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Multimodal connectivity of motor learning-related dorsal premotor cortex

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ABSTRACT

The dorsal premotor cortex (dPMC) is a key region for motor learning and sensorimotor integration, yet we have 23 limited understanding of its functional interactions with other regions. Previous work have started to examine 24 functional connectivity in several brain areas using resting state functional connectivity (RSFC) and 25 meta-analytical connectivity modelling (MACM). More recently, structural covariance (SC) has also been 26 proposed as a technique that may also allow delineation of functional connectivity. Here, we applied 27 these three approaches to provide a comprehensive characterization of functional connectivity with a 28 seed in the left dPMC that a previous meta-analysis of functional neuroimaging studies has identified as 29 playing a key role in motor learning. Using data from two sources (the Rockland sample, containing resting 30 state data and anatomical scans from 132 participants, and the BrainMap database, which contains peak activation 31 foci from over 10,000 experiments), we conducted independent whole-brain functional connectivity mapping 32 analyses of a dPMC seed. RSFC and MACM revealed similar connectivity maps spanning prefrontal, premotor, 33 and parietal regions, while the SC map identified more widespread frontal regions. Analyses indicated a relatively 34 consistent pattern of functional connectivity between RSFC and MACM that was distinct from that identified by SC. 35 Notably, results indicate that the seed is functionally connected to areas involved in visuomotor control and 36 executive functions, suggesting that the dPMC acts as an interface between motor control and cognition. 37 © 2015 Published by Elsevier Inc.

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43 Introduction

Converging evidence from single cell recordings, human neuroimag-44 ing, and neurostimulation paradigms indicate that the dorsal premotor 45cortex (dPMC) plays an important part in sensorimotor integration, 4647response selection, and motor learning. Importantly, single-cell recording studies in non-human primates indicate the dPMC has limited ability to 48 directly contribute to movement execution (Boudrias et al., 2010; Dum 49 50and Strick, 2005), but the region contains a high proportion of cells that respond to sensory cues, motor cues, or both (Weinrich and Wise, 51 1982). Thus, it has been suggested that the dPMC integrates sensory 5253and motor information (Roland et al., 1980; Weinrich and Wise, 1982). Converging evidence from neuroimaging, neurostimulation, and 5455neuropsychology indicates that the dorsal premotor cortex (dPMC) has 56a critical role in response selection (Bestmann et al., 2008; Halsband

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http://dx.doi.org/10.1016/j.neuroimage.2015.08.024 1053-8119/© 2015 Published by Elsevier Inc. et al., 1993; O'Shea et al., 2007; Rushworth et al., 2003; Zhang et al., 57 2011). There is also considerable evidence that the left dPMC in particular 58 plays a dominant role in visuomotor integration processes, while the right 59 dPMC is subservient (Bestmann et al., 2008; Hardwick et al., 2013; 60 Schubotz and von Cramon, 2002a, 2002b). Finally, a recent metaanalysis of human neuroimaging studies has shown that the left dorsal 62 premotor cortex (dPMC) is consistently activated across a wide range of 63 motor learning paradigms, regardless of movement execution or the 64 hand being used (Hardwick et al., 2013). As of yet, however, the function-65 al network of brain areas which interact with the left dPMC is relatively 66 unclear. Identifying the regions that functionally interact with the left 67 dPMC in humans would therefore further our understanding of how 68 this key node in the sensorimotor system contributes to response selection and motor learning. 70

Functional connectivity refers to the temporal coincidence of 71 spatially distant neurophysiological events (Friston, 1994). It is often 72 operationalized as a statistical relationship (usually a correlation) 73 between local neurobiological measures, and can therefore be considered 74 as a broad concept rather than one specific methodology. The advent of 75

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multiple connectivity analysis techniques in recent years has led to the 76 77 possibility of assessing different aspects of functional connectivity. Resting state functional connectivity (RSFC) is driven by changes in BOLD activity 78 79 in the absence of an experimental task (for a review, see Biswal, 2012). In seed-based correlation analysis, the time course of lower frequencies in 80 the BOLD response extracted from a seed region are then compared 81 with those of all voxels across the rest of the brain, with significant 82 83 positive correlations implying functional connectivity. RSFC analyses 84 offer the advantage of readily examining whole-brain connectivity 85 without the constraint of a particular task. In comparison, meta-analytic 86 connectivity modelling (MACM) provides a task-based approach to 87 functional connectivity. MACM uses databases of activation peaks from neuroimaging studies to identify consistent co-activations across 88 89 experiments (Eickhoff et al., 2010). While experiments are retrieved based on activation within a seed region, significant convergence of 90 coordinates outside the seed reflects above-chance co-activation and 91 hence implies functional connectivity. The large scale of the databases 92 93 from which MACM analyses are derived provide a great strength to the technique (e.g. the BrainMap database contains >10,000 contrasts 94 with >40,000 subjects). Finally, structural covariance (SC) uses the 95 strength of grey matter volume correlations across the brain as an 96 97 indicator of past co-activity. The underlying notion is that frequent acti-98 vation leads to plastic changes in grey matter volume (Draganski et al., 99 2004), and frequently interacting (co-activating) regions thus co-vary in their grey matter densities (see, for example, Lerch et al., 2006). 100 Thus, while SC uses a structural brain measure (grey matter volume), 101 it crucially hinges upon functional interaction between brain regions 10203 following the principle of Hebbian plasticity (Hebb, 1949). Examining relationships in grey matter volume allows the assessment of consistent 104 interaction between brain regions throughout development using a 105clearly defined measure, the physiological basis of which is clearly 106 107understood. In that context, it is important to also consider the different scales of integration (cf. Amunts et al., 2014) represented by these 108109different methods: RSFC is a within-subject measure, MACM integrates across group activation findings, and SC is a cross-subject measure and 110 cannot be determined on a single-subject basis. As previous studies 111 indicate that functional connectivity is associated with correlated grey 112 113 matter volumes (Seeley et al., 2009), we therefore regard it as a 'functional connectivity' measure (or, more precisely, a proxy for long-term 114 functional connectivity patterns) for the purposes of this paper. While 115 the degree to which SC can be used to infer functional networks has yet 116 117 to be established (Clos et al., 2014), it provides a further method for investigating co-activity with the seed region. 118

Thus, RSFC, MACM, and SC are well-established techniques with the 119 common goal of identifying brain networks interacting with the seed 120 region, and may be used to assess 'functional connectivity' in the human 121 122 brain. Each of these techniques probes 'functional connectivity' from a different angle, and has specific strengths and limitations. However, com-123 bining these tools provides a means to identify the core network of brain 124areas that consistently interacts with the chosen seed. To date, however, 125relatively few studies have directly compared results from these differing 126 127approaches. Recent papers combining the results of RSFC and MACM 128 analyses have suggested good correspondence between the two methodologies (Bzdok et al., 2013; Clos et al., 2014; Hoffstaedter et al., 2013a; 129Jakobs et al., 2012; Müller et al., 2013; Rottschy et al., 2013). Results 130from comparisons of RSFC and SC also report correspondence between 131 132the two methodological approaches (Segall et al., 2012). While a combination of RSFC, MACM, and SC has previously been implemented 133 as a method for parcellation (Kelly et al., 2012), only recently has a 134 comparison of seed-based functional connectivity patterns arising from 135these three techniques been considered (Clos et al., 2014). As all three 136 techniques use different methods to measure the same construct, 137 comparing and contrasting their results provides a more comprehensive 138 overview of 'functional connectivity'. In particular, a triangulation of 139their results would provide compelling evidence of the core functional 140 141 connectivity with the seed region.

The importance of the left dPMC as a hub for sensorimotor integration 142 makes it a prime candidate for examination using functional connectivity 143 techniques. A recent meta-analysis has identified an area of the left dPMC 144 that was the only region to consistently show increases in activity across a 145 wide variety of motor learning paradigms (Hardwick et al., 2013). The 146 essential role of this region in motor learning has not been recognized 147 in previous models, which have primarily focused on the roles of the 148 primary motor cortex and cerebellum in motor learning (e.g. Krakauer 04 and Mazzoni, 2011). Identifying regions that functionally interact with 150 this seed will therefore further our understanding of the network of 151 areas that may contribute to motor learning. Here, we applied RSFC, 152 MACM, and SC connectivity mapping techniques to provide a comprehensive overview of functional connectivity with this left dPMC seed 154 region. 155

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Material and methods

Seed region

A seed region in the left dPMC was defined based on the results of a 158 recent meta-analysis of motor learning (Hardwick et al., 2013). This 159 35 mm³ region (peak MNI coordinates – 32, – 12, 60) survived a series 160 of conjunctions across multiple subanalyses. These subanalyses strictly 161 controlled for potentially confounding activations related to movement 162 execution (i.e. considered only contrasts that compared movement 163 during learning with execution of a similar baseline movement), and 164 controlled for potential laterality effects due to the hand being used to 165 perform the task. This area was therefore consistently activated across a wide variety of motor learning tasks. Data from two sources were 167 utilized to assess functional connectivity with this seed region.

Data sources

The Rockland sample

The RSFC and SC analyses used data from the Nathan Kline Institute 171 "Rockland" cohort (Nooner et al., 2012), available online via the International Neuroimaging Data sharing initiative (http://fcon_1000.projects. 173 nitrc.org/indi/pro/nki.html). The sample used from this cohort consisted 174 of 132 healthy subjects (78 M, 54 F), aged 18–85 years (mean \pm SD: 175 42.3 \pm 18.1 years). This sample was chosen as it provides a representative sample, and thus provides results that can be assumed to be representative of the general population. 178

The BrainMap database

The MACM analysis was conducted using the BrainMap database 180 (Laird et al., 2011), using group average peak activation coordinates 181 from neuroimaging studies examining within-subject contrasts in 182 healthy individuals ("normal mapping", i.e., excluding any interventions 183 such as pharmacological challenges, any longitudinal designs, and patient 184 data, any between-group comparisons to test for differences, e.g. 185 between genders). The BrainMap database was employed to identify 186 task-based co-activation patterns across a large pool of neuroimag- 187 ing experiments. At the time of processing, the database contained 188 stereotaxic peak activation data including approximately 85,000 189 coordinates (foci) drawn from over 40,000 subjects across more 190 than 10,000 experiments.

Functional connectivity analyses

Seed-based resting state functional connectivity

Images were acquired using a Siemens Tim Trio 3 T scanner using 194 blood oxygen level-dependent (BOLD) contrast (260 whole-brain 195 echo-planar imaging (EPI) volumes per subject, gradient-echo EPI 196 pulse sequence, repetition time (TR) = 2.5 s, echo time (TE) = 30 ms, 197 flip angle = 80° , in-plane resolution = $3 \times 3 \text{ mm}^2$, 38 axial slices 198 (3 mm thickness)). A seed-based RSFC analysis compares endogenous 199

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fluctuations of BOLD activity in the seed region with that of all other 200 201 voxels in the brain as a marker of functional connectivity under 202 task-free conditions. Data were analyzed using SPM8 (Wellcome 203Trust Centre for Neuroimaging, London). The first four scans were discarded prior to analysis to allow for magnetic field saturation. 204The images were then corrected for movements by affine registration 205using a two-pass procedure. In the first step, images were aligned to 206 the initial volumes, then subsequently to the mean of all volumes. The 207208mean EPI image for each subject was then spatially normalized to the 209 Montreal Neurological Institute (MNI) single-subject template (Holmes 210et al., 1998) using the unified segmentation approach (Ashburner and 211 Friston, 2005). The resulting deformation was applied to the individual 212EPI volumes and images smoothed using a 5-mm full-width half-213maximum (FWHM) Gaussian kernel. Spurious correlations for the time-series of each voxel were reduced by regressing out the nuisance 214 variables of (1) the six motion parameters derived from image re-215 alignment; (2) their first derivatives; and (3) mean GM, WM, and 216 CSF intensity. Nuisance variables were entered into the model as 217 first- and second-order terms (see Satterthwaite et al., 2013 for an 218 evaluation of this approach). In a final step, the data was band-pass 219filtered with cutoff frequencies of 0.01–0.08 Hz. Meaningful resting 220state correlations occur predominantly within this frequency band 221 222due to the low-pass filter-like effect of the BOLD signal (Fox and 223Raichle, 2007; Power et al., 2012).

The time course was extracted from the functionally defined left 224dPMC seed volume for each subject by computing the first eigenvariate 225of the time-series' of those voxels whose grey matter probability was 226227above the median across all voxels in the ROI. Linear (Pearson) correlation coefficients were computed between this seed time series and the time 228series of all other grey matter voxels in the brain (Reetz et al., 2012; zu 229Eulenburg et al., 2012). The voxel-wise correlation coefficients were 230231transformed into Fisher's z-scores and tested for consistency across 232subjects by a second-level ANOVA (including non-sphericity correction). 233 This random effects analysis was family-wise error (FWE) corrected with a cluster level threshold of p < 0.05 (cluster forming threshold of 234*p* < 0.001 at voxel level). 235

236 Meta-analytic connectivity modelling

Meta-analytic connectivity modelling (MACM; Eickhoff et al., 2010; 237Robinson et al., 2010) assesses connectivity by determining brain areas 238that co-activate above chance with a seed region across multiple neuro-239imaging experiments. First, all experiments in the BrainMap database 240with at least one peak activation coordinate within the functionally 241 defined left dPMC seed region were identified. Custom-written MATLAB 242 243scripts were then utilized to conduct an Activation Likelihood Estimation 244(ALE) meta-analysis (Eickhoff et al., 2009, 2012; Turkeltaub et al., 2002, 2012) across these in order to identify areas of converging activity across 245these experiments. The ALE algorithm empirically determines whether 246spatial convergence of foci between studies is greater than expected by 247chance. The highest convergence between studies evidently occurs within 248249the seed (as all included experiments were selected based upon activity 250within the seed region). Significant convergence in areas beyond the seed is indicative of consistent co-activation (i.e. functional connectivity) 251252with the seed region. Inference in the MACM analysis was conducted at 253p < 0.05 level (corrected for multiple comparisons using permutation 254testing, controlling cluster-level FWE at p < 0.05). While it is possible to restrict the sample of studies that are examined by MACM analyses, 255for instance, to examine only studies looking at motor control (cf. 256Hoffstaedter et al., 2013a,b), we here considered all studies within 257the BrainMap database. A pre-selection would introduce a bias not 258present in the RSFC and SC analyses. Selecting studies based on the 259location of their activations alone, however, provides a purely objective 260and data-driven approach to the MACM analysis. This allowed for 261 unbiased comparisons between the results of the RSFC, MACM, and 262263 SC analyses.

Structural covariance

Structural covariance examines functional connectivity via correla- 265 tions between regional grey matter properties such as volume or cortical 266 thickness (Albaugh et al., 2013; He et al., 2007b; Lerch et al., 2006). Here, 267 we used local volume as estimated by Voxel-based morphometry (VBM) 268 on the anatomical T1 weighted MPRAGE scans from the 132 subjects in 269 the Rockland sample to assess structural covariance. Images were 270 acquired using a Siemens Tim Trio 3 T scanner as per the Rockland 271 sample protocol (MPRAGE sequence, repetition time (TR) = 2.5 s, echo 272time (TE) 3.5 ms, flip angle = 8°, in-plane resolution = $1 \times 1 \text{ mm}^2$, 192 273 sagittal slices (1 mm thickness). The anatomical scans were preprocessed 274 using the VBM8 toolbox (dbm.neuro.uni-jena.de/vbm) in SPM8 using 275 standard settings (DARTEL normalization, spatially adaptive non-linear 276 means denoising, a Markov random field weighting of 0.15 and bias 277 field modelling with a regularization term of 0.0001 and a 60 mm 278 FWHM cutoff). These normalized grey matter segments, modulated 279 only for the non-linear components of the deformations into standard 280 space, were smoothed using an 8 mm FWHM Gaussian kernel (this 281 normalization process accounts for differences in grey matter volumes 282 between subjects). Statistical analysis was conducted in FSL1 with non-283 parametric statistics using the FSL 'permute' function (Jenkinson et al., 284 2012; Smith et al., 2004). The volume for the functionally defined dPMC 285 seed was computed in each subject by integrating the modulated 286 voxel-wise grey matter probabilities under the seed cluster. This 287 subject-specific local volume for the dPMC seed was used as the 288 covariate of interest in the statistical group analysis. Statistical analysis 289 was performed using the standard GLM implementation in FSL testing 290 for each voxel whether the local volume of that particular voxel signif- 291 icantly covaried with the volume of the dPMC. Age was included in the 292 statistical model as a variable of no interest. Inter-individual differences 293 in brain volume were not included in the statistical model because they 294 were already accounted for in the grey-matter probability maps (grey 295 matter probability maps were modulated by non-linear components, 296 and the analysed voxel values represent the absolute amount of tissue 297 corrected for individual brain size). Significance was assessed at $p < 0.05_{298}$ as implemented by FSL (corrected for multiple comparisons using full 299 permutation testing of TFCE images, threshold-free cluster enhancement; 300 Smith and Nichols, 2009). 301

Difference analyses

Difference analyses identified which brain areas were most strongly 303 associated with each functional connectivity mapping technique 304 (Jakobs et al., 2012). These analyses were conducted in a multi-stage 305 process. First, subtraction analyses were generated to compare the 306 results from each functional connectivity analysis. The results of these 307 subtraction analyses were combined in a conjunction on the minimum 308 value, and masked by the original functional connectivity maps. The 309 resulting image was thresholded to provide a map of regions with 310 significantly higher connectivity values than in the counterpart analyses. 311 For example, to generate a map of the areas that were more strongly 312 associated with RSFC, the first step was to compute two subtraction 313 analyses (RSFC minus MACM, RSFC minus SC). These difference anal- 314 yses were combined in a conjunction, which identified the lowest 315 value from each analysis for each voxel. The resulting voxels thus 316 were significantly stronger connected to the seed in RSFC than in 317 either of the two other techniques. Results were then masked by 318 the original RSFC map (ensuring that regions most strongly associated 319 with the RSFC technique would have to demonstrate significant 320 connectivity during the original RSFC analysis). Finally, the resulting 321 map was thresholded such that only voxels with a z-score greater 322 than 1.96 (i.e. p < 0.05) were presented. The resulting map indicates 323 which areas are more strongly associated with one of the examined 324 connectivity mapping techniques compared to the other two 325 methods. 326

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327 Conjunction analyses

Conjunction analyses determined areas that were consistently 328 329 activated across multiple brain connectivity approaches. Pairwise conjunctions were conducted between the three connectivity analyses 330 in order to identify common results across the differing techniques. In 331 addition, a combined analysis was performed across the results of 332 RSFC, SC, and MACM. This combined conjunction thus identified areas 333 334 with highly consistent functional connectivity to the left dPMC seed 335 region. All conjunctions were computed by taking the minimum statistic (Jakobs et al., 2012; Nichols et al., 2005). Data from MACM 336 were transformed from 2 mm³ MNI space to 1 mm³ for comparison 337 with the RSFC and MACM data. 338

339 Volume comparisons

Previous studies have suggested that the volumes identified by RSFC, 340 MACM, and SC show 'good convergence' (Bzdok et al., 2013; Clos et al., 341 2014; Hoffstaedter et al., 2013a; Jakobs et al., 2012; Müller et al., 2013; 342 Rottschy et al., 2013). This has, however, been primarily examined 343 through visual overlay of the identified maps, without further quantifi-344 cation. Here, we compared the volumes identified by each analysis, then 345 346 guantified the volumes that were either uniquely identified by one analysis, or were identified by multiple analyses via conjunction. 347

348 Volume-matched analyses

349 Differences in the approaches employed by each of the analyses led to differences in the size of the total volumes of the brain that were 350 identified as having functional connectivity with the motor learning-351352 related seed region. A control analysis therefore aimed to determine 353whether the different functional connectivity mapping techniques 354examined identified broadly similar patterns of connectivity that differed mainly due to differences in statistical thresholding, or whether 355 the different techniques identified truly divergent networks. The 356 network with the smallest overall volume was identified (the MACM 357 358 map, with a volume of 76,749 mm³). The thresholds of the RSFC and SC connectivity maps were then iteratively increased until the volumes 359 they identified were approximately equal to that of the MACM network. 360 Further volume comparison analyses were then conducted on the 361 volume-matched maps (Fig. 1). 06

363 Labelling

364Results were anatomically labelled according to their most probable365macroanatomical and cytoarchitectonic locations using the SPM Anatomy

Toolbox (Eickhoff et al., 2005, 2007). Additional labels were derived from 366 a functional meta-analysis of motor cortical regions (Mayka et al., 2006). 367 Peak maxima of the reported coordinates are presented in 1 mm³ MNI 368 space. Only regions with 100 cohesive voxels were reported. 369

Results 370

Main analyses

Resting state functional connectivity

The RSFC analysis (Fig. 2A) identified regions where the BOLD time 373 course correlated with that in the left dPMC seed volume. This analysis 374 revealed a distributed network that contains large clusters in frontal and 375 parietal regions, and smaller clusters in the occipitotemporal cortex, 376 striatum, and cerebellum. Connectivity with most regions was bilateral, 377 but stronger in the left supratentorial regions and right cerebellar 378 regions, consistent with its connectivity with left-lateralized seed. 379 Specifically, a widespread frontal cluster spanned premotor regions 380 including the pre-SMA and SMA, ventral and dorsal premotor cortex, 381 and extended into the bilateral dorsolateral prefrontal cortex, left IFG 382 and the left anterior insula. A second large bilateral parietal cluster 383 spanned left inferior and superior parietal lobules, and the bilateral 384 precuneus. In addition, connectivity was found with the mid-cingulate 385 gyrus, bilateral fusiform gyrus, and bilateral ventral occipitotemporal 386 cortex roughly corresponding with area V5. This analysis was the 387 only one to identify striatal and cerebellar regions (see Table 1). 388 Specifically, RSFC connectivity was found with the bilateral thalamus Q7 and the bilateral dorsal striatum. Cerebellar connectivity was more 390 pronounced in the right cerebellar hemisphere, with a large cluster 391 spanning lobules HVI and HVII (Crus I and II), and a smaller cluster 392 in lobule HVIII. In the left cerebellar hemisphere, smaller clusters 393 were present in lobules HVII (Crus I and II) and HVIII. 394

Meta-analytical connectivity mapping

MACM (Fig. 2B) provided the most restricted network of all three 396 connectivity mapping techniques examined, revealing a bilateral 397 network of fairly localized premotor and posterior parietal cortical 398 structures (see Table 2). Consistent task-based co-activation with the 399 left dPMC seed region was identified in the contralateral dPMC, and 400 bilateral vPMC, SMA, and IFG, extending into the anterior insula. Addi- 401 tional connectivity was found in localized clusters in the left ventral 402 occipitotemporal cortex, bilateral precuneus and intraparietal cortex, 403 along with smaller clusters in the right angular gyrus and superior parietal 404 lobule. The MACM analysis was unique in identifying connectivity with 405 the left anterior insula. The MACM analysis did not reveal connectivity 406 with subcortical regions. 407



Fig. 1. The left dPMC seed region. A previous meta-analysis of motor learning (Hardwick et al., 2013) identified this seed as a key area for motor learning. The seed region was the sole area surviving multiple analyses that strictly controlled for both movement execution and hand use.

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Fig. 2. Results of the connectivity analyses. (A) The resting state analysis (red) revealed the largest functional connectivity network, including frontal-premotor, and parietal cortex, as well as the thalamus, putamen, and cerebellar regions. (B) Meta-analytical connectivity modelling (green) gave relatively focal results with a bilateral network of premotor and parietal cortical structures. (C) The structural covariance analysis (blue) identified a large functional connectivity network, with widespread clusters, predominantly in prefrontal and motor/premotor areas.

t1.1 Table 1

Resting state functional connectivity.

t1.2

Vol (mm³) Macro Cyto t-score **MNI** Coordinates t1.3 Χ Υ t1.4 t1.51 172,308 L dPMC 56.21 -26 4 R dPMC 27.62 26 8 t1.6 L SMA 1491 22 t1.7 -4t1.8 L vPMC Area 44 12.82 -466 t1.9 L inferior frontal gyrus (p. triangularis) Area 45 12.54 -4836 7.45 L putamen -168 t1.10 L thalamus Th-Temporal t1.11 7.37 -6-14t1.12R thalamus Th-Temporal 7.15 8 -20R vPMC Area 44 5.96 50 6 t1.13 2 151,208 L precuneus SPL (7A) 18.68 -64-6t1.14 L inferior parietal lobule hIP2 t1.15 1692 -52-42t1.16 L precuneus SPL (7P) 16.50 -8-72SPL (7P) 16.29 8 -70t1.17R precuneus L inferior parietal lobule IPC (PF) 15.53 -34t1.18 -52L inferior parietal lobule hIP2 15.46 -38-48t1.19 t1.20 L inferior parietal lobule hIP1 15.25 -36-48L superior parietal lobule SPL (7P) 14.74 -16-74t1.21R cerebellum Lobule VIIa Crus I (Hem) t1.22 3 24,072 12.31 36 -6430 R cerebellum Lobule VI (Hem) 11.71 -62t1.23 t1.24 R cerebellum Lobule VIIa Crus II (Hem) 8.78 38 -68R cerebellum Lobule VIIb (Hem) 8.69 30 -70t1.25t1.26 4 12,071 L inferior temporal gyrus 14.95 -58 _ - 58 4,405 R inferior temporal gyrus 7.58 64 -585 t1.27 Lobule IX (Hem) t1.28 6 4,205 R cerebellum 9.67 14 -52t1.29 R cerebellum Lobule VIIIb (Hem) 4.60 12 -62t1.30 7 4,063 L cerebellum Lobule VIIa Crus I (Hem) 7.51 -32 -62Lobule VIIa Crus II (Hem) L cerebellum 3.24 -48-48t1.31 3.529 9.51 -34-38 t1.32 8 L fusiform gyrus t1.33 9 2,013 L cerebellum Lobule IX (Hem) 7.99 -12-5210 1,977 R fusiform gyrus 6.04 34 -34 t1.341,315 L cerebellum Lobule VIIa Crus II (Hem) 5.75 -38 -70 t1.35 11 L cerebellum Lobule VIIb (Hem) 3 22 -24 -72 t1.36

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Table 2

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t2.2 Meta-analytical connectivity modelling

#	Vol	Macro	Cyto	z-score	MNI C	Coordin	ates
	(mm ³)				X	Y	Ζ
1	22,522	L dPMC		8.57	-26	4	60
		L SMA	Area 6	7.89	-2	12	54
		R SMA		7.51	6	22	46
2	12,497	L inferior parietal lobule	hIP3	7.30	-30	-56	48
		L precuneus	SPL (7P)	5.57	-12	-72	48
		L inferior parietal lobule	hIP2	4.26	-46	-36	44
		L inferior parietal lobule	Area 2	4.25	-44	-34	44
		L inferior parietal lobule	hIP1	3.56	-38	-44	44
3	12,293	L vPMC	Area 44	6.27	-52	10	32
		L inferior frontal gyrus		5.26	-44	32	20
		(p. triangularis)					
		L inferior frontal gyrus	Area 45	4.80	-46	28	28
		(p. triangularis)					
4	6,813	R angular gyrus		6.41	34	-62	44
		R middle occipital gyrus		5.51	32	-76	34
		R superior parietal lobule	SPL(7P)	4.56	16	-68	52
		R precuneus	SPL (7A)	4.16	8	-60	50
5	6.307	L insula lobe	. ,	6.95	-34	22	$^{-4}$
		L inferior frontal gyrus	Area 44	4.03	-48	16	4
		(p. triangularis)					
6	5,707	R dPMC		6.03	28	2	54
7	4.101	R vPMC		4.99	48	14	30
8	3,025	Right inferior frontal gyrus		5.29	34	24	-10
		(p. orbitalis)					
9	1.745	Right inferior parietal	hIP2	4.56	42	-42	44
		lobule					
		Right inferior parietal	IPC (PF)	3.75	48	-40	48
		lobule					
		Right inferior parietal	IPC (PFt)	3.67	50	-38	50
		lobule					
10	1,739	Left inferior temporal gyrus		5.43	-48	-62	-10

408 Structural covariance

The SC analysis (Fig. 2C) revealed areas where the grey matter volume correlates with the grey matter volume in the left dPMC seed region. This analysis yielded large areas spanning most of the frontal lobe, from the primary motor cortex to the orbitofrontal cortex. Smaller clusters were identified in the temporal and parietal lobes (see Table 3). The pattern was largely bilateral but stronger on the left, consistent with a leftlateralized seed. Frontal significant grey matter correlations were found

t3.1 Table 3

Structural covariance connectivity. t3.2 **MNI** Coordinates t3.3 # Vol Macro Cyto t-score (mm^3) Х Ζ t3.4 Υ 9 32 1 L dPMC 3 5 4 -47 t3.5 162 399 R dPMC 3.52 27 2 61 t3.6 R dPMC t3.7 Area 6 3.35 24 -1263 3.29 67 t3.8 L SMA Area 6 -1 -3 R inferior frontal gyrus (p. 3.24 48 36 27 t3.9 triangularis) L inferior frontal gyrus (p. opercularis) 3.21 21 33 t3.10 -43t3.11 R middle cingulate 3.16 3 -9 35 2 10.584 6 -79Area 18 2.29 21 t3.12 R cuneus t3.13 L cuneus 2.11 3 -7830 SPL t3.14 L superior occipital gyrus 1.91 -9 -8141 (7P) Area 17 1.90 -3 -8417 L cuneus t3.15 t3.16 L cuneus Area 18 1 90 -1 -8118 t3.17 3 4,569 L superior temporal gyrus 2.05 -57 -288 L superior temporal gyrus OP 4 2.00 -60-196 t3.18 1.98 13 L superior temporal gyrus TE 3 -61-31t3.19 t3.20 L middle temporal gyrus 1.94 -66-428 4 1,190 **R** S1 Area 3b 1.75 30 -3757 t3.21 57 t3.22 R S1 Area 2 1.73 30 - 42 1,000 27 5 R superior occipital gyrus 1.69 25 -88t3.23 t3.24 R middle occipital gyrus 1 68 30 -8724

bilaterally with the dPMC, IFG, SMA, and primary sensory and motor 416 cortex. Unique to the SC analysis, connectivity was also identified with 417 the mid-cingulate cortex, left middle temporal gyrus, right temporal 418 pole, bilateral cuneus, and occipital gyrus. Notably, no clusters were 419 identified in the parietal cortex, or in any subcortical regions. 420

Difference analyses

Resting state functional connectivity > (meta-analytic connectivity modelling 422 and structural covariance) 423

421

Consistent with the very robust pattern of activation revealed by the 424 RSFC analysis, the pattern of regions more strongly associated with this 425 analysis (Fig. 3A) is very similar to that identified in the main analysis 426 (Fig. 2A). The clusters most strongly associated with RSFC spanned 427 bilateral premotor and supplementary motor regions stretching into 428 the dorsolateral prefrontal cortex and anterior insula, as well as large 429 areas of bilateral precuneus, superior and inferior parietal lobules, 430 fusiform gyrus, and ventral occipitotemporal cortex. As the cluster 431 in the left thalamus, bilateral putamen, and bilateral cerebellar regions 432 were only identified as having connectivity with the seed by the 433 RSFC analysis, the same pattern of subcortical activity were evidently 434 more strongly associated with RSFC than the other techniques 435 examined. Thus, most regions identified by the RSFC analysis, were 436 more strongly identified with this method than with either the 437 structural covariance modelling or meta-analytic connectivity modelling 438 methods. 439

Meta-analytic connectivity modelling > (resting state functional connectivity 440 and structural covariance) 441

Areas in which MACM was stronger than RSFC and SC were relatively 442 small in volume. These areas included the bilateral anterior insula, left 443 dPMC (slightly dorsal from the seed region) and right vPMC, as well as 444 small clusters in the left inferior occipital gyrus and the superior parietal 445 lobule (see Fig. 3B). Of these regions, the right ventral prefrontal cortex 446 and right anterior cingulate cortex were solely identified in the MACM 447 analysis. In the parietal and occipital brain areas, RSFC and MACM 448 overlapped substantially, but small clusters were more strongly present 449 in the MACM. 450

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Fig. 3. Difference analyses presenting regions where one of the connectivity analyses provided significantly stronger scores than its counterparts. (A) Results were more strongly associated with RSFC, shown with red clusters. (B) Results were more strongly associated with MACM, shown with green clusters. (C) Results more strongly associated with SC, shown with blue clusters.

451 Structural covariance > (resting state functional connectivity and
 452 meta-analytic connectivity modelling)

Structural covariance yielded the strongest connectivity measures 453 454 bilaterally across large areas of the frontal lobe and medial wall (see Fig. 3C). In the majority of these areas, there was a correlation of the 455 grev matter volume between the dPMC seed and the grev matter 456volume in these regions, while the other two methods did not reveal 457significant connectivity with dPMC. Particularly striking are the robust 458bilateral clusters in the primary motor cortex, as well as the spread of 459the prefrontal cluster, which extended into the bilateral orbitofrontal 460 gyrus and right frontal and temporal pole (see Fig. 3B). In addition, 461 462 smaller clusters were found in the left superior temporal gyrus, left precuneus, and bilateral cuneus. 463

464 Conjunction analyses

Several conjunction analyses were carried out to shed light on 465regions commonly identified by the different connectivity analyses. 466 467The areas commonly identified in the RSFC and MACM analyses were 468 fairly localized bilateral clusters in frontal and parietal lobes, with larger clusters ipsilateral to the left dPMC seed region (see Fig. 4A). These 469clusters were present in the right dorsal and ventral premotor cortex, 470supplementary motor cortex, and the left ventral premotor cortex 471 472 extending into the dorsolateral prefrontal cortex and inferior frontal gyrus. Bilateral parietal clusters were present in the intraparietal sulcus 473 and superior parietal lobule. The conjunction of analyses based on the 474Rockland sample (i.e. RSFC and SC analyses) revealed a widespread 475network spanning bilateral prefrontal and motor cortex, along with a 476few much smaller clusters in the superior parietal lobule and precuneus 477 (see Fig. 4B). Only a small number of regions were commonly identified 478 by SC and MACM analyses; these were in the left vPMC, SMA, and right 479dPMC (see Fig. 4C). Finally, the combined conjunction of all three 480 481 connectivity analyses (i.e. RSFC, MACM, and SC; see Fig. 4D) was very similar to the conjunction of the MACM and SC analyses. Specifically, 482 these areas were the left vPMC, right dPMC, and the SMA. 483

Volume quantification

We quantified the volumes identified in each analysis to further 485 investigate the differences and similarities between RSFC, MACM, and 486 SC. We first quantified the total volumes identified by the RSFC, 487 MACM, and SC analyses (Fig. 5A). RSFC identified the largest overall 488 volume with functional connectivity with the seed (381,166 mm³). 489 The RSFC network was more than double the size of the SC network 490 (179,839 mm³), while the SC network was in turn more than double 491 the size of the MACM network (76,749 mm³). 492

We then compared the convergence and divergence of the networks 493 as examined in the conjunction analyses. Overlaying the RSFC and 494 MACM networks (Fig. 5B) revealed that 81% were unique to the RSFC 495 analysis, while only 3% was unique to the MACM analysis. The remaining 496 16% of the overall volume was identified as surviving the conjunction of 497 RSFC and MACM. Due to the disparity of their sizes, this meant that the 498 majority of the volume identified in the MACM analysis was also identi- 499 fied by the RSFC analysis (see Venn diagram illustrating overlap; Fig. 5B). 500 Pairwise comparisons indicated that 17% of the volume identified by 501 RSFC analysis survived conjunction with the MACM map (see Fig. 5F), 502 while 83% of the MACM map survived conjunction with the RSFC map 503 (see Fig. 5G). Overlaying the RSFC and SC networks (Fig. 5C) revealed 504 that 64% of the total volume identified was unique to RSFC, while 24% 505 was unique to SC. Thus, 12% of the total volume identified in both anal- 506 yses was shown to be commonly found in both techniques. Pairwise 507 comparisons of these maps revealed that 16% of the RSFC map survived 508 conjunction with the SC map (see Fig. 5H), while 34% of the SC map 509 survived conjunction with the RSFC map (see Fig. 5I). Overlaying the 510 MACM and SC networks (Fig. 5D) showed that 67% of the total network 511 was unique to the SC analysis, while 23% was unique to the MACM 512

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Fig. 4. Results of the conjunction analyses. (A) Conjunction of the RSFC and MACM analyses. (B) Conjunction of the RSFC and SC analyses. (C) Conjunction of the MACM and SC analyses. (D) A combined conjunction from all three analyses (RSFC, MACM, and SC), identifying a consistent 'core' network common to all connectivity mapping techniques considered.

analysis, and 10% was commonly identified in both maps. Pairwise comparisons showed that 29% of the MACM map survived conjunction with the SC map (see Fig. 5J), while 12% of the SC map survived conjunction with the MACM map 2(see Fig. 5K).

Finally, we considered the divergence and convergence between the 517RSFC, MACM, and SC maps in a combined analysis, overlaying all three 518functional connectivity maps. The majority of the volume identified by 519all three mapping techniques was unique to RSFC (54%) or the SC 520521analysis (23%). A relatively small volume was identified only by MACM (2%). Conjunctions indicated that similar overall volumes 522were identified by both RSFC and MACM but not SC (8%), or RSFC 523and SC but not MACM (9%). In comparison, the volume identified 524by both MACM and SC but not RSFC was extremely small (1%). 525526 Considered relative to the total volume identified by all three analyses, only a small volume was identified in the combined conjunction of the 527RSFC, MACM, and SC analyses (4%; Fig. 6). **Q8**

529 Volume-matched analyses

Results of the volume-matched control analysis were similar to those
 of the main analyses: RS and MACM identified relatively consistent
 networks of frontal, premotor, and parietal regions. In comparison, SC

revealed a network of areas more local to the seed, consisting mainly of 533 prefrontal and premotor regions. 534

Volume-matched analyses: volume comparisons

535

Volume-matched analyses controlled for potential differences in the 536 maps identified by each network arising from differences in the sizes of 537 the volumes they identified. The volume-matched analysis iteratively 538 increased the threshold of the RS and SC maps, reducing their volumes 539 until they were approximately equal to that of the MACM analysis (see 540 Fig. 7A). Overlaying the maps identified by the RSFC and MACM analyses 541 showed that 24% of this volume was common to both analyses. A total of 54239% of the volume of the volume-matched RSFC map survived conjunc- Q9 tion with the MACM map, and (due to the volume matching approach), 544 39% of the MACM map survived conjunction with the RSFC map (see 545 Fig. 7F,G). Overlaying the volume-matched RSFC analysis with the 546 volume-matched SC analysis identified an 8% overlap (Fig. 7C). Of the 547 volume-matched RSFC map, 15% survived conjunction with the volume- 548 matched SC map, and vice versa (Fig. 7H,I). Overlaying the MACM map 549 on the volume-matched SC map identified that 10% of the maps 550 overlapped (Fig. 7D). For the MACM map, 18% survived conjunction 551 with the volume-matched SC map, and vice versa (Fig. 7J,K). A combined 552

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Fig. 5. Volume comparisons of the total volumes identified by the analyses, and their unique contributions and overlap. (A) Total volumes identified by the RSFC, MACM, and SC analyses. Further sections of the figure illustrate the overlap and disparity between total volumes identified by (B) the RSFC and MACM analyses, (C) the RSFC and SC analyses, (D) the SC and MACM analyses, and (E) the RSFC, MACM, and SC analyses. (F–K) pairwise comparisons illustrating the degree of overlap for each combination of analyses.

overlay analysis of all three maps also identified that the volume-matched
 SC analysis had the least overlap with other networks, consistent with the
 main analysis (Fig. 7E).

556 Discussion

The dPMC plays an essential role in integrating sensory and motor information (Roland et al., 1980; Weinrich and Wise, 1982), and the left dPMC in particular is consistently activated during a wide range of motor learning tasks (Hardwick et al., 2013). Despite the importance of the dPMC for sensorimotor integration and motor learning, there is limited understanding of the areas that functionally interact with it. The present study therefore examined regions that have functional connectivity with a left dPMC region key to motor learning (Hardwick 564 et al., 2013). We employed resting state functional connectivity (RSFC), 565 meta-analytic connectivity mapping (MACM), and structural covariance 566 (SC), comparing and combining their results to provide a comprehensive 567 overview of connectivity with the seed. The maps resulting from the RSFC, 568 MACM, and SC analyses identified networks of varying size and 569 topography. Notably, the maps from the RSFC and MACM analyses 570 were qualitatively similar, primarily spanning premotor and parietal 571 regions. In comparison, the SC map identified predominantly frontal 572 and temporal regions. 573

The differences between the maps for RSFC, MACM, and SC may 574 be attributed to the methodological approaches employed by the 575 three techniques. RSFC networks are based on "spontaneous", task-free 576

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Fig. 6. Results of the conservatively thresholded RS and SC analyses in comparison to the results of the MACM analysis.

fluctuations in the BOLD signal, while MACM is based on the convergence 577578of peak co-activity between task-based fMRI and PET experiments. Thus, the signals from RSFC and MACM are similar in that they both primarily 579580encapsulate short term blood utilization in brain tissue. Note, however, that the RSFC analysis used only data from fMRI, while the MACM analysis 581amalgamated data from both fMRI and PET; these different modalities are 582 known to influence activation profiles (Veltman et al., 2000), which could 010 contribute to the differences seen between the RSFC and MACM analyses. 584In comparison, SC identifies correlations in grey matter volume between 585 brain regions, and as such has less in common with RSFC and MACM. In 586 addition, RSFC and MACM relate to comparatively short time spans, 587considering functional connectivity at rest (RSFC) or during the perfor-588589mance of specific tasks (MACM). The time span for SC is much longer, assessing differences in grey matter volume that have arisen throughout 590591life thus far. An additional consideration is that the present study aimed 592 to gain a comprehensive overview of functional connectivity with the dPMC seed region by examining *typical* applications of RSFC, 593594MACM, and SC. As such, there are methodological differences between implementations, as is the case when each technique is used 595individually in the present literature. While it could be argued that stan-596dardizing these approaches may have reduced between-technique noise, 597such an approach would lead to questionable methodological choices; for 598599instance, it is not feasible to assess VBM data (as used in SC) using cluster-600 level inference, which is standard in RSFC and MACM. Furthermore, attempting to rigidly match these procedures may artificially promote 601 the homogeneity of the results. The present approach therefore allows 602 further generalization of the results, allowing comparison of each 603 604 individual analysis with those presently found in the literature.

A further consideration is that none of these techniques can perfectly 605 capture functional connectivity, as each is subject to different sources of 606 inherent noise. The spontaneous BOLD signal from which RSFC is 607 derived is thought to be particularly susceptible to artefacts from 608 preprocessing and physiological noise (Chang and Glover, 2009; 609 Power et al., 2012). MACM is derived from peak coordinates from 610 task-based fMRI and PET studies, and is thus constrained by the tasks 611 possible to be performed in the scanner and the inherent spatial 612 613uncertainty of neuroimaging results (Eickhoff et al., 2009; Rottschy et al., 2012). Finally, as well as representing experiences such as repeated 614 practice of motor tasks (e.g. Gaser and Schlaug, 2003), differences in 615 brain structure detected by SC are influenced by both environmental 616 and hereditary factors throughout development (Alexander-Bloch 617 et al., 2013). 618

To date, relatively few studies have compared results from all three 619 of these techniques; most have compared RSFC with either MACM or 620 SC (Bzdok et al., 2013; Jakobs et al., 2012; Rottschy et al., 2013; Segall 621 et al., 2012). These investigations have generally reported that the two 622 techniques they have examined provide gualitatively similar results. 623 Here, we extended this work by quantifying the volumes identified by 624 each analysis and their conjunctions, which further illustrated the 625 relative similarities between the RSFC and MACM networks in compar- 626 ison to the results of the SC analysis. Notably, RSFC and MACM are well- 627 established methods for mapping functional connectivity (Biswal, 2012; 628 Robinson et al., 2010), while the degree to which anatomical covariance 629 networks as identified by SC are representative of functional connectivity 630 is debatable (Clos et al., 2014). As a result, we first discuss the common 631 functional connectivity network as identified by RSFC and MACM, then 632 consider the added benefit and potential problems to consider when 633 comparing their results to SC. 634

Areas with consistent functional connectivity: networks for motor learning 635 identified by RSFC and MACM 636

As noted above, visualization of connectivity maps and volume 637 quantifications indicated considerable convergence between the RSFC 638 and MACM maps. The conjunction of these maps identified a consistent 639 network of brain regions with functional connectivity to the motor 640 learning–related seed region, including the right dPMC, bilateral ventral 641 premotor cortex (vPMC), bilateral supplementary motor area (SMA), 642 left dorsolateral prefrontal cortex (DLPFC), bilateral posterior parietal 643 cortex, and left a V5/MT. This network is consistent with the role of 644 the left dPMC as a central hub for sensorimotor integration and motor 645 learning. 646

Interhemispheric dPMC interactions are well documented in motor 647 control. Simple unilateral movements are typically associated with 648

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Fig. 7. Volume comparisons for the volume-matched analyses.

increases in bilateral dPMC activity in both non-human primates (Cisek 649 650 et al., 2003; Tanji et al., 1988) and humans (Ward and Frackowiak, 2003). The left dPMC is dominant in action selection (Bestmann et al., 6512008), though the right dPMC can assume this role if the left dPMC is 652 compromised (O'Shea et al., 2007). Studies of sequence learning have 653 also identified increased right dPMC activity for the perceptual elements 654655 of sequences (Schubotz and von Cramon, 2002a, 2002b). The dPMC 656 therefore appears to play a key role in volitional movement preparation, with the left dPMC being dominant for action selection and initiation, 657 and the right dPMC playing a supportive role in acquisition and retrieval. 658 Bihemispheric recruitment of the vPMC is also frequently observed in 659 motor control (Binkofski et al., 1999; Davare et al., 2006; Ehrsson et al., 660 2000, 2001). The vPMC is specifically involved in the sensory guidance 661 of hand movement (Binkofski et al., 1999), especially in hand shaping 662 for precision grasp (Davare et al., 2006). 663

The SMA and left dPMC were also not only identified as having consistent connectivity across the RSFC, MACM, and SC analyses here but were also consistently linked with activation during motor learning in our previous meta-analysis (Hardwick et al., 2013). Moreover, consecutive days of motor training lead to parallel increases in their grey matter volumes (Hamzei et al., 2012). As both are active in motor learning tasks that control for simple motor activity (Hardwick et al., 670 2013), they therefore appear to play a role in motor learning beyond 671 movement execution itself. Both have been linked with movement 672 sequences; the SMA being more closely associated with those that 673 have been learned extensively (Wymbs and Grafton, 2013). The SMA 674 has also classically been linked with the self-initiation of voluntary 675 movements (Deecke and Kornhuber, 1978; Hoffstaedter et al., 2013b) 676 and in switching between ongoing movement tasks (Nachev et al., 677 2008; Obeso et al., 2013). Increases in pre-SMA activity have frequently 678 been associated with successful response inhibition (see Obeso et al., 679 2013; but also Criaud and Boulinguez, 2013). The SMA therefore likely 680 interacts with the dPMC in order to store movement sequences, and 681 to initiate, modify, and possibly inhibit (or coordinate the inhibition 682 of) actions.

Lesion studies in non-human primates indicate that the DLPFC plays 684 an important role in rule-driven action selection (Wise and Murray, 685 2000). Similarly, in humans, the DLPFC is associated with a role for 686 rule representation within the working memory network (Nee et al., 687 2013). The DLPFC may therefore contribute to motor learning through 688 providing declarative knowledge to be applied to motor output. 689 Interestingly, interfering with the normal function of the DLPFC through 690

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theta burst stimulation or cathodal transcranial direct current stimulation reduces declarative knowledge, but improves motor performance, presumably through placing an increased emphasis on implicit aspects of performance (Galea et al., 2010; Zhu et al., 2015). The DLPFC could therefore interact with the dPMC by providing declarative knowledge and relevant rules to guide motor output (see Wise and Murray, 2000).

The posterior parietal cortex receives multisensory inputs (see 697 Grefkes and Fink, 2005), and is involved in weighting their evidence in 698 699 order to produce appropriate motor output (Block et al., 2013). Notably, the regions demonstrating parietal connectivity in the conjunction of 700 701 the RSFC and MACM maps included the superior parietal lobule (SPL), 702 which was also found to be commonly activated in our recent 703 meta-analysis of 70 motor learning experiments (Hardwick et al., 704 2013; see supplementary methods for comparison). The SPL has known physiological connectivity with the primate dPMC (Matelli et al., 705 1998), and their interaction is important for visuomotor control (Wise 706 707 et al., 1997). Thus, multisensory input from the parietal lobe is thought to be processed to become motor output via an SPL-dPMC pathway 708(Cieslik et al., 2011; Johnson et al., 1993, 1996). 709

The inferior temporal cortex (ITC) is considered to be part of the 710 ventral visual stream (Gross, 2008). ITC neurons respond only to visual 011 stimuli (Gross et al., 1967, 1972), and are specialized for the recognition 712 of shapes regardless of size, color, contrast, or location within the visual 713 013 012 field (Schwartz et al., 1983; Rolls and Baylis, 1986). In humans, lesions of ITC lead to visual agnosia, characterized by an inability to recognize 715 visual stimuli (Bauer, 2006). Association of a ventral stream area with 716 motor control may seem surprising, as the dorsal visual stream is classi-717 718cally associated with movement (Goodale and Milner, 1992). However, functional connectivity with a region specialized in shape recognition is 719 consistent with the essential role of the dPMC plays in producing motor 720 721 responses to arbitrary visual stimuli (Wise and Murray, 2000).

722 Notable for a network involving motor control, the primary motor 723 cortex (M1) was not identified as being functionally connected with the seed in the combined RSFC and MACM conjunction. M1 was also 724 absent in the liberal analysis that removed thresholding from the 725MACM network (see supplementary results). This may seem surprising 726 727 as there are known physiological connections between dPMC and M1 728shown (Dum and Strick, 2005) and as dPMC excitability can affect M1 excitability in humans (Davare et al., 2009). However, RSFC connectivity 729does not always map onto anatomical connections (Di Martino et al., 7302008; Kelly et al., 2010; Uddin et al., 2008; Vincent et al., 2007), and a 731 732 previous study based on 1,000 subjects that parcellated the brain into RSFC networks did not show functional connectivity between M1 and 733 premotor regions such as dPMC (Yeo et al., 2011). In addition, the 734 absence of M1 from the MACM analysis may in large part be explained 735 by the contrasts present in the BrainMap database. Most neuroimaging 736 737 studies include controls for simple motor execution (see, for example, Daselaar et al., 2003; Inoue et al., 2000). Importantly, our previous 738 finding that such contrasts remove M1 activation but still show dPMC 739 activation (Hardwick et al., 2013) highlight the importance of the 740 dPMC in higher-order motor processing. 741

742 Connectivity with the cerebellum was present in the RSFC analysis. 743 In the right cerebellum, connectivity included regions associated with the lower hand representation in lobule HVIII (Thickbroom et al., 2003; 744Yeo et al., 2011), consistent with the importance of the cerebellum in 745motor control (Hardwick et al., 2013, 2014). Bilateral connectivity was 746 747 also identified with lobules HVII (Crus I and II), which are involved in cognitive and linguistic processes (Lesage et al., 2012; Stoodley and 748 Schmahmann, 2009), and are functionally connected to DLPFC and PPC 749 (Buckner et al., 2011; O'Reilly et al., 2010). Given the importance of the 750cerebellum in motor control and learning, and the presence of cerebellar 751 clusters of connectivity with the dPMC in the RSFC analysis, the absence of 752cerebellar clusters in the MACM analysis is perhaps surprising (though 753 the MACM analysis did not identify the cerebellum as having functional 754 connectivity with the dPMC, further analysis did identify multiple sub-755756 threshold clusters of cerebellar connectivity; see supplementary results). This difference can likely be attributed to the focus that many functional 757 imaging studies place on imaging the cerebral cortex; the standard 758 normalization process conducted in neuroimaging studies is not 759 optimized for the cerebellum (Diedrichsen, 2006). Furthermore, inferior Q14 portions of the cerebellum are sometimes not covered by the field of 761 view in many whole-brain fMRI studies, and when these regions are 762 acquired, the default bounding box for normalization in certain software 763 analysis packages do not include the entire cerebellum. This would lead 764 to the absence of and greater variability in cerebellar coordinates than 765 those in the cerebral cortex for many of the studies included in the 766 BrainMap database, and may explain why the MACM analysis detected 767 clusters in the cerebellum that did not survive thresholding. 768

Functional connectivity and structural covariance

As considered above, RSFC and MACM are previously established 770 methods for identifying functional connectivity with a seed region, 771 while the degree to which SC can determine functional connectivity is 772 currently a subject of ongoing debate (Clos et al., 2014). Notably, 773 while RSFC and MACM identified a similar network of frontal, premotor, 774 and parietal regions, SC identified a network of mainly frontal regions 775 that was more widespread than that revealed by the other two 776 methods. This is consistent with findings from graph-theoretical SC 777 analyses that report predominantly local connectivity (He et al., 778 2007a), and with data from seed-based SC analyses that identify regions 779 largely limited to the lobe in which the seed is defined (Clos et al., 2014; 780 Seeley et al., 2009; Zielinski et al., 2010). SC is thought to represent a 781 combination of developmental coordination or synchronized maturation 782 between brain areas (Alexander-Bloch et al., 2013). The SC network iden-783 tified here is consistent with both of these properties; the prefrontal, 784 premotor, and motor regions identified by SC are highly interconnected 785 via anatomical fiber tracts (Bürgel et al., 1999, 2006; Carmichael and 786 Price, 1995; Dum and Strick, 2005), and develop concurrently (Giedd 787 et al., 1999). 788

The Rockland sample and the BrainMap database

The RSFC and SC analyses in the present study used whole-brain 790 neuroimaging data from the Rockland sample. As data from the same 791 subjects were used in both the RSFC and SC analyses, these analyses 792 are therefore matched for factors such as age and gender. In contrast, 793 the MACM analysis was based on data from the BrainMap database, 794 which reports stereotaxic peak activation coordinates from published 795 neuroimaging studies. Using peak coordinates leads to the loss of spatial 796 information, but provides a pragmatic solution to the problems associated 797 with sharing large datasets (current technical and practical limitations 798 prevent the storage of whole-brain data from the 10,000 + neuroimaging 799 studies included in the BrainMap database). Moreover, in spite of begin- 800 ning data-sharing efforts, integrating published maxima coordinates are 801 currently the only approach that allows summarization of the entire 802 current literature. This loss of spatial information may account for the 803 relatively small size of the volume identified by the MACM analysis in 804 comparison to the RSFC and SC analyses. However, while these coordi- 805 nates present a relatively sparse representation of the original activation 806 maps they encapsulate, they also represent the most probable locations 807 of activity from the activation maps they encapsulate, and thus provide 808 a highly reliable source of data. Differences in sampling demographics 809 may also influence the connectivity maps identified by each technique. 810 The Rockland sample aims to produce a representative sample of individ- 811 ual subjects from the general population; in contrast, the BrainMap data- 812 base stores average information from groups of subjects, and the papers 813 from which this information is drawn do not always report demographic 814 information in a uniform manner (e.g. some papers report mean subject 815 ages, some report only age ranges). Similarly, it may be expected that 816 the corpus of studies and contrast types contained within the BrainMap 817 database could influence the results it provides; for example, as most 818

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studies require participants to visual stimuli (vs. other modalities), there 819 may be a bias toward finding activity in visual regions. However, sample 820 bias effects appear unlikely given the high level of consistency between 821 822 the MACM and RSFC maps (the latter of which by definition is not affected by task demands). Furthermore, it is notable that this study and others 823 have identified similar results using RSFC and MACM (Bzdok et al., 824 2013; Clos et al., 2014; Hoffstaedter et al., 2013a; Jakobs et al., 2012; 825 Müller et al., 2013; Rottschy et al., 2013). The consistency between results 826 827 from RSFC and MACM illustrate that harnessing the large and varied sample from the BrainMap database can provide a powerful approach 828 829 to functional connectivity.

830 Conclusions

831 Here, we employed multiple connectivity modelling techniques to identify areas functionally interacting with a left dPMC region identified 832 as key for motor learning. RSFC, MACM, and SC offer different method-833 ological and conceptual approaches to identifying functional connectivity 834 835 with a seed region, and were used here to provide a comprehensive assessment of functional connectivity with the dPMC (cf. Clos et al., 836 837 2014; Reid et al., 2015). Each approach identified networks with clear differences in both their size and topography. However, further analyses 838 indicated that RSFC and MACM revealed a relatively consistent network 839 of prefrontal, premotor, and parietal regions, while the SC map consisted 840 841 mainly of widespread frontal regions. All techniques identified a consistent 'core' network of functional connectivity with the left vPMC, right 842 dPMC, and the SMA, all of which play important roles in the motor 843 control and learning (Hardwick et al., 2013). Most notably, conjunction 844 of the RSFC and MACM networks identified a consistent functional 845 network consisting of the bilateral dPMC, vPMC, SMA, and PPC, as well 846 as left hemisphere connectivity with the DLPFC and ITC. This network is 847 consistent with the established role of the dPMC in response selection, 848 suggesting that it supports motor learning by acting as an interface 849 between higher cognitive functions and visuomotor control. 850

851 Appendix A. Supplementary data

852 Supplementary data to this article can be found online at http://dx.
 853 doi.org/10.1016/j.neuroimage.2015.08.024.

854 References

- Albaugh, M.D., Ducharme, S., Collins, D.L., Botteron, K.N., Althoff, R.R., Evans, A.C., Karama, S.,
 Hudziak, J.J., 2013. Evidence for a cerebral cortical thickness network anti-correlated
 with amygdalar volume in healthy youths: implications for the neural substrates of
 emotion regulation. Neuroimage 71, 42–49. http://dx.doi.org/10.1016/j.neuroimage.
 2012.12.071.
- Alexander-Bloch, A., Giedd, J.N., Bullmore, E., 2013. Imaging structural co-variance between human brain regions. Nat. Rev. Neurosci. 14, 322–336. http://dx.doi.org/ 10.1038/nrn3465.
- Amunts, K., Hawrylycz, M.J., Van Essen, D.C., Van Horn, J.D., Harel, N., Poline, J.-B., De Martino, F., Bjaalie, J.C., Dehaene-Lambertz, C., Dehaene, S., Valdes-Sosa, P., Thirion, B., Zilles, K., Hill, S.L., Abrams, M.B., Tass, P.A., Vanduffel, W., Evans, A.C., Eickhoff, S.B., 2014. Interoperable atlases of the human brain. Neuroimage 99, 525–532. http://dx.doi.org/10.1016/j.neuroimage.2014.06.010.
- Ashburner, J., Friston, K.J., 2005. Unified segmentation. Neuroimage 26, 839–851. http:// dx.doi.org/10.1016/j.neuroimage.2005.02.018.
- Q15Bauer, R.M., 2006. The Agnosias. In: Snyder, P.J., Nussbaum, P.D., Robins, D.L. (Eds.), Clinical871Neuropsychology: A Pocket Handbook for Assessment. American Psychological872Association, Washington, DC, pp. 508–533.
- Bestmann, S., Swayne, O., Blankenburg, F., Ruff, C.C., Haggard, P., Weiskopf, N., Josephs, O., Driver, J., Rothwell, J.C., Ward, N.S., 2008. Dorsal premotor cortex exerts state-dependent causal influences on activity in contralateral primary motor and dorsal premotor cortex. Cereb. Cortex 18, 1281–1291. http://dx.doi.org/10.1093/ cercor/bhm159.
- Binkofski, F., Buccino, G., Stephan, K.M., Rizzolatti, G., Seitz, R.J., Freund, H.J., 1999. A
 parieto-premotor network for object manipulation: evidence from neuroimaging.
 Exp. Brain Res. 128, 210–213.
- Biswal, B.B., 2012. Resting state fMRI: a personal history. Neuroimage 62, 938–944. http://
 dx.doi.org/10.1016/j.neuroimage.2012.01.090.
- Block, H., Bastian, A., Celnik, P., 2013. Virtual lesion of angular gyrus disrupts the relationship
 between visuoproprioceptive weighting and realignment. J. Cogn. Neurosci. 25,
 636–648. http://dx.doi.org/10.1162/jocn_a_00340.

- Boudrias, M.-H., McPherson, R.L., Frost, S.B., Cheney, P.D., 2010. Output properties and 886 organization of the forelimb representation of motor areas on the lateral aspect of 887 the hemisphere in rhesus macaques. Cereb. Cortex 20, 169–186. http://dx.doi.org/ 888 10.1093/cercor/bhp084. 889
- Buckner, R.L., Krienen, F.M., Castellanos, A., Diaz, J.C., Yeo, B.T.T., 2011. The organization of 890 the human cerebellum estimated by intrinsic functional connectivity. J. Neurophysiol. 891 106, 2322–2345. http://dx.doi.org/10.1152/jn.00339.2011. 892
- Bürgel, U., Schormann, T., Schleicher, A., Zilles, K., 1999. Mapping of histologically identified
 893
 long fiber tracts in human cerebral hemispheres to the MRI volume of a reference brain.
 894
 position and spatial variability of the optic radiation. Neuroimage 10, 489–499. http://
 895
 dx.doi.org/10.1006/nimg.1999.0497.
- Bürgel, U., Amunts, K., Hoemke, L., Mohlberg, H., Gilsbach, J.M., Zilles, K., 2006. White 897 matter fiber tracts of the human brain: three-dimensional mapping at microscopic 898 resolution, topography and intersubject variability. Neuroimage 29, 1092–1105. 899 http://dx.doi.org/10.1016/j.neuroimage.2005.08.040. 900
- Bzdok, D., Langner, R., Schilbach, L., Jakobs, O., Roski, C., Caspers, S., Laird, A.R., Fox, P.T., 901 Zilles, K., Eickhoff, S.B., 2013. Characterization of the temporo-parietal junction by 902 combining data-driven parcellation, complementary connectivity analyses, and 903 functional decoding. Neuroimage 81, 381–392. http://dx.doi.org/10.1016/j. 904 neuroimage.2013.05.046. 905
- Carmichael, S.T., Price, J.L., 1995. Sensory and premotor connections of the orbital and 906 medial prefrontal cortex of macaque monkeys. J. Comp. Neurol. 363, 642–664. 907 http://dx.doi.org/10.1002/cne.903630409. 908
- Chang, C., Glover, G.H., 2009. Effects of model-based physiological noise correction on 909 default mode network anti-correlations and correlations. Neuroimage 47, 1448–1459. 910 http://dx.doi.org/10.1016/j.neuroimage.2009.05.012. 911
- Cieslik, E.C., Zilles, K., Grefkes, C., Eickhoff, S.B., 2011. Dynamic interactions in the frontoparietal network during a manual stimulus-response compatibility task. Neuroimage 58, 860–869. http://dx.doi.org/10.1016/j.neuroimage.2011.05.089. 914
- Cisek, P., Crammond, D.J., Kalaska, J.F., 2003. Neural activity in primary motor and dorsal 915 premotor cortex in reaching tasks with the contralateral versus ipsilateral arm. 916 J. Neurophysiol. 89, 922–942. http://dx.doi.org/10.1152/jn.00607.2002. 917
- Clos, M., Rottschy, C., Laird, A.R., Fox, P.T., Eickhoff, S.B., 2014. Comparison of structural 918 covariance with functional connectivity approaches exemplified by an investigation 919 of the left anterior insula. Neuroimage 99, 269–280. http://dx.doi.org/10.1016/j. 920 neuroimage.2014.05.030.
- Criaud, M., Boulinguez, P., 2013. Have we been asking the right questions when assessing 922 response inhibition in go/no-go tasks with fMRI? A meta-analysis and critical 923 review. Neurosci. Biobehav. Rev. 37, 11–23. http://dx.doi.org/10.1016/j.neubiorev. 924 2012.11.003. 925
- Daselaar, S.M., Rombouts, S.A.R.B., Veltman, D.J., Raaijmakers, J.G.W., Jonker, C., 2003. 926
 Similar network activated by young and old adults during the acquisition of a 927
 motor sequence. Neurobiol. Aging 24, 1013–1019. 928
- Davare, M., Andres, M., Cosnard, G., Thonnard, J.-L., Olivier, E., 2006. Dissociating the role 929 of ventral and dorsal premotor cortex in precision grasping. J. Neurosci. 26, 930 2260–2268. http://dx.doi.org/10.1523/JNEUROSCI.3386-05.2006. 931
- Davare, M., Montague, K., Olivier, E., Rothwell, J.C., Lemon, R.N., 2009. Ventral premotor to 932 primary motor cortical interactions during object-driven grasp in humans. Cortex 45, 933 1050–1057. http://dx.doi.org/10.1016/j.cortex.2009.02.011. 934
- Deecke, L., Kornhuber, H.H., 1978. An electrical sign of participation of the mesial "supplementary" motor cortex in human voluntary finger movement. Brain Res. 159, 473–476. 936
- Di Martino, A., Scheres, A., Margulies, D.S., Kelly, A.M.C., Uddin, L.Q., Shehzad, Z., Biswal, B., 937 Walters, J.R., Castellanos, F.X., Milham, M.P., 2008. Functional connectivity of human 938 striatum: a resting state FMRI study. Cereb. Cortex 18, 2735–2747. http://dx.doi. 939 org/10.1093/cercor/bhn041. 940
- Draganski, B., Gaser, C., Busch, V., Schuierer, G., Bogdahn, U., May, A., 2004. Neuroplasticity: 941 changes in grey matter induced by training. Nature 427, 311–312. http://dx.doi.org/10.942 1038/427311a.943
- Dum, R.P., Strick, P.L., 2005. Frontal lobe inputs to the digit representations of the motor 944 areas on the lateral surface of the hemisphere. J. Neurosci. 25, 1375–1386. http:// 945 dx.doi.org/10.1523/JNEUROSCI.3902-04.2005. 946
- Ehrsson, H.H., Fagergrein, A., Jonsson, T., Westling, G., Johansson, R.S., Forssberg, H., 2000. 947
 Cortical activity in precision- versus power-grip tasks: an fMRI study. J. Neurophysiol. 948
 83, 528–536. 949
- Ehrsson, H.H., Fagergren, E., Forssberg, H., 2001. Differential fronto-parietal activation 950 depending on force used in a precision grip task: an fMRI study. J. Neurophysiol. 951 85, 2613–2623. 952
- Eickhoff, S.B., Stephan, K.E., Mohlberg, H., Grefkes, C., Fink, G.R., Amunts, K., Zilles, K., 2005. 953
 A new SPM toolbox for combining probabilistic cytoarchitectonic maps and functional 954
 imaging data. Neuroimage 25, 1325–1335. http://dx.doi.org/10.1016/j.neuroimage. 955
 2004.12,034. 956
- Eickhoff, S.B., Paus, T., Caspers, S., Grosbras, M.-H., Evans, A.C., Zilles, K., Amunts, K., 957 2007. Assignment of functional activations to probabilistic cytoarchitectonic 958 areas revisited. Neuroimage 36, 511–521. http://dx.doi.org/10.1016/j.neuroimage 959 2007.03.060. 960
- Eickhoff, S.B., Laird, A.R., Grefkes, C., Wang, L.E., Zilles, K., Fox, P.T., 2009. Coordinate-based 961 activation likelihood estimation meta-analysis of neuroimaging data: a random-effects 962 approach based on empirical estimates of spatial uncertainty. Hum. Brain Mapp. 30, 963 2907–2926. http://dx.doi.org/10.1002/hbm.20718. 964
- Eickhoff, S.B., Jbabdi, S., Caspers, S., Laird, A.R., Fox, P.T., Zilles, K., Behrens, T.E.J., 2010. 965
 Anatomical and functional connectivity of cytoarchitectonic areas within the 966
 human parietal operculum. J. Neurosci. 30, 6409–6421. http://dx.doi.org/10.1523/ 967
 JNEUROSCI.5664-09.2010. 968
- Eickhoff, S.B., Bzdok, D., Laird, A.R., Kurth, F., Fox, P.T., 2012. Activation likelihood estimation 969 meta-analysis revisited. Neuroimage 59, 2349–2361. http://dx.doi.org/10.1016/j. 970 neuroimage.2011.09.017. 971

R.M. Hardwick et al. / NeuroImage xxx (2015) xxx-xxx

972	Fox, M.D., Raichle, M.E., 2007. Spontaneous fluctuations in brain activity observed with func-	Matelli,
973 074	tional magnetic resonance imaging. Nat. Rev. Neurosci. 8, 700–711. http://dx.doi.org/10.	froi 327
974 975	Friston, K.J., 1994. Functional and effective connectivity in neuroimaging: a synthesis.	Mayka,
976	Hum. Brain Mapp. 2, 56–78. http://dx.doi.org/10.1002/hbm.460020107.	loca
977	Galea, J.M., Albert, N.B., Ditye, T., Miall, R.C., 2010. Disruption of the dorsolateral prefrontal	bra
978 979	cortex facilitates the consolidation of procedural skills. J. Cogn. Neurosci. 22, 1158–1164. http://dx.doi.org/10.1162/jocn.2009.21259	Müller
980	Gaser, C., Schlaug, G., 2003. Brain structures differ between musicians and non-musicians.	par
981	J. Neurosci. 23, 9240–9245.	cha
982	Giedd, J.N., Blumenthal, J., Jeffries, N.O., Castellanos, F.X., Liu, H., Zijdenbos, A., Paus, T.,	201 Na shav
983 084	EVANS, A.C., KAPOPORT, J.L., 1999. Brain development during childhood and adolescence: a longitudinal MRI study. Nat. Neurosci. 2, 861–863, http://dx.doi.org/10.1038/13158	Nachev
985	Goodale, M.A., Milner, A.D., 1992. Separate visual pathways for perception and action.	10.1
986	Trends Neurosci. 15, 20–25.	Nee, D.I
987	Grefkes, C., Fink, G.R., 2005. The functional organization of the intraparietal sulcus in	201
988	humans and monkeys. J. Anat. 207, 3–17. http://dx.doi.org/10.1111/j.1469-7580.	23, Nicholo
989	2005.00426.X. Gross C.G. Schiller P.H. Wells C. Gerstein G.L. 1967 Single-unit activity in temporal	INICIIOIS,
991	association cortex of the monkey. J. Neurophysiol. 30, 833–843.	neu
992	Gross, C.G., Rocha-Miranda, C.E., Bender, D.B., 1972. Visual properties of neurons in	Nooner,
993	inferotemporal cortex of the macaque. J. Neurophysiol. 35, 96–111.	L.J.,
994	Halsband, U., Ito, N., Ianji, J., Freund, H.J., 1993. The role of premotor cortex and the	Kar
995 996	(Pt 1) 243–266	Wo
997	Hamzei, F., Glauche, V., Schwarzwald, R., May, A., 2012. Dynamic gray matter changes	The
998	within cortex and striatum after short motor skill training are associated with their	Кор
999	increased functional interaction. Neuroimage 59, 3364–3372. http://dx.doi.org/10.	NK
1000	1016/J.neuroImage.2011.10.089. Hardwick R.M. Rottschy, C. Miall R.C. Fickhoff S.B. 2013. A quantitative meta-analysis	D'Reilly
1001	and review of motor learning in the human brain. Neuroimage 67, 283–297. http://	and
1003	dx.doi.org/10.1016/j.neuroimage.2012.11.020.	fun
1004	Hardwick, R.M., Lesage, E., Miall, R.C., 2014. Cerebellar transcranial magnetic stimulation:	cer
1005	the role of coil geometry and tissue depth. Brain Stimul http://dx.doi.org/10.1016/j.	O'Shea,
1000	He Y Chen 7.1 Evans A C 2007a Small-world anatomical networks in the human brain	doi
1008	revealed by cortical thickness from MRI. Cereb. Cortex 17, 2407–2419. http://dx.doi.	Obeso,
1009	org/10.1093/cercor/bhl149.	Stir
1010	He, Y., Wang, L., Zang, Y., Tian, L., Zhang, X., Li, K., Jiang, T., 2007b. Regional coherence	wit
1011	changes in the early stages of Alzheimer's disease; a combined structural and resting-state functional MRI study. Neuroimage 35, 488–500, http://dx.doi.org/10.	Power
1012	1016/j.neuroimage.2006.11.042.	svs
1014	Hoffstaedter, F., Grefkes, C., Caspers, S., Roski, C., Palomero-Gallagher, N., Laird, A.R., Fox,	mo
1015	P.T., Eickhoff, S.B., 2013a. The role of anterior midcingulate cortex in cognitive	10.0
1016	motor control: evidence from functional connectivity analyses. Hum. Brain Mapp.	Reetz, k
1017	Hoffstaedter F. Grefkes C. Zilles K. Fickhoff S.B. 2013b The "what" and "when" of	201
1019	self-initiated movements. Cereb. Cortex 23, 520–530. http://dx.doi.org/10.1093/	135
1020	cercor/bhr391.	Reid, A.
1021	Holmes, C.J., Hoge, R., Collins, L., Woods, R., Toga, A.W., Evans, A.C., 1998. Enhancement of	C.R.
1022	MR images using registration for signal averaging. J. Comput. Assist. Tomogr. 22,	late
1023	Inoue, K., Kawashima, R., Satoh, K., Kinomura, S., Sugiura, M., Goto, R., Ito, M., Fukuda, H.,	Robins
1025	2000. A PET study of visuomotor learning under optical rotation. Neuroimage 11,	con
1026	505–516. http://dx.doi.org/10.1006/nimg.2000.0554.	am
1027	Jakobs, O., Langner, R., Caspers, S., Roski, C., Cieslik, E.C., Zilles, K., Laird, A.R., Fox, P.T.,	Roland,
1028	a right temporo-parietal junction subregion involved in stimulus-context	137
1030	integration. Neuroimage 60, 2389–2398. http://dx.doi.org/10.1016/j.neuroimage.	Rottsch
1031	2012.02.037.	201
1032	Jenkinson, M., Beckmann, C.F., Behrens, T.E.J., Woolrich, M.W., Smith, S.M., 2012. FSL.	me
1033	Neuroimage 62, 782–790. http://dx.doi.org/10.1016/j.neuroimage.2011.09.015.	201 Rottsch
1034	Brain Res. 97, 361–365.	P.T.
1036	Johnson, P.B., Ferraina, S., Bianchi, L., Caminiti, R., 1996. Cortical networks for visual	"wl
1037	reaching: physiological and anatomical organization of frontal and parietal lobe	org
1038	arm regions. Cereb. Cortex 6, 102–119. Kally C. Uddin J.O. Shahrad 7. Margulian D.S. Cartellance, F.Y. Milham M.B. Petridee M.	Rushwo
1039	2010 Broca's region: linking human brain functional connectivity data and non-human	S89
1041	primate tracing anatomy studies. Eur. J. Neurosci. 32, 383–398. http://dx.doi.org/10.	Satterth
1042	1111/j.1460-9568.2010.07279.x.	Eicl
1043	Kelly, C., Toro, R., Di Martino, A., Cox, C.L., Bellec, P., Castellanos, F.X., Milham, M.P.,	frai
1044	2012. A convergent functional architecture of the insula emerges across imaging modulities. Neuroimage 61, 1129–1142, http://dx.doi.org/10.1016/j.peuroimage	the 240
1046	2012.03.021.	Schubo
1047	Laird, A.R., Eickhoff, S.B., Fox, P.M., Uecker, A.M., Ray, K.L., Saenz, J.J., McKay, D.R., Bzdok, D.,	spo
1048	Laird, R.W., Robinson, J.L., Turner, J.A., Turkeltaub, P.E., Lancaster, J.L., Fox, P.T., 2011. The	15,
1049	BrainMap strategy for standardization, sharing, and meta-analysis of neuroimaging data.	Schubo
1050 1051	Lerch, I.P., Worsley, K., Shaw, W.P., Greenstein, D.K., Lenroot, R.K. Giedd, I. Evans, A.C.	920
1052	2006. Mapping anatomical correlations across cerebral cortex (MACACC) using	Seeley.
1053	cortical thickness from MRI. Neuroimage 31, 993-1003. http://dx.doi.org/10.	dise
1054	1016/j.neuroimage.2006.01.042.	org
1055 1056	Lesage, E., Morgan, B.E., UISON, A.C., Meyer, A.S., MIAII, K.C., 2012. Cerebellar rIMS disrupts predictive language processing. Curr. Riol. 22, R704, R705, http://dx.doi.org/10.1016/	Segall, J
1057	j.cub.2012.07.006.	Nei
-		
	Please cite this article as: Hardwick, R.M., et al., Multimodal connectivi	ty of moto
	http://dx.doi.org/10.1016/j.neuroimage.2015.08.024	

Matelli, M., Govoni, P., Galletti, C., Kutz, D.F., Luppino, G., 1998. Superior	area 6 afferents	1058
from the superior parietal lobule in the macaque monkey. J. Com	p. Neurol. 402,	105
327–352.		106

M.A., Corcos, D.M., Leurgans, S.E., Vaillancourt, D.E., 2006. Three-dimensional 1061 ations and boundaries of motor and premotor cortices as defined by functional 1062 in imaging: a meta-analysis. Neuroimage 31, 1453–1474. http://dx.doi.org/10. 1063 6/j.neuroimage.2006.02.004. 1064

V.I., Cieslik, E.C., Laird, A.R., Fox, P.T., Eickhoff, S.B., 2013. Dysregulated left inferior 1065 ietal activity in schizophrenia and depression: functional connectivity and 1066 racterization, Front, Hum, Neurosci, 7, 268, http://dx.doi.org/10.3389/fnhum, 1067 3 00268 1068

P., Kennard, C., Husain, M., 2008. Functional role of the supplementary and 1069 -supplementary motor areas. Nat. Rev. Neurosci. 9, 856-869. http://dx.doi.org/ 1070 038/nrn2478. 1071

E., Brown, J.W., Askren, M.K., Berman, M.G., Demiralp, E., Krawitz, A., Jonides, J., 1072 3. A meta-analysis of executive components of working memory. Cereb. Cortex 1073 264-282. http://dx.doi.org/10.1093/cercor/bhs007. 1074

T., Brett, M., Andersson, J., Wager, T., Poline, J.-B., 2005. Valid conjunction inference 1075 h the minimum statistic. Neuroimage 25, 653-660. http://dx.doi.org/10.1016/j. 1076 roimage.2004.12.005. 1077

- K.B., Colcombe, S.J., Tobe, R.H., Mennes, M., Benedict, M.M., Moreno, A.L., Panek, 1078 Brown, S., Zavitz, S.T., Li, Q., Sikka, S., Gutman, D., Bangaru, S., Schlachter, R.T., 1079 niel, S.M., Anwar, A.R., Hinz, C.M., Kaplan, M.S., Rachlin, A.B., Adelsberg, S., 1080 eung, B., Khanuja, R., Yan, C., Craddock, C.C., Calhoun, V., Courtney, W., King, M., 1081 ood, D., Cox, C.L., Kelly, A.M.C., Di Martino, A., Petkova, E., Reiss, P.T., Duan, N., 1082 omsen, D., Biswal, B., Coffey, B., Hoptman, M.J., Javitt, D.C., Pomara, N., Sidtis, J.J., 1083 plewicz, H.S., Castellanos, F.X., Leventhal, B.L., Milham, M.P., 2012. The 1084 -Rockland sample: a model for accelerating the pace of discovery science in 1085 chiatry. Front. Neurosci. 6, 152. http://dx.doi.org/10.3389/fnins.2012.00152. 1086
- J.X., Beckmann, C.F., Tomassini, V., Ramnani, N., Johansen-Berg, H., 2010. Distinct 1087 overlapping functional zones in the cerebellum defined by resting state 1088 ctional connectivity. Cereb. Cortex 20, 953-965. http://dx.doi.org/10.1093/ 1089 cor/bhp157 1090

J., Johansen-Berg, H., Trief, D., Göbel, S., Rushworth, M.F.S., 2007. Functionally 1091 cific reorganization in human premotor cortex. Neuron 54, 479-490. http://dx. 1092org/10.1016/j.neuron.2007.04.021. 1093

- I., Cho, S.S., Antonelli, F., Houle, S., Jahanshahi, M., Ko, J.H., Strafella, A.P., 2013. 1094 nulation of the pre-SMA influences cerebral blood flow in frontal areas involved 1095 h inhibitory control of action. Brain Stimul. 6, 769–776. http://dx.doi.org/10. 1096 6/j.brs.2013.02.002. 1097
- J.D., Barnes, K.A., Snyder, A.Z., Schlaggar, B.L., Petersen, S.E., 2012. Spurious but 1098 ematic correlations in functional connectivity MRI networks arise from subject 1099 tion. Neuroimage 59, 2142–2154. http://dx.doi.org/10.1016/j.neuroimage.2011. 1100 018 1101
- , Dogan, I., Rolfs, A., Binkofski, F., Schulz, J.B., Laird, A.R., Fox, P.T., Eickhoff, S.B., 1102 2. Investigating function and connectivity of morphometric findings-exemplified 1103 cerebellar atrophy in spinocerebellar ataxia 17 (SCA17). Neuroimage 62, 1104 4-1366. http://dx.doi.org/10.1016/j.neuroimage.2012.05.058.
- T., Bzdok, D., Langner, R., Fox, P.T., Laird, A.R., Amunts, K., Eickhoff, S.B., Eickhoff, 1106 2015. Multimodal connectivity mapping of the human left anterior and posterior 1107 ral prefrontal cortex. Brain Struct. Funct. http://dx.doi.org/10.1007/s00429-015-1108 60-5. 1109
- on, J.L., Laird, A.R., Glahn, D.C., Lovallo, W.R., Fox, P.T., 2010. Metaanalytic 1110 nectivity modeling: delineating the functional connectivity of the human 1111 gdala. Hum. Brain Mapp. 31, 173–184. http://dx.doi.org/10.1002/hbm.20854. 1112

P.E., Skinhøj, E., Lassen, N.A., Larsen, B., 1980. Different cortical areas in man in 1113 anization of voluntary movements in extrapersonal space. J. Neurophysiol. 43, 1114 -150.1115

- y, C., Langner, R., Dogan, I., Reetz, K., Laird, A.R., Schulz, J.B., Fox, P.T., Eickhoff, S.B., 1116 2. Modelling neural correlates of working memory: a coordinate-based 1117 ta-analysis. Neuroimage 60, 830–846. http://dx.doi.org/10.1016/j.neuroimage. 1118 1.11.050. 1119
- y, C., Caspers, S., Roski, C., Reetz, K., Dogan, I., Schulz, J.B., Zilles, K., Laird, A.R., Fox, 1120 Eickhoff, S.B., 2013. Differentiated parietal connectivity of frontal regions for 1121 nat" and "where" memory. Brain Struct. Funct. 218, 1551–1567. http://dx.doi. 1122/10.1007/s00429-012-0476-4. 1123
- orth, M.F.S., Johansen-Berg, H., Göbel, S.M., Devlin, J.T., 2003. The left parietal 1124 premotor cortices: motor attention and selection. Neuroimage 20 (Suppl. 1), 1125 -S100. 1126
- waite, T.D., Elliott, M.A., Gerraty, R.T., Ruparel, K., Loughead, J., Calkins, M.E., 1127 khoff, S.B., Hakonarson, H., Gur, R.C., Gur, R.E., Wolf, D.H., 2013. An improved 1128 nework for confound regression and filtering for control of motion artifact in 1129 preprocessing of resting-state functional connectivity data. Neuroimage 64, 1130 -256. http://dx.doi.org/10.1016/j.neuroimage.2012.08.052. 1131

tz, R.I., von Cramon, D.Y., 2002a. Predicting perceptual events activates corre- 1132 nding motor schemes in lateral premotor cortex: an fMRI study. Neuroimage 1133 787-796. http://dx.doi.org/10.1006/nimg.2001.1043. 1134

tz, R.I., von Cramon, D.Y., 2002b. A blueprint for target motion: fMRI reveals 1135 ceived sequential complexity to modulate premotor cortex. Neuroimage 16, 1136 -935. 1137

W.W., Crawford, R.K., Zhou, J., Miller, B.L., Greicius, M.D., 2009. Neurodegenerative 1138 eases target large-scale human brain networks. Neuron 62, 42–52. http://dx.doi. 1139 10.1016/j.neuron.2009.03.024.

.M., Allen, E.A., Jung, R.E., Erhardt, E.B., Arja, S.K., Kiehl, K., Calhoun, V.D., 2012. 1141 respondence between structure and function in the human brain at rest. Front. 1142 roinform. 6, 10. http://dx.doi.org/10.3389/fninf.2012.00010. 1143

r learning-related dorsal premotor cortex, NeuroImage (2015),

R.M. Hardwick et al. / NeuroImage xxx (2015) xxx-xxx

- Smith, S.M., Nichols, T.E., 2009. Threshold-free cluster enhancement: addressing problems of smoothing, threshold dependence and localisation in cluster inference. Neuroimage 44, 83–98. http://dx.doi.org/10.1016/j.neuroimage.2008.03.061.
- Smith, S.M., Jenkinson, M., Woolrich, M.W., Beckmann, C.F., Behrens, T.E.J., Johansen-Berg,
 H., Bannister, P.R., De Luca, M., Drobnjak, I., Flitney, D.E., Niazy, R.K., Saunders, J.,
 Vickers, J., Zhang, Y., De Stefano, N., Brady, J.M., Matthews, P.M., 2004. Advances in
 functional and structural MR image analysis and implementation as FSL. Neuroimage
 23 (Suppl. 1), S208–S219, http://dx.doi.org/10.1016/j.neuroimage.2004.07.051.
- Stoodley, C.J., Schmahmann, J.D., 2009. Functional topography in the human cerebellum:
 a meta-analysis of neuroimaging studies. Neuroimage 44, 489–501. http://dx.doi.org/
 10.1016/i.neuroimage.2008.08.039.
- 1155Tanji, J., Okano, K., Sato, K.C., 1988. Neuronal activity in cortical motor areas related to ip-
silateral, contralateral, and bilateral digit movements of the monkey. J. Neurophysiol.115760, 325–343.
- 1158Thickbroom, G.W., Byrnes, M.L., Mastaglia, F.L., 2003. Dual representation of the hand in1159the cerebellum: activation with voluntary and passive finger movement. Neuroimage116018, 670–674.
- 1161 Turkeltaub, P.E., Eden, G.F., Jones, K.M., Zeffiro, T.A., 2002. Meta-analysis of the functional neuroanatomy of single-word reading: method and validation. Neuroimage 16, 765–780.
- 1164Turkeltaub, P.E., Eickhoff, S.B., Laird, A.R., Fox, M., Wiener, M., Fox, P., 2012. Minimizing
within-experiment and within-group effects in activation likelihood estimation
meta-analyses. Hum. Brain Mapp. 33, 1–13. http://dx.doi.org/10.1002/hbm.21186.
- 1167 Uddin, L.Q., Kelly, A.M.C., Biswal, B.B., Margulies, D.S., Shehzad, Z., Shaw, D., Ghaffari, M., 1168 Rotrosen, J., Adler, L.A., Castellanos, F.X., Milham, M.P., 2008. Network homogeneity 1169 reveals decreased integrity of default-mode network in ADHD. J. Neurosci. Methods 1170 169, 249–254. http://dx.doi.org/10.1016/j.jneumeth.2007.11.031.
- 1171 Vincent, J.L., Patel, G.H., Fox, M.D., Snyder, A.Z., Baker, J.T., Van Essen, D.C., Zempel, J.M.,
- 1172 Snyder, L.H., Corbetta, M., Raichle, M.E., 2007. Intrinsic functional architecture in
- 1173the anaesthetized monkey brain. Nature 447, 83–86. http://dx.doi.org/10.1038/1174nature05758.

- Ward, N.S., Frackowiak, R.S.J., 2003. Age-related changes in the neural correlates of motor performance. Brain 126, 873–888. 1176
- Weinrich, M., Wise, S.P., 1982. The premotor cortex of the monkey. J. Neurosci. 2, 1177 1329–1345
- Wise, S.P., Murray, E.A., 2000. Arbitrary associations between antecedents and actions. 1179 Trends Neurosci. 23, 271–276. 1180
- Wise, S.P., Boussaoud, D., Johnson, P.B., Caminiti, R., 1997. Premotor and parietal cortex: 1181 corticocortical connectivity and combinatorial computations. Annu. Rev. Neurosci. 1182 20, 25–42. http://dx.doi.org/10.1146/annurev.neuro.20.1.25. 1183
- Wymbs, N.F., Grafton, S.T., 2013. Contributions from the left PMd and the SMA during 1184 sequence retrieval as determined by depth of training. Exp. Brain Res. 224, 49–58. 1185 http://dx.doi.org/10.1007/s00221-012-3287-1. 1186
- Yeo, B.T.T., Krienen, F.M., Sepulcre, J., Sabuncu, M.R., Lashkari, D., Hollinshead, M., 1187
 Roffman, J.L., Smoller, J.W., Zöllei, L., Polimeni, J.R., Fischl, B., Liu, H., Buckner, R.L., 1188
 2011. The organization of the human cerebral cortex estimated by intrinsic functional 1189
 connectivity. J. Neurophysiol. 106, 1125–1165. http://dx.doi.org/10.1152/jn.00338.
 2011.
- Zhang, X., de Beukelaar, T.T., Possel, J., Olaerts, M., Swinnen, S.P., Woolley, D.G., Wenderoth, 1192
 N., 2011. Movement observation improves early consolidation of motor memory. 1193
 J. Neurosci. 31, 11515–11520. http://dx.doi.org/10.1523/JNEUROSCI.6759-10.2011. 1194
- Zhu, F., Yeung, A., Poolton, J., Lee, T., Leung, G., Masters, R., 2015. Cathodal transcranial 1195 direct current stimulation over left dorsolateral prefrontal cortex area promotes 1196 implicit motor learning in a golf putting task. Brain Stimul. http://dx.doi.org/10. 1197 1016/j.brs.2015.02.005. 1198
- Zielinski, B.A., Gennatas, E.D., Zhou, J., Seeley, W.W., 2010. Network-level structural 1199 covariance in the developing brain. Proc. Natl. Acad. Sci. U. S. A. 107, 18191–18196. 1200 http://dx.doi.org/10.1073/pnas.1003109107. 1201
- zu Eulenburg, P., Caspers, S., Roski, C., Eickhoff, S.B., 2012. Meta-analytical definition 1202 and functional connectivity of the human vestibular cortex. Neuroimage 60, 162–169. 1203 http://dx.doi.org/10.1016/j.neuroimage.2011.12.032. 1204