verbal working memory: Evidence from neuroimaging. *Proc Natl Acad Sci USA* 95:876–882.
15. Damoiseaux JS, et al. (2006) Consistent resting-state networks across healthy subjects. *Proc Natl Acad Sci USA* 103:13848–13853.
16. Friston KJ (1994) Functional and effective connectivity in neuroimaging: A synthesis. *Hum Brain Mapp* 2:56–78.
17. Fox MD, Raichle ME (2007) Spontaneous fluctuations in brain activity observed with functional magnetic resonance imaging. *Nat Rev Neurosci* 8:700–711.
18. Fransson P (2006) How default is the default mode of brain function? Further evidence from intrinsic BOLD signal fluctuations. *Neuropsychologia* 44:2836–2845.
19. Fox MD, Snyder AZ, Vincent JL, Raichle ME (2007) Intrinsic fluctuations within cortical systems account for intertrial variability in human behavior. *Neuron* 56:171–184.
20. Fox MD, Snyder AZ, Zacks JM, Raichle ME (2006) Coherent spontaneous activity accounts for trial-to-trial variability in human evoked brain responses. *Nat Neurosci* 9: 23–25.
21. Hesselmann G, Kell CA, Eger E, Kleinschmidt A (2008) Spontaneous local variations in ongoing neural activity bias perceptual decisions. *Proc Natl Acad Sci USA* 105: 10984–10989.
22. Fornito A, et al. (2011) Genetic influences on cost-efficient organization of human cortical functional networks. *J Neurosci* 31:3261–3270.
23. Glahn DC, et al. (2010) Genetic control over the resting brain. *Proc Natl Acad Sci USA* 107:1223–1228.
24. Cordes D, et al. (2001) Frequencies contributing to functional connectivity in the cerebral cortex in "resting-state" data. *AJNR Am J Neuroradiol* 22:1326–1333.
25. Van Dijk KR, et al. (2010) Intrinsic functional connectivity as a tool for human connectomics: Theory, properties, and optimization. *J Neurophysiol* 103:297–321.
26. Fox MD, et al. (2005) The human brain is intrinsically organized into dynamic, anticorrelated functional networks. *Proc Natl Acad Sci USA* 102:9673–9678.
27. Fox MD, Zhang D, Snyder AZ, Raichle ME (2009) The global signal and observed anticorrelated resting state brain networks. *J Neurophysiol* 101:3270–3283.
28. Fair DA, et al. (2007) A method for using blocked and event-related fMRI data to study "resting state" functional connectivity. *Neuroimage* 35:396–405.
29. Barnes A, Bullmore ET, Suckling J (2009) Endogenous human brain dynamics recover slowly following cognitive effort. *PLoS One* 4:e6626.
30. Harrison BJ, et al. (2008) Modulation of brain resting-state networks by sad mood induction. *PLoS One* 3:e1794.
31. Lewis CM, Baldassarre A, Committeri G, Romani GL, Corbetta M (2009) Learning sculpts the spontaneous activity of the resting human brain. *Proc Natl Acad Sci USA* 106:17558–17563.
32. Friston KJ, et al. (1997) Psychophysiological and modulatory interactions in neuroimaging. *Neuroimage* 6:218–229.
33. Gitelman DR, Penny WD, Ashburner J, Friston KJ (2003) Modeling regional and psychophysiological interactions in fMRI: The importance of hemodynamic deconvolution. *Neuroimage* 19:200–207.
34. Van Dijk KR, Sabuncu MR, Buckner RL (2012) The influence of head motion on intrinsic functional connectivity MRI. *Neuroimage* 59:431–438.
35. Power JD, Barnes KA, Snyder AZ, Schlaggar BL, Petersen SE (2012) Spurious but systematic correlations in functional connectivity MRI networks arise from subject motion. *Neuroimage* 59:2142–2154.
36. Beckmann CF, DeLuca M, Devlin JT, Smith SM (2005) Investigations into resting-state connectivity using independent component analysis. *Philos Trans R Soc Lond B Biol Sci* 360:1001–1013.
37. Rubinov M, Sporns O (2010) Complex network measures of brain connectivity: Uses and interpretations. *Neuroimage* 52:1059–1069.
38. Bullmore E, Sporns O (2009) Complex brain networks: Graph theoretical analysis of structural and functional systems. *Nat Rev Neurosci* 10:186–198.
39. Rubinov M, Sporns O (2011) Weight-conserving characterization of complex functional brain networks. *Neuroimage* 56:2068–2079.
40. Newman ME, Girvan M (2004) Finding and evaluating community structure in networks. *Phys Rev E Stat Nonlin Soft Matter Phys* 69:026113.
41. Guimerà R, Nunes Amaral LA (2005) Functional cartography of complex metabolic networks. *Nature* 433:895–900.
42. Fortunato S (2010) Community detection in graphs. *Phys Rep* 486:75–174.
43. Blondel VD, Guillaume J-L, Lambiotte R, Lefebvre E (2008) Fast unfolding of communities in large networks. *J Stat Mech-Theory E*, 10.1088/1742-5468/2008/10/P1008.
44. Good BH, de Montjoye YA, Clauset A (2010) Performance of modularity maximization in practical contexts. *Phys Rev E Stat Nonlin Soft Matter Phys* 81:046106.
45. van den Heuvel M, Mandl R, Hulshoff Pol H (2008) Normalized cut group clustering of resting-state FMRI data. *PLoS One* 3:e2001.
46. Meunier D, Achard S, Morcom A, Bullmore E (2009) Age-related changes in modular organization of human brain functional networks. *Neuroimage* 44:715–723.
47. Alexander-Bloch A, et al. (2012) The discovery of population differences in network community structure: New methods and applications to brain functional networks in schizophrenia. *Neuroimage* 59:3889–3900.
48. Steiger JH (2005) Comparing correlations: Pattern hypothesis tests between and/or within independent samples. *Contemporary Psychometrics: A Festschrift for Roderick P. McDonald*, eds Maydeu-Olivares A, McArdle J (Lawrence Erlbaum Associates Publishers, Mahwah, NJ), pp 377–414.
49. Murphy K, Birn RM, Handwerker DA, Jones TB, Bandettini PA (2009) The impact of global signal regression on resting state correlations: Are anti-correlated networks introduced? *Neuroimage* 44:893–905.

Study Phase	Test Phase
SUBJECT Laurel and Hardy	Laurel 1 = seen 2 = imagined
EXPERIMENTER bacon and ?	bacon 1 = seen 2 = imagined
SUBJECT Romeo and ?	Romeo 1 = self 2 = experimenter
EXPERIMENTER rock and roll	rock 1 = self 2 = experimenter

Fig. S1. Example of task stimuli used during the study (Left) and test (Right) phases. [Reproduced with permission from ref. 1 (Copyright 2008, MIT Press Journals).]

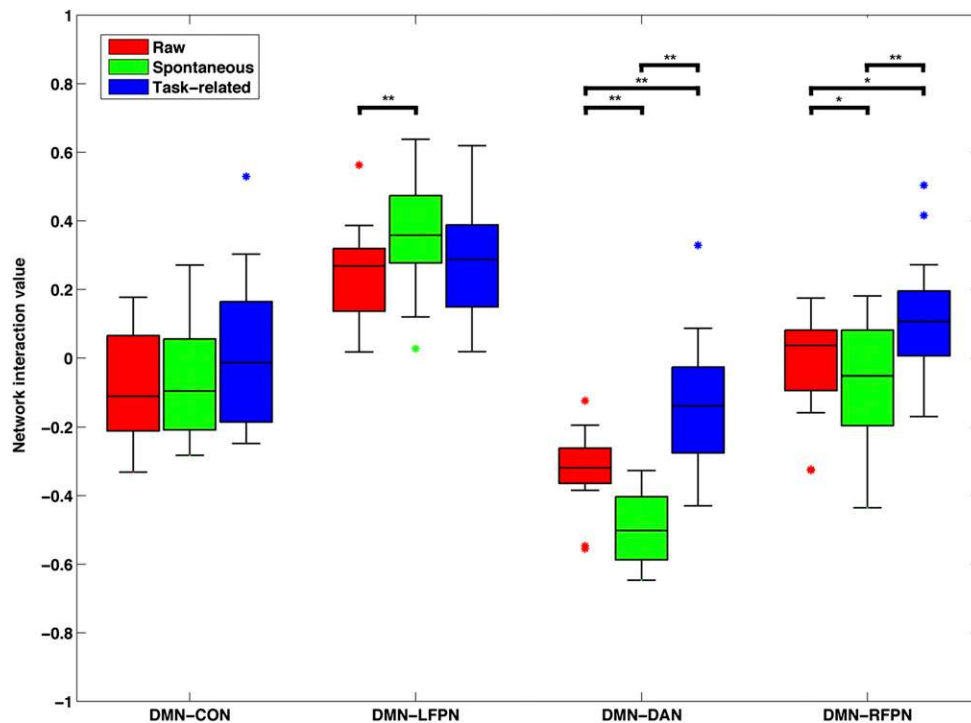
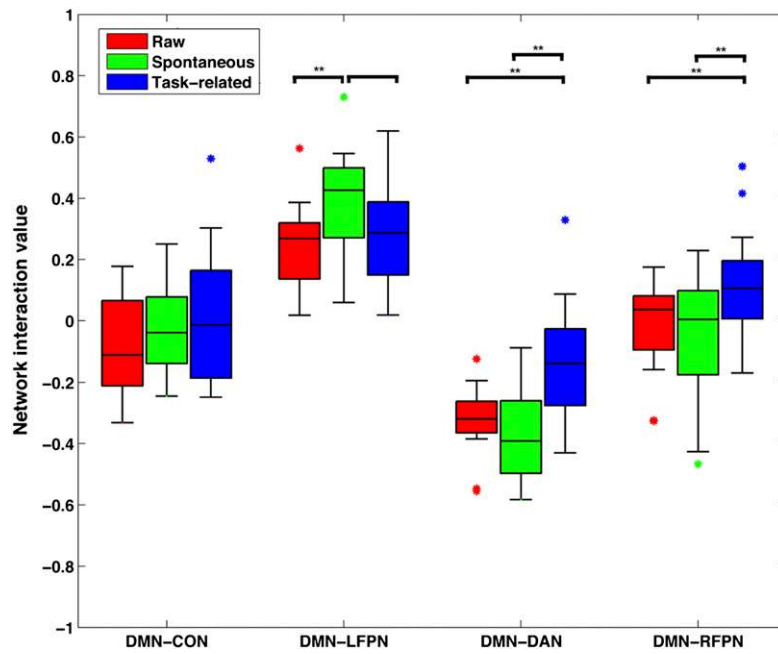
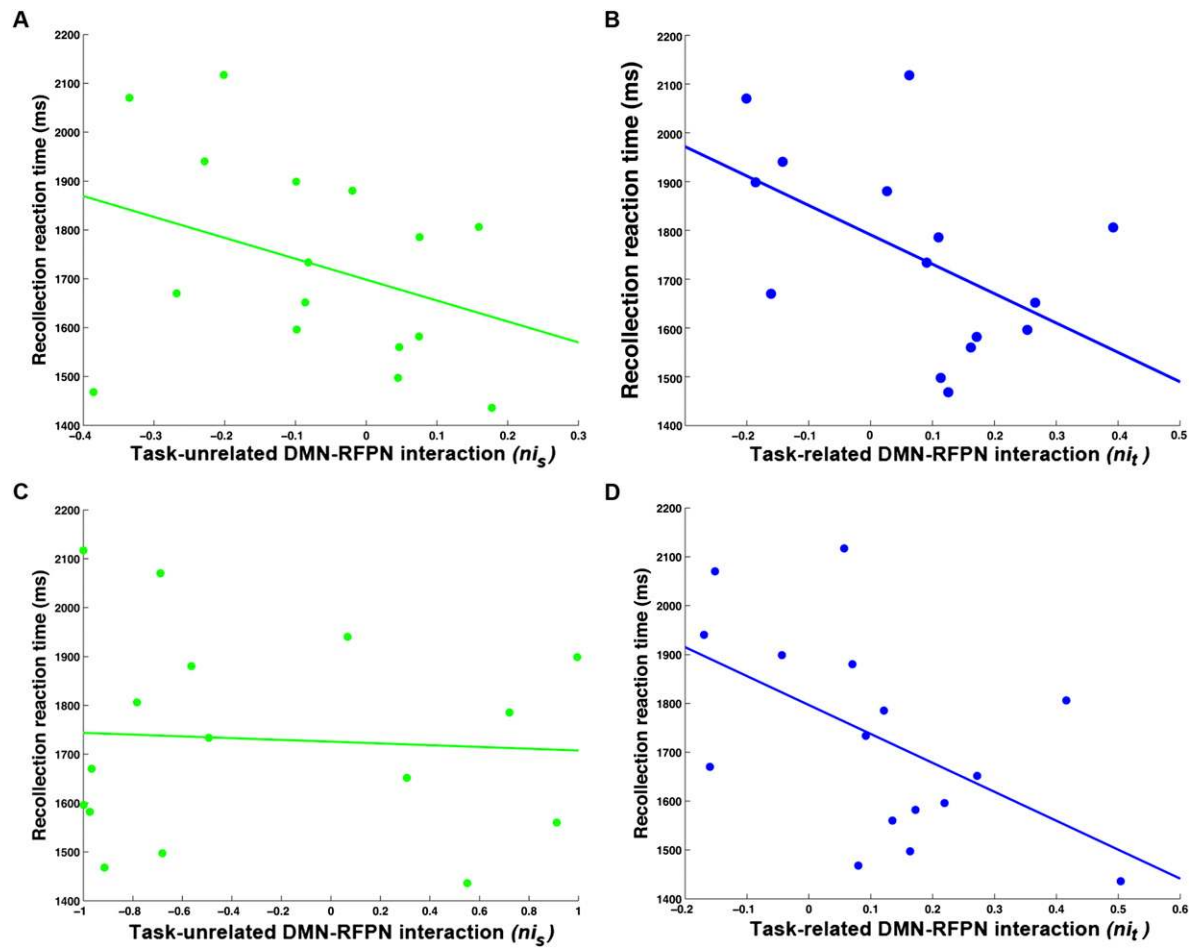


Fig. S2. Box-and-whisker plots illustrating the range of network interaction values observed for each network pair computed using raw network time courses (red), the task-unrelated, putative spontaneous component of these time courses (green), or the task-related component (blue). The central lines in each box represent the sample median, and the boxes represent the interquartile range. Whiskers mark the 5th and 95th percentiles; colored asterisks indicate values beyond this range. Thick horizontal lines indicate differences significant at  $P \leq 0.05$ . \* $P \leq 0.01$ ; \*\* $P \leq 0.001$ . CON, cinguloopercular network; DAN, dorsal attention network; DMN, default mode network; LFPN, left frontoparietal network; RFPN, right frontoparietal network.



**Fig. S3.** Box-and-whisker plots illustrating differences between raw, task-related, and task-unrelated (putative spontaneous) network interaction values, where task-unrelated interaction values have been estimated without global signal correction (raw and task-related interaction values remain unchanged from Fig. S2). The central lines in each box represent the sample median, and the boxes represent the interquartile range. Whiskers mark the 5th and 95th percentiles; colored asterisks indicate values beyond this range. Thick horizontal lines indicate differences significant at  $P \leq 0.05$ .  $**P \leq 0.001$ . CON, cingulo-opercular network; DAN, dorsal attention network; DMN, default mode network; LFPN, left frontoparietal network; RFPN, right frontoparietal network.





**Fig. S4.** Scatterplots of the association between recollection RT and DMN-RFPN interaction values. **A** shows the association between RT and task-unrelated interaction values computed after correcting for covariance with signals from the CON, DAN, and LFPN components. **B** shows the association between RT and task-related interaction values corrected in the same way. **C** and **D** show the associations between RT and task-unrelated and task-related interaction values, respectively, after correcting for covariance with signals from all other components estimated in the ICA.

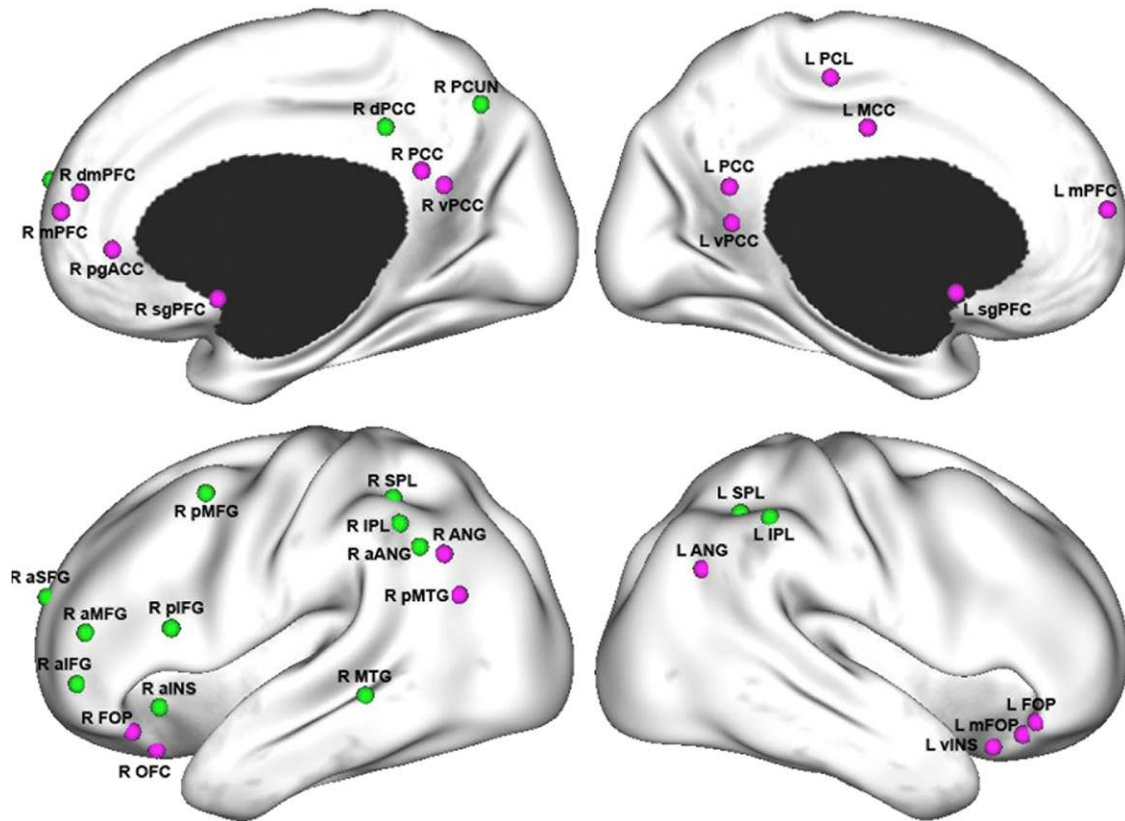


Fig. S5. Anatomical location of spherical regions of interest comprising the DMN (magenta) and RFPN (green) components as identified by the ICA.

**Table S1. Regions showing significant group-averaged functional connectivity within each ICA component**

Region	x	y	z	Size (voxels)	Z
<b>CON</b>					
L anterior insula	36	12	-3	443	7.59
R dorsal anterior cingulate cortex	3	33	27	1,188	7.40
R anterior insula	-45	12	-6	530	6.35
R midbrain	-3	-18	3	245	6.23
R caudate	15	9	15	70	6.05
L midcingulate cortex	-6	-21	33	60	5.79
R middle frontal gyrus	30	51	18	25	5.61
L precentral sulcus	-39	-3	51	25	5.35
L middle frontal gyrus	-30	51	24	40	5.22
R precentral sulcus	33	-3	54	10	5.15
<b>DAN</b>					
L intraparietal sulcus	-27	-69	39	1,093	7.30
R intraparietal sulcus	33	-45	48	926	6.72
R posterior superior temporal sulcus	51	-42	15	18	5.89
L frontal eye fields	-48	6	30	39	5.72
L dorsal precentral sulcus	-27	-6	63	30	5.50
L cuneus	-12	-102	3	11	5.22
<b>LFPN</b>					
L intraparietal lobule	-45	-66	39	818	7.19
L middle temporal gyrus	-60	-45	-6	264	6.90
L inferior frontal gyrus	-48	18	24	871	6.58
L dorsomedial prefrontal cortex	-6	36	42	267	6.45
L precuneus	-3	-63	39	29	6.00
L frontal operculum	-36	18	-18	10	5.48
L precuneus	-9	-45	39	12	5.46
<b>RFPN</b>					
R intraparietal lobule	54	-45	45	804	7.48
R precuneus	6	-72	48	72	6.92
R inferior frontal gyrus	36	48	-3	845	6.52
L superior parietal lobule	-39	-51	48	65	6.02
R anterior insula	39	24	-6	19	5.66
R dorsal posterior cingulate cortex	6	-39	39	34	5.56
R middle temporal gyurs	63	-36	-6	21	5.52
R inferior frontal gyrus	54	21	15	10	5.50
R middle frontal gyrus	21	57	24	13	5.32
<b>DMN</b>					
Anterior medial prefrontal cortex	0	63	15	2,378	>9
R posterior cingulate cortex	3	-51	27	234	6.75
L midcingulate cortex	-3	-18	39	65	6.38
R angular gyrus	54	-57	36	79	6.17
L angular gyrus	-45	-57	33	84	6
L frontal operculum	-36	27	-15	35	5.54
R frontal operculum	42	27	-15	32	5.46

CON, cinguloopercular network; DAN, dorsal attention network; DMN, default mode network; L, left hemisphere; LFPN, left frontoparietal network; R, right hemisphere; RFPN, right frontoparietal network.



**Table S2. Names and coordinates of regions of interest studied in the modularity analysis**

Region	Abbreviation*	x	y	z
<b>RFPN</b>				
L superior parietal lobule	L SPL	-39	-51	48
L inferior parietal lobule	L IPL	-51	-45	48
R dorsal posterior cingulate cortex	R dPCC	6	-39	39
R precuneus	R PCUN	6	-72	48
R anterior superior frontal gyrus	R aSFG	21	57	24
R posterior middle frontal gyrus	R pMFG	36	9	51
R anterior inferior frontal gyrus	R aIFG	36	48	-3
R anterior insula	R aINS	39	24	-6
R anterior middle frontal gyrus	R aMFG	45	45	15
R superior parietal lobule	R SPL	48	-42	51
R anterior angular gyrus	R aANG	51	-51	36
R inferior parietal lobule	R IPL	54	-45	45
R posterior inferior frontal gyrus	R pIFG	54	21	15
R middle temporal gyrus	R MTG	63	-36	-6
<b>DMN</b>				
L posterior cingulate cortex <sup>†</sup>	L PCC	-2	-57	21
L subgenual prefrontal cortex <sup>‡</sup>	L sgPFC	-2	6	-12
L medial prefrontal cortex <sup>§</sup>	L mPFC	-2	63	15
L midcingulate cortex	L MCC	-3	-18	39
L paracentral lobule	L PCL	-3	-30	51
L ventral posterior cingulate cortex	L vPCC	-6	-57	9
L ventral insula	L vINS	-30	18	-15
L middle frontal operculum	L mFOP	-36	27	-15
L angular gyrus	L ANG	-45	-57	33
L frontal operculum	L FOP	-48	27	-12
R ventral posterior cingulate cortex <sup>†</sup>	R vPCC	2	-57	21
R subgenual prefrontal cortex <sup>‡</sup>	R sgPFC	2	6	-12
R medial prefrontal cortex <sup>§</sup>	R mPFC	2	63	15
R posterior cingulate cortex	R PCC	3	-51	27
R pregenual anterior cingulate cortex	R pgACC	3	48	3
R dorsomedial prefrontal cortex	R dmPFC	3	54	21
R orbitofrontal cortex	R OFC	33	21	-21
R frontal operculum	R FOP	42	27	-15
R angular gyrus	R ANG	54	-57	36
R posterior middle temporal gyrus	R pMTG	54	-63	21

DMN, default mode network; L, left hemisphere; R, right hemisphere; RFPN, right frontoparietal network.

\*Abbreviations correspond to the region of interest (ROI) abbreviations used in Fig. 2.

<sup>†,‡,§</sup>These regional pairs were created from an original single cluster maximum located at  $x = 0$ . To avoid generating an ROI centered on the midline, where CSF is prevalent, two ROIs were instead created and symmetrically placed 2 mm from the midline with the same  $y$  and  $z$  coordinates.