Exploring neural correlates of behavioral and academic resilience among children in poverty

M.E. Ellwood-Lowe[1*+], C.N. Irving[1*], & S.A. Bunge[1,2]

[1]Department of Psychology and [2]Helen Wills Neuroscience Institute
University of California, Berkeley

*authors contributed equally

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[+]**Correspondence**:
Monica E. Ellwood-Lowe
2121 Berkeley Way
Berkley, CA 94704
mellwoodlowe@berkeley.edu

Abstract

Children in poverty must contend with systems that do not meet their needs. We explored what, at a neural level, helps explain children's resilience in these contexts. Lower coupling between lateral frontoparietal network (LFPN) and default mode network (DMN)—linked, respectively, to externally- and internally-directed thought—has previously been associated with better cognitive performance. However, we recently found the opposite pattern for children living in poverty. Here, we investigated trajectories of network coupling over ages 9-13, and their relation to academic achievement and attention problems. Critically, we explored if these relations differed meaningfully between children above and below poverty. In a pre-registered study, we analyzed longitudinal data from the first three yearly timepoints of the ABCD Study (N = 8366 children at baseline; 1303 below poverty). As predicted, higher LFPN-DMN connectivity was linked to worse grades and more attentional problems for children living above poverty, while children below poverty showed the opposite tendencies. Moreover, this interaction between LFPN-DMN connectivity and poverty status at baseline was associated with children's grades one year later, even controlling for baseline grades. Together, these findings suggest that network connectivity is differentially predictive of academic performance and attention problems for children above and below poverty.

Introduction

Resources are not equally distributed across a nation's population; in the United States, the inequity is particularly stark (Zucman, 2019). There is a large body of research focused on the detriments of growing up without as many economic and educational resources (low socioeconomic status, SES). By comparison, far less research has examined how some children in lower-resource contexts are able to adapt and ultimately thrive educationally, exhibiting resilience in the face of structural barriers to success. Measuring children's brain function is one way to investigate pathways to resilience. For example, one can ask whether children growing up with fewer resources rely on the same neural pathways as their well-off peers to perform well in school, or whether they achieve the same results through alternate means.

A number of brain imaging studies have shown environment-dependent differences in neural recruitment during cognitive tasks (Merz et al., 2019). These studies suggest that the homes, neighborhoods, and schools that form our lived experiences shape our mental and neural processes. This should hardly be surprising, given decades of animal research on experience-dependent brain plasticity (DeFelipe, 2006; Diamond et al., 1964).

In this study, we focus on patterns of brain activation that support cognitive task performance in childhood, and where they diverge as a function of family income, a proxy for resource access. One relevant study found that children from higher- and lower-income homes relied on different brain regions to perform well on a working memory task (Finn et al., 2017). Children from higher-income families showed more overall brain activation during task performance: the more they recruited temporal and frontal brain regions, the better they did. Children from lower-income families, on the other hand, showed less activation and did better the *less* they recruited temporal and frontal brain regions. Contrastive findings such as these abound; researchers have typically found differences in frontal and parietal lobe activation as a function of family income, and differences in the ways brain function and structure relates to children's performance on tasks such as working memory, rule learning, reasoning, and attention (Leonard et al., 2019; Merz et al., 2019; Sheridan et al., 2012).

Another way to test for experience-dependent differences in brain function is with resting state functional MRI (rs-fMRI); this method may more closely capture the cumulative effect of children's life experiences and thought patterns. With rs-fMRI, we measure children's unconstrained brain activity while they lie in the MRI scanner. The strength of functional connectivity between brain regions—that is, how often they fluctuate in tandem at "rest"—is thought to reflect recent history of coactivation of those regions. Advantages of this method are that it is not influenced by differences in children's strategy or effort on a particular MRI task, which can be confounds in group comparisons. Functional connectivity measured with rs-fMRI is sensitive to current mental states (e.g., Liston et al., 2009), but also captures brain network connectivity on a broader timescale than a single task performed on a single day (for a review, see Guerra-Carrillo et al., 2014).

Here, we focus specifically on children's resting-state functional connectivity between several brain networks relevant to cognitive and self-referential processing. The lateral frontoparietal network (LFPN) is consistently activated in higher-level cognitive tasks, such as those taxing executive functions or reasoning (Vincent et al., 2008). In contrast, the default mode network (DMN) is more active during internally oriented processing, such as reflecting on one's self (Raichle et al., 2001), as well as during tasks that require thinking outside of the here-and-now, such as thinking about the past or future (Spreng, 2012). Task-related fMRI studies have shown that stronger activation of the LFPN and stronger deactivation of the DMN is associated with better performance on tasks that require focus on externally presented stimuli (Weissman et al., 2006). On the other hand, engagement of both the LFPN and DMN is beneficial when performing tasks on which intentional mind-wandering is helpful (Christoff et al., 2009; Dixon et al., 2014; Kucyi et al., 2021).

A fairly consistent body of research with higher-income children and adults has found that relatively lower functional connectivity between LFPN and DMN is adaptive, in terms of cognitive, emotional, and behavioral outcomes (Chai et al., 2014; Lopez et al., 2020; Sherman et al., 2014; Whitfield-Gabrieli et al., 2020). Developmentally, both network segregation and integration have been reported, depending on the networks and the developmental period in question; it is thought that segregation supports network specialization (Baum et al., 2017; Grayson & Fair, 2017; Marek et al., 2015; Pines et al., 2021).

In a prior study, however, we found that lower connectivity between LFPN and DMN—an attribute previously linked to better cognitive performance and lower attentional problems (Sherman et al., 2014; Whitfield-Gabrieli et al., 2020)—was in fact only adaptive for children in families living above poverty (Ellwood-Lowe et al., 2020). Children from higher-income families tend to be overrepresented in neuroimaging studies, which may help to explain consistent results found previously. For children whose families had low incomes relative to their needs, higher LFPN-DMN connectivity was associated with marginally *better* cognitive test performance—perhaps a marker of adaptation relative to the demands of children's environments. Follow-up analyses found that even within the group of children in poverty, the direction of the relation seemed to differ meaningfully for children below poverty with different sets of experiences, such as parent-reported neighborhood safety and the type of school children attended. These follow-up analyses are in keeping with other work showing that different socioeconomic indicators and early experiences are differentially related to neural development (e.g., Elsayed et al., 2021; Johnson et al., 2016; Noble et al., 2015; Rakesh, Zalesky, et al., 2021; Taylor et al., 2020; Whittle et al., 2017). Our unexpected results suggest that in certain environments it may be adaptive to frequently coactivate LFPN and DMN (Ellwood-Lowe et al., 2020).

In our prior study, we also explored coupling between these two networks and the cingulo-opercular network (CON). This network, sometimes referred to as the "salience network," has been theorized to serve as an interface between LFPN and DMN. In particular, it is thought to be involved in alerting LFPN to a salient stimulus that may require a controlled response, and thus play an important role in switching from the so-called "default" mode to the top-down control mode (Sridharan et al., 2008). In our prior study, we found that lower connectivity between CON and LFPN was related to better test performance for children, regardless of income levels. For CON-DMN connectivity, however, we found a possible group interaction, whereby higher CON-DMN coupling tended to be associated with better cognitive test scores for children above poverty, but showed the opposite trend for children below poverty. As a result, we also examined CON network connectivity here.

Our initial study was cross-sectional, focusing on children when they first entered the study between ages 9–11; here we sought to track neural differences over three timepoints so as to understand whether the observed differences in brain-behavior correlations between children above and below poverty diminish, persist, or are enhanced as children continue to develop. In the current data, we looked at behavioral measures 1-2 years after the first assessment, and neuroimaging measures collected 2 years after the first assessment. With this longitudinal approach, we were better able to examine developmental trajectories between children above and below poverty across middle childhood and early adolescence, from ages 9–13.

We predicted that these networks would become generally less coupled with one another over development, based on some of the prior literature. However, we consider three alternative hypotheses for how network coupling interacts with poverty status: convergence, divergence, and stability. One possibility is that the dissociation we found at baseline between children's LFPN-DMN connectivity and test performance reflects different rates of brain development for children above versus below poverty: that is, children in poverty with higher LFPN-DMN connectivity might be showing more protracted development, which could be adaptive for them in some way. In this case, we would expect LFPN-DMN connectivity (and relations with behavior) to converge over development. A second possibility is that, as children continue to lead lives with different constraints, their patterns of adaptive behavior or thinking becomes more and more distinct. In this case, we would expect the relation between connectivity and performance to diverge over development. Finally, a third possibility is that the pattern of adaptive connectivity is relatively stable between ages 9–13; that is, the pattern of opposite relations between functional connectivity and performance would not change over this timeframe. Thus, by looking at longitudinal relations, we can try to disentangle these possibilities and better understand whether or how early environment shapes developmental trajectories.

In our prior work, the behavioral outcome of interest was performance on a battery of cognitive tests assessing executive functions and reasoning. Although children's scores on these fairly abstract tasks tend to be predictive of real-world outcomes (Firkowska-Mankiewicz, 2011), the metrics that are most relevant to their lives are the real-world outcomes themselves. Here, we sought to examine more ecologically valid indicators of behavior, namely children's grades and attention problems. Attention problems can pervade many aspects of children's lives, from their performance in school to self-esteem to relationships with peers, teachers, and family members (Harpin, 2005). Likewise, grades in school are an important marker of future educational and career opportunities. However, few studies have related academic performance to resting-state connectivity. An exception is Chaddock-Heyman et al. (2018), who found that greater network integration at ages 7-9 was associated with higher scholastic performance. By using these measures, we seek to better understand the neural basis of children's resilience with regard to societal constraints. Importantly, these measures—like rs-fMRI—assess functioning over a broader timeframe than their score on a set of tests completed on a single day.

In summary, the current pre-registered study had two primary aims. First, we sought to conduct longitudinal analyses characterizing trajectories of within-person change in network coupling over ages 9-13, as well as their relations to children's behavior. We considered three possible outcomes for the comparison between children living above and below poverty: convergence, divergence, or stability of the relation between connectivity and behavior. Second, we sought to measure children's grades and behavior problems as more real-world and temporally extended indicators of performance in their daily lives. We also planned to explore associations between these behavioral measures and LFPN-CON and DMN-CON connectivity, and—critically—whether they differed as a function of poverty status. Unlike studies that have examined brain differences between relatively higher- and lower-income children, this study included children living below the poverty line, some of whom are able to cope with severe adversity.

Methods

Parent study

Data were drawn from the Adolescent Brain Cognitive Development (ABCD) study, which was designed to recruit a large cohort of children who closely represented the United States populations (http://abcdstudy.org; see Garavan et al., 2018). The ABCD study is a multisite, longitudinal study intended to run for at least 10 years following 11,878 children, recruited at ages 9-11, into late adolescence. A wide variety of data are collected on each youth including mental and physical health assessments, behavioral data, imaging data, and more. This study was approved by the Institutional Review Board at each study site, with centralized IRB approval from the University of California, San Diego. Informed consent and assent were obtained from all parents and children, respectively. We include data from the first three timepoints: T0 (baseline assessment; ages 8.9-11.1), T1 (one-year follow-up; ages 9.1-12.4), and T2 (two-year follow-up; ages 10.6-13.6). More specifically, we include behavioral data from T0, T1 and T2, and functional MRI data from T0 and T2.

Present study

Planned analyses were pre-registered prior to data access (https://aspredicted.org/QWQ_C5N; https://aspredicted.org/NTG_RRB) and analysis scripts are available on the Open Science Framework (https://osf.io/gcjn8/?view_only=d0f098d6a8ab47d5bf0bbb290141bbd3). The original data are available with permissions on the NIMH Data Archive (https://nda.nih.gov/abcd). All deviations from the initial analysis plan are fully described in the Supplement.

Children from the full sample were excluded if they did not provide data on any of the measures used in our analyses. Specifically, children were excluded from analyses if their caregiver did not provide information about family income, if their resting state MRI data at baseline did not meet ABCD's usability criteria, or if there was no information about the child's age, sex, or family ID (used to track whether participants were siblings). After these initial exclusions, children who had data related to attention problems were included in analyses relevant to attention (*N* = 8366), and those with data related to grades in school were included in analyses relevant to grades (*N* = 7751; see Table 1). Because the former group included slightly more children, we used this sample when conducting analyses that did not include behavioral data.

We estimated poverty status for each child based on their combined family income bracket, the number of people living in the home, and the average supplemental poverty level for the study sites included in the sample, as in our previous work (Ellwood-Lowe et al., 2020). Based on the factors used to estimate poverty status, we considered children to be living below the poverty line if they were living in a household of 4 with a total income of less than $25,000, or a household of 5 or more with a total income of less than $35,000 at T0 (Table 1).

Timepoint		**Attention data (*N* = 8366)**		**Grades data (*N* = 7751)**	
		Above poverty	Below poverty	Above poverty	Below poverty
Baseline (T0)	*N*	7063	1303	6510	1241
	Sex	F: 3532 M: 3531	F: 653 M: 650	F: 3277 M: 3233	F: 624 M: 617
	Age	8.9-11.1	8.9-11.1	8.9-11.1	8.9-11.1
One-year follow-up (T1)	*N*	6780	1155	5984	1060
	Sex	F: 3386 M: 3394	F: 577 M: 578	F: 3018 M: 2966	F: 528 M: 532
	Age	9.1-12.4	9.1-12.4	9.7-12.4	9.7-12.4
Two-year follow-up (T2)	*N*	4087	640	3663	593
	Sex	F: 2013 M: 2074	F: 309 M: 331	F: 1814 M: 1849	F: 290 M: 303
	Age	10.6-13.6	10.6-13.6	10.6-13.6	10.6-13.6

Table 1. Sample sizes, age, and parent-reported child sex for children above and below poverty, at T0, T2, and T2. Sample sizes differ slightly for those analyses focusing on

grades and those focusing on attention, based on the number of children providing usable data.

Behavioral measures

Children's cognitive performance was measured at T0 with a cognitive test battery that included measures from the NIH Toolbox (http://www.nihtoolbox.org). The NIH Toolbox Fluid Cognition composite measure includes two tests of working memory (Picture Sequence Memory Test, List Sorting Working Memory Test), two tests of executive functions that tap into cognitive flexibility and inhibitory control (Dimensional Card Sort and Flanker tasks), and one test of processing speed (Pattern Comparison Processing Speed Test). The administered test battery also included the Matrix Reasoning Task from the Wechsler Intelligence Test for Children-V (WISC-V), a measure of abstract reasoning (Wechsler, 2014). More details on each of these tests and their administration in the current study is described elsewhere (Luciana et al., 2018).

Attention and behavioral problems were measured with the Attention subscale of the Child Behavior Checklist (CBCL). The CBCL is a standardized form which is used to characterize children's externalizing and internalizing behaviors (Achenbach & Ruffle, 2000). From the initial baseline assessment onwards, parents completed an automated version of the CBCL annually, reporting on their child's behavior over the past six months (Barch et al., 2018). Each item on the CBCL was rated using a three-point rating scale: "not true," "somewhat or sometimes true," "very true or often true." There were 11 items in the attention subscale. We used the mean of all items at T0, T1, and T2, separately, for each child. Higher scores indicated more attentional and behavioral problems.

Children's academic performance was measured via parent-reported grades in the ABCD Longitudinal Parent Diagnostic Interview for DSM-5 Background Items Full (KSAD). Parents were asked what kind of grades their child received on average: 1= As/excellent, 2 = B's/Good; 3 = C's/Average; 4 = D's/Below Average; 5 = F's/Struggling a lot; 6 = ungraded, -1 = unapplicable. This question was asked at T0, T1, and T2.

MRI Scan Procedure

Scans were collected on one of three types of 3T scanners (Siemens, Philips, or GE) with an adult-size head coil. Resting state scans were completed at T0 and T2. Scans were typically completed on the same day as the cognitive battery, but could also be completed at a second testing session. After completing motion compliance training in a simulated scanning environment, participants first completed a structural T1-weighted scan. Next, they completed three to four five-minute resting state fMRI scans, during which they were instructed to lay with their eyes open while viewing a crosshair on the screen. The first two resting state scans were completed immediately following the T1-weighted scan; children then completed two other structural scans, followed by one or two more resting state scans, depending on the protocol at each specific study site.

Structural and functional images underwent automated quality control procedures (including detecting excessive movement and poor signal-to-noise ratios) and visual inspection and rating (for structural scans) of images for artifacts or other irregularities (described in Hagler et al., 2019); participants were excluded if they did not meet quality control criteria, including at least 12.5 minutes of data with low head motion at the time of data collection (framewise displacement < 0.2 mm).

Scan parameters were optimized to be compatible across scanners, allowing for maximal comparability across the 19 study sites. T1-weighted scans were collected axially with $1mm^3$ voxel resolution, 256 x 256 matrix, 8º flip angle, and 2x parallel imaging. Other scan parameters varied by scanner platform (Siemens: 176 slices, 256 x 256 FOV, 2500 ms TR, 2.88 ms TE, 1060 ms TI; Philips: 255 slices, 256 x 240 FOV, 6.31 ms TR, 2.9 ms TE, 1060 ms TI; GE: 208 slices, 256 x 256 FOV, 2500 ms TR, 2 ms TE, 1060 ms TI). fMRI scans were collected axially with $2.4mm^3$ voxel resolution, 60 slices, 90 x 90 matrix, 216 x 216 FOV, 800ms TR, 30 ms TE, 52º flip angle, and 6 factor MultiBand Acceleration. Head motion was monitored during scan acquisition using real-time procedures (fMRI Integrated Real-time Motion Monitor; Dosenbach et al., 2017) to adjust scanning procedures and collect additional data as necessary (Casey et al., 2018). This prospective motion correction procedure significantly reduces scan artifacts due to head motion (Hagler et al., 2019), which are known to affect functional connectivity estimates (Power et al., 2015; Satterthwaite et al., 2013).

Resting state fMRI preprocessing

Data preprocessing was carried out using the ABCD pipeline and carried out by the ABCD Data Analysis and Informatics Core; more details are reported by Hagler et al. (2019). Briefly, T1-weighted MR images were corrected for gradient nonlinearity distortion and intensity inhomogeneity, and rigidly registered to a custom reference brain (Friston et al., 1995). These images were run through FreeSurfer's automated brain segmentation to derive white matter, ventricle, and whole brain ROIs.

Resting state fMRI data were first corrected for head motion, displacement estimated from field map scans, B0 distortions, and gradient nonlinearity distortions, and registered to the structural images using mutual information. Initial scan volumes were removed, and each voxel was normalized and de-meaned. Signal from estimated head motion timecourses (including six motion parameters, their derivatives, and their squares), quadratic trends, and mean timecourses of white matter, gray matter, and whole brain, plus first derivatives, were regressed out, and frames with more than 0.2mm displacement were excluded. The data then underwent temporal bandpass filtering (0.009 – 0.08 Hz).

Next, standard ROI-based analyses were adapted to allow for analysis in surface space (Hagler et al., 2019). Specifically, timecourses were projected onto FreeSurfer's cortical surface, upon which 13 functionally defined networks (Gordon et al., 2016) were mapped and timecourses for FreeSurfer's standard cortical and subcortical ROIs extracted (Desikan et al., 2006; Fischl et al., 2002). Correlations for each pair of ROIs, both within and across each of the 13 networks, were calculated. These pairwise correlations were z-transformed and averaged to calculate within-network connectivity for each network (the average correlation of each ROI pair within the network) and between-network connectivity across all networks (the average correlation of pairs of each ROI in one network with each ROI in another network). Here, we examined between-network LFPN-DMN, CON-DMN, and CON-LFPN connectivity.

Altogether, there was a four-step process for reducing the effect of head motion on rs-fMRI results. First there was real-time head motion monitoring and correction, as described above. Second, there was a thorough and systematic check of scan quality in collaboration with ABCD's Data Analysis and Informatics Center. Third, signal from motion timecourses was regressed out during preprocessing, and frames with greater than 0.2mm of framewise displacement were excluded from calculations altogether, as were time periods with less than five contiguous low-motion frames. Fourth, a final censoring procedure was employed to identify potential lingering effects of motion by excluding any frames with outliers in spatial variation across the brain (Hagler et al., 2019). In combination, these procedures reduce motion artifacts (Power et al., 2014).

Analyses

Analyses were performed using the software package R (version 4.0.2; R Core Team, 2017). To determine whether to include potential covariates in our model, we tested whether each of the following variables contributed significantly to model fit: (1) a random intercept of study site, (2) a random intercept of families, (3) a fixed effect of sex, (4) a fixed effect of child age, and (5) a fixed effect of head motion (mean framewise displacement) during the resting state scan. All covariates besides age contributed to model fit at a level of $p < .05$ and were thus retained in final models.

To determine significance in our models, we performed nested model comparison. In all cases, we compared models without the inclusion of the variable of interest to models with this variable included; we calculated whether the variable of interest contributed significantly to model fit using the *anova* function for likelihood ratio test model comparison. For models in which the dependent variable was continuous, we performed linear mixed effects models using the *lme4* package (Bates et al., 2015); for models in which this variable was an ordered factor (e.g., grades), we performed cumulative link mixed models using the *ordinal* package (Christensen, 2018).

Longitudinal changes in brain network connectivity

We examined network changes over early adolescence, and whether these changes differed as a function of poverty status. We performed three separate linear mixed effects models testing the interaction of timepoint (T0, T2) with poverty status (above, below), in association with (1) LFPN-DMN connectivity, (2) CON-DMN connectivity, and (3) CON-LFPN connectivity.

Behavioral measures

We assessed the concurrent and longitudinal relations between cognitive test performance and grades, and tested whether the relation varied as a function of poverty status. To this end, we conducted cumulative link mixed models to test grades in association with an interaction between poverty status and test performance. We had preregistered an analysis plan using linear mixed effects models to test these relations. However, because grades are a categorical ordered variable, cumulative link mixed models are more appropriate. Thus, we report the latter analyses for all tests including grades as an outcome variable. Results are not meaningfully different when performing the pre-registered linear mixed effects models. We also calculated pairwise correlation values for all behavioral measures: that is, NIH cognitive scores at baseline, grades at three timepoints, and attention scores at three timepoints.

Functional connectivity in relation to grades and attention

We investigated the relation between children's grades and LFPN-DMN connectivity at each timepoint. We performed three separate cumulative link mixed models to characterize the relation between children's academic performance and LFPN-DMN connectivity. The first model tested this relation at T0, with an interaction between LFPN-DMN connectivity and poverty status. The second and third models tested this relation longitudinally, to see whether LFPN-DMN at T0 and its interaction with poverty status related to children's academic performance at T1 and T2, respectively, when controlling for children's academic performance at T0.

In one analysis meant to follow up on an interaction, the cumulative link mixed model failed to converge; because this analysis was performed only to illustrate the direction of the effect for a subgroup, we report beta coefficients for a linear mixed effects model for that test and note this in the text.

Similarly to our analyses focused on grades, we examined the relation between children's attention problems and LFPN-DMN connectivity at each timepoint. As attention was a continuous variable, we performed three separate linear mixed effects models testing the interaction between LFPN-DMN connectivity with poverty status, in association with (1) attention problems at T0, (2) attention problems at T1, and (3) attention problems at T2, controlling for children's attention at T0.

In preregistered secondary analyses, we also examined relations between these behavioral measures and CON network connectivity.

Exploratory analyses

We conducted a number of additional analyses, following a similar analytic approach to those above, for which we did not have strong predictions. These additional analyses are reported in the main text and Supplementary Materials. Those that were not preregistered are indicated as exploratory.

Results

Longitudinal changes in network connectivity

First, we examined how network connectivity changes between T0 and T2 in LFPN-DMN resting-state functional connectivity. We had predicted that these networks would become less coupled between ages 9 and 13. However, there was no significant change in LFPN-DMN connectivity across the group over the course of the two years, $B = 0.001$, SD = 0.001, $\chi^2(2) = 1.01$, $p = .605$. Additionally, this relation did not differ as a function of poverty status, interaction: $B = -0.001$, SD = 0.002, $\chi^2(1) = 0.2$, $p = .651$. Rather, we observed marked individual variability in the slope and magnitude of change over time (Figure 1). Given the possibility that high- and low-performing children below the poverty line would show different developmental trajectories, we followed up on these results with exploratory analyses testing for an interaction between poverty status and cognitive test performance on change in functional connectivity in each of these networks; no such effect was observed (see Supplement). Thus, the lack of change in LFPN-DMN connectivity was consistent across poverty levels and cognitive performance.

We also examined changes in functional connectivity for CON-DMN and CON-LFPN, as secondary analyses. Based on prior studies, we expected that these networks would become increasingly decoupled during development, for both children above and below poverty. On average, CON-DMN connectivity decreased significantly over ages 9-13, confirming our prediction, B = -0.01, SD = 0.001, χ^2 (2) = 61.55, p < .001. Notably, this relation interacted significantly as a function of poverty status, interaction: B = -0.001, SD = 0.002, χ^2 (1) = 6.61, p = .010 (Figure 2). While children below poverty did not show a significant decrease in connectivity, this change was highly significant for children above poverty (below poverty: B = -0.004, SD = 0.003, χ^2 (1) = 1.52, p = .217; above poverty: B = -0.009, SD = 0.001, χ^2 (1) = 56.47, p < .001).

Similarly, CON-LFPN connectivity decreased significantly across the two years, on average, B = -0.005, SD = 0.001, χ^2 (2) = 19.28, p < .001. This main effect was qualified by a possible interaction as a function of poverty status, interaction: B = 0.005, SD = 0.003, χ^2 (1) = 3.55, p = .060 (Figure 3). Similar to the pattern for CON-DMN, children below poverty did not show a significant decrease in CON-LFPN connectivity, but this change was highly significant for children above poverty (below poverty: B = -0.001, SD = 0.003, χ^2 (1) = 0.07, p = .797; above poverty: B = -0.005, SD = 0.001, χ^2 (1) = 19.04, p < .001).

Thus, both CON-DMN and CON-LFPN network connectivity decreased on average over ages 9-13, but these changes were driven by children above poverty. Exploratory analyses testing for an interaction between poverty status and cognitive test performance revealed no difference in these trajectories as a function of cognitive performance (see Supplement).

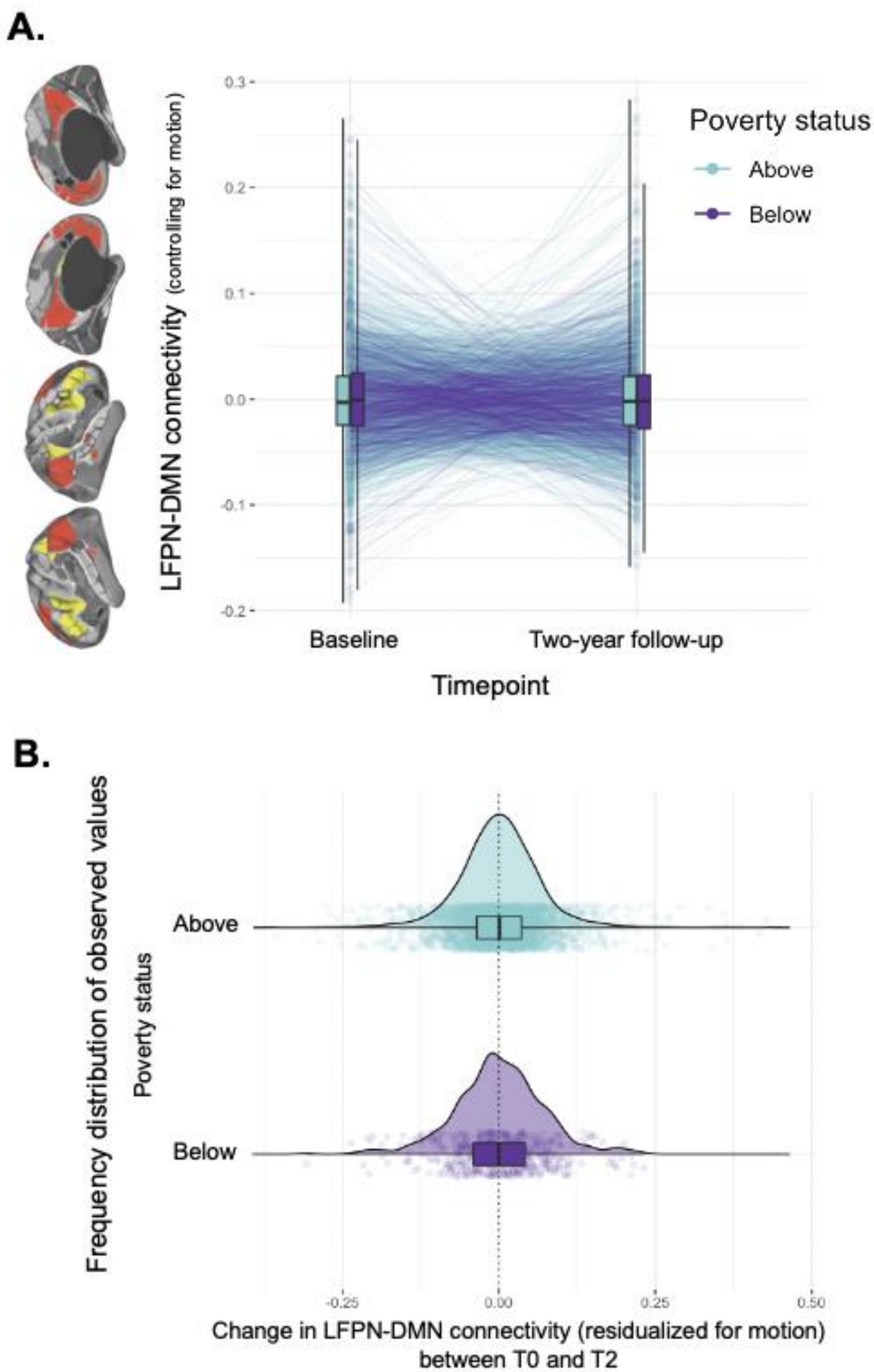

Figure 1. A. LFPN-DMN connectivity for each child, at the baseline (T0) and two-year follow-up (T2) assessments. Each line represents a different participant, connecting their values at T0 and T2; lighter teal color indicates children above poverty, while purple indicates children below poverty. Box plots for both groups at both timepoints also displayed. **B.** Change in LFPN-DMN connectivity for children above (top) and below poverty (bottom). Dotted line at zero indicates no change; negative values indicate a decrease between T0 and T2.

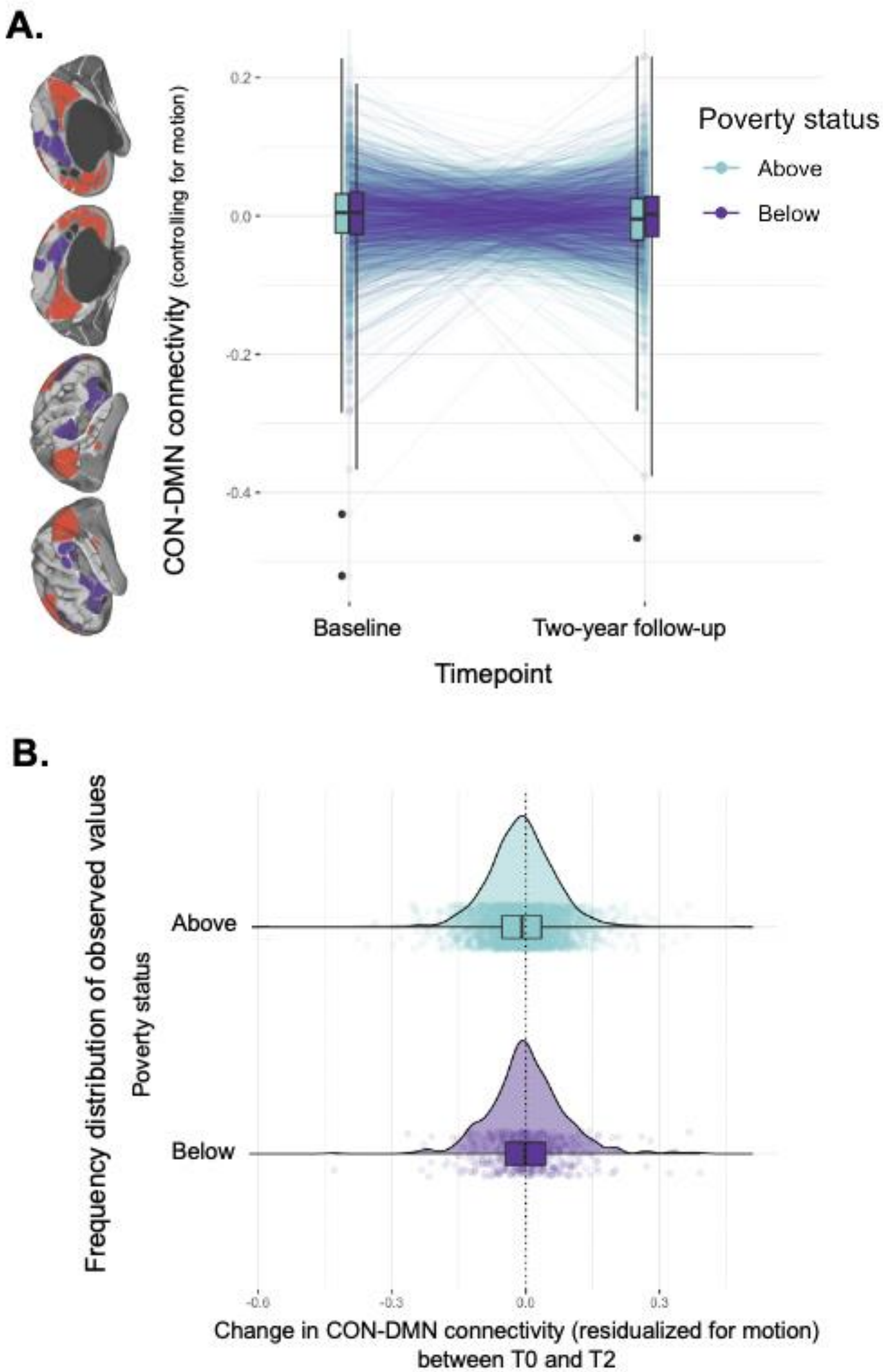

Figure 2. A. CON-DMN connectivity for each child, at the baseline (T0) and two-year follow-up (T2) assessments. Each line represents a different participant, connecting their values at T0 and T2; lighter teal color indicates children above poverty, while purple indicates children below poverty. Box plots for both groups at both timepoints also displayed. **B.** Change in CON-DMN connectivity for children above (top) and below poverty (bottom). Dotted line at zero indicates no change; negative values indicate a decrease between T0 and T2.

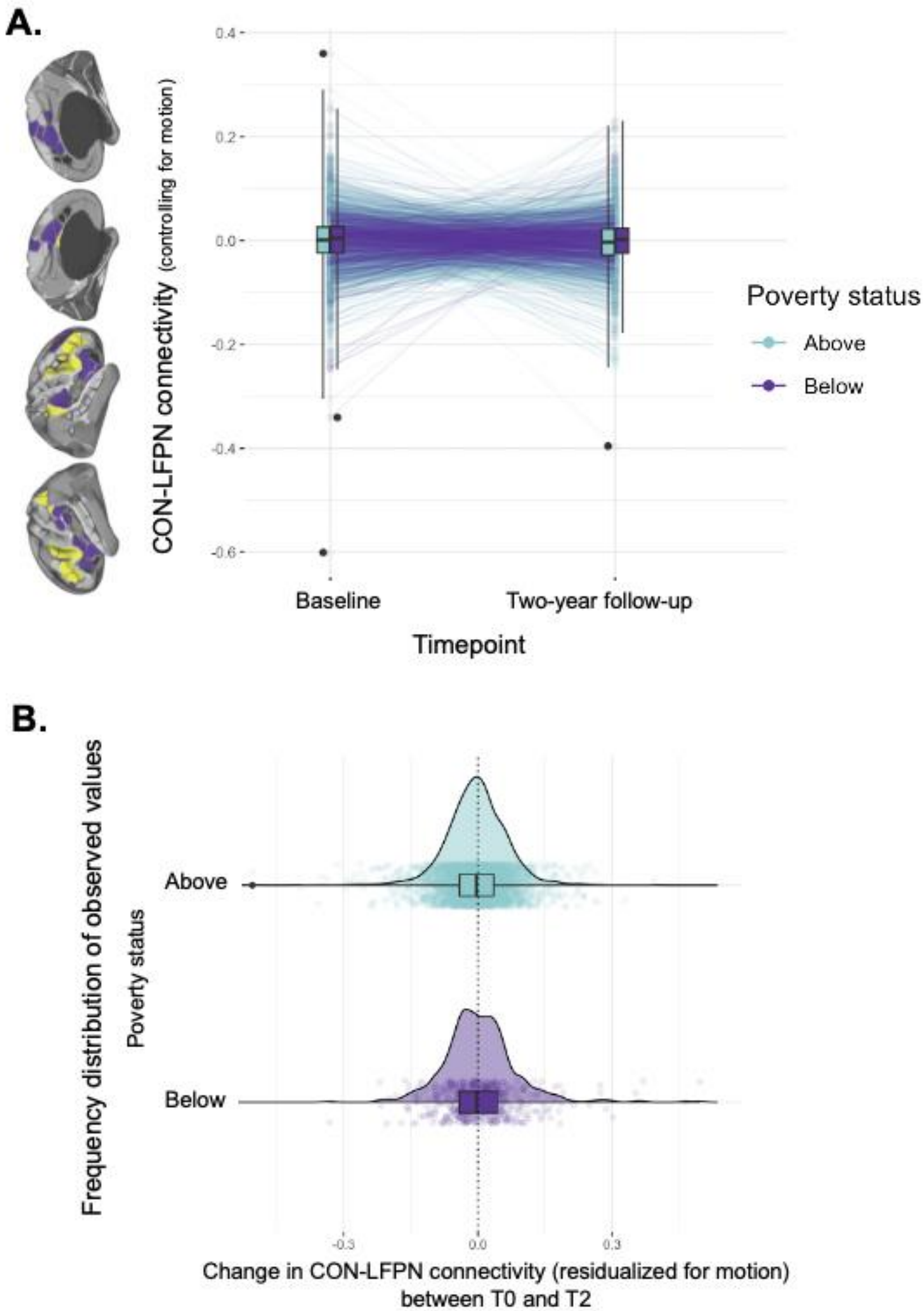

Figure 3. Panel A. CON-LFPN connectivity for each child, at the baseline (T0) and two-year follow-up (T2) assessments. Each line represents a different participant, connecting their values at T0 and T2; lighter teal color indicates children above poverty, while purple indicates children below poverty. Box plots for both groups at both timepoints also displayed. **Panel B.** Change in CON-LFPN connectivity for children above (top) and below poverty (bottom). Dotted line at zero indicates no change; negative values indicate a decrease between T0 and T2.

Behavioral measures

Most children in our sample were reported by their parents as receiving A's and B's, although the broader range from A-F was represented. On average, children below poverty received lower grades than children above poverty. In terms of attention, most children in our sample scored below the clinical range on the CBCL attention subscale at T0. On average, children in poverty had more attention problems than children above poverty.

All three behavioral measures—NIH cognitive test scores, grades, and attention—were significantly correlated with one another, although there was a range of r-values between concurrently tested variables (Figure 4. Notably, attention was relatively weakly correlated with NIH test scores (r = .14 at T0, the timepoint at which NIH test scores were available) but moderately concurrently related to grades (r = .36-.38 across three timepoints). Grades and NIH test scores were also moderately correlated (r = .33 at baseline). Thus, although these three variables were interrelated, they were by no means redundant with one another. Additionally, we found that attention was fairly stable over the three timepoints (r = .68 and .60 for T0 vs. the 1-year and 2-year follow-ups, respectively). So, too, were parent-reported grades (r = .74 and .68).

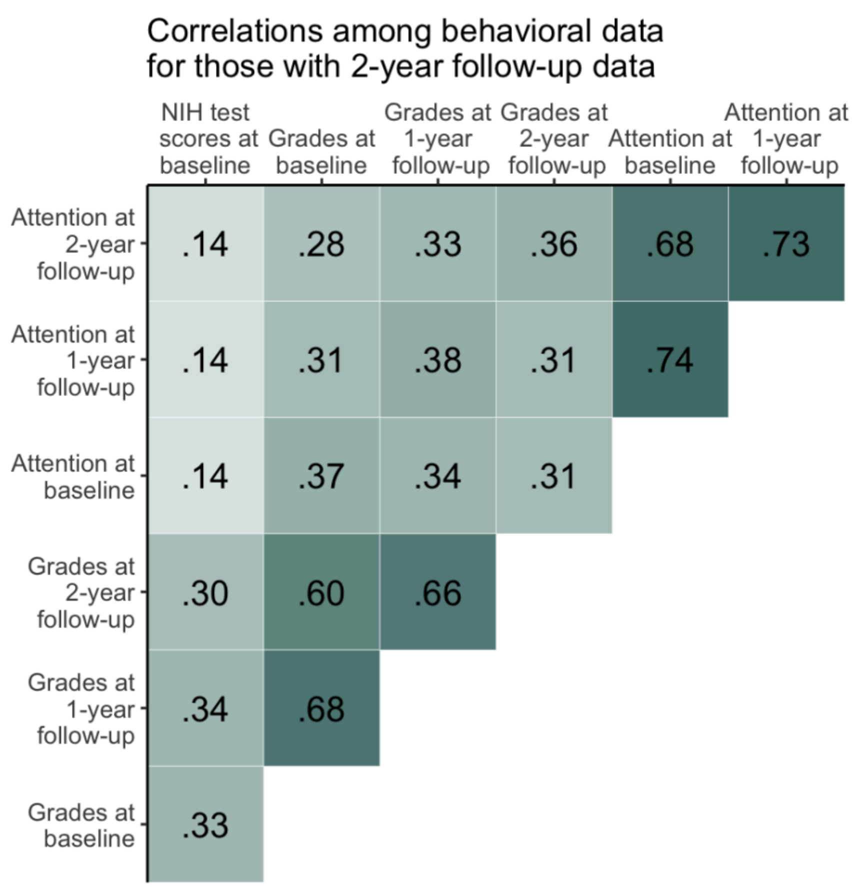

Figure 4. R-values for correlations among behavioral measures used in the current study, for children with data at all three timepoints. For the purposes of correlations, grades are treated as a continuous rather than categorical variable; all variables have also been recoded so that higher scores indicate better functioning (higher grades, fewer attention problems). All correlations are significant to the $p < .0001$ level.

Academic performance

Next, we tested for cross-sectional and longitudinal relations between parent-reported grades and cognitive test scores. We predicted that children's performance on cognitive tests at T0 would be concurrently related with their grades in school. Furthermore, we predicted that this relation would differ as a function of poverty status, with children in poverty showing a weaker relation. As predicted, higher scores on the NIH composite were related to better grades in school concurrently, $B = -0.08$, SD = 0.004, χ^2 (2) = 752.25, $p < .001$, and this interacted significantly as a function of poverty status, interaction: $B = 0.03$, SD = 0.01, χ^2 (1) = 24.31, $p < .001$ (Figure 5). Additionally, as predicted, the relation between cognitive performance and academic achievement differed as a function of poverty status. While the relation was highly significant for children above and below poverty, it was stronger for children above poverty (below poverty: $B = -0.04$, SD = 0.01, χ^2 (1) = 63.70, $p < .001$; above poverty: $B = -0.08$, SD = 0.004, χ^2 (1) = 688.89, $p < .001$). Thus, children's performance on cognitive tests at T0 is concurrently associated with their grades in school, albeit less so for children in poverty than those above poverty.

We expected to observe a similar pattern of results longitudinally – that is, when testing whether cognitive test performance at T0 predicts future academic performance. As predicted, we found that higher cognitive test scores were related to higher grades in school one year later, controlling for grades at T0, $B = -0.05$, SD = 0.004, χ^2 (2) = 174.99, $p < .001$. However, in contrast to our prediction, this relation did not differ significantly as a function of poverty status, interaction: $B = 0.01$, SD = 0.01, χ^2 (1) = 1.07, $p = .301$ (Figure 5). The same pattern was found at T2, such that higher cognitive test scores were related to higher grades two year later, controlling for grades at T0, $B = -0.04$, SD = 0.005, χ^2 (2) = 69.15, $p <.001$, though this relation did not interact significantly as a function of poverty status, interaction: $B = 0.02$, SD = 0.01, χ^2 (1) = 2.93, $p = .087$.

Thus, we found that cognitive test performance is somewhat predictive of concurrent and future academic performance, consistent with prior work. This relation was stronger for children above poverty at T0, but not longitudinally after controlling for T0. Taking into account that grades at the different timepoints were quite strongly correlated with one another (Figure 4), we conducted the same longitudinal analyses again at T1 and T2 without controlling for grades at T0. These exploratory analyses revealed significant interactions between children's cognitive test performance at T0 and their poverty status in predicting grades at all three timepoints (interaction at T1: X^2 (1) = 11.73, $p = 0.001$; interaction at T2: X^2 (1) = 9.55, $p = 0.002$).

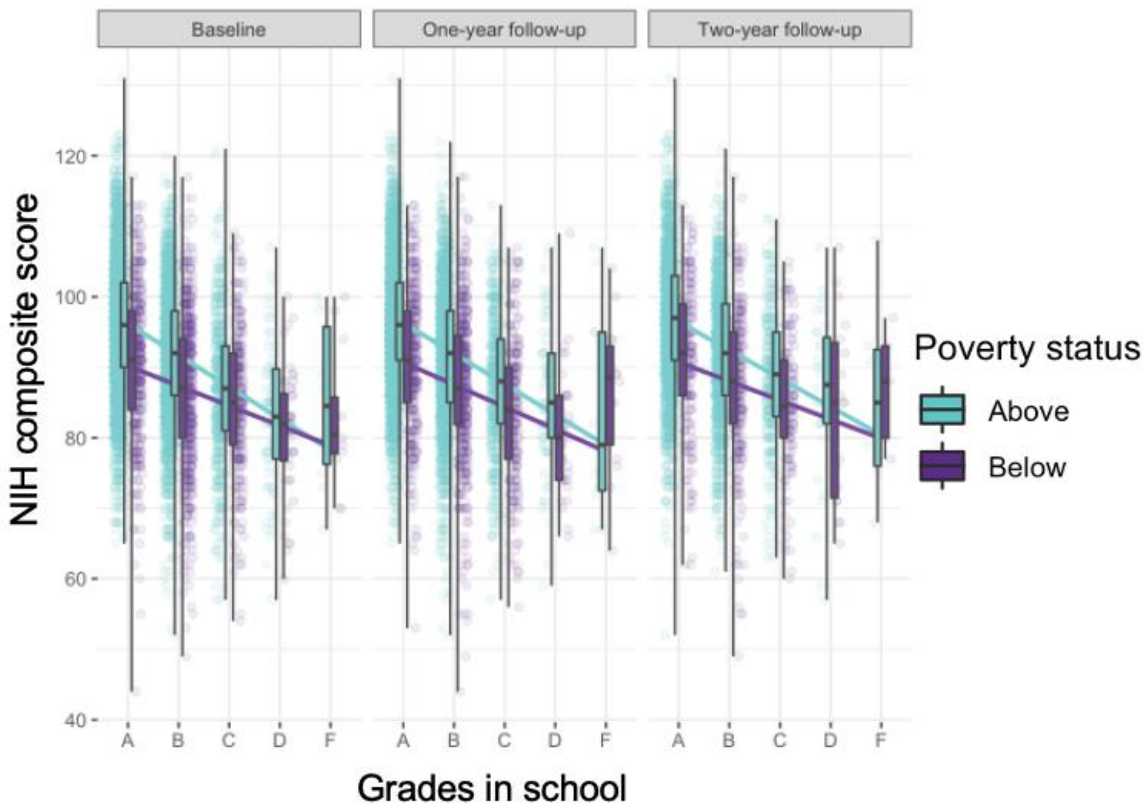

Figure 5. Relations between children's test performance at baseline (T0) and their grades in school at baseline (T0; left panel), one-year follow-up (T1; center panel), and two-year follow up (T2; right panel). Each point represents a different child; lighter teal color indicates children above poverty, while purple indicates children below poverty. Box plots for both groups at both timepoints are also displayed.

Relations between academic performance and LFPN-DMN connectivity

We next asked whether the concurrent relation between LFPN-DMN connectivity and children's academic performance at T0 differed as a function of poverty status. We predicted that higher LFPN-DMN connectivity would be associated with lower grades for children above poverty but higher grades for children in poverty.

On average, higher LFPN-DMN connectivity was related to worse grades concurrently at T0, *B* = 1.17, SD = 0.51, χ^2 (2) = 9.23, *p* = .010. However, as predicted, this relation differed significantly as a function of poverty status, interaction: *B* = -3.11, SD = 1.11, χ^2 (1) = 7.94, *p* = .005 (Figure 6). Higher LFPN-DMN connectivity was related to worse grades for children above poverty; by contrast, it was directionally, though non-significantly, related to better grades for children below poverty (above poverty: *B* = 1.20, SD = 0.51, χ^2 (1) = 5.51, *p* = .019; below poverty: *B* = -1.58, SD = 0.98, χ^2 (1) = 2.61, *p* = .106). Thus, as predicted, LFPN-DMN connectivity was differentially associated with academic performance for children above and below poverty.

We also conducted these analyses longitudinally, to test the hypothesis that LFPN-DMN connectivity supports knowledge acquisition over the course of two years.

We predicted that LFPN-DMN connectivity at T0 would be longitudinally associated with grades at T1 and T2. Consistent with this prediction, we found that higher LFPN-DMN connectivity was related to worse grades one year later, controlling for grades at T0, B = 1.78, SD = 0.61, χ^2 (2) = 13.31, p = .001. However, this relation differed significantly as a function of poverty status, interaction: B = -4.35, SD = 1.35, χ^2 (1) = 10.58, p = .001 (Figure 6). Specifically, higher LFPN-DMN connectivity appeared to be related to worse grades for children above poverty (clmm did not converge, parameters from lmer were B = 0.34, SD = 0.12), but directionally related to better grades for children below poverty: B = -1.90, SD = 1.05, χ^2 (1) = 3.33, p = .068.

This pattern did not carry over to the third timepoint: that is, there was no significant relation between LFPN-DMN connectivity and grades at T2 after controlling for T0 grades, B = 0.11, SD = 0.75, χ^2 (2) = 0.88, p = .645, and this relation did not differ as a function of poverty status, interaction: B = -1.52, SD = 1.69, χ^2 (1) = 0.81, p = .369. However, as noted above, grades were quite highly correlated across timepoints; thus, we also conducted the same analyses without controlling for grades at T0. These exploratory analyses revealed significant interactions between children's LFPN-DMN connectivity and their poverty status in predicting grades at all three timepoints (interaction at T1: X^2 (1) = 14.35, p < .001; interaction at T2: X^2 (1) = 4.73, p = .030).

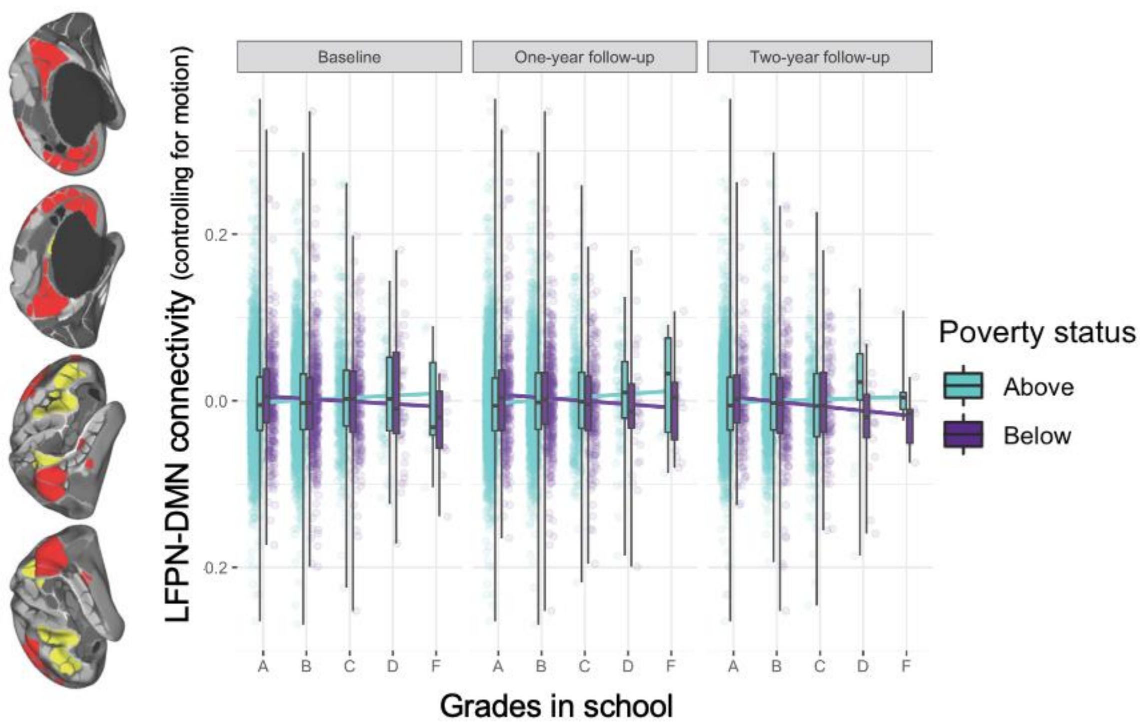

Figure 6. Relations between children's LFPN-DMN connectivity at baseline (T0), after controlling for head motion, and their grades in school at baseline (T0; left panel), one-year follow-up (T1; center panel), and two-year follow up (T2; right panel). Each point represents a different child; lighter teal color indicates children above poverty, while purple indicates children below poverty. Box plots for both groups at both timepoints are also displayed.

Relations between academic performance and CON-LFPN connectivity

Because CON has been posited to play a role in alerting LFPN to external challenges, we conducted a preregistered secondary analysis testing whether CON-LFPN connectivity was concurrently related to children's grades. Based on our prior work in this sample examining cognitive test performance, we predicted that stronger CON-LFPN connectivity would be associated with worse academic performance in both children above and below poverty. Indeed, we found that on average, higher CON-LFPN connectivity was related to worse grades concurrently at T0, B = 0.71, SD = 0.48, χ^2 (2) = 6.70, p = .035. This relation did not differ as a function of poverty status, interaction: B = -3.11, SD = 1.11, χ^2 (1) = 1.51, p = .219; therefore, we did not follow up with exploratory longitudinal analyses.

Relations between attention problems and LFPN-DMN connectivity

As with grades, we next tested associations between children's attention problems at T0, T1, and T2, and network connectivity at T0. We predicted that stronger LFPN-DMN connectivity would be associated with greater attention problems longitudinally. Moreover, given our prior findings, we hypothesized that children below poverty might show the opposite pattern, such that higher connectivity would be related to fewer attention problems.

On average, higher LFPN-DMN connectivity was related to more attention problems concurrently, B = 3.57, SD = 1.26, χ^2 (2) = 10.33, p = .006; importantly, however, this relation differed significantly as a function of poverty status, interaction: B = -7.58, SD = 2.95, χ^2 (1) = 6.61, p = .010 (Figure 7). While higher LFPN-DMN connectivity was related to more attention problems for children above poverty, it was not related to attention problems for children below poverty; if anything, however, this relation was in the opposite direction (above poverty: B = 3.72, SD = 1.20, χ^2 (1) = 9.55, p = .002; below poverty: B = -3.70, SD = 3.33, χ^2 (1) = 1.24, p = .265).

We next tested our hypothesis that higher LFPN-DMN connectivity would be associated with more attention problems longitudinally, controlling for attention at T0. Contrary to our prediction, we found no significant relation between LFPN-DMN and attention either at T1 or T2 when controlling for attention at T0 (T1: B = -0.89, SD = 0.84, χ^2 (2) = 1.49, p = .474; T2: B = -0.14, SD = 1.12, χ^2 (2) = 0.17, p = .919). Further, this relation did not differ significantly as a function of poverty status at either timepoint (interaction at T1: B = 1.98, SD = 2.02, χ^2 (1) = 0.97, p = .326; interaction at T2: B = 1.15, SD = 2.77, χ^2 (1) = 0.17, p = .684; Figure 7). There was similarly no interaction at either T1 or T2 when not controlling for attention at T0 (interaction at T1: X^2 (1) = 0.96, p = .328; interaction at T2: X^2 (1) = 0.10, p = .925). Thus, individual variability in attention problems was linked to LFPN-DMN connectivity only at ages 9-10—and at that time, it was linked in opposite directions as a function of poverty status.

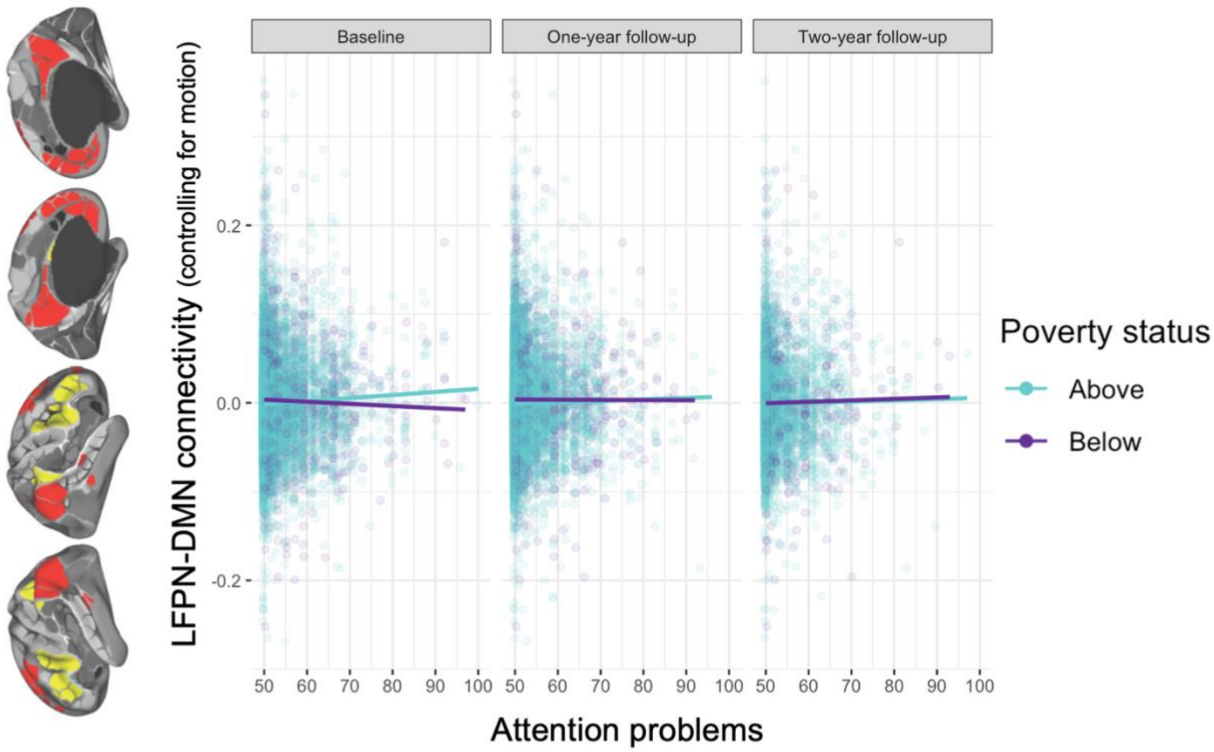

Figure 7. Relations between children's LFPN-DMN connectivity at baseline (T0), after controlling for head motion, and their attention problems at baseline (T0; left panel), one-year follow-up (T1; center panel), and two-year follow up (T2; right panel). Each point represents a different child; lighter teal color indicates children above poverty, while purple indicates children below poverty. Statistics for the interaction between poverty status and attention displayed with and without controlling for T0 attention.

Testing the contribution of CON connectivity to attention problems

CON has been theorized to serve as an intermediary between DMN and LFPN, enabling switching attention between internally and externally guided mental status. Thus, as secondary analyses, we tested—at baseline—whether these patterns of CON connectivity are differentially associated with attention problems for children above and below poverty, even after accounting for LFPN-DMN connectivity and its interaction with poverty status. The output of the model is displayed in Supplementary Table 1.

In this model including all three network pairings, higher LFPN-DMN and CON-DMN were related to worse attention on average; however, both of these associations with attention differed significantly as a function of poverty status (see Supplementary Table 1). We found that CON-DMN connectivity was associated with attention problems over and above LFPN-DMN connectivity; CON-LFPN connectivity was not.

As in our previous analyses focused solely on LFPN-DMN, this model showed a positive relation between LFPN-DMN connectivity and attention problems for children above poverty, but there was no significant relation for children below poverty (above poverty: B = 3.53, SD = 1.25, χ^2 (1) = 7.91, p = 0.005, below poverty: B = -4.02, SD = 3.47, χ^2 (1) = 1.36, p = 0.243). On the other hand, higher CON-DMN connectivity was associated with more attention problems for both children above and below poverty—

and the association was in fact stronger for children below poverty (above poverty: B = 3.43, SD = 1.11, χ^2 (1) = 9.58, p = 0.002, below poverty: B = 10.14, SD = 3.03, χ^2 (1) = 11.14, p = 0.001). Thus, in our study, the strongest concurrent predictor of attention problems among children below poverty was high CON-DMN connectivity. Exploratory follow-up analyses showed that this metric was not predictive of future attention problems when controlling for initial attention scores, although attention scores were moderately correlated over time. However, the interaction by poverty status was stable across the three timepoints (interaction at T1: B = 6.35, SE = 2,46, χ2 (1) = 6.65, p = .0099; interaction at T2: B = 11.08, SE = 3,12, χ2 (1) = 12.58, p = .0004).

Discussion

In this study, we sought to investigate trajectories of LFPN and DMN network coupling over middle childhood and early adolescence, and their relation to academic and behavioral resilience. To this end, we examined rs-fMRI network coupling longitudinally in relation to grades and attention problems in a diverse sample of participants at three yearly timepoints, spanning ages 9-13 across the sample. The central goal of this study was to assess whether associations between functional connectivity and performance differ meaningfully between children whose families lived above and below poverty.

In prior cross-sectional research with the ABCD dataset, also used here, we examined associations between brain connectivity and performance on a set of tests of executive functioning and reasoning. We replicated a consistent finding in the literature (Sherman et al., 2014; Whitfield-Gabrieli et al., 2020): that lower LFPN-DMN connectivity related to better cognitive test performance among children above the poverty line. By contrast, we found that lower LFPN-DMN connectivity tended to be associated with *worse* performance among children below poverty (Ellwood-Lowe et al., 2020). Here, we sought to further explore this unexpected result, both by examining the effect longitudinally and testing whether it extended to more real-world indicators of children's ability to navigate challenges in their lives.

Based on prior literature (Baum et al., 2017; Grayson & Fair, 2017; Sherman et al., 2014), we anticipated that the LFPN and DMN would become less coupled across timepoints across the full sample. However, we found that LFPN-DMN connectivity did not change consistently over the two-year study period; connectivity decreased for some individuals, and increased for others. This null result may reflect the relatively brief time window (two years) and/or the particular age range over which we examined changes (9-11 at the first timepoint; 10-13 at the third). We note that one prior study found increasing segregation between nodes of the DMN and LFPN longitudinally over ages 10-11, though this research used a seed-based approach that differed from our network-based approach (Sherman et al., 2014)

Critically, we had posited that developmental trajectories in connectivity might differ as a function of children’s poverty status. We considered three hypothetical patterns of data to be equally plausible: convergence, divergence, or stability of differences in functional connectivity between groups. The data were consistent with the third possibility: there was no consistent developmental change across this two-year delay for either group. However, because we had seen differential patterns of connectivity across poverty levels as a function of cognitive performance, we additionally conducted exploratory analyses testing whether children's cognitive test scores at baseline influenced the trajectory of change in connectivity. Contrary to this prediction, the trajectories of LFPN-DMN connectivity also did not differ as a function of children's initial cognitive test scores.

Other studies have provided evidence of accelerated physical and brain development among children growing up in adversity, which could help them to adapt more readily to harsher living conditions (Belsky, 2019; Callaghan & Tottenham, 2016; Gee et al., 2013; McDermott et al., 2021; Tooley et al., 2021). Here, we do not see evidence for accelerated rate of LFPN-DMN network development for children below poverty—at least, not at this point in development. However, it is possible that a differential trajectory of change is visible earlier in childhood, at a time when networks affiliations are changing more markedly and/or more consistently.

Given the fact that the LFPN and DMN interact with the CON, and that it has also been implicated in cognitive functioning, we also explored the development of CON connectivity. We found that CON-LFPN and CON-DMN connectivity decreased longitudinally, on average. These findings differ from past studies that found increased CON integration with other brain networks from ages 8-21 (Lopez et al., 2020) or 10-26 (Marek et al., 2015). This discrepancy could stem from the fact that our participants were at the youngest end of the broad age ranges reported in these cross-sectional studies; it is possible that two years was insufficiently long to see significant change. Additionally or alternatively, discrepancies in results could be related to the different connectivity metrics used across studies.

Most relevant to our present purposes, we tested whether the trajectory of change in between-network connectivity for the CON differed as a function of poverty status. Indeed, there was a significant interaction for CON-DMN, and it was trending for CON-LFPN. Only the children above poverty showed a decrease in CON-DMN and CON-LFPN connectivity. There was no significant change for children below poverty—and we showed subsequently that this did not depend on cognitive performance. This pattern of results suggests that the children living below poverty reached CON network maturity slightly earlier, potentially consistent with the accelerated development hypothesis. Of note, the rate of network change did not interact with children's cognitive test performance, leaving open what constitutes an "adaptive" rate of development. Continuing to follow these trajectories over time would help to confirm this possibility. As noted previously, we did not find evidence of accelerated maturation with regards to LFPN-DMN during this time period; then again, we found no consistent developmental changes within either group. To ascertain which neural systems show accelerated maturation in the face of adversity, it will be necessary to test for differential trajectories during a dynamic window of development for a given system.

Turning to associations with children's behavioral outcomes, we found that having lower LFPN-DMN connectivity was concurrently related to having better grades—but only among the children above poverty. For those children living below poverty, this association was in the opposite direction. This differential relation as a function of poverty status was stable across all three timepoints. Moreover, LFPN-DMN connectivity was also differentially predicative of grades one year later for children above and below poverty, *over and above* initial grades—even though the latter were strongly correlated with future grades. When measuring grades two years later, this pattern was still present but did not reach significance.

The fact that these differences in brain-behavior relations were stable over three timepoints results suggests that the high-performing children below poverty did not exhibit a pattern of connectivity that was beneficial at age 9-10 but that later became detrimental. Instead, there are qualitative differences in what appears to be academically adaptive for children above and below poverty; these differences may be established earlier in childhood and then remain relatively stable across middle childhood and early adolescence.

We also found that higher CON-LFPN was related to worse academic performance for both children above and below poverty, whereas prior evidence suggests that higher CON connectivity is related to better executive functioning (Marek et al., 2015). As there are a number of possible reasons for these discrepant findings, additional work will be needed to reconcile them.

With regard to children's attention problems, our primary hypotheses focused on longitudinal associations, given a prior study (Whitfield-Gabrieli et al., 2020). Specifically, we sought to replicate the finding that stronger LFPN-DMN connectivity at age seven was associated with greater attention problems four years later, controlling for attention problems at baseline. If this is a general phenomenon, we would expect children below poverty to show the same relation. However, given our prior findings regarding differential brain-behavior relations for cognitive performance, children below poverty could conceivably show the opposite pattern.

Broadly consistent with the prior study (Whitfield-Gabrieli et al., 2020), stronger LFPN-DMN connectivity was associated with greater attention problems—but only for children above poverty. These results differed in two ways from the prior study (which sampled children at age seven and again at age eleven, and which adopted a seed-based ROI approach). First, the relation was observed cross-sectionally in the present study; second, it was not observed longitudinally. The differential effect for children above and below poverty also did not endure longitudinally. Secondary and exploratory analyses in our study indicate that CON-DMN connectivity is a more reliable marker of attention problems than LFPN-DMN connectivity for children below poverty, both concurrently and longitudinally.

Overall, these results confirmed a prior study suggesting that lower LFPN-DMN connectivity is adaptive only for higher-income children (Ellwood-Lowe et al., 2020). Here, we extended this result in two ways: first, we show that this is true for more ecologically valid measures that capture children's resilience in real-world contexts. Second, we show that the dissociation observed previously is, at the very least, not linked to worse outcomes for high-performing children in poverty longer-term.

The phenomena established by these initial results across two studies lay a foundation for more detailed analysis of functional connectivity. For example, it may be useful to explore subnetworks of LFPN and DMN, given distinctions in their contributions to cognition (Buckner & DiNicola, 2019; Dixon et al., 2018; Fornito et al., 2012; Lopez et al., 2020). In addition, it will be important to assess individual-level networks (Seitzman et al., 2019), to see whether network boundaries differ meaningfully as a function of children's experiences. Further, it would be interesting to determine which specific aspects of children's home environment underlie the effects reported here, given that experiences differ markedly even among children living in poverty (DeJoseph et al., 2021; Ellwood-Lowe et al., 2020; Humphreys & Zeanah, 2015; McLaughlin et al., 2014; Rakesh, Seguin, et al., 2021; Rakesh, Zalesky, et al., 2021). While the differential patterns of brain activity we see here may reflect years of childhood experiences, other research has shown that rs-fMRI changes as a function of even brief experiences, even in adulthood (Guerra-Carrillo et al., 2014). Similarly, the developmental trajectory of brain coupling is likely not immutable; to the extent that an individual brain show stability in connectivity over time, this could in large part reflect stability in the context in which they live—their challenges and opportunities.

On the cognitive side, there is also not a universally strong link between performance on tests of executive functioning and more real-world indicators of academic and behavioral performance, despite countless studies showing relations between them (e.g., Best et al., 2011; Cowan, 2014; St Clair-Thompson & Gathercole, 2006; Willoughby et al., 2019).We found that cognitive test scores were more highly correlated to academic performance in children above than below poverty. This could be because of differences in the resources and quality of instruction between schools that primarily serve high- versus low-income students (Horng, 2005; Orfield & Lee, 2005; Reardon & Owens, 2014). Additionally or alternatively, it could be because children living in poverty face other forms of discrimination in school that lead them to perform worse academically independent of their abilities (Darling-Hammond, 2001; Hettleman, 2003; Scott et al., 2020). A similar pattern is true for attention problems, such that children in poverty's behavior problems were less strongly correlated with their grades in school.

Finally, it is important to note that effect sizes were quite small, and there was substantial overlap in network connectivity and its relation to behavior between children living above and below poverty. Because children below poverty are typically underrepresented in neuroimaging research, we chose to examine them as a separate group, defined based on their combined family income and the number of people in their household (see also Ellwood-Lowe et al., 2020). Of course, this is a somewhat arbitrary distinction based on an estimate of whether a child's family has the financial resources they need to meet their basic needs; more than likely, this dataset includes a substantial number of children in poverty who have more common experiences with those above poverty, and vice versa. Numerous experiences beyond financial resources shape mental processes. In addition, numerous other features of brain structure and function contribute to these individual differences in mental processing.

Taken together, these results show that the cognitive and neural factors that influence achievement are not exactly the same for children above and below poverty. Within a deficit framework, a goal toward promoting equity in academic achievement might be to "correct" brain networks, such that children below poverty show a pattern more closely resembling that of children above poverty. The findings presented here complicate this idea, suggesting that in the absence of taking children out of poverty, approaches that maximize their specific developmental trajectories and capacities may be needed. Our findings also highlight the importance of recruiting diverse samples for understanding human development; even among children living within the United States, who themselves share many experiences in common, there appear to be important experience-dependent differences in patterns of brain network development that support academic and behavioral resilience.

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