NeuroImage 202 (2019) 115965

Contents lists available at ScienceDirect

NeuroImage

journal homepage: www.elsevier.com/locate/neuroimage

Structural covariance networks in children and their associations with maternal behaviors

Sally Richmond [a,b,e,*], Richard Beare [b,f], Katherine A. Johnson [a], Nicholas B. Allen [a,d], Marc L. Seal [b,c,1], Sarah Whittle [a,e,1]

[a] Melbourne School of Psychological Sciences, The University of Melbourne, Parkville, VIC, 3010, Australia
[b] Murdoch Children's Research Institute, Parkville, 3052, Australia
[c] Department of Paediatrics, The University of Melbourne, Parkville, 3010, Australia
[d] Department of Psychology, University of Oregon, Eugene, OR, 97403, USA
[e] Melbourne Neuropsychiatry Centre, Department of Psychiatry, The University of Melbourne and Melbourne Health, Victoria, 3052, Australia
[f] Department of Medicine, Monash University, Melbourne, Australia

ARTICLE INFO

Keywords:
Cortical thickness
Graph theory
Magnetic resonance imaging
Parenting
Network efficiency

ABSTRACT

There is a substantial body of research documenting the influence of early adverse experience on brain development. In contrast, relatively little attention has been directed toward the influence of 'normative' variation in parenting behaviors. This study investigated associations between parenting behaviors and structural brain networks, as measured by structural covariance, in a community sample of children. One hundred and forty-five typically developing 8-year-olds and their mothers completed questionnaire measures and two observed parent-child interaction tasks. Structural MRI scans were also obtained from the children. Structural covariance networks based on partial correlation between cortical thickness estimates were constructed, and estimates of efficiency were obtained using graph theoretical analysis. Associations between affective and communicative maternal behaviors and these network metrics were investigated. High levels of observed negative affective and communicative maternal behaviors were associated with decreased local efficiency, whereas high levels of positive affective maternal behaviors were associated with increased local efficiency. The regions implicated (including the cingulate cortex, temporal pole, and temporo-parietal junction) are thought to be involved in the processing of social information. Minimal support was found for an association between global efficiency and maternal behaviors. Our findings suggest that variations in parenting behaviors are associated with structural organization of socio-emotional brain networks in children.

1. Introduction

There is a substantial body of research documenting the influence of adverse family environments (e.g., involving parenting in the form of child maltreatment and neglect) on brain development (Belsky and de Haan, 2011). In contrast, relatively less attention has been directed toward the influence of 'normative' variation in parenting behaviors (Morris et al., 2017). The influence of parental behaviors on brain development may be strongest during 'sensitive periods' when neuronal properties are particularly receptive to acquiring certain kinds of information and susceptible to modification by experience (Fuhrmann et al., 2015; Hensch, 2004; Pechtel et al., 2014). Late childhood, a time of intensive brain development, may be a sensitive period and consequently in this context, parental behaviors may 'shape' brain structure and function (Vértes and Bullmore, 2015; Walhovd et al., 2017).

Although still small, a growing literature has documented associations between parenting behaviors and the structure of cortical and subcortical regions have been reported across childhood and adolescence (Belsky and de Haan, 2011; Kok et al., 2015; Luby et al., 2012). For example, positive (warm and supportive) parenting behavior has been found to predict more mature gray matter growth (Luby et al., 2016; Whittle et al., 2014). Negative (aggressive and hostile) parenting behavior, in contrast, has been linked to less mature gray matter brain development in adolescence (Whittle et al., 2016).

* Corresponding author. Melbourne Neuropsychiatry Centre, Department of Psychiatry, The University of Melbourne 161 Barry St., Carlton, VIC, 3053, Australia.
E-mail address: richmond.s@unimelb.edu.au (S. Richmond).
[1] Senior author.

https://doi.org/10.1016/j.neuroimage.2019.06.043
Received 23 August 2018; Received in revised form 3 April 2019; Accepted 19 June 2019
Available online 20 June 2019

While these studies have contributed to our understanding of the impact of parenting on particular brain structures, there is growing recognition that applying a whole brain network approach may provide novel insights given that brain regions do not function in isolation. Functional magnetic resonance imaging (fMRI) research indicates the parent-child relationship is associated with resting state networks. Within community samples, associations have been demonstrated between maternal expression of anger and amygdala resting state connectivity for adolescents (Callaghan et al., 2017), between default mode network (DMN) connectivity and inter-parental conflict in infants (Graham et al., 2015), and between maternal sensitivity and amygdala and hippocampus connectivity, also in infants (Rifkin-Graboi et al., 2015). The mechanism by which parenting behaviors influence resting state connectivity networks is not clear, however the brain regions identified within the amygdala resting-state functional network and the DMN have been associated with social-cognitive processing in task based fMRI studies (Kennedy and Adolphs, 2012; Mars et al., 2012). Taken together the functional network literature indicates large-scale networks are involved in social-cognitive processing and are sensitive to variations in parenting behaviors.

In contrast to functional networks, the literature for structural networks has focused on exposure to adverse early environments where participants have been selected based on maltreatment criteria (Ohashi et al., 2017; Puetz et al., 2017; Sun et al., 2018a,b; Teicher et al., 2014). White matter network research (based on diffusion tensor imaging) has demonstrated that exposure to childhood maltreatment has been associated with reductions in global connectivity strength (Ohashi et al., 2017; Puetz et al., 2017) and local connectivity (Puetz et al., 2017). Gray matter network studies show exposure to maltreatment is associated with altered centrality (connectedness, 'importance'; Sun et al., 2018a,b; Teicher et al., 2014), reduced network clustering (a similar metric to local efficiency, see Latora and Marchiori, 2001), and modularity (Nikolova et al., 2018). No research to our knowledge has (a) investigated the influence of parenting behaviors on structural brain networks in community-based children, and in particular (b) investigated such important early environmental exposures on brain networks based on *structural covariance of gray matter*, despite growing evidence that such networks have relevance for understanding brain development (Khundrakpam et al., 2013; Nie et al., 2013), child functioning (Khundrakpam et al., 2016), and mental health (Jiang et al., 2016).

The examination of structural brain networks derived from structural covariance analysis of cortical thickness is based on the finding that inter-individual differences in the structure of one brain region often covary with inter-individual difference in other brain regions (Alexander-Bloch et al., 2013a,b). These synchronized changes may be attributable to common trophic influences and other genetic and environmental factors (Alexander-Bloch et al., 2013a,b). A large range of network metrics have been applied to investigate structural covariance networks and can be broadly divided into measures of integration and segregation (Richmond et al., 2016). Network efficiency is a fundamental network property that can be measured locally as communication between a node (i.e., cortical gray matter region) and its first neighbors to reflect the tendency for localized processing (segregation) within the network (Latora and Marchiori, 2001; Rubinov and Sporns, 2010). Global network efficiency can be conceptualized as the efficiency of parallel information transfer, where every node sends information concurrently along the edges (anatomical connections) of the network (Fan et al., 2011). Global efficiency is a measure of a network's ability to combine information from distributed brain regions (integration; Rubinov and Sporns, 2010).

Here we focus on network efficiency as it (a) provides insight into fundamental network organizational principles, (b) has been associated with family environments (aforementioned), and (c) changes across development. Although network development was not directly tested in this study, knowledge of preliminary developmental trends was utilized to hypothesize about associations between parenting and network efficiency. During late childhood (between 8 and 12 years of age), local efficiency has been observed to decrease relative to younger and older age groups (Khundrakpam et al., 2013; Nie et al., 2013; Richmond et al., 2016). For the same developmental period, global efficiency has been observed to peak and may flatten out in adolescence (Khundrakpam et al., 2013; Nie et al., 2013).

The aim of this study was to investigate the relationship between parenting behavior and efficiency of structural brain networks, as measured by structural covariance of cortical thickness, in late childhood. Late childhood was of particular interest given that it is a sensitive period of brain development, and it represents a period where parents are of particular importance prior to the transition to adolescence when peers begin to have a more influential role (Lamblin et al., 2017). We hypothesized that more positive and less negative parenting behaviors would be associated with more optimal network efficiency. Given higher global efficiency is thought to be optimal in children - it has been associated with higher verbal intelligence (Khundrakpam et al., 2016) and absence of conduct disorder (Jiang et al., 2016), we hypothesized more positive and less negative parenting behaviors would be associated with higher global efficiency. Findings for local efficiency, however, have been mixed, with both higher and lower estimates found to be 'optimal' (Bonilha et al., 2014; Hosseini et al., 2016; Jiang et al., 2016). Given that the emerging developmental trajectory for local efficiency indicates a decrease in late childhood (between 8 and 12 years of age) relative to younger and older age groups (Khundrakpam et al., 2013; Nie et al., 2013; Richmond et al., 2016) and our other work suggesting that positive parenting behaviors are associated with accelerated cortical development (Whittle et al., 2014), we hypothesized that more positive and less negative parenting behaviors would be associated with lower local efficiency.

2. Methods and materials

2.1. Participants and recruitment

The data included in this study came from the Families and Childhood Transitions Study (FACTS) conducted at The University of Melbourne, Australia. The research was approved by the human research ethics committee at The University of Melbourne, and written informed consent was obtained from each child and a parent/guardian. Abbreviated summaries and measures relevant to this analysis are provided below and further details can be sourced in the study protocol (Simmons et al., 2017). The current study included baseline data from FACTS, where participating dyads comprised 145 children and their mothers (Table 1).

Although not the case for all families, socioeconomic disadvantage has been associated with suboptimal parenting practices (Newland et al., 2013; Pereira et al., 2013). To ensure that we did not recruit a sample biased for high socioeconomic advantage and subsequent low variation

Table 1
Demographic and clinical participant information (N = 145).

Characteristic	
Child age, *M(SD)*, years	8.42 (0.33)
Males, No. (%)	68 (46.90)
CDI-2, *M(SD)*[a]	8.32 (6.07) T-Score 55, 'Average or Lower'
SCAS, *M(SD)*[b]	26.27 (13.07) T-Score 52, 'Normal'
LITE, *M(SD)*[c]	3.82 (2.33)
Child ethnicity	
Caucasian, No. (%)	102 (71.03)
Other, No. (%)	30 (20.70)
Maternal age, *M(SD)*, years	40.25 (5.5)
Maternal Occupational Status, *M(SD)*[d]	62.38 (19.94)

[a] Imputed data, The Children's Depression Inventory 2, maximum T-Score for boys and girls 7–12 years (Kovacs, 2011).
[b] Imputed data, The Spence Children's Anxiety Scale maximum T-Score for boy and girls aged 8–11 years (Spence, 1998).
[c] Lifetime Incidence Traumatic Events, $n = 143$ (Greenwald and Rubin, 1999).
[d] Socioeconomic Index 2006 (AUSEI06), $n = 138$ (McMillan et al., 2009).

in negative and positive parenting behaviors (Galea and Tracy, 2007), participant recruitment focused on suburbs of Melbourne that scored within the lowest tertile on the Socioeconomic Indexes for Areas (SEIFA) scale of advantage (Australian Bureau of Statistics, 2013).

Eight-year-old typically developing children were invited to participate in the study. Only mothers were recruited to take part in the assessment due to budget constraints. Participation was not restricted to families with biological mothers; one mother not biologically related to her child participated (0.69% of sample). Families who indicated they wished to participate were contacted for a brief telephone interview to assess the exclusion criteria, which included significant motor or sensory impairments, and criteria related to having a Magnetic Resonance Imaging (MRI) scan.

2.2. Procedure

Children and their mothers completed an assessment including a MRI scan and videotaped family interactions. Mothers completed an interview comprising questions about the children's demographics, health, and developmental histories.

2.2.1. Questionnaire measures

2.2.1.1. The Children's Depression Inventory 2 (CDI-2). The CDI-2 (Kovacs, 2011) is a 28 item self-report measure of cognitive, affective, and behavioral signs of depression in children and adolescents aged 7–17 years. Participants select one of three options for each item that described them best, based upon the previous two weeks. The CDI-2 yields a Total score, two scale scores (Emotional Problems, Functional Problems) and four subscale scores (Negative Mood/Physical Symptoms, Negative Self-Esteem, Interpersonal Problems, Ineffectiveness). Total and scale scores were examined. The CDI-2 has normative data in the relevant age range and reliability and validity evidence across community and clinical populations (Kovacs, 2011).

2.2.1.2. The Spence Children's Anxiety Scale (SCAS). The SCAS is a self-report measure of anxiety symptoms for children aged from 8 to 15 years (Spence, 1998). The measure comprises 44 items, on which participants rate the degree to which they have experienced an event, on a four-point scale, ranging from *never* to *always.* The SCAS yields a Total score and six sub-scale scores: Obsessive-compulsive Problems, Separation Anxiety, Social Phobia, Panic/Agoraphobia, Generalized Anxiety Symptoms, and Concerns of Physical injury (Spence, 1998). Total score was examined. The SCAS has been identified as a reliable and valid measure across diverse childhood populations (Essau et al., 2002; Holly et al., 2014).

2.2.1.3. The lifetime incidence of traumatic events (LITE). The LITE (Greenwald and Rubin, 1999) is a 16-item parent-report screening instrument which assesses the type of loss or trauma a child has experienced. The LITE parent report includes items that screen for exposure to events including car accidents, death of family members, and physical violence. Parents respond yes or no to each event, record how many times it occurred, at what age, how much it upset the child, and how it bothers the child now. Greenwald and Rubin (1999) report the measure has good reliability and adequate validity. The LITE parent report was adapted, at the request of The University of Melbourne Ethics Committee, by removing the two items on sexual abuse and adding items covering mother-child separations and domestic relocation. The LITE parent report has no standardized scoring system and was scored by summing the number of endorsed items (Greenwald and Rubin, 1999).

2.2.1.4. The australian Socioeconomic Index 2006 (AUSEI06). The AUSE106 was used to assess maternal occupational status (McMillan et al., 2009). The AUSEI06 is based upon 2006 Australian Census data and is a continuous measure of occupational status, ranging from 0, low status, to 100, high status (McMillan et al., 2009).

2.2.2. Family interaction assessment and measures

Mother-child dyads completed two 15-min laboratory-based interaction tasks, which were video recorded for subsequent coding using a modified version of The Family Interaction Macro-coding system (FIMS, see supplemental information; Holmbeck et al., 2007). An event-planning interaction (EPI) was completed first, followed by a problem-solving interaction (PSI; Gilboa and Revelle, 1994). In the EPI, dyads were asked to plan enjoyable activities together, such as vacations or common hobbies (MacPhillamy and Lewinsohn, 1982). In the PSI, the dyads were asked to discuss and try to resolve areas of conflict chosen (Prinz, Foster, Kent and O'Leary, 1979). The EPI and PSI tasks were intended to differentially elicit positive and negative behaviors, respectively.

To identify different aspect of maternal behavior, an exploratory principal components analysis was conducted using the FIMS mother-child data (Richmond et al., in press). In brief, the PCA was run for 155 mother-child dyads (10 of whom did not have MRI data) to obtain composite maternal parenting behavior scores. A four-factor solution explained a total of 56.76% of the variance, with components comprising 1) *Negativity EPI* - negative maternal behaviors during the EPI, such as negative and aggressive affect; 2) *Warmth.* - codes related to positive affect, such as humor and warmth; 3) *Negativity PSI* - negative maternal behavior during the PSI, such as negative and aggressive affect; and 4) *Communication* - codes related to listening, structuring dialogue, and clarity of thought (see Tables S1 and S2). Participant scores for each parenting component were estimated (Harman, 1976) and divided into tertiles: low-, moderate-, and high-. To evaluate whether results were dependant on these groupings, participants were also divided into two groups: low-, and high-, based on a median-split, and supplementary analyses were conducted. Groups were required because structural covariance networks are constructed from correlations of cortical thickness. Consequently, a structural covariance network represents a group of participants and not the network of an individual.

2.2.3. MRI acquisition and processing

The MRI procedure began with a mock scan in a replica MRI to minimize the likelihood of movement artefact, and participant anxiety. Neuroimaging data were acquired on the 3T Siemens TIM Trio scanner (Erlangen, Germany) at the Murdoch Children's Research Institute, Royal Children's Hospital, Melbourne. Participants lay supine with their head supported in a 32-channel head coil. T_1-weighted images were acquired during a 5:19 min sequence (MPRAGE: repetition time = 2530 msec; multiple echo times = 1.74; 3.6; 5.5; 7.3 msec; flip angle = 7°, field of view = 256×256 mm^2) and produced 176 contiguous 1.0 mm thick slices (voxel dimensions = 1.0 mm^3). Image quality was visually inspected at the time of acquisition by the radiographer. If movement artefact was detected and time permitted, with the participant's consent the sequence was repeated.

2.2.4. Structural image processing

FreeSurfer was used to generate models of the cortical surface and to model cortical thickness from the T_1-weighted images (Version 5.3; Fischl, 2012). The processing steps have been described in detail elsewhere (Dale et al., 1999; Fischl et al., 1999). All T_1-weighted images were subject to a manual quality assessment procedure involving visual inspection of all image slices per participant, manual edits were made where cortical surfaces were under- or over-estimated on four or more image slices. Of the 153 acquired scans, manual edits were made to 55 and one was excluded due to excessive motion. Outlier detection was used pre- and post-manual edits to assess image quality.

2.2.5. Missing data

There was no missing family interaction data. For CDI-2 and SCAS data, 19% and 18% of participants, respectively, had missing data on at least one item. For both questionnaire measures (CDI-2 and SCAS) the mechanism for missing data was investigated (see SI for details). To predict missing values, multiple imputation was carried out at the item level; five imputed data sets were generated and pooled results were reported (Enders, 2010; van Buuren and Groothuis-Oudshoorn, 2011). For SCAS data, one participant did not complete any items and was removed. For the LITE data, two participants did not complete any items and were removed. Missing items on the LITE were not imputed as the measure is a screen only, missing items were assumed as not endorsed. Similarly, missing maternal occupational data ($n = 7$) was not imputed.

2.2.6. *Structural covariance network definition*

Network nodes were defined by the FreeSurfer parcellation of the cortical gray matter into regions in accordance with the Destrieux atlas, 74 regions per hemisphere (Destrieux et al., 2010). Network edges were defined by partial correlations of average cortical thickness between pairs of nodes (correlations of cortical thickness after removing variance shared with other nodes; He et al., 2008; Teicher et al., 2014). A sparse partial correlation estimation procedure was applied to identify significant, non-zero partial correlations (Lasso, least absolute shrinkage and selection operator; Tibshirani, 1996, see supplemental information; 2011). Sparse inverse covariance estimates have been applied recently to characterize functional and structural networks in clinical populations and to identify statistically significant group differences (Lefort-Besnard et al., 2018). All networks were analyzed as binary and undirected, which assumes the edges have no orientation (Sporns, 2012).

2.2.7. *Structural covariance network analysis*

2.2.7.1. Parenting component characteristics. To establish whether there may be any variables confounding associations between parenting and brain networks, we investigated between-group differences for the low-, moderate, and high-groups for each of the four parenting components for the following variables using ANOVA: child age, sex, depression symptoms, anxiety symptoms, incidence of traumatic events, and maternal occupational status. We applied an FDR (5%) to adjust for the multiple comparisons across the four parenting components (i.e. 24 in total).

2.2.7.2. Network parameters. The binarized graphs were used to calculate global efficiency and local efficiency. Small-worldness was also calculated as a check of network properties. As the equations for these graph metrics are defined elsewhere only brief definitions are provided. Global efficiency was defined as the average inverse of the characteristic path length, where the characteristic path length was the minimum number of edges that must be traversed to go from one node to another (Bullmore and Sporns, 2009; Latora and Marchiori, 2001). Local efficiency, as a measure of integration between a node and its immediate neighbors, was defined with respect to the subgraph comprising all the node's neighbors, after removal of the node and its incident edges (Fornito et al., 2016). The local efficiency of each node was also averaged to estimate the *mean* local efficiency of a network.

The small-worldness of a network was quantified as the ratio of the normalized clustering coefficient and path length. Calculation of the normalized clustering coefficient involved construction of null networks (random graphs) using a rewiring algorithm, which generates undirected, connected simple graphs based on the degree distribution of the network of interest; an average of 100 networks was used.

2.2.7.3. Network parameter differences between parenting groups. To determine if differences in network parameters (mean local efficiency, global efficiency, and small-worldness) existed between the three parenting Groups (low-, moderate-, high-) for each of the four components (Negativity EPI, Warmth, Positivity PSI, Communication) a nonparametric permutation test procedure was carried out (Bullmore et al., 1999; He et al., 2007). First, for each parenting component, the networks properties were calculated for each group using the whole group regularization parameter. Next, to test the null hypothesis that differences between the low-, moderate-, and high-groups might occur by chance, participants were randomly allocated to one of three groups and networks were constructed per the sparse partial correlation estimation procedure detailed previously. Next, for each network property, the absolute maximum difference for the three pairwise comparisons was determined. The random allocation procedure was repeated 5000 times (per network property) and the 95 percentile points for each distribution were used as the critical values for a two-tailed test of the null hypothesis with a probability of type 1 error of 0.05.

We applied an FDR of 5% to adjust for the multiple comparisons of *mean* local and global efficiency across the between-group contrasts for the four parenting components (i.e. 2 (global, local) x 3 (group comparisons) x 4 (parenting components) = 24 in total). We investigated distributions of local efficiency using the Kolmogorov-Smirnov two-sample test which tests the hypothesis that two independent samples have been drawn for the same sample (Scheff, 2016). In addition, we performed a region-by-region comparison of group differences in local efficiency by applying the nonparametric permutation procedure described above. Adjustment for multiple comparisons was made using an FDR of 5% (Khundrakpam et al., 2016; Sun et al., 2018a,b). Post-hoc analyses of significant main effects used Fisher's least significant difference test to correct for multiple comparisons (Levin et al., 1994).

Key analysis resources are listed in Supplemental Table S6. Raw data is available by contacting the corresponding author.

3. Results

3.1. *Parenting group characteristics*

The descriptive statistics for the low-, moderate, and high-groups of each parenting component are listed in Table 2 and the distributions presented graphically in Supplemental Figs. S1–S4. Correlations between the parenting components are presented in Table S3 (FDR 5%). For each parenting component (Negativity PSI, Warmth, Negativity EPI, and Communication*)* no significant between-group differences were found for the low-, moderate-, and high-groups for age (child), sex, depression symptoms, anxiety symptoms, incidence of traumatic events, or maternal occupational status (FDR 5%; Table S4). In addition, no significant correlations were found between parenting component scores and depression symptoms, anxiety symptoms, incidence of traumatic events, or maternal occupational status (FDR 5%; Table S5). Distributions for depression symptoms, anxiety symptoms, incidence of traumatic events, and maternal occupational status presented graphically in Supplemental Figs. S5–S8.

3.2. *Sparse estimation*

The regularization parameter for the sparse estimation procedure, ρ was selected by cross-validation based on the data for all participants, for the Destrieux parcellation $\rho = 0.184$.

3.3. *Network parameter differences between parenting groups*

Comparative analyses (nonparametric permutation tests) of topological properties (global efficiency, mean local efficiency, local efficiency, and small-worldness) were performed for each of the four parenting components (Negativity EPI, Warmth, Negativity PSI, and Communication) between the three groups (low-, moderate-, and high-).

3.3.1. *Parenting and mean local efficiency*

Comparisons for mean local efficiency are presented in Fig. 1 and Table 3 (FDR 5%). For Negativity EPI, the low group had increased mean local efficiency compared with the moderate and high groups. For

Table 2
Group information from family interaction macro-coding system principal components analysis (N = 145).

Parenting Component	Skew	Kurtosis	Low-					Moderate-					High-				
			N	Min	Max	Range	Mean (SD)	N	Min	Max	Range	Mean (SD)	N	Min	Max	Range	Mean (SD)
Negativity EPI	2.44	7.73	49	−1.93	−0.48	1.45	−0.64 (0.23)	48	−0.47	−0.16	0.31	−0.33 (0.09)	48	−0.16	5.61	5.76	1.06 (1.21)
Warmth	0.24	1.28	49	−3.56	−0.45	3.11	−1.00 (0.55)	48	−0.44	0.29	0.73	−0.09 (0.23)	48	0.34	3.13	2.79	1.03 (0.65)
Negativity PSI	0.97	0.27	49	−1.39	−0.68	0.71	−0.96 (0.14)	48	−0.68	0.34	1.02	−0.24 (0.29)	48	0.38	3.38	3.00	1.20 (0.74)
Communication	−1.59	3.19	49	−4.24	−0.01	4.25	−1.11 (0.99)	48	0.02	0.52	0.50	0.31 (0.14)	48	0.53	1.85	1.32	0.85 (0.29)

Note. Abbreviations: EPI, event-planning interaction; Min, minimum; Max, maximum; PSI, problem-solving interaction.

Negativity PSI, the low group had increased mean local efficiency compared to the moderate and high groups. For Communication, the low group had increased mean local efficiency compared to the moderate and high groups. For Warmth, the moderate and high Groups had increased mean local efficiency compared to the low group.

Comparisons for mean local efficiency for the two-group analysis are presented in Table S7. The pattern of results was similar to that of the tertile groupings, however, the comparisons did not reach significance.

3.3.2. *Parenting and global efficiency*

For the four parenting components, there were no significant group differences for global efficiency. Comparisons for global efficiency for the two-group analysis are presented in Table S7 and reflected the same pattern as the tertile groupings.

3.3.3. *Parenting and small-worldness*

Each group (low-, moderate-, and high-) of the four parenting components displayed small-world topology (sigma >1; Table 4). For Negativity EPI, the low group had increased sigma compared to the moderate and high groups (Table 5, FDR 5%). For Negativity PSI, the high group had decreased sigma compared to the moderate and low groups. Changes in sigma across the parenting groups were driven by the clustering coefficients for these groups. (Table 5, FDR 5%).

3.3.4. *Parenting and local efficiency per region (node)*

The results for mean local and global efficiency were based on network averages. Given the eight significant differences identified (Table 3) for mean local efficiency between low-, moderate, and high-groups for each of four parenting components, we investigated efficiency for the regions (nodes). The Kolmogorov-Smirnov test identified three comparisons (e.g., low-Warmth compared to moderate-Warmth) where there was a statistically significant difference between the pairs (Table 6, FDR 5%). Four comparisons identified using the permutation based approach were not identified by the Kolmogorov-Smirnov test (e.g, difference in mean local efficiency for low and high levels of Negativity PSI (Table 3).

We identified 31 regions (15 unique) with a significant difference in local efficiency across the four parenting components (FDR adjusted at 5%; Table 7 and Fig. 2). Between low and moderate and low and high levels of Negativity EPI, all regions *decreased* in local efficiency, e.g., superior frontal gyrus, inferior temporal gyrus, and the superior part of the precentral gyrus. Between moderate and high levels of Negativity EPI, three of four regions *increased* in local efficiency, superior frontal gyrus, inferior temporal gyrus, and the superior part of the precentral gyrus.

For Warmth, significant differences in local efficiency were identified for all three group comparisons (four regions, low – moderate; two regions, low – high; two regions, moderate to high). In all regions except the middle-anterior part of the cingulate gyrus and sulcus (for the low to moderate comparison) local efficiency *increased*. The subcallosal gyrus and lateral occipito-temporal sulcus regions were observed to increase across low to moderate and low to high. The regions implicated are located within the occipital, parietal, medial prefrontal, and temporal cortices.

For Negativity PSI, significant differences in local efficiency were identified in two group comparisons (three regions, low – moderate; two regions, moderate – high). For low to moderate levels of negative parenting during the PSI task, two of three regions displayed a *decrease* in local efficiency (calcarine sulcus and superior parietal lobule). For moderate to high levels of negative parenting during the EPI task, the same two regions *increased* in local efficiency (calcarine sulcus and superior parietal lobule).

For Communication, significant differences in local efficiency were identified for all three group comparisons (three regions, low – moderate; one region, low – high; four regions, moderate – high). For an increase in Communication from low to moderate levels, all regions had *decreased*

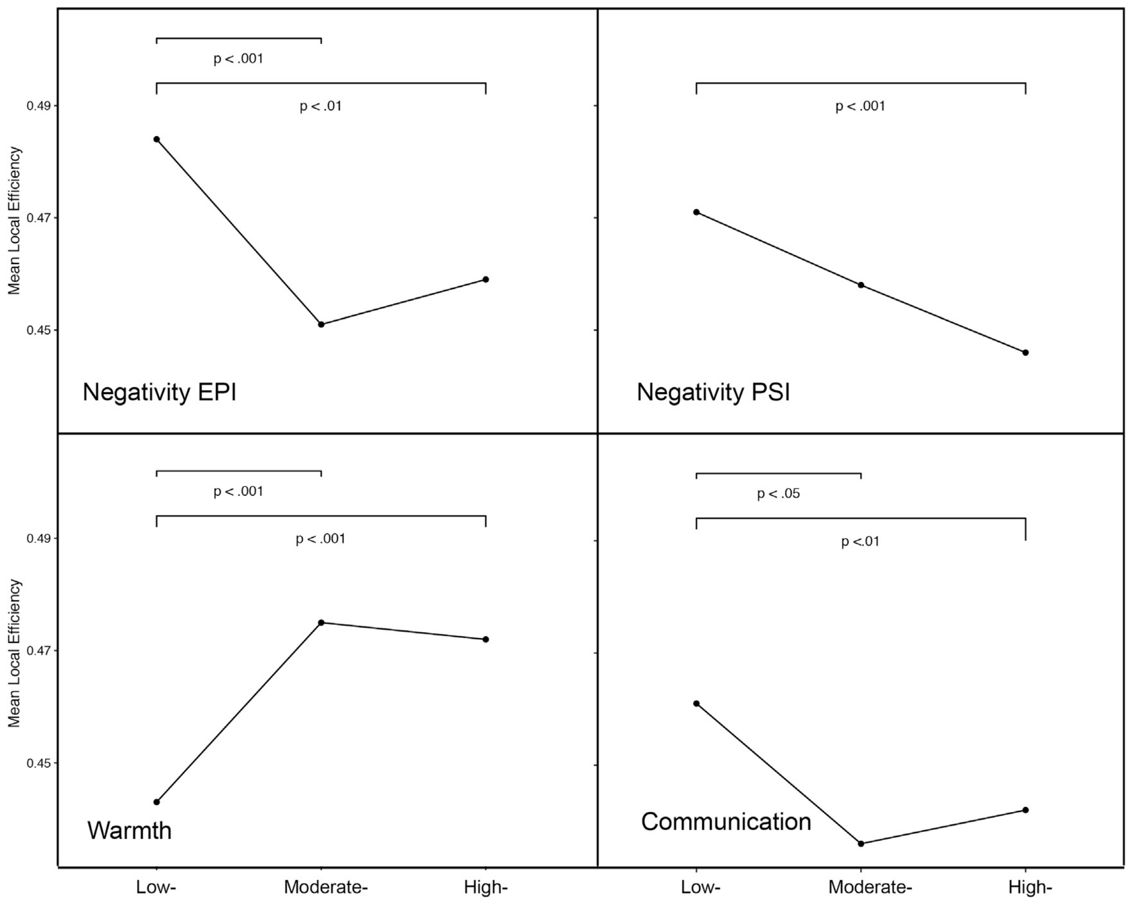

Fig. 1. Mean network efficiency for parenting components.

Table 3
Mean local efficiency, global efficiency, and absolute group differences.

Parenting Component	Low		Moderate		High		LE omnibus *p* values	Low – Moderate		Low - High		Moderate – High	
	LE	GE	LE	GE	LE	GE		LE diff	GE diff	LE diff	GE diff	LE diff	GE diff
Negativity EPI	.484	.553	.451	.549	.459	.549	$p < .001$	.032***	.004	.025**	.004	-.007	0.000
Warmth	.443	.548	.475	.550	.472	.549	$p < .001$	-.032****	-.002	-.030***	-.001	.002	0.002
Negativity PSI	.471	.549	.458	.544	.446	.550	$p < .001$	.013	.005	.025***	-.001	.012	−0.006
Comm	.461	.548	.436	.544	.441	.547	$p < .001$	.025**	.004	.020*	.002	-.006	−0.003

Note. Abbreviations: diff, difference; EPI, event-planning interaction; GE, global efficiency; LE, local efficiency; PSI, problem-solving interaction; Comm, communication.
FDR (5%) *adjusted p*-values.
$^*p < .05$.
$^{**}p < .01$.
$^{***}p < .001$.

Table 4
Small-world index.

Parenting Component	Low			Moderate			High		
	Sigma	L/L_{rand}	C/C_{rand}	sigma	L/L_{rand}	C/C_{rand}	Sigma	L/L_{rand}	C/C_{rand}
Negativity EPI	1.488	1.947/1.926	0.192/0.128	1.395	1.965/1.942	0.178/0.126	1.406	1.967/1.940	0.182/0.128
Warmth	1.415	1.965/1.948	0.177/0.124	1.470	1.957/1.938	0.188/0.126	1.488	1.966/1.937	0.189/0.125
Negativity PSI	1.469	1.966/1.939	0.187/0.125	1.477	1.987/1.957	0.183/0.122	1.379	1.960/1.942	0.173/0.125
Communication	1.432	1.968/1.942	0.183/0.126	1.418	1.985/1.962	0.173/0.121	1.441	1.974/1.952	0.181/0.124

Note. Abbreviations: EPI, event-planning interaction; PSI, problem-solving interaction; rand, random.

local efficiency. Regions implicated were located in parietal and temporal cortices. For low to high levels of Communication, the middle-anterior part of the cingulate gyrus and sulcus *increased* in local efficiency. For moderate to high levels of Communication, three of four regions displayed an *increase* in local efficiency: inferior temporal gyrus, superior temporal sulcus, and the middle-anterior part of the cingulate gyrus.

Table 5
Absolute group differences, small-worldness.

Parenting Component	Low – Moderate	Low – High	Moderate – High
Negativity EPI	0.093*	0.082*	−0.011
Warmth	−0.055	−0.073	−0.018
Negativity PSI	−0.007	0.103*	0.110***
Communication	0.014	−0.009	−0.023

Note. Abbreviations: EPI, event-planning interaction; PSI, problem-solving interaction.
FDR (5%) adjusted *p*-values.
*$p < .05$.
**$p < .01$.
***$p < .001$.

Table 6
Kolmogorov-Smirnov Test for equality of local Efficiency distributions.

Parenting Component	Low – Moderate	Low – High	Moderate – High
Negativity EPI	.196*	.148	.128
Warmth	.189*	.223*	.095
Negativity PSI	.095	.155	.149
Communication	.135	.169	.101

Note. Abbreviations: EPI, event-planning interaction; PSI, problem-solving interaction.
FDR (5%) adjusted *p*-values *$p < .05$. **$p < .01$. ***$p < .001$.

4. Discussion

This study, for the first time, demonstrates associations between maternal parenting behaviors and efficiency of structural brain networks in late childhood in a community-based sample. We hypothesized that more positive and less negative maternal parenting behaviors would be associated with lower local and higher global efficiency. Associations were found; however, they were not as predicted. Indeed, (a) minimal support was found for a relationship between global efficiency and maternal behaviors; (b) more negative maternal affective parenting was associated with *decreased* local efficiency; (c) more positive affective maternal parenting was associated with *increased* local efficiency.

Overall, for non-optimal (i.e., high negative and low positive) affective maternal parenting, mean local efficiency decreased. More regions displayed decreased local efficiency when the parenting behavior and the context were not congruent (i.e., Negativity EPI, negative parenting during a task designed to elicit positive affective behaviors) compared to when they were congruent (i.e., Negativity PSI, negative parenting during a task designed to elicit negative affective behaviors). Earlier work has highlighted the importance of affective context on parenting behaviors with respect to predicting child mental health (Schwartz et al., 2012, 2014). In our previous longitudinal study of adolescents, rates of maternal aggressive behavior in a non-congruent context significantly predicted major depressive disorder onset (Schwartz et al., 2014), but aggressive behavior in a congruent context did not. Further, we have also found that maternal aggressive behavior in a non-congruent context predicts poor functioning in adolescents via alterations in structural brain development (Whittle et al., 2016). Thus, it is possible that negative maternal behavior that is 'out of context' may have more of a consistent (and potentially negative) impact on child brain organization and mental health.

Although no previous literature has investigated links between maternal parenting behavior and structural brain networks, our results for negative parenting are consistent with the recent findings of Nikolova et al. (2018). Nikolova et at. (2018) demonstrated that exposure to childhood maltreatment was associated with lower network clustering, a parameter comparable to local efficiency, in young adults. Further, using the unpredictable chronic mild stress paradigm in mice, Nikolova et al. (2018) identified a stress-related loss of network clustering. The authors suggest that this cross-species evidence for large-scale brain network

Table 7
Cortical regions (nodes) with significant between-group differences in local efficiency.

Cortical region (node)	No.[a]	Local Efficiency		Difference
Negativity EPI: low to moderate		low	moderate	
Superior frontal gyrus (R)	16	0.588	0.415	L > H*
Inferior temporal gyrus (L)	37	0.567	0.311	L > H*
Middle temporal gyrus (L)	38	0.565	0.308	L > H*
Superior part of the precentral gyrus (L)	69	0.559	0.255	L > H**
Negativity EPI: low to high		**low**	**high**	
Orbital sulci (L)	64	0.657	0.314	L > H**
Subparietal sulcus (L)	71	0.523	0.205	L > H**
Negativity EPI: moderate to high		**moderate**	**high**	
Superior frontal gyrus (R)	16	0.415	0.577	M < H*
Inferior temporal gyrus (L)	37	0.311	0.507	M < H*
Superior part of the precentral gyrus (L)	69	0.255	0.608	M < H**
Subparietal sulcus (L)	71	0.560	0.205	M > H***
Warmth: low to moderate		**low**	**moderate**	
Angular gyrus (R)	25	0.392	0.577	L < H*
Subcallosal area, subcallosal gyrus (R)	32	0.045	0.386	L < H*
Lateral occipito-temporal sulcus (R)	60	0.119	0.502	L < H**
Middle-anterior part of the cingulate gyrus and sulcus (aMCC) (L)	7	0.513	0.278	L > H*
Warmth: low to high		**low**	**high**	
Subcallosal area, subcallosal gyrus (R)	32	0.045	0.386	L < H*
Lateral occipito-temporal sulcus (R)	60	0.119	0.502	L < H**
Warmth: moderate to high		**moderate**	**high**	
Superior temporal sulcus (parallel sulcus) (R)	73	0.432	0.601	M < H*
Middle-anterior part of the cingulate gyrus and sulcus (aMCC) (L)	7	0.278	0.530	M < H*
Negativity PSI: low to moderate		**low**	**moderate**	
Supramarginal gyrus (R)	26	0.301	0.530	L < M**
Calcarine sulcus (R)	44	0.534	0.311	L > M*
Superior parietal lobule (L)	27	0.470	0.236	L > M*
Negativity PSI: moderate to high		**moderate**	**high**	
Calcarine sulcus (R)	44	0.311	0.627	M < H**
Superior parietal lobule (L)	27	0.236	0.559	M < H*
Communication: low to moderate		**low**	**moderate**	
Angular gyrus (R)	25	0.563	0.358	L > M**
Inferior temporal gyrus (R)	37	0.590	0.256	L > M**
Superior temporal sulcus (parallel sulcus) (R)	73	0.564	0.341	L > M**
Communication: low to high		**low**	**high**	
Middle-anterior part of the cingulate gyrus and sulcus (aMCC) (L)	7	0.278	0.617	L < H**
Communication: moderate to high		**moderate**	**high**	
Inferior temporal gyrus (R)	37	0.256	0.592	M < H**
Superior temporal sulcus (parallel sulcus) (R)	73	0.341	0.531	M < H**
Middle-anterior part of the cingulate gyrus and sulcus (aMCC) (L)	7	0.262	0.617	M < H***
Pericallosal sulcus (L)	66	0.551	0.182	M > H*

Note. Abbreviations: L, left; R, right.
FDR (5%) *adjusted* *p*-values *$p < .05$. **$p < .01$.
[a] Anatomical parcellation based on Destriuex atlas (Destrieux et al., 2010).

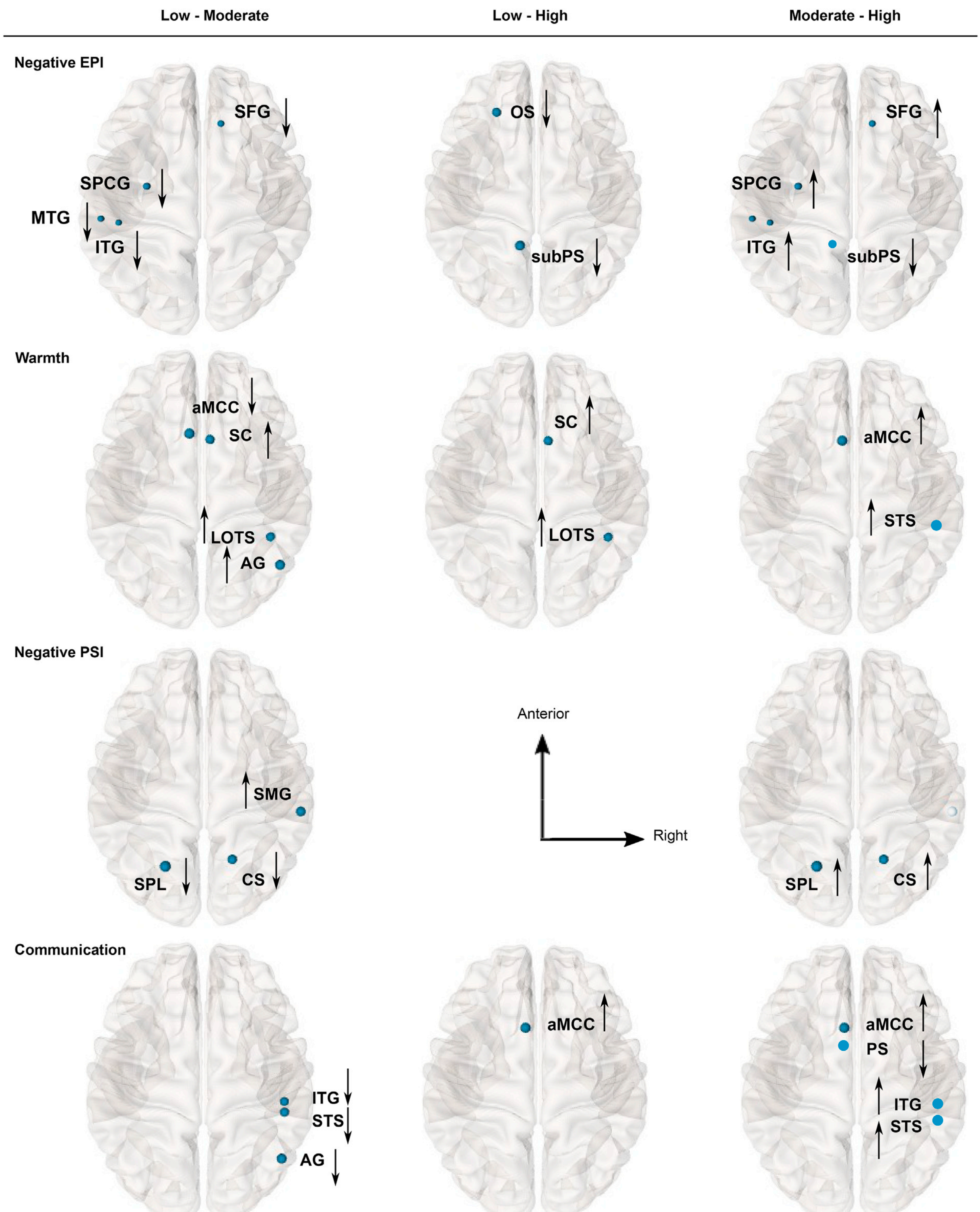

Fig. 2. Nodes showing significant between-group differences (FDR adjusted at 5%) in local efficiency based on pair-wise comparisons among low-, moderate- and high-maternal parenting groups. Abbreviations: aMCC, Middle-anterior part of the cingulate gyrus and sulcus; AG, angular gyrus; CS, calcarine sulcus; ITG, inferior temporal gyrus; LOTS, Lateral occipito-temporal sulcus; MTG, middle temporal gyrus; OS, orbital sulci; PS, pericallosal sulcus; subPS, subparietal sulcus; SC, subcallosal area, subcallosal gyrus; SFG, superior frontal gyrus; SPL, superior parietal lobule; SMG, supramarginal gyrus; SPCG, superior part of the precentral gyrus; STS, superior temporal sulcus.

alterations associated with chronic stress may indicate a mechanistic pathway for psychopathology.

While the consistency between our local efficiency findings and those of Nikolova et al. (2018) is promising, our findings were not as predicted. We hypothesized that more optimal (i.e., more positive and less negative) parenting would be associated with reduced local efficiency, which we speculated reflects accelerated maturation (or exaggeration) of the normal pattern of reducing local efficiency during late childhood (Khundrakpam et al., 2013; Nie et al., 2013). Although the developmental studies from which we drew our hypothesis appear convergent, the age ranges for the trajectory turning points are wide and the lowest value for local efficiency has been observed between approximately 8 and 12 years of age (Khundrakpam et al., 2013; Nie et al., 2013). Thus, we only have a preliminary idea of the developmental trajectory of local efficiency and finer grained, age specific results are required.

It is possible that low network efficiency represents an adaptive mechanism. Given that high levels of negative affective and low levels of positive affective parenting are likely to be detrimental to children's development, it is plausible that these children have had to mature more quickly to 'adapt' to non-optimal parenting. In terms of local efficiency, faster maturation might be reflected in an acceleration or exaggeration of the normative pattern (i.e., decreased) for late childhood. This notion is consistent with functional MRI studies of the amygdala-prefrontal cortex circuit that indicate accelerated connectivity, in children and adolescents, in response to early deprivation (Gee et al., 2013) and insensitive parenting (Thijssen et al., 2017).

High-levels of communicative behaviors were associated with deceased local efficiency, in a pattern similar to the negative affective parenting behaviors. Given communicative parental behaviors have been linked to enhanced child functioning, and found to be protective in the development of psychopathology in adolescents, this result was unexpected (Davidson and Cardemil, 2009; Ohannessian, 2013; Thomas and Zimmer-Gembeck, 2007). Decreased local efficiency particularly for the high-Communication group might suggest an adaptive mechanism related to more mature structural networks, as suggested above for high negative and low positive parenting.

It is important to note that the interpretation of local efficiency based on maturation and adaptation is speculative, particularly given that the current study was not longitudinal, and because our hypothesis was drawn from structural covariance findings of correlations of cortical thickness (Khundrakpam et al., 2013; Nie et al., 2013), and not partial correlations as was the case for the current study. Further, our interpretation of 'optimal' parenting behaviors is speculative, and it would be helpful to extrapolate what the levels of observed maternal behaviors (low-, moderate-, and high-) in the interaction tasks may represent in terms of more naturalistic, everyday maternal-child communication, and also how they predict different aspects of child functioning.

The cingulate cortex (middle-anterior), an area implicated in emotional processing, demonstrated a differential pattern of local efficiency for increasing levels of communication and warmth. This region has been classified as part of the medial prefrontal cortex (mPFC) and is considered part of the 'social brain' (Frith, 2007; Sandi and Haller, 2015). In addition, these areas are consistent with a resting state functional connectivity study that demonstrated that infants exposed to higher inter-parental conflict had stronger connectivity between the posterior cingulate cortex (PCC) and the anterior medial prefrontal cortex (Graham et al., 2015); two core Default Mode Network regions. These regions have been shown to be an important for regulating stress and emotions in fMRI work in children and adults (Fonzo et al., 2010; Gee et al., 2013; Meyer-Lindenberg and Tost, 2012). Taken together, these findings suggest regions of the social brain and Default Mode Network (DMN) may be susceptible to parenting behaviors.

Children exposed to high levels of negative affective (EPI) and communicative behaviors, demonstrated changes in local efficiency in the temporal gyri (inferior and middle) and sulci (superior). These regions run into the anterior temporal lobe, an area thought to play a critical role in representing and retrieving social knowledge (facts about people and social situations) and identified as part of the 'social brain' (Frith, 2007; Olson et al., 2013). Developmental functional connectivity studies confirm the temporal gyri/temporal cortex as part of the amygdala resting network and have demonstrated associations with maternal depression and expression of anger (Callaghan et al., 2017; Qiu et al., 2015). Our findings are consistent with the temporal lobe as an area relevant to the processing of social knowledge.

Of note, for warmth (low to moderate) and communicative behaviors (low to moderate) the angular gyrus, which is located within the area of the temporoparietal junction (TPJ), was identified to have significant changes in local efficiency. Similarly, for low to moderate negative behaviors during the PSI the supramarginal gyrus, also located within the TPJ, was observed to have decreased local efficiency. The TPJ is theorized to be important to social cognition as it enables individuals understand others' mental states, and to appreciate that these may differ from our own, referred to as Theory of Mind (Frith, 2007; Gallagher and Frith, 2003). Specifically, within this mentalizing network, although other regions have been acknowledged, the anterior dorsal mPFC and bilateral TPJ are the most consistently activated across different tasks and modalities, (Molenberghs et al., 2016). Identification of regions located in the vicinity of the TPJ for high levels of warmth, communicative and negative maternal behaviors, may suggest that these behaviors are related to efficiency of processing another person's perspective.

There are several important analytical choices that underlie and strengthen our local efficiency findings (a) the group differences (e.g., Communication: low to moderate): that were investigated at the regional level were first identified as significant from averaging local efficiency across all regions (i.e. based on the *mean* local efficiency) to minimize multiple comparisons and spurious findings; (b) all *p*-values, whether averaged (mean local and global efficiency) or at the regional level were corrected for multiple comparisons using a FDR of 5%; (c) given no between-group differences were identified for age (child), sex, depression symptoms, anxiety symptoms, incidence of traumatic events, or maternal occupational status it is unlikely that these variables are driving the differences in network efficiency.

Overall, compared to local efficiency findings, no support was found for an association between observed parenting behaviors and global efficiency. Given the lack of findings for global efficiency, it is possible that the structural covariance analytical technique used in the current study is not sensitive to changes in global efficiency or alternatively, global efficiency may not be sensitive to the effects of parenting as measured in this study. All groups demonstrated small-world organization and the small-world index results followed a similar pattern to the local efficiency findings. By visual inspection, the small-world index typically reached its highest value for parenting groups with the highest clustering coefficient and since the clustering coefficient is a similar concept to local efficiency, these results are consistent with the definitions of graph theory.

There are a number of limitations of this work that should be considered in interpreting findings. First, we were unable to examine the relative contribution of fathers' behavior due to budget constraints. Fathers play a significant role in the emotional development of their children and the findings relating to mother's affective parental behaviors may not generalize to fathers (Cassano et al., 2014; Schwartz et al., 2016). Second, because dyads were predominantly Caucasian with children aged 8-years, care should be taken in generalizing the findings to ethnic minority families or to older or younger children. Third, as discussed, the findings are limited by the cross-sectional nature of the data. Fourth, we did not investigate the bi-directional nature of dyadic interactions. Fifth, we were restricted to a between-subjects design and power may have been an issue. A power analysis would be difficult to conduct because, to the best of our knowledge, the available meta-analyses generally assess difference between groups with disease/disorder and healthy controls (e.g., Ioannidis, 2011 for brain volume abnormalities) and would be likely to overestimate effect size in typical development. In addition, given that covariance analysis does not provide network metrics for individuals it was not possible to calculate a standard measure of effect size. Estimating plausible effect sizes is important for reproducibility and is an area of exploration for future work. Sixth, we cannot rule out that the association between parenting and structural brain networks in offspring is based on genetic factors. For example, mothers high on communicative behaviours could have more efficient structural brain networks and then have biological children with more efficient networks. Finally, structural covariance in general, and more specifically the sparse partial correlation estimation applied in the current study, is a relatively new methodology for constructing structural brain networks and therefore the results should be interpreted with caution. Ultimately, exploring structural covariance using different methodologies is likely to increase our understanding but it is also important to consider underlying assumptions and limitations. We analyzed the data based on the Destrieux parcellation. It is plausible that other parcellations may be more biologically meaningful (Eickhoff et al., 2018) and that the results would be impacted if an alternative parcellation scheme was considered (Zalesky et al., 2010). Future work in this area might include comparisons across multiple parcellation schemes. In contrast to our between-subjects approach, future work might also consider how individual differences in maternal behavior relate to structural covariance between pairs of regions (nodes; Valk et al., 2017).

In the current study, regression was not used to remove the effect of any confounding variables. Previous work has typically accounted for the impact of multiple scanners, age, and sex (e.g., Khundrakpam et al., 2016; Teicher et al., 2014). Here, age was tightly controlled and all scans were conducted on the same scanner, so neither of these variables warranted attention. It is likely though that sex may be related to structural covariance networks, given the findings for sex differences in brain structure (Cosgrove et al., 2007). Here the impact of sex was not investigated because under the current design, had we grouped by sex, the number of participants in the low-, moderate- and high-parenting groups would have been small (approximately 20 participants per group) and we were concerned the findings would have been under-powered. Future work in this area could evaluate the use of residual variances on our analytic approach, sparse partial correlation estimation.

We employed a number of steps to address possible motion induced artefact in the current study (Vijayakumar et al., 2018). As described above, prior to scanning, participants were prepared using a mock-scan. During scanning head cushioning was used and image quality was assessed and re-acquired if appropriate. Data quality was assessed by visual inspection and outlier detection during image processing. The criteria for intervening and the number of manual corrections undertaken was reported. Future work could benefit from the inclusion of a quantitative measurement of motion.

5. Conclusion

This study is the first to explore the association between variations in parenting behavior and gray matter structural brain networks in childhood. The results provide preliminary evidence that variations in the affective and communicative aspects of typical family environments are associated with the efficiency of structural covariance networks. It is possible that these alterations in the properties of structural brain networks are one mechanism by which affective parental behaviors exert their influence on symptoms of psychopathology (Schwartz et al., 2016; Shortt et al., 2016). It would be of interest for future research to explore whether parenting behaviors are related to the development of structural covariance networks and psychopathology over time.

Declaration of interests

The authors declare no competing financial interests.

Acknowledgments

SR was supported by an Australian Postgraduate Award. SW was supported by a National Health Medical Research Council Career Development Fellowship (ID: 1007716). MLS was supported by the Royal Children’s Hospital Foundation. This research was conducted within the Developmental Imaging research group, Murdoch Children’s Research Institute and the Children’s MRI Centre, Royal Children's Hospital, Melbourne, Victoria. It was supported by the Australian Research Council (Discovery Grant ID: DP130103551), and the Murdoch Children’s Research Institute, the Royal Children’s Hospital, Department of Paediatrics, The University of Melbourne and the Victorian Government's Operational Infrastructure Support Program. The project was generously supported by RCH1000, a unique arm of The Royal Children's Hospital Foundation devoted to raising funds for research at The Royal Children’s Hospital. We thank the RCH Medical Imaging staff for their assistance and expertise in the collection of the MRI data included in this study.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.neuroimage.2019.06.043.

References

Alexander-Bloch, A., Giedd, J.N., Bullmore, E., 2013a. Imaging structural co-variance between human brain regions. Nat. Rev. Neurosci. 14 (5), 322–336. https://doi.org/10.1038/nrn3465.

Alexander-Bloch, A., Raznahan, A., Bullmore, E., Giedd, J., 2013b. The convergence of maturational change and structural covariance in human cortical networks. J. Neurosci. 33 (7), 2889–2899. https://doi.org/10.1523/JNEUROSCI.3554-12.2013.

Australian Bureau of Statistics, 2013. Technical Paper, Socio-Economic Indexes for Areas (SEIFA) 2011, 2033.0.55.001.

Belsky, J., de Haan, M., 2011. Annual Research Review: parenting and children's brain development: the end of the beginning. JCPP (J. Child Psychol. Psychiatry) 52 (4), 409–428.

Bonilha, L., Tabesh, A., Dabbs, K., Hsu, D.A., Stafstrom, C.E., Hermann, B.P., Lin, J.J., 2014. Neurodevelopmental alterations of large-scale structural networks in children with new-onset epilepsy. Hum. Brain Mapp. 35 (8), 3661–3672. https://doi.org/10.1002/hbm.22428.

Bullmore, E., Sporns, O., 2009. Complex brain networks: graph theoretical analysis of structural and functional systems. Nat. Rev. Neurosci. 10 (4), 186–198. https://doi.org/10.1038/nrn2618.

Bullmore, E., Suckling, J., Overmeyer, S., Rabe-Hesketh, S., Taylor, E., Brammer, M.J., 1999. Global, voxel, and cluster tests, by theory and permutation, for a difference between two groups of structural mr images of the brain. IEEE Trans. Med. Imaging 18 (1), 32–42.

Callaghan, B.L., Dandash, O., Simmons, J.G., Schwartz, O., Byrne, M.L., Sheeber, L., Whittle, S., 2017. Amygdala resting connectivity mediates association between maternal aggression and adolescent major depression: a 7-year longitudinal study. J. Am. Acad. Child Adolesc. Psychiatry 56 (11), 983–991. https://doi.org/10.1016/j.jaac.2017.09.415 e983.

Cassano, M., Zeman, J.L., Sanders, W.M., 2014. Responses to children's sadness: mothers' and fathers' unique contributions and perceptions. Merrill-Palmer Q. 60 (1), 1–23. https://doi.org/10.13110/merrpalmquar1982.60.1.0001.

Cosgrove, K.P., Mazure, C.M., Staley, J.K., 2007. Evolving knowledge of sex differences in brain structure, function, and chemistry. Biol. Psychiatry 62 (8), 847–855. https://doi.org/10.1016/j.biopsych.2007.03.001.

Dale, A.M., Fischl, B., Sereno, M.I., 1999. Cortical surface-based analysis: I. Segmentation and surface reconstruction. Neuroimage 9 (2), 179–194. https://doi.org/10.1006/nimg.1998.0395.

Davidson, T.M., Cardemil, E.V., 2009. Parent-child communication and parental involvement in latino adolescents. J. Early Adolesc. 29 (1), 99–121. https://doi.org/10.1177/0272431608324480.

Destrieux, C., Fischl, B., Dale, A., Halgren, E., 2010. Automatic parcellation of human cortical gyri and sulci using standard anatomical nomenclature. Neuroimage 53 (1), 1–15. https://doi.org/10.1016/j.neuroimage.2010.06.010.

Eickhoff, S.B., Yeo, B.T.T., Genon, S., 2018. Imaging-based parcellations of the human brain. Nat. Rev. Neurosci. 19 (11), 672–686. https://doi.org/10.1038/s41583-018-0071-7.

Enders, C.K., 2010. Applied Missing Data Analysis. The Guildford Press, New York.

Essau, C.A., Muris, P., Ederer, E.M., 2002. Reliability and validity of the spence children's anxiety scale and the screen for child anxiety related emotional disorders in German children. J. Behav. Ther. Exp. Psychiatry 33 (1), 1–18. https://doi.org/10.1016/S0005-7916(02)00005-8.

Fan, Y., Shi, F., Smith, J.K., Lin, W., Gilmore, J.H., Shen, D., 2011. Brain anatomical networks in early human brain development. Neuroimage 54 (3), 1862–1871. https://doi.org/10.1016/j.neuroimage.2010.07.025.

Fischl, B., 2012. FreeSurfer. *Neuroimage* 62 (2), 774–781. https://doi.org/10.1016/j.neuroimage.2012.01.021.

Fischl, B., Sereno, M.I., Dale, A.M., 1999. Cortical surface-based analysis: II. Inflation, flattening, and a surface-based coordinate system. Neuroimage 9 (2), 195–207. https://doi.org/10.1006/nimg.1998.0396.

Fonzo, G.A., Simmons, A.N., Thorp, S.R., Norman, S.B., Paulus, M.P., Stein, M.B., 2010. Exaggerated and disconnected insular-amygdalar blood oxygenation level-dependent response to threat-related emotional faces in women with intimate-partner violence posttraumatic stress disorder. Biol. Psychiatry 68 (5), 433–441. https://doi.org/10.1016/j.biopsych.2010.04.028.

Fornito, A., Zalesky, A., Bullmore, E., 2016. Fundamentals of Brain Network Analysis. Elsevier Science.

Frith, C.D., 2007. The social brain? Phil. Trans. Biol. Sci. 362 (1480), 671–678. https://doi.org/10.1098/rstb.2006.2003.

Fuhrmann, D., Knoll, L.J., Blakemore, S.J., 2015. Adolescence as a sensitive period of brain development. Trends Cognit. Sci. 19 (10), 558–566. https://doi.org/10.1016/j.tics.2015.07.008.
Galea, S., Tracy, M., 2007. Participation rates in epidemiologic studies. Ann. Epidemiol. 17 (9), 643–653. https://doi.org/10.1016/j.annepidem.2007.03.013.
Gallagher, H.L., Frith, C.D., 2003. Functional imaging of 'theory of mind'. Trends Cognit. Sci. 7 (2), 77–83. https://doi.org/10.1016/S1364-6613(02)00025-6.
Gee, D.G., Gabard-Durnam, L.J., Flannery, J., Goff, B., Humphreys, K.L., Telzer, E.H., Tottenham, N., 2013. Early developmental emergence of human amygdala-prefrontal connectivity after maternal deprivation. Proc. Natl. Acad. Sci. U.S.A. 110 (39), 15638–15643.
Gilboa, E., Revelle, W., 1994. Personality and the structure of affective responses. In: Emotions: Essays on Emotion Theory. Lawrence Erlbaum Associates, Inc, Hillsdale, NJ, pp. 135–159.
Graham, A.M., Pfeifer, J.H., Fisher, P.A., Carpenter, S., Fair, D.A., 2015. Early life stress is associated with default system integrity and emotionality during infancy. J. Child Psychol. Psychiatry Allied Discip. 56 (11), 1212–1222. https://doi.org/10.1111/jcpp.12409.
Greenwald, R., Rubin, A., 1999. Assessment of posttraumatic symptoms in children: development and preliminary validation of parent and child scales. Res. Soc. Work. Pract. 9 (1), 61–75. https://doi.org/10.1177/104973159900900105.
Harman, H.H., 1976. Modern Factor Analysis, 3d ed. University of Chicago Press, Chicago.
He, Y., Chen, Z., Evans, A., 2008. Structural insights into aberrant topological patterns of large-scale cortical networks in Alzheimer's disease. J. Neurosci. 28 (18), 4756–4766. https://doi.org/10.1523/JNEUROSCI.0141-08.2008.
He, Y., Chen, Z.J., Evans, A.C., 2007. Small-world anatomical networks in the human brain revealed by cortical thickness from MRI. Cerebr. Cortex 17 (10), 2407–2419. https://doi.org/10.1093/cercor/bhl149.
Hensch, T.K., 2004. Critical period regulation. Annu. Rev. Neurosci. 27, 549–579. https://doi.org/10.1146/annurev.neuro.27.070203.144327.
Holly, L.E., Little, M., Pina, A.A., Caterino, L.C., 2014. Assessment of anxiety symptoms in school children: a cross-sex and ethnic examination. J. Abnorm. Child Psychol. 43 (2), 297–309. https://doi.org/10.1007/s10802-014-9907-4.
Holmbeck, G.N., Zebracki, K., Johnson, S.Z., Belvedere, M., Hommeyer, J.S., 2007. Parent-child Interaction Macro-Coding Manual. Loyola Univeristy Manual, Chicago.
Hosseini, S.M.H., Mazaika, P., Mauras, N., Buckingham, B., Weinzimer, S.A., Tsalikian, E., Reiss, A.L., 2016. Altered integration of structural covariance networks in young children with type 1 diabetes. Hum. Brain Mapp. 37 (11), 4034–4046. https://doi.org/10.1002/hbm.23293.
Ioannidis, J.A., 2011. Excess significance bias in the literature on brain volume abnormalities. Arch. Gen. Psychiatr. 68 (8), 773–780. https://doi.org/10.1001/archgenpsychiatry.2011.28.
Jiang, Y., Liu, W., Ming, Q., Gao, Y., Ma, R., Zhang, X., Huang, B., 2016. Disrupted topological patterns of large-scale network in conduct disorder. Sci. Rep. 6 https://doi.org/10.1038/srep37053.
Kennedy, D.P., Adolphs, R., 2012. The social brain in psychiatric and neurological disorders. Trends Cognit. Sci. 16 (11), 559–572. https://doi.org/10.1016/j.tics.2012.09.006.
Khundrakpam, B.S., Lewis, J.D., Reid, A., Karama, S., Zhao, L., Chouinard-Decorte, F., Evans, A.C., 2016. Imaging structural covariance in the development of intelligence. Neuroimage. https://doi.org/10.1016/j.neuroimage.2016.08.041.
Khundrakpam, B.S., Reid, A., Brauer, J., Carbonell, F., Lewis, J., Ameis, S., Evans, A.C., 2013. Developmental changes in organization of structural brain networks. Cerebr. Cortex 23 (9), 2072–2085.
Kok, R., Thijssen, S., Bakermans-Kranenburg, M.J., Jaddoe, V.W., Verhulst, F.C., White, T., 2015. Normal variation in early parental sensitivity predicts child structural brain development. J. Am. Acad. Child Adolesc. Psychiatry 54. https://doi.org/10.1016/j.jaac.2015.07.009.
Kovacs, M., 2011. Children's Depression Inventory, second ed. (Retrieved from).
Lamblin, M., Murawski, C., Whittle, S., Fornito, A., 2017. Social connectedness, mental health and the adolescent brain. Neurosci. Biobehav. Rev. 80 (Suppl. C), 57–68. https://doi.org/10.1016/j.neubiorev.2017.05.010.
Latora, V., Marchiori, M., 2001. Efficient behavior of small-world networks. Phys. Rev. Lett. 87 (19), 198701/198701-198701/198704.
Lefort-Besnard, J., Bassett, D.S., Smallwood, J., Margulies, D.S., Derntl, B., Gruber, O., Bzdok, D., 2018. Different shades of default mode disturbance in schizophrenia: subnodal covariance estimation in structure and function. Hum. Brain Mapp. 39 (2), 644–661. https://doi.org/10.1002/hbm.23870.
Levin, J.R., Serlin, R.C., Seaman, M.A., 1994. A controlled, powerful multiple-comparison strategy for several situations. Psychol. Bull. 115 (1), 153–159.
Luby, J.L., Barch, D.M., Belden, A., Gaffrey, M.S., Tillman, R., Babb, C., 2012. Maternal support in early childhood predicts larger hippocampal volumes at school age. Proc. Natl. Acad. Sci. U.S.A. 109 https://doi.org/10.1073/pnas.1118003109.
Luby, J.L., Belden, A., Harms, M.P., Tillman, R., Barch, D.M., 2016. Preschool is a sensitive period for the influence of maternal support on the trajectory of hippocampal development. Proc. Natl. Acad. Sci. U.S.A. 113 https://doi.org/10.1073/pnas.1601443113.
MacPhillamy, D.J., Lewinsohn, P.M., 1982. The pleasant events schedule: studies on reliability, validity, and scale intercorrelation. J. Consult. Clin. Psychol. 50 (3), 363–380. https://doi.org/10.1037/0022-006X.50.3.363.
Mars, R.B., Neubert, F.X., Noonan, M.P., Sallet, J., Toni, I., Rushworth, M.F.S., 2012. On the relationship between the "default mode network" and the "social brain". Front. Hum. Neurosci. 1–9. https://doi.org/10.3389/fnhum.2012.00189.
McMillan, J., Beavis, A., Jones, F.L., 2009. The AUSEI06: a new socioeconomic index for Australia. J. Sociol. 45 (2), 123–149. https://doi.org/10.1177/1440783309103342.
Meyer-Lindenberg, A., Tost, H., 2012. Neural mechanisms of social risk for psychiatric disorders. Nat. Neurosci. 15, 663. https://doi.org/10.1038/nn.3083.
Molenberghs, P., Johnson, H., Henry, J.D., Mattingley, J.B., 2016. Understanding the minds of others: a neuroimaging meta-analysis. Neurosci. Biobehav. Rev. 65, 276–291. https://doi.org/10.1016/j.neubiorev.2016.03.020.
Morris, A.S., Criss, M.M., Silk, J.S., Houltberg, B.J., 2017. The impact of parenting on emotion regulation during childhood and adolescence. Child Development Perspectives 11 (4), 233–238. https://doi.org/10.1111/cdep.12238.
Newland, R.P., Crnic, K.A., Cox, M.J., Mills-Koonce, W.R., 2013. The family model stress and maternal psychological symptoms: mediated pathways from economic hardship to parenting. J. Fam. Psychol. 27 (1), 96–105. https://doi.org/10.1007/s10567-008-0034-z.
Nie, J., Li, G., Shen, D., 2013. Development of cortical anatomical properties from early childhood to early adulthood. Neuroimage 76, 216–224.
Nikolova, Y.S., Misquitta, K.A., Rocco, B.R., Prevot, T.D., Knodt, A.R., Ellegood, J., Banasr, M., 2018. Shifting priorities: highly conserved behavioral and brain network adaptations to chronic stress across species. Transl. Psychiatry 8 (1). https://doi.org/10.1038/s41398-017-0083-5.
Ohannessian, C.M., 2013. Parental problem drinking and adolescent psychological problems. Youth Soc. 45 (1), 3–26. https://doi.org/10.1177/0044118X11408931.
Ohashi, K., Anderson, C.M., Bolger, E.A., Khan, A., McGreenery, C.E., Teicher, M.H., 2017. Childhood maltreatment is associated with alteration in global network fiber-tract architecture independent of history of depression and anxiety. Neuroimage 150, 50–59. https://doi.org/10.1016/j.neuroimage.2017.02.037.
Olson, I.R., McCoy, D., Klobusicky, E., Ross, L.A., 2013. Social cognition and the anterior temporal lobes: a review and theoretical framework. Soc. Cognit. Affect Neurosci. 8 (2), 123–133. https://doi.org/10.1093/scan/nss119.
Pechtel, P., Lyons-Ruth, K., Anderson, C.M., Teicher, M.H., 2014. Sensitive periods of amygdala development: the role of maltreatment in preadolescence. Neuroimage 97, 236–244. https://doi.org/10.1016/j.neuroimage.2014.04.025.
Pereira, M., Negrão, M., Soares, I., Mesman, J., 2013. Predicting harsh discipline in at-risk mothers: the moderating effect of socioeconomic deprivation severity. J. Child Fam. Stud. https://doi.org/10.1007/s10826-013-9883-2.
Prinz, R.J., Foster, S., Kent, R.N., O'Leary, K.D., 1979. Multivariate assessment of conflict in distressed and nondistressed mother-adolescent dyads. J. Appl. Behav. Anal. 12 https://doi.org/10.1901/jaba.1979.12-691.
Puetz, V.B., Parker, D., Kohn, N., Dahmen, B., Verma, R., Konrad, K., 2017. Altered brain network integrity after childhood maltreatment: a structural connectomic DTI-study. Hum. Brain Mapp. 38 (2), 855–868. https://doi.org/10.1002/hbm.23423.
Qiu, A., Anh, T.T., Li, Y., Chen, H., Rifkin-Graboi, A., Broekman, B.F.P., Meaney, M.J., 2015. Prenatal maternal depression alters amygdala functional connectivity in 6-month-old infants. Transl. Psychiatry 5 (2). https://doi.org/10.1038/tp.2015.3.
Richmond, S., Johnson, K.A., Seal, M.L., Allen, N.B., Whittle, S., 2016. Development of brain networks and relevance of environmental and genetic factors: a systematic review. Neurosci. Biobehav. Rev. 71, 215–239. https://doi.org/10.1016/j.neubiorev.2016.08.024.
Richmond, S., Schwartz, O., Johnson, K.A., Seal, M.L., Bray, K., Deane, C., Whittle, S., 2018. Exploratory Factor Analysis of Observational Parent-Child Interaction Data. Assessment. https://doi.org/10.1177/1073191118796557.
Rifkin-Graboi, A., Kong, L., Sim, L.W., Sanmugam, S., Broekman, B.F.P., Chen, H., Qiu, A., 2015. Maternal sensitivity, infant limbic structure volume and functional connectivity: a preliminary study. Transl. Psychiatry 5 (10). https://doi.org/10.1038/tp.2015.133.
Rubinov, M., Sporns, O., 2010. Complex network measures of brain connectivity: uses and interpretations. Neuroimage 52 (3), 1059–1069. https://doi.org/10.1016/j.neuroimage.2009.10.003.
Sandi, C., Haller, J., 2015. Stress and the social brain: behavioural effects and neurobiological mechanisms. Nat. Rev. Neurosci. 16 (5), 290–304. https://doi.org/10.1038/nrn3918.
Scheff, S.W., 2016. In Fundamental Statistical Principles for the Neurobiologist. Academic Press, pp. 157–182.
Schwartz, O.S., Byrne, M.L., Simmons, J.G., Whittle, S., Dudgeon, P., Yap, M.B.H., Allen, N.B., 2014. Parenting during early adolescence and adolescent-onset major depression: a 6-year prospective longitudinal study. Clinical Psychological Science 2 (3), 272–286. https://doi.org/10.1177/2167702613505531.
Schwartz, O.S., Dudgeon, P., Sheeber, L.B., Yap, M.B., Simmons, J.G., Allen, N.B., 2012. Parental behaviors during family interactions predict changes in depression and anxiety symptoms during adolescence. J. Abnorm. Child Psychol. 40 (1), 59–71.
Schwartz, O.S., Simmons, J.G., Whittle, S., Byrne, M.L., Yap, M.B.H., Sheeber, L.B., Allen, N.B., 2016. Affective parenting behaviors, adolescent depression, and brain development: a review of findings from the orygen adolescent development study. Child Development Perspectives. https://doi.org/10.1111/cdep.12215.
Shortt, J.W., Katz, L.F., Allen, N.B., Leve, C., Davis, B., Sheeber, L.B., 2016. Emotion socialization in the context of risk and psychopathology: mother and father socialization of anger and sadness in adolescents with depressive disorder. Soc. Dev. 25 (1), 27–46. https://doi.org/10.1111/sode.12138.
Simmons, J.G., Schwartz, O.S., Bray, K., Deane, C., Pozzi, E., Richmond, S., Whittle, S.L., 2017. Study protocol: families and childhood transitions study (FACTS) – a longitudinal investigation of the role of the family environment in brain development and risk for mental health disorders in community based children. BMC Pediatr. 17 (1), 153. https://doi.org/10.1186/s12887-017-0905-x.
Spence, S., 1998. A measure of anxiety symptoms among children. Behav. Res. Ther. 36 (5), 545–566. https://doi.org/10.1016/S0005-7967(98)00034-5.
Sporns, O., 2012. *Networks of the Brain*: Cambridge, Mass. MIT Press, 2012.

Sun, D., Haswell, C.C., Morey, R.A., De Bellis, M.D., 2018a. Brain structural covariance network centrality in maltreated youth with PTSD and in maltreated youth resilient to PTSD. Dev. Psychopathol. 1–15. https://doi.org/10.1017/S0954579418000093.

Sun, D., Peverill, M.R., Swanson, C.S., McLaughlin, K.A., Morey, R.A., 2018b. Structural covariance network centrality in maltreated youth with posttraumatic stress disorder. J. Psychiatr. Res. 98, 70–77. https://doi.org/10.1016/j.jpsychires.2017.12.015.

Teicher, M.H., Anderson, C.M., Ohashi, K., Polcari, A., 2014. Childhood maltreatment: altered network centrality of cingulate, precuneus, temporal Pole and insula. Biol. Psychiatry 76 (4), 297–305. https://doi.org/10.1016/j.biopsych.2013.09.016.

Thijssen, S., Muetzel, R.L., Bakermans-Kranenburg, M.J., Jaddoe, V.W.V., Tiemeier, H., Verhulst, F.C., Van Ijzendoorn, M.H., 2017. Insensitive parenting may accelerate the development of the amygdala-medial prefrontal cortex circuit. Dev. Psychopathol. 29 (2), 505–518. https://doi.org/10.1017/S0954579417000141.

Thomas, R., Zimmer-Gembeck, M.J., 2007. Behavioral outcomes of parent-child interaction therapy and triple P-positive parenting program: a review and meta-analysis. J. Abnorm. Child Psychol. 35 (3), 475–495. https://doi.org/10.1007/s10802-007-9104-9.

Tibshirani, R., 1996. Regression shrinkage and selection via the lasso. J. R. Stat. Ser. Soc. B Stat. Methodol. 58 (1), 267–288.

Valk, S.L., Bernhardt, B.C., Böckler, A., Trautwein, F.M., Kanske, P., Singer, T., 2017. Socio-cognitive phenotypes differentially modulate large-scale structural covariance networks. Cerebr. Cortex 27 (2), 1358–1368. https://doi.org/10.1093/cercor/bhv319.

van Buuren, S., Groothuis-Oudshoorn, K., 2011. mice: multivariate imputation by chained equations in R. J. Stat. Softw. 45 (3), 1–67.

Vijayakumar, N., Mills, K.L., Alexander-Bloch, A., Tamnes, C.K., Whittle, S., 2018. Structural brain development: a review of methodological approaches and best practices. Dev. Cogn. Neurosci. 33, 129–148. https://doi.org/10.1016/j.dcn.2017.11.008.

Vértes, P.E., Bullmore, E.T., 2015. Annual research review: growth connectomics - the organization and reorganization of brain networks during normal and abnormal development. JCPP (J. Child Psychol. Psychiatry) 56 (3), 299–320. https://doi.org/10.1111/jcpp.12365.

Walhovd, K.B., Fjell, A.M., Giedd, J., Dale, A.M., Brown, T.T., 2017. Through thick and thin: a need to reconcile contradictory results on trajectories in human cortical development. Cerebr. Cortex 27 (2), 1472–1481. https://doi.org/10.1093/cercor/bhv301.

Whittle, S., Simmons, J.G., Dennison, M., Vijayakumar, N., Schwartz, O., Yap, M.B.H., Allen, N.B., 2014. Positive parenting predicts the development of adolescent brain structure: a longitudinal study. Dev. Cogn. Neurosci. 8, 7–17. https://doi.org/10.1016/j.dcn.2013.10.006.

Whittle, S., Vijayakumar, N., Dennison, M., Schwartz, O., Simmons, J.G., Sheeber, L., Allen, N.B., 2016. Observed measures of negative parenting predict brain development during adolescence. PLoS One 11 (1). https://doi.org/10.1371/journal.pone.0147774.

Zalesky, A., Fornito, A., Harding, I.H., Cocchi, L., Yücel, M., Pantelis, C., Bullmore, E.T., 2010. Whole-brain anatomical networks: does the choice of nodes matter? Neuroimage 50 (3), 970–983. https://doi.org/10.1016/j.neuroimage.2009.12.027.