

# Relationships between cortical myeloarchitecture and electrophysiological networks

Benjamin A. E. Hunt<sup>a</sup>, Prejaas K. Tewarie<sup>a</sup>, Olivier E. Mougin<sup>a</sup>, Nicolas Geades<sup>a</sup>, Derek K. Jones<sup>b</sup>, Krish D. Singh<sup>b</sup>, Peter G. Morris<sup>a</sup>, Penny A. Gowland<sup>a</sup>, and Matthew J. Brookes<sup>a,1</sup>

<sup>a</sup>Sir Peter Mansfield Imaging Centre, School of Physics and Astronomy, University of Nottingham, Nottingham NG7 2RD, United Kingdom; and <sup>b</sup>Cardiff University Brain Research Imaging Centre, School of Psychology, Cardiff CF24 4HQ, United Kingdom

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**The human brain relies upon the dynamic formation and dissolution of a hierarchy of functional networks to support ongoing cognition. However, how functional connectivities underlying such networks are supported by cortical microstructure remains poorly understood. Recent animal work has demonstrated that electrical activity promotes myelination. Inspired by this, we test a hypothesis that gray-matter myelin is related to electrophysiological connectivity. Using ultra-high field MRI and the principle of structural covariance, we derive a structural network showing how myelin density differs across cortical regions and how separate regions can exhibit similar myeloarchitecture. Building upon recent evidence that neural oscillations mediate connectivity, we use magnetoencephalography to elucidate networks that represent the major electrophysiological pathways of communication in the brain. Finally, we show that a significant relationship exists between our functional and structural networks; this relationship differs as a function of neural oscillatory frequency and becomes stronger when integrating oscillations over frequency bands. Our study sheds light on the way in which cortical microstructure supports functional networks. Further, it paves the way for future investigations of the gray-matter structure/function relationship and its breakdown in pathology.**

network | functional connectivity | myelination | magnetoencephalography | MRI

The way in which integration of functionally specific brain regions supports ongoing cognition is one of the most important questions in neuroscience, and noninvasive in vivo imaging provides a tool to investigate this interregional connectivity in terms of both brain function and structure. Functional connectivity refers to statistical interdependencies between patterns of brain “activity” measured at separate cortical locations (1) and, even in the “resting state,” measured spontaneous brain activity defines non-random networks that are related to cognitive processes (2). The way in which these functional networks are supported by structural white-matter pathways is reasonably well understood (3). However, it is likely that the structure–function association extends to gray-matter morphology, for which fundamental understanding is lacking. Structural morphology of the cortex is known to vary significantly between individuals, and does so in an organized fashion. For example, individuals with a high cortical volume in Broca’s area typically exhibit high cortical volume in Wernicke’s area, reflecting a language network (4). Similar observations can be made between other associated cortical regions (5, 6). This is known as structural covariance (7–9) and it allows the formation of matrices showing how structural properties of individual brain regions covary over subjects. In this paper, we assess structural covariance based upon cortical myeloarchitecture and probe its relationship to functional networks that are assessed based upon measured spontaneous brain activity.

Noninvasive mapping of cortical myeloarchitecture (10, 11) has grown in popularity in recent years, fueled by an increased interest in myelination-based parcellation (12). The general finding is that primary sensory cortices tend to be heavily myelinated whereas regions associated with multisensory integration are less myelinated

(10, 13). More localized spatial changes in myelination also exist; for example, subtle subdivisions between regions are apparent in visual (14, 15), somatosensory (16), and auditory (17) cortices. There is evidence of cross-species changes in myelination (18), with the brains of nonhuman primates more heavily myelinated than those of humans. Although still unproven, findings suggest that cortical myelin may inhibit plasticity; for example, early sensory areas may require less plasticity, and therefore more myelin, whereas higher-order areas have less myelination, which might enable greater plasticity (10). Cortical myelination has been shown to change throughout development, and is not established fully until the third decade of life (19, 20). However, no studies have yet used myelin mapping to examine structural covariance or the link between a cortical myelin network and functional connectivity. Previous work does show a direct link between myeloarchitecture and function (21–23). For example, a recent study (24) showed that optogenetic stimulation directed to increase neuronal firing in premotor cortex of mice promotes oligodendrogenesis and therefore myelination, thus providing a link between neuroelectrical activity and myeloarchitecture. Further work (25) suggests that the amount of cortical myelin in a region predicts the magnitude of electrophysiological responses. Taken together, the evidence converges to a hypothesis that, if neuronal firing acts to shape the spatial signature of myeloarchitecture, then networks reflecting the brain’s primary pathways of functional connectivity should be predictive of structural networks of intracortical myelin.

Magnetoencephalography (MEG) characterizes electrical activity in the brain via measurement of extracranial magnetic fields (26). The MEG signal from any one brain region is dominated by neural oscillations (rhythmic changes in electrical activity) that are observable in the 1- to 200-Hz frequency range. Evidence suggests that these oscillations represent an intrinsic process by which both

## Significance

**This paper identifies a significant relationship between cortical myeloarchitecture and functional connectivity in the human brain. This is a significant step toward understanding the role of myelin in shaping large-scale neural networks. Our results extend recent work showing that electrical activity promotes myelination and add significant weight to the argument that neural oscillations are a core mediator of brain connectivity.**

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Data deposition: MEG and MT adjacency matrices have been deposited at [www.figshare.com](http://www.figshare.com) and can be found with DOI: [10.6084/m9.figshare.4056441](https://doi.org/10.6084/m9.figshare.4056441).

<sup>1</sup>To whom correspondence should be addressed. Email: [matthew.brookes@nottingham.ac.uk](mailto:matthew.brookes@nottingham.ac.uk).

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short- and long-range functional connections in the brain are maintained. With this in mind, a growing body of work has begun to show that, via appropriate modeling of MEG data, networks of electrophysiological functional connectivity can be mapped (27–29). The rich temporal complexity of MEG signals means that multiple ways to characterize functional connectivity exist (30). However, one of the most robust methods is amplitude envelope correlation (AEC), which probes temporal relationships between the envelope of oscillations, in a frequency band of interest, at spatially separate brain regions. Our previous work has shown that this intrinsic mechanism of (noninvasively measured) electrophysiological coupling underpins many of the observable resting state networks (RSNs) (27, 31). Given that these measurements represent the principal long-range functional connections in the brain, and given the evidence that electrical activity mediates myelination, we hypothesized that networks of oscillatory envelope correlation, measured between parcellated regions and in multiple frequency bands, would allow prediction of a network of structural covariance representing myeloarchitecture.

## Results

Fifty-eight volunteers ( $39 \pm 12$  y old, 27 male) took part in the study. Using ultra-high field MRI, we measured magnetization transfer (MT) (32) across the brain, which serves as a marker of myelin. These measurements were parcellated into 64 cortical regions according to the automated anatomical labeling (AAL) atlas (Table S1) and normalized by region volume to give myelin density estimates. Following this, assessment of structural covariance between all possible AAL region pairs allowed derivation of a network matrix showing the degree to which separate (AAL) regions exhibit similarities in their myeloarchitecture (see *SI Further Analyses* and Fig. S1 for an alternative methodology). The same individuals also underwent resting-state MEG acquisition. MEG data were parcellated according to the same atlas, and RSNs characterizing functional connectivity, between all possible AAL region pairs, were derived using AEC in five frequency bands. With the aid of a recently developed framework (31), we then characterized the relationship between the structural network, representing myelin density, and functional networks, representing the major pathways of electrophysiological communication.

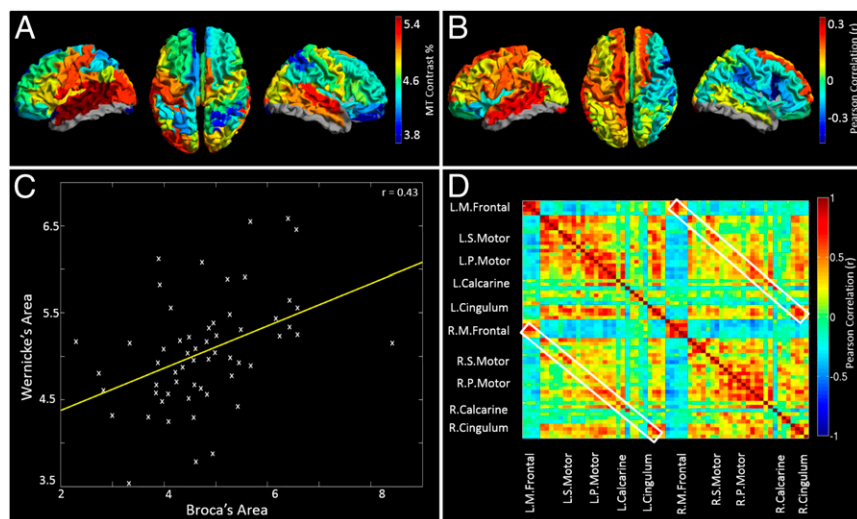
**Myelin Maps.** Fig. 1A shows the measured MT, averaged across subjects and plotted for all AAL regions. Red corresponds to high myelin density, blue indicates low myelin density, and gray shows regions where scan coverage was insufficient to gain an accurate

estimate. High myelination was observed in primary sensory cortices, with statistical tests showing that this spatial variation was significant; for example, significantly ( $P < 0.001$ ) higher myelination was found in primary motor cortex compared with the dorsolateral prefrontal cortex. A hemispheric division was also noted with significantly ( $P < 0.01$ ) higher MT in left compared with right sensorimotor cortex. Fig. 1B maps the cortical variation of correlation between myelin density and handedness (the latter measured using the Edinburgh Handedness Inventory). A positive correlation denotes regions where right handers have more myelin than left handers; a negative correlation denotes regions where left handers have more myelin than right-handed individuals. Note a significant ( $P < 0.05$ ) split in the polarity of the correlation between hemispheres.

**MT Structural Covariation.** The principle of structural covariance and the structural network are shown in Fig. 1C and D, respectively. Fig. 1C shows correlation across subjects between myelin concentrations measured in left frontal inferior operculum (capturing Broca's area) and left supramarginal gyrus (encompassing Wernicke's area). Results show a significant ( $P < 0.001$ ) positive correlation across subjects. Equivalent correlations can be derived between all possible AAL region pairs, and results are shown in Fig. 1D. Note that structural covariance between adjacent AAL regions is generally denoted by matrix elements close to the leading diagonal, whereas structural covariance between distal regions is represented far from the diagonal. The white boxes show structural covariance between homologous regions.

**MEG Networks.** MEG functional connectivity matrices are shown in Fig. 2. All networks are represented by a matrix similar to that in Fig. 1D. The 3D brains display all connections within 5% of the maximum value. It is clear that network structure differs between bands: Theta oscillations support connections in frontal occipital and parietal areas whereas alpha band-mediated connections are predominantly occipital. The beta band shows more widespread connectivity but is dominated by parietal and occipital connections. The low-gamma band was dominated by a sensorimotor network.

**The Relationship Between Structural Covariance and MEG.** Fig. 3A shows a “seed-based” structural covariance map (i.e., a single column in the matrix in Fig. 1D). Here, a seed region has been placed in right inferior parietal cortex; high values depict brain areas that show high structural covariance to the seed. A cross-hemispheric pattern is observable with high structural covariance between homologous regions. Fig. 3B shows the equivalent seed-based map



**Fig. 1.** In vivo myelination measures and the structural network. (A) Mean MT contrast percentage for all AAL regions. High MT is reflective of high myelination. Note high levels of myelination in primary cortical regions. (B) Correlation between MT and handedness. Positive correlations show regions where myelin is higher in right handers. Negative correlations show regions where myelin is higher in left handers. (C) Example plot showing correlation over subjects between MT measured in the AAL regions capturing Broca's and Wernicke's areas. These correlations are the basis of the structural network. (D) The myelin structural network, represented as a matrix. Each element denotes cross-subject correlation in MT between two brain regions.





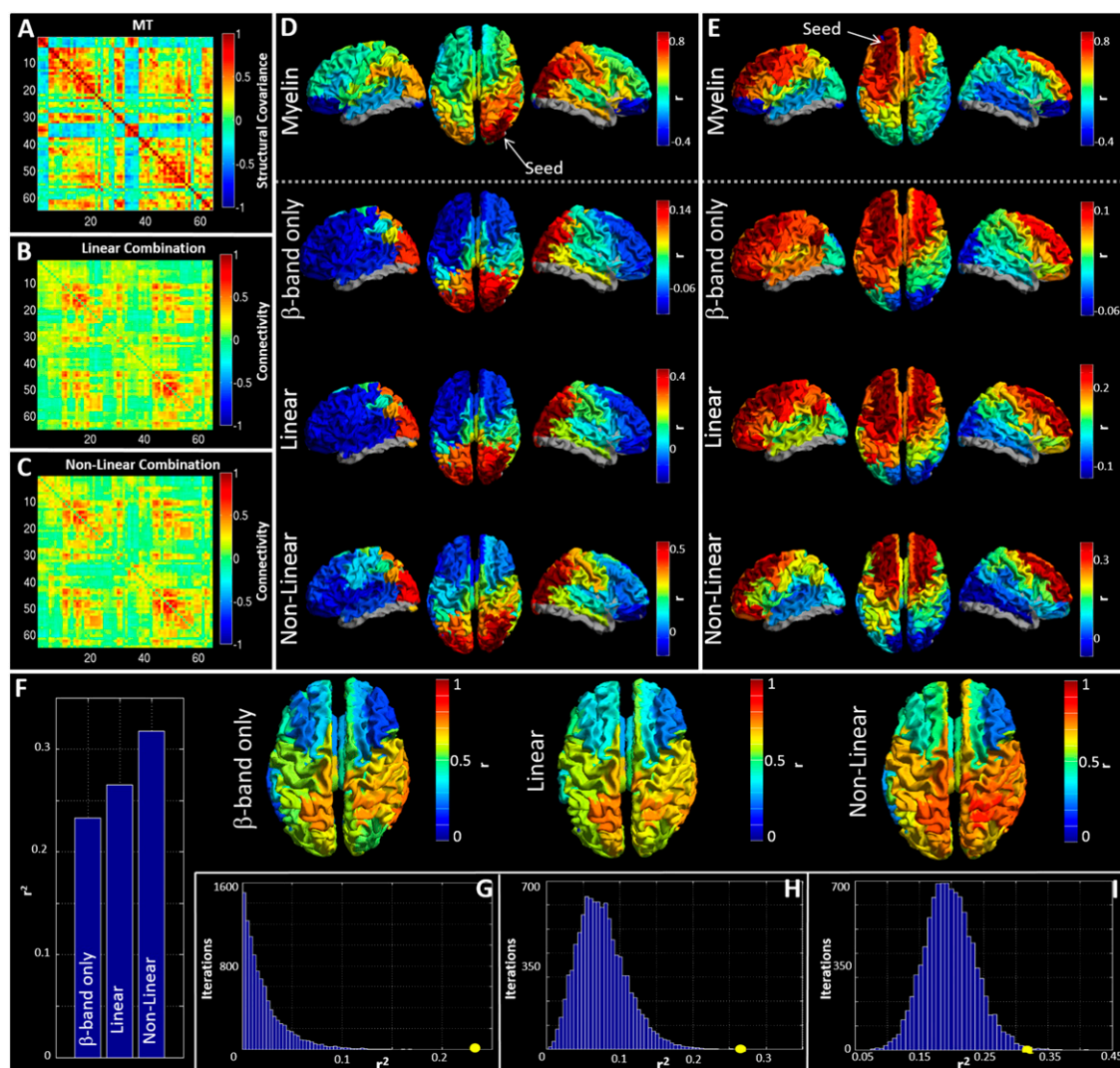
images show seed regions for which structural covariance is best predicted by the functional networks. Fig. 4 *G–I* show the  $r^2$  values plotted alongside their representative null distributions. In all cases, correlation between the structural network and MEG networks falls outside the null distribution. Note also that this relationship gets stronger when allowing integration over frequency bands.

## Discussion

Although recent years have seen significant progress in mapping the human connectome, the relationship between functional networks and cortical microstructure remains poorly understood. A recent study (24) in animals suggests that electrical activity promotes myelination. We therefore reasoned that, if functional networks represent major pathways of electrophysiological communication, then those pathways should shape myeloarchitecture and a significant relationship between functional connectivity and myelin should be observable. Our results support this, with significant correlation between the structural network and functional networks mediated by neural oscillations in the beta and low-gamma bands.

This relationship became stronger when integrating MEG networks across frequency bands, suggesting that myeloarchitecture supports networks at all measurable electrophysiological timescales.

The fact that our functional networks are measured directly using electrophysiological imaging (as distinct from indirectly using hemodynamics) adds an extra (frequency) dimension to our study. In the past, neural oscillations were largely ignored in favor of measurements of evoked responses. However, the last decade has seen a surge of interest, showing these oscillations to be an integral feature of brain function. Recent work suggests that oscillations gate information flow in the cortex (33) and implies that oscillations are an intrinsic form of functional coupling (34). Measurable connectivity depends critically on the frequency band studied; indeed, this is shown in Fig. 2 with marked spatial differences between bands. The fact that the relationship between functional networks and myelin was strongest in the beta band is not surprising given that previous work (27, 31) has shown that beta oscillations mediate long-range connections in a large number of RSNs (see also *SI Further Analyses*, *Functional Connectivity*



**Fig. 4.** Predicting myelination based on integrated MEG networks. (A–C) Matrices representing (A) the MT network, (B) the best linear combination of MEG frequency bands to estimate MT, and (C) the best nonlinear prediction of MT. (D and E) Seed-based visualizations of structural and functional networks with seed regions in right lateral visual cortex (D) and left superior frontal cortex (E). The lower three rows show beta band and the linear and nonlinear predictions of the MT network (Top). (F)  $r^2$  values describing goodness-of-fit between structure and function for the best-fitting single frequency band (beta) and predictions based upon linear and nonlinear combinations of MEG frequency bands. The inset images show the seed regions driving these correlations. (G–I) The  $r^2$  values (circles) plotted against the null distributions for the beta band (G) linear (H) and nonlinear (I) combinations.

and Myeloarchitecture in RSNs and Fig. S2). The ubiquitous nature of beta-mediated connections is therefore the likely reason why the structural network correlates best with this band. However, it should be pointed out that an inherent problem with MEG is signal-to-noise ratio (SNR), which drops with increasing frequency; it is possible that, at high frequency, the drop in correlation between functional connectivity and myeloarchitecture reflects this SNR limitation. This said, the significant improvement in prediction when combining frequency bands does imply that oscillations across all timescales relate significantly to myelin structure. Interestingly, the addition of nonlinear terms also improved prediction; given that these additional terms represent brain regions that share common connections it is tempting to suggest that shared connectivity also affects myeloarchitecture.

Our estimation of myelin was based upon measurement of MT. Although serving as an efficient marker of myelination, it is important to note that there is no one-to-one relation between MT and myelin density. Further, if the present method was to be used in pathology care should be taken because the MT/myelin relationship may break down. Nevertheless, our results are in agreement with others, showing that the highest myelin concentration occurs in sensorimotor, auditory, and visual cortices. This finding supports an argument that myelin acts as a means to increase the speed of processing and inhibit plasticity in these primary sensory areas. On average, there was more myelin in left sensorimotor cortex than in right, and this likely reflects the fact that our cohort was biased toward right handers. In agreement with this, the hemispheric split shown in Fig. 1B suggests that this finding is reversed in left handers, implying that brain structure evolves to increase the speed of processing in the dominant hemisphere. Although such asymmetries in myelin have not been previously reported, associated asymmetries in function and structure have been shown previously both in humans (35–37) and animals (38). A potential limitation of our methods is that myelin concentration was parcellated according to the AAL atlas. Although this parcellation allowed derivation of network graphs that could be compared with MEG, the regional parcellation afforded by the AAL atlas does not take into account known differences in myelin signature throughout the cortex. In future studies, a brain parcellation based upon myeloarchitecture (as distinct from cytoarchitecture) would be of high value (12). Although our study is unique in characterizing structural covariance based upon myelin density, previous work has shown that structural covariance networks can also be formed based on macroscopic properties such as cortical thickness (4), and further that such networks correlate with functional connectivity (39). Here, myelin content was normalized by region volume, meaning that our finding of correlation between a structural network and functional connectivity is not related trivially to the previous finding on cortical thickness. However, the question of how myelin density relates to cortical thickness remains, and this should be the topic of future work.

Given that the primary role of myelin is to increase the speed at which nerve impulses travel through neuronal pathways, it is intuitive that cortical myelination is shaped to support functional networks because this will act to maximize the efficiency of their formation. More speculative, however, is the process by which this structural support network evolves. Given that electrical activity on some particular pathway induces myelination, and given that RSNs emerge as early as the third trimester of gestation (40), it is tempting to argue that even before birth myeloarchitecture is being shaped by functional connectivity. Of course, the resulting structural changes would, in turn, refine functional connections and so the likelihood is that changes in myeloarchitecture and functional networks are linked intimately. This notion is supported by the fact that both myelination and functional connectivity change on a similar timescale throughout neurodevelopment. In the present study, our data preclude direct investigation of this interplay between structure and function. However, our study does

pave the way for new investigations of this process via longitudinal studies of development. In addition, studies investigating how changing behavior alters both structure and function are becoming popular. This idea is not new (41), and recent evidence (42) suggests that both white-matter and gray-matter structure changes, even on a relatively fast timescale, when learning new skills. This research area would benefit from the use of tools presented here. Perhaps more importantly, our results have implications for future studies of disorders, in particular those involving demyelination or dysconnectivity. For example, gray-matter atrophy, lesions, and demyelination are a better correlate of physical disability and cognitive decline in multiple sclerosis than white-matter lesion load (43). In addition, inefficiency of functional networks has also been reported (39) in this disease. Our method might offer a means to link these findings. Similarly, severe psychosis has been linked with dysconnectivity (44), and recent work has begun to relate this to structural deficiencies (45). Once again, our work might offer a framework to link these abnormalities.

## Conclusion

We have probed the relationship between gray-matter myelination and electrophysiological networks, showing a significant correlation. This relationship is strongest for networks mediated by beta oscillations but becomes stronger when integrating across frequency bands, suggesting that myeloarchitecture supports connectivity across all bands. Our study sheds light on the way in which cortical microstructure supports functional networks, the latter being mediated by neural oscillations. Further, it paves the way for future investigations of the structure/function relationship and its breakdown in pathology.

## Methods

**Myelination and Structural Covariance.** Participants gave written informed consent and ethical approval was granted by the University of Nottingham Medical School Research Ethics Committee. MRI data were collected using a Phillips Achieva 7T system. A phase-sensitive inversion recovery  $T_1$  weighted image was acquired and used for MEG coregistration. MT data were obtained from z-spectra acquired using an MT-TFE sequence (46). MT imaging provides contrast based on the exchange of magnetization between free water and protons bound in macromolecules. Although it is likely that no one-to-one relationship exists, experimental and human studies have shown that MT is highly correlated with myelination, which is probably related to the high fraction of water in close proximity to myelin macromolecules. The procedure for extracting MT data from our imaging sequence has been described elsewhere (47). Briefly, z-spectra were corrected for  $B_0$  variation and fitted to a database of simulated spectra to extract myelination maps. To investigate structural covariation of myelin within the AAL regions, gray-matter-masked MT data were registered to the AAL atlas and a mean MT value was calculated for each region, for each participant. Due to confounding factors such as scanner drift, the modal value for each individual's MT data was regressed from that individual's regional values (7) (Fig. S3). Pearson correlation, measured across subjects, was used to quantify the relationship between MT values measured in AAL region pairs (Fig. 1C). These correlation values form elements of the structural matrix in Fig. 1D. An average MT map (Fig. 1A) was also generated by averaging regional MT values over participants. The relationship between myelination and handedness was probed via correlation between MT and handedness score.

**Resting-State MEG: Connectivity Analysis.** Three hundred seconds of eyes-open resting-state MEG data were acquired using a 275-channel CTF MEG system operating in third-order synthetic gradiometer configuration (sampling frequency of 1,200 Hz). Three head position indicator coils were placed at fiducial locations on the subject's head and energized to facilitate continuous tracking of head location. Before acquisition, a 3D head digitization procedure was completed. Coregistration between MEG system geometry and individual brain anatomy was achieved by matching the digitized head surface to the equivalent surface extracted from an anatomical MRI. Functional connectivity was calculated between AAL regions. A scalar beamformer was used to obtain a single MEG signal representative of each region. These regional signals were frequency-filtered to the bands of interest and the confound of signal leakage mitigated using pairwise orthogonalization (48). The magnitude of the analytic signal, computed via a Hilbert transform, was used to generate the amplitude envelope of oscillations, for each regional time course in all frequency bands. Pearson correlation was then

computed between envelopes for each region pair. In this way we generated a single adjacency matrix for each subject, and frequency band, representing whole-brain connectivity. These matrices were averaged over subjects.

**The Relationship Between MT and MEG.** We measured correlation ( $r^2$ ) between the structural covariance matrix (Fig. 1D) and the group-averaged MEG networks (Fig. 2). To test statistically whether these correlation values were significant, we used a permutation test. A set of “pseudo-MEG matrices” were generated, each having spatial properties similar to the real matrices, but crucially they were not

based on genuine data (*SI Methods* and *Figs. S4* and *S5*). This approach accounts for the inherent spatial smoothness in the MEG-derived networks (*SI Methods*). Correlation between the structural matrix and 10,000 pseudomatrices yielded an empirical null distribution, and comparison of the genuine  $r^2$  value with the null distribution allowed computation of a  $P$  value.

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