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Similar but distinct – Effects of different socioeconomic indicators on resting state functional connectivity: Findings from the Adolescent Brain Cognitive Development (ABCD) Study®

Divyangana Rakesh [a,*], Andrew Zalesky [a,b], Sarah Whittle [a]

[a] *Melbourne Neuropsychiatry Centre, Department of Psychiatry, The University of Melbourne and Melbourne Health, VIC, Australia*
[b] *Melbourne School of Engineering, University of Melbourne, Melbourne, Australia*

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ABSTRACT

Early socioeconomic status (SES) has consistently been associated with child health and cognitive outcomes, in addition to alterations in brain function and connectivity. The goal of the present study was to probe the effects of different facets of SES (parent education, income, and neighborhood disadvantage), that likely represent varying aspects of the environment, on resting state functional connectivity (rsFC). We investigated this question in a large sample of 9475 children (aged 9–10 years) from the Adolescent Brain Cognitive Development (ABCD) Study. Specifically, we analyzed the association between household SES (parent education, income-to-needs ratio) and neighborhood disadvantage, and system-level rsFC using within-sample split-half replication. We then tested whether the associations were unique to each SES measure, and whether household SES and neighborhood disadvantage had interactive effects on rsFC. SES measures had both common and distinct effects on rsFC, with sensory-motor systems (e.g., sensorimotor network) and cognitive networks (e.g., front-parietal network) particularly implicated. Further, the association between neighborhood disadvantage and sensorimotor network connectivity was less pronounced in the presence of high income-to-needs. Findings demonstrate that different facets of SES have distinct and interacting effects on rsFC, highlighting the importance of considering different indicators when studying the effects of SES on the brain.

1. Introduction

Socioeconomic status (SES) encompasses different facets of the environment and access to material resources (such as income, occupation, education, and neighborhood characteristics). SES has been known to have an impact on children's neurocognitive performance and mental health (Farah et al., 2006; Forns et al., 2012; Koutra et al., 2012; Noble et al., 2007; Packard et al., 2011; Ruijsbroek et al., 2011). For example, children from low SES families tend to have lower performance in several cognitive domains (Noble et al., 2007) and higher incidence rates of mental health issues, such as depression and anxiety (Samaan, 2000). While links between low SES and outcomes are well established, the precise neurobiological mechanisms that transmit these effects are yet to be characterized.

SES can influence children's psychosocial and physical environments (Evans, 2004), which can affect brain development (Hackman et al., 2010). Several different factors that often go hand in hand with low SES (such as stress exposure, low cognitive stimulation, toxins in the environment, prenatal stress, and nutrition) may alter neural development during sensitive periods (such as childhood and adolescence; Hackman et al., 2010). This is likely to occur through alterations in biological intermediaries (e.g., glucocorticoid secretion, activity-dependent synapse formation, and synaptic pruning; Hackman et al., 2010). Indeed, different indicators of low SES (i.e., socioeconomic disadvantage) have been shown to be associated with alterations in brain structure and function during childhood and adolescence (Farah, 2016; Hackman and Farah, 2009). These alterations, in turn, have been suggested to play a role in the association between exposure to disadvantage and mental health and cognitive outcomes (Farah, 2018; Johnson et al., 2016). Given that aberrant neural interactions between different regions of the brain are considered relevant for both cognition and mental health (DiMartino et al., 2014; Fornito et al., 2017), work is needed to examine

* Corresponding author at: Melbourne Neuropsychiatry Centre, Department of Psychiatry, The University of Melbourne, Alan Gilbert Building (level 3), 161 Barry Street, 3053 VIC, Melbourne, Australia.

E-mail addresses: divyangana.rakesh@gmail.com (D. Rakesh), swhittle@unimelb.edu.au (S. Whittle).

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associations between different aspects of disadvantage and neural *connectivity*.

Neural connectivity has been shown to develop throughout adolescence (for review see Stevens, 2016), and is suggested to play an important role in the development of cognitive and social function during the same period (Dumontheil, 2016; Ernst et al., 2015; Stevens, 2016; Stevens et al., 2009). As such, disruption of normative changes in the development of functional connectivity during adolescence as a function of low SES could contribute to negative cognitive and mental health outcomes. These questions are particularly relevant to address given the substantial number of youth exposed to early socioeconomic disadvantage (Jiang et al., 2016).

Resting state functional connectivity (rsFC) analyses, which allow for the examination of multiple functional systems at rest (Fox and Greicius, 2010), are often used to probe the association between SES and neural circuitry. Resting state fMRI also poses lower cognitive demands on individuals and is therefore well suited to developing populations (Campbell and Schacter, 2017; Fox and Greicius, 2010). Several studies have examined the effects of different facets of the socioeconomic environment on rsFC. For instance, studies have shown that low household income is associated with reduced connectivity in the default mode network (DMN) and between emotion regulation and cognitive control networks, as well as between the amygdala and hippocampus and a number of regions (e.g., superior frontal cortex, lingual gyrus) in youth (Barch et al., 2016; Brody et al., 2019; Sripada et al., 2014). Low income has also been shown to impact circuitry of amygdala and ventromedial prefrontal cortex (vmPFC; Hanson et al., 2019), and posterior cingulate and mPFC connectivity (Weissman et al., 2018) in youth. Further, neighborhood disadvantage has been shown to be associated with reduced positive connectivity between the ventral striatum and mPFC in adolescents (Marshall et al., 2018). Other work has shown associations between parent education and increased connectivity between frontal and temporal regions in adolescents (Su et al., 2021).

Importantly however, these studies have not examined the associations between different SES metrics (and therefore their unique and overlapping effects) and rsFC within the same sample. Our recent work on the sample reported on here has shown widespread associations between neighborhood disadvantage and rsFC patterns (Rakesh et al., 2021a); however, in that study, we did not consider the unique/similar and additive/synergistic effects of different facets of SES. Indeed, SES represents access to both material (usually indexed by income) and non-material (such as parental education, occupational prestige, and neighborhood quality) resources (Farah, 2017). Generally, these different metrics of SES tend to be moderately correlated with one another (i.e., better education goes hand in hand with greater occupational prestige, higher income, and better neighborhood quality), but not always (e.g., an adjunct professor may have attained a higher level of education than a plumber but may make less money) (Farah, 2017). SES therefore represents a complex composite of these distinct – but often correlated – metrics, that may represent varying aspects of the environment and distinct predictors of mental health and other outcomes (Braveman et al., 2005; Chen and Paterson, 2006; Farah, 2017; Winkleby et al., 1992). Accordingly, it has been suggested that examining SES using single measures might be sacrificing valuable information (Duncan and Magnuson, 2012). For example, parental income-to-needs could represent access to material resources (which can influence [among other things] nutrition, enriched home learning environments, quality of child care), whereas parental educational attainment might be more reflective of parent-child interactions (i.e., cognitive stimulation, language input, and amount of time spent with the child) (Duncan et al., 2012; Duncan and Magnuson, 2012). Neighborhood SES is likely to capture a host of factors with significant developmental consequences, such as exposure to green space, crime, violence, pollution, etc. (Evans, 2004). While different aspects of SES have been shown to have unique effects on brain structure (Noble et al., 2015; Taylor et al., 2020; Whittle et al., 2017; Rakesh et al., 2021b), less is known about brain functional connectivity in this context, and no studies, to our knowledge have examined the unique effects of parent education, income-to-needs, and neighborhood quality on resting state functional connectivity. Further, prior work on associations between SES and rsFC has almost exclusively examined effects on single connections (between nodes or networks). Given our recent work on the same sample (Rakesh et al., 2021a), and other work linking SES to alterations in the topology of several neural systems (Tooley et al., 2019), an unbiased whole-brain approach (that examines connections between several neural systems at rest) is warranted.

Therefore, the goal of the present study was to examine unique associations between different socioeconomic indices (i.e., parent education, parent income-to-needs, and neighborhood disadvantage) and whole brain resting state functional connectivity. Further, it has also been suggested that different facets of the socioeconomic environment (i.e., parent income, parent education, and neighborhood SES), could have interactive or synergistic effects on a child's development (Gordon et al., 2003; Morrissey and Vinopal, 2018). For example, high household income or education could potentially mitigate some effects of neighborhood disadvantage and vice-versa. Accordingly, in exploratory analyses, we investigated interactions between the three socioeconomic metrics. To address these aims, we used data from the Adolescent Brain Cognitive Development (ABCD) study (ages 9–10, N > 11,500).

Given that different socioeconomic indicators are moderately correlated (Oakes and Rossi, 2003), and represent both similar and unique facets of the environment (Farah, 2017), we expected to see some degree of overlap in findings, as well as some distinct effects. While our prior work showed that neighborhood disadvantage was associated with widespread within- and between-network connectivity of both sensorimotor and higher-order systems (e.g., default mode network, dorsal attention network) (Rakesh et al., 2021a), we expected household SES indicators to be associated with more localized effects. For example, parent education can have a significant influence on parent-child interactions, and therefore on cognitive and language stimulation received by the child (Duncan and Magnuson, 2012). Such stimulation plays an important role in the development of child language and cognitive function (Perkins et al., 2013). As such, we expected parent education to be associated with the connectivity of the auditory network and systems associated with executive and cognitive function (e.g., frontoparietal network, dorsal attention network). Conversely, given that income-to-needs often represents access to material resources (and thus sources of cognitive stimulation as well as quality of schooling and child care) (Duncan and Magnuson, 2012), we hypothesized that income-to-needs would be associated with within- and between-network connectivity of prefrontal systems commonly associated with cognitive function (Dumontheil, 2016; Ernst et al., 2015; Stevens, 2016).

2. Methods

Given the substantial analytical flexibility that comes with large open datasets, analysis plans were pre-registered on the Open Science Framework (https://osf.io/6znrs). Any deviations from the original plan have been fully described.

2.1. Participants

Participants were from the ongoing ABCD study (https://abcdstudy.org/; baseline assessment of ABCD [release 2.0.1]). The ABCD study is a large multi-site longitudinal study which has recruited over 11,500 children (aged 9–10 years) in order to comprehensively characterize psychological and neurobiological development from early adolescence to early adulthood (Casey et al., 2018; Garavan et al., 2018). After excluding for motion (mean framewise displacement [FD] > 0.5 mm), the final sample consisted of 9475 participants (See Table 1 for demographic information and SI for details).

Table 1
Demographic information.

		Mean ± SD
N		9475 (4713 F)
Age (months)		119.36 ± 7.51
ADI		39.66 ± 27.16
Education (years)	Average	15.18 ± 2.6
	Maximum	15.92 ± 2.85
	Primary Caregiver	15.36 ± 2.72
Household Income (N)	< $5000	279
	$5000–$11,999	296
	$12,000–$15,999	210
	$16,000–$24,999	389
	$25,000–$34,999	520
	$35,000–$49,999	744
	$50,000–$74,999	1196
	$75,000–$99,999	1299
	$100,000–$199,999	2709
	> $200,000	1048
Income-to-needs ratio		3.56 ± 2.3
Framewise Displacement		0.19 ± 0.12
Race (N)	White	5103
	Black	1269
	Hispanic	1901
	Asian	199
	Other	987

2.2. SES measures

We used the Area Deprivation Index (ADI), which is a composite measure of neighborhood socioeconomic disadvantage for the United States that uses data from 17 factors including income, education, employment, and housing quality. ADI provides rankings of neighborhoods by socioeconomic disadvantage as a national percentile (Kind et al., 2014; Singh, 2003), where higher values indicate higher disadvantage. See Supplementary Information (SI) for list of items contributing to ADI. Parent education was calculated based on the average educational attainment of both parents in years. The educational attainment of one parent was used when data for both parents was not available. Income-to-needs ratio was calculated as the median value of the income band divided by the federal poverty line for the respective household size. Accordingly, a value of one would signify being at the poverty threshold, and values greater than and less than one would signify being above and below the threshold respectively. See SI for distributions and correlations.

2.3. Imaging acquisition, preprocessing, and resting-state functional connectivity data

Imaging procedures have been described in detail in Casey et al. (2018). Participants were imaged across sites using harmonized protocols, and completed 4–5 five-minute resting state scans (eyes open) to ensure at least eight minutes of relatively low-motion data. For details see SI and Hagler et al. (2019). Preprocessing was carried out by the ABCD Data Analysis and Informatics Core using the standardized ABCD pipeline (for details see Hagler et al., 2019). Next, fMRI time courses were projected onto FreeSurfer's cortical surface. Using these time courses, within- and between-network connectivity (Pearson correlation) were calculated on the basis of the Gordon parcellation scheme (Gordon et al., 2016) for 12 predefined resting state networks (RSN) (i.e., AN = Auditory Network, CON = Cingulo Opercular Network, CPN = Cingulo Parietal Network, DAN, DMN, FPN, RTN = Retrosplenial Temporal Network, SMN (H) = Sensorimotor Network (hand), SMN (M) = Sensorimotor Network (mouth), SN, VAN, VN = Visual Network) and then Fischer Z transformed – leading to 78 dependent variables (66 between-network connectivity variables and 12 within-network connectivity variables [within-network connectivity reflects the average of the correlation over all pairs of regions within a network]).

2.4. Statistical methods

2.4.1. Examining the association between SES measures and rsFC

Although this was not explicitly stated in the pre-registration, for the sake of comparability with existing work, we first conducted analyses that examined associations between individual SES measures and rsFC, and then sought to determine whether effects were robust to the inclusion of other SES metrics in the model. Further, given the large dataset, although not pre-registered, in the interest of robustness we employed a within-sample split-half replication to identify key connectivity variables that were associated with each SES measure. Briefly, to ensure that findings were robust, the final sample was randomly split into 4738 discovery and 4737 replication cases using the *cvpartition* function in MATLAB with 50% of the data in the discovery set and 50% in the holdout replication sample. The discovery and replication samples did not show differences in demographic data (including age, sex, site, and SES [all three measures]; $p > 0.5$). We examined whether each SES measure (as the predictor variable in separate models) was associated with connectivity ($n = 78$ response variables) in both the discovery and replication samples using linear mixed models (LMM; using lme::nlme) in R version 4.0.2. Separate models were fitted for each connectivity variable. To assess for significance of effects we used a false discovery rate (FDR) of $p < 0.016$ (to account for three SES variables; 78 comparisons in each model) in discovery and replication samples. Only variables that survived FDR correction in both the discovery and replication analyses at $p\text{FDR} < 0.016$ were considered significant. We also tested the correlation between the t-value across discovery and replication samples for all 78 connectivity variables to assess reproducibility. We covaried for age, sex, scanner type, mean FD in our analyses. In addition, site, and family nested within site (to account for multiple children from the same family) were modelled as random factors.

2.4.2. Examining the unique effects of each SES measure on rsFC

Next, in order to assess whether the effects observed were unique to a specific SES indicator, for all significant connectivity variables (from the individual analyses described above), we included all three SES measures as predictors in the same model across the whole sample. Effects were considered significant if they survived FDR correction for the specific SES measure ($p < 0.05$; with the number of comparisons dependent on the number of significant variables for each SES measure from the analyses described in Section 2.4.1). We verified that using all three SES variables in the same model was not problematic with respect to multicollinearity using variance inflation factor (VIF) values. We covaried for age, sex, scanner type, and mean FD in our analyses. In addition, site, and family nested within site (to account for multiple children from the same family) were modelled as random factors. Further, we conducted sensitivity analyses to determine whether results were robust to the inclusion of child intelligence (total intelligence score based on the NIH cognition battery) and child psychopathology (total mental health problems from the Child Behavior Checklist) as covariates. Finally, we covaried for race/ethnicity (in addition to age, sex, scanner, mean FD, child intelligence, and child psychopathology) to account for race/ethnicity-associated effects. However, due to the confounded nature of race and socioeconomic disadvantage in the present sample (see distribution of SES variables by race/ethnicity in the SM), effects of race/ethnicity and disadvantage are difficult to disentangle, which is particularly problematic for interpretating results (Meghani and Chittams, 2015). Results covarying for race/ethnicity can be found in the SM. Of note, covarying for race/ethnicity reduces the number of significant connections for all three SES indicators (but least so for education).

2.5. Exploratory analyses

2.5.1. Examining the effect of a composite SES index on rsFC

Although not pre-registered, we also examined associations between a composite measure of SES and rsFC. We implemented a principal component analysis (PCA) on the data (that included parent education, income-to-needs, and neighborhood SES) in order to obtain a composite SES score. Only participants that had data for all three SES variables were included in this analysis (n = 8104). KMO and Bartlett's test indicated that the data were suitable for PCA (Kaiser-Meyer-Olkin Measure of Sampling Adequacy = 0.67, Bartlett's test of sphericity $p < 0.001$). All three variables loaded onto the first component (loadings for education, income-to-needs, and ADI [reversed coded] respectively: 0.58, 0.61, 0.54) which explained ~67% of the variance. This first component was used in subsequent analyses. The same procedures as described in Section 2.4.1 were implemented for analyses. We utilized a threshold of pFDR < 0.016 for the sake of comparability with the individual SES metrics. Results for this analysis can be found in the Supplement.

2.5.2. Examining the interactive effects of household and neighborhood SES on rsFC

Further, in exploratory analyses, we examined the interactive effects of the three socioeconomic indicators (i.e., two-way interactions of i) ADI x education, ii) ADI x income-to-needs, and iii) education x income-to-needs). Of note, main effects are automatically included in models. Significant effects were assessed using the FDR ($p < 0.05$; 78 comparisons in each model) (Benjamini and Hochberg, 1995).

3. Results

3.1. Demographic information

Sample demographic information and descriptive statistics are presented in Table 1.

3.2. Associations between individual SES indicators and rsFC

Using within-sample split-half replication we found that the three SES indicators were associated with connectivity variables similarly across discovery and replication samples. Specifically, ADI was associated with 25 and 26, parent income-to-needs ratio 25 and 31, and parent educational attainment 26 and 27 connectivity variables in discovery and replication samples respectively (pFDR < 0.016; 78 comparisons each in discovery and replication samples). Significant variables were those that overlapped between discovery and replication samples (n = 16, 19, and 21 for ADI, income-to-needs, and education respectively). Correlation of t-values between discovery and replication was found to be very high for all three SES variables (Pearson correlation > 0.86), thus indicating high reproducibility.

3.2.1. Neighborhood disadvantage

ADI was found to be significantly associated with 16 connections (Fig. 1), and in most cases higher ADI was associated with reduced connectivity (i.e., higher neighborhood disadvantage associated with lower rsFC). Specifically, ADI was associated with reduced connectivity between the AN and higher-order cognitive systems (i.e., CON, CPN, DMN, FPN, SN). ADI was also associated with greater connectivity within and between sensory-motor systems and between the SMN and both AN and higher-order networks (e.g., CPN and DAN). Finally, higher ADI was also found to be associated with CON and CPN connectivity to other higher-order networks (e.g., lower within-CON and CON-CPN and higher CPN-FPN rsFC).

3.2.2. Income-to-needs ratio

Higher household income-to-needs ratio was found to be associated with lower AN-SMN (hand and mouth) connectivity as well as increased connectivity of the AN and SMN to higher-order cognitive networks (e.g., AN-CPN, AN-DMN, AN-FPN, AN-SN, FPN-SMN [hand and mouth], CPN-SMN [hand and mouth]; Fig. 2). Further, income-to-needs ratio was also associated with increased connectivity between cognitive functional systems (e.g., within-CON, CON-CPN, CPN-DAN, CPN-FPN, DMN-VAN, and SN-VAN).

3.2.3. Educational attainment

Educational attainment was found to be associated generally with the connectivity of both within and between sensory-motor networks (Fig. 3). For example, higher educational attainment predicted reduced AN connectivity to the VN and SMN (hand and mouth) and reduced connectivity within and between SMN networks. Further, higher educational attainment was also associated with increased rsFC of the AN to higher-order cognitive networks (i.e., CPN, DMN, FPN, and SN), connectivity of the SMN networks to the FPN, SN, and CPN, and VAN-VN rsFC. Finally, educational attainment was associated with increased connectivity between systems implicated in higher-order cognitive function (i.e., within-CON, CON-CPN, DMN-VAN, and SN-VAN).

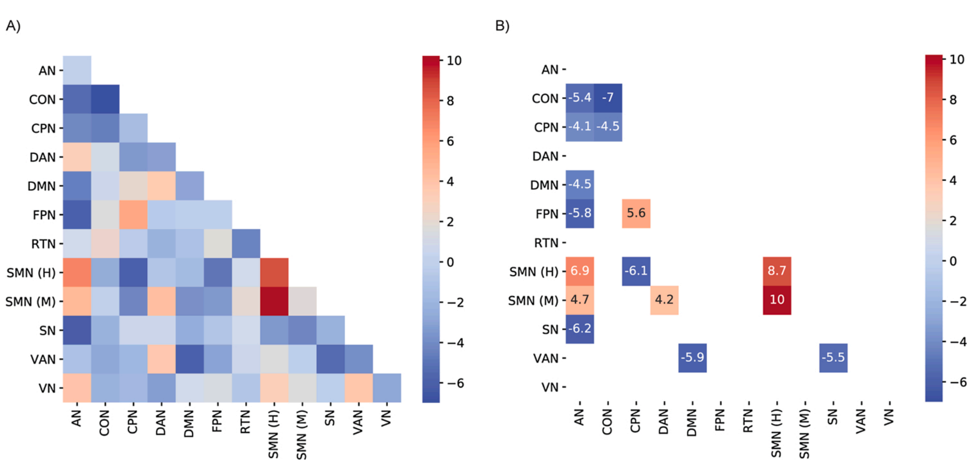

Fig. 1. Association between ADI and rsFC. (A) Heatmap of the t-statistic values (from LMMs) of the association between ADI and all connectivity variables (n = 78) across the whole sample; (B) Heatmap of the t-statistic values of the association between ADI and significant connectivity variables (overlapping significant variables after correction for multiple comparisons in both discovery and replication sets [n = 16]; t statistic values were extracted from analyses using the whole sample). Only the bottom half of the matrix has been displayed for ease of readability. For heatmaps of Cohen's D values see SI.
Abbreviations: AN = Auditory Network, CON = Cingulo Opercular Network, CPN = Cingulo Parietal Network, DAN = Dorsal Attention Network, DMN = Default Mode Network, FPN = Frontoparietal Network, RTN = Retrosplenial Temporal Network, SMN (H) = Sensorimotor Network (hand), SMN (M) = Sensorimotor Network (mouth), SN = Salience Network, VAN = Ventral Attention Network, VN = Visual Network.

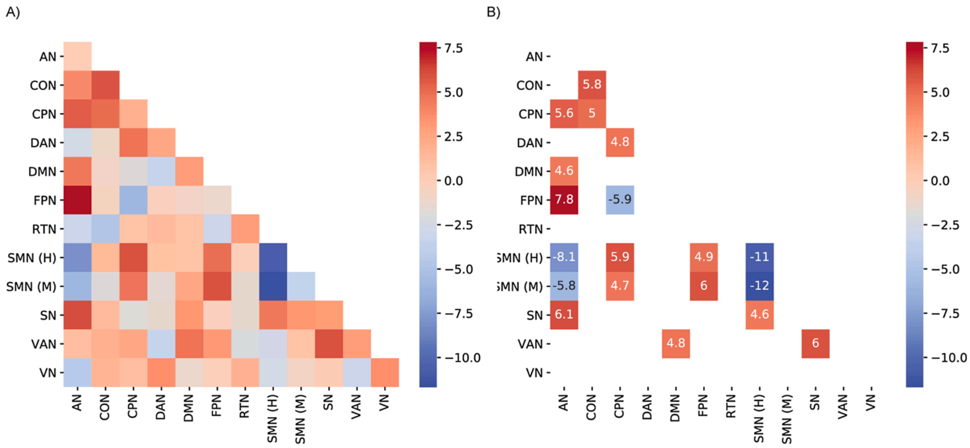

Fig. 2. Association between income-to-needs ratio and rsFC. (A) Heatmap of the t-statistic values (from LMMs) of the association between income-to-needs ratio and all connectivity variables (n = 78) across the whole sample; (B) Heatmap of the t-statistic values of the association between ADI and significant connectivity variables (overlapping significant variables after correction for multiple comparisons in both discovery and replication sets [n = 19]; t statistic values were extracted from analyses using the whole sample). Only the bottom half of the matrix has been displayed for ease of readability. For heatmaps of Cohen's D values see SI.
Abbreviations: AN = Auditory Network, CON = Cingulo Opercular Network, CPN = Cingulo Parietal Network, DAN = Dorsal Attention Network, DMN = Default Mode Network, FPN = Frontoparietal Network, RTN = Retrosplenial Temporal Network, SMN (H) = Sensorimotor Network (hand), SMN (M) =Sensorimotor Network (mouth), SN = Salience Network, VAN = Ventral Attention Network, VN = Visual Network.

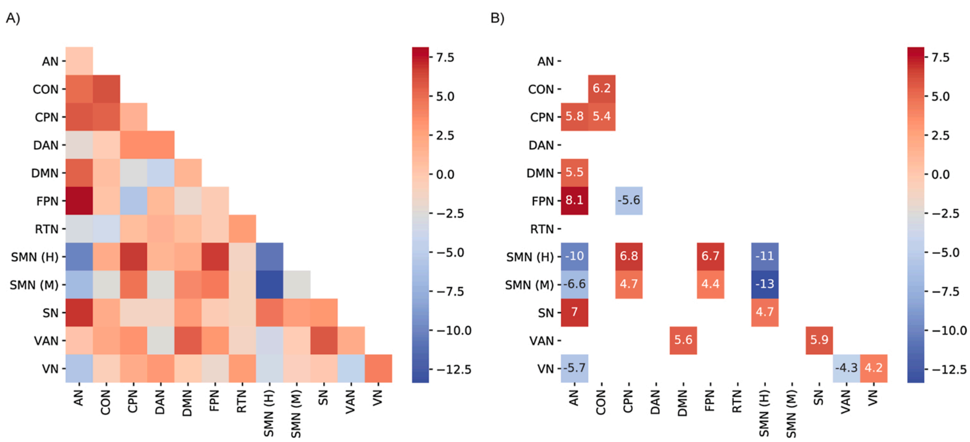

Fig. 3. Association between educational attainment and rsFC. (A) Heatmap of the t-statistic values (from LMMs) of the association between educational attainment and all connectivity variables (n = 78) across the whole sample; (B) Heatmap of the t-statistic values of the association between educational attainment and significant connectivity variables (overlapping significant variables after correction for multiple comparisons in both discovery and replication sets [n = 21]; t statistic values were extracted from analyses using the whole sample). Only the bottom half of the matrix has been displayed for ease of readability. For heatmaps of Cohen's D values see SI.
Abbreviations: AN = Auditory Network, CON = Cingulo Opercular Network, CPN = Cingulo Parietal Network, DAN = Dorsal Attention Network, DMN = Default Mode Network, FPN = Frontoparietal Network, RTN = Retrosplenial Temporal Network, SMN (H) = Sensorimotor Network (hand), SMN (M) = Sensorimotor Network (mouth), SN = Salience Network, VAN = Ventral Attention Network, VN = Visual Network.

3.3. Unique associations between SES indicators and rsFC

When all three SES variables (i.e., ADI, income-to-needs ratio, and parent educational attainment) were included in the model simultaneously, we found significant effects for all three variables for some common and some distinct connections (Fig. 4, Table 2). VIF values when all three SES variables were included in the same model were found to be reasonable (< 2; See SI). Of note, effect sizes were relatively small (see Table 2). For scatterplots see SI. Sensitivity analyses revealed that results were largely unchanged when child intelligence and psychopathology were included as covariates (see SI for model output).

3.3.1. Overlapping associations

All three variables were found to be associated with within-SMN (hand) and SMN (hand) to SMN (mouth) connectivity such that higher disadvantage was associated with increased connectivity. Further, ADI shared common connections with both educational attainment (n = 3; CPN-SMN (hand), DMN-VAN, and AN-SN) and income-to-needs ratio (n = 1; SN-VAN). Income-to-needs ratio and educational attainment also had several overlapping connections (n = 4; SN-SMN [hand and mouth], FPN-SMN (hand), and FPN-AN).

3.3.2. Independent associations

ADI was found to be uniquely associated with three connections (i.e., within-CON, AN-CON, and DAN-SMN [hand]). Income-to-needs ratio and educational attainment were independently associated with two connections each (i.e., CPN-FPN, CPN-AN and CPN-CPN, AN-DMN respectively).

3.4. Interactive effects of different socioeconomic indicators on rsFC

In exploratory analyses, we found that household (specifically income-to-needs ratio) and neighborhood SES interacted to predict connectivity between the sensory-motor systems ($B = -0.005$, $SE = 0.001$, $t = -3.46$, $p < 0.001$). Specifically, the association between ADI and SMN (hand) and SMN (mouth) connectivity was less pronounced (i.e., less positive) in the presence of high income-to-needs ratio (Fig. 5). No other rsFC variables survived correction for multiple comparisons in any of the models.

4. Discussion

The present study aimed to investigate the association between different socioeconomic indicators and rsFC in a large sample of children

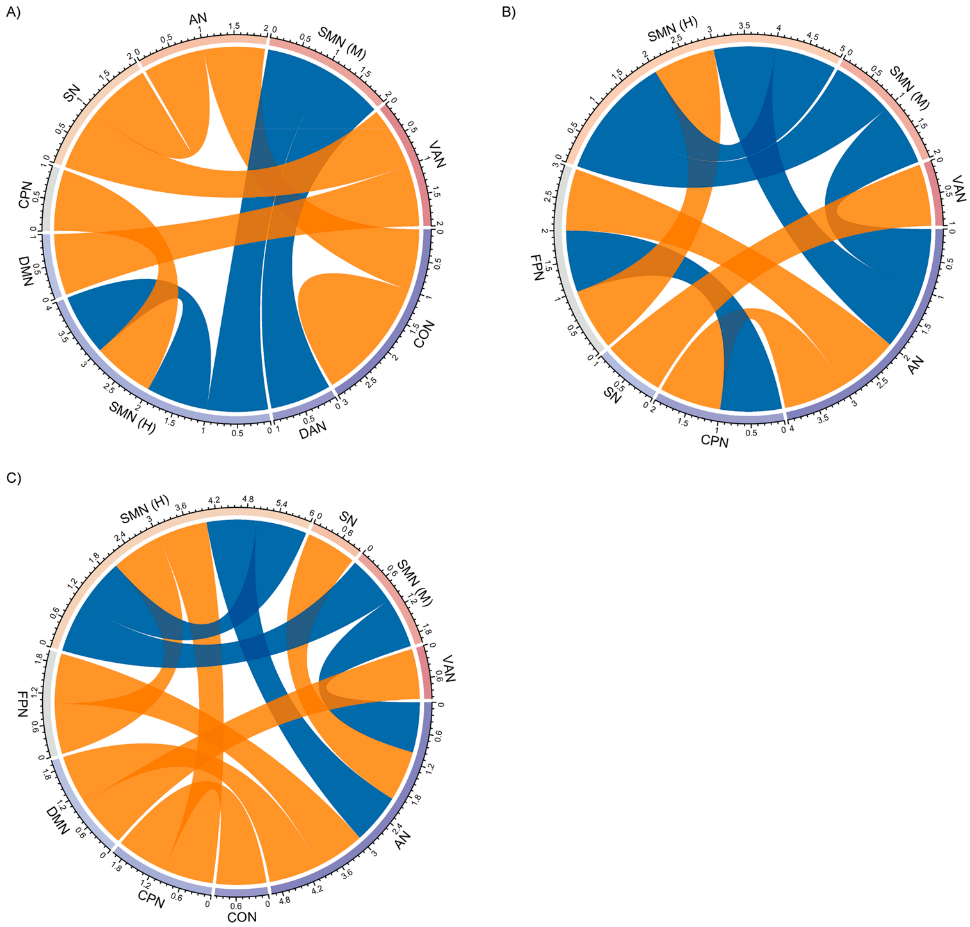

Fig. 4. Unique effects of SES on rsFC for neighborhood advantage (A), household income-to-needs ratio (B), and parent educational attainment (C). Orange and blue chords represent SES-associated increased and decreased connectivity respectively. To allow direct comparison between the indices, the direction of ADI has been inversed for this figure whereby orange chords represent higher connectivity associated with higher advantage for all three metrics. Values along the circumference represent the number of connections implicated (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).
Abbreviations: AN = Auditory Network, CON = Cingulo Opercular Network, CPN = Cingulo Parietal Network, DAN = Dorsal Attention Network, DMN = Default Mode Network, FPN = Frontoparietal Network, RTN = Retrosplenial Temporal Network, SMN (H) = Sensorimotor Network (hand), SMN (M) = Sensorimotor Network (mouth), SN = Salience Network, VAN = Ventral Attention Network, VN = Visual Network.

aged 9–10 years from the ABCD study. We found that neighborhood disadvantage, parental educational attainment, and income-to-needs ratio had both common and distinct effects on rsFC. We also found that the association between neighborhood disadvantage and sensorimotor network (hand) to sensorimotor network (mouth) connectivity was less pronounced in the presence of high income-to-needs ratio.

All three SES measures were associated with the connectivity of similar networks. For example, high neighborhood advantage, high parent educational attainment, and high household income-to-needs ratio were all associated with reduced within and between sensorimotor network connectivity, and increased sensorimotor network connectivity to frontal functional networks. This suggests that connectivity of the sensorimotor network may be particularly sensitive to several aspects of the socioeconomic environment, including both inside and outside of the home. Why this might be the case is challenging to comment on given that previous studies have focused on specific regions and connections, and limited work has examined the association between SES and structure, function, and connectivity of sensorimotor regions. Of note, however, whole-brain structural MRI work has also implicated sensory-motor regions (e.g., postcentral gyrus) in analyses (King et al., 2020; Mackey et al., 2015; Noble et al., 2015), and other recent work on myelin growth has demonstrated similar associations with SES for somatosensory and motor areas (Ziegler et al., 2020). Although not tested here, we speculate that given the roles of these regions in motor function, these alterations may be due to low parental support or access to appropriate environments in the neighborhood for motor development, and may account for alterations in motor skills in economically disadvantaged youth (Morley et al., 2015).

Further, reduced connectivity of the frontoparietal to sensory networks (auditory network and sensorimotor network) was found for both household indices, and cingulo-opercular/cingulo-parietal rsFC (to different systems) was also often implicated for all three socioeconomic indicators. These fronto-parietal-cingulate networks are considered relevant for cognitive control (Posner and Huang, 2011), reading ability (Horowitz-Kraus et al., 2015), and a diverse range of cognitive functions (Dosenbach et al., 2008; Sheffield et al., 2016). We thus speculate that their connectivity may play a role in the association between SES (generally speaking) and alterations in reading skills, cognitive control, and cognitive function (Duncan and Magnuson, 2012; Noble et al., 2005; Sarsour et al., 2011). Further, auditory network connectivity was also found to be implicated across SES measures. This was not consistent with our hypothesis of finding unique associations between parent educational attainment and auditory network rsFC; however, this finding indicates the importance of the socioeconomic environment (generally) in language development (Hoff, 2006; Hoff and Tian, 2005).

Connectivity of the frontoparietal network was uniquely associated with both educational attainment and income-to-needs ratio, which suggests that it may be susceptible to the *household* environment. In particular, positive parent-child interactions, and increased cognitive stimulation available at home, which have both been linked with higher parental education and income (Duncan and Magnuson, 2012), may impact the development of frontoparietal connectivity.

It is noteworthy that SES (generally speaking) was associated with the connectivity of somatosensory (e.g., auditory network, visual network), motor (e.g., sensorimotor network), and frontal cognitive systems (e.g., dorsal attention network, ventral attention network, frontoparietal network) alike. This is consistent with work showing associations between other types of adversity and widespread alterations in rsFC in youth (Rakesh et al., 2020). We note that previous work in this space has primarily focused on frontal, temporal, and subcortical

Table 2
Model output for significant effects.

SES measure	Connection	B	SE	T	P	D
ADI	CON – CON	−0.006	0.001	−4.427	1.07E-05	0.047
	AN – CON	−0.005	0.001	−3.871	0.000116	0.041
	DAN – SMN (M)	0.004	0.001	3.355	0.000825	0.035
	SMN (H) – SMN (M)*	0.006	0.002	3.196	0.001441	0.034
	SMN (H) – SMN (H)*	0.005	0.002	3.119	0.001871	0.033
	DMN – VAN**	−0.003	0.001	−2.748	0.006114	0.029
	CPN – SMN (H)**	−0.004	0.002	−2.672	0.007679	0.028
	SN – VAN#	−0.004	0.001	−2.661	0.007933	0.028
	AN – SN**	−0.004	0.002	−2.572	0.010274	0.027
Income-to-needs ratio	SMN (H) – SMN (H)*	−0.007	0.001	−4.662	3.59E-06	0.049
	FPN – SMN (H) ##	0.005	0.001	4.379	1.33E-05	0.046
	SMN (H) – SMN (M)*	−0.007	0.002	−3.933	9.02E-05	0.041
	AN – FPN##	0.003	0.001	3.638	0.00029	0.038
	SN – VAN#	0.004	0.001	2.932	0.00345	0.031
	CPN – FPN	−0.003	0.001	−2.502	0.012516	0.026
	AN – CPN	0.004	0.002	2.438	0.014946	0.026
	AN – SMN (M) ##	−0.004	0.002	−2.397	0.016739	0.025
	AN – SMN (H) ##	−0.003	0.001	−2.341	0.019442	0.025
Educational attainment	SMN (H) – SMN (M)*	−0.010	0.002	−6.144	1.19E-09	0.065
	AN – SMN (H) ##	−0.006	0.001	−5.055	5.19E-07	0.053
	AN – SMN (M) ##	−0.005	0.002	−3.336	0.000884	0.035
	FPN – SMN (H) ##	0.003	0.001	3.313	0.000957	0.035
	CON – CPN	0.004	0.001	3.090	0.002061	0.033
	AN – FPN##	0.003	0.001	3.014	0.002651	0.032
	SMN (H) – SMN (H)*	−0.004	0.001	−2.983	0.002933	0.031
	CPN – SMN (H)**	0.004	0.001	2.667	0.007785	0.028
	AN – DMN	0.003	0.001	2.592	0.009682	0.027
	DMN – VAN**	0.002	0.001	2.531	0.011543	0.027
	AN – SN**	0.004	0.002	2.419	0.015748	0.025

Abbreviations: ADI = Area Deprivation Index, AN = Auditory Network, CON = Cingulo Opercular Network, CPN = Cingulo Parietal Network, D = Cohen's D calculated as t-value/$\sqrt{\text{sample size}}$. DAN = Dorsal Attention Network, DMN = Default Mode Network, FPN = Frontoparietal Network, RTN = Retrosplenial Temporal Network, SMN (H) = Sensorimotor Network (hand), SMN (M) = Sensorimotor Network (mouth), SN = Salience Network, VAN = Ventral Attention Network, VN = Visual Network.

* Common between all three SES indicators.
** Common between ADI and educational attainment.
\# Common between ADI and income-to-needs ratio.
\#\# Common between educational attainment and income-to-needs ratio.

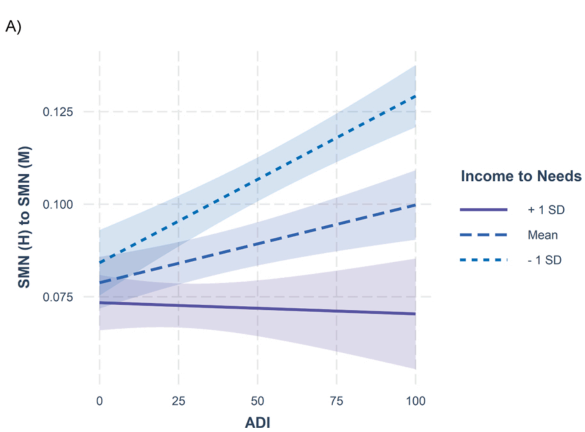

Fig. 5. Interactive effects of ADI and income-to-needs on rsFC. Association between ADI (x axis) and SMN (hand) to SMN (mouth) rsFC (y axis) has been depicted at different levels of income-to-needs ratio. Slopes represent mean ± 1 SD of income-to-needs ratio values.
Abbreviations: SMN (H) = Sensorimotor Network (hand), SMN (M) = Sensorimotor Network (mouth).

regions (Farah, 2017, 2018; Johnson et al., 2016), and it has previously been highlighted that findings supporting the effect of adversity on regions associated with sensory processing (e.g., visual regions) are rarely interpreted (McLaughlin et al., 2019). Accordingly, continued focus on frontal networks, while seemingly overlooking other functional systems, could impede our understanding of the impact of SES on neurodevelopment. We suggest that future work should examine these associations from a more holistic perspective. Further, it has been suggested that somatosensory and motor systems play an important role in shaping cognitive and executive function (Rosen et al., 2019). A relatively recent model stipulates that cognitive stimulation (which includes access to complex learning environments, a diverse range of sensory, linguistic, motoric, and social experiences, language/semantic input, and appropriate caregiver-child interactions, etc.) provides the opportunity for children to regulate attention, resolve conflict between different sensory inputs, learn the ability to distinguish objects, and enhance semantic skills. According to the model, this, in turn, shapes prefrontal structure and development of cognitive function (Rosen et al., 2019). As such, we speculate that alterations in somatosensory and motor functional connectivity (as a function of SES) could play a role in SES-associated individual variation in cognitive abilities (Duncan and Magnuson, 2012).

The difference in the direction of the association between SES and rsFC of sensory-motor systems and higher-order frontal networks is notable. That is, low SES was associated with lower connectivity within sensory-motor networks and between sensory-motor networks and frontal networks, and higher connectivity between frontal higher-order networks. While we know little about normative patterns of rsFC development during late childhood and early adolescence, given that brain developmental patterns have been shown to exhibit regional heterogeneity, whereby sensory-motor regions and frontal regions mature at differ ages and paces (Sowell et al., 2004), it is plausible that exposure to disadvantage impacts their connectivity differentially depending on both the developmental stage and timing of exposure.

In contrast to our hypothesis, we did not find within-network connectivity to be robustly implicated (across discovery and replication sets) for neither neighborhood disadvantage (with the exception of within-sensorimotor network and within-CON rsFC) nor income-to-needs ratio. Given that within-network connectivity changes throughout adolescence (Rakesh et al., 2020; Truelove-hill et al., 2020), it is possible that stronger effects will be evident later in development.

Importantly, despite considerable overlap and the networks generally implicated, specific connections were found to have associations with individual SES measures above and beyond the influence of the other two. Notably, there was more overlap in the connections between the household SES indices (i.e., education and income-to-needs) than between neighborhood and individual household indices, and there was more overlap in the connections implicated for neighborhood disadvantage and parent educational attainment than neighborhood disadvantage and income-to-needs ratio. Why specific connections are independent vs overlapping between SES indices and the underlying mechanisms of the association between a specific SES measure and connection are challenging to comment on due to a dearth of imaging literature on this subject. Nevertheless, our findings of unique as well as similar effects of educational attainment, income-to-needs ratio, and neighborhood SES on rsFC are in line with the notion of different facets of the socioeconomic context reflecting both unique and similar aspects of the developmental context (Braveman et al., 2005; Chen and Paterson, 2006; Farah, 2017; Winkleby et al., 1992), and perhaps acting in unison (along with other aspects of the environment) to shape brain and, in turn, child development. Indeed, evidence indicates that while correlated, neighborhood income, family assets and income, and parental cognitive skills have differential effects on children's cognitive abilities (i.e., mathematics and reading skills; Sastry and Pebley, 2010). Further, different aspects of SES may capture variation in other aspects of the environment (e.g., neighborhood SES may also reflect exposure to trauma/crime/violence (Pratt and Cullen, 2005) and/or toxins (Trentacosta et al., 2016)) that could also be linked with alterations in brain development (Guxens et al., 2018; McLaughlin et al., 2019; Rakesh et al., 2020). Therefore, based on this, and other recommendations (National Center for Education Statistics, 2012), we suggest that future work consider multiple aspects of the socioeconomic context when investigating the influence of SES on neurodevelopment and functioning.

Finally, we found that income-to-needs ratio moderated the effects of neighborhood disadvantage on within-sensorimotor network connectivity, such that the strength of the association between neighborhood SES and rsFC was significantly reduced in the presence of high household income-to-needs ratio. As above, we speculate that links between SES and sensorimotor network connectivity might reflect alterations in motor, in addition to cognitive function and development. Further, higher sensorimotor network connectivity has previously been implicated with worse mental health and cognition in the same sample (Rakesh et al., 2021a). Therefore, these results suggest that high income-to-needs may be able to *buffer* the effects of neighborhood disadvantage on a wide range of motor, cognitive, and mental health outcomes to some extent via sensorimotor network connectivity.

It is important to note most of our interpretations were more in line with the 'deficit model' of adversity (whereby SES-associated alterations are considered as maladaptive). However, they could also reflect adaptive mechanisms (Ellwood-Lowe et al., 2020) for outcomes not tested (Ellis et al., 2017). Therefore, future work examining associations between SES, rsFC, and mental health and cognition should adopt both deficit-based and adaptation-based approaches (Humphreys and Salo, 2020).

While this study has strengths (such as the large sample size and the use of multiple socioeconomic indicators), interpretations must be considered in light of some limitations. First, given that the present study was cross-sectional, and we were unable to test for the association between SES and longitudinal change in connectivity, any interpretations of directional or causal links between disadvantage and alterations in functional connectivity are speculative. Second, timing of exposure, which has been shown to be relevant for brain development (Gard et al., 2021), should be explored in future research. Third, we did not control for race/ethnicity in our main analyses as interpreting and disentangling effects (i.e., ascertaining the degree to which our observed effects were specific to SES [versus race/ethnicity]) would be challenging. Future work should examine these associations in large samples (given the small effect sizes) where race/ethnicity and SES are not highly correlated. Fourth, we are unable to comment on the mechanisms through which different facets of socioeconomic environment may impact neural connectivity, and why only specific connections are impacted. Fifth, we did not directly examine associations between SES, rsFC, and behavioral outcomes, and are therefore unable to comment on whether these SES-associated alterations in rsFC are adaptive or maladaptive. Sixth, given the important role that parcellation schemes can play in determining findings, we recommend that future work test associations between SES and rsFC using multiple functional atlases. Seventh, given that we did not test associations between rsFC and cognitive, motor, or language outcomes, our interpretations are highly speculative. Therefore, future longitudinal work should test these associations explicitly (Ellwood-Lowe et al., 2016). Finally, future work would benefit from leveraging genetic data available in the ABCD study to advance our understanding of the influence of gene-environment interactions on brain development.

In summary, our findings demonstrate that different facets of SES have both distinct and common effects on rsFC. This work provides further support for the importance of consideration of the different socioeconomic contexts in understanding child brain and behavioral outcomes.

Data sharing statement

Data used in the preparation of this article were obtained from the Adolescent Brain Cognitive Development (ABCD) Study (https://abcdstudy.org), held in the NIMH Data Archive (NDA). This is a multisite, longitudinal study designed to recruit more than 10,000 children aged 9–10 and follow them over 10 years into early adulthood. A full list of supporters is available at https://abcdstudy.org/federal-partners.html. A listing of participating sites and a complete listing of the study investigators can be found at https://abcdstudy.org/scientists/workgroups/. ABCD consortium investigators designed and implemented the study and/or provided data but did not participate in the analysis or writing of this report. This manuscript reflects the views of the authors and may not reflect the opinions or views of the NIH or ABCD consortium investigators.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.dcn.2021.101005

References

Barch, D.M., Pagliaccio, D., Belden, A., Harms, M.P., Gaffrey, M., Sylvester, C.M., Tillman, R., Luby, J., 2016. Effect of hippocampal and amygdala connectivity on the relationship between preschool poverty and school-age depression. Am. J. Psychiatry 173 (6), 625–634. https://doi.org/10.1176/appi.ajp.2015.15081014.

Benjamini, Y., Hochberg, Y., 1995. Benjamini-1995.pdf. J. R. Stat. Soc. Ser. B 57 (1), 289–300. https://doi.org/10.2307/2346101.

Braveman, P.A., Cubbin, C., Egerter, S., Chideya, S., Marchi, K.S., Metzler, M., Posner, S., 2005. Socioeconomic status in health research: one size does not fit all. J. Am. Med. Assoc. 294 (22), 2879–2888. https://doi.org/10.1001/jama.294.22.2879.

Brody, G.H., Yu, T., Nusslock, R., Barton, A.W., Miller, G.E., Chen, E., Holmes, C., McCormick, M., Sweet, L.H., 2019. The protective effects of supportive parenting on the relationship between adolescent poverty and resting-state functional brain connectivity during adulthood. Psychol. Sci. 30 (7), 1040–1049. https://doi.org/10.1177/0956797619847989.

Campbell, K.L., Schacter, D.L., 2017. Ageing and the resting state: is cognition obsolete? Lang. Cogn. Neurosci. 32 (6), 661–668. https://doi.org/10.1080/23273798.2016.1227858.

Casey, B.J., Cannonier, T., Conley, M.I., Cohen, A.O., Barch, D.M., Heitzeg, M.M., et al., 2018. The Adolescent Brain Cognitive Development (ABCD) study: imaging acquisition across 21 sites. Dev. Cogn. Neurosci. 32, 43–54. https://doi.org/10.1016/j.dcn.2018.03.001. Elsevier Ltd.

Chen, E., Paterson, L.Q., 2006. Neighborhood, family, and subjective socioeconomic status: How do they relate to adolescent health? Health Psychol. 25 (6), 704–714. https://doi.org/10.1037/0278-6133.25.6.704.

DiMartino, A., Fair, D.A., Kelly, C., Satterthwaite, T.D., Castellanos, F.X., Thomason, M. E., et al., 2014. Unraveling the miswired connectome: a developmental perspective. Neuron 83 (6), 1335–1353. https://doi.org/10.1016/j.neuron.2014.08.050.

Dosenbach, N.U.F., Fair, D.A., Cohen, A.L., Schlaggar, B.L., Petersen, S.E., 2008. A dual-networks architecture of top-down control. Trends Cogn. Sci. (Regul. Ed.) 12 (3), 99–105. https://doi.org/10.1016/j.tics.2008.01.001.

Dumontheil, I., 2016. Adolescent brain development. Curr. Opin. Behav. Sci. 10, 39–44. https://doi.org/10.1016/j.cobeha.2016.04.012.

Duncan, G.J., Magnuson, K., 2012. Socioeconomic status and cognitive functioning: moving from correlation to causation. WIREs Cognit. Sci. 3 (3), 377–386. https://doi.org/10.1002/wcs.1176.

Duncan, G.J., Magnuson, K., Kalil, A., Ziol-Guest, K., 2012. The importance of early childhood poverty. Soc. Indic. Res. 108 (1), 87–98. https://doi.org/10.1007/s11205-011-9867-9.

Ellis, B.J., Bianchi, J.M., Griskevicius, V., Frankenhuis, W.E., 2017. Beyond risk and protective factors: an adaptation-based approach to resilience. Perspect. Psychol. Sci. 12 (4), 561–587. https://doi.org/10.1177/1745691617693054.

Ellwood-Lowe, M.E., Sacchet, M.D., Gotlib, I.H., 2016. The application of neuroimaging to social inequity and language disparity: a cautionary examination. Dev. Cogn. Neurosci. 22, 1–8. https://doi.org/10.1016/j.dcn.2016.10.001.

Ellwood-Lowe, M.E., Whitfield-Gabrieli, S., Bunge, S.A., 2020. What is an adaptive pattern of brain activity for a child? It depends on their environment. BioRxiv. https://doi.org/10.1101/2020.05.29.124297, 2020.05.29.124297.

Ernst, M., Torrisi, S., Balderston, N., Grillon, C., Hale, E.A., 2015. fMRI functional connectivity applied to adolescent neurodevelopment. Annu. Rev. Clin. Psychol. 11 (1), 361–377. https://doi.org/10.1146/annurev-clinpsy-032814-112753.

Evans, G.W., 2004. The environment of childhood poverty. Am. Psychol. 59 (2), 77–92. https://doi.org/10.1037/0003-066X.59.2.77.

Farah, M.J., 2016. Child poverty and brain development. Scientists Making a Difference: One Hundred Eminent Behavioral and Brain Scientists Talk About Their Most Important Contributions, pp. 20–23. http://ovidsp.ovid.com/ovidweb.cgi?T=JS&PAGE=reference&D=psyc13&NEWS=N&AN=2016-48867-004.

Farah, M.J., 2017. The neuroscience of socioeconomic status: correlates, causes, and consequences. Neuron 96 (1), 56–71. https://doi.org/10.1016/j.neuron.2017.08.034. Cell Press.

Farah, M.J., 2018. Socioeconomic status and the brain: prospects for neuroscience-informed policy. Nat. Rev. Neurosci. 19 (7), 428–438. https://doi.org/10.1038/s41583-018-0023-2. Nature Publishing Group.

Farah, M.J., Shera, D.M., Savage, J.H., Betancourt, L., Giannetta, J.M., Brodsky, N.L., Malmud, E.K., Hurt, H., 2006. Childhood poverty: specific associations with neurocognitive development. Brain Res. 1110 (1), 166–174. https://doi.org/10.1016/j.brainres.2006.06.072.

Fornito, A., Bullmore, E.T., Zalesky, A., 2017. Opportunities and challenges for psychiatry in the connectomic era. Biol. Psychiatry Cogn. Neurosci. Neuroimaging 2 (1), 9–19. https://doi.org/10.1016/j.bpsc.2016.08.003.

Forns, J., Torrent, M., Garcia-Esteban, R., Cáceres, A., Pilar Gomila, M., Martinez, D., Morales, E., Julvez, J., Grimalt, J.O., Sunyer, J., 2012. Longitudinal association between early life socio-environmental factors and attention function at the age 11 years. Environ. Res. 117, 54–59. https://doi.org/10.1016/j.envres.2012.04.007.

Fox, M.D., Greicius, M., 2010. Clinical applications of resting state functional connectivity. Front. Syst. Neurosci. 4 https://doi.org/10.3389/fnsys.2010.00019.

Garavan, H., Bartsch, H., Conway, K., Decastro, A., Goldstein, R.Z., Heeringa, S., Jernigan, T., Potter, A., Thompson, W., Zahs, D., 2018. Recruiting the ABCD sample: design considerations and procedures. Dev. Cogn. Neurosci. 32, 16–22. https://doi.org/10.1016/j.dcn.2018.04.004.

Gard, A.M., Maxwell, A.M., Shaw, D.S., Mitchell, C., Brooks-Gunn, J., McLanahan, S.S., Forbes, E.E., Monk, C.S., Hyde, L.W., 2021. Beyond family-level adversities: exploring the developmental timing of neighborhood disadvantage effects on the brain. Dev. Sci. 24 (1), e12985. https://doi.org/10.1111/desc.12985.

Gordon, R.A., Savage, C., Lahey, B.B., Goodman, S.H., Jensen, P.S., Rubio-Stipec, M., Hoven, C.W., 2003. Family and neighborhood income: additive and multiplicative associations with youths' well-being. Soc. Sci. Res. 32 (2), 191–219. https://doi.org/10.1016/S0049-089X(02)00047-9.

Gordon, E.M., Laumann, T.O., Adeyemo, B., Huckins, J.F., Kelley, W.M., Petersen, S.E., 2016. Generation and evaluation of a cortical area parcellation from resting-state correlations. Cereb. Cortex 26 (1), 288–303. https://doi.org/10.1093/cercor/bhu239.

Guxens, M., Lubczyńska, M.J., Muetzel, R.L., Dalmau-Bueno, A., Jaddoe, V.W.V., Hoek, G., van der Lugt, A., Verhulst, F.C., White, T., Brunekreef, B., Tiemeier, H., El Marroun, H., 2018. Air pollution exposure during fetal life, brain morphology, and cognitive function in school-age children. Biol. Psychiatry 84 (4), 295–303. https://doi.org/10.1016/j.biopsych.2018.01.016.

Hackman, D.A., Farah, M.J., 2009. Socioeconomic status and the developing brain. Trends Cogn. Sci. 13 (2), 65–73. https://doi.org/10.1016/j.tics.2008.11.003.

Hackman, D.A., Farah, M.J., Meaney, M.J., 2010. Socioeconomic status and the brain: mechanistic insights from human and animal research. Nat. Rev. Neurosci. 11 (9), 651–659. https://doi.org/10.1038/nrn2897.

Hagler, D.J., Hatton, S.N., Cornejo, M.D., Makowski, C., Fair, D.A., Dick, A.S., et al., 2019. Image processing and analysis methods for the adolescent brain cognitive development study. NeuroImage 202. https://doi.org/10.1016/j.neuroimage.2019.116091.

Hanson, J.L., Albert, W.D., Skinner, A.T., Shen, S.H., Dodge, K.A., Lansford, J.E., 2019. Resting state coupling between the amygdala and ventromedial prefrontal cortex is related to household income in childhood and indexes future psychological vulnerability to stress. Dev. Psychopathol. 31 (3) https://doi.org/10.1017/S0954579419000592. No-Specified.

Hoff, E., 2006. How social contexts support and shape language development. Dev. Rev. 26 (1), 55–88. https://doi.org/10.1016/j.dr.2005.11.002.

Hoff, E., Tian, C., 2005. Socioeconomic status and cultural influences on language. J. Commun. Disord. 38 (Spec. Iss. (4)), 271–278. https://doi.org/10.1016/j.jcomdis.2005.02.003.

Horowitz-Kraus, T., Toro-Serey, C., DiFrancesco, M., 2015. Increased resting-state functional connectivity in the cingulo-opercular cognitive-control network after intervention in children with reading difficulties. PLoS One 10 (7). https://doi.org/10.1371/journal.pone.0133762 e0133762.

Humphreys, K.L., Salo, V.C., 2020. Expectable environments in early life. Curr. Opin. Behav. Sci. 36, 115–119. https://doi.org/10.1016/j.cobeha.2020.09.004.

Jiang, Y., Ekono, M., Skinner, C., 2016. Basic Facts about Low-income Children: Children Under 6 Years, 2014. https://doi.org/10.7916/D8-5BZC-PV86.

Johnson, S.B., Riis, J.L., Noble, K.G., 2016. State of the art review: poverty and the developing brain. Pediatrics 137 (4). https://doi.org/10.1542/peds.2015-3075.

Kind, A.J.H., Jencks, S., Brock, J., Yu, M., Bartels, C., Ehlenbach, W., Greenberg, C., Smith, M., 2014. Neighborhood socioeconomic disadvantage and 30-day rehospitalization: A retrospective cohort study. Ann. Intern. Med. 161 (11), 765–774. https://doi.org/10.7326/M13-2946.

King, L.S., Dennis, E.L., Humphreys, K.L., Thompson, P.M., Gotlib, I.H., 2020. Cross-sectional and longitudinal associations of family income-to-needs ratio with cortical and subcortical brain volume in adolescent boys and girls. Dev. Cogn. Neurosci. 44, 100796 https://doi.org/10.1016/j.dcn.2020.100796.

Koutra, K., Chatzi, L., Roumeliotaki, T., Vassilaki, M., Giannakopoulou, E., Batsos, C., Koutis, A., Kogevinas, M., 2012. Socio-demographic determinants of infant neurodevelopment at 18 months of age: Mother-Child Cohort (Rhea Study) in Crete, Greece. Infant Behav. Dev. 35 (1), 48–59. https://doi.org/10.1016/j.infbeh.2011.09.005.

Mackey, A.P., Finn, A.S., Leonard, J.A., Jacoby-Senghor, D.S., West, M.R., Gabrieli, C.F. O., Gabrieli, J.D.E., 2015. Neuroanatomical correlates of the income-achievement gap. Psychol. Sci. 26 (6), 925–933. https://doi.org/10.1177/0956797615572233.

Marshall, N.A., Marusak, H.A., Sala-Hamrick, K.J., Crespo, L.M., Rabinak, C.A., Thomason, M.E., 2018. Socioeconomic disadvantage and altered corticostriatal circuitry in urban youth. Hum. Brain Mapp. 39 (5), 1982–1994. https://doi.org/10.1002/hbm.23978.

McLaughlin, K.A., Weissman, D., Bitrán, D., 2019. Childhood adversity and neural development: a systematic review. Ann. Rev. Develop. Psychol. 1 (1), 277–312. https://doi.org/10.1146/annurev-devpsych-121318-084950.

Meghani, S.H., Chittams, J., 2015. Controlling for socioeconomic status in pain disparities research: all-else-equal analysis when "all else" is not equal. Pain Med. 16 (12), 2222–2225. https://doi.org/10.1111/pme.12829.

Morley, D., Till, K., Ogilvie, P., Turner, G., 2015. Influences of gender and socioeconomic status on the motor proficiency of children in the UK. Hum. Mov. Sci. 44, 150–156. https://doi.org/10.1016/j.humov.2015.08.022.

Morrissey, T.W., Vinopal, K.M., 2018. Neighborhood poverty and children's academic skills and behavior in early elementary school. J. Marriage Fam. 80 (1), 182–197. https://doi.org/10.1111/jomf.12430.

National Center for Education Statistics, 2012. Improving the Measurement of Socioeconomic Status for the National Assessment of Educational Progress: A Theoretical Foundation: Recommendations to the National Center for Education Statistics (Issue November). ERIC Clearinghouse. https://doi.org/10.1016/b978-0-407-72903-2.50010-1.

Noble, K.G., Norman, M.F., Farah, M.J., 2005. Neurocognitive correlates of socioeconomic status in kindergarten children. Dev. Sci. 8 (1), 74–87. https://doi.org/10.1111/j.1467-7687.2005.00394.x.

Noble, K.G., McCandliss, B.D., Farah, M.J., 2007. Socioeconomic gradients predict individual differences in neurocognitive abilities. Dev. Sci. 10 (4), 464–480. https://doi.org/10.1111/j.1467-7687.2007.00600.x. Dev Sci.

Noble, K.G., Houston, S.M., Brito, N.H., Bartsch, H., Kan, E., Kuperman, J.M., et al., 2015. Family income, parental education and brain structure in children and adolescents. Nat. Neurosci. 18 (5), 773–778. https://doi.org/10.1038/nn.3983.

Oakes, J.M., Rossi, P.H., 2003. The measurement of SES in health research: current practice and steps toward a new approach. Soc. Sci. Med. 56 (4), 769–784. https://doi.org/10.1016/S0277-9536(02)00073-4.

Packard, C.J., Bezlyak, V., McLean, J.S., Batty, G.D., Ford, I., Burns, H., Cavanagh, J., Deans, K.A., Henderson, M., McGinty, A., Millar, K., Sattar, N., Shiels, P.G., Velupillai, Y.N., Tannahill, C., 2011. Early life socioeconomic adversity is associated in adult life with chronic inflammation, carotid atherosclerosis, poorer lung function and decreased cognitive performance: a cross-sectional, population-based study. BMC Public Health 11 (1), 1–16. https://doi.org/10.1186/1471-2458-11-42.

Perkins, S.C., Finegood, E.D., Swain, J.E., 2013. Poverty and language development: Roles of parenting and stress. Innov. Clin. Neurosci. 10 (4), 10–19. Matrix Medical Communications. /pmc/articles/PMC3659033/?report=abstract.

Posner, Huang, L., 2011. Cognitive Neuroscience of Attention, 2nd ed. https://www.guilford.com/books/Cognitive-Neuroscience-of-Attention/Michael-Posner/9781609189853/contents.

Pratt, T.C., Cullen, F.T., 2005. Assessing macro-level predictors and theories of crime: a meta-analysis. Crime Justice 32, 373–450. https://doi.org/10.1086/655357. University of Chicago Press.

Rakesh, D., Kelly, C., Vijayakumar, N., Zalesky, A., Allen, N.B., Whittle, S., 2020. Unraveling the consequences of childhood maltreatment: deviations from typical functional neurodevelopment mediate the relationship between maltreatment history and depressive symptoms. Biol. Psychiatry Cogn. Neurosci. Neuroimaging 6 (3), 329–342. https://doi.org/10.1016/j.bpsc.2020.09.016.

Rakesh, D., Seguin, C., Zalesky, A., Cropley, V., Whittle, S., 2021a. Associations between neighborhood disadvantage, resting-state functional connectivity, and behavior in the Adolescent Brain Cognitive Development (ABCD) Study®: moderating role of positive family and school environments. Biol. Psychiatry Cogn. Neurosci. Neuroimaging. https://doi.org/10.1016/j.bpsc.2021.03.008.

Rakesh, D., Cropley, V., Zalesky, A., Vijayakumar, N., Allen, N.B., Whittle, S., 2021b. Neighborhood disadvantage and longitudinal brain-predicted-age trajectory during adolescence. Dev. Cogn. Neurosci. 101002. https://doi.org/10.1016/J.DCN.2021.101002.

Rosen, M.L., Amso, D., McLaughlin, K.A., 2019. The role of the visual association cortex in scaffolding prefrontal cortex development: a novel mechanism linking socioeconomic status and executive function. Dev. Cogn. Neurosci. 39, 100699. https://doi.org/10.1016/j.dcn.2019.100699. Elsevier Ltd.

Ruijsbroek, A., Wijga, A.H., Kerkhof, M., Koppelman, G.H., Smit, H.A., Droomers, M., 2011. The development of socio-economic health differences in childhood: results of the Dutch longitudinal PIAMA birth cohort. BMC Public Health 11. https://doi.org/10.1186/1471-2458-11-225.

Samaan, R.A., 2000. The influences of race, ethnicity, and poverty on the mental health of children. J. Health Care Poor Underserved 11 (1), 100–110. https://doi.org/10.1353/hpu.2010.0557.

Sarsour, K., Sheridan, M., Jutte, D., Nuru-Jeter, A., Hinshaw, S., Boyce, W.T., 2011. Family socioeconomic status and child executive functions: the roles of language, home environment, and single parenthood. J. Int. Neuropsychol. Soc. 17 (1), 120–132. https://doi.org/10.1017/S1355617710001335.

Sastry, N., Pebley, A.R., 2010. Family and neighborhood sources of socioeconomic inequality in children's achievement. Demography 47 (3), 777–800. https://doi.org/10.1353/dem.0.0114.

Sheffield, J.M., Kandala, S., Burgess, G.C., Harms, M.P., Barch, D.M., 2016. Cingulo-opercular network efficiency mediates the association between psychotic-like experiences and cognitive ability in the general population. Biol. Psychiatry Cogn. Neurosci. Neuroimaging 1 (6), 498–506. https://doi.org/10.1016/j.bpsc.2016.03.009.

Singh, G.K., 2003. Area deprivation and widening inequalities in US mortality, 1969-1998. Am. J. Public Health 93 (7), 1137–1143. https://doi.org/10.2105/AJPH.93.7.1137.

Sowell, E.R., Thompson, P.M., Leonard, C.M., Welcome, S.E., Kan, E., Toga, A.W., 2004. Longitudinal mapping of cortical thickness and brain growth in normal children. J. Neurosci. 24 (38), 8223–8231. https://doi.org/10.1523/JNEUROSCI.1798-04.2004.

Sripada, R.K., Swain, J.E., Evans, G.W., Welsh, R.C., Liberzon, I., 2014. Childhood poverty and stress reactivity are associated with aberrant functional connectivity in default mode network. Neuropsychopharmacology 39 (9), 2244–2251. https://doi.org/10.1038/npp.2014.75.

Stevens, M.C., 2016. The contributions of resting state and task-based functional connectivity studies to our understanding of adolescent brain network maturation. Neurosci. Biobehav. Rev. 70, 13–32. https://doi.org/10.1016/j.neubiorev.2016.07.027.

Stevens, M.C., Pearlson, G.D., Calhoun, V.D., 2009. Changes in the interaction of resting-state neural networks from adolescence to adulthood. Hum. Brain Mapp. 30 (8), 2356–2366. https://doi.org/10.1002/hbm.20673.

Su, M., Li, P., Zhou, W., Shu, H., 2021. Effects of socioeconomic status in predicting reading outcomes for children: the mediation of spoken language network. Brain Cogn. 147 (May 2020), 105655. https://doi.org/10.1016/j.bandc.2020.105655.

Taylor, R.L., Cooper, S.R., Jackson, J.J., Barch, D.M., 2020. Assessment of neighborhood poverty, cognitive function, and prefrontal and hippocampal volumes in children. JAMA Network Open 3 (11). https://doi.org/10.1001/jamanetworkopen.2020.23774 e2023774.

Tooley, U.A., Mackey, A.P., Ciric, R., Ruparel, K., Moore, T.M., Gur, R.C., Gur, R.E., Satterthwaite, T.D., Bassett, D.S., 2019. Associations between neighborhood SES and functional brain network development. Cereb. Cortex 30 (April), 1–19. https://doi.org/10.1093/cercor/bhz066.

Trentacosta, C.J., Davis-Kean, P., Mitchell, C., Hyde, L., Dolinoy, D., 2016. Environmental contaminants and child development. Child Dev. Perspect. 10 (4), 228–233. https://doi.org/10.1111/cdep.12191.

Truelove-hill, M., Erus, G., Bashyam, V., Varol, E., Sako, C., Gur, R.C., Gur, R.E., Koutsouleris, N., Zhuo, C., Fan, Y., Wolf, D.H., Satterthwaite, T.D., Davatzikos, C., 2020. A multidimensional neural maturation index reveals reproducible developmental patterns in children and adolescents. J. Neurosci. 40 (6), 1265–1275.

Weissman, D.G., Conger, R.D., Robins, R.W., Hastings, P.D., Guyer, A.E., 2018. Income change alters default mode network connectivity for adolescents in poverty. Dev. Cogn. Neurosci. 30, 93–99. https://doi.org/10.1016/j.dcn.2018.01.008.

Whittle, S., Vijayakumar, N., Simmons, J.G., Dennison, M., Schwartz, O., Pantelis, C., Sheeber, L., Byrne, M.L., Allen, N.B., 2017. Role of positive parenting in the association between neighborhood social disadvantage and brain development across adolescence. JAMA Psychiatry 74 (8), 824–832. https://doi.org/10.1001/jamapsychiatry.2017.1558.

Winkleby, M.A., Jatulis, D.E., Frank, E., Fortmann, S.P., 1992. Socioeconomic status and health: how education, income, and occupation contribute to risk factors for cardiovascular disease. Am. J. Public Health 82 (6), 816–820. https://doi.org/10.2105/AJPH.82.6.816.

Ziegler, G., Moutoussis, M., Hauser, T.U., Fearon, P., Bullmore, E.T., Goodyer, I.M., Fonagy, P., Jones, P.B., Lindenberger, U., Dolan, R.J., 2020. Childhood socio-economic disadvantage predicts reduced myelin growth across adolescence and young adulthood. Hum. Brain Mapp. 41 (12), 3392–3402. https://doi.org/10.1002/hbm.25024.