Characterizing relationships between resource insecurity, internalizing symptoms, and functional brain connectivity in children

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ABSTRACT

Exposure to poverty is associated with a variety of negative developmental effects in children. However, poverty is a complex, multidimensional concept that can be defined from a material, social, and/or economic perspective, giving rise to many potential mediators that may each have different developmental effects. Prior research has found a relationship between poverty and the development of internalizing symptomatology in children and adolescents, but little is known about the neurodevelopmental effects of specific dimensions of poverty such as resource insecurity. In this study, we pursued a novel measure of resource insecurity, defined as an inability to pay for food, housing/utilities, or medical care due to cost. To that end, after establishing a relationship between resource insecurity and internalizing symptom scores in a sample of 4,351 9-10-year-old children using open-source data acquired from the Adolescent Brain Cognitive Development (ABCD) Study, we identified neural signatures of resource insecurity based on whole-brain functional connectivity patterns. Although the strength of functional brain networks that differed between resource secure and insecure children did not vary with internalizing symptom scores, psychopathology often does not manifest until later in adolescence, and future research should examine longitudinal relationships between resource insecurity and the development of psychopathology. Our findings underscore the importance of examining measures of poverty that reflect experience and suggest that resource insecurity is a sensitive measure for detecting risk for clinical symptoms and associated differences in neural circuitry.

INTRODUCTION

According to the U.S. Census Bureau, 17.5% (or 12.8 million) of people under the age of 18 were living in poverty in 2017, a higher rate than any other age group. Exposure to poverty has been shown to correlate with a variety of negative developmental effects in children, impacting behavior, cognition, and brain function and structure (Lipina & Posner, 2012; Blair & Raver, 2016; Hair et al., 2015). However, "poverty" is a multidimensional term that can be defined from a material, social, and/or economic perspective, giving rise to numerous potential mediating factors (e.g., prenatal maternal health, maternal stress, and the co-occurrence of adversities) that may each have different developmental effects (Lipina & Evers, 2017; McLaughlin et al., 2014; McLaughlin et al., 2011; Raver et al., 2017). Additionally, economic measures of poverty, such as family income or income-to-needs ratio, do not necessarily explain an individual's experience of poverty, as there is great variation in lived experiences even within an income level (Johnson et al., 2016; Merz et al., 2018). Given the prevalence of poverty, especially among children, who are more likely to live in poverty than adults or the elderly, it is important that we understand how different experiences of poverty affect development (U.S. Census Bureau, 2018).

Researchers have studied other measures that better represent an experience of poverty, correlate with economic measures of poverty, and have also been associated with developmental effects in children, including "poverty-related adversity", "early-life stressors/trauma", or maltreatment (Raver et al., 2017; Demir et al., 2016; Thomason et al., 2015; Herringa et al., 2013). For instance, chronic exposure to stress and adversity have been linked to problems with emotion and stress regulation, as well as the development of internalizing disorders, such as major depressive disorder and generalized anxiety disorder (Duncan et al., 2017; Raver et al., 2017; Tandon et al., 2009). In fact, emotion dysregulation itself has been shown to predict the development of internalizing disorders (McLaughlin et al., 2011). Food insecurity, another measure that captures a specific experience of poverty, has also been associated with internalizing symptoms in children, and, moreover, it has been shown to be a better predictor of internalizing symptoms in children than poverty level (Slopen et al., 2010; Wight et al., 2014).

In addition to behavioral developmental effects, these experiences of poverty have also been linked to altered functional brain connectivity measured with functional magnetic resonance imaging (fMRI) in children (Demir et al., 2016; Thomason et al., 2015). These studies linked early-life stress to altered prefrontal resting-state functional connectivity (Demir et al., 2016) and trauma to altered amygdala functional connectivity (Thomason et al., 2015). Consequently, in the present study we investigate the relationships between resource insecurity (defined as the inability to afford access to food, housing/household utilities [i.e., gas, electricity, and phone], or healthcare), internalizing symptoms, and resting-state functional connectivity in children. Given prior research linking various measures of poverty to internalizing symptoms, we predict group-level differences in internalizing symptom scores based on resource insecurity, as well as a positive association between resource insecurity and internalizing symptoms. Additionally, we hypothesize altered resting-state functional connectivity in participants who have experienced resource insecurity, compared to participants who have not, and that these group-level differences in functional brain network strengths will then predict internalizing symptom scores.

Defining poverty and resource insecurity

The literature is rich with examinations of the developmental effects of "poverty," which has been associated not only with negative behavioral outcomes, but also with changes in brain structure, function, and connectivity (Pungello et al., 1996; Luby et al., 2013; Merz et al., 2018; Hair et al., 2015; Noble et al., 2015; Blair & Raver, 2016; Sheridan et al., 2012; Johnson et al., 2016). Socioeconomic status (SES) is one of the most common measurements used to study poverty, and although it can be defined differently, SES is typically measured in terms of social factors such as (parental) educational attainment and occupational status and economic factors such as an income-to-needs ratio (Farah, 2017; Ursache & Noble, 2016). For instance, the U.S. Census Bureau's annually calculated Federal Poverty Level (FPL) is an income-to-needs ratio that estimates the minimum income an average family needs to cover the bare necessities (e.g., food, shelter, and clothing), and the FPL was $25,100 for a household of four in 2018. However, although widely accepted due to its ease of use, this official poverty measure has been critiqued for inadequately gauging the true needs and circumstances of families, resulting in the more nuanced supplemental poverty measure in 2011 (Hutto et al., 2011). Moreover, while low SES may suggest an economic circumstance of poverty, it does not necessarily describe an individual's subjective experience of poverty (Johnson et al., 2016; Farah, 2017; Evans, 2004).

In order to examine particular experiences of poverty, researchers have utilized measurements such as exposure to chronic stress or stressful life events (e.g., residential relocation, extended parent-child separation; Demir et al., 2016; Evans & Schamberg, 2009; Evans & Kim, 2010; Luby et al., 2013); food insecurity (Wight et al., 2014; Slopen et al., 2010); and "poverty-related adversity," which aggregates family household income, family size, and exposure to stressors resulting from financial hardship (e.g., not being able to pay bills, not having heat, not having phone, having electricity shut off; Raver et al., 2017). These measurements often help constrain our interpretations of the effects of SES because they address the experiences of material deprivation and financial instability that result from having a low income. Thus, in the present study we measure resource insecurity. This measure captures the experience of material hardship that results from low income that other researchers have also tried to address with their measures. By allowing us to narrow in on the poverty-related experience of not being able to afford basic necessities, studying resource insecurity helps provide a more nuanced picture of the potential effects of poverty (Neckerman et al., 2016).

Resource insecurity and internalizing symptoms

Resource insecurity encompasses three types of material hardship: food insecurity, housing hardship, and medical hardship. Other studies that utilized similar measures of material hardships, whether individually or as part of a broader measure incorporating a combination of types of material hardships, have revealed behavioral effects on, for instance, executive function and control, academic achievement, and emotion regulation (Johnson et al., 2016; Raver et al., 2013; Cutts et al., 2011; Raver et al., 2017). Financial strain (i.e., "the degree to which families had enough money in the household to cover the costs of housing, food, clothing, and medical care") was found to be predictive of 4-year-old children's performance on measures of executive function (Raver et al., 2013). This finding is of particular note considering the mediating role that executive function has been shown to play in the development of childhood internalizing disorders, such as depression (Morris et al., 2014; McLaughlin, 2016; Hankin et al., 2016).

Several studies have revealed a significant relationship between measures related to resource insecurity and internalizing symptoms (i.e., behaviors and moods associated with anxiety, depression, and withdrawal, such as having low self-esteem or being fearful; Achenbach & Ruffle, 2000). A study of 2,810 children (ages 4-14 years, mean age 8.2 years) who participated in the longitudinal Project on Human Development in Chicago Neighborhoods focused on the role of poverty and food insecurity on the risk for childhood psychopathology and found that children from households that were persistently food insecure over a two-year period were 1.5 times more likely to have higher internalizing symptoms than children from food secure households (Slopen et al., 2010). A similar relationship was found between food insecurity and mental disorders (as opposed to symptom scores) in a U.S. national sample (n=6,483) of adolescents (ages 13-17 years), and a study measuring poverty-related adversity, which included food insecurity, housing hardship, and medical hardship, also found a positive relationship with internalizing symptomatology in 8- to 11-year-old children (McLaughlin et al., 2012; Raver et al., 2017). Furthermore, these studies revealed not only that food insecurity was associated with internalizing symptoms and disorders, but also that food insecurity was more strongly related to internalizing symptoms and disorders than traditional SES measurements (e.g., parental education and income), implicating food security as a novel risk factor for mental well-being in children and adolescents (Slopen et al., 2010; McLaughlin et al., 2012). These findings also highlight the sensitivity of children to their environment and the importance of studying poverty through the lens of resource insecurity. Consequently, given these findings, we expect to find a similarly positive relationship between resource insecurity and internalizing symptom scores.

Resource insecurity, internalizing symptoms, and the brain

Despite the existing literature on the relationship between indicators of resource insecurity and internalizing symptoms, there is a lack of research examining the potential impact of resource insecurity on functional brain connectivity. To our knowledge, there has been no research on the relationship between resource insecurity and functional brain connectivity to date. Additionally, although there is an abundance of studies that have examined the impact of poverty via other measures, especially SES, on the developing brain (Raizada et al., 2008; Lipina & Posner, 2012; Johnson et al., 2016), these studies have primarily revealed effects on structure, such as differences in regional brain volume (Noble et al., 2012; Luby et al., 2013) and in cortical surface area (Noble et al., 2015), rather than functional connectivity.

Investigations of functional brain connectivity have only begun to surge in recent years, and of the few studies that have explored the relationship between poverty and functional brain connectivity, many are retrospective and primarily examine functional connectivity in adults who had previously experienced poverty during childhood (Sripada et al., 2014; Thomason et al., 2015). However, a study of children and adolescents (ages 7-12 years) by Barch et al. (2016) described that lower income-to-needs in early childhood was associated with reduced resting-state functional connectivity between the amygdala and hippocampus. Moreover, the study found that hippocampal and amygdala connectivity mediated the relationship between income-to-needs and negative mood/depression severity, providing novel data associating poverty with both brain development and negative mental health outcomes (Barch et al., 2016).

There is also a growing body of literature examining resting-state functional connectivity and major depressive disorder (MDD; Wang et al., 2012; Kaiser et al., 2015; Jalbrzikowski et al., 2017). MDD, an internalizing disorder, has been linked to large-scale network dysfunction, with hypoconnectivity within the frontoparietal network and hyperconnectivity within the default mode network in adults and teens (ages 13-80 years; mean age 37.77 years; Kaiser et al., 2015), as well as altered resting-stating functional connectivity between the amygdala and ventromedial prefrontal cortex in children and young adults (ages 10-22 years; Jalbrzikowski et al., 2017). Another study examining functional connectivity in adolescents (n=26, ages 15-19 years) with MDD, as well as various comorbid anxiety disorders (e.g., generalized anxiety disorder, social phobia), found they exhibited decreased functional connectivity between subgenual anterior cingulate cortex (ACC) and a network of cortical areas, such as the supragenual ACC, right medial frontal cortex, and left inferior and superior frontal cortex (Cullen et al., 2009). These studies employed hypothesis-driven analyses, focusing on a specific network or seed region, primarily in the frontal lobe. However, given the lack of research in this topic and prior findings of large-scale, aberrant functional connectivity, we instead analyze whole-brain functional connectivity patterns and build a connectome-based predictive model (Finn et al., 2015) to assess the relationships between resource insecurity, internalizing symptoms, and functional brain connectivity using a data-driven approach. We predict that there will be differences in resting-state functional connectivity between resource secure and resource insecure children, and that, given a positive correlation between resource insecurity and internalizing symptom scores, these network strength differences will be able to predict internalizing symptom scores.

METHODS

The ABCD study design and sample

We obtained open-source data from the Adolescent Brain Cognitive Development (ABCD) Study. The ABCD Study is a national, longitudinal study tracking a baseline cohort of 11,872 9-10-year-old children for 10 years, and both behavioral and fMRI data are collected at 21 sites across the United States. The ABCD Data Release 1.1 (November 2018) includes 4,521 participants (47.5% female, mean age 10 years ± 7 months) from 21 sites (ranging from n=35-430). Excluding for subjects with autism spectrum disorder (n=90), epilepsy (n=33), or missing demographics questionnaire data for items regarding resource insecurity (n=47) left 4,351 participants (48.1% female, mean age 10 years ± 7 months). There was no missing data for internalizing symptom scores. After the exclusion criteria were applied, the number of participants from each of the 21 sites ranged from n=34 to 416. Table 2 shows the characteristics of the study sample.

One child per family replication sample

Since siblings have the same demographics questionnaire data for items regarding resource insecurity and could thus skew our findings, we created a subsample with only one child randomly selected from each family (based on self-report) in order to replicate our results from the original sample. After limiting the original sample to one child per family, analyses were restricted to 3,778 subjects (47.2% female, mean age 10 years ± 7 months). We investigated for potential differences in results between the full sample and this subsample using two-sample t-tests. However, there were no significant differences in demographic variables (e.g., age, sex, race/ethnicity) between the two samples ($p>0.05$). Additionally, removing siblings had no significant effect on the positive relationship between resource insecurity and internalizing symptoms ($r=0.12$, $p<0.01$) or on the difference in internalizing symptom scores between the resource secure (mean=47.92, s.d.=10.12) and resource insecure (mean=51.69, s.d.=11.26) children ($p<0.001$). Thus, results based on data from the full sample are presented in the main text. Characteristics of this subsample are displayed in Table 2.

Resource insecurity

The present study used resource insecurity to narrow in on the specific poverty-related experience of not being able to afford basic necessities. Parents of participants were administered a comprehensive demographics survey uniquely developed by the ABCD Study (Barch et al., 2018). It included seven questions that were used to evaluate resource insecurity, to which parents could respond: “Yes,” “No,” or “Refuse to answer” (Table 1).

Binary measure. Responses were used to create a discrete, binary measure: resource secure vs. resource insecure. Participants were categorized as resource secure (n=3,552, 81.6%)

if the parent responded negatively to all 7 questions, or resource insecure (n=799, 18.4%) if the parent responded affirmatively to at least 1 of the 7 questions. (If the parent responded "Refuse to answer" to at least one question, the participant was excluded for missing data, as previously mentioned in the exclusion criteria.)

Continuous measure. Responses were also used to create a continuous measure of resource insecurity. This measure was only for exploratory purposes, as the two groups of the binary measure are too unequal in sample size for further analyses to be feasible. This dimensional measure scored how many of the seven questions the parent responded affirmatively to and thus ranges from 1 through 7.

In the past 12 months, has there been a time when you and your immediate family experienced any of the following:	*n*
1. Needed food but couldn't afford to buy it or couldn't afford to go out to get it?	277
2. Were without telephone service because you could not afford it?	196
3. Didn't pay the full amount of the rent or mortgage because you could not afford it?	393
4. Were evicted from your home for not paying the rent or mortgage?	39
5. Had services turned off by the gas or electric company, or the oil company wouldn't deliver oil because payments were not made?	209
6. Had someone who needed to see a doctor or go to the hospital but didn't go because you could not afford it?	214

7. Had someone who needed a dentist but couldn't go because you could not afford it?	404

Table 1. Demographics survey questions used to evaluate resource insecurity. This table presents the 7 questions from the demographics survey that were used to evaluate resource insecurity. It additionally provides the number of participants whose parent responded "Yes" to each question.

Internalizing symptom scores

Internalizing symptom scores were measured using the Child Behavior Checklist (CBCL) for children ages 4 to 18 years. The CBCL is a widely used, standardized parent-report survey used to assess behavioral and emotional problems in children across eight syndrome scales (i.e., aggressive behavior, anxious/depressed, attention problems, rule-breaking behavior, somatic complaints, social problems, thought problems, and withdrawn/depressed) and two broad-band scales (i.e., internalizing and externalizing; Achenbach & Ruffle, 2000). The internalizing subscale of the CBCL sums the scores of the anxiety, depression, and withdrawal syndrome scales. T-scores, which are adjusted for age, gender, and race, were used for analyses.

Statistical analyses

The present study aimed to assess a relationship between resource insecurity and internalizing symptom scores in children. Due to the unequal sample sizes in the resource secure vs. resource insecure groups, we used a Mann-Whitney u-test to determine a difference in the distribution of internalizing symptom scores between the two groups. The Mann-Whitney u-test is a nonparametric test that does not assume normal distributions, unlike the t-test.

In addition, to characterize the relationship between the degree of resource insecurity experienced and internalizing symptom scores, we created a linear best-fit model relating the continuous measure of resource insecurity to internalizing symptom scores.

MRI data acquisition and preprocessing

Structural and functional MRI data were acquired via the ABCD Fast Track data release. 5,642 participants had a high-resolution anatomical scan that passed visual quality control and at least one functional scan with acceptable levels of head motion (i.e., maximum head displacement <3 mm, maximum rotation <3 degrees, and mean frame-to-frame displacement <0.15 mm). Of these, 3,452 children had at least one 5-minute run of resting-state data. Task data were not analyzed here. Participants without demographics questionnaire or internalizing symptom score data were excluded from this sample, leaving 2,432 participants for the analyses examining the potential neurodevelopmental effects of resource insecurity.

Preprocessing was performed using BioImage Suite (Joshi et al., 2011) and custom Matlab scripts as described in Finn et al. (2015). Steps included head motion correction; regression of covariates including head motion parameters, linear and quadratic drift, and mean signal from cerebrospinal fluid, white matter, and gray matter; and temporal smoothing with a zero mean unit variance Gaussian filter.

Resting-state functional connectivity patterns were defined using a 268-node atlas including cortical, subcortical, and cerebellar brain regions (Shen et al., 2013). The atlas was warped from MNI space into single-subject space, and a time course was calculated for each node, which represented a distinct brain region, by averaging the time courses of all of the voxels that comprised the node. Pearson correlation coefficients between the time courses of all possible pairs of nodes were computed and used to produce symmetric 268 x 268 connectivity matrices, in which each element represented the connection strength, or edge, between a pair of nodes.

fMRI data analysis

To examine whether resource insecurity is reflected in patterns of resting-state functional brain connectivity, the whole-brain connectivity matrices were used for connectome-based predictive modeling (CPM), a data-driven method of developing predictive models used to establish a relationship between brain connectivity data and behavioral measures (Finn et al., 2015; Rosenberg et al., 2016; Shen et al., 2017). The CPM method includes a within-dataset cross-validation loop to assess model generalizability. Thus, after matching the fMRI data to the behavioral data of the same participant, subjects were randomly sorted into training and testing sets for cross-validation. 90% (n=2,188) of the sample was randomly selected to comprise the training set, while the remaining 10% comprised the testing set. To account for potential skewing from the random selections of the training and testing samples, we ran this iterative model 1,000 times.

Group-level differences in resting-state functional connectivity. The training set was used to first determine if group-level differences in resting-state functional connectivity arise based on resource insecurity (i.e., between participants who have and have not experienced resource insecurity), as hypothesized. For each functional connection, or edge, a Mann-Whitney u-test was used to compare the strength of the edge between the resource insecure and resource secure groups. Significant contrasts ($p<0.01$) were used to create a positive network of connections stronger in the resource insecure group and a negative network of connections stronger in the resource secure group.

Predicting resource insecurity. Next, we examined if these networks constructed from the training set generalized such that the testing set could identify whether a participant was in the resource secure or insecure group. If the testing set could not accurately categorize participants, we could not expect the model to predict internalizing symptoms. For each participant in the testing set, the mean strength of all significant positive edges (as previously determined by the training set) and the mean strength of all significant negative edges were calculated. A Mann-Whitney u-test was used to compare the means between the resource secure and resource insecure groups, and a one-sample t-test was used to compare the resulting z-scores. We confirmed not only that there is a group-level difference in resting-state functional connectivity based on resource insecurity, but also that the model can use the resulting positive and negative networks to distinguish between the resource insecure and resource secure groups.

Predicting internalizing symptoms. Based on our hypotheses that there would be a group-level difference in functional brain connectivity based on resource insecurity, as well as a positive association between resource insecurity and internalizing symptoms, we also hypothesized that there would be a positive association between the group-level difference in strengths of functional networks based on resource insecurity and internalizing symptom scores. To assess the ability of our model to predict internalizing symptom scores in a novel population, we tested for a Spearman correlation between each test set participant's overall strength in the positive and negative networks (i.e., the sum of all functional connections in these networks) and their internalizing symptom scores. One-sample t-tests were used to analyze the resulting correlation coefficients.

RESULTS

Characteristic	**Full sample** *n=4,351*		**1 child per family subsample** *n=3,778*	
	n	%	*n*	%
Biological Sex				
Female	2,092	48.1	1,785	47.2
Male	2,259	51.9	1,993	52.8
Race/Ethnicity				

White	2,553	58.7	2,167	57.4
Hispanic	846	19.4	782	20.7
Black	433	10.0	373	9.9
Asian	100	2.3	91	2.4
American Indian/Alaska Native (AIAN)	13	0.3	13	0.3
Native Hawaiian/Pacific Indian (NHPI)	5	0.1	4	0.1
Mixed	368	8.5	318	8.4
Other	24	0.6	22	0.6
N/A	9	0.2	8	0.2
Resource insecurity				
Resource secure	3,552	81.6	3,056	81.0
Resource insecure	799	18.4	722	19.0
Site				
1	123	2.8	118	3.1
2	220	5.1	158	4.2
3	267	6.1	256	6.8
4	318	7.3	296	7.8
5	108	2.5	103	2.7
6	205	4.7	190	5.0
7	124	2.8	118	3.1
8	145	3.3	141	3.7
9	272	6.3	256	6.8
10	112	2.6	105	2.8
11	109	2.5	105	2.8
12	296	6.8	276	7.3
13	292	6.7	165	4.4
14	164	3.8	152	4.0
15	416	9.6	375	9.9
16	258	5.9	250	6.6
17	126	2.9	123	3.3
18	254	5.8	145	3.8
19	249	5.7	163	4.3
20	259	6.0	249	6.6
21	34	0.8	34	0.9

Table 2. Demographic characteristics of full sample and 1 child per family subsample. To assure that findings were not driven by the fact that participants from the same family have the same demographics data and thus the same measure of resource insecurity, we created a subsample with only one randomly selected child from each family. This table displays the

biological sex, race/ethnicity, and resource insecurity of the participants of both the full sample and the 1 child per family subsample, as well as the site at which they were recruited. Two-sample t-tests were performed, which revealed that there are no significant differences in any of the characteristics between the full sample and the 1 child per family subsample (p>0.05).

Characteristic	**Resource Secure** *n=3,552*		**Resource Insecure** *n=799*	
	n	%	*n*	%
Biological Sex				
Female	1,723	48.5	369	46.2
Male	1,829	51.5	430	53.8
Race/Ethnicity				
White	2,279	64.2	274	34.3
Hispanic	604	17.0	242	30.3
Black	257	7.2	176	22.0
Asian	97	2.7	3	0.4
American Indian/Alaska Native (AIAN)	8	0.2	5	0.6
Native Hawaiian/Pacific Indian (NHPI)	3	0.1	2	0.3
Mixed	281	7.9	87	10.9
Other	16	0.5	8	1.0
N/A	7	0.2	2	0.3
Site				
1	98	2.8 (79.7)	25	3.1 (20.3)
2	209	5.9 (95.0)	11	1.4 (5.0)
3	188	5.3 (70.4)	79	9.9 (29.6)
4	213	6.0 (67.0)	105	13.1 (33.0)
5	93	2.6 (86.1)	15	1.9 (13.9)
6	180	5.1 (87.8)	25	3.1 (12.2)
7	117	3.3 (94.4)	7	0.9 (5.6)
8	129	3.6 (89.0)	16	2.0 (11.0)
9	205	5.8 (75.4)	67	8.4 (24.6)
10	85	2.4 (75.9)	27	3.4 (24.1)
11	89	2.5 (81.7)	20	2.5 (18.3)
12	247	7.0 (83.4)	49	6.1 (16.6)
13	263	7.4 (90.1)	29	3.6 (9.9)
14	102	2.9 (62.2)	62	7.8 (37.8)

15	338	9.5 (81.3)	78	9.8 (18.7)
16	242	6.8 (93.8)	16	2.0 (6.2)
17	115	3.2 (91.3)	11	1.4 (8.7)
18	215	6.1 (84.6)	39	4.9 (15.4)
19	187	5.3 (75.1)	62	7.8 (24.9)
20	207	5.8 (79.9)	52	6.5 (20.1)
21	30	0.8 (88.2)	4	0.5 (11.8)

Table 3. Demographic characteristics of full sample, by resource insecurity. This table provides the biological sex, race/ethnicity, and site of the resource secure and resource insecure groups of the full sample. For sites, in parentheses is the percentage of participants from that site who are resource secure (or insecure), as opposed to the percentage of resource secure (or insecure) participants from each site.

Behavioral measure: Relating resource insecurity to internalizing symptom scores

. As hypothesized, a Mann-Whitney u-test revealed a significant group-level difference in internalizing symptom scores, based on resource insecurity ($p<0.001$). The resource insecure group had higher internalizing symptom scores (mean=51.37, s.d.=11.30) than the resource secure group (mean=47.70, s.d.=10.09; Fig. 1). This finding was replicated in the 1 child per family subsample ($p<0.001$; resource insecure: mean=51.69, s.d.=1.26; resource secure: mean=47.92, s.d.=10.12).

Furthermore, a linear best-fit model revealed a positive association between resource insecurity and internalizing symptom scores, both when analyzing only the data of children who have experienced resource insecurity ($r=0.12$, $p<0.001$, Fig. 2) and when incorporating the resource secure group as resource insecurity = 0 ($r=0.13$, $p<0.001$), replicating prior research (Slopen et al., 2010; McLaughlin et al., 2012; Raver et al., 2017). Thus, also as hypothesized, higher internalizing symptom scores correlated with greater degree of resource insecurity experienced. This finding was replicated in the 1 child per family subsample ($r=0.12$, $p<0.01$).

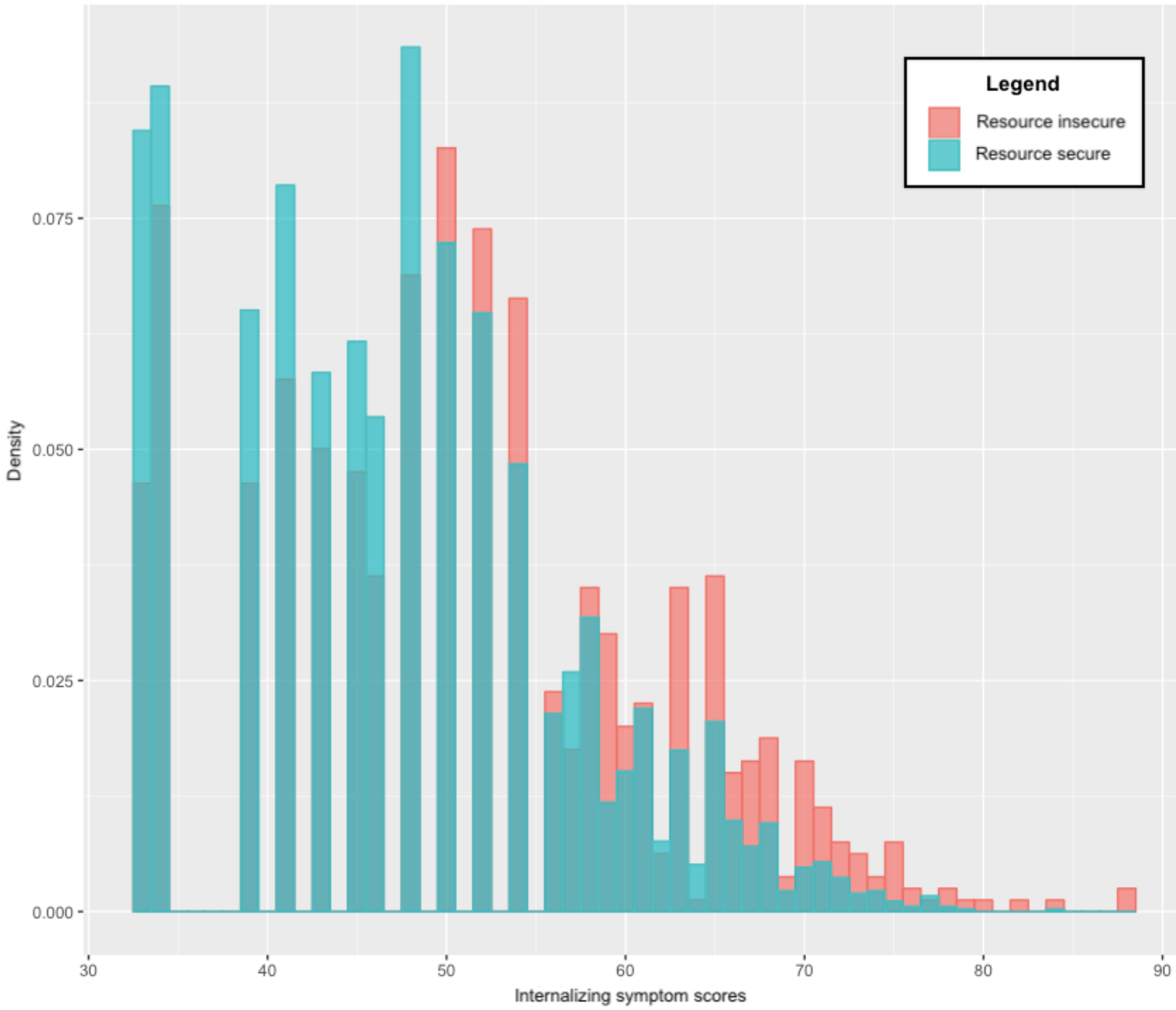

Fig. 1. Group-level difference in internalizing symptom scores, by resource insecurity. This density histogram shows the statistically significant ($p<0.001$) difference in the distribution of internalizing symptom scores between the resource secure (in blue) and resource insecure (in red) groups. The darker shade shows the overlap between the two groups for each score. The resource insecure children had greater internalizing symptom scores (mean=51.37, s.d.=11.30) than the resource secure children (mean=47.70, s.d.=10.09). We used a density histogram, which shows the relative proportion (rather than absolute count) of participants with each internalizing symptom score in each group, due to the significantly unequal sizes of the two groups.

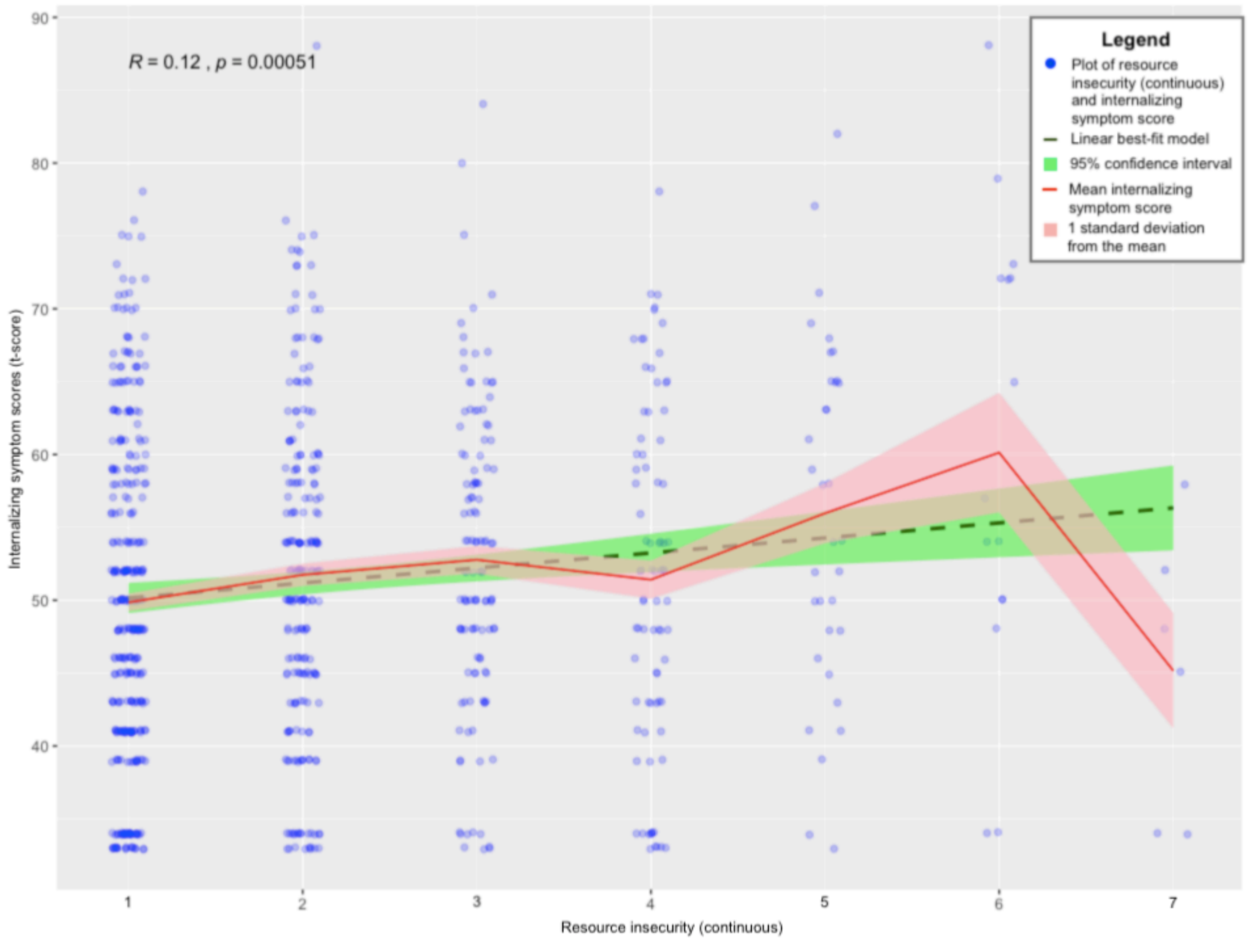

Fig. 2. Positive correlation between continuous measure of resource insecurity and internalizing symptom scores. This jittered scatterplot displays the internalizing symptom scores of only resource insecure participants. A linear best-fit model (dashed green line) of the internalizing symptom scores by the continuous measure of resource insecurity revealed a positive association between the two variables ($r=0.12$, $p<0.001$). The surrounding green area of the linear best-fit model represents the 95% confidence interval. The solid red line depicts the mean internalizing symptom score for each level of resource insecurity; the surrounding pink area represents 1 standard deviation from the mean.

fMRI data: Group-level differences in resting-state functional connectivity

Since we are interested in the potential neurodevelopmental effects of resource insecurity, we constructed whole-brain connectivity matrices using resting-state data. Mann-Whitney u-tests were used to compare the connection strengths between the resource insecure and resource secure groups for each edge of the connectivity matrices in the training set (90% of the imaging sample), and statistically significant contrasts ($p<0.01$) revealed a group-level difference in resting-state functional connectivity, as hypothesized.

The contrasts were used to construct a preliminary positive network of connections stronger in the resource insecure group (compared to the resource secure group) and a preliminary negative network of connections stronger in the resource secure group (compared to the resource insecure group). Analyses of the testing set confirmed that these preliminary networks generalized to novel populations such that the model could utilize them to distinguish between participants who had and had not experienced resource insecurity (Fig. 3).

fMRI data: Predicting for internalizing symptom scores?

Our predictive model was not able to use the neural signatures of resource insecurity found in the training set (Fig. 4) to predict for internalizing symptom scores in the novel testing set (Fig. 5). One-sample t-tests revealed that the correlation coefficients of the relationship between the mean strength of positive edges and internalizing symptom scores were greater than 0 ($p<0.001$), but the mean effect size (mean=0.020) was negligible. Another one-sample t-test revealed that the correlation coefficients of the relationship between the mean strength of negative edges and internalizing symptom scores were not significantly greater than 0 ($p>0.05$). Thus, the strength of the functional brain networks constructed using the training set did not correlate with internalizing symptom scores of the participants in the testing set. We explore potential explanations and provide suggestions for future directions in the Discussion.

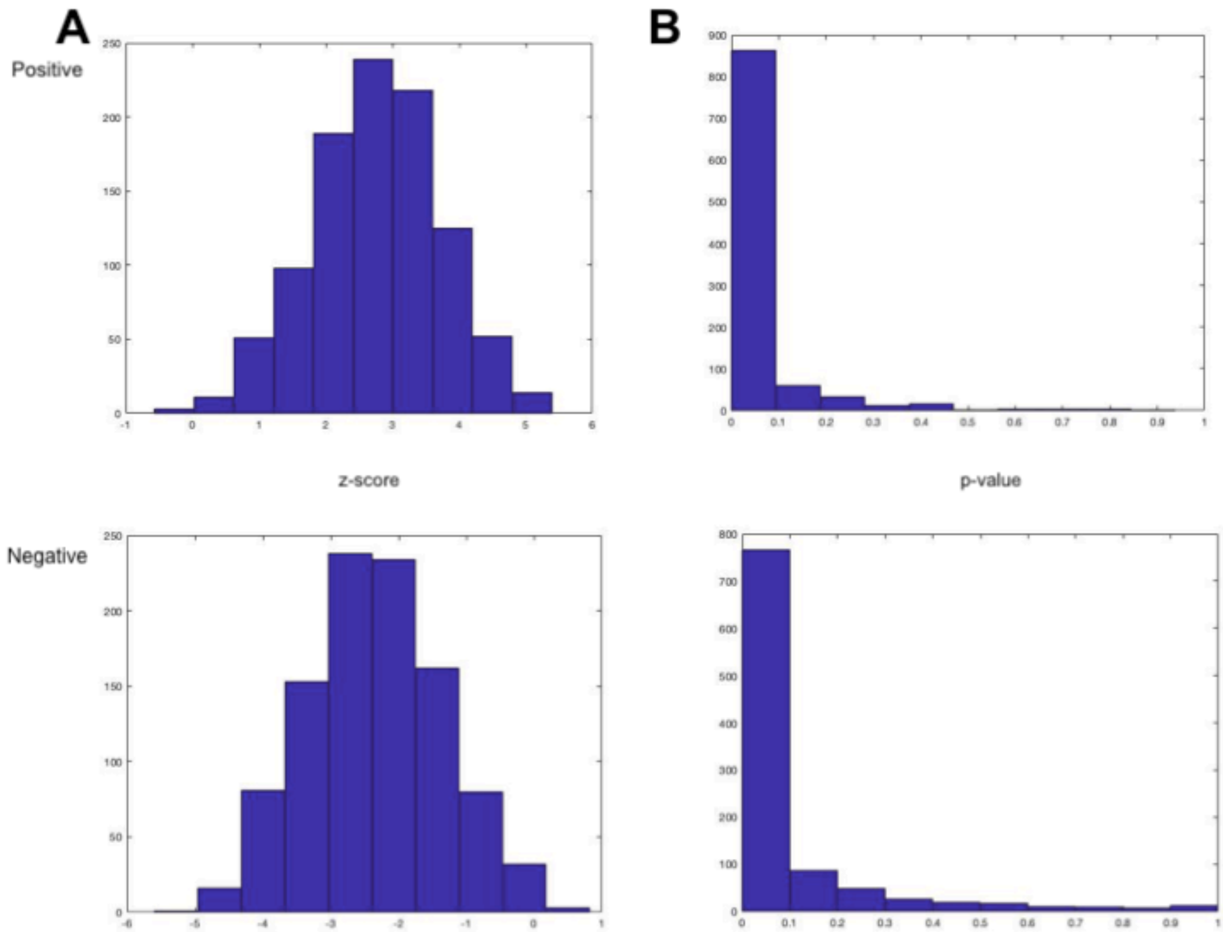

Fig. 3. Network strengths predict resource insecurity. These histograms display results of the 1,000 iterative runs of our predictive model, showing (**A**) z-scores and (**B**) p-values of the comparisons. A Mann-Whitney u-test was used to compare the mean strength of the positive edges, and then the mean strength of the negative edges, between resource secure and insecure participants. One-sample t-tests of the resulting z-scores revealed that the strengths of positive edges (top row) were significantly greater in resource insecure participants ($p<0.001$), while the strengths of negative edges (bottom row) were significantly greater in resource secure

participants (p<0.001), and that the positive and negative network strengths were thus able to predict resource insecurity in participants.

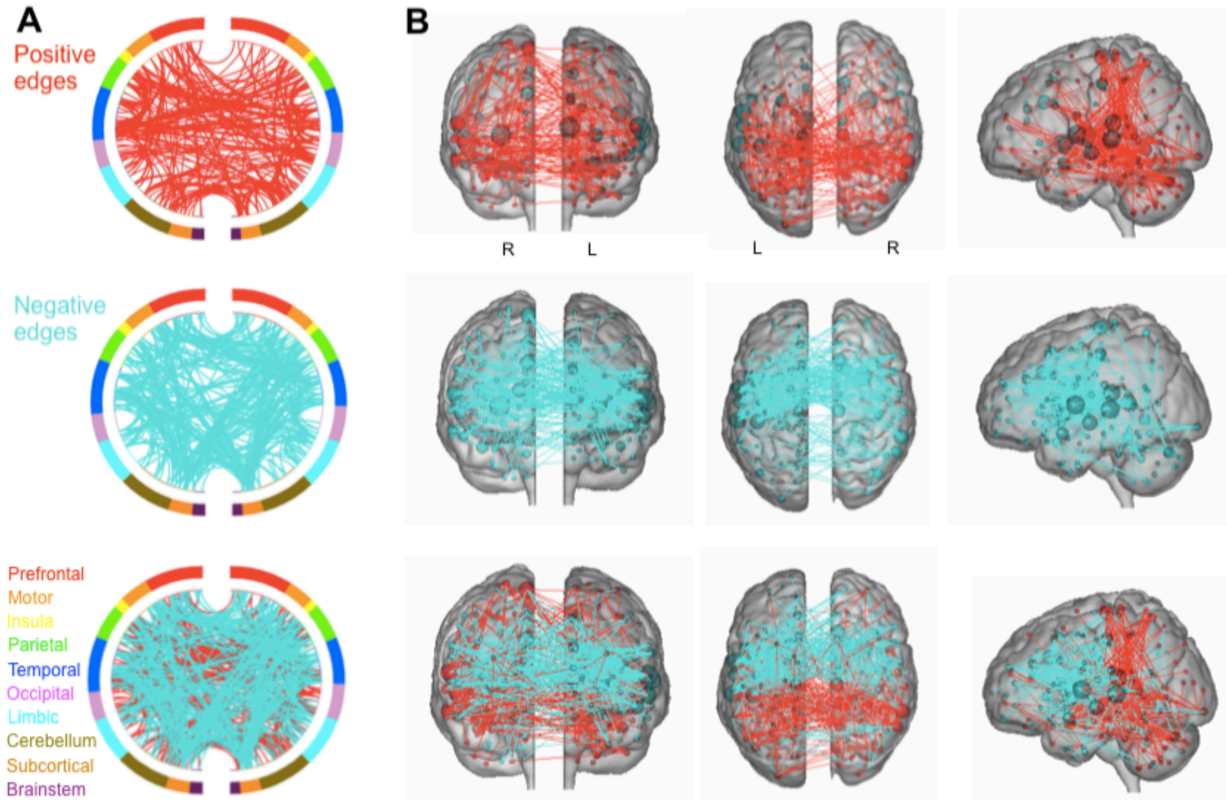

Fig. 4. Visualizing positive and negative networks (group-level differences). Using connections between nodes (i.e., edges) that appeared in all 1,000 iterations of cross-validation, these illustrations were created using BioImage Suite Connectivity Viewer (Joshi et al., 2011). (**A**) The circle plots show positive edges (in red), which are the network connections significantly stronger in the resource insecure group, and negative edges (in blue), which are the network connections significantly stronger in the resource secure group (p<0.01). Nodes are arranged in two half-circles reflecting approximate brain anatomy from anterior (top of circle) to posterior (bottom of circle), color-coded by cortical lobe (Shen et al., 2017). (**B**) The glass brain plots show the specific nodes, with the size of the node reflecting the number of connections

extending from the node, from frontal, dorsal, and lateral (left) perspectives.

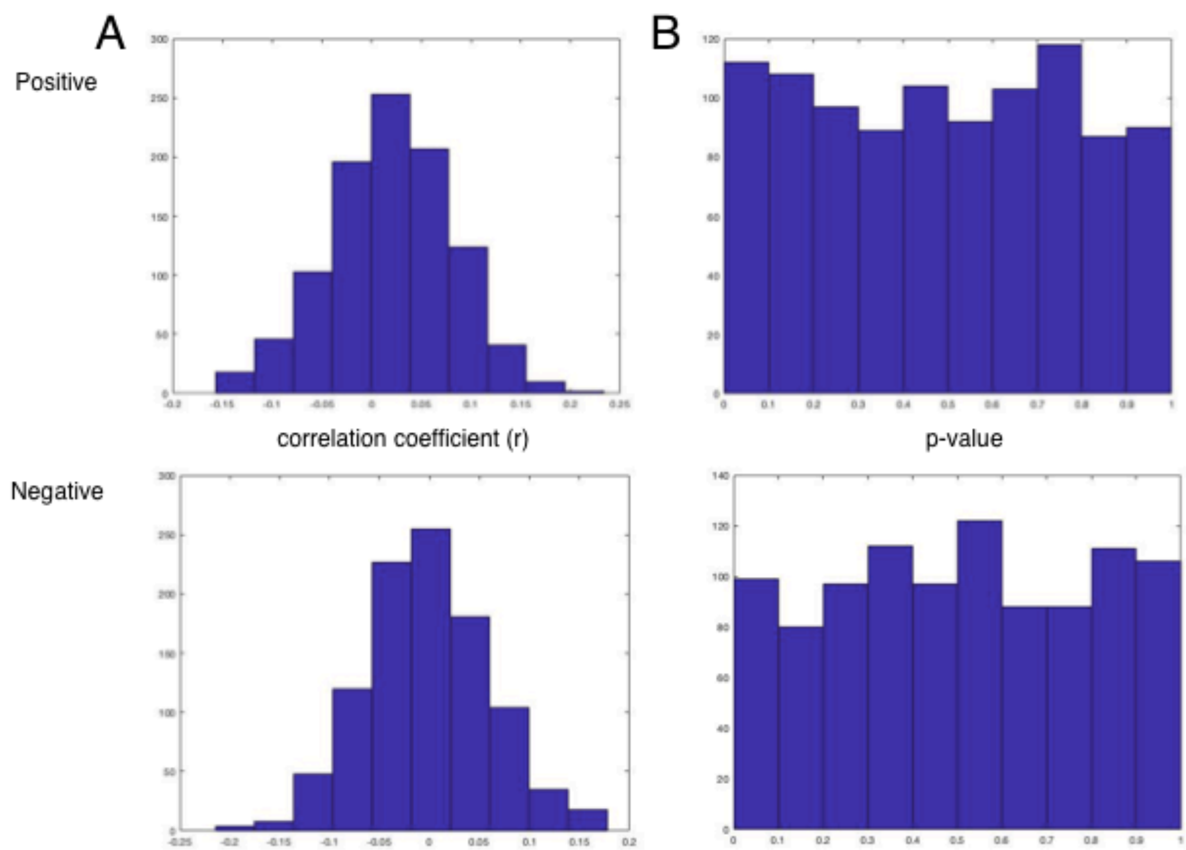

Fig. 5. No correlation between positive or negative network strengths and internalizing symptom scores in testing set. We attempted to use the positive (top row) and negative (bottom row) network strengths to predict for internalizing symptom scores in the testing set, but were ultimately unsuccessful. The histograms show the results of the 1,000 iterative runs of our predictive model, providing (**A**) correlation coefficients and (**B**) p-values. One-sample t-tests revealed that the correlation coefficients of the relationship between the mean strength of positive edges and internalizing symptom scores were greater than 0 ($p<0.001$), but the mean effect size (mean=0.020) was negligible. Another one-sample t-test revealed that the correlation coefficients of the relationship between the mean strength of negative edges and internalizing symptom scores were not significantly greater than 0 ($p>0.05$).

DISCUSSION

This study demonstrates that experiences of resource insecurity are positively associated with higher internalizing symptom scores in 9- to 10-year-old children. Furthermore, we show that resource insecurity is linked not only with behavioral differences in children, but also with differences in their functional brain connectivity. Whole-brain resting-state functional connectivity analyses revealed a positive network of connections stronger in children who have experienced resource insecurity, as well as a negative network of connections stronger in children who have not experienced resource insecurity in the past 12 months. These findings demonstrate that resource insecurity is an important measure of poverty that has significant associations with behavioral and neural developmental differences in children, and they also highlight the importance of studying measures that account for experiences of poverty.

These results are in line with our hypotheses and with prior research, replicating several studies that found a positive relationship between measures related to resource insecurity and internalizing symptom scores, as well as the development of internalizing disorders (Slopen et al., 2010; McLaughlin et al., 2012; Raver et al., 2017). Moreover, this study addresses a gap in the literature and contributes as the first study to examine the potential neurodevelopmental effects of resource insecurity rather than, for example, of socioeconomic status.

In addition, the anatomy of our networks seems to align with previous research that examined resting-state functional connectivity in subjects with MDD, an internalizing disorder, and in subjects who have experienced early-life stress. For instance, Kaiser et al. (2015) found hypoconnectivity in the frontoparietal network in teens and adults with MDD, and Cullen et al. (2009) found decreased functional connectivity with the subgenual ACC (located in the frontal lobe) in adolescents with MDD. Demir et al. (2016) also linked early-life stress with altered prefrontal resting-state functional connectivity in children (ages 4-7 years). Similarly, we found that the negative network is primarily anterior to the positive network, suggesting that resting-state functional brain connectivity in the frontal lobe is stronger in resource secure children, and thus weaker in resource insecure children, who had higher internalizing symptom scores.

Contrary to our hypotheses, however, the strength of the functional brain networks that differed between participants who had and had not experienced resource insecurity did not vary with internalizing symptom scores. A possible explanation for why our model did not predict higher internalizing symptoms in children who have experienced resource insecurity is that our sample consisted of 9- to 10-year-old children, and internalizing disorders typically do not manifest until later in adolescence or adulthood (de Lijster et al., 2017). Additionally, our sample was cross-sectional, utilizing the first data release set of the ABCD Study. Future studies will be able to analyze longitudinal data for changes in functional brain connectivity and internalizing symptom scores and to reassess the predictive abilities of resource insecurity in the same sample of participants through adolescence and young adulthood. However, it is still important to note that, even at this younger age of 9 to 10 years, we are able to find significant differences in internalizing symptom scores and resting-state functional connectivity based on resource insecurity, highlighting the extent to which environmental variables may influence child mental health and development.

Several limitations should be considered when evaluating the present findings. First, our measure of resource insecurity was assessed using questionnaire data self-reported by the parent, and certain experiences described by the parent (e.g., not being able to afford food) may not necessarily describe the experience of the child. In addition, our measure of resource insecurity encompasses three types of material hardship: food insecurity, housing hardship, and medical hardship. While all are experiences of poverty, each may have different potential developmental effects and should also be further studied independently to assess for more nuanced associations. Third, there are 21 research sites at which data is collected for the ABCD Study, and statistical analyses revealed that there were greater proportions of resource insecure participants recruited at certain sites than at other sites (Table 3). Consequently, site differences may be potential covariates that are unaccounted for in our predictive model. However, given the current size of the sample and the range in participants from each site (n=34-416), single-site analyses were not feasible. Future studies may be able to address these limitations once datasets of larger sample sizes are released by the ABCD Study.

CONCLUSION

Resource insecurity, which encompasses food insecurity, housing hardship, and medical hardship, is an important predictor of physical and mental health in both children and adults (Ma et al., 2008; Kushel et al., 2006), as is poverty in general (Farah, 2017; Comeau & Boyle, 2017). Previous investigations into the developmental effects of poverty have often done so through the lens of socioeconomic status, but in this study, we used a measure of resource insecurity that we found to be linked with higher internalizing symptom scores and differences in resting-state functional connectivity in children, suggesting that resource insecurity is a sensitive measure for detecting risk for clinical symptoms and associated differences in neural circuitry.

These findings have implications for policy recommendations, providing evidence in support of the necessity of policies such as food assistance programs, affordable or universal healthcare, and affordable housing. This is especially important in light of today's political climate. In March 2019, the current administration released its budget for the upcoming year, and its key proposals included budget cuts of hundreds of billions of dollars from the Supplemental Nutrition Assistance Program (SNAP), which provides nutritional support for over 40 million people nationwide (U.S. Department of Agriculture, 2019); Medicaid, which provides health insurance coverage for 65 million individuals, half of which are children (Centers for Medicare & Medicaid Services, 2019); and the U.S. Department of Housing and Urban Development (HUD), which provides various services, including rental assistance for 5 million households, half of which are families with children (Center on Budget and Policy Priorities, 2019; Rabinowitz & Uhrmacher, 2019). These are the very same programs that address the material hardships faced by the resource insecure participants in this study—food insecurity, medical hardship, and housing instability—and without which (or without enough funding) even more individuals, and more children, would experience resource insecurity and, perhaps, its potential effects on mental health and functional brain connectivity.

Of course, resource insecurity is not the only hardship experienced by individuals living in poverty; it is not the only measure of the experience of poverty. Ultimately, our findings underscore the importance of studying poverty via measures that, like resource insecurity, reflect lived experiences of poverty, not just economic circumstances of poverty. Identifying such measures and their effects is crucial to developing interventions specific to those experiences and informed policies with the aim of not only mitigating the detrimental effects of poverty, but reducing the level of poverty overall.

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