A key question in developmental neuroscience involves understanding how and when the cerebral cortex is partitioned into distinct functional areas. The present study used functional connectivity MRI mapping and graph theory to identify putative cortical areas and generate a parcellation scheme of left lateral parietal cortex (LLPC) in 7 to 10-year-old children and adults. Results indicated that a majority of putative LLPC areas could be matched across groups (mean distance between matched areas across age: 3.15 mm). Furthermore, the boundaries of children's putative LLPC areas respected the boundaries generated from the adults' parcellation scheme for a majority of children's areas (13/15). Consistent with prior research, matched LLPC areas showed age-related differences in functional connectivity strength with other brain regions. These results suggest that LLPC cortical parcellation and functional connectivity mature along different developmental trajectories, with adult-like boundaries between LLPC areas established in school-age children prior to adult-like functional connectivity.

Keywords: brain development, functional areas, functional connectivity, parietal lobe

Introduction

A fundamental question in developmental neurobiology involves understanding how and when the cerebral cortex is partitioned into areas that can be identified by their unique patterns of connectivity, function, architectonics, and topography (Rakic 1988; O’Leary 1989; Felleman and Van Essen 1991). However, the developmental time course of human cortical arealization is unclear. Only a handful of studies have addressed the timing of arealization directly, with mixed findings. In postmortem tissue samples from 10 subjects ranging in age from birth to 30 years, the size and location of Brodmann’s areas 44 and 45 were estimated to be adult-like by age 7 years, as indexed by cytoarchitectonic features (Uylings et al. 2005). In contrast, retinotopic mapping using functional magnetic resonance imaging (fMRI) to identify visual areas revealed small but statistically reliable reductions in areal size in 10 children ages 9-12 years compared with 10 adults (Conner et al. 2004). Both of these studies have relatively small sample sizes, and the development of arealization remains unexplored in other regions of the cerebral cortex. This report proposes a parcellation scheme of left lateral parietal cortex (LLPC) in children and a matched group of adults, using the functional connectivity of putative LLPC areas to address whether and how parcellation schemes and areal functional connectivity profiles change over development.

Although nonhuman animal research suggests that a combination of intrinsic (e.g., genetic) and extrinsic (e.g., thalamocortical afferent mediated activity) factors work in concert to pattern the cerebral cortex into areas prenatally and in the first year of life (O’Leary and Nakagawa 2002; Sur and Rubenstein 2005; Rakic et al. 2009), humans may have a more protracted course for cortical arealization. Many aspects of brain structure and function mature throughout adolescence, such as task-evoked recruitment of brain regions (Paul 2005; Blakemore and Choudhury 2006; Bunge and Wright 2007; Casey et al. 2008; Luna et al. 2010), gray matter density (Huttenlocher and Dabholkar 1997; Giedd and Rapoport 2010), myelination (Yakovlev and Lecours 1967), structural connectivity (Asato et al. 2010), and functional connectivity (Power et al. 2010; Vogel et al. 2010). Since such factors could act as extrinsic influences upon arealization, it is important to determine the developmental trajectory of cortical arealization in humans.

Multiple factors prevent the broader application of existing noninvasive mapping techniques to questions about human cortical arealization. One approach involves examining the extent of stimulus-evoked activation with “functional localizers.” These methods can be deployed when the topographic organization of a cortical area is relatively well understood (e.g., retinotopic mapping to locate boundaries between visual areas, Fox et al. 1986). However, as it is yet unclear how to map the topography in many parts of the cerebral cortex, there is considerable debate about the appropriateness of functional localizer methods. Another problem emerges when estimates of cortical areal size are derived from “voxel-counting” (i.e., counting voxels with statistical thresholds above a threshold) because such estimates may be impacted by group differences in task performance. For example, the extent of fMRI activation can be impacted by the number of errors a subject makes (Murphy and Garavan 2004) or by group differences in performance speed and accuracy (Schlaggar et al. 2002; Palmer et al. 2004; Brown et al. 2005; Church et al. 2010). The limitations of prevalent methods suggest that novel methods are needed to study cortical arealization in human development.

Noninvasive functional connectivity mapping (fc-Mapping) methods developed by Cohen et al. (2008) and extended by Nelson et al. (2010) can be used to study cortical arealization. fc-Mapping uses resting-state functional connectivity MRI (rs-fcMRI) data to identify locations in the cerebral cortex where the whole-brain patterns of functional connectivity change abruptly, consistent with boundaries between cortical areas. This method also identifies locations where the whole-brain patterns of functional connectivity are relatively stable, consistent with putative areas between cortical boundaries. Nelson et al. (2010) used fc-Mapping methods to identify...
putative areas in LLPC and proposed a set of functional distinctions by grouping fc-Mapping derived putative LLPC areas on the basis of their patterns of functional connectivity. Specifically, the authors used community detection upon networks built from the putative functional areas and their “neighbors” (i.e., brain regions with strong functional connectivity to the putative areas in LLPC). These methods grouped putative LLPC areas into 4 pieces, with an apparent hierarchical organization. Two of the four pieces were capable of additional divisions, yielding a 6-part parcellation of LLPC. Importantly, the parcellation scheme was corroborated with fMRI data from a meta-analysis of memory retrieval studies (Nelson et al. 2010). The observation that putative LLPC areas within each parcellation have distinct functional connectivity profiles and distinct functional time course profiles converges with criteria (i.e., function and connectivity) put forth for identifying cortical areas (Felleman and Van Essen 1991) (though we emphasize that functional and anatomical connectivity are distinct; see Vincent et al. 2007).

LLPC is a suitable place to test for developmental differences in cortical arealization because its maturation is protracted in human development. Developmental differences in LLPC recruitment have been seen across a range of fMRI studies examining reading (Schlaggar et al. 2002; Booth et al. 2004; Brown et al. 2005; Church et al. 2008), numerical processing (Rivera et al. 2005; Cantlon et al. 2009), attention (Casey et al. 2004; Konrad et al. 2005), and working memory (Crone et al. 2006; Geier et al. 2009). Structural connectivity (Asato et al. 2010) and functional connectivity (Fair et al. 2007, 2008, 2009; Stevens et al. 2009; Dosenbach et al. 2010 but see Supekar et al. 2010) differences throughout childhood and adolescent development have also been documented in LLPC. Furthermore, measures of LLPC cortical thickness and gray matter density also change across development (Sowell et al. 1999, 2001, 2004; Gogtay et al. 2004), suggesting ongoing changes in cytoarchitecture and neuropil (e.g., synaptic pruning). Critically, many of these changes were seen throughout adolescence and into young adulthood, suggesting a protracted period during which extrinsic influences could exert their effects on cortical arealization. Given the documented changes in LLPC function and structure through adolescence, one might expect to see differences in LLPC arealization for 2 groups on either side of adolescence (i.e., young adults and school-age children, the age groups examined in the present study).

Our study asked a pair of related questions. First, to what extent are LLPC parcellation schemes similar in children and adults? Second, using the same rs-fcMRI data, do putative areas detected in LLPC show developmental differences in functional connectivity strength with other brain regions? The first question provides a way to assess cortical arealization non-invasively and the second question provides a way to compare the present data to previous reports of developmental changes in functional connectivity. We applied fc-Mapping and community detection methods to the LLPC in data from 30 healthy children ages 7–10 years and data from 30 healthy young adult ages 23–28 years. Based on animal studies, primarily with rodents (O’Leary et al. 1994; O’Leary and Nakagawa 2002; Sur and Rubenstein 2005; Rakic et al. 2009), and human studies showing adult-like parcellation of prefrontal cortex regions in 7-year-old children (Uylings et al. 2005), one could hypothesize that LLPC parcellation schemes would be similar in children and adults.

Data consistent with this hypothesis would suggest that cortical arealization is adult-like in school age children. In contrast, one could hypothesis that LLPC parcellation schemes would differ in children and adults based on the protracted structural and functional maturation of LLPC and also on fMRI retinotopic mapping studies showing differences in visual areal size between 9 and 12-year-old children and adults (Conner et al. 2004). Data consistent with this hypothesis would suggest that cortical arealization has a more protracted time course in human development. In regards to our second question, based upon the functional connectivity studies described above, we expected that putative LLPC areas’ functional connectivity profiles with other brain regions would differ between children and adults.

**Materials and Methods**

**Participants**

Data from 30 children (16 males) ages 7–10 years and 30 adults (17 males) ages 23–28 years were used (see Table 1). Resting-state fMRI data were included on a runwise basis for each participant, with a movement cutoff of root mean square (RMS) < 0.60 mm per run. All resting-state data meeting the movement cutoff for children were used, and adult data were selected to match on movement and minutes of data per subject. Resting state data were acquired during runs of relaxed visual fixation lasting at least 5 min 10 s (see MR data acquisition).

Participants were recruited from Washington University in St. Louis and the surrounding community. To ensure that participants had no current or past history of neurological or psychological diagnosis, adult participants were screened with a self-report questionnaire and parents completed a questionnaire for child participants. Informed consent was obtained for all adult participants. Children gave assent with parental consent. All participants were compensated monetarily for their participation. All participants were right-handed and native English speakers. Adult data were culled from 5 studies, which included memory, reading, and attention tasks and relaxed fixation. Child data were culled from 6 studies, which included reading, attention, and visual detection tasks and relaxed fixation. The Washington University Human Studies Committee approved all studies.

Three factors differed between children and adults. First, the percentage of high-quality data (see rs-fcMRI data quality assessment) was greater in adults than children, \( t_{df} = 3.70, P = 0.004 \). Second, full-scale IQ estimates from the Weschler Abbreviated Scale of Intelligence (Wechsler 1999) (administered to 17 adults and 29 children; we have no reason to suspect that untested subjects were from a different population) were higher in adults than children, \( t_{df} = 3.38, P = 0.002 \). Third, average intracranial volume (ICV) estimates were larger in adults than children, \( t_{df} = 2.93, P = 0.005 \). The potential effects of these confounding factors were explored in subsidiary analyses (see Results).

**MR Data Acquisition**

Data were acquired on a Siemens 3-T MAGNETOM Trio system (Erlanger, Germany) with a Siemens 12 channel Head Matrix Coil. To
help stabilize head position, each subject was fitted with a thermoplastic mask fastened to holders on the head coil. Structural images were obtained using a sagittal magnetization-prepared rapid gradient echo (MP-RAGE) 3D $T_1$-weighted sequence (time echo [TE] = 3.08 ms, time repetition [TR] (partition) = 2.4 s, time to inversion [TI] = 1000 ms, flip angle = 8°, 176 slices with $1 \times 1 \times 1$ mm voxels). Functional images were obtained using a blood oxygen level-dependent (BOLD) contrast sensitive gradient echo-planar sequence (TE = 27 ms; volume TR = 2.5 s for 59 subjects, TR = 2.0 s for 1 subject, flip angle = 90°, in-plane resolution = $4 \times 4$ mm). Whole brain coverage was obtained with 32 contiguous interleaved $4 \times 1$ mm axial slices. Between 76 and 133 volumes per run were acquired. Steady-state magnetization was assumed after 4 frames (i.e., $8-10$ s). An auto align pulse sequence protocol provided in the Siemens software was used to align the acquisition slices to the anterior and posterior commissure (AC–PC) plane and centered on the brain. A $T_2$-weighted turbo spin echo structural image (TE = 84 ms, TR = 6.8 s, 32 slices with $1 \times 1 \times 1$ mm voxels) was also obtained in the same anatomical plane as the BOLD images to improve alignment to the atlas.

During functional scans, subjects viewed a centrally presented crosshair that subtended <1° visual degree and were instructed to relax and maintain fixation on the crosshair. Depending on the study in which the subject participated, the fixation crosshair was either white on a black background or black on a white background.

**MR Preprocessing**

MR preprocessing was conducted separately for each subject. Functional images were first processed to reduce artifacts (Miezin et al. 2000). These steps included: 1) removal of a central spike caused by MR signal offset, 2) correction of odd versus even slice intensity differences attributable to interleaved acquisition without gaps, 3) correction for head movement within and across runs, and 4) intensity normalization to a whole-brain mode value of 1000 for each run. Atlas transformation of the functional data was computed for each individual via the MP-RAGE and $T_2$-weighted scans. Each run was then resampled in atlas space on an isotropic 3 mm grid combining movement correction and atlas transformation (12 parameter affine coregistration) in one interpolation (Lancaster et al. 1995; Snyder 1996) The target atlas (TRIO_KY_NDC, http://nrg.wikispaces.com/atlas_targets) was created from MP-RAGE scans from thirteen 7 to 9-year-old children (7 males) and twelve 21 to 50-year-old adults (6 males) scanned on the Siemens 3-T MAGNETOM Trio used for data acquisition in the present study and was made to conform to the Washington University 711-2B atlas space.

**rs-fcMRI Preprocessing**

rs-fcMRI preprocessing was conducted separately for each subject to reduce spurious variance (e.g., heart rate and respiration) unlikely to reflect neuronal activation using methods following Fox et al. (2005). These steps included: 1) temporal band-pass filtering (0.009 Hz < $f$ < 0.08 Hz) and spatial smoothing ($6 \text{ mm full-width at half-maximum}$), 2) regression of 6 parameters obtained by rigid body head motion correction, 3) regression of whole-brain signal averaged over the whole brain, 4) regression of ventricular signal averaged from ventricular ROIs, and 5) regression of white matter signal averaged from white matter ROIs. Regression of first order derivative terms for the whole-brain, ventricular, and white matter signals and any trend term from the movement regressors was also included in the preprocessing.

**rs-fcMRI Data Quality Assessment**

Data quality was coded on a framewise basis (J.D. Power, K.A. Barnes, A.Z. Snyder, B.L. Schlaggar, and S.E. Petersen, unpublished data). Frames were coded as high quality if 1) the frame-by-frame displacement (calculated as the sum of the 3 translational motion parameters and 3 rotational motion parameters at a distance of 50 mm) of the brain was less than 0.5 mm and 2) the RMS of the temporal derivative of the BOLD signal at every voxel for each frame was less than 5% signal change/frame. Frames 1 forward and 2 back from "low-quality" frames were also coded as "low-quality."

**Surface-Based Registration**

Surface-based registration was conducted separately for each group. Following Nelson et al. (2010), the PALS atlas family of surfaces was used as a starting point to obtain common surface coordinates to use across each group of surfaces (Van Essen 2005). The PALS atlas "fiducial" surface represents the average of 12 individual gray midthickness surfaces, each volumetrically registered to the 711-2B atlas. While the PALS fiducial surface does not represent the actual surface of any specific individual, it can be used to approximate average fiducial surface locations in group-averaged data in the same volumetric atlas space. Using Caret 5.3 software (Van Essen et al. 2001), a grid of seed points was generated on the spherical PALS surface over LLPC. The volumetric locations of the seed points in 711-2B atlas space were obtained.

**fc-Mapping**

fc-Mapping was performed as in Cohen et al. (2008) and Nelson et al. (2010). The set of volumetric coordinates from the patch over LLPC was used to generate a set of $729 \times 729 \times 729$ etas in which each column represents the similarities between a particular ROI's volumetric average correlation map and all other ROIs' volumetric average correlation maps. Each group's full eta2 matrix was then reorganized as a series of $729 \times 2$ "patch-based" matrices such that each patch-based matrix (henceforth, an eta2 profile image) represents the spatial organization of the similarity between the ROI's correlation map and all other ROIs' correlation maps.

Since each eta2 profile image is a 2D array of values across the cortical surface, it can also be treated as a flat image. To find salient boundaries, the Canny edge-detection algorithm (Canny 1986), as implemented in the Image Processing Toolbox (v7.8) of the MATLAB software suite (The Mathworks, Natick, MA), was applied to each ROI's eta2 profile image.

The Canny method applies a Gaussian filter to smooth each eta2 profile image to reduce noise and then creates a gradient image that locates regions that retain high-spatial derivatives. High-gradient values represent locations where the similarity between the ROIs' correlation maps is changing rapidly (i.e., they are peaks in the first derivative). After eliminating pixels in the eta2 profile image that are not local maxima in the gradient image, the algorithm tracks along the highlighted regions of the image and categorizes each location as a boundary or not. To prevent hysteresis, both a high and a low threshold are used. If the gradient magnitude of the pixel is below the low threshold it is set to zero. If the magnitude is above the high threshold, it is considered a boundary. If the magnitude is between the 2 thresholds, the location is only considered a boundary if a neighboring pixel is also a boundary. These results method in a result of a binary images (edge maps) for each group that represent the locations of rapid change in each ROI's eta2 profile image. Since the boundary determination is binary, averaging across the entire set of edge maps generates a probabilistic boundary location map in which intensity represents how likely a location is to be a putative functional boundary.

**Area Detection**

Inverting the probabilistic boundary location maps separately for each group provides a map of centroid locations, which can be used to generate putative cortical areas using 2D local extrema algorithms (MATLAB v7.8, Image Processing Toolbox, v6.3) as well as custom-written software that approximates in-house methods for peak detection (peak_idp written by Avi Snyder) for detecting volumetric peaks of activation in task-evoked fMRI studies. The corresponding
volumetric locations for each peak were then used to generate spherical (9 mm diameter) ROIs that will be referred to as putative LLPC areas and used in further analyses below.

**Matching Putative LLPC Areas across Groups**
To assess the similarity of the putative LLPC areal locations identified in adults and children, a modified version (Cao 2008) of the Hungarian assignment algorithm (Munkres 1957) and in-house MATLAB code was used (henceforth, modified Hungarian assignment algorithm). The Hungarian assignment algorithm assigns items from one group to items from another group by minimizing the “cost” of assignment. To assign putative LLPC areas across groups, Euclidean distance between adult and child putative LLPC areas was used as a cost function. To generate assignments when a different number of putative LLPC areas were detected in adults and children, all combinations of putative LLPC areas were searched to find the best (i.e., lowest cost) match where all matches were within 9 mm of one another. If, for example, 13 putative LLPC areas were searched to find the best (i.e., lowest cost) match where all combinations of 13 areas yielded a set of matched pairs within 9 mm, then all combinations of 12 areas were searched, and so on.

**Direct Comparison of Correlation Maps from Matched Putative LLPC Areas**
Between groups t-tests were conducted on z-transformed correlation maps for child and adult putative LLPC areas identified as matches in the modified Hungarian assignment algorithm to determine whether there were any developmental differences in the patterns of functional connectivity from putative LLPC areas.

**Parietal-Cortical Neighborhood Generation**
To generate parietal-cortical neighbor networks for parcellation schemes, the sets of regions that were most strongly correlated (termed neighbors) were identified for each putative LLPC area for each group. A peak-finding algorithm was employed to determine the 15 strongest peaks of positive correlation for each putative LLPC area. To eliminate overlap among neighbors (i.e., peaks identified as neighbors for 2 or more seeds) in each group, peaks within 9 mm of one another were replaced with the average of their stereotactic coordinates. In the event that any neighbors were within 9 mm of putative LLPC areas, those neighbors were eliminated.

**Community Detection Using Modularity Optimization**
Modularity optimization (Newman 2006) was used to identify community structure within each group’s parietal-cortical network. Networks with N nodes were mathematically represented as an N × N matrix of relationships, where cell $ij$ contained the measure of the relationship between nodes $i$ and $j$. In our analyses, the relationship was the correlation coefficient of region $i$ with region $j$. These matrices can be thresholded, where cells below threshold are set to zero and values above the threshold are maintained. Effectively, these constitute thresholded weighted networks. If cell $ij$ contains an above threshold value, nodes $i$ and $j$ are connected by an edge. As the threshold increases, the density of edges in the network decreases, and at some point the network begins to fragment into disconnected components. It is important to explore a range of thresholds because results may vary across thresholds.

Communities (i.e., highly interconnected groups of nodes with relatively few nodes between them) were detected with modularity optimization algorithms (Newman 2006) and described in Fair et al. (2009). The modularity ($Q$) of a given set of community assignments for a network is a measure of the number of connections found within the assigned community versus the number predicted in a random network with equivalent degree distribution. A positive $Q$ indicates that the number of intracommunity connections exceeds those predicted statistically. A wide range of $Q$ may be found for a network, depending on how nodes are assigned to communities.

Modularity optimization returns the set of node assignments that yields the highest $Q$ that is, the optimal modular description of the data. For each group, modularity optimization algorithms were run across a range of thresholds. The lower bound was initially set to $r = 0$ to avoid negative correlations and the upper bound was set to the $r$ value at which point the network was no longer fully connected. Within this range, we explored the resultant community structure using thresholded weighted graphs. To generate a consensus assignment of nodes to communities, we computed a pairwise coassignment matrix represented as an N × N matrix, where cell $ij$ was equal to 1 if nodes $i$ and $j$ were assigned to the same community at that threshold and was equal to 0 if nodes $i$ and $j$ were not assigned to the same community. The pairwise coassignment matrices were averaged to generate a probabilistic coassignment matrix (i.e., cell $ij$ contained the probability of nodes $i$ and $j$ being assigned to the same community across the explored thresholds). A second iteration of modularity optimization was run on the probabilistic coassignment matrix to generate the “consensus” community structure. This analysis was designed to bypass the difficult question of matching communities (Fortunato 2010) to ask, instead, “in what proportion of analyses were a pair of ROIs placed in the same community?”

Parcellation schemes were generated for adults by drawing borders between community divisions in LLPC. The adult parcellation schemes were applied to the children’s parietal-cortical networks to determine how well the children’s community structure respected the adult parcellation scheme.

**Results**

**LLPC fc-Mapping and Putative Area Detection**
For each age group, fc-Mapping was performed on a $27 \times 27$ grid of 6 mm ROIs placed over LLPC (Fig. 1A). The spatial correlation of LLPC boundary maps between age groups was high ($r = 0.63$, $P < 0.0001$), which suggests that children and adults had similar LLPC topography (Fig. 1B). Peak-finding algorithms identified a similar number of putative LLPC areas in adults (13) and children (15) (Fig. 1C). There was apparent
We next tested whether the degree of overlap between children and adults' putative LLPC areas could have been found by chance with a simulation of the primary data set's peak detection and assignment results. For 1000 samples, 13 LLPC "peaks" were randomly selected for group 1 (to simulate our adult sample) and 15 LLPC "peaks" were generated for group 2 (to simulate our child sample). To approximate our peak detection algorithm, simulated peaks were separated by >9 mm. To quantify the degree of overlap between simulated peaks, we used the modified Hungarian algorithm and identified the assignment costs incurred when matching 11 simulated peaks. The mean distance between matches in our child and adult data (3.15 mm) was outside the 95% confidence intervals for 1000 samples (simulated mean cost: $M = 7.15$ mm, 95% CI: 5.07-9.22 mm), suggesting that the amount of overlap in putative LLPC areas detected in children and adults was greater than what would be expected by chance. Furthermore, the worst match of our child and adult data (7.35 mm between child and adult peaks) was also outside the 95% confidence intervals for 1000 samples (simulated maximum cost: $M = 13.22$ mm, 95% CI: 7.88-18.56 mm). The simulation thus corroborates our interpretation that 11 "matched" putative LLPC areas out of the detected peaks (13 in adults; 15 in children) constitutes a high degree of correspondence in putative LLPC areas across cohorts.

**Functional Connectivity of Putative LLPC Areas**

A second question motivating this study was: do putative LLPC areas show developmental differences in functional connectivity strength with other brain regions?

Unpaired *t*-tests were performed on the functional connectivity maps for each set of matched putative LLPC areas in adults and children. Statistically reliable differences in functional connectivity strength with the matched putative LLPC areas and other brain regions were found for all LLPC areas. Functional connectivity maps for each group and the *t*-test results for 2 putative areas, one in angular gyrus (Fig. 2A) and one in posterior inferior parietal lobule (Fig. 2B), are displayed because they are anatomically near to angular gyrus default mode network regions, which were regions of interest in prior developmental studies. A variety of effects drove significant developmental differences between groups (Fig. 2C). Children did not simply have overall weaker or stronger functional
connectivity with putative areas in LLPC, as different putative areas showed different patterns. Figure 2C also highlights that both the angular gyrus and the posterior inferior parietal lobule seeds showed stronger functional connectivity with regions in ventromedial prefrontal cortex in adults than in children, converging with past reports of weaker functional connectivity in children than adults between regions in angular gyrus and ventromedial prefrontal cortex (Fair et al. 2008, 2009; Dosenbach et al. 2010).

**Parietal–Cortical Neighbor Network Generation**

We next sought to assess the similarity of a systems-level parcellation of LLPC in children and adults using methods from graph theory. To generate systems-level networks, we first identified the “top” 15 brain regions with which putative LLPC areas were most strongly correlated (their “neighbors”) for each group. (Similar results were seen in networks built from 10 to 20 neighbors, see Supplementary Figs S2–S3.) Figure 3A depicts putative areas’ maps and neighbors in each group. Before proceeding to community detection, we tested whether the neighbors showed any differences in functional connectivity strength between children and adults. If parietal-cortical functional connectivity was weaker overall in one group, then properties of networks composed of putative LLPC areas and their neighbors might differ across groups as well. LLPC area functional connectivity strength (the Fisher r-to-z functional connectivity values for each neighbor with its putative LLPC area converted into Z-scores) did not differ between adults and children (Adults: \( M = 6.03 \), standard deviation [SD] = 0.72; Children: \( M = 6.01 \), SD = 0.93), \( P = 0.74 \). Edge density, a related network metric, defined as the number of existing edges at a threshold, did not differ between children and adults across the range of explored thresholds, \( P = 0.85 \) (see Supplementary Fig. S4).

The sets of neighbors were then consolidated to eliminate overlap (following Nelson et al. 2010), creating a parietal-cortical neighbor network for each group (Fig. 3B). The resultant parietal–cortical neighbor networks were composed of a comparable number of nodes in adults (13 putative LLPC areas and 87 unique neighbors for 100 nodes) and children (15 putative LLPC areas and 79 unique neighbors for 94 nodes). (Neighbor location information is in Supplementary Tables S1 and S2.)

**Generating Parcellation Schemes from Parietal–Cortical Neighbor Networks**

Modularity optimization (Newman 2006) was used to organize nodes in the parietal–cortical neighbor network into...
communities on the basis of their relationships (rs-fcMRI correlation coefficients) with one another. This analysis was done to examine whether parcellation schemes, which may reflect a functional systems-level description of cortical organization, were also similar in children and adults.

In adults, 4 communities were detected across the range of explored thresholds (see Materials and Methods and Supplementary Material, a consensus threshold is presented in Figure 4, coloring of the modules for each group is arbitrary). The first community (shown in purple, Fig. 4) included putative LLPC areas in the angular gyrus and neighbors in posterior cingulate cortex, superior frontal gyrus, and dorsal and ventral medial prefrontal cortex. The second community (shown in light blue, Fig. 4) included putative LLPC areas in the intraparietal sulcus (IPS) and superior parietal lobule and neighbors in dorsolateral prefrontal cortex. The third community (shown in pink, Fig. 4) included putative areas in the supramarginal gyrus and neighbors in the insula and cingulate cortex. Finally, the fourth community (shown in maroon, Fig. 4) contains nodes in anterior superior parietal cortex and neighbors in somatosensory and motor cortex. Borders were drawn on the basis of these community divisions to generate an adult LLPC parcellation scheme. There is a high degree of overlap between the present results and the first level, 4-part parcellation scheme of Nelson et al. (2010), and there is good correspondence of these communities to reported functional networks, for example, our angular gyrus community and the default mode network (Raichle et al. 2001; J.D. Power, K.A. Barnes, A.Z. Snyder, B.L. Schlaggar, and S.E. Petersen, unpublished data).

Community detection was then performed on children's parietal-cortical network. In children, 3 communities were detected. The first community (shown in blue, Fig. 4) includes putative areas in angular gyrus and neighbors in posterior cingulate cortex, superior frontal gyrus, and dorsal and ventral medial prefrontal cortex, similar to the adult angular gyrus community. The second community (shown in red, Fig. 4) contained putative areas in IPS and superior parietal lobule and a very small set of neighbors outside the parietal lobes in lateral temporal cortex and lateral frontal cortex, corresponding to an immature frontal-parietal control network. The third community (shown in green, Fig. 4) contained putative areas in superior parietal lobule and supramarginal gyrus and neighbors in sensorimotor cortex.

To examine the similarity between adult and child LLPC parcellation schemes, the LLPC borders drawn on the basis of the adult community divisions were applied to the child parietal-cortical network community divisions (Fig. 4D). Of the 15 putative LLPC areas detected in children, community assignments for a majority (13/15) respected the borders from the adult parcellation scheme. The 2 putative LLPC areas in children that failed to respect the adult parcellation scheme, indicated by stars (right panel, Fig. 4) resulted from the absence of a community division between anterior portions of the supramarginal gyrus and superior parietal lobule in children. At higher thresholds ($r > 0.4$), 2 neighbors in the supramarginal gyrus did break off into their own community (see Supplementary Fig. S3), but this division was not generally present.

**Discussion**

Our main finding, the existence of a similar LLPC parcellation in children and adults, was borne out across multiple analyses. First, fc-Mapping in 7 to 10-year-old children and adults revealed similar boundary map topography for LLPC, as indicated by the large spatial correlation between groups. Second, the putative LLPC areas generated from the fc-Mapping data were in highly similar locations across groups (11 "matches" within an average distance of 3.15 mm between the regions as assigned using the modified Hungarian algorithm out of the 13 putative areas detected in adults and 15 putative areas detected in children). Finally, the parcellation schemes generated on the basis of the whole-brain functional connectivity relationships between the putative LLPC areas and their neighbors in adults captured a majority of the community-level distinctions seen in children, with 13/15 child putative areas respecting the borders generated from adult data. Collectively, these observations suggest that cerebral cortical arealization in LLPC is adult-like in school age children, consistent with nonhuman animal research indicating that cortical arealization is complete early.
in development (O’Leary and Nakagawa 2002; Rakic et al. 2009) and with postmortem cytoarchitectural analysis of Brodmann’s areas 44 and 45 suggesting these areas are adult-like in size and location by age 7 years (Uylings et al. 2005).

The present results intersect with one of the main goals of developmental neuroscience, that is, understanding how developmental changes in the brain relate to developmental changes in cognition and behavior. Our finding of a similar LLPC parcellation in children and adults speaks against changes in the size or topographical organization of cortical areas in LLPC as mechanisms of developmental change in cognitive abilities. Further work is needed to determine whether more subtle changes in cortical parcellation (which might have gone undetected in the present study) or community structure might relate to the development of cognitive abilities. At present, we lack data to test this hypothesis directly. Nonetheless, our interpretation of the present findings differs from certain “maturational” accounts of development (rather than interactive specialization or skill learning accounts, see Johnson 2001), wherein change in area size is explicitly invoked as a mechanism of cognitive development (e.g., developing face recognition abilities and developmental changes in the spatial extent of a fusiform gyrus region that responded more to faces than other classes of visual objects, Golarai et al. 2007). Our observations of comparable fc-Mapping topography, matched putative LLPC areas, and similar parcellation schemes in LLPC for children and adults suggest that gross changes in LLPC areal size or topography during middle childhood are unlikely to underlie developmental changes in cognitive abilities linked to LLPC. In light of our finding of similar LLPC parcellation schemes, we would not predict, for example, that dramatic changes in the size of IPS areas during middle childhood contribute to developing mathematical abilities. Rather, we might predict that developing mathematical abilities are the result of established IPS areas changing their patterns of functional connectivity (a prediction consistent with our finding of immature functional connectivity but not parcellation schemes) which changes the information going to and/or coming from the IPS, thereby changing its information processing role. This account is redolent of Johnson’s (2001) interactive specialization account and Posner and colleagues’ (1988) approach to localizing cognition in brain networks. Further experimentation is needed to test this hypothesis.

The observation of adult-like LLPC parcellation in 7 to 10-year-old children may raise concerns about sample selection—perhaps we had selected exceptionally “adult-like” children. However, we do not think this is the case for several reasons. First, developmental differences in functional connectivity between putative LLPC areas and other brain regions were present in the functional connectivity maps of every putative LLPC area examined. The present results also replicate prior reports of developmental differences in functional connectivity with regions in parietal cortex identified from meta-analyses of functional MRI data (Fair et al. 2007, 2008, 2009; Dosenbach et al. 2010) and from independent components analysis (Stevens et al. 2009). Second, we found group differences in ICV consistent with observations that children’s brain volumes are approximately 95% of adults between ages 7 and 10 years and reach adult-like volumes by ages 10–12 years (Pfefferbaum et al. 1994; Courchesne et al. 2000). In our sample, children were approximately 94% of adults’ average ICV. These small but statistically reliable volumetric differences ought not to have been sufficient to introduce distortion in functional MRI analyses (Burgund et al. 2002), and comparable results were found when we examined ICV-matched subsets. Third, despite using high-quality data matched on runwise movement estimates, the percentage of “high-quality” frames was approximately 10% higher in adults ($M = 91.85\%$) versus children ($M = 81.07\%$), suggesting that within-run movement may have been higher in children than adults, an observation familiar to those who have conducted MRI studies with children. Importantly, the reported effects persisted after analyzing only high-quality frames. Thus, it seems unlikely that a particularly adult-like cohort of children generated a spurious result of similar LLPC parcellation schemes between groups.
A related limitation is that the standardized IQ estimates were larger in adults than children. It is unclear how or whether IQ relates to cortical arealization, but comparable results were found in an IQ-matched subset of children and adults, suggesting that IQ differences did not contribute significantly to the results. Nonetheless, further work could explore this issue, especially in light of the particularly high-IQ adult sample ($M \approx 130$) in the present study, which limits the generalizability of our results.

One final concern is that the effects of global signal regression may have differed across children and adults and that this difference may have generated spuriously similar fc-Mapping results. Though more work is needed to fully address these effects in development, a recent study by Kim et al. (2010) reported similar functional connectivity–based parcellation schemes for medial frontal with and without the performance of global signal regression (Kim et al. 2010, Fig. 4 vs. Supplementary Fig. S4).

As noted above, the present adult data correspond quite well with the published LLPC parcellation scheme from Nelson et al. (2010) and a recent study from Uddin et al. (2010). First, the fc-Mapping boundary maps reported in Nelson et al. (2010) and the present data (reanalyzed after removing data from 6 adults who overlapped across cohorts) were strongly correlated, $r = 0.79$. It is unclear whether the higher correlation between cohorts of adults than the child and adult fc-Mapping results reported in the present study ($r = 0.63$) resulted from higher quality data in the adults in the present study and in Nelson et al.’s analysis, where matching movement estimates to children was not a consideration or a truly larger degree of similarity between cohorts of adults than cohorts of children and adults. Further work is needed to resolve this issue. Second, there was a strong correspondence between the 4 communities detected in the systems-level parcellation in the present analysis and the first level of community detection in Nelson et al. (2010). Finally, the present adult data converge with results from Uddin et al. (2010), in that fc-Mapping detected multiple, distinct peaks within the angular gyrus and IPS, consistent with Uddin and colleagues’ observations that different regions within the inferior parietal lobe have different functional and structural connectivity profiles.

The present study was an initial attempt to address questions about cortical arealization in vivo using fc-Mapping and graph theory–based groupings of putative LLPC areas, but there are many unresolved questions for future research. Most critically, this study leaves questions about how LLPC development relates to developing abilities such as reading, attention, and mathematics unanswered. It seems unreasonable to propose developmental changes in LLPC parcellation as a mechanism of change during middle childhood when comparable parcellation schemes were seen in adults and children. However, efforts are underway to develop fc-Mapping methods for individual subjects (A.L. Cohen, S.M. Nelson, F.M. Miezin, B.L. Schlaggar, and S.E. Petersen, unpublished data). Such methods would allow for a number of questions to be explored in future developmental studies. Importantly, individual fc-Mapping data would enable statistical comparisons (e.g., by generating variance estimates across subject, one could test whether border strength differs across age groups or varies with age or abilities [e.g., IQ, mathematics, or reading]). With individual data, questions about developmental trajectories, in both typical development and developmental disorders, could be more precisely explored. Finally, though we focused on LLPC because its protracted functional and structural development made it a strong testing ground for developmental differences in cortical arealization, fc-Mapping techniques could be applied to other regions of the cerebral cortex to assess whether arealization proceeds at different rates in different regions.

**Supplementary Material**

Supplementary material can be found at: http://www.cercor.oxfordjournals.org/

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