The control of brain network dynamics across diverse scales of space and time

Evelyn Tang, Graham L. Baum, David R. Roalf, Theodore D. Satterthwaite, Fabio Pasqualetti, and Danielle S. Bassett

The human brain is composed of distinct regions that are each associated with particular functions and distinct propensities for the control of neural dynamics. However, the relation between these functions and control profiles is poorly understood, as is the variation in this relation across diverse scales of space and time. Here we probe the relation between control and dynamics in brain networks constructed from diffusion tensor imaging data in a large community based sample of young adults. Specifically, we probe the control properties of each brain region and investigate their relationship with dynamics across various spatial scales using the Laplacian eigenspectrum. In addition, through analysis of regional modal controllability and partitioning of modes, we determine whether the associated dynamics are fast or slow, as well as whether they are alternating or monotone. We find that brain regions that facilitate the control of energetically easy transitions are associated with activity on short length scales and fast time scales. Conversely, brain regions that facilitate control of difficult transitions are associated with activity on long length scales and slow time scales. Built on linear dynamical models, our results offer parsimonious explanations for the activity propagation and network control profiles supported by regions of differing neuroanatomical structure.

The brain is an inherently networked system that displays incredibly rich and complex dynamics [1, 2]. Building accurate models of those dynamics remains a key challenge that is fundamental to the field of neuroscience, with the potential to inform personalized medicine by predicting a patient’s disease progression and response to therapy [3–6]. Efforts to build such models necessarily depend on the development of interdisciplinary approaches informed by dynamical systems theory, statistical physics, and network science as well as substantial knowledge of the intricacies of the underlying biology [7]. Because of the multiscale nature of the system [8, 9], there are some regimes of function or modalities of measurement whose dynamics are well-fit by one mathematical model and others whose dynamics are well-fit by another mathematical model [2, 10–12]. On the one hand, large-scale measurements of brain activity can display a wave-like nature and other characteristics consistent with linear, diffusive dynamics instantiated on a physically embedded system [13, 17]. On the other hand, fine time scale measurements of brain activity can display oscillatory characteristics consistent with nonlinear, synchronization dynamics thought to support distributed communication and computation [18–21].

Evidence for the first type of dynamics comes, for example, from studies of both large- and small-scale neuronal processes whose intrinsic or endogeneous activity can be partially explained by simple linear models [13, 14]. Moreover, wave-like activity has been observed using functional magentic resonance imaging (fMRI) in the visual cortex, where traveling wave responses to visual stimuli are observed to propagate out from the fovea [10]. Notably, such traveling waves with various timescales have been observed across different regions of the brain [22], and it has been posited that the direction and wavelength of the wave could encode information transmitted between regions [23]. In addition to the outward propagation of activity, spiral waves also occur frequently in the neocortex in vivo, both during pharmacologically induced oscillations and during sleep-like states [24], while seizures may manifest as recurrent spiral waves that propagate in the neocortex [17].

Such multiplicity of phenomena motivates the use of dynamical models that emphasize the spatially embedded nature of brain networks [25], and the extended versus transient responses that embedding can support [26]. An example is the use of finite element modeling to simulate the propagation of brain stimulation [27, 28], where effects are distributed on a localized part of brain tissue [29]. Another example is that of diffusive models, where network diffusion over long time scales has been used to model disease progression in the brain for dementia [15], or to predict longitudinal patterns of atrophy and metabolism in Alzheimer’s disease [30].

Evidence for the second type of dynamics comes from studies of both large- and small-scale ensembles that produce rhythmic or oscillatory activity [18, 19, 51]. For example, scalp electrodes in humans can be used to measure rhythms of certain frequencies, which in turn have been associated with different cognitive processes and behav-
ioral responses [20, 21]. For example, attentional control via the inhibition of behaviorally irrelevant stimuli and motor responses has been associated with the synchronization of $\alpha$ and $\beta$ rhythms between right inferior frontal and primary sensory neocortex [32]. Similarly, higher frequency $\gamma$ rhythms in local synchronization have been observed during visual responses, while lower frequency $\beta$ rhythms reflecting coherence over parietal and temporal cortices have been observed during activities that required more multi-modal sensory integration [33]. Initial efforts sought to explain such phenomena using a simple neuronal model with conduction delays, where excitatory units describe pyramidal cells and inhibitory units describe interneurons [34]. More recent work suggests that the $\beta$ rhythms specifically can emerge from the integration of nearly synchronous bursts of excitatory synaptic drive targeting proximal and distal dendrites of pyramidal neurons, where the defining feature of a $\beta$ event was a strong distal drive to supragranular and infragranular layers of cortex that lasted one $\beta$ period [35]. Notably, the laminar architecture of the neocortical network has also proven critical for explaining $\gamma$ rhythms [36].

Although empirical studies find pervasive evidence of these two distinct types of dynamics, there is little theoretical framework to model how the spatiotemporal characteristics of these dynamics can inform the control properties of specific brain regions, which are interconnected by a fixed structural network. To address this question, recent efforts have begun to study how such distinct dynamics can be guided or controlled by local energy input [37]. For the control of those features of the dynamics that are well-approximated by linear systems theory, efforts have stipulated a linear model of the dynamics dependent upon the structural network implicit in white matter connectivity [38, 39]. This framework of network control has been useful to understand brain anatomy and regional function across multiple species including the nematode C. elegans [40], the fly Drosophila [41], the mouse [42], the macaque [43], and the human [44]. Network control theory has also been used to explore the control profiles of brain regions based on their network connectivity [45], and hence to map control propensities onto to canonically understood cognitive functions [38] [42, 44] and their alterations in psychiatric disorders [45]. For the control of those features of the dynamics that require nonlinear systems theory, network control is more difficult [46, 47], but some initial work has begun to assess the utility of control principles for seizure abatement [39] and to determine routes along which information can be propagated by transient synchrony [20, 21]. In extending these ongoing efforts, a key challenge remains to build models that can predict not only the generic control properties of a system, but also the length scales over which control-induced dynamics will propagate, and to link these length scales to the time scales of dynamical transitions or control of activity enacted by regional drivers.

Here, we perform initial numerical experiments to address this challenge by relating new developments in the linear control of regional activity in brain networks and their predicted time scales, with the length scales implicit in nonlinear dynamical models of inter-regional synchronization. We use the framework of network control [48] to probe the relation between control and dynamics in brain networks constructed from diffusion tensor imaging data in a young adult subset of the Philadelphia Neurodevelopmental Cohort, a large community based sample of youth [49, 50]. Use of this large sample allows us to probe relations between control and dynamics in an ensemble of brain networks in which control propensities vary extensively [12]. The paper is organized as follows. Following a description of the formalism in Sec. I, we turn in Sec. II to a review of network controllability metrics and their predictions regarding the control profiles of certain brain regions (see the Appendix for details regarding brain network construction from neuroimaging data). In Sec. III, we consider metrics for the characterization of spatial scales of synchronization in network dynamics [51] and for the control of such synchronization [52]. In Sec. IV, we consider metrics for the characterization of temporal scales of control in network dynamics, specifically assessing the role of modal controllers in driving transient versus extended temporal modes of brain activity [53]. In Sec. V, we compare the relation between control of time scales and control of length scales that we observe in brain networks to those that we observe in networks constructed via the rules of preferential attachment, gaining insight into the dependence of spatiotemporal control on the underlying topology. In Sec. VI, we place our findings within the broader context of empirical results from neuroimaging experiments. We also discuss the implications of our findings for our understanding of how various controllers are associated with distinct types of dynamics, and in turn how distinct dynamics are associated with different regional controllers. We close with a brief discussion of potential future directions.

I. MATHEMATICAL FRAMEWORK

In this section, we describe a formalism for building network models of brain architecture and states, and for studying network controllability of brain dynamics.

A. Network models of brain architecture and states

Here, we study 190 brain networks describing the white matter connectivity of youth in the Philadelphia Neurodevelopmental Cohort. For each network composed of $N = 234$ cortical and subcortical brain regions, $A \in \mathbb{R}^{N \times N}$ is a symmetric and weighted adjacency matrix whose elements indicate the number of white matter streamlines connecting two different brain regions indexed with $(i, j)$. For further details regarding the construction of brain networks from neuroimaging data see the Appendix, and for prior work in this data set see
Average controllability provides an intuitive measure of the structural support for moving the brain to easy-to-reach states. Modal controllability provides an intuitive measure of the structural support for moving the brain to difficult-to-reach states. (b) Diffusion tensor imaging measures the direction of water diffusion in the brain. From this data, white matter streamlines can be reconstructed that connect brain regions over time, and the size of the vector $x$ is given by $N$, and the value of $x$ describes the brain activity of that region.

B. Network controllability of brain dynamics

To assess controllability of this networked system, we must first ensure its stability and define input points for the injection of control energy. We note first that the diagonal elements of the matrix $A$ satisfy $A_{ij} = 0$. Next we note that to assure Schur stability, we divide the matrix by $1 + \xi_0(A)$, where $\xi_0(A)$ is the largest singular value of $A$. The input matrix $B_K$ identifies the control points $K$ in the brain, where $K = \{k_1, \ldots, k_m\}$ and

$$B_K = [e_{k_1} \cdots e_{k_m}],$$

and $e_i$ denotes the $i$-th canonical vector of dimension $N$. The input $u_K : \mathbb{R}_{\geq 0} \rightarrow \mathbb{R}^m$ denotes the control strategy.

We can now study the controllability of this dynamical system, which refers to the possibility of driving the state of the system to a specific target state by means of an external control input $u_K$ in the brain. Classic results in control theory ensure that controllability of the network [1] from the set
of nodes $\mathcal{K}$ is equivalent to the controllability Gramian $W_K$ being invertible, where

$$W_K = \sum_{\tau=0}^{\infty} A^\tau B_K B_K^T A^\tau. \quad (3)$$

Consistent with [57, 22, 44, 45], we use this framework to choose control nodes one at a time, and thus the input matrix $B_K$ in fact reduces to a one-dimensional vector, e.g., $B_K = (1 \ 0 \ 0 \ ...)^T$ when the first brain region is the control node. In this case, $\mathcal{K}$ simply describes this control node, i.e. the controllability Gramian can be indexed by the $i$-th control node that it describes: $W_i$.

II. CONTROLLABILITY METRICS FOR BRAIN NETWORKS

Within the network controllability framework, we study two different control strategies that describe the ability to move the network into different states defined as patterns of regional activity. Intuitively, average controllability describes the ease of transition to many states nearby on an energy landscape, while modal controllability describes the ease of transition to a state distant on this landscape (see Fig. 1b).

**Average controllability** of a network equals the average input energy from a set of control nodes and over all possible target states. As a known result, average input energy is proportional to $\text{Trace}(W_K^{-1})$, the trace of the inverse of the controllability Gramian. Instead and consistent with [57, 42, 44], we adopt $\text{Trace}(W_K)$ as a measure of average controllability for two main reasons: first, $\text{Trace}(W_K^{-1})$ and $\text{Trace}(W_K)$ satisfy a relation of inverse proportionality, so that the information obtained from the two metrics are correlated with one another and, second, $W_K$ is typically very ill-conditioned even for coarse network resolutions, so that $\text{Trace}(W_K^{-1})$ cannot be accurately computed even for small brain networks. It should be noted that $\text{Trace}(W_K)$ encodes a well-defined control metric, namely the energy of the network impulse response or, equivalently, the network $H_2$ norm [57]. As discussed above, when a brain region $i$ serves as a control node, the resulting Gramian can be indexed as $W_i$, in order to compute the regional average controllability.

**Modal controllability** refers to the ability of a node to

---

**Figure 2: Synchronizability and the spatial extent of predicted oscillatory modes.** (a) Spatial distribution of the eigenvector $\phi_i$ for the smallest Laplacian eigenvalue $\lambda_1$, showing which regions on a group-averaged brain network most strongly contribute to this large-scale mode. (b) Spatial distribution of the eigenvector $\phi_{N-1}$ for the largest Laplacian eigenvalue $\lambda_{N-1}$, showing which regions most strongly contribute to this small-scale mode. (c) Regions most relevant for this large-scale mode $|\phi_1^i|$ are positively correlated with regions of high modal controllability: $r = 0.27$, $df = 233$, $p < 1 \times 10^{-4}$. (d) Regions most relevant for this small-scale mode $|\phi_{N-1}^i|$ are positively correlated with regions of high average controllability: $r = 0.90$, $df = 233$, $p < 1 \times 10^{-5}$. 

---
control each time-evolving mode of a dynamical network, and can be used to identify states that are difficult to control from a set of control nodes. Modal controllability is computed from the eigenvector matrix \( V = [v_{ij}] \) of the network adjacency matrix \( A \). By extension from the PBH test \([57]\), if the entry \( v_{ij} \) is small, then the \( j \)-th mode is poorly controllable from node \( i \). Following \([58]\), we define

\[
\phi_i = \sum_j (1 - \xi_j^2(A))v_{ij}^2,
\]

as a scaled measure of the controllability of all \( N \) modes \( \xi_0(A), \ldots, \xi_{N-1}(A) \) from the brain region \( i \) allowing the computation of regional modal controllability. Regions with high modal controllability are able to control all of the dynamics of the network, and hence to drive the dynamics towards hard-to-reach configurations.

We study these metrics in the 190 structural brain networks derived from diffusion tensor imaging data (see Fig. 1). On a group-representative brain network constructed by averaging all 190 subject-specific networks, we calculate these controllability metrics and show their distribution across the brain (see Fig. 1c.i). Consistent with prior work in this and other data sets \([38, 42]\), we find that regions with high average controllability tend to be located in network hubs associated with the default-mode system, a set of regions that tend to be active during intrinsic processing. Interestingly and again consistent with prior work in this and other data sets \([38, 42, 45, 59]\), regions with high modal controllability tend to display low average controllability (see Fig. 1c.ii), and are predominantly found in regions of the brain that become active during tasks that demand high levels of executive function or cognitive control.

### III. Controllability of Spatial Scales: Network Dynamics in Harmonic Waves

To complement efforts in the previous section to study the control of brain state transitions via a simple linear model of network dynamics, here we turn to the question of how to control the synchrony of oscillatory states which naturally arise from the same underlying white matter architecture. Notably, extensive prior work in the dynamical systems literature has considered ways in which to measure the synchronizability of a networked system. To be clear, here we define the synchronizability as a measure of the ability of a network to persist in a single synchronous state \( s(t) \), i.e. \( x_1(t) = \ldots = x_n(t + 1) = s(t) \). The master stability function (MSF) allows analysis of the stability of this synchronous state without detailed specification of the properties of the dynamical units (see Fig. 1h; \([53]\)). Within this framework, linear stability depends upon the positive eigenvalues \( \{\lambda_i\}, i = 1, \ldots, N - 1 \) of the Laplacian matrix \( L \) defined by \( L_{ij} = \delta_{ij} \sum_k A_{ik} - A_{ij} \).

![Figure 3: Extracting fast or slow, and alternating or monotone modes of network dynamics. Here we show the histogram of \( N = 234 \) eigenvalues of the group representative brain network, constructed by averaging all 190 subject-specific brain networks. We make partitions of \( |\xi_j| < 0.2, 0.2 < |\xi_j| < 0.6, \) and \( |\xi_j| > 0.6 \) for the positive and negative eigenvalues, respectively, which correspond to the monotone and alternating modes of the system. From left to right, these groups are \( \xi_j < -0.6 \) (fast alternating), \( -0.2 < \xi_j < 0 \) (slow alternating), \( 0 < \xi_j < 0.2 \) (slow monotone), and \( \xi_j > 0.6 \) (fast monotone) respectively.](image)

For the purposes of control, it is useful to note that the structure of the graph Laplacian provides information regarding the most likely modes of oscillatory dynamics: the vibrational states of an oscillating system in which the frequency of vibration is the same for all elements. These modes are given by the eigenvectors of the graph Laplacian. For example, the eigenvector \( \phi_1 \) of the smallest positive Laplacian eigenvalue \( \lambda_1 \) is an odd mode associated with large-scale oscillations \([53]\) (Fig. 2a). In contrast, the eigenvector \( \phi_{N-1} \) of the largest Laplacian eigenvalue \( \lambda_{N-1} \) is an even mode associated with small-scale oscillations (Fig. 2b). Recent developments in push-pull control capitalize on these relations to control the transition into and out of synchrony by targeting network nodes that have a large weight for a given extremal eigenvector of the Laplacian \([52]\).

To investigate the control of synchrony in the oscillatory dynamics of brain networks, we calculate the eigenvectors of the Laplacian for each subject, and then average the eigenvectors across all of the 190 subjects. We observe that the strength of control for oscillatory modes of a network can be understood in terms of the network’s predisposition to average and modal control. First, we observe that the regional strength of the large-scale oscillations \( |\phi_1^2| \) is positively correlated with regional modal controllability (Spearman correlation coefficient \( \rho = 0.27, df = 233, p < 1 \times 10^{-4}; \) Fig. 2c). This relation suggests that regions that enable synchronous behavior over long distances are also predicted to be effective in moving the brain to energetically distant states (see a list of the highest and lowest such regions in Table 4 of the Appendix). Second, we observe that the
The regional strength of the small-scale oscillations $|\phi_{N-1}^i|$ is positively correlated with regional average controllability (Pearson’s correlation coefficient $r = 0.90$, $df = 233$, $p < 1 \times 10^{-5}$; Fig. 2). This relation suggests that regions that enable synchronous behavior over short distances are also predicted to be effective in moving the brain to energetically nearby states (see a list of the highest and lowest such regions in Table I of the Appendix).

IV. CONTROLLABILITY OF TEMPORAL SCALES: NETWORK DYNAMICS IN FAST OR SLOW, ALTERNATING OR MONOTONE MODES

To complement the findings reported in the previous section explicating the spatial scales of control, we next turn to a consideration of the time scales of control. We note that in a discrete-time system, the eigenvalues of the network adjacency matrix $A$ give the rate of decay of the various supported modes of activity. In particular, the eigenvalues with large magnitude decay quickly while the eigenvalues with small magnitude decay slowly. The relationship between eigenvalues and the rate of decay of associated modes of activity suggests that the control of such modes can be analyzed separately for different time scales. While our prior expression for modal controllability (Eq. 4) summed over all $N$ modes of the adjacency matrix $A$, we can instead partition the sum into different groups based on the eigenvalues $\xi_j$ of the modes. For instance, a region $i$ can be evaluated for its controllability of slow modes with $\phi_i^{\text{slow}} = \sum_{j}^{\text{small}} \xi_j v_{ij}^2$, and for its controllability of fast modes with $\phi_i^{\text{fast}} = \sum_{j}^{\text{large}} \xi_j v_{ij}^2$. Note that in the above expression we have also removed the scaling factor in Eq. 4 of $(1 - \xi_j^2(A))$ as this factor is unnecessary for the calculation of control time-scales; in supporting calculations, we also verified that the inclusion or exclusion of this factor does not alter our subsequent findings.

To investigate regional propensities for the control of fast versus slow modes, we considered the group-representative network constructed by averaging all 190 subject-specific brain networks. We examined the spectrum of this representative network (see Fig. 3), and partitioned the eigenvalues into three groups that differed in their relevant time scales: $|\xi_j| < 0.2$ (slow), $0.2 < |\xi_j| < 0.6$ (medium), and $|\xi_j| > 0.6$ (fast). Now, it is also important to note that eigenvalues carry additional information: the sign of the eigenvalue determines the nature of the system’s response, where a mode with a positive eigenvalue decays monotonically with each time step, while a mode with a negative eigenvalue has a decaying response that alternates between positive and neg-
that support for slow monotone dynamics (eigenvalues \( \xi_j < -0.6 \)), showing which regions on a group-representative brain network most strongly contribute. Similarly, we find that support for fast alternating dynamics (eigenvalues \( -0.2 < \xi_j < 0 \)), showing which regions on a group-representative network most strongly contribute. Moreover, we find that the degree to which a regional controller supports fast alternating dynamics is strongly and positively correlated with regional average controllability (Spearman correlation coefficient \( \rho \approx 0.59, df = 233, p < 1 \times 10^{-4} \); Fig. 5c), providing support for energetically more difficult state transitions.

When studying the control of alternating dynamics, we find that support for fast alternating dynamics (eigenvalues \( \xi_j < -0.6 \)) differs across the brain with greatest support located in the temporoparietal junction, inferior frontal gyrus, and precuneus (Fig. 5c; see a list of the highest and lowest such regions in Table IV of the Appendix). In addition, we find that the degree to which a regional controller supports slow monotone dynamics is strongly and positively correlated with regional average controllability (Spearman correlation coefficient \( \rho = 0.83, df = 233, p < 1 \times 10^{-4} \); Fig. 5b), providing support for energetically easy state transitions. Lastly, we also find that support for slow alternating dynamics (eigenvalues \( -0.2 < \xi_j < 0 \)) differs across the brain with greatest support located in several midline structures (Fig. 5d; see a list of the highest and lowest such regions in Table VI of the Appendix). In this case, we find that the degree to which a regional controller supports slow alternating dynamics is strongly and positively correlated with regional modal controllability (Spearman correlation coefficient \( \rho = 0.24, df = 233, p < 2 \times 10^{-5} \)).
used in the brain network, i.e. groups of $|\xi_j| < 0.2$, $0.2 < |\xi_j| < 0.6$, and $|\xi_j| > 0.6$ for both positive and negative eigenvalues, respectively (see Fig. 6). Interestingly, we find that the distribution of eigenvalues differs significantly in the Barabasi-Albert network in comparison to the group-representative brain network, with the striking absence of fast alternating modes. When we consider only the slow alternating modes, we observe that the relationship between the controllers of these slow modes and the modal controllers is inverted in the Barabasi-Albert network in comparison to the group-representative brain network (see Fig. 7). In the brain, the degree to which a regional controller supports slow alternating dynamics tracks the degree to which that same regional controller supports energetically more difficult transitions. In the Barabasi-Albert network, the degree to which a regional controller supports slow alternating dynamics is anti-correlated with the degree to which that same regional controller supports energetically more difficult transitions (Spearman correlation coefficient $\rho = -0.91$, $df = 233$, $p < 1 \times 10^{-4}$).

VI. DISCUSSION

The human brain displays a variety of different types of dynamics. Here we use two different models to compare the control profiles of various brain regions: diffusion dynamics and network control, respectively. Through these analyses we find that brain regions with high average controllability are also predicted to effectively control dynamics on short length scales, while regions of high modal controllability are predicted to do the converse. In addition, regions of high average controllability are also predicted to effectively control dynamics on fast scales, while regions of high modal controllability are predicted to do the converse. Our findings that certain regions enable fast dynamics on short scales, while others have the opposite profile, are consistent with EEG recordings which demonstrate that $\gamma$ rhythms (higher frequency) are associated with local synchronization, while $\beta$ rhythms (lower frequency) are associated with long-distance coherence between parietal and temporal cortices [20]. The work provides a mechanistic explanation of these empirical findings based on the architecture of underlying structural connectivity estimated from white matter. Collectively, our results expand our understanding of the relations between brain network dynamics and control, and the relative roles that different brain regions can play in controlling the diverse length and time scales of neural dynamics.

Pertinent Theoretical Considerations. There are two important theoretical considerations relevant to our work: the relation between linear and nonlinear network control, and the nature of the Master Stability Function. Regarding the first, we note that while the brain certainly displays non-linear activity, modelling of brain activity in large-scale regional networks shows that the
linear approximation provides fair explanatory power of resting state fMRI BOLD data. Further, studies of this controllability framework using non-linear oscillators connected with coupling constants estimated from large-scale white matter structural connections shows a good overlap with the linear approximation. While the model we employ is a discrete-time system, this controllability Gramian is statistically similar to that obtained in a continuous-time system, through the comparison of simulations run using MATLAB’s `lyapunov` function. Regarding the second, we note that we have plotted a typical example of a Master Stability Function (MSF) for a network of oscillators schematically in Fig. 1; however, specific details will depend on the dynamics of individual nodes and the connectivity between them. The shape of the MSF for various families of dynamical systems is typically convex for generic oscillator systems, including chaotic oscillators that have stable limit cycles.

Future Directions. Our work provides an initial foray into the combined study of brain network dynamics and control, and how the two depend upon the length scales and time scales of brain states and state transitions. From a mathematical perspective, it would be interesting to study these relations in other graph models with different topologies, and also to work to find analytical forms for the relations we observe in numerical experiments. From a neurophysics perspective, future efforts could extend our work into other age groups, or into clinical groups of patients with psychiatric disease or neurological disorders where such relations might be altered. Efforts could also determine whether our findings in humans are recapitulated in other animals, and across different spatial resolutions of imaging data. Another avenue for further investigation could be the use of directed brain networks, such as those that are available from tract-tracing studies of macaques, which would display complex eigenvalues thereby providing additional oscillatory time-scales for more extensive study.

VII. ACKNOWLEDGEMENTS

D.S.B. and E.T. acknowledge support from the John D. and Catherine T. MacArthur Foundation, the Alfred P. Sloan Foundation, the ISI Foundation, the Paul Allen Foundation, the Army Research Laboratory (W911NF-10-2-0022), the Army Research Office (Bassett-W911NF-14-1-0679, Grafton-W911NF-16-1-0474, DCIST-W911NF-17-2-0181), the Office of Naval Research, the National Institute of Mental Health (2-R01-DC-009209-11, R01 MH112847, R01-MH107235, R21-M MH-106799), the National Institute of Child Health and Human Development (1R01HD086888-01), National Institute of Neurological Disorders and Stroke (R01 NS099348), and the National Science Foundation (BCS-1441502, BCS-1430087, NSF PHY-155488 and BCS-1631550). The content is solely the responsibility of the authors and does not necessarily represent the official views of any of the funding agencies.
VIII. APPENDIX

All data were acquired from the Philadelphia Neurodevelopmental Cohort (PNC), a large community-based study of brain development. This resource is publicly available through the Database of Genotypes and Phenotypes. Each subject provided their informed consent according to the Institutional Review Board of the University of Pennsylvania who approved all study protocols. These subjects had no gross radiological abnormalities that distorted brain anatomy, no history of inpatient psychiatric hospitalization, no use of psychotropic medications at the time of scanning, and no medical disorders that could impact brain function. Each included subject also passed both manual and automated quality-assessment protocols for DTI [68] and T1-weighted structural imaging [69], and had low in-scanner head motion (less than 2mm mean relative displacement between $b=0$ volumes). Here we study a subset of the full group previously reported in [42]; specifically, we consider the 190 young adults aged 18 to 22 years.

Structural connectivity was estimated using 64-direction DTI data. The diffusion tensor was estimated and deterministic whole-brain fiber tracking was implemented in DSI Studio using a modified FACT algorithm, with exactly 1,000,000 streamlines initiated per subject after removing all streamlines with length less than 10mm [38]. A 234-region parcellation [70] was constructed from the T1 image using FreeSurfer. Parcels were dilated by 4mm to extend regions into white matter, and registered to the first non-weighted ($b=0$) volume using an affine transform. Edge weights $A_{ij}$ in the adjacency matrix were defined by the number of streamlines connecting each pair of nodes end-to-end. All analyses were replicated using an alternative edge weight definition, where weights are equal to the number of streamlines connecting each node pair divided by the total volume of the node pair, as well as using probabilistic fiber tracking methods. A schematic for structural connectome construction is depicted in Fig. 1b.

### TABLE I: Brain regions with highest and lowest weights for the largest-scale Laplacian eigenvector (Fig. 2a)

| Highest | Lowest |
|---------|--------|
| Postcentral 6 (L) | Brainstem (L) |
| Supramarginal 2 (L) | Precentral 1 (L) |
| Supramarginal 3 (L) | Superior frontal 8 (L) |
| Supramarginal 1 (L) | Caudate (L) |
| Postcentral 7 (L) | Postcentral 1 (L) |

### TABLE II: Brain regions with highest and lowest weights for the smallest-scale Laplacian eigenvector (Fig. 2b)

| Highest | Lowest |
|---------|--------|
| Brainstem (L) | Postcentral 6 (L) |
| Precentral 6 (R) | Postcentral 7 (L) |
| Postcentral 5 (R) | Supramarginal 3 (L) |
| Thalamus proper (R) | Supramarginal 2 (L) |
| Thalamus proper (L) | Postcentral 1 (R) |

### TABLE III: Brain regions that provide the highest and lowest support for the control of fast monotone dynamics (Fig. 4a)

| Highest | Lowest |
|---------|--------|
| Brainstem (L) | Postcentral 6 (L) |
| Precentral 6 (R) | Superior temporal 1 (L) |
| Thalamus proper (R) | Supramarginal 3 (L) |
| Thalamus proper (L) | Banks STS 1 (L) |
| Superior frontal 8 (L) | Transverse temporal 1 (R) |

### TABLE IV: Brain regions that provide the highest and lowest support for the control of slow monotone dynamics (Fig. 4b)

| Highest | Lowest |
|---------|--------|
| Superior frontal 8 (R) | Brainstem (L) |
| Middle temporal 4 (L) | Superior frontal 8 (L) |
| Insula 2 (L) | Thalamus proper (L) |
| Transverse temporal 1 (L) | Thalamus proper (R) |
| Superior temporal 2 (R) | Precentral 6 (R) |

### TABLE V: Brain regions that provide the highest and lowest support for the control of fast alternating dynamics (Fig. 5a)

| Highest | Lowest |
|---------|--------|
| Brainstem (L) | Rostral middle frontal 2 (L) |
| Precentral 6 (R) | Lateral orbitofrontal 1 (L) |
| Postcentral 5 (R) | Precuneus 2 (R) |
| Precentral 3 (L) | Banks STS 1 (L) |
| Precentral 2 (L) | Inferior parietal 3 (L) |

### TABLE VI: Brain regions that provide the highest and lowest support for the control of slow alternating dynamics (Fig. 5b)

| Highest | Lowest |
|---------|--------|
| Lateral occipital 3 (R) | Brainstem (L) |
| Lateral occipital 1 (R) | Thalamus proper (L) |
| Precuneus 2 (L) | Superior frontal 8 (L) |
| Lingual 3 (L) | Thalamus proper (R) |
| Accumbens area (L) | Superior frontal 5 (R) |
[1] D. S. Bassett and O. Sporns, Nat Neurosci 20, 353 (2017).
[2] M. Breakspear, Nat Neurosci 20, 340 (2017).
[3] K. Bansal, J. Nakuci, and S. F. Muldoon, Curr Opin Neurobiol 52, 42 (2018).
[4] T. Proix, F. Bartolomei, M. Guye, and V. K. Jirsa, Brain 140, 641 (2017).
[5] M. I. Falcon, V. Jirsa, and A. Soloedkin, Curr Opin Neurol 29, 429 (2016).
[6] M. Schirner, S. Rothmeier, V. K. Jirsa, A. R. McIntosh, and P. Ritter, Neuroimage 117, 343 (2015).
[7] D. S. Bassett, P. Zurn, and J. I. Gold, Nat Rev Neurosci Epub Ahead of Print (2018).
[8] M. Breakspear and C. J. Stam, Philos Trans R Soc Lond B Biol Sci 360, 1051 (2005).
[9] R. F. Betz and D. S. Bassett, Neuroimage 160, 73 (2017).
[10] K. J. Friston, Annu Rev Psychol 56, 57 (2005).
[11] K. Friston, PLoS Comput Biol 4, e1000211 (2008).
[12] G. Deco, V. K. Jirsa, P. A. Robinson, M. Breakspear, and K. Friston, PLoS Comput Biol 4, e1000092 (2008).
[13] C. J. Honey, O. Sporns, L. Cammoun, X. Gigandet, J. P. Thiran, R. Meuli, and P. Hagmann, Proc Natl Acad Sci U S A 106, 2035 (2009).
[14] R. Fernández Galán, PLoS One 3, e2148 (2008).
[15] A. Raj, A. Kuceyeski, and M. Weiner, Neuron 73, 1204 (2012).
[16] K. M. Aquino, M. M. Schira, P. A. Robinson, P. M. Drysdale, and M. Breakspear, PLOS Computational Biology 8, 1 (2012).
[17] J. Viventi, D.-H. Kim, L. Vigeland, E. S. Frehette, J. A. Blanco, Y.-S. Kim, A. E. Avrin, V. R. Tiruvad, S.-W. Hwang, A. M. Vanleer, D. F. Wulsin, K. Davis, C. E. Gelber, L. Palmer, J. Van der Spiegel, J. Wu, J. Xiao, Y. Huang, D. Contraseras, J. A. Rogers, and B. Litt, Nature Neuroscience 14, 1599 (2011).
[18] N. J. Kopell, H. J. Gritton, M. A. Whittington, and M. A. Kramer, Neuron 83, 1319 (2014).
[19] P. Fries, Neuron 88, 220 (2015).
[20] A. Palmigiano, T. Geisel, F. Wolf, and D. Battaglia, Nat Neurosci 20, 1014 (2017).
[21] C. Kirst, M. Timme, and D. Battaglia, Nat Commun 7, 11061 (2016).
[22] L. Muller, F. Chavane, J. Reynolds, and T. J. Sejnowski, Nature Reviews Neuroscience 19, 255 (2018) review Article.
[23] S. Heitmann, T. Boonstra, and M. Breakspear, PLOS Computational Biology 9, 1 (2013).
[24] X. Huang, W. Xu, J. Liang, K. Takagaki, X. Gao, and J. young Wu, Neuron 68, 978 (2010).
[25] J. Stiso and D. S. Bassett, arXiv 1807, 04691 (2018).
[26] R. Chaudhuri, K. Knoblauch, M.-A. Gariel, H. Kennedy, and X.-J. Wang, Neuron 88, 419 (2015).
[27] A. Cancelli, C. Cotton, F. Tecchio, D. Q. Truong, J. Dmochowski, and M. Bikson, Journal of Neural Engineering 13, 036022 (2016).
[28] S. Lopes, N. Davies, C. Toumazou, and N. Grossman, in 2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society (2012) pp. 4152–4155.
[29] M. K. Metwally, Y. S. Cho, H. J. Park, and T. S. Kim, in 2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society (2012) pp. 5514–5517.
[30] A. Raj, E. LoCastro, A. Kuceyeski, D. Tosun, N. Relkin, and M. Weiner, Cell Reports 10, 359 (2015).
[31] S. R. Jones, Curr Opin Neurobiol 30, 72 (2016).
[32] M. D. Sacchet, R. A. LaPlante, Q. Wan, D. L. Pritchett, A. K. Lee, M. Hamalainen, C. I. Moore, C. E. Kerr, and S. R. Jones, J Neurosci 35, 2074 (2015).
[33] A. von Stein, P. Rappelsberger, J. Sarnthein, and H. Petsche, Cerebral Cortex 9, 137 (1999).
[34] N. Kopell, G. B. Ermentrout, M. A. Whittington, and R. D. Traub, Proceedings of the National Academy of Sciences 97, 1867 (2000).
http://www.pnas.org/content/97/4/1867.full.pdf.
[35] M. A. Sherman, S. Lee, R. Law, S. Haegens, C. A. Thorn, M. S. Hamalainen, C. I. Moore, and S. R. Jones, Proc Natl Acad Sci U S A 113, E4885 (2016).
[36] S. Lee and S. R. Jones, Front Hum Neurosci 7, 869 (2013).
[37] E. Tang and D. S. Bassett, Rev. Mod. Phys. 90, 031003 (2018).
[38] S. Gu, F. Pasqualetti, M. Cieslak, Q. K. Telesford, B. Y. Alfred, A. E. Kahn, J. D. Medaglia, J. M. Vettel, M. B. Miller, S. T. Grafton, et al., Nature communications 6 (2015).
[39] P. N. Taylor, J. Thomas, N. Sinha, J. Dauwels, M. Kaiser, T. Thesen, and J. Ruths, Front Neurosci 9, 202 (2015).
[40] G. Yan, P. E. Vértes, E. K. Towlson, Y. L. Chew, D. S. Walker, W. R. Schafer, and A.-L. Barabási, Nature 550, 519523 (2017).
[41] J. Z. Kim, J. M. Soffer, A. E. Kahn, J. Vettel, F. Pasqualetti, and D. S. Bassett, Nat Phys 14, 91 (2018).
[42] E. Tang, C. Giusti, G. L. Baum, S. Gu, E. Pollock, A. E. Kahn, D. R. Roalf, T. M. Moore, K. Ruparel, R. C. Gur, R. E. Gur, T. D. Satterthwaite, and D. S. Bassett, Nat Commun 8, 1252 (2017).
[43] F. Pasqualetti, S. Zampieri, and F. Bullo, IEEE Transactions on Control of Network Systems 1, 40 (2014).
[44] E. J. Cornblath, E. Tang, G. L. Baum, T. M. Moore, A. Adelbinpe, D. R. Roalf, R. C. Gur, R. E. Gur, F. Pasqualetti, T. D. Satterthwaite, and D. S. Bassett, Neuroimage 188, 122 (2018).
[45] J. Jeganathan, A. Perry, D. S. Bassett, G. Roberts, P. B. Mitchell, and M. Breakspear, Neuroimage Clin 19, 71 (2018).
[46] A. E. Motter, Chaos 25, 097621 (2015).
[47] S. F. Muldoon, F. Pasqualetti, S. Gu, M. Cieslak, S. T. Grafton, J. M. Vettel, and D. S. Bassett, PLoS Comput Biol 12, e1005076 (2016).
[48] Y.-Y. Liu and A.-L. Barabási, Rev. Mod. Phys. 88, 035006 (2016).
[49] T. D. Satterthwaite, J. J. Connolly, K. Ruparel, M. E. Calkins, C. Jackson, M. A. Elliott, D. R. Roalf, K. P. Ryan Hopsona, M. Behr, H. Qiu, F. D. Mentch, R. Chivacci, P. M. Steinman, R. C. Gur, H. Hakonarson, and R. E. Gur, Neuroimage 124, 1115 (2016).
[50] M. E. Calkins, K. R. Merikangas, T. M. Moore, M. Burstein, M. A. Behr, T. D. Satterthwaite, K. Ruparel, D. H. Wolf, D. R. Roalf, F. D. Mentch, H. Qiu,
R. Chiavacci, J. J. Connolly, P. M. A. Sleiman, R. C. Gur, H. Hakonarson, and R. E. Gur, J Child Psychol Psychiatry 56, 1356 (2015).

[51] S. Atasoy, I. Donnelly, and J. Pearson, Nature Communications 7, 10340 (2016).

[52] Z. He, X. Wang, G.-Y. Zhang, and M. Zhan, Phys. Rev. E 90, 012909 (2014).

[53] L. M. Pecora and T. L. Carroll, Phys. Rev. Lett. 80, 2109 (1998).

[54] G. L. Baum, R. Ciric, D. R. Roalf, R. F. Betzel, T. M. Moore, R. T. Shinohara, A. E. Kahn, S. N. Vandekar, P. E. Rupert, M. Quarmley, P. A. Cook, M. A. Elliott, K. Ruparel, R. E. Gur, R. C. Gur, D. S. Bassett, and T. D. Satterthwaite, Curr Biol 27, 1561 (2017).

[55] G. L. Baum, D. R. Roalf, P. A. Cook, R. Ciric, A. F. G. Rosen, C. Xia, M. A. Elliott, K. Ruparel, R. Verma, B. Tunc, R. C. Gur, R. E. Gur, D. S. Bassett, and T. D. Satterthwaite, Neuroimage 173, 275 (2018).

[56] R. E. Kalman, Y. C. Ho, and K. S. Narendra, Contributions to Differential Equations 1, 189 (1963).

[57] T. Kailath, Linear systems, Vol. 1 (Prentice-Hall Englewood Cliffs, NJ, 1980).

[58] F. Pasqualetti, S. Zampieri, and F. Bullo, Control of Network Systems, IEEE Transactions on 1, 40 (2014).

[59] E. Wu-Yan, R. F. Betzel, E. Tang, S. Gu, F. Pasqualetti, and D. S. Bassett, J Nonlinear Sci Epub Ahead of Print 1 (2018).

[60] E. Bullmore and O. Sporns, Nat Rev Neurosci 13, 336 (2012).

[61] D. S. Bassett and E. T. Bullmore, Neuroscientist Epub ahead of print (2016).

[62] D. S. Bassett and E. Bullmore, Neuroscientist 12, 512 (2006).

[63] R. F. Betzel, J. D. Medaglia, and D. S. Bassett, Nat Commun 9, 346 (2018).

[64] R. Albert and A.-L. Barabasi, Reviews of Modern Physics 74, 47 (2002).

[65] D. J. d. S. Price, Journal of the American Society for Information Science 27, 292 (1976).

[66] A. L. Barabasi and R. Albert, Science 286, 509 (1999).

[67] L. Huang, Q. Chen, Y.-C. Lai, and L. M. Pecora, Phys. Rev. E 80, 036204 (2009).

[68] D. R. Roalf, M. Quarmley, M. A. Elliott, T. D. Satterthwaite, S. N. Vandekar, K. Ruparel, E. D. Gennatas, M. E. Calkins, T. M. Moore, R. Hopson, K. Prabhakaran, C. T. Jackson, R. Verma, H. Hakonarson, R. C. Gur, and R. E. Gur, Neuroimage 125, 903 (2016).

[69] S. N. Vandekar, R. T. Shinohara, A. Raznahan, D. R. Roalf, M. Ross, N. DeLeo, K. Ruparel, R. Verma, D. H. Wolf, R. C. Gur, R. E. Gur, and T. D. Satterthwaite, The Journal of Neuroscience 35, 599 (2015).

[70] A. Daducci, S. Gerhard, A. Griffa, A. Lemkaddem, L. Cammoun, X. Gigandet, R. Meuli, P. Hagmann, and J.-P. Thiran, PLoS ONE 7, 1 (2012).