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Measurement matters: An individual differences examination of family socioeconomic factors, latent dimensions of children's experiences, and resting state functional brain connectivity in the ABCD sample

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ABSTRACT

The variation in experiences between high and low-socioeconomic status contexts are posited to play a crucial role in shaping the developing brain and may explain differences in child outcomes. Yet, examinations of SES and brain development have largely been limited to distal proxies of these experiences (e.g., income comparisons). The current study sought to disentangle the effects of multiple socioeconomic indices and dimensions of more proximal experiences on resting-state functional connectivity (rsFC) in a sample of 7834 youth (aged 9–10 years) from the Adolescent Brain Cognitive Development (ABCD) study. We applied moderated nonlinear factor analysis (MNLFA) to establish measurement invariance among three latent environmental dimensions of experience (material/economic deprivation, caregiver social support, and psychosocial threat). Results revealed measurement biases as a function of child age, sex, racial group, family income, and parental education, which were statistically adjusted in the final MNLFA scores. Mixed-effects models demonstrated that socioeconomic indices and psychosocial threat differentially predicted variation in frontolimbic networks, and threat statistically moderated the association between income and connectivity between the dorsal and ventral attention networks. Findings illuminate the importance of reducing measurement biases to gain a more socioculturally-valid understanding of the complex and nuanced links between socioeconomic context, children's experiences, and neurodevelopment.

1. Introduction

Socioeconomic inequality in the United States is prevalent and disproportionately affects youth—especially youth of color (Koball and Jiang, 2018; Henry et al., 2019). Given the stressors families face from resource scarcity and intersecting forms of systemic racial inequity, socioeconomic disparities in mental and physical health have been found between children from low- and high-socioeconomic status (SES) homes, and this gap widens as children age (Evans and Kantrowitz, 2002; Fletcher and Wolfe, 2014). The variation in lived experiences between high and low-SES contexts are thought to play a crucial role in shaping the developing brain and may explain observed differences in subsequent outcomes (Dufford et al., 2020). Yet, much of the literature on SES and brain development has been limited to categorial and/or coarse proxies of these experiences—often comparing groups of children designated as "high" or "low" on some broad-scale SES indicator like family income (Blair and Raver, 2012; Hanson et al., 2013; Noble et al., 2015). A comprehensive and nuanced investigation into the ways SES alters brain development is crucial for identifying malleable environmental factors that can inform programs aimed at reducing socioeconomic disparities across developmental domains. Doing so calls for careful, valid measurement of the socioeconomic context as well as a multivariate individual differences approach, which we apply in the present study using the Adolescent Brain and Cognitive Development Study (ABCD) dataset (Casey et al., 2018).

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1.1. Associations between SES and resting-state functional connectivity

Burgeoning research at the intersections of neuroscience and psychology has begun investigating the neurodevelopmental correlates of SES, providing insight into the ways such inequalities come to affect children's wellbeing. Here we focus on brain resting-state functional network connectivity (rsFC), thought to represent intrinsically correlated patterns of neural activity (independent of task performance) cultivated by a prior history of temporal co-activation within and between key brain networks (Gordon et al., 2016; Graham et al., 2021). Individual differences in rsFC are apparent across childhood and have been shown to predict behavioral variation, providing insight into early markers of adaptive functioning (Marek et al., 2019; Casey et al., 2005).

Studies have found SES-related differences in children's functional resting state networks that support emotional, cognitive, and reward processing. Broadly, these studies demonstrate greater within- and between-network connectivity among youth growing up in high-SES homes compared to youth from more socioeconomically disadvantaged homes (for a comprehensive review and meta-analysis, see Yaple and Yu, 2020). The most pronounced converging evidence comes from research showing less frontolimbic rsFC in low-SES youth (Barch et al., 2016; Marshall et al., 2018; Gellci et al., 2019; Park et al., 2021) that persists into adolescence and early adulthood (Brody et al., 2019; Tooley et al., 2020). Childhood poverty has also been shown to predict decreased connectivity in key networks in adulthood (Sripada et al., 2014), and a longitudinal study by Gao et al. (2015) suggests that these relations may emerge as early as the first year of life. Collectively, research has connected SES to differences in rsFC. However, key gaps remain in part due to limitations in the operationalization and measurement of socioeconomic advantage and disadvantage.

1.2. A case for ensuring valid measurement of experiences implicated across the socioeconomic context

SES is a multidimensional construct that includes measures of economic resources and is associated with a wide variation of both positive and negative psychosocial experiences. Yet, most of the research to date has relied on the use of income or parental education as interchangeable proxies of SES. Although income and parental education are correlated, they reflect different social and economic components, and there is an accumulating consensus that they should not be used interchangeably or without additional contextual factors (Hackman and Farah, 2009; Duncan and Magnuson, 2012). Certainly, income and parental education in and of themselves do not directly affect the brain; rather, they are distal indices that exert their influence in interactions with more proximal environmental factors, such as material deprivation or food insecurity (Farah, 2017; Smith and Pollak, 2021). Indeed, one recent study showed that supportive parenting moderated the association between cumulative childhood poverty and rsFC in networks underlying self-regulation in adulthood (Brody et al., 2019). Emerging evidence demonstrates that measuring SES without proximal environmental measures may obscure important heterogeneity in relations between SES and child outcomes (DeJoseph et al., 2021; Raver et al., 2015; Hurwich-Reiss et al., 2019).

A core aim of the current study is to deploy more proximal environmental measures to clarify the key factors by which SES-related adversity may influence brain development. Here we incorporate contemporary dimensional and topological models of adversity (McLaughlin and Sheridan, 2016; Ellis et al., 2020; Smith and Pollak, 2021) to shed light on the links between early experience and brain function. Although these approaches span multiple and sometimes opposing views (McLaughlin et al., 2020), we chose to adopt elements from both. Specifically, we distinguish between effects of deprivation and threat (as the dimensional approach urges) while also utilizing measures that can reflect the intensity of those experiences as subjectively experienced by the child (as the topological model urges).

Accumulating evidence suggests that early deprivation and threat are associated with different brain networks underlying cognition (e.g., cingulo-opercular, salience, dorsal attention; Herzberg et al., 2021; Rakesh et al., 2021a) and emotion regulation (e.g., fronto-amygdala network connectivity; Gee et al., 2013; Thijssen et al., 2020), respectively. Given this body of research, we believe that it is prudent to continue to distinguish between these sources of adversity. However, we aim to build on this work and move beyond using SES to index deprivation, and to instead use measures that more directly index how children's home environments confer opportunities for sociocognitive stimulation (e.g., Rosen et al., 2019). We do this by including measures of both subjective material deprivation and quality of caregiver social support, the latter of which builds upon past work that illustrates the promotive and protective roles that high-quality caregiving and social support have on self-regulation and underlying neurobiological development (Blair and Raver, 2012; Brody et al., 2019; Perry et al., 2019; Palacios-Barrios and Hanson, 2019).

Although studies using the ABCD sample have begun uncovering associations between aspects of children's environments and rsFC (Thijssen et al., 2020; Modabbernia et al., 2021; Ellwood-Lowe et al., 2020; Hong et al., 2021; Rakesh et al., 2021b), approaches that aim to disentangle the effects of broader socioeconomic context (e.g., SES, parental education) from youths' downstream experiences of these broader contexts (e.g., their home environment) remain to be explored. Based on prior work mentioned above (e.g., Brody et al., 2019), it is likely that the magnitude of SES effects on brain connectivity will be stronger in the context of proximal environmental factors. Indeed, prominent conceptual models of child development highlight the importance of considering interactions between more macro sociopolitical contexts with more proximal experiences occurring within the children's immediate home environments (Bronfenbrenner and Ceci, 1994).

It is our view that while it is important to select measures that distinguish between different dimensions of SES-related adversity and protective factors, quality measurement work is necessary for making valid comparisons of these dimensions across individual differences in SES. To do so, it is essential that the measures we use to represent constructs of deprivation, threat, and support are *invariant* (measurement invariance (MI); Meredith, 1993; Widaman et al., 2010), meaning they reflect common substantive and qualitative scales across development and sociodemographic groups. Testing and adjusting for measurement *non*-invariance (i.e., when the meaning of a scale differs across groups)—also known as differential item functioning (DIF)—ensures that conclusions are drawn from true differences on dimensions of experience, rather than by measurement artifacts that may result in spurious associations. In other words, there may be developmental, socioeconomic, or racial group differences in how the items in a given environmental measure operate. For example, on a measure capturing social support where the "true" latent level is constant over development, younger children may endorse an item like "My parent makes me feel better when talking about my worries with them" more often than older children whose peers tend to be more salient sources of support. When using a raw sum or mean score that weights all items in the construct equally, one would erroneously conclude that social support decreased with age. Extending this example to group differences by race or social class, such biased conclusions have potentially large implications for policy and the effectiveness of individualized intervention efforts that aim to serve diverse groups of families (for a detailed review of MI and its implications for socioeconomically diverse samples, see DeJoseph et al., 2021). With a sample as large and diverse as the ABCD, and the benefits that the conclusions from such a study could have for the wellbeing of children, careful consideration of the quality of our measures is critical.

1.3. The present study

In the current study, we leveraged recent advances in psychometrics to test two primary aims. The first aim was to replicate and extend the measurement model of environmental adversity and resources presented in DeJoseph et al. (2021), which used a population-based sample of children living in predominantly low-income rural communities, and extend it to the ABCD sample (a population-based socioeconomically diverse sample of children in urban communities). We chose three measures characterizing key dimensions of children's environments (i.e., material/economic deprivation, caregiver social support, and psychosocial threat) to examine the extent to which the measures were commensurable across key sociodemographic variables. To do this we used moderated nonlinear factor analysis (MNLFA; Bauer, 2017; Bauer and Hussong, 2009; Curran et al., 2014). MNLFA allows one to empirically test and adjust for possible sociodemographic bias at the item level, resulting in factor scores that reflect true differences at the latent construct level (see Fig. 1 for a conceptual overview of MNLFA). We hypothesized that income, parental education, and racial group membership would contribute to measurement artifacts that ultimately manifest in biases in the latent representations of the constructs of interest. Finally, given the tight age range of the sample (9- to 10-year--olds), we anticipated less pronounced effects of age. Exploratory analyses as a function of reported sex at birth were also conducted.

Our second aim sought to examine the associations of continuous measures of both family income-to-needs and parental education on a subset of rsFC networks (Gordon et al., 2016) purportedly associated with cognitive, emotional, and behavioral regulation. Based on prior literature, we hypothesized that higher income and education would be associated with greater connectivity in these a priori selected networks. We further explored whether individual differences in more proximal and subjective experiences, measured via the latent factors established in our first aim, moderated the relation between SES and rsFC to provide a more comprehensive understanding of how SES shapes brain development.

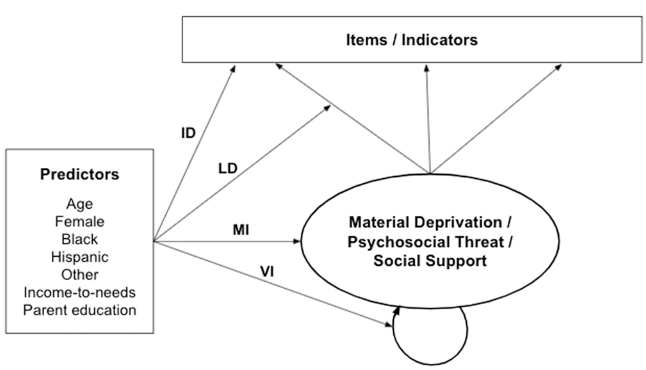

Fig. 1. Simplified illustration of moderated nonlinear factor analysis (MNLFA; Cole et al., 2020). MNLFA hypothesizes that the items/indicators on a given environmental measure all measure the same construct (i.e. material/economic deprivation, psychosocial threat, or social support) and iteratively tests and subsequently adjusts for non-invariance or DIF. All the indicators are related to the latent variable via factor loadings, which represent the predicted change in items associated with a one-unit shift in the latent variable. Each indicator includes an intercept, which represents the predicted value of the indicator when the value of the latent variable is zero. Ultimately, MNLFA generates adjusted person-specific estimates from questionnaire data to reduce the degree of measurement bias attributable to demographic factors such as age, sex, socioeconomic status, or race. Importantly, MNLFA factor scores assure a common scale of measurement across groups and age, as well as adjust for measurement DIF that would have otherwise bias substantive analyses. *Note.* DIF paths, in which covariates affect the measurement of the items: ID (intercept DIF); LD (loading DIF). Impact paths, in which covariates affect the latent variable itself: MI (mean impact); VI (variance impact). The three arrows from environmental latent construct (oval) to the indicators generically represent factor loadings; the curved arrow on the latent construct represents its variance. Only DIF for ID, LD, and MI were tested in the current manuscript.

2. Methods

2.1. Participants

The ABCD study (http://abcdstudy.org) is a prospective, longitudinal neuroimaging study of approximately 11,000 children and caregivers across the United States. Using a multi-stage probability sampling approach (Heeringa et al., 2010), 9- and 10-year-old children were recruited across 21 sites to yield a nationally representative sample of youth in urban areas. Procedures were approved by individual sites' institutional review boards and all participants and legal guardians gave informed consent. For more information on ABCD recruitment and sampling procedures, see Garavan et al. (2018).

Data from the baseline assessment (ABCD DEAP version 2.0.1, N = 11,685 youths) were included in this study if the rsFC data met minimal quality control criteria (see Hagler et al., 2019). Of the data available, we excluded children whose rsFC data were collected using Philips scanners due to internal communication about processing errors (n = 1512). We further excluded cases that had less than 375 TRs (time resolution or sampling rate) (n = 1593), as directed by ABCD's usability criteria (Hagler et al. 2019). Finally, cases that had implausible rsFC values across any of the chosen networks (i.e., r values above 0.9 or below −0.9) were removed (1.4%).

Families in this final analytic sample (N = 7834) reported an average income-to-needs ratio (INR; see measures section for how INR was calculated) of 3.7 (range =0.10 - 12.13) and a mean parent education level of 20 years (range = 9–24 years). Approximately 13.8% identified as Black, 20.1% as Hispanic, 53.5% White, and the remainder (9% mixed, 2% Asian, .3% American Indian and Alaskan Native (AIAN), .1% Native Hawaiian and Pacific Islander (NHPI)) were collapsed into an "other-race" category due to low base rates that posed model convergence issues (see measures below). See Table 1 for more demographic information on the analytic sample.

2.2. Imaging procedure

The imaging parameters used in the ABCD study have been reported in detail elsewhere (Casey et al., 2018). Briefly, imaging sessions were completed using one of three 3 T scanner models, depending upon site—Prisma (Siemens, Munich, Germany), Discovery MR750 (GE Healthcare, Chicago, IL), or Achieva dStream (Philips, Amsterdam, Netherlands) all using a 32-channel head coil. Participants completed T1-weighted and T2-weighted structural scans (1 mm isotropic) with prospective motion correction as determined by the ABCD pipeline (Hagler et al., 2019). Subjects completed four 5-minute eyes-open resting-state blood oxygen level-dependent scans. These resting-state images were acquired in the axial plane using an echo-planar imaging (EPI) sequence (2.4 mm isotropic voxels, TR = 800 ms, multiband acceleration factor = 6). Other resting-state image parameters varied by 3 T scanner type and are detailed elsewhere (Casey et al., 2018).

The Multi-Model Pressing Stress software package was used to analyze rsFC data using a combination of neuroimaging software packages (see Hagler et al., 2019 for a detailed review). Functionally defined cortical ROI time series (n = 333; Gordon et al., 2016) were calculated as the mean across all vertices in the surface representation and subcortical time series were calculated as the mean across all included voxels in the subcortical ROIs (n = 30; Fischl et al., 2002). Pairwise Pearson correlation values were generated for each of the [(N roi*Nroi-1)/2] possible pairs of ROIs and then Fisher-z transformed. Each ROI was assigned to a previously defined functional network (Hagler et al., 2019). Average within-system connectivity was computed using the average Fisher transformed correlation between each unique

Table 1
Participant and collection site characteristics for cases included in the final sample (N = 7834).

	N (%)
Site	
site02	480 (6.1)
site03	502 (6.4)
site04	599 (7.6)
site05	284 (3.6)
site06	442 (5.6)
site07	249 (3.2)
site08	222 (2.8)
site09	328 (4.2)
site10	505 (6.4)
site11	325 (4.1)
site12	433 (5.5)
site13	509 (6.5)
site14	467 (6.0)
site15	281 (3.6)
site16	928 (11.8)
site18	254 (3.2)
site20	541 (6.9)
site21	454 (5.8)
site22	31 (0.4)
Child race	
Black	1084 (13.8)
Hispanic	1574 (20.1)
Other (mixed, Asian, AIAN, NHPI)	983 (12.5)
White	4193 (53.5)
Child sex	
Female	3922 (50.1)
Male	3912 (49.9)
	M (SD)
Child age (mo)	119.3 (7.52)
Income-to-needs	3.73 (2.41)
Parent highest education (yrs)	20.28 (2.48)

pair of ROIs in the network. Similarly, between-system connectivity was computed by averaging the Fisher transformed correlation between each ROI in one network and all of the ROIs in a second network. Finally, network-to-ROI relationships were calculated by averaging the Fisher transformed correlations between each ROI in a given network and three subcortical ROIs (averaged across right and left hemispheres): the amygdala, hippocampus, and nucleus accumbens. These subcortical ROIs were chosen because of prior demonstrated relations between adverse childhood experiences and frontolimbic connectivity (e.g., Yaple and Yu, 2020).

2.3. Measures

2.3.1. Socioeconomic indices

Income-to-needs ratios (INR) were calculated by first taking the average of each binned income (<$5000, $5,000 - $11,999, $12,000 - $15,999, $16,000 - $24,999, $25,000 - $34,999, $35,000 - $49,999, $50,000 - $74,999, $75,000 - $99,999, $100000 - $199999, >=$200000) as a rough approximation of the family's total reported income. Income was then divided by the federal poverty threshold for the year at which a family was interviewed (range = $12,486 – $50,681), adjusted for the number of persons in the home. Highest education (in years) out of the two caregivers (or one if a second caregiver was not provided) was used as a continuous variable.

2.3.2. Material and economic deprivation

A total of seven items pertaining to economic hardship were chosen from the caregiver-reported ABCD Demographics Questionnaire. Specifically, seven items assess whether or not (1 =Yes; 0 =No) a family experienced any of the following financial-related hardships over the last 12 months: could not afford food, went without telephone service, could not pay rent or mortgage, were evicted, had gas or electric services suspended, and had a family member unable to visit the doctor or dentist.

2.3.3. Psychosocial threat

Threat exposure in the home was measured using youth reports on the 9-item ABCD Youth Family Environment Scale (FES). Items assess youths' perceived conflict within their family (e.g., *We fight a lot in our family, Family members sometimes get so angry they throw things, Family members sometimes hit each other*; 1 = True; 0 = False). Two items were positively-valenced and thus reverse-scored so that higher scores indicated greater experiences of threat.

2.3.4. Caregiver social support

The ABCD Children's Report of Parental Behavior Inventory (CRPBI) was used to measure levels of caregiver social support. While some youth reported on both caregivers, only five items corresponding to the primary caregiver (85% biological mother) were used to maximize the available data. Youth were asked how true (1 =Not like him/her; 2 =Somewhat like him/her; 3 =A lot like him/her) each of the following statements applies to their primary caregiver: *Makes me feel better after talking over my worries with him/her, Smiles at me very often, Is able to make me feel better when I am upset, Believes in showing his/her love for me*, and *Is easy to talk to.* Across all items, a score of 1 was endorsed in less than 1% of cases and therefore scores were collapsed and dichotomized such that a score of 1 or 2 was recoded to 0 and a score of 3 was recoded to 1.

2.3.5. Sociodemographic covariates

Child race and sex were included as control covariates in our substantive analytic models. Informed by group base rates (see Participants section above), child race was collapsed into 4 levels (White, Black, Hispanic, Other) and subsequently dummy-coded with White (the most numerous racial group) serving as the reference category in all models. Child sex was dichotomized such that 1 = Female and 0 = Male. Child age (in months) was used as a continuous variable and centered on the mean.

2.4. Statistical analyses

2.4.1. Establishing invariant measures of adversity and support

In an effort to ensure valid measurement of our environmental dimensions of experience, we conducted a series of psychometric analyses. Items from the ABCD demographics survey, family conflict survey, and caregiver support survey were chosen to represent measures of material/economic deprivation, psychosocial threat, and caregiver social support, respectively. Initial item screening was conducted via a series of graphical and descriptive statistics. For categorical items that did not meet a minimum covariance cell coverage (i.e., scores that did not have at least 1% endorsement), items were collapsed so that the models could be identified (this was the case for the caregiver social support items).

We then applied confirmatory factor analysis (CFA) models to assess the unidimensionality of each construct. CFA models for each construct demonstrated reasonable model fit, based on commonly-used thresholds (Hu and Bentler, 1999; Material and economic deprivation: χ^2 = 22534.32, p = .00, CFI =.96, RMSEA ==0.075 Psychosocial threat: χ^2 = 16532.77, p = .00, CFI =.=0.95RMSEA =.053; Caregiver social support: χ^2 = 176.27, p = .00, CFI =.9=0.99MSEA =.0=0.054). To test and subsequently adjust for partial measurement invariance among each of the established constructs, we then conducted MNLFA models (Fig. 1) using the automated MNLFA (aMNLFA; Gottfredson et al., 2019) R package Version 1.1.0 (Cole et al., 2021). Specifically, we tested for differences in the factor means, item intercepts/thresholds, and item factor loadings as a function of age, sex, race/ethnicity, INR, and parental education. In all models, the factor mean and factor variance were constrained to 0 and 1 when all covariates were centered (designating White 9.9-year-old boys with a college graduate parent and a family INR of 3.6 as the reference group). All models were fitted using a maximum likelihood estimator with Monte Carlo integration.

After testing for heterogeneity in the factor means and variances as a function of each of the sociodemographic covariates, heterogeneity in the loadings and the measurement intercepts were tested iteratively for each indicator variable. Benjamini-Hochberg adjustments were applied in this step to account for inflated type-1 error rates. A final model was generated by retaining all significant covariate effects on the factor (mean and variance) and items (thresholds and loadings) and fitted to the entire sample. Factor scores (expected *a posteriori* estimates) were then extracted from this final model and used in the main substantive analyses. In short, MNLFA factor scores assure a common scale of measurement across groups and age, as well as adjust for measurement DIF that would have otherwise biased our substantive analyses.

2.4.2. Investigating main and interactive effects of SES and environmental experiences on resting state functional connectivity

A series of mixed-effects models were fitted with distal indices of SES (INR and parent education) and environmental exposures (MNLFA scores) as predictors. Model outcomes (based on prior literature) included (1) within-network connectivity for the cingulo-opercular (CON), default mode (DMN), dorsal attention (DAN), ventral attention (VAN), frontoparietal (FPN), and salience networks (SAL); (2) between-network connectivity between the default mode (DMN) and SAL networks as well as the DAN and VAN networks; and (3) network-subcortical connectivity, specifically CON connectivity with the amygdala, hippocampus, and nucleus accumbens. To examine the robustness and predictive utility of our models, all model fitting steps were estimated with a randomly selected training set ($^2/_3$ of the sample, n = 5172). Final models were then used to predict rsFC outcomes in the holdout test set (n = 2662), and cross-validated R^2 was calculated to estimate the proportion of variance explained in data the model had not been fit to. Rates of missing data were low (less than 10% across all predictors) and missing predictors were interpolated using predictive mean matching (MICE package in R; Groothuis-Oudshoorn and Van Buuren, 2011). All models used a Nelder-Mead optimizer.

For each rsFC outcome, linear mixed-effects models were conducted using the lme4 package (Bates et al., 2015) in R 3.3. Specifically, we fitted a taxonomy of models. First, to address our key questions regarding the main-effect relations between our environmental measures and neural connectivity, we regressed each of the respective connectivity metrics on our key environmental measures and control covariates. This included sensitivity checks (e.g., quadratic terms) to confirm the linear nature of the relation of interest. We note that while race/ethnicity had to be retained as control covariates in our mixed models due to MNLFA requirements (see above), we do not interpret observed effects of race/ethnicity on rsFC. This is because such racial categories are confounded by historical and structural forms of marginalization that we did not measure explicitly (Henry et al., 2019), making any main effects challenging to thoroughly disentangle.

Each outcome was fitted in its own model and random effects for research site and family were included in all models to account for site- and family-level (i.e., sibling) nesting. Second, we then tested the extent to which the magnitude of the relation between common, broad markers of SES (i.e., income and parent education) and resting connectivity varied as a function of children's experiences of threat, deprivation, and support. Specifically, we examined the INR x threat and INR x support interactions, followed by parent education x threat, parent education x support interactions. Interactions between SES and material deprivation were not examined due to the potential for extrapolation (i.e., there were very few cases for which a child had high SES and high material deprivation). Significant interaction effects were probed for significance of simple slopes at one standard deviation below and one standard deviation above the mean for the moderator variable. All comparisons of nested models were conducted using likelihood ratio tests and changes in AIC.

The predictive utility of our final models was assessed by calculating R^2 in the held-out set, with an $R^2 > 0$ indicating that the model performed above chance in predicting variation in new data (Meteyard and Davies, 2020). Models that fell below an R^2 of 0 were deemed unreliable. We note that although this is a low threshold, R^2 from a cross-validated approach is more sensitive than from what is calculated in models fit to the full dataset, which are likely to be overfit and thus result in inflated R^2. Model estimates for models with cross-validated R2 > 0 were then estimated using the full sample. Models were adjusted for false discovery rate (FDR; $p < .05$) to correct for multiple comparisons and the adjusted p-values are reported (Benjamini and Hochberg, 1995).

Code for analyses presented here is available at https://osf.io/ma3sh/?view_only=c01ce6fbf24d46c29899d3624d164eb3.

3. Results

3.1. Measurement model of environmental experiences

Significant findings of non-invariant items, and non-invariant factor means and variances are reported below (for detailed model results see Table 2). Observed DIF effects were on item intercepts (i.e., predicted value of the indicator when the value of the latent variable is zero) and loadings (i.e., predicted change in items associated with a one-unit shift in the latent variable). In other words, even after controlling for the level of the latent variable, there were still some items that differed as a function of child age, racial group, sex, INR, and/or parental education level.

3.1.1. Material and economic deprivation

DIF testing via MNLFA indicated that five of the seven items were non-invariant as a function of income, parent education, and race. Specifically, holding the latent factor scores of material and economic deprivation constant, children from lower SES families, and children who identify as Black tended to endorse items referring to greater economic strain at different frequencies (see Table 2 and Fig. S2). Loading DIF was also found for three items as a function of INR, indicating a stronger association between those items and the latent factor. After adjusting for this non-invariance (i.e. DIF) at the item level, average group differences at the latent construct level indicated that children identifying as Black and children identifying as members of the other race category were exposed to greater levels of material and economic deprivation (B = 0.437, $p < .001$ and B = 0.248, $p <$ [TS8201 0.001ctively). Group differences were also found with parental education and INR, such that families with greater years of parental education and higher income had lower average deprivation exposure ($B = -0.059$, $p < .001$; $B = -0.298$, $p < .001$, respectively).

3.1.2. Psychosocial threat

Intercept and loading DIF was found across eight of the nine items of the youth-reported family conflict scale, indicating large amounts of DIF as a function of multiple sociodemographic characteristics (Table 2 and Fig. S2). Notably, while children from Black and less educated households endorsed threat items more frequently than other groups, there were no "true" substantive differences at the latent construct level after adjusting for these measurement biases. Average latent differences were found for age ($B = -0.009$, $p < .001$), with experiences of threat decreasing as children age. Children identifying as female ($B = -0.137$, $p < .001$) and children from higher-income families ($B = -0.093$, $p < .001$) experienced less threat, on average.

3.1.3. Caregiver social support

The MNLFA results indicated DIF for three items in the youth-reported CRPBI scale. Specifically, intercept DIF was found for three items as a function of several sociodemographic covariates and loading DIF was found for one item as a function of child sex. Notably, while Black children and children from higher educated homes endorsed two items more frequently, there were no corresponding substantive

Table 2
Results from final MNLFA models for material and economic deprivation, psychosocial threat, and caregiver social support constructs. In all models, the latent means are constrained to 0 and variances are constrained to 1 when all covariates are set to 0 for categorical covariates and mean-centered for continuous covariates (designating White 9.9-year-old boys with a college graduate parent and a family INR of 3.7 as the reference group).

	Differences at the latent level (factor means) and item level (DIF)						
Material deprivation (last 12 months)	Sex	Age	Black	Hispanic	Other	INR	Education
Factor mean: 0.00[a]	–	–	0.44 * **	–	0.25 * **	-0.30 * **	-0.06 * **
Factor variance: 1.00[a]	–	–	–	–	–	–	–
Item 1. Needed food but couldn't afford to buy it or couldn't afford to go out to get it?							
Threshold: 7.31	–	–	–	–	–	-0.92 * **	–
Loading: 3.25	–	–	–	–	–	0.39 * *	–
Item 2. Were without telephone service because you could not afford it?							
Threshold: 12.49	–	–	0.50 * **	–	–	-2.37 * **	–
Loading: 4.81	–	–	–	–	–	0.87 * **	–
Item 3. Didn't pay the full amount of the rent or mortgage because you could not afford it?							
Threshold: 4.69	–	–	–	–	–	–	–
Loading: 2.33	–	–	–	–	–	–	–
Item 4. Were evicted from your home for not paying the rent or mortgage?							
Threshold: 10.50	–	–	–	–	–	-1.31 * *	–
Loading: 3.29	–	–	–	–	–	0.49 * *	–
Item 5. Had services turned off by the gas or electric company, or the oil company wouldn't deliver oil because payments were not made?							
Threshold: 5.49	–	–	–	–	–	–	–
Loading: 2.14	–	–	–	–	–	–	–
Item 6. Had someone who needed to see a doctor or go to the hospital but didn't go because you could not afford it?							
Threshold: 5.11	–	–	–	–	–	0.01	0.12 * **
Loading: 1.95	–	–	–	–	–	–	–
Item 7. Had someone who needed a dentist but couldn't go because you could not afford it?							
Threshold: 3.94	–	–	-1.07 * **	–	–	-0.15 * **	–
Loading: 1.76	–	–	–	–	–	–	–
Psychosocial threat	Sex	Age	Black	Hispanic	Other	INR	Education
Factor mean: 0.00[a]	-0.14 * **	-0.01 * **	0.08	-0.03		-0.09 * **	0.01
Factor variance: 1.00[a]	–	–	–	–	–	–	–
Item 1. We fight a lot in our family.							
Threshold: 1.85	–	–	–	–	–	–	–
Loading: 2.12	–	–	–	–	–	–	–
Item 2. Family members rarely become openly angry.[b]							
Threshold: 0.88	0.12 *	–	0.23 * *	–	–	–	-0.04 * **
Loading: 0.93	0.33 * **	–	-0.24 *	–	–	–	0.05 * **
Item 3. Family members sometimes get so angry they throw things.							
Threshold: 2.60	–	–	–	-0.42 * **	–	-0.11 * **	–
Loading: 1.46		–	–	–	–	–	
Item 4. Family members hardly ever lose their tempers.[b]							
Threshold: 0.56	-0.04	–	-0.17	-0.31 * **	–	0.05 * *	-0.04 * *
Loading: 1.38	0.29 * *	–	-0.31 * *	–	–	0.07 * *	–
Item 5. Family members often criticize each other.							
Threshold: 1.86	–	–	0.12	–	–	–	–
Loading: 1.37	–	–	–	–	–	–	–
Item 6. Family members sometimes hit each other.							
Threshold: 1.60	-0.24 * **	-0.02 * **	–	-0.51 * **	–	-0.06 * **	–
Loading: 1.63	–	–	–	–	–	–	–
Item 7. If there's a disagreement in our family, we try hard to smooth things over and keep the peace.[b]							
Threshold: 2.66	–	–	–	–	–	-0.04 *	–
Loading: 1.02	–	–	–	–	–	–	–
Item 8. Family members often try to one-up or outdo each other.							
Threshold: 1.46	–	0.020 * **	–	–	–	–	–
Loading: 1.07	–	–	–	–	–	–	–
Item 9. In our family, we believe you don't ever get anywhere by raising your voice.[b]							
Threshold: 1.15	-0.14 * *	–	–	–	–	–	–
Loading: 0.61	–	–	–	–	–	–	–
Caregiver social support	Sex	Age	Black	Hispanic	Other	INR	Education
Factor mean: 0.00[a]	0.19 * **	0.01 * *	-0.02	–	-0.15 * **	0.02 *	-0.004
Factor variance: 1.00[a]	–	–	–	–	–	–	–
Item 1. Makes me feel better after talking over my worries with him/her.							
Threshold: − 2.05	–	–	0.37 * **	–	–	–	–
Loading: 2.13	–	–	–	–	–	–	–
Item 2. Smiles at me very often.							
Threshold: − 1.40	0.27 * **	–	–	–	–	0.07 * **	0.05 * *
Loading: 1.48	–	–	–	–	–	–	–
Item 3. Is able to make me feel better when I am upset.							
Threshold: − 2.46	–	–	–	–	–	–	–

(*continued on next page*)

Table 2 (*continued*)

Material deprivation (last 12 months)	Differences at the latent level (factor means) and item level (DIF) Sex	Age	Black	Hispanic	Other	INR	Education
Loading: 2.42	–	–	–	–	–	–	–
Item 4. Believes in showing his/her love for me.							
Threshold: – 4.72	–	–	–	–	–	–	–
Loading: 2.59	–	–	–	–	–	–	–
Item 5. Is easy to talk to.							
Threshold: – 1.13	-0.12	-0.02 * **	–	–	–	–	–
Loading: 1.34	0.39 * **	–	–	–	–	–	–

*p < .05, * *p < .01, * **p < .001.

[a] Indicates parameter values are fixed to identify the model and set the scale of the latent variable.

[b] Indicates item-reverse coded for interpretability.

differences at the latent construct level. Of the average differences on the latent construct that were found, older children ($B = 0.006$, $p < .001$), children identifying as female ($B = 0.188$, $p < .001$), and higher-income children ($B = 0.015, p = .032$) experienced greater social support from caregivers. Children in the other-race category experienced less social support compared to White children, on average ($B = -0.154$, $p < .001$).

3.2. Associations between SES, environmental factors, and rsFC

3.2.1. Associations between SES and environmental factor scores

Correlations between our environmental factor scores of material deprivation, psychosocial threat, and material support ranged between $r = -0.26$ to 0.04, highlighting the limited overlap of these constructs. These environmental measures were also associated with broader measures of SES, like INR and parental education (see Fig. 2 and Supplementary Figs. S1 and S3). Specifically, as expected, the material and economic deprivation factor was more strongly correlated with INR ($r = -0.71$) and less so for parental education ($r = -0.19$). In contrast, psychosocial threat exhibited only modest negative correlations with INR ($r = -0.25$) and parental education ($r = -0.12$). Even weaker correlations were found for caregiver social support and INR ($r = 0.04$) and education ($r = -0.001$). See Fig. S1 in Supplemental Material for a full and partial correlation matrix.

3.2.2. Associations with rsFC

As outlined above, the predictive utility of measures of SES and our environmental MNLFA factor scores on rsFC were investigated via mixed-effects models. All final models discussed below performed above chance ($R^2 > 0$ in the held-out test set), explaining between.7 – 3.5% of the variance in the held-out sample. Although this range is notably small, this represents a more robust indicator than the R^2 of models fit to the data used to generate the models themselves, which are prone to overfitting and thus can result in inflated R^2 estimates. Model estimates for statistically significant models were then estimated using the full sample, and are described in more detail below. Models reported below were adjusted for false discovery rate (FDR; $p < .05$) to correct for multiple comparisons (Benjamini and Hochberg, 1995). Full model results can be seen in Table 3 and Fig. 3.

3.2.2.1. Main effects of interest. Contrary to hypotheses and prior literature, few statistically significant associations between SES indices or environmental variables and rsFC were evident. Of the relations that reached statistical significance, standardized effect sizes were minimal in traditional terms but are nonetheless considered meaningful for a sample of this size according to recent reports by ABCD study team members (see Dick et al., 2021; Owens et al., 2020). Specifically, higher parental education was related to greater connectivity in the SAL network ($\beta = 0.04$; $p < .05$), as well as greater CON-hippocampus connectivity ($\beta = 0.04$; $p < .05$). With respect to our environmental MNLFA scores, greater psychosocial threat was related to less CON-amygdala ($\beta = -0.05$; $p < .001$) and CON-hippocampus connectivity ($\beta = -0.03$; $p < .05$). Notably, all of the aforementioned effect sizes fall around the ABCD median in-sample absolute value of.03 (Owens et al., 2020).

3.2.2.2. Interactions between SES and environmental factors on rsFC. We found that psychosocial threat moderated the association between INR and DAN-VAN connectivity ($\beta = -0.03$; $p < .05$). Although estimates are based on threat as a continuous variable, visualizations of this interaction using + /- one SD above (0.77) and below (−0.89) the mean (−0.06) (Fig. 3) illustrate that for DAN-VAN connectivity, children from lower-income families combined with higher levels of threat exhibited more connectivity than those who experienced lower levels of threat. The reverse was true for children from higher income families, such that children from higher-income homes combined with higher levels of threat demonstrated less connectivity than those who experienced lower

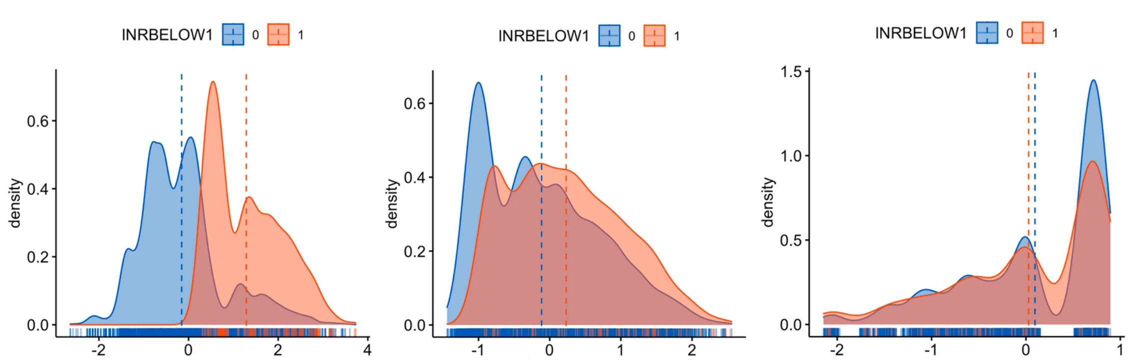

Fig. 2. Density plots illustrating overlap of MNLFA-derived dimensions of experience as a function of family income. Red = Families that fall at or below an income-to-needs ratio of 1 (i.e., 100% of the federal poverty threshold) and blue = those above an INR of 1. Plots demonstrate substantial individual variation in latent dimensions of children's experiences across high and low SES indices, further supporting the utility in moving beyond group comparisons of children designated as "high" or "low" on broad-scale SES indicators like family income.

Table 3
Final mixed effects models for resting-state connectivity outcomes that exhibited significant main or interactive effects of interest that survived correction. INR =income-to-needs ratio. INR and highest parent education are mean-centered. Material/Economic Deprivation, Caregiver Social Support, and Psychosocial Threat are MNLFA scores.

	SAL		DAN-VAN		CON-Amygdala		CON-Hippocampus	
Predictors	*Estimate (Standardized)*	*95% CI*	*Estimate (Standardized)*	*95% CI*	*Estimate (Standardized)*	*95% CI*	*Estimate (Standardized)*	*95% CI*
Intercept	-0.02	-0.10 – 0.06	0.03	-0.05 – 0.10	0.01	-0.04 – 0.06	-0.00	-0.05 – 0.04
Motion	-0.09 ***	-0.11 – -0.07	0.12 ***	0.10 – 0.15	-0.05 ***	-0.08 – -0.03	0.03 *	0.01 – 0.06
Age	-0.03 *	-0.05 – -0.01	-0.01	-0.03 – 0.02	-0.00	-0.02 – 0.02	-0.02	-0.05 – -0.00
Female	-0.01	-0.03 – 0.01	-0.02	-0.05 – -0.00	0.00	-0.02 – 0.02	-0.00	-0.02 – 0.02
Black	-0.04 **	-0.07 – -0.02	0.04 *	0.01 – 0.07	-0.13 ***	-0.15 – -0.10	-0.12 ***	-0.15 – -0.10
Hispanic	-0.01	-0.03 – 0.02	-0.00	-0.03 – 0.02	-0.05 ***	-0.08 – -0.03	-0.07 ***	-0.10 – -0.04
Other	-0.01	-0.03 – 0.01	0.00	-0.02 – 0.03	-0.03 *	-0.05 – -0.01	-0.01	-0.03 – 0.01
INR	0.01	-0.03 – 0.05	-0.03	-0.07 – 0.01	0.03	-0.01 – 0.07	0.01	-0.03 – 0.05
Highest Ed	0.04 *	0.01 – 0.06	-0.01	-0.04 – 0.02	0.01	-0.02 – 0.04	0.04 *	0.01 – 0.07
Material/Economic Deprivation	-0.01	-0.04 – 0.03	0.00	-0.04 – 0.04	-0.01	-0.05 – 0.03	-0.01	-0.05 – 0.03
Psychosocial Threat	0.02	-0.01 – 0.04	0.03 *	0.01 – 0.06	-0.05 ***	-0.07 – -0.02	-0.03 *	-0.05 – -0.01
Caregiver Social Support	0.02	-0.00 – 0.05	0.02	-0.00 – 0.05	-0.01	-0.03 – 0.02	-0.02	-0.04 – 0.01
INR x Psychosocial Threat			-0.03 *	-0.05 – -0.01				
ICC	0.06		0.13		0.10		0.02	
N	6828 $_{rel\_family\_id}$		6828 $_{rel\_family\_id}$		6828 $_{rel\_family\_id}$		6828 $_{rel\_family\_id}$	
	19 $_{sitenum}$		19 $_{sitenum}$		19 $_{sitenum}$		19 $_{sitenum}$	
Observations	7834		7834		7834		7834	
Marginal R^2 / Conditional R^2	0.015 / 0.070		0.026 / 0.155		0.032 / 0.127		0.027 / 0.050	
AICc	-6492.955		-21927.487		-8549.394		-14231.499	
log-Likelihood	3261.508		10979.778		4289.728		7130.780	

* $p<0.05$ ** $p<0.01$ *** $p<0.001$

levels of threat. Johnson-Neyman plots and analysis of simple slopes further showed that the relation between INR and DAN-VAN was only statistically significant for children experiencing high levels of threat (+1 SD: $\beta = -0.002$; $p = .01$; Mean: $\beta = -0.001$; $p = .13$; −1 SD: $\beta = 0.00$; $p = .93$ (Supplementary Fig. S4)). No other statistically significant interactions were found.

4. Discussion

An accumulating body of research has begun elucidating the neural correlates of socioeconomic differences in childhood. This work has largely been distinct from much of the developmental psychology literature, which has increasingly adopted more nuanced approaches to measuring the SES context and children's experiences to better understand sources of risk, resilience, and adaptation in child outcomes. In this study, we sought to advance our understanding of the neural correlates of SES by disentangling the effects of individual variation in continuous indices of SES as well as dimensions of more proximal and subjective experiences. To do this, we adopted moderated nonlinear factor analysis to ensure our measures were valid representations of true individual differences at the latent construct level (MNLFA; Bauer, 2017). MNLFA afforded empirical tests and subsequent statistical adjustment for measurement DIF—or biases—as a function of key sociodemographic covariates including child age, sex, racial group, family INR, and parental education level. Broadly, our findings illuminate the importance of reducing measurement biases to gain a more socioculturally-valid understanding of the complex links between the environment and brain development.

4.1. Measuring dimensions of experience: Do these measures mean the same thing for diverse groups of children in the ABCD study?

Our first aim sought to characterize individual variation in key aspects of children's experiences. We found substantial item-level measurement biases across all three dimensions of experience, suggesting that these scales did not mean the same thing for children from diverse sociodemographic groups. This was a critical finding given that such measurement DIF can lead to biased conclusions if left unadjusted. Psychosocial threat—indexed via child-reported family conflict in the home—showed the most extensive sociodemographic measurement differences. Specifically, eight out of nine items that make up this measure showed evidence for DIF as a function of at least one of the sociodemographic covariates tested except for the 'other' racial group category. The most notable effects came from DIF for the Black and household education covariates, which importantly did not show corresponding significant effects at the latent construct level. In other words, children who identified as Black and children from lower-educated households were more likely to endorse several items corresponding to more severe family conflict regardless of their actual levels of threat. A typical summary score would have inaccurately suggested that Black and lower SES children experience more psychosocial threat than White or higher SES children, despite the true latent construct being the same across groups. Evidence for such racial and class measurement biases has far reaching implications that could compromise our collective efforts for a more socioculturally-appropriate cumulative science. MNLFA's ability to empirically adjust for this measurement bias demonstrates the utility of the method.

Our measure of material and economic deprivation revealed that lower-income as well as Black families tended to endorse items related to difficulty paying for certain services and food—irrespective of their true value on the latent construct. In other words, beyond broad material deprivation, certain groups face specific barriers to accessing particular resources. Our measure of caregiver social support exhibited the fewest instances of DIF, with stronger endorsement of positive caregiver interactions from Black children and children from higher SES homes. Child sex and age also showed DIF for one item referring to ease of communication with their caregiver, reflecting normative developmental changes in the meaning of caregiver-child relationship (Larson

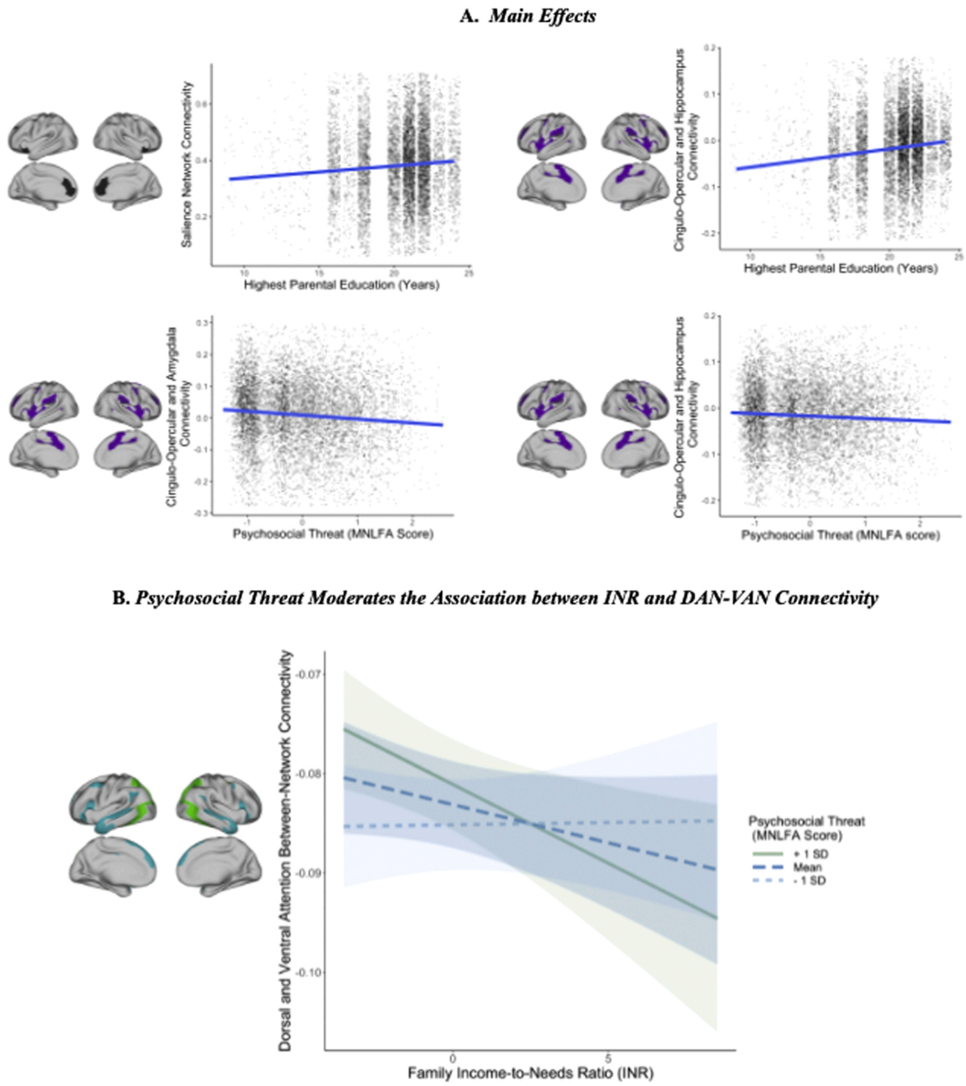

Fig. 3. (A) Main effects relations between socioeconomic and environmental variables and child resting-state functional connectivity. (B) Interactive effect of income-to-needs ratio (INR) and psychosocial threat MNLFA score on DAN-VAN connectivity. Only effects that remained statistically significant following correction in final mixed models are illustrated. Blue lines indicate the predicted effect superimposed on the raw data points. Abbreviations: MNLFA = moderated nonlinear factor analysis; DAN = dorsal attention network; VAN = ventral attention network. Hippocampus and amygdala ROIs not shown.

et al., 1996).

At the latent construct level, average group and individual differences were found across all three environmental factors, highlighting how key dimensions of experience are uniquely characterized for different children. For the material and economic deprivation factor, Black children, children from the other-race category, and children from lower-income or lower educated households experienced greater deprivation. We speculate that these differences in families' levels of resource scarcity are a reflection of the ways both race and education intersect with historical forms of racial segregation and social stratification in the U.S., with persisting racial wealth gaps and barriers to accessing social safety nets (Henry et al., 2019; Gibson-Davis et al., 2021; Parker et al., 2016). For both the psychosocial threat and caregiver social support factors, similar effects were found. First, average differences were found for sex and age, which could reflect sex-specific and developmental shifts in children's ability to recognize and appraise emotional and social interactions (for a review, see McClure, 2000). Children from the other-race category also experienced less caregiver support, whereas children from lower-income families experienced greater threat and less caregiver support. These findings align with prior research demonstrating how financial hardship and/or being a part of a marginalized racial group places added pressures on families (Coll et al., 1996; Henry et al., 2019). Such pressures may lead families to adopt more culturally- and ecologically-adaptive socialization processes that better equip children with the tools needed to navigate social and racial marginalization (Wang et al., 2020).

Descriptively, minimal to moderate correlations between all but one of the factor scores and SES indices illuminate the importance of moving beyond income or education to better understand the rich heterogeneity in adversity and support that children across the socioeconomic spectrum experience. In this large population-based sample of children spanning a wide SES range, we found significant overlap in our environmental constructs between high- and low-SES children—providing further support for incorporating methods that account for individual variation in several key contextual and ecological factors. These descriptive findings also replicate and extend the relations found in an MNLFA model, composed of similar environmental constructs among a population-based sample of children living in rural poverty (DeJoseph et al., 2021). Collectively, these observations support the growing appreciation in the field for individual differences in children's environmental experiences to better understand sources of strength and risk implicated in socioeconomic advantage and disadvantage (Ellis et al., 2020; Merrick et al., 2019).

4.2. Associations with resting-state functional brain connectivity: Disentangling the effects of SES and environmental experiences

Our second aim sought to test the unique and interactive effects of

SES and our newly-derived dimensions/factors of child experiences on an a priori subset of rsFC networks underlying cognitive, emotional, and behavioral regulation. Overall, we found very few statistically significant relations and did not replicate many environmental and SES brain relations typically observed in prior work. However, given our measurement approach and large sample size, our findings offer enhanced precision to detect small but nonetheless important effects. Beginning with findings related to SES, parent education was uniquely associated with greater connectivity in the SAL network, which is responsible for voluntary top-down attentional control as well as detecting and filtering salient stimuli (Grayson and Fair, 2017). Parent education, over income, may be related to this more goal-directed attention monitoring network given the ways experiences with caregivers shape individual differences in higher order cognitive processes (e.g., Rosen et al., 2019). We also found parental education to be a unique predictor of CON-hippocampus connectivity, which aligns with prior work showing relations between education and patterns of activation involved in working memory processes (e.g., Sheridan et al., 2012). These findings for education, which were not demonstrated for income, could be suggestive of the more direct role parent education has for scaffolding executive networks. Similarly, these findings highlight the importance of using multiple indices of SES and align with recent meta-analyses showing variations in neural and cognitive outcomes depending on how SES is operationalized (Yaple and Yu, 2020; Chuan-Peng, Cai, Fried, Forschner, 2021).

Beyond the effects of socioeconomic factors, only one of our environmental variables uniquely predicted rsFC. Greater levels of psychosocial threat were associated with lower CON-amygdala and CON-hippocampus connectivity. This finding aligns with prior work suggesting that threat may be primarily associated with stress and affect regulation—with greater threat linked to more “adult-like” or negative frontolimbic coupling (Gee et al., 2013; Rosen et al., 2019; McLaughlin and Sheridan, 2016; Tian et al., 2021).

We found little support for our hypotheses about the potentially interactive role of proximal experiences on SES-rsFC relations. The association between INR and DAN-VAN connectivity—networks that are known to interact to control dynamic top-down and bottom-up shifts in attention (Vossel et al., 2014)—was moderated by psychosocial threat. In the context of higher threat, children from lower-income homes showed amplified connectivity whereas children from more affluent homes showed attenuated connectivity. It may be the case that the combination of both economic scarcity and high threat results in the recruitment of more sustained hypervigilance, which may not be as critical in more economically-resourced homes. This interpretation is consistent with both neural and behavioral evidence showing enhanced attention biases to threat in the context of adversity (e.g., Raver et al., 2017; Silvers et al., 2017; Dufford et al., 2019). In other words, due to compounding constraints, what is adaptive in one context may not be adaptive in another, and recent brain-behavior evidence in the ABCD supports this (Ellwood-Lowe et al., 2020). Disentangling how these observed patterns are related to behavior and wellbeing is an important future direction.

Linking the above findings to our first aim, the absence of many of our predicted associations highlight the importance of testing and adjusting for potential measurement biases. Indeed, prior work in the ABCD study has shown relations between the environmental measures used in the current study and various neurodevelopmental metrics (e.g., Thijssen et al., 2020; Modabbernia et al., 2021; Hong et al., 2021; Rakesh et al., 2021b). We may not have come to similar conclusions due to the way in which MNLFA creates person-specific scores that empirically adjust for sociodemographic heterogeneity in item responses. Instead of weighting each item equally as is done implicitly in any sum or mean score, MNLFA creates adjusted factor scores that statistically weight each item as a function of person-level measurement biases as well as variation in the type and severity of each item’s relation to the latent construct (Gottfredson et al., 2019). Not accounting for DIF and item-level weighting in this way can lead to substantively different conclusions, which our team has shown in prior work (DeJoseph et al., 2021). Thus, a notable benefit of MNLFA is that it increases confidence that associations between environmental dimensions and neurodevelopment are driven by variation at the *construct level* rather than by measurement artifact.

While we can speculate about what the aforementioned environment-brain associations may mean, we are limited in our ability to make any strong conclusions given the cross-sectional nature of our approach and the lack of behavioral measures included in the current study. Developmental theory rests on the idea that dynamic fluctuations in one’s environment bi-directionally interact across multiple levels of analysis over time (Gottlieb, 1991). In the present study, we were only able to capture a very small snapshot of time, and thus an important next step in the ABCD (and beyond) is to examine the role that timing, chronicity, and dosage of these environmental dimensions play across brain-environment and brain-behavior patterns (Hyde et al., 2020; Smith and Pollak, 2021; McLaughlin et al., 2020). It is also critical to move beyond racial group membership as a proxy for systemic racial injustices which are inextricably linked to accessibility to a range of health, school, and community resources that can affect brain development (Graham et al., 2021). An intersectional approach that considers the complex relationship between race and class in the U.S. will be required to better understand how structural dynamics intersect with the more proximal dimensions of experience like those examined in the current study (for a review, see Henry et al., 2019). Indeed, recent work has demonstrated various approaches to measuring structural inequities (e.g., Dougherty et al., 2020), and such measures can be considered as an additional dimension that should be empirically tested when adopting dimensional models of adversity. Finally, the integration of both adversity and strengths-based perspectives will be essential in understanding how socioeconomic disadvantage both undermines *and* enhances aspects of neurodevelopment under various ecological conditions—informing remedial programs as well as efforts that leverage unique stress-adapted strengths (Ellis et al., 2020; Frankenhuis et al., 2020).

4.3. Methodological considerations

Although this study has numerous strengths, several limitations are worth noting. As mentioned, we only used the first full wave of data, precluding our ability to examine causal or developmental processes that could be driving associations between the environment and rsFC. The use of cross-sectional data also prevented any valid tests of statistical mediation (Kline, 2015), which will be an important future direction to further probe the ways in which dimensions of experiences explain broader relations between SES and neural connectivity over time. Second, our study assessed three environmental dimensions of experience limited to three representative measures, but the inclusion of additional measures and dimensions that incorporate the broader ecological context is warranted. For example, measures of unpredictability and the home linguistic environment are thought to shape brain development in important ways, and direct examination of these associations is an important avenue for future investigation. Third, while our factor scores afforded enhanced individual variation, summary measures of network connectivity may obscure heterogeneity necessary for detecting certain effects. Indeed, research has demonstrated substantial individual differences in node-to-node connectivity that will be an important area of future inquiry in this sample (Cui et al., 2020). Fourth, recent research has highlighted the interpretive importance of the choice of brain parcellation used in studies of resting-state functional connectivity (Bryce et al., 2021). However, we restricted our analyses to the tabulated data in the ABCD repository which only includes the Gordon parcellation, thus future research should attempt to replicate these results using alternative parcellations or individual-specific brain atlases. Fifth, we are unable to draw meaningful conclusions about the observed effects for the other-race category (mixed, Asian, AIAN, NHPI), which was collapsed due to low cell counts that posed issues with model identification. Future work should examine these relationships in more direct ways via subgroups analyses or person-centered approaches. Finally, the generalizability of our findings is constrained to 9-to-10-year-old children living in predominantly urban U.S. cities, and therefore future analyses with similar types of variables to those assessed here will be important for assessing measurement validity of environmental constructs and respective associations with brain development.

5. Conclusions

Collectively, the current study provides critical insights into sociodemographic measurement biases in commonly-used environmental measures in the ABCD, providing a methodological solution for testing and adjusting for these psychometric biases resulting in more socioculturally accurate conclusions. We further demonstrated how the greater socioeconomic context additively contributes to, and interacts with, such environmental measures to predict select brain connectivity networks supporting cognitive, emotional, and behavioral regulation. Importantly, the brain is highly malleable during adolescence, which can be viewed as a period of opportunity for promoting resilience in the face of hardship. As we reflect on growing inequalities stemming from the COVID-19 pandemic and persistent racial injustices, ensuring valid measurement of our constructs should remain a top priority for meaningful scientific progress that aims to guide policies serving diverse children and families. Our results lend support for legislation that invests in families through supplemental income, like the recent child tax credit expansion, which is likely to promote children's healthy brain development. Our findings also shed light on the more proximal experiential factors that may serve as targets for intervention as we wait for large-scale policy reform. Taken together, a more nuanced understanding of the complex ways the socioeconomic context and children's day-to-day experiences interact to shape neurodevelopment holds promise to yield insights that promote and protect the wellbeing of today's youth.

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CRediT authorship contribution statement

Meriah DeJoseph: Conceptualization, Methodology, Software, Formal analysis, Resources, Data curation, Writing – original draft, Visualization, Project administration. **Max Herzberg**: Conceptualization, Data curation, Writing - MRI Methods and Writing – review & editing. **Robin Sifre**: Software, Validation, Writing – review & editing. **Daniel Berry***:* Supervision, Methodology, Writing – review & editing. **Kathleen Thomas**: Conceptualization, Supervision, Project administration, Writing – review & editing.

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.

Data Availability

Data for this study is available through the NIMH ABCD Data Repository (https://nda.nih.gov/abcd).

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.dcn.2021.101043.

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