Characterizing the Association Between Material Hardship Across Development and Connectome-Wide Brain Connectivity in Adolescents

By

Jaime A. Muñoz-Velázquez

A dissertation submitted in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
(Psychology)
in The University of Michigan
2021

Doctoral Committee:

Associate Professor Luke W. Hyde, Co-Chair
Professor Christopher S. Monk, Co-Chair
Professor Vonnie C. McLoyd
Research Associate Professor Colter Mitchell
Associate Professor Chandra Sripada

Jaime A. Muñoz-Velázquez

jaimemv@umich.edu

ORCID iD: 0000-0002-2114-2396

DEDICATION

For my mother, whose sacrifices and unconditional support have allowed me to reach for the stars. Eternally grateful.

Para mi madre, porque todos tus sacrificios y apoyo incondicional me han dejado soñar en grande. Eternamente agradecido.

ACKNOWLEDGMENTS

I will begin by thanking God, who has made all that I am possible. Next, I will thank all the families who agreed to participate in our Study of Adolescent Neural Development (SAND). Thank you for being open to sharing your time and life experiences with me, I was truly humbled and inspired by your resilience and strength. I am also grateful to the support and guidance provided by my primary advisor, Christopher Monk. Thank you for allowing me an opportunity to discover myself as a scientist. I thank my dissertation committee members and mentors Luke Hyde, Vonnie McLoyd, Colter Mitchell, and Chandra Sripada for their investment in me and my work. Thank you for the encouragement to think deeply about my work.

Additionally, I want to express my appreciation for my fellow lab members, past and present: Whitney Mattson, Tyler Hein, Leigh Goetschius, Kristen Stauffer, and Juliana Calabrese. I have learned so much about collaboration from all of you. To my other U of M research collaborators, Melissa Peckins, David Cordova, Rosario Ceballo, James A. Cranford, Ioulia Kovelman and Stephanie Rowley. Thank you for your mentorship and for being patient with me as I developed new skills, I consider myself an interdisciplinary researcher because of the breadth of research skills I was able to learn from all of you.

I am also thankful to my mentors outside of the University of Michigan. First, I want to express my deepest gratitude to Dr. Nancy Segal because without your wisdom and encouragement, my PhD journey would have never begun. Thank you for being an amazing mentor and role model. Second, I thank my MARC family at CSUF for all your unconditional

support when things got tough. Dr. Amybeth Cohen, it was an honor to be mentored by you. Your experience and advice were invaluable as I began this journey. Dr. Laura Arce, your encouragement and mentorship helped me believe in myself. Lastly, Mr. Prutter, my high school English teacher, thank you for believing that I was capable of much more than I was ever told I could be. Your decision to petition for me to be in classes that challenged me helped me discover my passion for lifelong learning.

Outside of the lab, I was blessed to have surrounded myself with amazing people who may have begun as strangers, but over the last 8 years, have grown to be *familia*. Frania Mendoza, *si mi hermana estuviera aquí conmigo, desearía que fuera tan fuerte como tú.* Thank you for bringing me a piece of home to Ann Arbor and for being there for me through it all. Gabriel Jones, the most balanced person I know and who I have had the pleasure to see become an amazing human being. Thank you for giving me a shot despite the 'report'. Francheska Alers-Rojas, *gracias por ser como eres – fuerte, llena de compasión y de consejos*—you are an amazing friend, and the world is much better because you are in it. Iván Chaar López, thank you for the jokes, fun conversations, game nights and the wine. Thank you to פלא לבה, נפש תאומה שלי for helping me uncover what I had lost. מצא ידיד נאמן, מוצא אוצר. Petal L. Grower, thank you for always helping me the best version of me and for your generous support through all the phases of this journey. To all of you, thank you for making Ann Arbor feel like my home away from home.

Lastly, I thank those closest to me. Muchas gracias a mi madre, Teresa Velázquez, sin todos sus sacrificios, amor incondicional, y sabios consejos, yo no hubiese llegado aquí. Gracias por ser un ejemplo de fortaleza, valentía, y por enseñarme a luchar, a levantarme cuando caigo, a aprender de mis fracasos y a soñar en grande. A mi hermanita Nayeli, aunque nuestro tiempo

juntos fue breve, la huella que dejaste en mi corazón fue profunda. Pensar en ti es sentir que el cariño y el abrazo cálido me envuelven. Ni la distancia, ni lo que vivamos podrá apagar este cariño. A mi hermano, “Quique” gracias por creer en mí y por siempre preguntarme “*¿y para qué tanto?*”. Y por apoyarme frente a las adversidades de la vida. A mi sobrino, J. Devin Muñoz (“Chango”), gracias por ser una bendición de Dios, fuente de amor y alegría en los momentos más difíciles de esta jornada. Tu foto en mi oficina siempre me llenaba de alientos para no rendirme cuando sentía no poder más. Y también, gracias al resto de mi familia por brindarme su apoyo que me permitió llegar hasta aquí. Last, but not least, to my best and dearest friend, Joanna Castañeda, who believed in me from the start and whose support helped me through the early trials of this journey. Thank you for always reminding to pray and to trust in God. Sin la ayuda de Dios nada es posible. *¡Muchas Gracias!*

TABLE OF CONTENTS

LIST OF TABLES

TABLE

LIST OF FIGURES

FIGURE

LIST OF APPENDICES

APPENDIX

ABSTRACT

Experiencing poverty during childhood may prompt experience-dependent neural adaptations. These manifest through functional connectivity patterns across networks thought to support cognitive and socio-emotional processing. Interrelated network connectivity disruptions have been associated with the development of internalizing disorders. Connectome-wide network characterizations of functional connectivity in adolescents who grew up in poverty are lacking. To this end, this dissertation aimed to characterize the association between family material hardship, connectome-wide network connectivity and internalizing symptoms in adolescence. The introductory chapter proposes material hardship, which directly measures a family's experiences with unmet basic needs (e.g., no access to food) as a better alternative to income-based measures used in research. Subsequently, in Chapters Two and Three, network contingency analyses were conducted to characterize connectome-wide connectivity associated with lifetime family material hardship for adolescents drawn from a national longitudinal study. Correlational analyses evaluating the association between network connectivity and current adolescent internalizing symptoms were done. Notably, the mixed findings across the two studies suggest that connectome-wide adaptations confer both cost and benefits to youth who experienced material hardship. Data suggests that altered network connectivity may be protective and that not everyone who experiences material hardship develops internalizing symptoms. In the final chapter, the limitations and implications of the present findings are discussed. Recommendations for more multi-method research to better characterize the association between brain function and poverty are made.

CHAPTER I
Poverty, Children, and Measurement Issues: A General Introduction

Poverty in the U.S.

Despite the declining poverty rate in the United States of America from 14.8% in 2014 to 11.8% in 2018, the number of families in poverty remains in the millions (Semega, Kollar, Crearmer, & Mohanty, 2019). For a family to be considered "in poverty", their annual pre-tax household income must be below the Official Federal Poverty threshold measure (OPM), a guideline that is adjusted yearly based on family size and income. Of the 38.1 million Americans in poverty in 2018, 18.5 million are in *deep poverty*, which refers to households with a total income below 50% of the poverty threshold. Although individuals in deep poverty represent 5.7% of the U.S. population, they represent 46.7% of those in poverty (Semega et al., 2019).

Furthermore, the rates of individuals growing up in poverty have disproportionately affected families based on other relevant demographic characteristics such as race, family composition, parental education, age, employment status, and immigration status (National Academies of Science, Engineering and Medicine, 2019). Even though race may be a social construct (Helms, Jernigan, & Mascher, 2005; Smedley & Smedley, 2005), it is a construct that has influenced and maintained long-standing economic inequalities in the U.S. reflected by poverty rates being historically higher for non-white families in the U.S.; the 2018 census data reports that 20.8% of Blacks, 17.6% of Hispanics, and 10.1% of Asians live in poverty, relative to 8.1% of non-Hispanic whites (Semega et al., 2019). The dynamics underlying these race-based wealth gaps are engrained in the historical foundations of the U.S. and have been of concern in American politics and policy ever since the 1960's President Johnson's 'War on Poverty' social reforms (Cellini, McKernan, & Ratcliffe, 2008).

Recent longitudinal research using the Panel Study of Income Dynamics (PSID) data that examined intergenerational mechanisms of how these disparities persist identified that higher rates of economic disadvantage for Black American families was associated with their kin's socioeconomic resources (e.g., educational attainment, home ownership) and socioeconomic disadvantages (e.g., at least one member of household is unemployed) relative to non-Hispanic White families (Park, Wiemers, & Seltzer, 2019). In the same vein, transfer of intergenerational wealth seems to influence the social mobility capabilities of families such that historically Black families who start with less economic advantages tend to face hardships over generations, while non-White families tend to start with more advantages and maintain them (Pfeffer & Killewald, 2019). Overall, these wealth gaps arise from both the historical disadvantage reflected in the unequal starting positions of Black and White children, and contemporary processes that hinder the closing of the gaps including institutional discrimination such as racial segregation in the U.S. (e.g., concentrations of poverty across the U.S. differ by race; Lichter, Parisi, & Taquino, 2012).

The persistence of these race-based socioeconomic disadvantages are of great concern to poverty researchers given the adverse health outcomes associated with poverty (Ananat, 2011; Grusky & Hill, 2018; Iceland, 2019; Lichter et al., 2012). Specially for young children in families who are in poverty are one of the most vulnerable populations; in fact, one in five children (individuals under the age of 18) grow up in poverty in the U.S. (Koball & Jiang, 2018). Given these sobering statistics, further research investigating the impact of growing up in poverty on normative development is essential. Research evaluating the effect of family income and the availability to resources to meet a family's basic needs on children's normative development on domains such as socio-emotional development and brain function would inform how poverty gets underneath the skin. Lastly, following the recent American Psychological Association's recommendations to refer to people in poverty as "low-income and economically marginalized" (LIEM), this dissertation followed the APA's guidance and broadly incorporated many aspects of what it means to be economically oppressed, including access to limited financial resources and marginalization related to social class (American Psychological Association, 2019).

Poverty and Health Outcomes

To date, research on the association between a family's level of income (i.e., a proxy for poverty) and health outcomes demonstrates the damaging effects of growing up in poverty. For example, growing up in low-income families has been associated with poorer health outcomes in childhood such as difficulties with socio-emotional regulation (Bradley & Corwyn, 2002; Chaudry & Wimer, 2016; Mohamed & Toran, 2018), impaired cognitive function (Mani, Mullainathan, Shafir, & Zhao, 2013), adverse mental health (Bøe, Øverland, Lundervold, & Hysing, 2012), higher levels of inflammation (Chiang et al., 2015; Pietras & Goodman, 2013), lower academic achievement (Sirin, 2005), lower reading ability (Chen, Kong, Gao, & Mo, 2018), and more behavioral problems (Hosokawa & Katsura, 2018), relative to children growing up in higher-income families. Furthermore, the effects of early childhood poverty have downstream consequences that also emerge in adulthood, such as reduced cardiovascular health (Lipowicz, Koziel, Hulanicka, & Kowalisko, 2007), difficulties with working memory (Evans & Schamberg, 2009), and a shorter life expectancy (Bor, Cohen, & Galea, 2017; Chetty et al., 2016; Mode, Evans, & Zonderman, 2016). These findings demonstrate the downstream effects of poverty on development throughout the life course. Yet, given the complicated circumstances around poverty conditions, it may be necessary to operationalize poverty in a more precise manner to elucidate how this association manifests.

Poverty: Definition and Measurement

Defining poverty is challenging given the multidimensional nature of this condition (Alkire, 2007; Anand & Sen, 1997; Spicker, Gordon, & Scotland, 2009; Tsui, 2002), but broadly speaking, poverty is understood to limits a person's opportunities. Sen's "capabilities" theory posited that an individual's chances to choose between different states of being are limited when deprived of such capabilities due to poverty (Sen, 2005). Beyond the limited opportunities, there is less agreement on what circumstances count as a dimension of poverty, such as low income, limited access to resources, or low levels of education (Atkinson, 2003). However, there are three main approaches in which to conceptualize poverty: (a) as a material condition, characterized by patterns of deprivation and limited access to resources (b) as an economic circumstance, focusing on the standards of living, inequality and economic positions and (c) as a social circumstance, linking access to financial security with an individual's social class that by consequence will be exclusionary (Lipina & Evers, 2017). These approaches tap into distinct and intersecting dimensions of poverty that are likely to interact with each other.

Regarding the first approach, the most commonly quoted definition of material poverty is Townsend's (1979), a British sociologist:

> "Individuals, families, and groups in the population can be said to be in poverty when they lack the resources to obtain the type of diet, participate in the activities and have the living conditions and amenities which are customary, or at least widely encouraged, or approved, in the societies to which they belong. Their resources are so seriously below

those commanded by the average individual that they are, in effect, excluded from ordinary living patterns, customs, and activities" (p. 31).

Groups considered to be LIEM families under Townsend's definition disagreed with being labeled as individuals "in poverty"(Sen, 1985; Shaw, 1988), suggesting that an individual's subjective view of their living conditions might be relevant to consider as well. Although Townsend proposed a comparative standard of poverty based on disproportionate deprivation relative to available resources and a societal standard of living, in practice developing countries use an absolutist definition where a single income-based indicator identifies those LIEM families (Chen & Ravallion, 2007; dos Santos, 2017). However, an absolutist interpretation cannot be applied equally to all people without regard to the individualized contextual factors that foster the circumstances LIEM families face (Boltvinik, 1999; Dutta, Foster, & Mishra, 2011).

Despite this shortcoming, the U.S. still favors this absolutist approach of calculating an official federal poverty threshold based on a family's pre-tax annual income earnings from sources such as wages, salaries, Social Security benefits, pensions, or other retirement income. The official poverty threshold favored in the U.S. estimates that families spend one-third of their annual income on a food diet basket (cost of a minimum food diet) from 1963 and multiplies a family's food costs by three based on the current year's food cost estimates (Orshansky, 1963, 1965). However, these estimates incorrectly allocate one–third of a family's income to only food costs, which underestimates the role of increasing housing costs that are typically more than one-third of a family's income. Because of this underestimation, the pre-taxed annual income used to determine the threshold for poverty does not accurately reflect a family's needs or available resources (Fass & Cauthen, 2008). Additionally, although the cost of living is adjusted annually for inflation, some families' yearly income remains fixed due to an unchanged federal minimum wage, a factor not considered when calculating the federal poverty threshold. For these reasons, the federal poverty threshold has been harshly criticized for its heavy reliance on a family's reported income and unrealistic cost of living estimates (Blank, 2008; Cauthen, 2007).

Among the many income-based alternative poverty indexes proposed to better capture a family's experiences with poverty (Iceland, 2005; Short & Garner, 2002), the U.S. government introduced a second estimate of poverty in 2011. Unlike the Official Poverty Measure (OPM) threshold determined by a select few sources of income, the Supplemental Poverty Measure (SPM) estimate accounts for more sources of a family's income, such as the governmental benefits received to help families meet their basic needs. The SPM also considers a more realistic cost of living by geographical region, accounting for other necessary expenses beyond a food basket such as clothing, shelter, utilities, payroll taxes, health care costs, commuting costs for all workers, and childcare expenses while parents work, at today's prices (U.S. Census Bureau, 2018). By more accurately representing families' cost of living, the SPM index identifies a wider group of individuals in poverty compared to the Official Poverty Measure. For example, in 2016, based on the OPT, 12.7% of the U.S. population was deemed to be in poverty, whereas with the SPM index, the rate was slightly higher at 14% (Fox, 2018).

Looking at youth under the age of 18, we see a different pattern: the OPM estimates 18% of youth to be in poverty, relative to the 15.2% based on the SPM. Though this lower SPM rate for youth may more accurately reflect a family's sources of income, it still does not accurately account for the direct costs of children's basic needs for care and healthy development (Mirowsky & Ross, 1999). The average costs of raising a child from birth through age 17 in the U.S. is $233,610, according to the 2017 report from the U.S. Department of Agriculture, based on 2015 data (Lino, Kuczynski, Rodriguez, & Schap, 2017), meaning that a family should expect to spend $13,750 per year per child. It has been estimated that the poverty threshold is too low and that it should be doubled (e.g., $22,050 for the year 2009) to accurately reflect what it would cost for a family of four to meet their needs (e.g., estimated money needed to not be in poverty in the U.S. ranges from $42,748 to 66,840; Fass, 2009). Taken together, neither of the most prominent income measures used to define poverty are sufficient to adequately identify all the families facing socio-economic disadvantage because the indexes do not consider their everyday challenges to make ends meet. Perhaps a more direct measure of a family's inability to meet their needs is merited.

Poverty and Material Hardship

Children growing up in LIEM families are caught up in their parents' economic struggles. There are several ways they experience the consequences of economic hardship such as through unmet needs, attending low-quality schools, and living in unstable family circumstances (Gershoff, Aber, Raver, & Lennon, 2007; Ratcliffe, 2015). Much like the U.S. government's income-based poverty index, child development researchers have opted to capture these experiences of unmet needs through self-reported income-based indicators (Hauser, 1994), often supplementing this information with additional information about a family's eligibility for free or reduced lunch, parental education, income-to- needs ratio and parental job status. Some researchers studying measures of material hardship have attempted to create indices of deprivation (Bauman, 2002; Beverly, 2001; Callan, Nolan, & Whelan, 1993; Mayer & Jencks, 1989). These indices share some similarities: 1) they all define hardship in terms of direct measures of families' experiences and their actual living conditions, and 2) they all include a core set of basic needs and food security indicators. Some methodological work seems to support this approach (Bauman, 2002; Mayer & Jencks, 1989), but this research is preliminary, and the question remains whether it is valid to treat all indicators of material hardship in a unified way (Ouellette, Burstein, Long, & Beecroft, 2004). This lack of consensus of an operational definition for material hardship makes comparing findings across studies challenging. Despite this conceptual lack of clarity, material hardship has been defined as an inability to meet basic needs and an individual's lack of access to or deprivation of resources, relative to the acceptable living conditions encouraged by the rest of society (Nelson, 2011). These material hardship items typically rely on the parent's knowledge and perception about their experience counting as a hardship for their family. Determining what counts as material hardship is further complicated by the survey's lack of specificity of who is affected by the hardship, assuming that all family members are equally affected. Yet, few questions, if any, ask about material hardship events that directly affect the children in the home. Including these types of questions would provide a direct measure of deprivation and unmet need that an income indicator does not.

Asking about a family's experiences with material hardship reveals an understudied dimension of poverty not captured by the federal income poverty threshold, as evidenced by the small association (r =.18; r =0.33) between material hardship and the poverty threshold (Hamilton et al., 1997; Short, 2005). Although findings are mixed when evaluating the association between material hardship and a family's level of income in the U.S., with direction depending on how poverty is coded (r= -.07; Ashiabi & O'Neal, 2007). Other studies estimate that income level explains about 14% of the variation in the number of material hardships a family reports, while an income-to-needs ratio (which accounts for the division of available resources among the family; McLoyd, 1998) can explain up to 23.6% of the variance of the total number of material hardships reported (Mayer & Jencks, 1989). Nonetheless, the expected likelihood that low-income families experience more material hardship due to a reduced capacity to meet their needs is a consistent finding in the literature relative to higher income families (Levy, 2015). One study that evaluated the overlap in dimensions of poverty estimated that you are 2.32 times more likely to be 'necessities poor' (i.e., face material hardships) if you are income poor (Bradshaw & Finch, 2003). Additionally, children have been found to be two to four times more likely to be in household facing material hardship relative to older senior adults, another vulnerable population affected by high rates of poverty (Rodems & Shaefer, 2020). However, other contextual factors may play an important role in this observed relation (e.g., parent's ability to budget, parent's mental health, not having a checking account; Sullivan, Turner, & Danziger, 2008; family instability Heflin, 2014; or length of time in poverty; Cellini, McKernan, & Ratcliffe, 2008). Because the underlying reasons for a family's material hardship can vary, income should not be the only indicator used to assess a family's financial circumstances.

First, material hardship improves upon income-based measures because is not based solely on consumption estimates or costs of living. For example, a previous study characterized four dimensions of material hardship: health, food, bill-paying, and housing hardship; yet these changes can arise from distinct processes (e.g., unexpected disability) rather than just a families' limited income (Heflin, Sandberg, & Rafail, 2009). Second, material hardship avoids misrepresenting actual household economic and material resources that may not be captured by income. In particular, material hardship rates increase when families are living below the poverty line, suggesting a robust association between depth of poverty and material hardship (e.g., food insecurity, difficulty paying bills), while the association between material hardship and housing or neighborhood issues is less robust (Iceland & Bauman, 2004). Indeed, LIEM families are more likely to report material hardship given that, on average, their income does not reach twice the federal poverty level, which has been estimated as necessary for a family to meet their basic needs (Cauthen, 2007). Third, reports of material hardships provide better representation of how the available resources may be allocated differently for each family based on their individual needs (Beverly, 2001). Lastly, material hardship allows us to capture all families' experience with hardship across the socioeconomic spectrum, including those low-income families above the poverty threshold who may still be unable to meet their basic needs (Beverly, 2001; Gershoff et al., 2007; Iceland & Bauman, 2004; Neckerman, Garfinkel, Teitler, Waldfogel, & Wimer, 2016; Nelson, 2011).

Families with incomes above the poverty line may also experience material hardship. Low-income families (who technically are not below the official federal poverty threshold) are more likely to experience material hardship, given that any unexpected material hardship will tap into a limited income (Baek & DeVaney, 2010; Meyer & Sullivan, 2004). For example, in a nationally representative internet-based study, the Urban Institute's Well-Being and Basic Needs Survey (WBNS), families with children (n=1,4154; under 19 years old) reported that over half of low-income parents (i.e., income below 200% of the federal poverty line) experienced food insecurity, 42.8% medical hardship, 33% problems paying utilities, and 27.6% problems making a rent or mortgage payment (Karpman, Gonzalez, Zuckerman, & Adams, 2018). A study that examined material hardship responses in the Survey of Income and Program Participation (SIPP) data from 1993 – 2011 found that over that time period approximately 15% of all U.S. families reported facing difficulties in meeting household "essential expenses", which included families in poverty as well as, responses from families who did not meet the federal criteria for poverty (Heflin, 2014). When separating responses to this "essential expense" hardship by families in poverty versus not in poverty, those categorized to be in poverty based on the official guidelines reported (36.2%) higher difficulties in meeting their essential household expenses, relative to those not in poverty (12.3%) (Rector, Johnson, & Youssef, 1999). A more recent study reported that one third of the households with children facing material hardships are above the 200% poverty line (Rodems & Shaefer, 2020). Lastly, the race-based income disparities are also observed with increased risk for experiencing hardship with White and Asian children reporting the lowest rates of hardship, relative to Black and Hispanic children (Rodems & Shaefer, 2020). These findings suggest that facing material hardship is not limited to LIEM families whose income is below the poverty line, but families of color are at higher risk of experiencing material hardship. This indicates and that defining poverty through material hardship broadens the inclusion criteria to identify children from families facing financial hardships would not be captured through traditional income-based methods.

Rates of reported material hardship vary in cross-sectional studies specific to the sample and time of sampling. The most reported material hardship items are food insecurity and utility disconnection (Bauman, 2002; Boushey & Gundersen, 2001; Cancian & Meyer, 2004; Heflin, Sandberg, & Rafail, 2009; Mayer & Jencks, 1989). Fewer studies have examined longitudinal reports of material hardship, and those that have revealed that certain material hardship items are experienced more chronically. A longitudinal study investigating employment data from 753 Michigan mothers over five years who were asked to report on six different types of material hardship found that the most prevalent items, ordered from highest to lowest rates, were: unmet medical needs, telephone disconnection, food insufficiency, housing problems, utility disconnection, improper winter clothing (Heflin, 2006). Another longitudinal study (i.e., two-time points) with 798 New York City families with at least one child younger than 18 years of age examined five types of material hardship based on a ten-item questionnaire (food insecurity, housing hardship, unmet medical needs, utility cutoffs, and financial uncertainty). They found that 39% of those families experienced at least one type of material hardship during the year of the study. Given the challenges to recruit low-income families for research, these families provided better insight into how disadvantaged circumstances increase material hardship. Additionally, when this longitudinal study aggregated families by subgroups based on a poverty threshold, "poor families" vs. "nonpoor families," they found that "poor" families (55%) reported more material hardship than the "nonpoor" families (33%). When examining the dynamics of material hardship, they found that 81% of the families facing poverty reported material hardship both at baseline and follow-up (Neckerman et al., 2016). Regardless of grouping, all the families who reported material hardship had a child, leaving the question as how experiences of material hardship impact children's development.

In summary, the findings from behavioral studies of LIEM families using income-based indicators are insufficient to capture a family's daily experiences with economic hardship. Income-based indicators do not capture a family's struggle to meet basic needs such as medical care, food, and rent. Furthermore, material hardship captures how income resources are allocated independently of a family's income level and may capture temporary experiences of economic hardship for children from both non-LIEM and LIEM families. Given that there is no consensus on what items comprise material hardship (Blank, 2008; Ouellette et al., 2004), the present dissertation focused on a weighted sum score from eight different types of hardship that represent different dimensions of material hardship such as housing hardship, medical hardship, and food insecurity. This multidimensional composite score allowed me to assess the variety of possible hardships experienced by low-income families and by families regardless of income, including infrequent events such as needing to borrow money to pay the bills or homelessness.

Material Hardship and Children's Well-Being

Studies examining the unique association between a family's material hardship and their child's well-being outcomes report extensive adverse effects during a child's development from in utero through adolescence. The timing at which a child experiences material hardship is also associated with the types of health outcomes that are affected. For example, a study examining low-income women's mental health during pregnancy found that both mother's depression and anxiety were uniquely associated with lower income and higher material hardship, even after controlling for age, race/ethnicity, relationship status, and the number of children in the home (Katz, Crean, Cerulli, & Poleshuck, 2018). These findings suggest that the impact of material hardship on expecting mothers' health may disadvantage the unborn child at the time of birth because the mother's health may impact the care, they can provide their child.

Material hardship also affects children after birth. For example, family material hardships have been associated with shortened sleep duration across infancy and toddlerhood in low-income Hispanic families (e.g., food insecurity, housing disrepair, financial difficulties; Duh-Leong et al., 2020). Similarly, multisite data from families with infants 4 to 36 months reported that increased material hardship was associated with decreased infant well-being, as measured by a pediatric wellness index that included parent reports of infant health as well as, score on a multidimensional pediatric scale (Frank et al., 2010). In a similar vein, a study of Latino mother-child dyads found that high food hardship and 3 to 4 other hardships (e.g., housing despair, difficulty paying bills, neighborhood stress) was associated with the infant's lower orienting and regulatory temperament capacity (Fuller, Messito, Mendelsohn, Oyeku, & Gross, 2018). This temperamental capacity may be a precursor to later childhood internalizing behavior problems between age 3-5 and externalizing problems between ages 6-12 (Slack & Yoo, 2005). Another two-year longitudinal study focusing on food insecurity reported that children from homes with high food insecurity had more internalizing and externalizing behavior problems (Slopen, Fitzmaurice, Williams, & Gilman, 2010).

A few longitudinal studies based on data from The Fragile Families Child Wellbeing Study, FFCWS have found that other types of material hardship affect child socioemotional development as well. Namely, a family's inability to pay bills, having their utility services cut-off, and having unmet medical needs when a child is three years of age was associated with negative socioemotional behaviors (e.g., aggressive, withdrawn, anxious/depressed) at age 5 (Zilanawala & Pilkauskas, 2012). Follow-up studies with the same FFCWS sample at age nine showed that boys in the sample who lived in homes where more than one material hardship was reported were three times as likely to exhibit externalizing behaviors (Bellair, McNulty, Roscigno, & Lei, 2019). Similarly, a FFCWS sample of children whose families reported food and energy hardships within the last two years (i.e., an inability to pay the gas/oil/electricity bill) showed greater internalizing and externalizing behaviors at age 9 (Fernández, Yomogida, Aratani, & Hernández, 2018). Given that economic interventions during early childhood (~age 4) aiming to reduce material hardship alleviated the negative socioemotional development observed in the literature (Huang, Nam, Sherraden, & Clancy, 2016; Huang, Sherraden, Kim, & Clancy, 2014), understanding material hardship in greater depth is particularly important.

Unsurprisingly, other studies examining children's development (5-11 years old) identified a strong relationship between households' food hardship and poor physical health outcomes (Yoo, Slack, & Holl, 2009). This strong association between food hardship and poor health was observed above and beyond the other commonly reported hardships: housing stability, housing quality, overcrowding, difficulty paying bills, unmet medical needs, and lack of adequate transportation. Associations between material hardship and obesity (Eisenmann, Gundersen, Lohman, Garasky, & Stewart, 2011) and delayed language development have also been reported (Sonik, Parish, Akobirshoev, Son, & Rosenthal, 2017). Some evidence suggests that specific parenting practices and parental attitudes mediate the relationship between material hardship and children's mental health (McConnell, Breitkreuz, & Savage, 2011; Yoo, Slack, & Holl, 2010). Taken together, these studies demonstrate that the developmental effects of food hardship experienced during childhood can be immediately observed and alter normative development through inadequate nutrition.

Studies focusing on the association between a family's material hardship and adolescent adjustment outcomes provide further evidence for the need to continue examining these effects on youth development. One study found that material hardship indirectly affected adolescents' internalizing and externalizing problem behaviors through parental depression and negative parenting, though no direct effects were found (Sun, Li, Zhang, Bao, & Wang, 2015). Similarly, family economic hardship seems to be associated with youth's poor sleep quality (Bao et al., 2016), lower self-esteem (Bolger, Patterson, Thompson, & Kupersmidt, 1995), higher depression (particularly loneliness; Lempers, Clark-Lempers, Simons, 1989), increased parent-adolescent conflict (Ponnet, 2014) and increased engagement in adolescent drinking (Hardaway & Cornelius, 2014). This body of research would suggest that the role of material hardship should be examined across multiple domains of well-being over time.

Poverty and Psychopathology

Growing up in poverty has been theorized to be an etiological factor in the development of psychopathology; the sequelae of childhood poverty on psychological well-being seem to cascade into later life stages. The negative association between current SES and depression has been well documented in adult populations (Angelini, Howdon, & Mierau, 2019; Domènech-Abella et al., 2019; Freeman et al., 2016). However, retrospective cohort studies of early childhood poverty and adulthood psychopathology have yielded mixed findings for internalizing disorders such as depression and anxiety. Studies concluded that adults who retrospectively reported experiencing higher early childhood poverty were more likely to be diagnosed with major depression (three times more likely; Domènech-Abella et al., 2019; two times more likely, Gilman, Kawachi, Fitzmaurice, & Buka, 2002). Relatedly, those who reported experiencing lower childhood poverty reported more depressive symptoms in adulthood, though at sub-clinical levels (Luo & Waite, 2005). Similar evidence exists for anxiety, where early childhood adversity increases the likelihood of adult-onset anxiety disorder (by 1.21 times, Benjet, Borges, & Medina-Mora, 2010). Yet, other studies have reported no link between childhood experiences of poverty (measured by income) with adult depression; but did identify a link between poverty and externalizing symptoms (Evans, 2016; Poulton et al., 2002). Despite somewhat equivocal findings, growing up in poverty does seem to increase a person's risk for developing psychopathological symptoms.

Early childhood poverty has been associated with other types of psychopathology during different life stages. Some researchers have explored whether the recency of the event plays a role in the manifestation of symptoms. For example, a few studies demonstrated that parent reported current childhood SES is linked to childhood mental illnesses such as emotional/behavioral disorder symptoms, ADHD, conduct problems and anxiety (e.g., Reiss, 2013), whereas other studies have found no correlation between parent reported SES and depressive symptoms among their 8 to 16-year-old children (Twenge & Nolen-Hoeksema, 2002). One cohort study with 2,111 children and adolescents reported an association between current SES level and parent-reported child mental health problems, independently of family structure and children's mental health at baseline (when children were ages 7-17, $M_{age} = 11$; Reiss et al., 2019). Other studies have focused on the likelihood of developing any type of psychopathology associated with growing up with material hardship, rather than focusing on concurrent experiences of hardship and psychopathology. For example, Benjet and colleagues (2010) conducted 2,362 semi-structured interviews and evaluated the likelihood of onset for mood and anxiety disorders with participants who reported more early life economic adversity. Interestingly, those who reported high occurrences of economic hardship were less likely to report an onset of an internalizing disorder during childhood (ages 4-12 OR 0.80) or adolescence (ages 13-24 OR 0.68; Benjet et al., 2010). These studies, and particularly the contradiction between the longitudinal and cross-sectional work, suggest that economic hardship may serve as a catalyst to other early life stressors linked to psychopathology, but that longitudinal data may be necessary to see these downstream effects.

Studies focused on the relationship between material hardship and psychopathology are limited. To date, most research examining this relationship has focused on the parents of children facing economic adversity (i.e., adults). Another study examining a rural African American subsample (N=250), found that those reporting more material hardship had poorer self-rated physical health and had higher levels of depressive symptoms and psychological distress relative to those who had lower material hardship (Weaver, Taylor, Chatters, & Himle, 2018). Studies evaluating children and adolescent mental health around material hardship are lacking. Thus far, these studies show that material hardship can negatively impact the mental health of children's parents, which in term affects their children (Ashiabi & O'Neal, 2007) . Moreover, these results highlight the need to study the brain as a mediator of the effect of poverty on the development of psychopathology. This is a particularly important mediating mechanism to investigate given that neurological changes may elucidate the mixed findings in the literature.

Poverty and Brain Function

To date, indirect evidence that socioeconomic disadvantage is associated with altered brain function across a variety of domains is well established. For example, several behavior-based studies support the link between early childhood poverty and poor cognitive performance across several processes, language development (Berger, Paxson, & Waldfogel, 2009; Fernald, Marchman, & Weisleder, 2013), cognition (executive function, Lawson, Hook, & Farah, 2018; Raver, Blair, & Willoughby, 2013); verbal memory/processing speed; Hazzouri et al., 2017), memory, (Evans & Fuller-Rowell, 2013; Markant, Ackerman, Nussenbaum, & Amso, 2016), academic achievement (Hair, Hanson, Wolfe, & Pollak, 2015; Jotterand, 2018), and poor mental health outcomes (McLaughlin, Costello, Leblanc, Sampson, & Kessler, 2012; McLaughlin, Green, et al., 2012; Sommet, Morselli, & Spini, 2018). Moreover, the neurological basis of these associations has been studied at different levels of analysis. For example, reduced white matter is often observed in the frontal and parietal lobes of socioeconomically disadvantage children relative to their advantaged peers (Hanson, Adluru, et al., 2013; Johnson, Riis, & Noble, 2016) as well as reduced brain surface area (Noble et al., 2015). While cortical thickness has not been found to be associated with cognitive skills, reduced cortical surface area mediates the association between SES and cognitive outcomes (Brito, Piccolo, & Noble, 2017). Similarly, evidence from a large cohort of LIEM families (n=36,443) whose children exhibited neurological abnormalities at 4 months old, and 7 years old, as well as display autonomic nervous system dysfunction at 7 years old that was not accounted for by perinatal factors, suggests that altered nervous system development contributes to these associations (Hung et al., 2015). Taken together, these studies suggest that growing up in poverty can adversely affect brain development in ways that are detectable through behavioral assessments, white matter imaging, or neurological testing.

Applying neuroscience methodology, the interconnectivity of brain patterns of individuals who grew up in poverty can be characterized through functional connectivity, which can be evaluated both from elicited (i.e., task-based) and at-rest (i.e., non-task based) paradigms (Rogers, Morgan, Newton, & Gore, 2007). A review that evaluated several child behavioral studies related to attention, reading and language development found links between altered brain network function and growing up in low-SES (Lipina & Posner, 2012). Taken together, these studies demonstrate that the effects of early childhood poverty on cognition are pronounced and varied, suggesting that these behavioral changes are related to changes in brain connectivity.

Theoretical Frameworks

The interactive adjustment of biological human development by experience is referred to as experiential canalization (Gottlieb, 1991). Two possible guiding frameworks that relate experiential canalization to material hardship aim to describe how these experiences of material hardship change brain development and function through neurological adaptations. These adaptations are neither good nor bad, but rather seen as necessary for survival. First, if we consider material hardship as an environmental stressor, then brain development and function is altered through adaptations to neurobiological mechanisms that respond to stress (McEwen &

McEwen, 2017). Researchers refer to the body's ability to adapt its stress response systems (e.g., body temperature) to different types of chronic or sporadic stressors, as 'allostatic load'. A higher allostatic load, assessed through various metabolic systems in the body (e.g., HPA axis functioning) would reflect the biological effect of accumulated 'wear and tear' on the body's response systems to environmental stressors.

In keeping with this 'allostatic load' framework, material hardship must exert its effects on neurocognitive systems whose adaptations are associated with unfavorable mental health and poor cognitive performance outcomes. Indeed, greater allostatic loads have been observed in children growing up in poverty relative to children who do not grow up in poverty (Blair et al., 2011; Chen, Miller, Brody, & Lei, 2015; Rainisch & Upchurch, 2013). Poverty-related stressors affect multiple body systems differently (e.g., cardiac system, de Mestral & Stringhini, 2017; HPA-axis, Burke, Fernald, Gertler, & Adler, 2005 ; amygdala responsivity, Kim et al., 2013) and as such specific system changes have been proposed as biological mediators that link early life economic hardships to later life adverse outcomes. However, given the biological interactions between all the systems that work together to achieve body homeostasis, no one pathway is solely responsible for how material hardship gets "underneath the skin", and more than likely all systems contribute to the allostatic load "weathering" effects on development (Geronimus, Hicken, Keene, & Bound, 2006).

Alternatively, if we view material hardships as part of the cultural and social circumstances in the environment then these adaptations come about through recurrent, active, and long-term engagement in scripted behavioral response sequences. As anthropologist Oscar Lewis wrote in 1959, "The culture of poverty is not just a matter of deprivation or disorganization, a term signifying the absence of something. It is a culture in the traditional anthropological sense in that it provides human beings with a design for living, with a ready-made set of solutions for human problems, and so serves a significant adaptive function" (Lewis, 1966). Notably, Lewis was also referring to the structural forces such as capitalism, racism and lack of access to education to name a few that perpetuate poverty conditions for some families in the U.S. Therefore, these neural modifications are reflecting necessary adaptations that are good and favorable for the child's own environment. The fine tuning of the neurological systems comes about through this neuro-culture interaction that brings about systemic changes to neural connectivity of the brain through cultural practices or repeated behaviors (Kitayama & Uskul, 2011). Although poverty research findings have heavily focused on negative outcomes associated with poverty, it is important to emphasize that not everyone who experiences material hardship develops psychopathology or has negative health outcomes. One area of research that hints at these protective adaptations is found in resilience literature where it has been suggested that early adversity fosters protective traits that strengthen a person's ability to overcome adversity (Williamson, Steven Witzel, & Steven, 2016). Other work has reported adolescent resilience buffered the development of depression symptoms in poverty contexts (Sun, Li, Zhang, Bao, & Wang, 2015), suggesting that these culturally-based modifications to the brain had significant adaptive value.

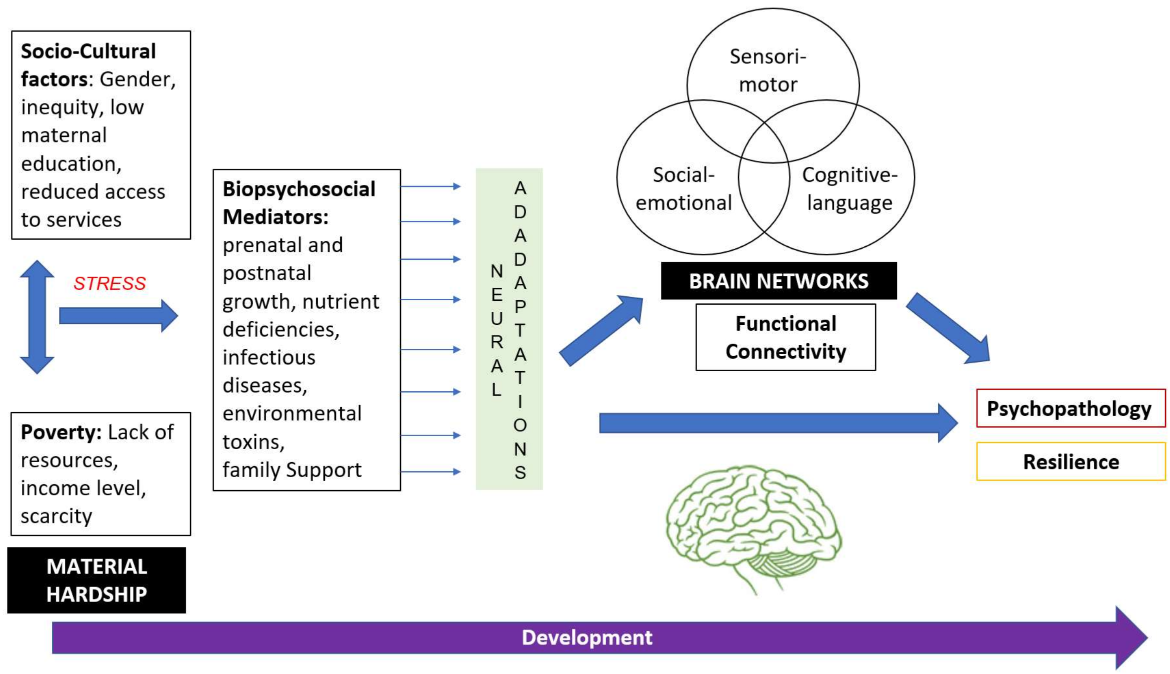
In either case, the interplay of brain and environment continues to influence brain development through these neural adaptations that sculpt brain development of the individual regions or circuits that support social and emotion processing functions. To study these adaptations across the whole brain in a systematic manner, one can examine connectome-wide functional connectivity patterns organized into large-scale networks that provide meaning and specificity related to the purported function. Networks such as the frontoparietal network (FN), involved in top-down regulation of attention and emotion; the default mode network (DMN) and dorsal attention network (DAN), involved in internally or externally oriented attention as well as, the ventral attention network (sometimes called the salience network; Seeley et al., 2007) involved in the processing of emotion or monitoring of salient events (Yeo et al., 2011). Furthermore, these networks can be grouped into three major networks whose altered connectivity patterns have been theorized to contribute to deficits in cognitive an emotion processing functions that are believed to underly depression and anxiety symptoms.

Of relevance to this dissertation are Menon's tripartite model networks: the Salience Network (SAL), the Central Executive Network (CEN), and the Default Mode Network (DMN). Each of these three networks is purported to be involved in cognitive processes that support healthy functioning. The network functions are of the salience network has been associated with an individual's ability to detect threat in their environments, as well as support the relay of information between the SN and the other two major networks. The Central Executive Network is recruited when attentional tasks are engaged, while the Default Mode Network has been associated with inner thought and mood regulation (Sylvester et al., 2012).

In support of their relevance to the current study, the theorized dysregulated functioning of these three networks has been associated with the manifestation of psychopathology in various pediatric and adult samples (Menon, 2011). Furthermore, Menon argues that dysregulation in one network has consequences for the functioning of the other large-scale networks that co-activate together when executing any specific function such as emotion processing. These co-activation imbalances can create disruptions to cognitive and emotional processing that have been hypothesized to support the emergence of depression and anxiety symptoms.

The proposed framework guiding this dissertation borrows from all these theoretical frameworks to characterize how material hardship gets "underneath the skin" to alters neural mechanisms that support adolescent brain function. Additionally, I provide a rationale for my focus on early childhood, age 1 to 3, and argue for it to be a crucial period in development to provide context for the neural changes that are associated with that time period.

Figure 1: Proposed Functional Adaptation Framework



Proposed Framework

The proposed framework for this dissertation asserts that greater material hardship will promote biological adaptations that change functional connectivity brain patterns across multiple large-scale networks. These neural adaptations across socio-emotional and cognitive networks are of concern given that these large-scale networks underlie important cognitive and emotion processing functions whose dysregulation has been theorized to support the emergence of psychopathology or resilience.

By examining family material hardship, I will be able to characterize how unmet basic needs during early childhood are associated with adolescent functional connectivity. My focus on early childhood (ages 1 to 3) was motivated by previous work that identified externalizing and internalizing problems in young children in this age range associated with living in poverty (e.g., Duncan, Brooks-Gunn, & Klebanov, 1994; Duncan, Magnuson, Kalil, & Ziol-Guest, 2012; Frank et al., 2010). Additionally, the emerging evidence of structural brain differences in children growing up in poverty such as reduced brain volume (Butterworth, Cherbuin, Sachdev, & Anstey, 2012; Noble, Houston, Kan, & Sowell, 2012) , inefficient connectome network organization (Kim et al., 2019), demonstrates the heightened sensitivity of brain development to poverty-related stressors (Bashat et al., 2005; Leijser, Siddiqi, & Miller, 2018; Mukherjee et al., 2001; Paus et al., 2001). Indeed, these differences in brain development seem to persist from infancy to adulthood (Hackman & Farah, 2009; Lipina & Posner, 2012) if no intervention to remedy living conditions occurs (Lipina & Posner, 2012), and perhaps are exacerbated by the decreased rate of brain growth and maturation associated with growing up in poverty (Hanson, Hair, et al., 2013). Consequently, the altered development of these neural structures is likely to affect the organization of the functional connectome as well (Power, Fair, Schlaggar, & Petersen, 2010). Recent evidence lends support to the one-to-one mapping of structural and functional network topology organization and interregional connectivity (Casey, Giedd, & Thomas, 2000; Haimovici, Tagliazucchi, Balenzuela, & Chialvo, 2013; Wang, Dai, Gong, Zhou, & He, 2015) .

One possible biological mechanism through which these altered neural adaptations occurs is through neural plasticity, which describes experience-dependent changes to brain function and structure (Lillard & Erisir, 2011; Voss, Thomas, Cisneros-Franco, & de Villers-Sidani, 2017). Neural plasticity is supported by collection of biological mechanisms involved in the organization and the reorganization of neural structures and connections that occur throughout the life cycle (Lledo, Alonso, & Grubb, 2006). Individual experiences during a sensitive period such as material hardship in early childhood would prompt the developing neural circuits to become customized to a child's needs in their environment (Knudsen, 2004). Therefore, any observed changes to functional connectivity brain patterns associated with early childhood family material hardship will reflect underlying brain adaptations that occurred before adolescence.

Connectome Network Framework

The mature brain organizes into distinct neural networks defined by strong functional connectivity correlations between different brain regions that collectively form the human connectome (Collin & Van Den Heuvel, 2013; Lebel, Walker, Leemans, Phillips, & Beaulieu, 2008; Sporns, 2013). Most commonly, functional connectivity employs Pearson cross-correlations of hemodynamic time courses (Li, Guo, Nie, Li, & Liu, 2009). Similar connectome-wide network organization has been documented in children and adolescents (Dennis & Thompson, 2013). Although this network organization has been shown to have weaker internal connectivity and to be less functionally segregated in younger children relative to adults (Fair et al., 2009), adolescent network organization is spatially similar to that of an adult (Sherman et al., 2014).

Connectome-wide functional connectivity better characterizes the interconnected nature of co-activation across different brain regions that occurs during cognitive and emotion processes relative to a single region focus (Bassett & Sporns, 2017; Bressler & Menon, 2010; Sporns, 2014). Connectome-wide connectivity can be organized and interpreted through large-scale network parcellations that have been identified through data driven approaches (e.g., Power, Schlaggar, & Petersen, 2014; Smith et al., 2013). These large-scale networks represent brain regions linked by ‘edges’ which can represent a physical or statistical connections between ‘nodes’ across individual regional time-series data (Bullmore & Sporns, 2009; Friston, 2013; Sporns, 2013). Additionally, these functional networks are highly variable and dynamic when evaluated in both task-based and at-rest neuroimaging fMRI paradigms (Cole, Marin, & Dennis, 2004). Previously connectome-wide analyses were limited by the statistical methodology used to assess functional connectivity in single regions of interest. Specifically, the issue of correcting for multiple comparisons when evaluating functional connectivity in more than one single region (Lindquist & Gelman, 2009; Rousselet & Pernet, 2012). However, recent advances in analytical approaches of neuroimaging data allow us to examine these large-scale functional networks simultaneously (e.g., Sripada et al., 2014). Thus, the present dissertation will evaluate connectome-wide connectivity organized using the Power and colleagues (2011) thirteen large-scale network parcellation. Utilizing a large-network parcellation allows us to have location specificity and interpretation that references biological regions of any interrelated network functional connectivity elicited by a task or in the absence of the task (e.g., resting-state connectivity).

Limitations of Current Poverty and Brain Research

Although scientific advancements on understanding the consequences of growing up in poverty on brain function have been made, several important limitations exist. First, a large amount of brain research and poverty has focused on characterizing structure and region-specific functional connectivity associated with a specific cognitive outcome, but recent methodological advances now allow us to examine how overall brain function has been changed through adaptations in response to poverty-related stressors. Second, brain research to date tends to define experiences in poverty based on income-based guidelines, but few studies have looked at other dimensions of poverty such as family material hardship that capture everyday difficulties with meeting their basic needs. Third, fMRI poverty researchers have not been able to successfully overcome the challenges in recruiting samples that are representative of the general population, therefore community-based and nationally representative samples are recommended to gather a more nuanced understanding of how poverty affects individuals from understudied populations. Furthermore, the present dissertation will improve upon the existing research by proposing a connectome-based network approach to examining how early childhood family material hardships (i.e., poverty) impacts adolescent brain function. Accordingly, the proposed work will evaluate adolescents' connectome-wide functional connectivity at two levels of analysis, through resting-state and while performing a task.

Summary

Neuroimaging poverty research has primarily measured family economic hardship using income-based measures which do not capture how LIEM family income is distributed to meet basic needs. I argued for the operationalization of poverty through material hardship, which measures families' experiences with their inability to meet their basic needs due to the absence of resources. Next, I proposed that neural adaptations in response to material hardship stress would be evident through functional connectivity using at-rest and task-based methodology. Specifically, I argued that unmet basic needs in early childhood (ages 1 to 3) will affect underlying brain development and subsequently alter adolescent brain functional connectivity patterns. The aim of this dissertation is to characterize altered functional connectivity at age 15 as a possible biological pathway through which early childhood poverty manifests in development.

CHAPTER II
Material Hardship and Adolescent Resting-State Functional Connectivity

Abstract

An understudied environmental effect on neural development is the experience of family material hardship during early childhood, which may act as both a chronic stressor and an environmental insult on brain function. Indeed, poverty has been associated with neural adaptations across large-scale cognition and emotion processing networks, which have been implicated as prerequisites to developing depression and anxiety symptoms. The triple network theory posits that disruptions across the Salience (SAL), the Central Executive (CEN), and the Default Mode (DMN) networks undergird the development of psychopathology. The present study applied a large-scale network connectome analyses to characterize the association between adolescent brain function at-rest and a family's experience of material hardship when the adolescent was between ages 1 and 3. Guided by the triple network theory, results did not support my prediction that adolescents whose families reported greater material hardship during early childhood would be associated with altered at-rest network connectivity across the SAL, CEN, and DMN networks. Furthermore, study results did not support my hypothesis that these network alterations would be positively associated with current depression and anxiety symptoms. Exploratory analyses evaluating the period-specific and the incremental effects of material hardship were non-significant. Correlational analyses identified significant associations between extracted network connectivity and internalizing symptoms, independently of material hardship. Study limitations and implications of these findings are discussed.

Introduction

Youth growing up in families who experience material hardship—the inability to meet basic needs such as food, housing, or medical care—face a host of developmental challenges that increase their risk for socioemotional problems (Huang, Kim, & Sherraden, 2017). Despite the many studies reporting that youth from low-income families report higher internalizing (Goosby, 2007; Heflin & Iceland, 2009; McLoyd, 2011; Rushton, Forcier, & Schectman, 2002) and externalizing (Bellair, McNulty, et al., 2019; Skinner, Elder, & Conger, 1992) symptoms, research linking material hardship and youth internalizing psychopathology remains understudied. Specifically, this research has yet to examine how the association between poverty and psychopathology may be mediated by brain connectivity. Commonly reported associations between mother's material hardship and an infant's adverse emotional reactions (e.g., negative affect and temperament; Fuller, Messito, Mendelsohn, Oyeku, & Gross, 2018; psychological distress; Gross, Mendelsohn, & Messito, 2018), may serve as precursors to later psychopathology (Mezulis, Priess, & Hyde, 2011; Sidor, Fischer, & Cierpka, 2017). Research on adult populations commonly report small, but significant correlations between current material hardship and internalizing symptoms (Heflin & Iceland, 2009; Huang, Heflin, & Validova, 2021). However, some adult studies posit that only some types of material hardship such as problems paying bills and disconnected phone service were positively correlated with depression (Neckerman et al., 2016), while other researchers using a 6 item material hardship (items included: 'I have enough food in the house', 'My housing is safe', 'I have access to a working phone', 'I have appropriate clothing', 'My housing is stable', and 'I have transportation') scale reported significant positive correlations to both depression (r = .29) and anxiety (r =.31) (Katz et al., 2018).

To date, studies that used a family's income level to infer economic hardship have characterized how levels of SES were associated with brain network development during the first year of life. Gao and colleagues evaluated nine critical functional networks and determined that the typical maturation sequence of several networks was interrupted in lower SES infants (the primary sensorimotor/auditory to visual to attention/default-mode and final to executive control networks; Gao et al., 2015). Another study reported that childhood (age 10) household income was associated with altered coupling between the amygdala and the ventromedial prefrontal cortex at age 15 (Hanson et al., 2019). This altered functional connectivity coupling has been proposed to signal a future psychological vulnerability to stress, which may increase the likelihood of psychopathology (Hanson et al., 2019). Furthermore, Lipina and Posner (2012) reviewed studies examining the link between material deprivation (i.e., poverty) and brain network function related to attention, language and literacy, and numeracy. Their review of the available evidence demonstrated that decreased connectivity across large-scale networks is associated with reduced cognitive skills for children growing up in poverty, suggesting that levels of SES influence brain development. Given that previous literature has demonstrated a link between poverty and internalizing symptoms and between poverty and altered functional connectivity in the brain, it is of interest to better assess how material hardship impacts brain connectivity to support the emergence of adolescent depression.

Resting-State Functional Connectivity Explained

Resting-state functional connectivity (RSFC) has become a non-invasive approach for assessing experience-dependent neuroplasticity to brain architecture, organization, and function (Kelly & Castellanos, 2014). RSFC captures spontaneous low-frequency oscillations (0.01-0.1Hz) that reflect both unique and universal aspects of an individual's interactions with their world through patterns of co-activation that echo lived experiences and social contexts that is impacted the interplay between the environment and an individual (Biswal et al., 2010). It is this dependence on experience that makes RSFC ideal to capture undergoing neural adaptations that occur in development. For example, ongoing brain development can be observed through the reorganization of RSFC patterns as different networks mature (Hoff, Van den Heuvel, Benders, Kersbergen, & De Vries, 2013), meaning changing RSFC patterns reflect the integration or segregation of functional large-scale networks. Differences in RSFC patterns organized by large-scale network affiliation can be interpreted through their associations with behavior, its observed localization within expected cortex topography (Biswal, Yetkin, Haughton, & Hyde, 1995; Stevens, 2016a).

Moreover, the RSFC patterns reflect the adaptations underlying the dynamic nature of multiple brain processes that range from short-term transient brain states (e.g., during mindfulness; Parkinson, Kornelsen, & Smith, 2019) to long-term enduring conditions (e.g., chronic fatigue; Gay et al., 2016). RSFC susceptibility to changes due to biological variations of human systems (e.g., cicadian rhythms; Facer-Childs, Campos, Middleton, Skene, & Bagshaw, 2019; genetic variation; Meyer-Lindenberg, 2009; Meyer et al., 2016; HPA axis function; Thomason, Hamilton, & Gotlib, 2011) makes this a valuable tool for clinical research aiming to identifying unique neural signatures to inform treatment and diagnosis of mental health disorders.

Recent work has examined the associations between RSFC and distinct adolescent behavioral-health outcomes, and found that by and large, differences in RSFC reflect the outcomes under study. For example, RSFC in adolescents demonstrates associations between RSFC and major depressive disorder (Chattopadhyay et al., 2017; Cullen et al., 2014; Mulders, van Eijndhoven, Schene, Beckmann, & Tendolkar, 2015; Sacchet et al., 2016; Zhang, 2017), emotional dysregulation related to MDD (Ho et al., 2015), gender dysphoria (Garcia, 2018), schizotypal trait expression (Lagioia, van de Ville, Debbané, Lazeyras, & Eliez, 2010), adolescent risk-taking behavior (DeWitt, Aslan, & Filbey, 2014), substance use (Orr et al., 2013), adolescent conduct disorder (Cao et al., 2019) and higher-order cognitive functions (i.e., general ability, speed/flexibility, learning/memory; Sripada et al., 2020).

RSFC can be an advantageous method to examine underlying brain adaptations associated with poverty related stressors and ongoing brain development and function, whose interpretation can be framed through large-network organization. Consequently, the present study will utilize Power et al., 13 network parcellation that was identified though data driven approaches using RSFC (2011).

Large-Scale Networks in Resting-State Connectivity

While prior neuroimaging research examining the link between early childhood poverty and brain function has made extensive contributions to our understanding of how individual brain regions are affected (e.g., hippocampus and amygdala), large-scale network functional connectivity evidence characterizing these associations at a connectome-wide level are limited. The available resting-state connectivity evidence that has taken a large-scale network approach suggests that children growing up in poverty exhibit altered resting state connectivity relative to children who are not growing up in poverty. For example, Sripada and colleagues (2014) examined altered hypothalamic-pituitary-adrenal (HPA) axis function as a possible biological mediator, linking poverty and altered resting-state connectivity. In this study, researchers recruited a matched sample of adults (~ age= 24 years old, n=26), one group with a history of childhood poverty at age nine, and the other from middle-income families. Using seed-based correlation analysis (SCA) with strategically placed ROIs serving as proxies for large-scale networks with the DMN (PCC; posterior cingulate cortex seed) and the salience network (dACC/SMA; dorsal anterior cingulate cortex/supplementary motor area seed), the authors reported that adults with a history of childhood poverty had decreased connectivity in the DMN relative to the middle-income group. However, they found no association between SN connectivity and level of poverty. Despite this mixed finding, this study provides some evidence that financial status in childhood may relate to brain function in adulthood. Another study that examined income changes and large-scale network connectivity in adolescents demonstrated divergent patterns of connectivity in the DMN and regions of the central executive function, depending on when they experienced the lowest income (Weissman, Conger, Robins, Hastings, & Guyer, 2018). Taken together, these resting-state findings suggest that early childhood poverty is associated with disruptions of resting-state connectivity within networks that subserve key cognitive and emotion processing functions. This is of note because disruptions in these same cognition and emotion processing large-scale networks are implicated in the development of psychopathology (Barch, 2017; Lopez, Luby, Belden, & Barch, 2018; Menon, 2011; Sha, Wager, Mechelli, & He, 2019). As such, these disruptions may be one possible mechanism through which children and adolescents growing up in low-income families are at an increased likelihood of developing mental health problems (Cohen, Janicki-Deverts, Chen, & Matthews, 2010; Currie & Lin, 2007; Reiss, 2013). However, not everyone living in poverty will develop any psychopathology, nor does this commonly reported association indicate that experiencing poverty-related stressors will inevitably support the emergence of depression or anxiety symptoms.

Given the previous research to date, I evaluated the interrelated coactivation patterns at-rest (i.e., connectome-wide RSFC) across 13 large-scale networks, including the Salience Network, the Default Mode Network, and the Central Executive Network, for youth who grew up in families who experienced material hardship during their early childhood (i.e., ages 1 to 3). Focus on this early childhood period is motivated by (1) the empirical evidence of the deficits in language and cognition associated with growing up in poverty that become apparent as early as 3 years of age and get larger by age 5 (Black et al., 2017; Campbell, Pungello, Miller-Johnson, Burchinal, & Ramey, 2001) and (2) the brain growth that occurs during early childhood has been linked to later cognitive function (Gale, O'Callaghan, Godfrey, Law, & Martyn, 2004), implying that disruption of the development of the neural correlates underlying the large-scale networks may have downstream cognitive impairments (3) the timing and type of hardship seems to be important for certain child outcomes at this age (e.g., internalizing vs. externalizing behaviors), highlighting early childhood as a crucial period that establishes the neural functions and structures that shape future cognition and socioemotional networks (Duncan et al., 1994, 2012).

The present study extends previous research on material hardship and brain function in several ways. First, I use longitudinal data of material hardship from low-income families and minority parents that allow me to better understand the patterns of family material hardship. Specifically, I examined eight items of material hardship (i.e., inability to pay bills, food insecurity, housing insecurity, medical hardship, having the utilities cut off, needing to borrow money to pay bills, needing to sleep in a shelter) to determine how childhood family material hardship is associated with both brain connectivity at-rest and with current psychopathology in adolescents. Second, the current study investigated the impact of family material hardship on resting state functional connectivity and the presence of internalizing symptoms among a nationally representative community sample of predominately African American families with children from non-marital births, which may differ from the families in deep poverty that have been previously studied. Third, I used functional connectivity at a connectome level of analysis, parceling out 264 ROIS into 13 large-scale networks, to evaluate the large-network functional connectivity interrelationships. Specially focusing on three major networks, the Salience Network, the Default Mode Network, and the Central Executive Network during adolescence. Lastly, this study used an innovative analytical methodology, a Network Contingency Analysis (NCA), to evaluate large-scale network functional connectivity at-rest organized through correlations between equally spaced ROIs, while controlling for multiple comparisons issue that correlations between 264 ROIs produces by using non-parametric significance testing.

Furthermore, there are several benefits to using the NCA method with connectome data. First, this method is applied to grid-based connectomes that represent patterns of connectivity across the entire brain and does not require potentially arbitrary choices of seed regions that may bias the results. Second, this method uses data-driven network structure identification (i.e., Power et al., 2011) to directly assess questions about the interrelationships of large-scale network connectivity, while providing a meaningful organized network framework. Third, this approach avoids univariate tests (i.e., t-tests) and the pitfalls (e.g., normality assumption) of such analyses with neuroimaging data by instead conducting a single permutation test for each large-brain network pair investigated across all seven major networks. Lastly, these permutation tests are robust to violations regarding assumptions of normality and independence. Thus, combining the strengths of resting-state connectivity with an NCA analysis, the present study examined the simultaneous resting state connectivity interrelationships between the thirteen canonical networks identified by Power et al. (2014).

The aim of this study is to characterize altered resting-state connectivity of adolescents who grew up in families who reported experiencing material hardship using a connectome-wide approach. I predicted that greater material hardship during early childhood (ages 1 to 3) would be associated with altered resting state connectivity across the functional connectivity interrelationships of three networks the Central Executive Network (CEN), the Default Mode Network (DMN) and the Salience Network (SAL). Specifically, I expected that from those network pairs affected by material hardship would be positively associated with current adolescent (age 15) psychopathology (i.e., depression and anxiety) symptoms.

Additionally, guided by previous reports that the incremental effects of material hardship have stronger associations with child internalizing and externalizing behaviors (Frank et al., 2010; Zilanawala & Pilkauskas, 2012), I conducted exploratory analyses characterizing the association between family material hardship reports across ages 1,3,5,9,15 both by time period and incrementally and at-rest connectivity at age 15. The incremental effects of material hardship were examined by sequentially grouping material hardship reports by increasing age (e.g., 1 to 3, 1 to 5). Furthermore, the association between extracted at-rest network connectivity and current depression/anxiety symptoms was evaluated, independently of material hardship. No specific predictions were formally tested with these exploratory analyses.

Methods

Participants

The study sample was drawn from 237 families from Detroit, Toledo, or Chicago who were part of the Study of Adolescent Neural Development (SAND; see table 2.1). These 237 families were a subsample from the larger longitudinal nationally representative Fragile Families and Child Wellbeing Study (FFCWS; Reichman, Teitler, Garfinkel, & McLanahan, 2001). The FFCWS longitudinal cohort of 4,898 families with children born in 20 large U.S. cities between 1998-2000 were oversampled for low-income families with non-marital births (~3:1; Reichman et al., 2001). One child (i.e., target child) from each of the 237 families was followed overtime. Target children were predominantly female (52%) and 76% self-identified as non-Hispanic Black/African American, as well as White/Caucasian (13%), other non-Hispanic groups (2%), Hispanic/Latino (4%) and 5% identified as being Multi-Ethnic/Race. Youth were 15.41 years old (*SD* =0.54) on average at the time of assessment. The majority of primary caregivers (48%; n =113) reported an annual household income between $29,999 or less, while 24% (n=57) reported $30,000-$59,999, 11% (n=24) reported $60,000-$89,999, 10% (n=22) reported $90,000 or more and 8% (n=21) of did not report household income (See table 2.1 for sample descriptives). Of the 237, one hundred and eighty-six (186) participants completed a resting state scan. From these 186 participants, 172 were included in the connectome-analysis following specific exclusionary criteria (See Table 2.4).

Procedure

All participants completed the surveys below and a resting state scan as part of their visit. Parental or guardian consent and child assent were obtained. All protocols and procedures were approved by the ethical review board at the University of Michigan.

Self-Reported Measures

Ethnic-Racial Identity

Ethnic-Racial Identity (ERI) was constructed using two items. Priority was given to the adolescent reported ethnic identity write-in question, “What is your ethnic identity?”. Next, parent's report of child's race was considered if first item was ambiguous or unclear (e.g., "American"). ERI refers to "a subjective, self-ascribed sense of oneself as a member of an ethnic or racial group"(Rivas-drake et al., 2014; Schwartz et al., 2014, p. 59). By constructing adolescent's ERI using this approach, gave those youth who at first identified as Biracial an opportunity to self-identify with a group of choice.

Material Hardship

At ages 1 (12 items), 3 (10 items), 5 (14 items), 9 (11 items), and 15 (11 items), caregivers indicated whether they experienced housing, utility, food, medical, and financial hardship within the past year. These questions were derived from the "Basic Needs – Ability to Meet Expenses" section of the Survey on Income and Program Participation (SIPP) 1996 Panel Wave 8 Adult Well-Being Topical Module Questionnaire (SIPP, 1998) and the 1997 & 1999 New York City Social Indicators Survey (SIS). Material hardship items were coded as 0 (no) or 1 (yes). The following eight items were asked at all waves (SAND sample KR20 α =.57-67):

(1) In the past twelve months, did you receive free food or meals?

(2) In the past twelve months, did you not pay the full amount of gas or electricity bill?

(3) In the past twelve months, did you borrow money from friends or family to help pay bills?

(4) In the past twelve months, did you ever not pay the full amount of rent or mortgage payments?

(5) In the past twelve months, did you stay at a shelter, in an abandoned building, an automobile, or any other place not meant for regular housing, even for one night?

(6) In the past twelve months, were you evicted from your home or apartment for not paying the rent or mortgage?

(7) In the past twelve months, was there anyone in your household who needed to see a doctor or go to the hospital but couldn't go because of the cost?

(8) In the past twelve months, did you move in with other people even for a little while because of financial problems?

Children did not necessarily live with the birth mother at all waves and material hardship can vary between households. Therefore, material hardship at each wave was based on primary caregiver reports (i.e., the caregiver the child lived with for most of the time). The primary caregiver was the mother if the child lived with their mother for at least half of the time. If the mother was not the primary caregiver, the father was considered the primary caregiver if the child lived with their father for at least half of the time. The 8-item composite score was combined into a weighted sum, where the weights for each indicator are based on the proportion of individuals not deprived by the indicator (e.g., Muffels, Ruud & Fouarge, Didier, 2001). These weighted indicators better represent those individuals who have experienced the rarer types of hardship (e.g., living in a shelter, abandoned building, or in their automobile in the past 12 months), underscoring statistically the fact that these more severe forms of material hardship may be more impactful on a family's wellbeing. Therefore, the weighted average of material hardship for each wave was used. Lastly, any participant who had missing data for a particular wave was filled in with the nearest next wave weighted average value (missing entries were less than 5% at any one wave).

Depression

Symptoms of depression were screened for using adolescent self-reported Children's Depression Inventory (CDI; Kovacs & Beck, 1977). The CDI is a 27-item measure (SAND sample α =.86), each consisting of three statements ranging from no symptomatology to severe symptomatology. The child selects one of the three statements for each item that best describes them within the past 2 weeks. Previous research has found the CDI to be a reliable and valid self-report measure of depressive symptoms in both clinical and non-clinical samples of children ages 6 to 17 (Huberty, 2012, α = .70 -.92). Symptoms are scored “0” to “2”, yielding a maximum score of 54. Additionally, the total score can be separated into 5 factors (Negative Mood, Interpersonal Problems, Ineffectiveness, Anhedonia, Negative Self-Esteem) to offer more precise descriptions of the nature of the symptoms (See Appendix B for full measure).

Anxiety

Screening for anxiety symptoms was completed with The Screen for Child Anxiety Related Disorders (SCARED; Birmaher et al., 1997, α=.7-.9). The SCARED is a 38-item (SAND sample α =.92) inventory rated on a 3-point Likert-type scale (0 = Almost Never, 1 = Sometimes and 2 =Often). Sample items include: “I worry about being as good as other kids” and “I am a worrier” (See Appendix C for full measure). The items assess for DSM-IV classification of anxiety disorders: panic/somatic, generalized anxiety, separation anxiety, social phobia, pertinent simple phobia, and school phobia. Other studies have found good psychometric properties with demographically diverse non-clinical samples (Birmaher, et al., 1999, α = .90; Arab et al., 2016, α = .80).

Gender

Adolescent self-reports of gender were determined using the Pubertal Development Scale (Petersen, Crockett, Richards, & Boxer, 1988) which has had high correlations (r= 0.61–0.67) with physician rating (Brooks-Gunn, Warren, Rosso, & Gargiulo, 1987). Scores range from 1 to 4. Gender was determined from the specific female or male set of questions on the scale.

Age

Age was calculated from date of birth provided by teen and confirmed by parent on the fMRI safety screener, and then the date of the visit to calculate age in months.

Resting-State fMRI Data and Preprocessing

MRI Acquisition

MRI image data for the SAND study were acquired on a GE Discovery MR750 3T MRI scanner with an 8-channel head coil. Data acquisition included a T1-weighted structural scan and an 8-minute resting-state fMRI scans obtained using functional T2*-weighted BOLD images with a gradient echo spiral sequence (TR = 2000 ms, TE = 30 ms, 40 contiguous 3 mm axial slices, flip angle = 90°, FOV = 22 cm, voxel size = 3.44 mm × 3.44 mm x 3 mm) aligned with the AC-PC plane. Resting state functional images were collected while participants were awake, passively viewing a fixation cross at the end of the scanning session. Slices were acquired contiguously, which optimized the effectiveness of the movement post-processing algorithms. Images were reconstructed off-line using processing steps to remove distortions caused by magnetic field inhomogeneity and other sources of misalignment to the structural data, which yields excellent coverage of subcortical areas of interest. Standard preprocessing, slice-timing, realignment, and coregistration to the structural scans, and normalization to MNI 152 space, and a spatial smoothing using a Gaussian kernel (6-mm) was completed in SPM12 using defaults. Next, the top five white matter components were regressed out as well. Finally, all brain activity was filtered through a bandpass filter between .01 to .1hz, our wavelength of interest.

Image Processing

Resting-state fMRI data were preprocessed using CONNTOOL scripts from the Psychiatry Methods Core repository using statistical parametric mapping software (SPM12).

Scans were slice-time corrected, realigned to the tenth scan in the experiment for correction of head motion, and coregistered with the high-resolution T1-weighted image. Normalization was performed using the voxel-based morphometry toolbox implemented in SPM12. The high resolution T1-weighted image was segmented into biased corrected tissue types. Smoothing of functional data was performed with a 6 mm3 kernel and the top five cerebral spinal fluid (CSF) components were regressed out. Next, the top five white matter components were regressed out as well. Finally, all brain activity was filtered through a bandpass filter between .01 to .1hz, our wavelength of interest.

Motion and Denoising Correction Strategy

Because head motion confounds the interpretation of RSFC, the following strategies were used with our BOLD data to identify and correct for motion. First, 8-minute scans were motion scrubbed to identify and remove motion artifacts from the fMRI time series, using a mean frame displacement (FD) cut-off value of .5 mm (Power et al., 2012). FD criteria quantifies head movement from one volume to the next at every time point, which is used to identify how many slices are to be removed from the total available volumes (Goto et al., 2016). We identified and removed subjects who did not have at least 4 minutes of usable data. Secondly, ICA-AROMA was applied to data at the subject-level to remove motion related artifacts (Pruim, Mennes, Buitelaar, & Beckmann, 2015; Pruim, Mennes, van Rooij, et al., 2015). ICA-AROMA increases the reproducibility of RSFC networks and limits the loss of temporal degrees of freedom (Pruim et al., 2015). A conservative approach was taken to address motion correction by combining both strategies in deciding who was kept or removed from subsequent analyses(Parkes, Fulcher, Yu¨cel, & Fornitod, 2017).

Brain Connectome Generation

To produce a whole-brain resting functional connectome, we placed 264 regions of interest (ROIs) encompassing approximately nineteen 3x3x3 mm voxels in a regular grid overlapped across the entire brain, following the Power et al., (2011) 13-network parcellation (See figure 2.1) As such, groups of ROIs (network nodes) that defined the networks were spaced apart at 12 mm intervals from center-to-voxel-center radius, creating an artificial sphere of voxels (i.e., pseudospheres), throughout the brain. None of the ROIs are near brain edges to avoid perception of false activation. Each region of interest (ROI) consisted of a 3.2 voxel center-to-voxel center radius pseudosphere, allowing for the measurement of the edges between the individual ROIs.

Analytical Approach

The aim of this study was to characterize the association between connectome-wide resting-state functional connectivity for adolescent youth who grew up in families experiencing material hardship. To that end, data analyses were completed in several steps. Descriptive statistics, zero-order correlations, and chi-square tests were completed using SPSSv27. Imaging data analyses were conducted using the following software SPM12 (SPM - Statistical Parametric Mapping (ucl.ac.uk) and Psychiatry Methods Core Scripts (Release 1.6; ConnTool & Network Contingency Analysis). Given that the network contingency analysis requires non-missing behavioral data to model the individual connectomes, weighted means were created for our material hardships scores and near neighbor substitution was completed for missing data points (less 5%).

Network Contingency Analysis

To avoid the multiple comparison corrections across all 264 ROIs that would be typically necessary when using a mass univariate approach, I will apply a nonparametric network contingency analysis for significance testing. This analysis addresses the question of whether the functional connectivity for each set of edges linking two nodes within each large-scale network is different because of the variation in reported in family material hardship than one would expect by chance. This Network Contingency Analysis (NCA) has three sequential steps (See Figure 2.2):

Step 1. Subtraction and Thresholding: Each edge represents a multiple regression model that models the effects of material hardship while controlling for the effects of gender, motion, age, race, and current age 15 material hardship. For each edge, we fit the following multiple regression model:

$$y_i = 1 + \beta_1 X_{MH(age\ 1\text{-}3)} + \beta_2 X_{age} + \beta_3 X_{race} + \beta_4 X_{gender} + \beta_5 X_{pre\text{-}corrected\ motion}$$
$$+ \beta_6 X_{MH(Current\sim 15)} + \varepsilon$$

where yi is the magnitude of connectivity at edge i; X_2 through X_6 are covariates: current age, gender, pre-corrected motion, current age material hardship, and ethnic-racial identity. β_1-β_6 are the estimated betas; ε is the mean error term. Only the edges whose mean activation met statistical significance (thresholded at $p < 0.005$) were retained for plotting in a cross-tabulation map. The rationale for this threshold is based on a prior study that systematically tested different p-values {0.0001, 0.0005, 0.001, 0.005, 0.01, 0.05, 0.1} to identify their effect on the robustness of the network analyses (Sripada, Kessler, et al., 2014) To test for robustness of analysis different threshold values were tested (0.005, 0.001) if network results were significant. Covariates individually modeled and were retained in the final model due to their influence on the overall functional connectivity (i. e., gender); race was included as a covariate because of its previously demonstrated association with economic disadvantage related to material hardship.

Step 2. Organize edges based on network affiliation: Network organization was identified using the 13-network Power et al., (2011) large scale network map (See Figure 2.2). A cross-tabulation map is generated with non-redundant cells where each cell represents the set of edges linking two nodes, and both inter- and intra- network relationships are represented. Each edge is represented in each crosstab map cell by colored dots, blue or red, indicating decreasing or increasing connectivity, respectively.

Step 3. Cell-wise contingency analysis: In this step, we test the hypothesis that the number of observed edges in a cell of the thresholded network cross-tabulation map exceeds the number that would be expected by chance alone. Only the observed edges that remain significant from Step 2 are retained for analysis. Next, this value is compared to the number of edges that would be expected by chance under the null hypothesis that material hardship has no effect on resting state connectivity. To evaluate the null distribution, this cross-tabulation analysis uses a non-parametric test that is robust to deviations from independence assumptions of parametric tests such as Bernoulli or chi-square tests. This distribution was generated from the drawing of random edges repeated 10,000 times and $N_{observed}$ edges were calculated at each iteration, yielding a distribution of $N_{observed}$ values. The *p*-value of the actual $N_{observed}$ values was calculated as the number of $N_{observed}$ values in the permutation that exceeded the actual value divided by 10,000. Since the permutation test is performed for a multiple regression model that includes covariates (see step 1), Freedman and Lane’s (1983)was followed. In brief, this procedure first estimates a multiple regression model with covariates alone, and its residuals are formed and permuted. The covariate effect is then added back in, creating an approximate realization of the data under the null hypothesis. The statistical test of interest is then calculated on this data.

We performed a cell-wise contingency analysis separately for each cell of the thresholded network cross-tabulation map and corrected for multiple comparisons with the false discovery rate (FDR) correction procedure (Benjamini & Hochberg, 1995). Cells that survived FDR correction were next shaded. Since we were also interested in the directionality of network connectivity changes, the cell was shaded more red as the proportion of suprathreshold cells that exhibit positive change approaches one and more blue as this number approaches zero (predominantly negative changes).

Lastly, each of these $p_{\text{threshold}}$ values yielded an p-value map (one p-value for each of the 78 cells that make up the map). We then generated a weighted mean of these p values across the thresholds by calculating a normalized area under the curve. In doing this calculation, the $p_{\text{threshold}}$ values were first z-transformed so that the distance between $p_{\text{threshold}}$ values was well scaled. This procedure yielded a single weighted mean p value map. We then performed False Discovery Rate correction for multiple comparisons on these adjusted values, set at a p <.05. Figure 2.3 depicts these analytical steps in a diagram.

Selection of Covariates

To provide a rigorous test of our network contingency analysis (NCA)models of at-rest connectivity, we controlled for important covariates that might confound the association between early childhood material hardship and at-rest network connectivity. Several theoretical, statistical, and prior work support the inclusion of the following covariates in our models including age, gender, motion, ethnic racial identity, and current age 15 material hardship. Additionally, the covariates also reflect an effort to remove any confounding effects of these covariates related to brain development, experiences of poverty, and internalizing symptoms. Specifically, NCA models included age, gender, scanner motion, and current age 15 material hardship. Of note, ethnic racial identity was included as a covariate given the persistence of structural and institutional discrimination that perpetuates income inequalities in the U.S., as well as reports of increased likelihoods of facing material hardship when you identify as Black or Hispanic in the U.S. (See Rodems & Shaefer, 2020).

Network Contingency Analysis Models Tested

Based on previous literature and grounded in theoretical rationale, NCA models evaluated the association between early childhood (age 1 to 3) and resting-resting state connectivity, controlling for age, gender, ethnic-racial identity, scanner motion, and current age 15 material hardship. Next, given the extant literature on the timing and cumulative effects of material hardship on brain connectivity, the following exploratory analysis were completed to characterize the association between material hardship reported between ages 1 to 15 during development. Therefore, material hardship scores were independently modeled by wave (i.e., reports at age 1, age 3, age 5, age 9, age 15) with covariates to characterize the individual effect of these events on age 15 functional connectivity at-rest. Lastly, the incremental additive effect of material hardships was tested including our covariates from ages 1 to 15 (i.e., 1-3, 1-5, 1-9, 1-15). All models whether testing the effect of family material hardship in one wave or the additive effect across several waves included the following covariates: age, ethnic-racial identity, gender, and pre-corrected motion based following previous analyses.

Resting-state Networks and Internalizing Symptoms

One of the primary interests of this study was to identify how large-scale network RSFC dysregulation accounting for material hardship is associated with psychopathology. To test for these associations in our adolescent sample, independent zero-order correlations were performed between depression or anxiety symptom scores and the extracted mean network activation associated with material hardship from statistically significant networks identified from our first hypothesis. Also, an exploratory correlation analyses evaluating the association between the extracted at-rest network functional connectivity and current psychopathology was completed, independently of material hardship.

Results

Demographics

Table 2.1 summarizes our sample demographic variables, weighted family material hardship scores, and psychopathology outcomes (N=237). Next, preliminary descriptive analyses of the demographic and outcome variables for the 174 adolescents retained for our neuroimaging analysis were completed. Group differences between included (n=53) and excluded youth were done (n= 53; of which n=51 did not complete scan and n=2 had excessive movement during scanning session; See Table 2.4 for exclusionary criteria). No significant sample differences between included and excluded youth in any of the demographic variables were found, suggesting that across these characteristics the sub-sample retained for analysis was representative of the youth who were excluded. No group differences were identified in material hardship reports at any age. No sex differences were found in weighted mean family material hardship at any age. Additionally, most excluded adolescents from the connectome analysis did not complete a resting state scan. Lastly, there were no differences in internalizing symptoms reported (See Table 2.5). Overall, the lack of group differences between those included in the analyses and those excluded suggest that our sample of 174 was representative of the larger sample 237. Specifically, the 174-youth included in the analyses were predominantly female

(56%) and 78% self-identified as non-Hispanic Black/African American, as well as White/Caucasian (10%), other non-Hispanic groups (2%), Hispanic/Latino (5%) and 4% identified as being Multi-Ethnic/Race. Youth were 15.43 years old (*SD* =0.55) on average at the time of assessment. (See Table 2.5).

Family Material Hardship

Table 2.3 summarizes the weighted family material hardship 8-item composite score proportions by wave (i.e., age 1, age, 3, age 5, age 9, and age 15) for the whole sample (N=237). These analyses showed that on average between 51% to 67% of the primary caregivers of these 237 adolescents consistently reported facing at least one material hardship during any wave of data collection. Across all waves the top three types of hardship reported were struggles to pay their utility bills (i.e., gas or electricity; 23% to 38%), needing to borrow money to meet their needs (23% to 48%), and struggling with rent or mortgage payments (12% to 24%). The least reported material hardship across the five waves of data collection were needing to sleep in a car or non-shelter location (1% to 3%) and facing home eviction (2% to 4%). Although this study controlled for any ethnicity and race effects, preliminary analyses of material hardship differences by ethnic-racial identity demonstrated higher weighted material hardship average scores for Black and Hispanic families from age 1 to age 3, relative to lower reports of material hardship of White youth during this same period (See Figure 2.1). Furthermore, this early difference in material hardship becomes more pronounced over time, whereby a difference gap between Black and White families is evident relative to the other groups in the study.

Of the 237 youth who completed the study, 174 were included in the connectome analyses for this study. No statistical differences were found between reported material hardship patterns between the two groups(See Table 2.5). Specifically, more than half (between 51% to

68%) of the primary caregivers reported at least one material hardship during any wave of data collection. The top hardship items endorsed by the families across the 5 waves of data were an inability to pay gas or electricity bills (between 24% to 40%), needing to borrow money to pay bills (27% to 43%), and inability to pay the rent or mortgage (12% to 26%). The least reported hardships were seeking shelter for the night (between 2 - 3%), facing housing eviction (2% to 5%) and an inability to go see a doctor when needed (4% to 7%).

For the participants in the sub-sample included in the present analyses (See Table 2.7), age 15 material hardship and annual income at age 15 were not significantly correlated (r = -0.05, p =.59). Primary caregiver income data from previous waves was not included in the present analyses and therefore no correlations between income and their respective material hardship scores were reported. The weighted material hardship 8-item composite scores between age 1 and age 3 were positively correlated with each other (r = 0.57, p <.001). Overall, correlational analyses of all weighted material hardship scores between age 1 through age 15 had significant magnitudes of association across time (r =0.22 to r=0.55, all significant at p <.001). Additionally, weighted family material hardship scores reported closer in time had higher positive associations to each other (r= 0.45 to r = 0.57, all significant at p<.001). Of note, weighted family material hardship reported at age 3 was negatively correlated with current age (age 15; r =-0.16, p=.04). No other significant associations between any of the demographic variables and any material hardship score were found.

Connectome-Wide Network Connectivity

Primary Hypotheses

Family material hardship during early childhood (age 1 to 3) was hypothesized to alter adolescent resting-state functional connectivity network patterns, across three major large-scale networks: Central Executive Network, Salience Network and Default Mode Network. To test the primary hypothesis, we modeled the cumulative effect of family material hardship from ages 1 to 3, while controlling for adolescent's race, gender, mean frame displacement (i.e., in-scanner motion metric) and current reports of family material hardship. Next, a visual summary plot of the edges retained for significance testing illustrated overall increased node connectivity (i.e., more red dots) across all 13-large scale networks (See Figure 2.6). Overall, the visual plot shows that increased material hardship between age 1 to 3 was related with increased node connectivity across all 13 large-scale networks, including the default mode network, the memory network, the visual network , the frontoparietal network, and the salience network. However, non-parametric significance testing of this pattern of edges identified in our age 1 to 3 model did not survive the false discovery rate adjusted correction at $p < .05$, yielding non-significance of any network interrelationship. Table 2.8 contains the specific adjusted p-values across the networks in a contingency table for material hardship during ages 1-3. Therefore, these data did not support the first hypothesis because no altered network interrelated co-activation was deemed statistically significant across any of the three hypothesized networks.

Given the extant literature on the timing and cumulative effects of material hardship on brain connectivity, the following exploratory analysis were completed to examine the association between material hardship by wave and the additive increments in consecutive order from ages 1 through 15. All exploratory models testing the association between material hardship and at-rest connectivity included the following co-variates: age, ethnic-racial identity, gender, and pre-corrected motion, and current age 15 material hardship to remain consistent with the initially hypothesized model. The evaluation of the individual material hardship effects on overall connectome-wide at-rest connectivity demonstrated a higher number of increased connectivity nodes (i.e., red dots, see Figure 2.7) at age 1 and age 3, relative to a reduced number of increased connectivity nodes at age 5, age 9, age 15. Additionally, from age 5 through 9 an equal number of decreased nodes (i.e., blue dots) and increased connectivity nodes were present across all 13 networks. Non-parametric significance testing of these connectome patterns did not identify any significant associations between individual material hardship reports at age 1, age 3, age 5, age 9 and age 15 and interrelated at-rest connectivity (i.e., all FDR-corrected p-values were between .43 to 1.0). Interestingly, when evaluating the incremental effects of material hardship during early childhood age 1 through 5, the thresholded connectome shows a higher number of nodes with increased connectivity across all 13 networks relative to the incremental effects of ages 1 through 9 or ages 1 through 15. The incremental effects of family material hardship from ages 1-5, 1-9, 1-15 on adolescent functional connectivity were not associated with any significant interrelated network connectivity (i.e., all p-values were 1).

Internalizing Symptoms

Overall, adolescent (i.e., age 15) reports of internalizing symptoms within the sub-sample of 174 youth were low with sex differences by internalizing disorder. First, age 15 depression symptoms were positively correlated with age 15 anxiety symptoms (r =0.45, p<.001). The average depression symptom score for the youth in the sub-sample was 8.82(SD = 6.78). Although females (M=9.48, SD=7.09) reported higher depression symptoms relative to and males (M=7.99, SD=6.33), these differences were not significant; $t(172)=1.45$, p =.15. Similarly, the sub-sample reported low anxiety symptoms on average (M=17.25, SD=11.25). Females reported significantly more anxiety symptoms (M=20.45, SD=11.84) compared to male reports (M=13.27, SD=9.07); $t(171)$ =4.38, p =.001, Cohen's d=0.67, 95%CI [0.36,0.98].

Of note, two additional associations between the psychopathology measures and our variables of interest emerged within the full sample data. First, adolescent anxiety symptoms and depression symptoms were negatively correlated with gender (r= -0.33, p<.001; r= -0.16, p=.02, respectively), meaning that reports of psychopathology were more commonly associated with being female (based on variable coding). Second, a positive association between family material hardship reported at age 15 and current adolescent depression symptoms (r=0.14, p=.04) was found, but not with youth's anxiety symptom scores (r=0.09, p=0.16; See Table 2.3).

Additionally, since no association between at-rest network co-activation and material hardship was significant, I was unable to test my second hypothesis that predicted a positive association between significant altered network connectivity and current reports of psychopathology at age 15. However, an exploratory analysis characterizing the association between network connectivity, independent of material hardship, and adolescent psychopathology symptoms identified interrelated connectivity by type of internalizing disorders. Table 2.9 summarizes the correlations between extracted network connectivity at-rest and depression. Higher depression symptoms were negatively correlated with decreased within-network connectivity in the cingular opercular task control (COT-COT; r= -0.17, p=0.02) and auditory network (AUD-AUD; r= -0.16, p=0.03). In contrast, higher anxiety symptoms were positively associated with increased interrelated network-coactivation during rest. Specifically, within network coactivation of the memory retrieval (MEM-MEM; r =0.18, p=.02) was positively correlated with higher anxiety symptoms. Similarly, higher anxiety symptoms were positively associated with network co-activation of the default mode and the somatosensory mouth network (DMN-SSM; r=0.17, p=0.02), and the memory retrieval network (DMN-MEM; r=0.16, p=.03). Moreover, increased memory retrieval coactivation with the salience network

(MEM-SAL; r=0.17, p=.03) and the limbic network (MEM-LIM; r=0.17, p=.03) was also positively associated with higher anxiety symptoms. Lastly, higher anxiety symptoms were positively associated with increased co-activation between the cerebellar network and three other networks: the somatosensory hand (CER-SSH; r=0.16, p=.03), the auditory network (CER-AUD; r=0.18, p=.02), and the limbic network (CER-LIM; r=0.16, p=.03; see Table 2.10).

Discussion

Poverty is a multi-dimensional construct and income-based measures should not be the only indicator of a family's financial well-being because they do not characterize their everyday experiences with economic hardship. Addressing this concern, the present study used an eight item composite score of family material hardship that documented past year hardships such as not being able to pay the utility bills or rent to characterize a family's unmet basic living needs (Gershoff et al., 2007). The aim of this study was to characterize the association between early childhood (Age 1 to 3) material hardship and connectome-wide adolescent functional connectivity at- rest. Our study revealed that early childhood material hardship was not associated with alterations of at-rest network connectivity at age 15. Additionally, through follow-up exploratory analyses we reveal two important findings. First, there was no significant associations between the individual or incremental effects of material hardship from ages 1 through age 15 on at-rest network connectivity. Next, both positive and negative associations between psychopathology symptoms and extracted resting-state network connectivity were observed across distinct networks.

The current study identified that more than half of the families in our study had reported at least one material hardship item over the past 12 months across all five waves of data collection and that Black and Hispanic families reported higher material hardship over time relative to the White families in our sample. This characterization of material hardship is in line with findings from other national studies of low-income families (Karpman, Gonzalez, Zuckerman, & Adams, 2018; Rodem & Shaefer, 2020). Surprisingly, there was no significant association between concurrent family material hardship and annual household income at age 15, which has been found in other larger studies of material hardship (*r*=-0.07; Ashiabi & O'Neal, 2007; *r*=-0.18; Bellair et al., 2019). This could be due to our modest sample size and the different material hardship items used in our composite score, yet other item hardship specific studies have also reported mixed associations with family income (e.g., food hardship, *r* =-.39, Gershoff et al., 2007; *r* =-.07, *ns;* Slack & Yoo, 2005). Taken together, this suggests that material hardship characterizes experiences in poverty differently than income-based measures and at least in our sample are not necessarily correlated.

Moreover, the current study examined the association between early childhood (Age 1 to 3) material hardship and connectome-wide adolescent functional connectivity at- rest. Through our network contingency analysis, we identified that higher material hardship during early childhood was associated with positive node connectivity patterns across all 13 networks for the youth in our sample, yet contrary to the primary hypothesis these patterns did not associate with greater material hardship after non-parametric significance testing was applied. Our findings differ from with the reported associations between childhood poverty and adolescent resting state connectivity such as altered resting state connectivity in ROIs situated within the default mode network (Weissman et al, 2018) or the weakened resting state connectivity coupling between the amygdala and the ventral prefrontal cortex in low-income adolescents who had been followed since the age of 9 from a sample with a diverse income range (Hanson et al., 2019). Other retrospective fMRI poverty studies have also identified childhood poverty impacting adult resting-state connectivity with reduced default mode network connectivity at-rest for those who reported greater degrees of poverty (Sripada, Swain, Evans, Welsh, & Liberzon, 2014). Perhaps, there were protective factors that we did not account for, such as supportive parenting, which has been found to offsets the association between living in poverty and altered resting-state connectivity of neural networks that support cognition and emotion regulation during young adulthood (Brody et al., 2019). Overall, our findings reinforce the need for more multidimensional approaches in poverty research and suggest that available family income and material hardship are distinct dimensions of poverty that impact brain function in different ways.

Follow-up exploratory analyses to characterize the cumulative effects or individual effects of material hardship between ages 1 through 15 did not find any significant associations with adolescent at-rest network connectivity. Despite the reported associations between the cumulative effects of poverty and poor developmental consequences relative to individual incidents of hardship (Evans & Cassells, 2014; Evans, Li, & Whipple, 2013), this association was not present with material hardship for our sample. Given the persistence of material hardship for some of our families since early childhood, it is surprising that adolescent resting state connectivity did reflect any underlying neurological adaptations in response to growing up in families facing material hardships. Our results contribute to the mixed findings about the cumulative effects of material hardship with some studies reporting significant associations with well-being (Frank et al., 2010) while others reporting none (Yoo et al., 2009). Overall, the exploratory models were not significant, suggesting that early life material hardship experiences did not have an association with at-rest connectivity at age 15.

One possible reason why the association between early childhood material hardship and adolescent at-rest connectivity was not identified in our sample could be that resting-state connectivity seems to be more sensitive to changes in cognitive ability rather than environmental stressors such as poverty (Millar et al., 2020). More support for this possibility comes from other connectome-wide studies that reported that structural connectivity disruptions mediated the relationship between SES and cognitive ability, while no association with internalizing and externalizing symptoms were found (Astle, Johnson, Bathelt, Akarca, & Team, 2020; Mill, Ito, & Cole, 2017). Yet a recent study using a large sample from the Adolescent Brain and Cognitive Development (ABCD) sample (N=3,778) reported a positive association between youth in families facing resource insecurity (i.e., material hardship) measured through a 7-item composite score asking about past year immediate family experiences with hardships (e.g., food insecurity, unable to pay rent, evicted from home, utilities cut-off) and internalizing symptoms (r=0.12, p<.001; Oh, 2019). Given that the association of material hardship and network connectivity is so small, it suggests that future studies should seek to conduct connectome wide analyses with larger samples to be able to detect any associations.

Although previous work suggests that higher early childhood material hardship events increase the likelihood of depression symptoms in adolescence (Joinson, Kounali, & Lewis, 2017), we could not test our second prediction that network connectivity accounting for early childhood material hardship would be associated with current adolescent psychopathology. On average depression and anxiety symptom reports were low for our youth from a community-based non-clinical sample. Similar low reports of anxiety and depression symptoms for Black youth relative to White youth has been reported in nationally representative samples, with Black youth having a higher likelihood of endorsing mood and anxiety symptoms relative to their White peers(McLaughlin, Hilt, & Nolen-Hoeksema, 2007; Palmer, Oosterhoff, Bower, Kaplow, & Alfano, 2018). However, it may be possible that the low reports of anxiety and depression may reflect adolescent resilience fostered in the face of economic adversity; resilience that moderates the relationship between material hardship and current internalizing symptoms (Sun et al., 2015).

Motivated by the theorized triple network disruptions (default mode network, DMN; central executive network, CEN; salience network, SAL) associated with psychopathology (Sylvester et al., 2012; Menon, 2011) and empirical work testing those theories in clinical samples (Gong & He, 2015; Jacobs et al., 2016), we conducted an exploratory analyses of extracted network connectivity and current psychopathology symptoms in our community based-sample. The present study revealed differences in the pattern of activation , but also deactivation associated with specific internalizing symptoms. First, within network co-activation of the cingular opercular task (COT-COT) and the auditory network (AUD-AUD) were negatively correlated with depression symptoms. Although these networks are not part of the three large networks, they have been associated with different cognitive functions that support emotion-cognition processing such as, the COT network has been purported to help maintain alertness, and cue selective attention, as well as, be indicative of faster response speed (Coste & Kleinschmidt, 2016). While less is known about the AUD network and its association with depression symptoms, it has been implicated in schizophrenic hallucinatory symptoms (Li et al., 2019). Given that our sample does not meet criteria for major depression disorders, these negative correlations may be indicative of the phenotypic variability of depression symptoms (Vaidya & Gordon, 2013).

In contrast, we observed a positive association between higher anxiety symptoms and network connectivity between the DMN and the somatosensory mouth (DMN-SSM) and memory retrieval network (DMN-MEM) as well as the salience (SAL-MEM) were observed.

The increased network co-activation associated with anxiety may reflect the increased alertness and interrupted processing of inner thought and memory retrieval which has been observed to be negatively biased in youth with anxiety disorders (Gagnon & Wagner, 2016). As for the memory network, this network seems to be vulnerable to acute stress such that it may negatively bias attention and processing with other networks (Hitchcock, Werner-Seidler, Blackwell, & Dalgleish, 2017). People with high trait anxiety and anxiety disorders generally show a similar pattern of network dysfunction(Sylvester et al., 2012). Lastly, the increased coactivation of the cerebellar and three other networks CER-SSH, CER-AUD, CER-limbic network (LIM) maybe indicative of changes to automatic processes and information processing directed by the cerebellar network (Córdova-Palomera et al., 2016; Lee et al., 2020). By and large, these associations have been proposed to reflect state of anxiety rather than trait anxiety (Li et al., 2019). Taken together these associations provide additional information that characterizes symptom level associations with at-rest network connectivity which may be relevant to understand how these symptoms, affect mood and anxiety that compromise the pursuit of important goals such as an education. Lastly, understanding race-ethnic differences among these disorders is especially important to address racial disparities in health access and treatment.

Limitations and Future Directions

The present study is not without its limitations. The connectome-wide study may have been underpowered for two reasons, the eight-minute resting state scan may not have provided sufficient data to detect the small environmental effects of material hardship (See Oh, 2020, reporting r =-.02 using an n= 3778) and the sample size needs to be increased (~1000 + participants) to detect the small material hardship effect size on brain connectivity. Recommendations to increase the sample size through collaborations with multi-site projects would be ideal as well as extending the scan time may improve data quality and yield a better signal-to-noise ratio for connectome analysis that are data intensive approaches to identify behavioral and environmental effects associated with functional connectivity (Power, Schlaggar, & Petersen, 2015). Next, even though I created weighted items to reflect the potentially more potent effects by type of material hardship and then averaged the eight items to create comprehensive composite scores of material hardship (e.g., used a similar approach Bellair et al., 2019), some of the eight items used identified material hardship by asking if the primary caregiver 'had received free food' or 'borrowed money from friends to pay for bills'. The wording of these items conflates family material hardship with receiving some type of relief or aid that addresses the material hardship rather than describe the occurrence of the hardship. I would encourage future work to explore the unique associations that each type of hardship d (e.g., unable to pay gas or electric bill versus experiencing housing evictions) may have on mental health and functional connectivity outcomes. Additionally, efforts to examine material hardship through multi-dimensional indices that better represent those experiences with material hardship (Alkire, 2007) to include duration, timing and resolution would disentangle some of these confounds that may have impacted our ability to detect any at-rest functional connectivity. Lastly, children's subjective experience with family material hardship would be important to measure to best characterize how the awareness of not having their individual needs met mediates the relationship between childhood adversity and brain function.

Future replications testing the strong theoretically grounded predictions made by the current study are crucial even though the reproducibility of neuroimaging studies has come into question (Sato et al., 2016; Shrout & Rodgers, 2018). Ways to address the difficulties in reproducing neuroimaging findings should be a priority for poverty researchers whose data support conclusions that assert deficits in brain development and function for individuals growing up in poverty. Specially since some of the work produced will be used as evidence to inform public social policies that will directly affect those most in need. Researchers should make efforts to be more critical with the statistical pipelines used in analyzing neuroimaging data by being sensitive to sample specific characteristics such as cultural norms and the participant lived experiences while also to be adequately powered for the proposed analysis (Anderson & Maxwell, 2017). In similar ways to how we select the most representative sample in clinical research through careful preliminary evaluation of behavioral data from multiple sources to characterize the individual's understudy. By applying a similar approach, while being sensitive to poverty-related factors, we can begin to elucidate important social factors that should be present in neuroimaging research to increase reproducibility across different samples. Granted no one solution can attend to the individual differences of each sample, but efforts to include those social variables in the analyses should be made. Lastly, efforts to identify other buffers such as resilience or other potential mediators of the neural adaptations that occur in response to a family's material hardship could provide potential areas for the development of future cognitive and behavioral interventions.

Summary

The present study aimed to characterize the association between early childhood material hardship and resting-state connectivity in adolescence. Despite finding no association between early childhood family material hardship and adolescent resting-state functional connectivity, the null findings underscored the need to examine and compare the detrimental effects of different dimensions of poverty on brain function and development. Additionally, analyses of behavioral data revealed the chronic nature of family material hardships faced by some of the families in our sample, as well as, adolescent depression was associated with current age material hardship, suggesting that having unmet needs affects mental health. Indeed, our exploratory analyses of psychopathology revealed unique associations by type of internalizing symptoms and extracted network connectivity, independently of material hardship. Overall, reporting null findings is important because it generates new questions and invites researchers to revisit previous literature more critically.

CHAPTER III
Material Hardship and Adolescent Task-Based Functional Connectivity

Abstract

Associations between neural adaptations within emotion processing networks and poverty-related stressors such as family material hardship have been reported. Aberrant functional connectivity across large-scale networks that support emotion processing: Salience(SAL), Central Executive (CEN), and Default Mode (DMN) networks confer a risk of developing internalizing symptoms. The present study applied connectome-wide psychophysiological interaction (PPI) analyses to characterize the association between childhood material hardship (ages 1 to 3) and adolescent task-based functional connectivity across the SAL, CEN, and DMN during a gender identification task with implicit emotion processing. PPI results indicated that greater material hardship during early childhood was associated with increased co-activation of the Frontoparietal and Dorsal Attention Networks (FPN-DAN, $p < .03$), subnetworks situated within the CEN while youth viewed 'fearful' faces, supporting our prediction. However, non-significant correlational analyses between FPN-DAN and adolescent depression and anxiety symptoms (r =-0.06; r =-0.03, respectively) did not support our second hypothesis. Exploratory analyses of period-specific and incremental effects of material hardship and 'fearful' network connectivity were non-significant. Correlational analyses identified significant associations between extracted 'fearful' network connectivity and internalizing symptoms, independently of material hardship. Study limitations and implications of the association between early life material hardship and adolescent altered emotion processing to fearful faces are discussed.

Introduction

One in five children in the U.S. is growing up in families with annual incomes below the federal poverty line, with child poverty rates highest among Black (29%) and Latino (25%) Americans (Census, 2017). Unfortunately, not children growing up in families facing poverty-related hardships are not represented in those statistics because their family's income is above the official poverty threshold (Rodems & Shaefer, 2020). However, reports of household income are subject to unreliable recall, can fluctuate, and income assumes an equal distribution within the household (Bradshaw & Finch, 2003). Therefore, the present study examined a more proximal measure, material hardship, an understudied dimension of poverty, which captures the lived conditions of economic hardship through instances when demands on the families' resources exceed the available resources, resulting in families having unmet basic needs such as food or electricity (Chaudry & Wimer, 2016; Neckerman et al., 2016).

Studies examining the correlation between material hardship and family income have reported small associations and identified material hardship as a separate and distinct construct (Ouellette et al., 2004). Nonetheless, more than two-thirds (68.5%) of low-income parents (i.e., income is 200% above poverty threshold) living with children under the age of 19 reported material hardships in paying for housing, utilities, food, or medical care in the past year (Karpman et al., 2018). However, not all families living in poverty experience material hardship, and not all families in poverty may have access to federal assistance programs (Wimer, Nam, Waldfogel, & Fox, 2016), but they may have strong social supports (e.g., church; Iceland, 2005) Because the underlying reasons for a family's material hardship can vary, income should not be the only indicator used to assess a family's economic hardships.

The developmental consequences for children who grow up in families experiencing material hardship are widespread, ranging from cognitive deficits to socio-emotional dysregulation (Gershoff et al., 2007; Ratcliffe, 2015). Material hardships in early childhood may be particularly detrimental to the rapid brain development that occurs during this time because material hardship confers a risk to disrupt brain development (Duncan, Ziol-Guest, & Kalil, 2010; Shonkoff, Boyce, & McEwen, 2009). For example, children who experience food hardship display disrupted emotional development which has consequences across various life domains, including vulnerabilities to psychopathology (Althoff, Ametti, & Bertmann, 2016). Material hardship has been associated with higher internalizing and externalizing symptoms in children, even after accounting for family income (Bellair, Mcnulty, et al., 2019; Zilanawala & Pilkauskas, 2012). It is theorized that the neural mechanisms that may be affected are based in the socio-emotional networks (Mueller, 2011). Yet, the neural mechanisms underlying these associations are not well understood.

Poverty and Emotion Processing

Biologically based models of emotion suggest that lacking resources may directly impact the normative development of the neural correlates that support emotion processing (Perry et al., 2019), affecting how those neural correlates may function in different social situations. To date, behavioral evidence suggests that one's ability to recognize emotion in another person is a crucial factor in healthy emotional development and regulation (Saarni, Campos, Camras, & Witherington, 2008). Indeed, emotion recognition has been theorized to play a crucial role in the emotion processing and emotional development that underlies social interactions (Batty & Taylor, 2006; Eckman, 1973; Taylor, Batty, & Itier, 2004). These processes are vulnerable to poverty related stressors, which may have long-term consequences into adulthood. Evidence from a longitudinal behavioral study aimed at identifying links between early life age-specific periods of income poverty and emotion distress in adulthood (~ age 37) reported a small negative correlation between poverty during age 11 to age 15 ($r = -.25$, $p < .01$), but no links between early (prenatal to age 5) or middle childhood (age 6 to 10), demonstrating that timing of poverty may confer different vulnerabilities to emotion circuit development that persist into adulthood (Duncan, Ziol-Guest, & Kalil, 2010).

Behavioral evidence from children growing up in poverty suggests that challenges in recognizing and accurately describing the emotion a face is displaying have been linked to adverse mental health outcomes (Guyer, Choate, Grimm, Pine, & Keenan, 2011). Moreover, it has been reported that children growing up in contexts of neglect process emotions differently. A study of children (N =46) with economically diverse representation (i.e., half of the sample was living in poverty based on their income-to-needs ratio) examined how the group living in poverty fared worse in an emotion recognition task. Specifically, youth in the low-income group required higher levels of emotional intensity displayed by morphed faces to accurately identify the emotion (Erhart, Dmitrieva, Blair, & Kim, 2019). These group differences in the processing of emotion were attributed to the child's time in poverty, suggesting that some underlying biological changes may have occurred that altered how the brain perceives and processes emotion-based cues.

Similarly, other studies have also reported that children growing up in low-income contexts who have difficulties with emotion recognition performed poorly in assessments of emotion knowledge skills (Miller et al., 2005). In particular, the children were unable to produce an adequate response to hypothetical scenarios where knowledge of emotions was key to identifying an appropriate response behavior. Moreover, evidence from behavioral studies from children who grew up in low-income families suggests that a lower ability to recognize others' emotions accurately was associated with emotion regulation difficulties (Raver, 2004; Raver, Roy, Pressler, Ursache, & McCoy, 2017). Furthermore, these emotion recognition difficulties were associated with an increased risk of psychopathology (Fine, Izard, Mostow, Trentacosta, & Ackerman, 2003; Izard et al., 2001). These studies describe deficits in children's socio-emotional functioning that vary due to differences in a family's socio-economic status that impact the home environment in which children grow up. The difficulties in emotion processing seem to suggest that the income-based differences in our environments promote different neural adaptations in a child's socio-emotional circuitry.

Altered Co-Activation within Socio-Emotional Circuitry

Early life stress due to poverty-related stressors has been associated with neural adaptations that alter emotion processing circuits which confers a vulnerability that may support the emergence of psychopathology in adulthood (VanTieghem & Tottenham, 2018). Early work that identified two brain regions that showed distinct relationships retrospective reports of income hardship at age 9 were linked to altered left amygdala activations in adulthood (age 24) during an emotion reappraisal task, while the additive effect of chronic stressors reported from age 9 to 17 (including poverty related stressors) mediated executive function connectivity in adulthood (Kim et al., 2013).

However, advances in analytical approaches now allow researchers to examine the co-activation of these neural structures through psychophysiological interactions (PPI), which allow for the evaluation of how different brain areas co-activate in response to various emotionally valanced stimuli or tasks. Indeed, the coactivation ("coupling") between the amygdala and other frontocortical regions during emotion processing tasks (the subgenual ACC, the frontal/cingulate cortex has been shown to be a reliable biomarker of emotion processing (DMFC; Nord, Gray, Robinson, & Roiser, 2019). Indeed, altered co-activation of these regions has been associated with adolescent depression (Ho et al., 2014), and adolescent Generalized Anxiety Disorder(Monk et al., 2008). Additionally, age differences in the co-activation of the amygdala-ventral/dorsal prefrontal cortex have been reported with adolescents showing decreased activation of the ventrolateral prefrontal cortex in response to a task that distinguishes negative emotional reactivity from reappraisal ability relative to adults (McRae et al., 2012) Thus, there are normative age-related changes in connectivity that may be a consequence of the still developing neural architecture.

In a study that measured poverty in two distinct ways first reported that relative to adults from middle income households, a study of 25 Caucasian adults who grew up in poverty identified a direct association between altered co-activation of left amygdala- medial prefrontal cortex and the processing of negative emotions (e.g., anger, fear ; Javanbakht et al., 2015). However, the coactivation between the structures was not evident when childhood poverty was assessed using income-to-needs ratio, leaving only amygdala activation to be negatively correlated the processing of negative emotions (2015). Although the previous studies used retrospective reports of poverty, they demonstrated poverty measured through different approaches consistently identified altered connectivity in the amygdala-prefrontal cortex coupling. Importantly, these studies also demonstrated that timing of when poverty occurs during development, the operationalization of poverty and the duration of poverty (i.e., additive effects) are factors to consider when assessing the multidimensional nature of poverty.

Evidence of how childhood poverty affects the coupling integrity between the amygdala and other brain regions recruited during emotion processing in pediatric samples is limited. A recent pediatric (ages 5 -7) study that examined how the structural connectivity of an amygdala-prefrontal cortex (i.e., the uncinate fasciculus that connects the orbitofrontal cortex and the amygdala) circuit mediated the association between poverty (measured in two ways) and internalizing symptoms reported sex differences for this mediation. Interestingly, when poverty was measured using material hardship, greater material hardship was associated with lower fractional anisotropy (FA) in the uncinate fasciculus UNC and smaller amygdala volume, which in turn was associated with higher internalizing symptoms for girls, but not boys. Yet, when this mediation was tested using family income-to-need ratio no associations between any of the structures or internalizing symptoms were found, indicating a unique effect of material hardship on this amygdala-prefrontal cortex structure (Lichtin et al., 2020). Similar altered functional connectivity has been observed in adolescent samples that examined the association between household income and functional connectivity, lower income was associated with weaker coupling of these structures, which was associated with more internalizing and externalizing symptoms (Hanson et al., 2019). Taken together these studies suggest that different dimensions of poverty can impact emotion processing structures in similar ways, whose altered activation has been associated with the presence of psychopathology.

However, this amygdala coupling with other prefrontal regions during emotion processing does not always occur in all types of emotion processing. A neuroimaging study with young adults (age 22) who grew up in poverty examined the association between implicit emotion regulation and functional connectivity during a shifted-attention emotion appraisal task. During this task, participants viewed grayscale pictures of faces displaying emotion (fearful or neutral) superimposed onto indoor or outdoor backgrounds while engaging with cognitive appraisals of the images (male/female, indoor/outdoor, like/dislike, face/place). For youth who grew up in poverty, measured through income-to-needs ratio at age 9, they had lower activation in the left dorsolateral prefrontal cortex during emotion regulation by cognitive appraisal, which also was negatively associated with recognition task performance. However, given the many features of possible appraisal, childhood poverty also was associated with increased insula and reduced hippocampal activation (Liberzon et al., 2015). Although the previous task tapped into various emotion-cognition processes recruited in emotion processing, the complexity can inform those difficult to disentangle emotion-cognition interactions that are likely to occur in everyday context and interactions. Other evidence suggests that amygdala reactivity is not always present during undirected processing of affective stimuli, but that activation across other brain regions associated with emotion processing was still present (Pessoa & Adolphs, 2010). Research on neural response to explicit emotion processing found that regions involved with perception and somatosensory cortices were important for this type of processing (Winston, O'Doherty, & Dolan, 2003). Childhood poverty has consistently been associated with altered functional connectivity in adulthood, however the variable activation of amygdala-prefrontal structures to different stimuli and tasks highlights the complexity of brain regions involved with emotion processing.

Connectome-Wide Emotion Processing in the Brain

The "Billiard Ball Model" proposes that emotion processing occurs in a "spreading of activation" fashion across neural circuitry involved in response to affective visual stimuli (Pessoa, 2018). Additionally, Pessoa and McMenamin argue that emotion processing circuitry is distributed across the brain with different regions participating more actively in some networks than in others during differently valanced emotions (Pessoa & McMenamin, 2017). Adding to this complexity of network level emotion processing is adolescent ongoing brain development of cortical regions recruited in emotion processing. A review identified common brain regions reported in adolescent emotion neuroimaging research to include the dorsolateral prefrontal cortex (dlPFC), the medial prefrontal cortex (mPFC), the anterior cingulate cortex (ACC), as well as subcortical structures like the amygdala, however the activation patterns elicited during explicit and implicit emotion processing vary widely and depend on the fMRI paradigm being used (Ahmed, Bittencourt-Hewitt, & Sebastian, 2015). Additionally, emotion processing recruits cognition-based functions that create emotion-cognition interactions that are difficult to disentangle when emotion tasks can vary so widely, but whose influence on emotion-processing must be considered (Bell & Wolfe, 2004; Dolcos, Wang, & Mather, 2014; Ochsner & Gross, 2005). Thus, a connectome-wide evaluation will afford us an ability to better characterize emotion processing in adolescents across large-scale networks rather than the individual neural structures, allowing for a global assessment of the emotion-cognition interactions across different networks. Further advancing our ongoing understanding of network neuroscience associated with human behavior.

To date, connectome-wide neuroimaging studies examining how early poverty affects adolescent emotion regulation are limited. Recent connectome-based work examining the effect of poverty at age nine (defined by income-to-needs ratio) on emotion regulation in young adults had no findings using a PPI connectome approach (Sripada, Angstadt, et al., 2014). However, motivated by the previous findings of poverty being associated with various altered patterns of functional connectivity, as well as the specificity of these effects to the operationalization of poverty during emotion processing. I proposed to characterize the relationship between early childhood material hardship and task-based functional connectivity elicited while youth performed a gender identification task with implicit emotion processing.

In this study, I sought to characterize the unique adolescent connectome-wide neural patterns evoked during an emotion processing task and their association with family material hardship during early childhood. I hypothesized that higher reports of family material hardship during 1 to 3 years of age would be associated with adolescent altered functional connectivity patterns during emotion processing conditions (Happy, Sad, Anger, Fear) across three major networks: the Central Executive Network (CEN), the Salience Network (SAL) and the Default Mode Network (DMN). In addition, I predicted that altered large-scale network connectivity associated with early childhood material hardship would be positively correlated with higher depression and anxiety symptoms at age 15.

Exploratory analysis of the independent (e.g., age 9) and incremental effects of material hardship (i.e., age 1 to 3, age 1 to 5, age 1 to 9, age 1 to 15) were examined, for any emotion condition deemed statistically significant by our primary hypothesis. By doing so, I could gather nuanced information about how period specific or lifetime experiences of material hardship together contribute to a stronger association between material hardship and this specific task-based emotion. Additionally, to evaluate specificity of altered task-based interactions to emotion a network contingency analysis model testing the condition contrast of all emotions versus neutral was completed. Lastly, given that this is a non-clinical and understudied sample it was of interest to characterize the relationship between task-based network functional connectivity for any emotion condition deemed significant and youth's current depression and anxiety symptoms, independently of material hardship. No specific predictions were formally tested with these exploratory analyses.

Methods

Participants

The adolescent sample for this study completed informed assent and their primary caregivers provided written consent for their child to participate in the study. Recruitment efforts aimed to recruit as many youth from the Detroit, Toledo or Chicago subsamples of the Fragile Families and Child Wellbeing Study (FFCWS; Reichman, Teitler, Garfinkel, & McLanahan, 2001) as possible. 237 youth were successfully recruited and invited to complete fMRI scanning and behavioral surveys. Of those 237, 104 were removed from the current analysis due to exclusionary criteria outlined in Table 3.1 that included: incomplete resting fMRI scan, ASD diagnosis, excessive motion and less than 70% task performance. The 134 participants who completed the faces tasks did not differ on any demographic characteristic from the total sample (Appendix Table A). All study procedures were approved by the IRB.

Procedures

fMRI data acquisition

Functional T2*-weighted BOLD images were acquired using a reverse spiral sequence (Glover and Law, 2001) of 40 contiguous axial 3 mm slices (TR=2000 ms, TE=30 ms, flip angle=90°, FOV=22 cm, voxel size=3.44 mm x 3.44 mm x 3 mm, sequential ascending acquisition). Slices were prescribed parallel to the AC-PC line (same locations as structural scans). Images were reconstructed into a 64x64 matrix. Slices were acquired contiguously, which optimized the effectiveness of the movement post-processing algorithms. Images were reconstructed off-line using processing steps to remove distortions caused by magnetic field inhomogeneity and other sources of misalignment to the structural data, which yields excellent coverage of subcortical areas of interest. Preprocessing of these images was completed with SPM12 defaults.

Motion Detection and Correction

Beyond regressing the BOLD time series signal against the 6 head motion parameters from the three translational axes of X, Y, and Z and three rotational axes of pitch, roll, and yaw, segmentation in SPM12 was used to generate non-gray matter tissue probability maps. Segmentation in SPM12 was completed to capture non-neuronal origin signal from different tissues that do not include gray matter. WM and CSF tissue masks were extracted using the SPM12 tissue probability maps. Threshold erosion for the CSF and WM masks was set to conservative standards (WM, threshold of .9; CSF, threshold of .7) to ensure minimal contamination with the GM voxels. Subject specific masks were produced and binarized. Additionally, volumes with an excessive mean frame displacement (meanFD) value that exceeded 0.9mm of motion (for reference, FD values in very still subjects range from 0 to 0.2mm), a summary statistic for quantifying the degree of person-specific head motion is the temporal mean of their FD time series. Given the large number of ROIs – motion is a concern because typically head movement has a more pronounced influence on short-range connectivity near neighboring ROIs (Power et al., 2015, VanDijk et al., 2012).

Gender Identification fMRI Task

The youth completed an implicit emotion face processing task during a continuous fMRI acquisition session. Before entering the scanner room, all participants completed a practice trial with the same facial affect stimuli in black and white. Next, in an event-related design, participants viewed images with expressions of facial affect expressed by different actors varying on race (black or white) and gender (male or female). In this task, youth were asked to identify the gender of the actor by pressing their thumb for males or their index finger for females on a button box. Facial affect images were from the NimStim set (Tottenham et al., 2009). Gender and race were counterbalanced. There were 100 pseudo-randomized trials, 20 trials each of the following emotions: fearful, happy, sad, neutral, and angry. Each trial consisted of a fixation cross (500 ms), followed by a face (250 ms), then a black screen (1500 ms) during which participants responded to the face being displayed, and finally a second black screen (jittered inter-trial interval: 2, 4, or 6 s). Participant performance was measured as accuracy on the correct gender identification of target picture. To reach a minimum 70% accuracy rate, the task difficulty is adjusted over the course of the task. One hundred and sixty-eight (168) participants completed the gender identification task (Correct Identification: *M*= 87.49, *SD*=19.38, n =168). After removing participants with below the 70% accuracy benchmark and due to other exclusionary criteria, the average accuracy across the task increased (Correct Identification: *M*= 93.51, *SD* = 5.63; n =134)

Self-Reported Measures

Ethnic-Racial Identity

Ethnic-Racial Identity (ERI) was constructed using two items. Priority was given to the adolescent reported ethnic identity write-in question, “What is your ethnic identity?”. Next, parent’s report of child’s race was considered if first item was ambiguous or unclear (e.g., “American”). ERI refers to “a subjective, self-ascribed sense of oneself as a member of an ethnic or racial group”(Rivas-drake et al., 2014; Schwartz et al., 2014, p. 59). By constructing adolescent’s ERI using this approach, gave those youth who at first identified as Biracial an opportunity to self-identify with a group of choice.

Material Hardship

At ages 1 (12 items), 3 (10 items), 5 (14 items), 9 (11 items), and 15 (11 items), caregivers indicated whether they experienced housing, utility, food, medical, and financial hardship within the past year. These questions were derived from the "Basic Needs – Ability to Meet Expenses" section of the Survey on Income and Program Participation (SIPP) 1996 Panel Wave 8 Adult Well-Being Topical Module Questionnaire (SIPP, 1998) and the 1997 & 1999 New York City Social Indicators Survey (SIS). Material hardship items were coded as 0 (no) or 1 (yes). The following eight items were asked at all waves (SAND sample KR20 α =.57-67):

(1) *In the past twelve months, did you receive free food or meals?*

(2) *In the past twelve months, did you not pay the full amount of gas or electricity bill?*

(3) *In the past twelve months, did you borrow money from friends or family to help pay bills?*

(4) *In the past twelve months, did you ever not pay the full amount of rent or mortgage payments?*

(5) *In the past twelve months, did you stay at a shelter, in an abandoned building, an automobile, or any other place not meant for regular housing, even for one night?*

(6) *In the past twelve months, were you evicted from your home or apartment for not paying the rent or mortgage?*

(7) *In the past twelve months, was there anyone in your household who needed to see a doctor or go to the hospital but couldn't go because of the cost?*

(8) *In the past twelve months, did you move in with other people even for a little while because of financial problems?*

Children did not necessarily live with the birth mother at all waves and material hardship can vary between households. Therefore, material hardship at each wave was based on primary caregiver reports (i.e., the caregiver the child lived with for the majority of the time). The primary caregiver was considered to be the mother if the child lived with their mother for at least half of the time. If the mother was not the primary caregiver, the father was considered the primary caregiver if the child lived with their father for at least half of the time.

The 8-item composite score was combined into a weighted sum, where the weights for each indicator are based on the proportion of individuals not deprived by the indicator (e.g., Muffels, Ruud & Fouarge, Didier, 2001). These weighted indicators better represent those individuals who have experienced the rarer types of hardship (e.g., living in a shelter, abandoned building, or in their automobile in the past 12 months), underscoring statistically the fact that these more severe forms of material hardship may be more impactful on a family's wellbeing. Therefore, the weighted average of material hardship for each wave was used. Lastly, any participant who had missing data for a particular wave was filled in with the nearest next wave weighted average value (missing entries were less than 5% at any one wave).

Depression

Symptoms of depression were screened for using adolescent self-reported Children's Depression Inventory (CDI; Kovacs & Beck, 1977). The CDI is a 27-item measure (SAND sample α =.86), each consisting of three statements ranging from no symptomatology to severe symptomatology. The child selects one of the three statements for each item that best describes them within the past 2 weeks. Previous research has found the CDI to be a reliable and valid self-report measure of depressive symptoms in both clinical and non-clinical samples of children ages 6 to 17 (Huberty, 2012, α = .70 -.92). Symptoms are scored "0" to "2", yielding a maximum score of 54. Additionally, the total score can be separated into 5 factors (Negative Mood, Interpersonal Problems, Ineffectiveness, Anhedonia, Negative Self-Esteem) to offer more precise descriptions of the nature of the symptoms (See Appendix B for full measure).

Anxiety

Screening for anxiety symptoms was completed with The Screen for Child Anxiety Related Disorders (SCARED; Birmaher et al., 1997, α=.7-.9). The SCARED is a 38-item (SAND sample α =.92) inventory rated on a 3-point Likert-type scale (0 = Almost Never, 1 = Sometimes and 2 =Often). Sample items include: "I worry about being as good as other kids" and "I am a worrier" (See Appendix C for full measure). The items assess for DSM-IV classification of anxiety disorders: panic/somatic, generalized anxiety, separation anxiety, social phobia, pertinent simple phobia, and school phobia. Other studies have found good psychometric properties with demographically diverse non-clinical samples (Birmaher, et al., 1999, α = .90; Arab et al., 2016, α = .80).

Gender

Adolescent self-reports of gender were determined using the Pubertal Development Scale (Petersen et al., 1988) which has had high correlations (r= 0.61–0.67) with physician ratings (Brooks-Gunn et al., 1987). Scores range from 1 to 4. Gender was determined from the specific female or male set of questions on the scale.

Age

Age was calculated from date of birth provided by teen and confirmed by parent on the fMRI safety screener, and then the date of the visit to calculate age in months.

Analytical Approach

The aim of Study 2 was to characterize connectome-wide task-based functional connectivity patterns evoked during an emotion processing task for adolescents who grew up in families experiencing material hardship. To that end, data analyses were completed in several steps. Descriptive statistics, zero-order correlations, and chi-square tests were completed using SPSSv27. Imaging data analyses were conducted using the following software SPM12 (SPM - Statistical Parametric Mapping (ucl.ac.uk) and Psychiatry Methods Core Scripts (Release 1.6; ConnTool & Network Contingency Analysis). Given that the network contingency analysis requires non-missing behavioral data to model the individual connectomes, weighted means were created for our material hardships scores and near neighbor substitution was completed for missing data points (less 5%).

PPI Interaction Regressors

Psychophysiological interaction (PPIs) analysis is a method for investigating task-specific changes in functional connectivity across different brain areas (Friston et al., 1997). A PPI analysis will allow me to obtain condition-specific information regarding brain areas involved during a task, and how functional connectivity can change across different regions across the brain during specific tasks (O'Reilly, 2012).

In the first step of a PPI analysis, we extract representative activation real-time time course data from a seed region of interest, based on task condition of interest (Physiological Variable, e.g., Happy Faces). In the current study, the seed region of interest is each individual ROI from the 264 Power et al., (2011) parcellation. In the second step, we create a psychological vector or contrast of interest (e.g., "main effect of emotion", psychological variable) in neuronal space estimates (in SPM12). These neuronal space estimates are then deconvolved with the HRF function to match BOLD activation. In the third step, we calculate element-by-element interaction term products (PPI-regressors) between the physiological and psychological time courses (psychophysiological interaction (PPI) variable, e.g., functional connectivity). This step generates an interaction term for each of the 264 ROIs, using each ROI as a seed to produce the interactions terms across the whole brain by condition. In step four, we build a new model to search for ROIs whose time courses are reliably correlated with the PPI regressor (ROI). Finally, in step 5, we produce separate connectivity maps for each task condition. These condition connectivity maps are then subtracted to investigate connectivity across conditions of interest (i.e., contrasts related to key hypotheses under study).

Network Connectome Matrix Construction

After pre-processing, we generated functional connectivity PPI matrices based on 264 ROI locations contained within the predetermined 13 networks identified by Power et. al., (2011). A PPI interaction term was generated between each ROI and the other 263 ROIs by condition. This process is repeated with each ROI set as the seed, meaning that the connectomic PPI places the seeds through the whole brain, and not just within a single region of interest. Notably, because PPI is a multiple regression-based approach that quantifies unique interactions between every ROI in the brain, the repeated process of making each ROI both a target and a seed will not necessarily generate redundant information between two neighboring ROIs when creating the edges (node to node distance). Each condition-specific connectome has 69,696 ROIs, yielding 69,432 unique edges (where a small number of edges are dropped from the analyses because they represent the interaction of an ROI with itself). These edges refer to the connection between each pair of ROIs and their relationship is interpreted as a PPI interaction term, described by beta weights that represent the interaction between a task condition and connectivity. Only those edges that survive the p <.005 threshold are retained (see Sripada et al., 2014 and Study 1 for rationale). These connectomes are then read into the nonparametric network contingency analysis following the same procedure as described in Study 1, except that the resultant edges represent ROI psychophysiological interaction terms rather than ROI standardized correlations.

Selection of Covariates

To provide a rigorous test of our network contingency models of task-based connectivity, we controlled for important covariates that might confound the association between early childhood material hardship and at-rest network connectivity. Several theoretical, statistical, and prior work support the inclusion of the following covariates in our models including age, gender, motion, ethnic racial identity and current age 15 material hardship. Additionally, the covariates also reflect our effort to remove any confounding effects of age, gender, scanner motion, and current material hardship since they tend to co-occur with brain development, poverty, and internalizing symptoms. Specifically, NCA models included age, gender, scanner motion, and current age 15 material hardship. Of note, ethnic racial identity was included as a covariate given the persistence of structural and institutional discrimination that perpetuates income inequalities in the U.S., as well as reports of increased likelihoods of facing material hardship when you identify as Black or Hispanic in the U.S. (See Rodems & Shaefer, 2020).

NCA Models Tested

Several theoretical, statistical, and prior work support the inclusion of the following covariates in our models including age, gender, motion, ethnic racial identity and current age 15 material hardship, as well as their relationships with adolescent functional connectivity and psychopathology symptoms. Additionally, age 15 material hardship was kept as a covariate due to its temporal and contextual relevance to the current age functional connectivity.

Based on previous literature and grounded in theoretical rationale, NCA models evaluated the association between early childhood (age 1 to 3) family material hardship and task-based functional connectivity evoked during an emotion processing paradigm, controlling for age, gender, ethnic-racial identity, scanner motion, and current age 15 material hardship. Our analytic approach using psychophysiological interactions in a connectome network analysis allowed us to test the hypothesis using contrasts between emotion condition to baseline (e.g., Happy vs. Baseline). A total of five emotion conditions were tested (Happy, Sad, Anger, Fear, Neutral).

Lastly, given the extant literature on the timing and cumulative effects of material hardship on brain connectivity, the following exploratory analysis were completed to characterize the association between material hardship reported between ages 1 to 15 during development. Both the independent material hardship scores were modeled by wave (i.e., reports at age 1, age 3, age, 5 and age 9) and the incremental additive effect of material hardship was tested including our covariates from ages 1 to 15 (i.e., ages 1-3, 1-5, 1-9, 1-15) for those conditions that were found to have altered connectivity. This was done to explore if the altered network connectivity finding would hold at later ages. All models whether testing the effect of family material hardship in one wave or the additive effect across several waves included the following covariates: age, ethnic-racial identity, gender, and pre-corrected motion based on analyses previous analyses with covariates.

Task-Based Networks and Internalizing Symptoms

One of the primary interests of this study was to identify how large-scale network connectivity dysregulation during a task is associated with psychopathology. To test for these associations, independent zero-order correlations between depression or anxiety symptom scores and the extracted mean activation across each of the 13 large-scale networks were conducted, only for altered networks connectivity deemed significant through our non-parametric testing. An exploratory correlation analyses evaluating the association between the extracted task-based functional connectivity by network for any condition deemed significant and current psychopathology was completed, independently of material hardship.

Results

Demographics

Table 2.1 presents whole sample (N=237) descriptive statistics for demographic variables, weighted family material hardship scores, and psychopathology outcomes. Next, preliminary descriptive analyses of the demographic and outcome variables for those 134 (See table 3.2) adolescents retained for the NCA-PPI neuroimaging analysis were completed, as well as group difference testing versus those 113 youth who were excluded from the analysis (See Table 3.1 for exclusionary criteria). No significant sample differences between included and excluded youth in any of the demographic variables, material hardship and psychopathology outcomes were found, suggesting that across these characteristics the sub-sample retained for analysis was representative of the youth who were excluded.

Family Material Hardship

Table 2.3 summarizes the weighted family material hardship 8-item composite score proportions by wave (i.e., age 1, age, 3, age 5, age 9, and age 15) for the whole sample (N=237). These analyses showed that on average between 51% to 67% of the primary caregivers of these 237 adolescents consistently reported facing at least one material hardship during any wave of data collection. Across all waves the top three types of hardship reported were struggles to pay their utility bills (i.e., gas or electricity; 23% to 38%), needing to borrow money to meet their needs (23% to 48%), and struggling with rent or mortgage payments (12% to 24%). The least reported material hardship across the five waves of data collection were needing to sleep in a car or non-shelter location (1% to 3%) and facing home eviction (2% to 4%).

Although this study controlled for any ethnicity and race effects, preliminary analyses of material hardship differences by ethnic-racial identity demonstrated higher weighted material hardship average scores for Black and Hispanic families from age 1 to age 3, relative to lower reports of material hardship of White youth during this same period (See Figure 2.1). Furthermore, this early difference in material hardship becomes more pronounced over time, whereby a difference gap between Black and White families is evident relative to the other groups in the study.

Of the 237 youth who completed the study, 134 were included in the connectome analyses for this study. No statistical differences were found between reported material hardship patterns between the two groups. Preliminary analysis of material hardship showed that the families of these 134 adolescents were consistently facing three types of material hardship across the five waves of data. The most reported types of material hardship by the primary caregiver were needing to borrow money to meet their needs (25% to 47%), struggling to pay their utilities (i.e., gas or electricity; 23%-41%), and struggling to pay rent or mortgage payments (11%-28%). The least reported material hardships across the five waves were lacking medical attention (6%-10%), facing home eviction (2%-3%), and sleeping in a car or non-shelter location (2%-5%). Overall, between 53 to 69% of the families reported at least one material hardship during the 5 waves of data collection from ages 1 through age 15. In contrast, between 31% to 46% reported never facing material hardship during the same period (See Table 3.3).

For the participants in the sub-sample included in the present analyses (See Table 3.4), age 15 material hardship and annual income at age 15 were not correlated (r =-0.01, *ns*). Primary caregiver income data from previous waves was not included in the present analyses and therefore no correlations between income and their respective material hardship scores were reported. The material hardship 8-item composite scores between age 1 and age 3 were positively correlated with each other (r = 0.53, p <.01). Overall, correlational analyses of all weighted material hardship scores between age 1 through age 15 had significant magnitudes of association across time (r =0.25 to r=0.59, all significant at p <.001). Additionally, weighted family material hardship scores reported closer in time had higher positive associations to each other (r= 0.45 to r = 0.59, all significant at p<.001).

Interactions Between Network Connectivity and Emotion Contrasts

Primary Hypothesis

To characterize the association between family material hardship in early childhood (ages 1 to 3) and adolescent task-based functional connectivity while performing an emotion processing task, we regressed the cumulative effect of material hardship from ages 1-3 by condition. All subsequent NCA models represent contrasts between baseline and the condition of interest, adjusted for ethnic-racial identity, gender, mean frame displacement and material hardship at age 15.

Fearful. Model of material hardship at ages 1-3 predicted differences in functional connectivity during the fearful condition relative to baseline. Visual inspection of the suprathreshold tabulation map showed that the nodes retained for analysis were predominately displaying increased connectivity (i.e., red dots) within the frontoparietal task network and mixed connectivity across all other 12 networks (See Figure 3.2). Non-parametric statistical testing identified predominately increased and significant co-activation between the frontoparietal task network (FPT) and dorsolateral attention network (DAN) (p = .03; FDR corrected; Cohen's d = 0.01, 95% CI [-0.51,0.48]). No other altered network connectivity interrelationships were identified. Results from non-parametric significance testing for all networks for early childhood (age 1 to 3) are displayed in Table 3.5. Next, support for our second prediction that altered network connectivity would be positively correlated with current psychopathology was not supported. FPT-DAN mean activation not correlated with age 15 depression scores (r = -.06, p=.47) or anxiety scores (r= -.02, p =.81),

Lastly, exploratory analysis of the association between task-based network activation and independent material hardship scores or the additive increments across other age periods (i.e., 1-5, 1-9, 1-15) did not yield any significant network dysregulation in the fearful condition, meaning all non-parametric network tests had p-values equal to 1. Interestingly, the network connectivity evoked by viewing fearful faces was significantly associated with only the incremental material hardship from age 1 to 3, and at no other time frame. The absence of node patterns for the individual material hardship waves shows that for the fearful condition no one period of time was uniquely associated with the observed pattern identified in early childhood

(Age 1 to 3; see Figure 3.3). Yet the observed 'L' pattern of coactivation across the frontoparietal network and all other 12 networks including the dorsal attention network, the ventral attention network, the limbic network, the salience network, and the default mode network was evident when including all material hardship from age 1 to age 15 (See Figure 3.4).

Anger. Model of material hardship at ages 1-3 did not predicted differences in functional connectivity during the anger condition relative to baseline. Similar to fear a faint 'L' pattern of increased connectivity nodes was visible across the frontoparietal network and all other 12 networks. Nonparametric testing did not identify any significant interrelated connectivity of any network (See Figure 3.2).

Sad. Model of material hardship at ages 1-3 did not predicted differences in functional connectivity during the sad condition relative to baseline. Node connectivity patterns show a concentration of increased node connectivity within the frontoparietal network (FPT-FPT). However, no altered interrelated connectivity was identified across any of the networks.

Happy. Model of material hardship at ages 1-3 did not predicted differences in functional connectivity during the happy condition relative to baseline. This condition had an absence of node connectivity patterns with only 4 nodes surviving thresholding. No altered interrelated connectivity was identified across any of the networks.

Neutral. Model of material hardship at ages 1-3 did not predicted differences in functional connectivity during the neutral condition relative to baseline. Node connectivity in this condition was spread across the FPT and all other 12 networks, as well as across the cerebellar network. No significant interrelated connectivity was identified.

All Emotions V. Neutral. Contrast model of material hardship at ages 1-3 to examine if early adversity predicted differences during task-based functional connectivity in a contrast condition that aggregated evoked connectivity to all emotions (i.e., Happy, Sad, Angry, Fear) versus neutral. Node connectivity patterns seemed to concentrate across the FPT, and somatosensory network. No discernable increased or decreased pattern of node connectivity was observed. NCA model did not produce any significant network pairs (all adjusted p-values equal to 1) across the network cross-tabulation map, suggesting that early childhood (age 1-3) material hardship was not associated with emotion processing more broadly.

Internalizing Symptoms and Extracted Network Connectivity

Of note, a positive association between family material hardship reported at age 15 and current adolescent depression symptoms (r=0.14, p<.05) was found, but not with youth's anxiety symptom scores (r=0.09, *ns*) in our overall sample. For the 134-youth kept in the network contingency analysis, report of internalizing symptoms was low with sex differences by internalizing disorder. First, age 15 depression symptoms were positively correlated with age 15 anxiety symptoms (r =0.49, p<.001). On average depression symptom score for the youth in the sub-sample was 9.09(SD = 6.77). Of the youth included in the connectome network contingency analyses, the females reported more depression symptoms (M=10.15, SD =7.11) relative to males (M =7.80, SD= 6.14); t(132)=2.02, p =.04, Cohen's d = 0.35, 95% CI [0.07,0.69]. Similarly, the sub-sample reported low anxiety symptoms on average (M=20.35, SD=17.74). Significant sex differences in anxiety symptoms were found. Females reported more anxiety symptoms (M=23.78, SD=16.18) compared to male reports (M=16.12, SD=18.77); t(132) =2.53, p =.01, Cohen's d=0.44, 95% CI[0.10,0.79]. For the 134 youth, there was a small positive correlation between their ethnic-racial identity and anxiety scores (r=0.21, p=0.02), meaning that higher anxiety symptoms were associated with non-white youth.

Exploratory analyses evaluating the association between extracted task-based network connectivity evoked by viewing fearful faces and depression and anxiety symptoms identified a few significant associations. Coactivation between the Frontal Parietal Network and the Cerebellar Network (FPT-CER) was negatively associated with depression symptoms (r =-.20, p <.03; see table 3.6). In contrast, we saw increased within network co-activation in the somatosensory mouth (SSM-SSM) and between network coactivation in the somatosensory mouth and the somatosensory hand (SSM-SSH) networks that were positively correlated with higher anxiety symptoms (r =.22, p <.05; r =.21, p <.05, respectively; see table 3.7).

Discussion

The current study examined task-based fMRI data from an understudied population sample who completed a gender identification task with implicit emotion processing of five facial affect conditions. Using subject specific psychophysiological interaction (PPI) connectome maps generated for each facial affect condition, I modeled the effect of early childhood (age 1-3) family material hardship on task-based functional connectivity, which revealed increased and decreased node connectivity unique to each affect condition. However, non-parametric significance testing indicated that only the co-activation network patterns between the frontoparietal network (FPN) and the dorsal attention network (DAN) in response to viewing fearful faces were statistically significant. Early childhood material hardship was not associated with any other altered network connectivity in response to the other emotion conditions (i.e., sad, anger, neutral and happy). This finding supports our first hypothesis that material hardship during early childhood would be associated with current age 15 network dysregulation across three major networks (Central Executive Network, Salience Network, and Default Mode Network), though this support is tempered by the lack of significant findings for the other emotional conditions. Moreover, our second prediction that this increased FPN-DAN co-activation associated with material hardship would be positively correlated with current anxiety and depression symptoms was not supported. Follow-up exploratory network contingency analyses evaluating the magnitude of the association between period specific or incremental material hardships indicated that network connectivity observed while viewing fearful faces was not associated with any other period of material hardship. Lastly, anxiety symptoms were positively associated with extracted 'fearful' coactivation of the frontoparietal-cerebellar network, on the other hand, depression symptoms were negatively correlated with interrelated co-activation in the somatosensory networks.

Income-based measures of poverty are insufficient to characterize a family's experiences with economic hardship. Household income reports are subject to unreliable recall, can fluctuate, and income assumes an equal distribution within the household (Bradshaw & Finch, 2003). The present study used self-reported family material hardship which inform about the extent to which families can meet their basic needs to complement the income-based research. Over half of families in the current sample reported at least one type of material hardship over the last 5 waves of data collection. Specifically, families in the current sample reported commonly having trouble paying bills and needing to borrow money to paying utility bills. Although these reports are higher than the national averages of material hardship reports (Ouellette et al., 2004; Rodems & Shaefer, 2020), these families provide evidence that low-income families are indeed at a higher likelihood of experiencing material hardships. Additionally, ethnic-racial differences are apparent in the rates of material hardship reported with non-Hispanic Black and Hispanic families reporting higher material hardship, on average over the 5 waves of data, relative to White families.

Childhood poverty has been associated with altered connectivity between brain regions recruited for emotion processing (Hackman & Farah, 2009; Kim et al., 2013). However, emotion processing activation has been theorized to "spread" across the brain(Pessoa, 2018), and adolescent studies that examine the association between connectome-wide emotion processing and material hardship are lacking. Although a previous connectome-wide study found no association between poverty (measured using income-to-needs ratio) at age 9 and emotion regulation (Sripada et al., 2019), the present study provides evidence of an association between early childhood material hardship and altered emotion processing specific to 'fearful' faces during adolescence.

The present findings contribute empirical evidence of an association between early childhood (age 1 to 3) material hardship and increased co-activation of the FPN-DAN in response to a 'fearful' face, suggesting that material hardship has downstream consequences for emotion processing networks that are evident in adolescence not just in adulthood, as commonly reported with retrospective studies of poverty. The increased co-activation between the frontoparietal network (FPN) and the dorsal attention network (DAN) in response to a 'fearful' facial expression aligns with previous neuroimaging findings that have identified associations between childhood poverty and altered processing of negative emotions in adulthood (i.e., fearful and angry faces; Javanbakht et al., 2015; Moulson, Fox, Zeanah, & Nelson, 2009). Interestingly, this 'fearful' condition network connectivity was only associated with early childhood material hardship, and not to any specific period during development, or any other incremental range (i.e., 1 to 5, 1 to 9, 1 to 15). This finding stands in contrast to behavioral studies commonly reporting that cumulative lifetime material hardship has a stronger association with behavioral outcomes (e.g., Li, & Whipple, 2013). This was not the case with task-based connectivity, which suggests early childhood (age 1 to 3) as especially vulnerable time period to environmental stressors.

Specifically, the frontoparietal network has been implicated as a “flexible hub” that interacts with other content-specific networks (i.e., salience network) to guide processing across multiple cognitive domains (Zanto & Gazzaley, 2013). As part of the ‘Central Executive Network’, the FPN will interact with other networks depending on the demands of the task (Dixon et al., 2018). The DAN is engaged during externally directed attentional tasks and comprised of functionally connected brain regions including the visual motion area (Spreng, Sepulcre, Turner, Dale, & Schacter, 2013). Moreover, the increased co-activation of the FPN-DAN has been found to be indicative of the degree to which one implements cognitive control processes necessary to maintain goals, inhibit distractions and shift behaviors in goal directed behaviors (Vincent et al., 2008). For example, a study evaluating two conditions found increased FPN-DAN connectivity was associated with an exaggerated finger tapping task, while movie watching was associated with decreased FPN-DAN coactivation and increased Default Mode Network Activation-DAN(Gao & Lin, 2012). The previous finding suggests that the observed increased FPN-DAN connectivity to fearful images by youth in our sample may be indicative of adaptations in network functioning associated with emotion processing. Importantly, recent behavioral studies suggest that these adaptations are malleable to cognitive-emotion regulation strategy training, and in fact, these strategies have greater benefit for lower-SES individuals relative to their higher income counterparts (Troy, Ford, McRae, Zarolia, & Mauss, 2017).

An alternative explanation for these findings relates to adolescent’s selective attention to fearful faces. Recent work examining how adolescent attention may affect emotion processing reported that adolescent’s attention seems to be captured by fearful faces more than any other type of emotion relative to adults, suggesting that processing of emotional faces is qualitatively different for adolescents (Grose-Fifer, Rodrigues, Hoover, & Zottoli, 2013). Other researchers have shown that adolescents have more difficulty ignoring emotional faces than adults. For example, Monk and colleagues reported no differences in terms of the youth's accuracy and reaction times in identifying emotion, but when asked to evaluate a non-emotional aspect (nose width) of fearful faces, there were differences in task performance for adolescents, suggesting an involuntary attentional capture of fearful faces for adolescents than adults (2003).

Although the low depression and anxiety scores were comparable to reports from other samples of similarly aged adolescents (Brown et al., 2006; Goosby, 2007; McLaughlin et al., 2007), our prediction that FPN-DAN connectivity would be positively corelated with adolescent anxiety or depression symptoms was not supported. Therefore, altered task-based connectivity associated with early childhood material hardship did not correlate with the current adolescent psychopathology. However, follow up exploratory analyses identified that depression symptoms were negatively correlated with co-activation of the FPN and cerebellar network (CER), independently of material hardship. In other words, reduced FPN-CER network coactivation when viewing 'fearful' faces was associated with an increase of depression symptoms. These networks are part of the fronto-cerebellar neural networks (Arnsten & Rubia, 2012) involved in selective and sustained attention and motivation (Steinlin, 2007). Indeed, reduced FPN-CER co-activation has been suggested to be a compensatory response in attention and reward during motivated attention, but not unmotivated attention for youth who have been diagnosed with Major Depression Disorder (MDD; Chantiluke et al., 2012). In the opposite direction, higher anxiety symptoms were positively correlated with coactivation within the somatosensory mouth (SSM-SSM) and the coactivation between somatosensory hand and mouth networks (SSM-

SSH). Importantly, this increased somatosensory network connectivity during a fearful condition supports the notion that increased connectivity within the sensory-motor activity networks and anxiety are reflecting somatic symptoms associated with the processing of fear (Bertini & Elisabetta, 2021). In fact, a meta-analysis of psychopathology and its association with somatosensory networks suggests that disruptions in sensory networks may be indicative of the early signs of developing psychopathology associated with emotion processing deficits (Levit-binnun, Davidovitch, & Golland, 2013).

Lastly, an exploratory network contingency analysis modeling the contrast of all emotions versus the neutral found no significant association between early childhood material hardship and interrelated task-based network connectivity during adolescence. Yet, recent connectome-wide PPI work has provided evidence for interrelated network activation in youth (N=843) with Social Anxiety Disorders who are viewing angry and fearful faces (Markett, Jawinski, Kirsch, & Gerchen, 2020). This suggests that perhaps the modulation of the other emotions may not have been apparent in our sample due to a sample size that may not be sensitive to smaller effects. By and large, network level connectivity is an emerging field, and the present finding provides support for network level emotion processing as well as, contributes to our understanding of how emotion is processed across the brain. The present findings characterize emotion processing adaptations observed in early adolescence associated with early childhood material hardship, suggesting that the neural adaptations commonly reported in adult with retrospective reports of poverty may begin as early as age 15. This is important because efforts to create interventions and preventative programs should target this age group to reduce the impact of material hardship on brain function.

Limitations and Future Directions

The present study is not without limitations that should be addressed in future research. First, the gender identification task used in this study with pictures of faces displaying emotions at full intensity may not adequately evoke the emotion processing circuitry activation engaged in typical interactions for youth who may already have altered emotion processing due to early adversity. Second, the implicit nature of the task may have presented a disadvantage for youth who had never been inside a scanner and whose sense of discomfort or anxiety would prime the activation in these networks(Winston et al., 2003). Additionally, the neural activation reliability of an implicit face task has come into question perhaps signaling that different tasks should be used (Haller et al., 2018). Perhaps, an emotion task that engages cognitive processes such as the reappraisal task used by Liberzon and colleagues(2015) might provide a more nuance characterization of the dynamic cognitive interactions that support emotion-based processes, or using tasks that require an endogenous generated emotion by the participant have also shown promise in network level emotion studies (Engen, Kanske, & Singer, 2017). Third, the event-related fMRI design during the scanning session may have limited the application of the PPI analytical approach, given that the events do not allow for full estimation of activation during the presentation of a certain type of emotion, as would be possible in a block design. Future PPI work could leverage multi-method imaging data with block and event-related design to better discern the extent to fMRI design may be modified to allow for the application of PPI in both types of design.

Summary

To summarize, the present study leveraged longitudinal reports of material hardship for a diverse sample with overrepresentation of understudied African American youth to examine a connectome-wide PPI network contingency analysis to characterize how large-scale network functional connectivity was associated with different types of emotion. Specifically, greater material hardship experienced in early childhood (ages 1-3) increased large-scale network connectivity between the frontoparietal network and the dorsal attention network in response to fearful faces, but not for other emotional faces. Findings from our connectome-wide approach contribute to the emerging field of connectome-based functional connectivity and generates new questions related to how the complexities of emotion is processed during adolescence.

CHAPTER IV
Discussion

Poverty and income inequalities in the U.S. remain crucial public health concerns that require ongoing research efforts to elucidate possible areas for prevention and intervention. More than 48 million people in the United States live in low-income working families, and more than 10.3 million working families earn less than the 200% of the government's official poverty income threshold level, which is thought to be the minimum income needed by families to meet a basic standard of living. As recommended by APA, these families should not be referred to as being "poor" or in poverty, but rather as individuals who are low-income and economically marginalized (LIEM) (2019). The label describes the persisting social, political, and educational barriers that disproportionately marginalize these families, whose consequences are reflected in their economic well-being. Moreover, LIEM families are more likely to be non-White, which reflects the historical marginalization of non-White people in the U.S. through structural and individual racism. Consequently, my dissertation presented arguments and research studies that improved upon the existing poverty research by using innovative methodological approaches to better characterize the dynamic and complex nature of poverty in neuroimaging research.

In the first chapter, I reviewed the history of an income-based indicator commonly used in the U.S., the Official Poverty Measure threshold that mischaracterizes a family's financial well-being which increases the likelihood of not identifying children growing up in families facing economic hardship. I presented the argument for the need of a more direct measure of family's economic well-being to complement the income-based poverty research to date. I proposed to operationalize poverty through a family's material hardships which better characterize their lived experiences and struggles in meeting basic living needs, independently of their household income. Moreover, I discussed how material hardships disproportionately affect non-White LIEM families and their children's development with focus on their increased risk of developing internalizing disorders, which has downstream consequences that persist until adulthood. As such, I provided a rationale to support my interest in examining how early childhood (Age 1 to 3) material hardship would be associated with adolescent brain function. Lastly, I proposed a functional adaptation framework that purported experience dependent neural adaptations over development (i.e., brain plasticity) to be one of the biological mediators that link material hardship to brain development, which can be measured through connectome-wide functional connectivity.

The aim of Study 1 (Chapter 2) was to characterize the association between early childhood material hardships and adolescent brain functional connectivity at-rest. Youth in this study completed neuroimaging assessments at age 15 and were recruited from a nationally representative study, the Fragile Families and Child Wellbeing Study. As such, I had access to longitudinal information over 5 waves of data for one target child at age 1, 3, 5, 9 and 15 and their family's material hardship reports over this time. Although Study 1 combined innovative sampling, statistical, and neuroimaging techniques to conduct a data-driven connectome-wide analysis of at-rest adolescent functional connectivity, my primary hypothesis was not supported. At-rest connectivity did not have an association between increased material hardship during early childhood and altered adolescent at-rest network connectivity across the Salience Network, the Central Executive Network, and the Default Mode Network. Nonetheless, increased node connectivity was observed across 13 brain networks, but this increased connectivity was deemed to be statistically non-significant, as such no follow-up testing of interrelated networks connectivity and current internalizing symptoms was completed. Additionally, exploratory analyses demonstrated that no single material hardship period or their incremental effects had any associations with altered at-rest network connectivity. However, exploratory correlational analyses of network connectivity and internalizing symptoms, independently of material hardship identified both positive and negative correlations with a few interrelated networks. Based on these results that did not align with the current resting-state poverty literature, I concluded that income-based poverty and material hardship are indeed distinct dimensions of poverty and impact brain function differently. Importantly, the null findings of study one should not be used to dismiss or undercut the negative impact that material hardships have on child development, family functioning and quality of life.

In Study 2 (Chapter 3), I used a connectome-wide psychophysiological interaction (PPI) approach to characterize altered functional connectivity involved in emotion processing using the same sample of adolescents from Study 1. Given that dysregulated emotion processing has been implicated in the development of psychopathology, Study 2 examined adolescents' responses to a gender recognition task with actors expressing five emotions (i.e., happy, sad, fearful, anger and neutral). The aim of study 2 was to characterize the association between adolescent emotion processing and early childhood material hardship. Towards this end, I used multiple different contrasts (e.g., sad vs. baseline, neutral versus all emotions) within a connectome framework to pinpoint the nature of altered emotion processing while simultaneously evaluating whole brain activation as opposed to emotion circuit specific regions. I was interested in examining how material hardship experienced during important early childhood critical periods (e.g., 1 to 3) may be especially impactful. I hypothesized that adolescents who had experienced more material hardship would show cognitive and emotional processing difficulties relative to adolescents who had experienced less material hardship and that this dysregulation would support the emergence of psychopathology. Despite previous research to the contrary, the current study did not find any significant differences between conditions tested, except in the case of the task-based activation elicited while viewing 'fearful' faces.

Specifically, adolescents who had experienced more material hardship between ages 1 and 3 showed greater coactivation between the frontoparietal and the dorsal attention networks at age 15 in response to viewing 'fearful' faces. However, this increased coactivation was not associated with any current adolescent internalizing symptoms. Furthermore, exploratory analyses testing the association between the individual periods and incremental periods (e.g., age 1 to 15) of material hardship with the task-activation during the 'fearful' condition were not significant. However, extracted functional connectivity while viewing 'fearful' faces across a few networks was associated with current internalizing symptoms, independently of material hardship. These findings were in line with previous research and highlighted the importance of evaluating brain function through a multi-method approach to characterize the differential impact of material hardship on brain function.

Although this study had several methodological strengths and sought to fill an important gap in the literature, it also had some limitations. One limitation of the current study that may have influenced the null findings in Study 1 could be the way in which I conceptualized family material hardship. To characterize how all types of material hardship were associated with multi-method functional connectivity, I aggregated eight weighted items to produce an average score. Although my review of the literature supported the weighted mean approach, which aimed to not treat all types of material hardship as ‘equally’ impactful, important information such as the most reported types of hardships and the subtle fluctuations by type of material hardship over the five waves of data collection were lost when items were averaged. This loss of information contributed to the low variability across the weighted averages (See Figure 2.2). Indeed, material hardship item-based analyses (See Figure 2.3) demonstrated the complex variability underlying the weighted material hardship averages. Based on the individual item variability within the sample, it suggests that perhaps a more nuanced approach was merited. Perhaps a dimensional approach to measuring material hardship is necessary to better characterize how different features of material hardship such as type of hardship, the duration of hardship, and resolution of hardship alter social and physical child development in different contexts. In fact, previous studies exploring these distinct dimensions of material hardship separately have indicated different relationships with different child outcomes (e.g., food insecurity associated with poor academic performance). Additionally, both traditional material hardship items and items that assess families’ subjective sense of material hardship may prove informative as well, given the emerging research that has found strong links between subjective reports of economic hardship and health outcomes.

Although studies examining the effects of material hardship on children do not survey the children themselves about their experiences directly, one valuable direction for future research may be to develop material hardship items that either ask parents directly about children’s needs that may have gone unmet or that ask children themselves, in developmentally appropriate terms, about their needs that may have been unmet. Perhaps a more focused measure that targeted child-specific material hardship would improve the accuracy and validity of material hardship measures oriented towards children. Therefore, a multidimensional and multi-informant approach (e.g. parent and teacher reports) may help triangulate and better focus our assessment of material hardship affecting children.

Next, the use of the SAND sample in this study is a both a strength and a limitation. On the one hand, the subsample used in this study is drawn from a nationally representative sample of LIEM families, but the participants included in this study were predominantly African American families from urban areas. Accordingly, these results may not be generalizable to LIEM families from, for example, other racial/ethnic backgrounds or who struggle with material hardship in nonurban environments. That said, this study does shed light on this group's experiences, which is valuable in its own right. Moreover, the use of an implicit emotion processing task (i.e., gender recognition task) may not have been the most appropriate for assessing adolescent's reactivity to emotional stimuli. the actors in the images were all adults, this may have prompted a low priority of emotion processing for adult faces by the adolescents. Especially given the age, gender, and race differences between the youth and the actors. To improve on this, perhaps the use of faces that reflect similar demographic characteristics (e.g., age, race, gender) and that are representative of the youth they would be exposed to at school and in other social situations daily would improve engagement with the task. Additionally, the use of an event-related design versus a block design may not have provided sufficient presentation time of each of the emotions to capture the associated activation required for PPI analyses, which may have been low to begin with given the implicit nature of the emotion processing task.

Despite these limitations, the finding that material hardship experienced between ages 1 and 3 does have downstream impacts on network level emotion processing at age 15 is noteworthy and a valuable contribution to the literature. Income effects, or other social variables that serve as proxies for poverty effects (e.g., maternal education), tend to be small and thus difficult to identify in small samples using neuroimaging functional connectivity, which may have reduced our ability to detect an effect during resting state connectivity, but it is likely the case that the use of the connectome wide PPI analysis isolating conditions gave us stronger signal to detect effects. These findings reflect that many of the environmental stressors that are of concern to development may require larger sample sizes or more sensitive approaches to identify the small effect sizes on brain function. Careful evaluation of the available methodology and surveys should be conducted to reduce noise and confounds with our current approaches.

Although these studies failed to identify all the relations initially hypothesized, it is important to note that this work should not be used to discredit the powerful impact of material hardship, particularly in early life. There is a plethora of behavioral data that has repeatedly demonstrated the role of poverty in general and material hardship in the development of internalizing and externalizing symptoms, as well as in other domains of development. As described above, there are a variety of different reasons why the functional connectivity findings did not emerge as expected; however, the mixed findings of this dissertation provide valuable information to advance our understanding of material hardship and research practices. The altered co-activation of networks identifies a possible area for the development of executive function interventions for those youth whose increased connectivity may be interfering with general executive skills in other domains of life such as school or work. Additionally, the finding regarding emotional processing differences for fearful faces is a valuable piece of information that could be incorporated in intervention programs for children from LIEM families, as part of targeted socioemotional learning curriculum, or to reduce the severity of any potential emergent psychopathology that could arise due to a hyperactive Central Executive Network.

More broadly, this dissertation examined comparable youth drawn from the same sample through task-based and at-rest functional connectivity. The use of a multi-method approach demonstrated that research questions may have opposing findings, which is valuable to our understanding of how environmental stressors such as material hardship impact brain function differently. Recommendations to publish multi-method work are suggested. Research that has attempted to reconcile mixed findings between task-based and at-rest connectivity often finds equally valuable contributions to the research field (e.g., Stevens, 2016). Next, the null findings of study one encourages reflection about the important value of publishing null findings. Understandably, there is a preference to publish poverty research studies with statistically significant findings. However, much can be learned from publishing studies with null findings that also help advance scientific knowledge in psychology or any field for that matter by shedding light on new questions. Barring this approach, encouraging more replication studies would be equally as important, which would address our ongoing 'replication crisis' in neuroimaging research. Pre-registration of studies may help address these concerns by allowing the publication of scientifically sound research with null findings while documenting the methodology, and proposed analyses prior to project completion.

TABLES AND FIGURES

Table 2.1 SAND Sample: Demographic characteristics, N=237.

Measures	N = 237
Age in Years (Mean, SD)	15.41(0.54)
Gender (%, Count)	
Female	52% (124)
Male	48% (113)
Ethnic Racial Identity (%, Count)	
Black/African American (non-Hispanic)	76% (181)
White/Caucasian (non-Hispanic)	13% (30)
Other Non-Hispanic Groups (Asian, Native Americans, Arabs)	2% (5)
Hispanic/ Latino	4% (10)
Multi-Ethnic/Race	5% (11)
Household Annual Income at Age 15 (%, Count)	
$4,999 or less	12% (28)
$5,000 - $9,999	2% (5)
$10,000 - $14,999	8% (20)
$15,000 - $19,000	7% (16)
$20,000 - $24,999	14% (33)
$25,000 - $29,999	5% (11)
$30,000 - $39,999	10% (23)
$40,000 - $49,999	9% (21)
$50,000 - $59,999	5% (13)
$60,000 – $69,999	5% (11)
$70,000 - $79,999	3% (8)
$80,000 - $89,000	2% (5)
$90,000 or more	9% (22)
No Response	9% (21)
Weighted 8-Item Material Hardship (Mean, SD)	
Age 1	.10(0.13)
Age 3	.10(0.13)
Age 5	.11(0.13)
Age 9	.12(0.12)
Age 15	.11(0.14)
Material Hardship Occurrence (%, Count)	
Families Who Never Reported Material Hardship	13% (32)
Families who Reported Material Hardships at All Waves	17% (40)
Internalizing Symptoms Scales (Mean, SD)	
Depression-CDI	8.42(6.52)
Anxiety-SCARED	16.96(11.20)

Note. SAND: Study of Adolescent Neural Development; SD: Standard Deviation; CDI: Children's depression inventory, score range 0-54, SCARED: Screen for Child Anxiety Related Disorder, score range 0-76.

Table 2.2 SAND Sample: Material hardship correlated with variables of interest.

Variables	1	2	3	4	5	6	7	8	9	10	11
1. Age in Years	-										
2. Gender	.04	-									
3. ERI	-.01	.00	-								
4. Annual Income[a]	.06	-.05	.00	-							
5. Age 1 MH -wM	-.11	.02	.04	-.11	-						
6. Age 3 MH -wM	-.17[c]	.05	.06	-.05	.56[d]	-					
7. Age 5 MH -wM	-.12	.07	.09	.05	.41[d]	.53[d]	-				
8. Age 9 MH -wM	-.09	.12	.12	-.07	.26[d]	.36[d]	.42[d]	-			
9. Age 15 MH -wM	-.03	.04	.07	-.05	.28[d]	.37[d]	.35[d]	.52[d]	-		
10.SCARED	-.03	-.33[d]	.08	.01	.02	.04	.09	.06	.09	-	
11.CDI	.05	-.16[b]	-.01	.01	.04	.11	.11	.12	.14[b]	.46[d]	-

Note. N=237; values are Pearson correlation coefficients ; SAND: Study of Adolescent Neural Development; ERI: Ethnic-Racial Identity; MH: Material Hardship; '-wM': weighted mean; SCARED: Screener for Child Anxiety Disorders; CDI: Children's Depression Inventory; [a] household income at age 15 assessment; [b]p<.05; [c] p<.01; [d] p<.001

Table 2.3 SAND Sample: Weighted material hardship by item and average score by wave.

N=237	Age 1	Age 3	Age 5	Age 9	Age 15
MH Item (%, Count)					
Receive Food Meals	9% (22)	12% (28)	12% (29)	10% (23)	20% (48)
Gas or Electricity	23% (54)	26% (61)	32% (75)	44% (105)	38% (90)
Borrow Money	24% (57)	22% (53)	29% (69)	41% (96)	29% (69)
Rent Mortgage	16% (38)	12% (29)	14% (34)	24% (57)	18% (42)
Shelter	3% (7)	3% (7)	3% (6)	1% (3)	2% (5)
Evicted	4% (10)	2% (5)	3% (8)	4% (9)	2% (5)
No Doctor	5% (12)	8% (18)	9% (21)	5% (11)	6% (14)
Move In w Friend/Family	10% (24)	11% (27)	10% (24)	11% (25)	7% (17)
MH Reported (%, Count)					
None	49% (116)	48% (114)	42% (98)	33% (78)	44% (103)
At least One Hardship	51% (121)	52% (123)	59% (139)	67% (159)	57% (134)
MH 8-Item Composite (Mean, SD)					
MH-*non-weighted*	0.12(0.16)	0.12(0.16)	0.15(0.17)	0.19(0.18)	0.15(0.18)
MH-*weighted*	0.10(0.13)	0.10(0.13)	0.11(0.13)	0.12(0.12)	0.11(0.14)

Note. SAND: Study of Adolescent Neural Development; SD: Standard Deviation; [a] original data average sum non-weighted averages reported for interpretability and completeness.

Table 2.4 Sample attrition for resting state analysis.

Reasons for Exclusion	Number of Subjects
Original Sample	237
Did not attempt MRI scan	29
Incomplete fMRI scan	4
fMRI scan quality issues (e.g., cut off structural images)	26
Autism Spectrum Disorder	2
Sample size prior to motion correction for connectome analyses	176
Censored Volumes (>50%); less than 4 minutes of data	2
Loss to Excessive Motion (Mean FD > 0.5mm)	0
Incomplete/Missing Material Hardship Wave Data	0
Total Sample Included in rs-fMRI Connectome Analyses	174

Note. Motion correction used AROMA-ICA that allowed for the inclusion of more participants; FD: Frame displacement.

Table 2.5 Resting-state sample: Demographic characteristics, N=174.

Measure	N=237	N=174	ANOVA or X^2
Age in Years (Mean, SD)	15.41(0.54)	15.43(0.55)	$F(1,235)=0.91$, $p=.34$
Gender (%, Count)			$\chi^2(1)=3.08$, $p=.08$
Female	52% (124)	56% (97)	
Male	48% (113)	44% (77)	
Ethnic Racial Identity (%, Count)			$\chi^2(4)=5.10$, $p=.28$
Black/African American (non-Hispanic)	76% (181)	78% (136)	
White/Caucasian (non-Hispanic)	13% (30)	10% (18)	
Other Non-Hispanic Groups (Asian, Native Americans)	2% (5)	2% (4)	
Hispanic/ Latino	4% (10)	5% (9)	
Multi-Ethnic/Race	5% (11)	4% (7)	
Weighted Material Hardship Score(Mean, SD)			
Age 1	.10(0.13)	.10(0.13)	$F(1,235)=0.12$, $p=.73$
Age 3	.10(0.13)	.11(0.13)	$F(1,235)=0.91$, $p=.34$
Age 5	.11(0.13)	.12(0.13)	$F(1,235)=2.98$, $p=.09$
Age 9	.12(0.12)	.12(0.13)	$F(1,235)=0.98$, $p=.32$
Age 15	.11(0.14)	.12(0.14)	$F(1,235)=1.04$, $p=.31$
Internalizing Scales (Mean, SD)			
Depression-CDI	8.42(6.52)	8.82(6.78)	$F(1,234)=2.48$, $p=.12$
Anxiety-SCARED	16.96(11.20)	17.25(11.25)	$F(1,228)=0.48$, $p=.49$

Note. Weighted material hardship score is derived from an 8-item composite sum; SD: Standard Deviation; CDI: Children's depression inventory, score range 0-54, SCARED: Screen for Child Anxiety Related Disorder, score range 0-76; group differences were testing the excluded versus included youth in the sample used for connectome analyses.

Table 2.6 Resting-state sample: Weighted material hardship by item and average score by wave.

N = 174	Age 1	Age 3	Age 5	Age 9	Age 15
MH Item (%, Count)					
Receive Food Meals	10% (18)	13% (23)	15% (26)	9% (16)	20% (34)
Gas or Electricity	24% (41)	28% (49)	35% (60)	47% (81)	40% (68)
Borrow Money	27% (47)	26% (45)	32% (56)	43% (52)	31% (53)
Rent Mortgage	13% (23)	12% (21)	16% (27)	26% (45)	20% (35)
Shelter	3% (6)	3% (5)	3% (5)	2% (3)	2% (4)
Evicted	5% (8)	3% (5)	5% (8)	3% (6)	2% (4)
No Doctor	5% (9)	6% (11)	9% (15)	4% (7)	7% (12)
Move In w Friend/Family	10% (18)	12% (21)	11% (19)	12% (21)	6% (11)
MH Reported (%, Count)					
None	49% (85)	45% (79)	39% (68)	32% (55)	42% (73)
At least One Hardship	51% (89)	55% (95)	61% (106)	68% (119)	58% (101)
MH 8-Item Composite (Mean, SD)					
MH-*non-weighted*	0.13(0.16)	0.13(0.16)	0.16(0.17)	0.20(0.19)	0.16(0.19)
MH-*weighted*	0.10(0.13)	0.11(0.13)	0.12(0.13)	0.12(0.13)	0.12(0.14)

Note. MH: Material Hardship; SD: Standard Deviation; original data average sum non-weighted averages reported for interpretability and completeness.

Table 2.7 Resting-state sample: Material hardship correlated with variables of interest.

Variables	1	2	3	4	5	6	7	8	9	10	11
1. Age in Years	-										
2. Gender	.01	-									
3. ERI	.04	.00	-								
4. Annual Income[a]	.01	-.07	.08	-							
5. Age 1 MH -wM	-.13	.00	-.02	-.06	-						
6. Age 3 MH -wM	-.16[b]	.04	-.01	-.13	.57[d]	-					
7. Age 5 MH -wM	-.12	.06	.03	.05	.39[d]	.52[d]	-				
8. Age 9 MH -wM	-.03	.12	.10	-.07	.22[d]	.33[d]	.45[d]	-			
9. Age 15 MH -wM	.00	.07	.05	-.05	.30[d]	.37[d]	.33[d]	.55[d]	-		
10.SCARED	-.08	-.32[d]	.14	-.04	.04	.05	.13	.13	.08	-	
11. CDI	.03	-.11	.00	-.03	-.03	.07	.10	.12	.13	.45[d]	-

Note. N=174; values are Pearson correlation coefficients; ERI: Ethnic-Racial Identity; MH: Material Hardship; '-wM': weighted mean; SCARED: Screener for Child Anxiety Disorders; CDI: Children's Depression Inventory; [a] household income at age 15 assessment; [b]p<.05; [c] p<.01; [d] p<.001

Table 2.8 Non-parametric significance testing (FDR, *p* <.05): Adjusted p-values for material hardship during age 1-3 and network connectivity at-rest.

Network	1	2	3	4	5	6	7	8	9	10	11	12	13
1. SSH	1	.73	.93	.88	.73	.88	.73	1	.79	1	1	1	1
2. SSM		1	.73	.73	.73	1	.88	.73	.73	.73	1	.73	1
3. COT			1	1	.73	1	.73	1	1	.88	1	1	1
4. AUD				1	.73	.73	.73	.73	.77	.73	1	1	1
5. DMN					.99	1	.88	1	.73	1	1	.88	1
6. MEM						1	.93	.73	.79	1	1	.73	1
7. VIS							1	1	.73	.73	1	1	1
8. FPN								1	.73	1	1	.88	1
9. SAL									.73	.73	1	1	1
10. LIM										1	1	1	1
11. VAN											1	1	1
12. DAN												.73	1
13. CER													1

Note. N=174; values are corrected False Discovery Rate p-values (FDR, *p* <.05), Networks: SSH: Somato Sensory Hand; SSM: Somato Sensory Mouth; COT: Cingular Opercular Task Control; AUD: Auditory; DMN: Default Mode; MEM: Memory Retrieval; VIS: Visual; FPN: Frontoparietal Task Control; SAL: Salience; LIM: Limbic; VAN: Ventral Attention; DAN: Dorsal Attention; CER: Cerebellum; Network Contingency Analysis Model adjusted for mean frame displacement motion value, ethnic-racial identity and gender and current age 15 material hardship.

Table 2.9 Zero-order correlation between extracted at-rest network connectivity and depression symptoms.

Network	1	2	3	4	5	6	7	8	9	10	11	12	13
1. SSH	-.08	-.05	-.11	-.09	-.03	.02	-.08	-.04	-.05	.00	-.13	-.06	.04
2. SSM		-.13	-.09	-.15	.04	.04	-.06	.07	.02	.00	-.06	-.05	-.06
3. COT			-.17[a]	-.14	-.01	.00	-.10	-.06	-.10	-.06	-.09	-.08	-.02
4. AUD				-.16[a]	-.03	.03	-.07	-.01	-.06	-.04	-.13	-.03	-.01
5. DMN					-.08	.02	.00	-.03	-.01	-.01	-.05	.00	-.02
6. MEM						.08	.02	-.03	.02	.03	-.01	.04	.02
7. VIS							-.12	.01	-.07	-.05	-.01	-.09	-.11
8. FPN								-.11	-.07	-.04	-.07	-.09	-.02
9. SAL									-.07	-.06	-.10	-.07	-.03
10. LIM										-.04	-.06	-.01	-.02
11. VAN											.02	-.03	-.03
12. DAN												-.15	-.03
13. CER													.02

Note. N=174; values are Pearson correlation coefficients; Networks: SSH: Somato Sensory Hand; SSM: Somato Sensory Mouth; COT: Cingular Opercular Task Control; AUD: Auditory; DMN: Default Mode; MEM: Memory Retrieval; VIS: Visual; FPN: Frontoparietal Task Control; SAL: Salience; LIM: Limbic; VAN: Ventral Attention; DAN: Dorsal Attention; CER: Cerebellum;
[a] $p < .05$

Table 2.10 Zero-order correlation between extracted at-rest network connectivity and anxiety symptoms.

Network	1	2	3	4	5	6	7	8	9	10	11	12	13
1. SSH	-.01	.05	-.02	.09	.04	.10	.01	.05	.00	.11	.04	.02	.16^{a}
2. SSM		-.02	.01	.05	.17^{a}	.09	.06	.10	.05	.07	.09	.01	.07
3. COT			-.01	.00	.03	.07	.00	.07	.00	.12	.05	.03	.13
4. AUD				.04	.08	.11	.07	.09	.00	.10	.00	.06	.18^{a}
5. DMN					.02	.16^{a}	.04	.04	.08	.08	.01	.02	.07
6. MEM						.18^{a}	.13	.06	.17^{a}	.17^{a}	.08	.10	.10
7. VIS							.13	.09	.04	.07	.10	.06	.05
8. FPN								-.02	.07	.12	.00	.00	.11
9. SAL									.05	.13	.03	.03	.09
10. LIM										.13	.08	.12	.16^{a}
11. VAN											.09	.03	.10
12. DAN												-.06	.08
13. CER													.10

Note. N=174; values are Pearson correlation coefficients; Networks: SSH: Somato Sensory Hand; SSM: Somato Sensory Mouth; COT: Cingular Opercular Task Control; AUD: Auditory; DMN: Default Mode; MEM: Memory Retrieval; VIS: Visual; FPN: Frontoparietal Task Control; SAL: Salience; LIM: Limbic; VAN: Ventral Attention; DAN: Dorsal Attention; CER: Cerebellum;
^{a} p <.05; ^{b} p<.01; ^{c} p<.001

Table 3.1 Sample attrition for PPI connectome analyses

Reasons for Exclusion	Number of Subjects
Original Sample	237
Did not attempt MRI scan	29
Incomplete fMRI scan	4
fMRI scan quality issues (e.g., structural artifacts)	21
Alternate faces ask version	2
Autism Spectrum Disorder	2
Inconsistent Tasks Response Pattern	11
Total Faces Task Sample Prior to Motion Exclusion	168
Exclusionary Criteria	
White Matter/CSF Masks (e.g., warped masks)	11
Minimum (>4 Minutes) time of Uncensored Volumes	0
Excessive Mean Frame Displacement (>.5mm)	6
Low (<70%) accuracy on faces tasks	17
Missing Behavioral Data	0
Total Sample Included in PPI Connectome Analyses	134

Table 3.2 Faces task sample: Demographic characteristics, N=134.

Measure	N=237	N=134	ANOVA or X^2
Age in Years (Mean, SD)	15.41(0.54)	15.40(0.54)	$F(1,235)=0.09$, $p=.76$
Gender (%, Count)			$\chi^2(1)=1.04$, $p=.30$
Female	52% (124)	55% (74)	
Male	48% (113)	45% (60)	
Ethnic Racial Identity (%, Count)			$\chi^2(4)=1.85$, $p=.76$
Black/African American (non-Hispanic)	76% (181)	77% (103)	
White/Caucasian (non-Hispanic)	13% (30)	12% (16)	
Other Non-Hispanic Groups (Asian, Native Americans)	2% (5)	3% (4)	
Hispanic/ Latino	4% (10)	5% (6)	
Multi-Ethnic/Race	5% (11)	4% (5)	
Weighted Material Hardship Score(Mean, SD)			
Age 1	.10(0.13)	.10(0.13)	$F(1,235)=0.01$, $p=.94$
Age 3	.10(0.13)	.11(0.13)	$F(1,235)=0.18$, $p=.68$
Age 5	.11(0.13)	.12(0.14)	$F(1,235)=0.65$, $p=.42$
Age 9	.12(0.12)	.12(0.13)	$F(1,235)=0.90$, $p=.34$
Age 15	.11(0.14)	.12(0.15)	$F(1,235)=0.06$, $p=.82$
Internalizing Scales (Mean, SD)			
Depression-CDI	8.42(6.52)	9.10(6.78)	$F(1,234)=3.34$, $p=.07$
Anxiety-SCARED	16.96(11.20)	17.25(11.73)	$F(1,228)=.87$, $p=.35$

Note Weighted material hardship score is derived from an 8-item composite sum; SD: Standard Deviation; CDI: Children's depression inventory, score range 0-54, SCARED: Screen for Child Anxiety Related Disorder, score range 0-76; group differences were testing the excluded versus included youth in the sample used for connectome analyses.

Table 3.3 Faces task sample: Weighted material hardship by item and average score by wave.

N = 134	Age 1	Age 3	Age 5	Age 9	Age 15
MH Item (%, Count)					
Receive Food Meals	10% (14)	12% (16)	14% (19)	10% (13)	19% (26)
Gas or Electricity	23% (31)	29% (39)	35% (47)	49% (65)	41% (55)
Borrow Money	28% (37)	25% (34)	32% (43)	47% (59)	28% (37)
Rent Mortgage	18% (24)	11% (15)	14% (19)	28% (37)	19% (26)
Shelter	5% (6)	2% (2)	3% (4)	2% (3)	3% (4)
Evicted	3% (4)	3% (4)	5% (6)	3% (4)	2% (3)
No Doctor	7% (9)	8% (11)	10% (13)	5% (6)	5% (7)
Move In w Friend/Family	10% (13)	10% (14)	10% (14)	10% (14)	6% (8)
MH Reported (%, Count)					
None	46% (62)	46% (61)	40% (54)	31% (41)	44% (59)
At least One Hardship	53% (72)	55% (73)	60% (80)	69% (93)	56% (75)
MH 8-Item Composite (Mean, SD)					
MH-*non-weighted*	0.13(0.16)	0.13(0.17)	0.16(0.18)	0.20(0.18)	0.16(0.19)
MH-*weighted*	0.10(0.13)	0.10(0.13)	0.12(0.14)	0.12(0.13)	0.12(0.15)

Note. N=134; MH: Material Hardship; SD: Standard Deviation; original data average sum non-weighted averages reported for interpretability and completeness.

Table 3.4 Faces task sample: Material hardship correlated with variables of interest.

Variables	1	2	3	4	5	6	7	8	9	10	11
1. Age in Years	-										
2. Gender	-.02	-									
3. ERI	-.01	.01	-								
4. Annual Income[a]	.03	-.04	-.01	-							
5. Age 1 MH -wM	-.10	-.05	.08	-.07	-						
6. Age 3 MH -wM	-.13	.07	.04	.04	.53[d]	-					
7. Age 5 MH -wM	-.07	.05	.09	.06	.41[d]	.59[d]	-				
8. Age 9 MH -wM	-.01	.15	.14	-.08	.25[d]	.39[d]	.45[d]	-			
9. Age 15 MH -wM	-.01	.06	.03	-.01	.32[d]	.44[d]	.32[d]	.56[d]	-		
10.SCARED	-.06	-.39[d]	.13	.11	.06	.07	.16	.00	.07	-	
11. CDI	.00	-.17[b]	-.01	.12	-.03	.07	.09	.09	.05	.49[d]	-

Note. N=134; values are Pearson correlation coefficients; ERI: Ethnic-Racial Identity; MH: Material Hardship; '-wM': weighted mean; SCARED: Screener for Child Anxiety Disorders; CDI: Children's Depression Inventory; [a] household income at age 15 assessment; [b]p<.05; [c] p<.01; [d] p<.001

Table 3.5 Non-parametric significance testing (FDR, *p* <.05): Adjusted p-values for material hardship during age 1-3 and network connectivity while viewing fearful faces.

Network	1	2	3	4	5	6	7	8	9	10	11	12	13
1. SSH	1	.52	1	1	1	.75	.66	1	1	1	1	1	1
2. SSM		1	1	1	1	.22	.88	.11	1	1	1	1	.52
3. COT			1	1	1	1	1	1	1	1	1	1	1
4. AUD				1	1	.23	.66	.11	1	1	1	1	1
5. DMN					1	1	1	1	1	1	1	1	1
6. MEM						.42	1	.42	1	.68	1	1	1
7. VIS							1	.68	.91	.68	1	1	1
8. FPN								.11	.07	.19	.22	.03*	1
9. SAL									1	1	1	1	.79
10. LIM										1	1	1	1
11. VAN											1	1	1
12. DAN												1	1
13. CER													1

Note. N=134; values are corrected False Discovery Rate p-values (FDR, p <.05), Networks: SSH: Somato Sensory Hand; SSM: Somato Sensory Mouth; COT: Cingular Opercular Task Control; AUD: Auditory; DMN: Default Mode; MEM: Memory Retrieval; VIS: Visual; FPN: Frontoparietal Task Control; SAL: Salience; LIM: Limbic; VAN: Ventral Attention; DAN: Dorsal Attention; CER: Cerebellum; FPN-DAN, p=.03 adjusted FDR, Cohen's d = 0.01, 95% CI [-0.51,0.48]; Network Contingency Analysis Model adjusted for mean frame displacement motion value, ethnic-racial identity and gender and current age 15 material hardship.

Table 3.6 Zero-order correlations between extracted task-based network connectivity evoked during 'fearful' condition and depression symptoms.

Network	1	2	3	4	5	6	7	8	9	10	11	12	13
1. SSH	.00	.02	-.06	.06	.06	.09	.04	-.09	-.02	-.08	-.03	-.15	-.04
2. SSM		.10	-.07	-.04	.01	.07	.06	.04	.08	-.11	-.07	-.11	-.06
3. COT			-.02	.02	-.03	.06	.09	-.01	-.01	-.12	-.05	-.12	.00
4. AUD				.02	-.02	.04	.02	.06	.01	-.14	.03	-.16	.02
5. DMN					-.03	-.01	.05	-.01	-.08	-.02	-.02	-.05	-.10
6. MEM						.02	-.11	-.02	-.01	-.04	.04	-.15	.04
7. VIS							.02	.02	-.10	-.06	-.01	-.06	-.05
8. FPN								.01	-.01	.02	.00	-.06	-.20[a]
9. SAL									.01	.03	-.01	-.09	-.03
10. LIM										-.07	.12	-.07	-.03
11. VAN											.04	-.08	-.03
12. DAN												-.13	-.04
13. CER													-.12

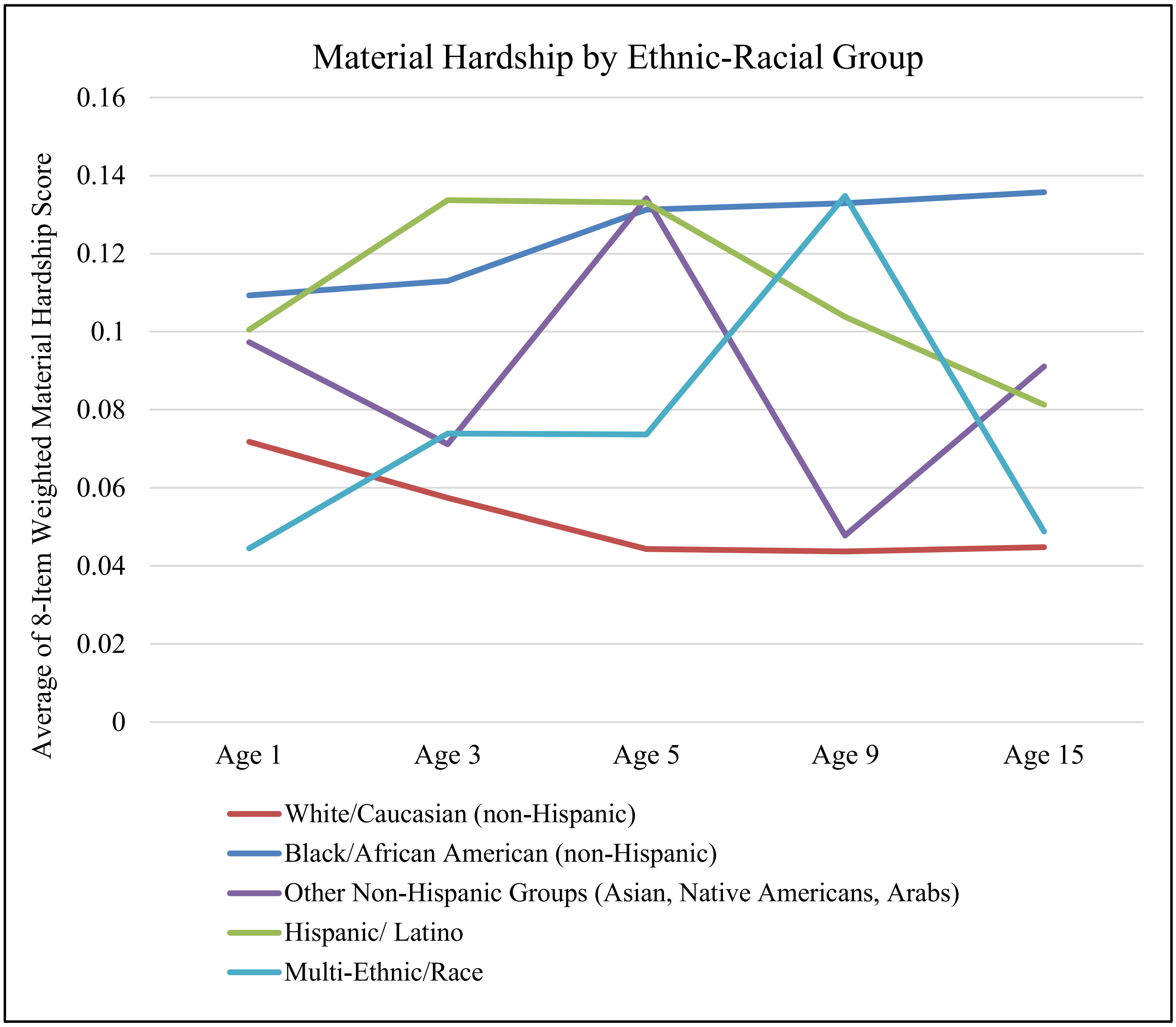
Note. N=134; values are Pearson correlation coefficients; Networks: SSH: Somato Sensory Hand; SSM: Somato Sensory Mouth; COT: Cingular Opercular Task Control; AUD: Auditory; DMN: Default Mode; MEM: Memory Retrieval; VIS: Visual; FPN: Frontoparietal Task Control; SAL: Salience; LIM: Limbic; VAN: Ventral Attention; DAN: Dorsal Attention; CER: Cerebellum; [a] p <.05

Table 3.7 Zero-order correlations between extracted task-based network connectivity evoked during 'fearful' condition and anxiety symptoms.

Network	1	2	3	4	5	6	7	8	9	10	11	12	13
1. SSH	-.12	.21[a]	.06	.11	.00	-.05	.04	-.15	-.11	-.03	.01	-.04	-.01
2. SSM		.22[a]	.03	.05	.08	-.05	.05	-.13	-.09	.03	.06	-.04	.00
3. COT			.06	.09	-.02	-.13	.07	-.02	.01	.01	-.01	-.06	.04
4. AUD				.16	.01	-.03	.09	-.03	-.07	-.05	.10	.01	.09
5. DMN					-.05	-.01	.03	-.10	-.10	.08	.03	-.04	.05
6. MEM						.07	.00	-.01	-.13	-.06	.03	.00	-.02
7. VIS							.09	-.15	-.06	.05	.11	-.03	.01
8. FPN								-.03	.01	.08	.03	-.03	.03
9. SAL									.05	.09	-.08	-.01	.03
10. LIM										.03	.11	-.07	.06
11. VAN											.13	.02	.03
12. DAN												-.02	.04
13. CER													-.04

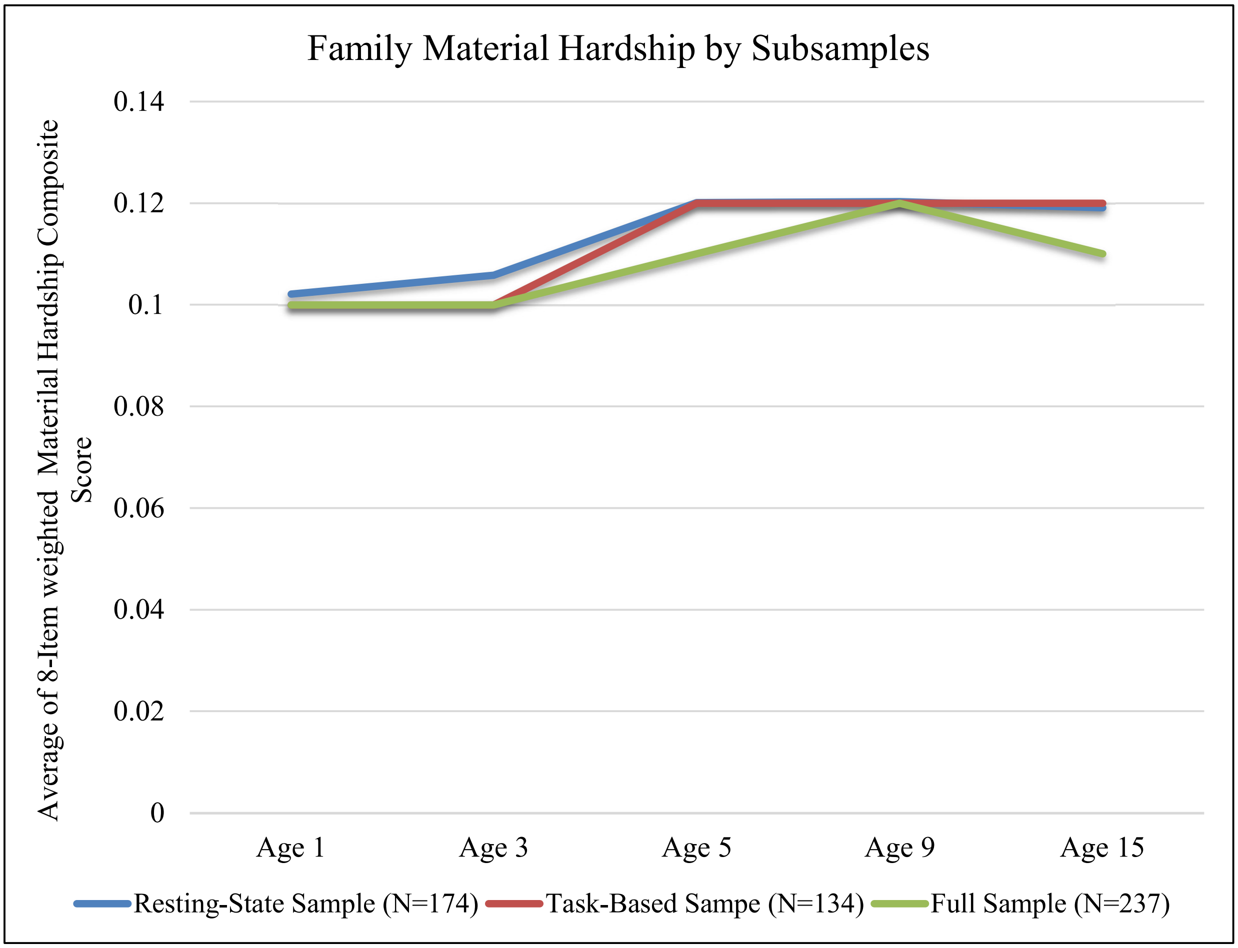
Note. N=134; values are Pearson correlation coefficients; Networks: SSH: Somato Sensory Hand; SSM: Somato Sensory Mouth; COT: Cingular Opercular Task Control; AUD: Auditory; DMN: Default Mode; MEM: Memory Retrieval; VIS: Visual; FPN: Frontoparietal Task Control; SAL: Salience; LIM: Limbic; VAN: Ventral Attention; DAN: Dorsal Attention; CER: Cerebellum;
[a] $p < .05$

Figure 2.1 SAND Sample: Weighted family material hardship 8-item average plotted by ethnic-racial group membership.



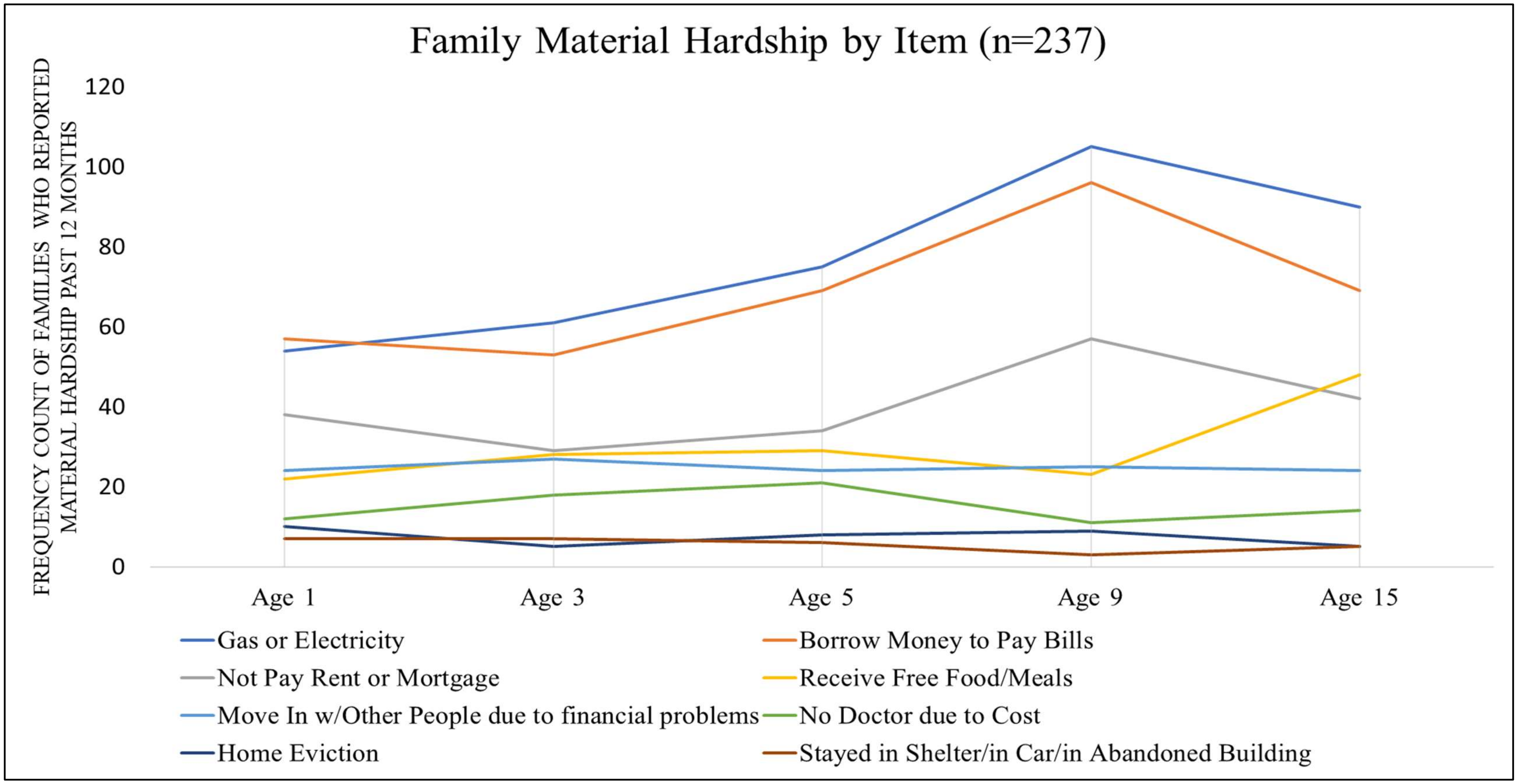
Note. Higher weighted averages reflect more material hardship; SAND: Study of Neural Development; No statistically significant ethnic-racial group differences were identified in the family material hardship reports in our sample. However, age 9 and age 15 group differences in material hardship are trending towards significance (p=.06 & p=.06)

Figure 2.2 SAND Sample: Average of 8-item weighted material hardship score by study specific sample.



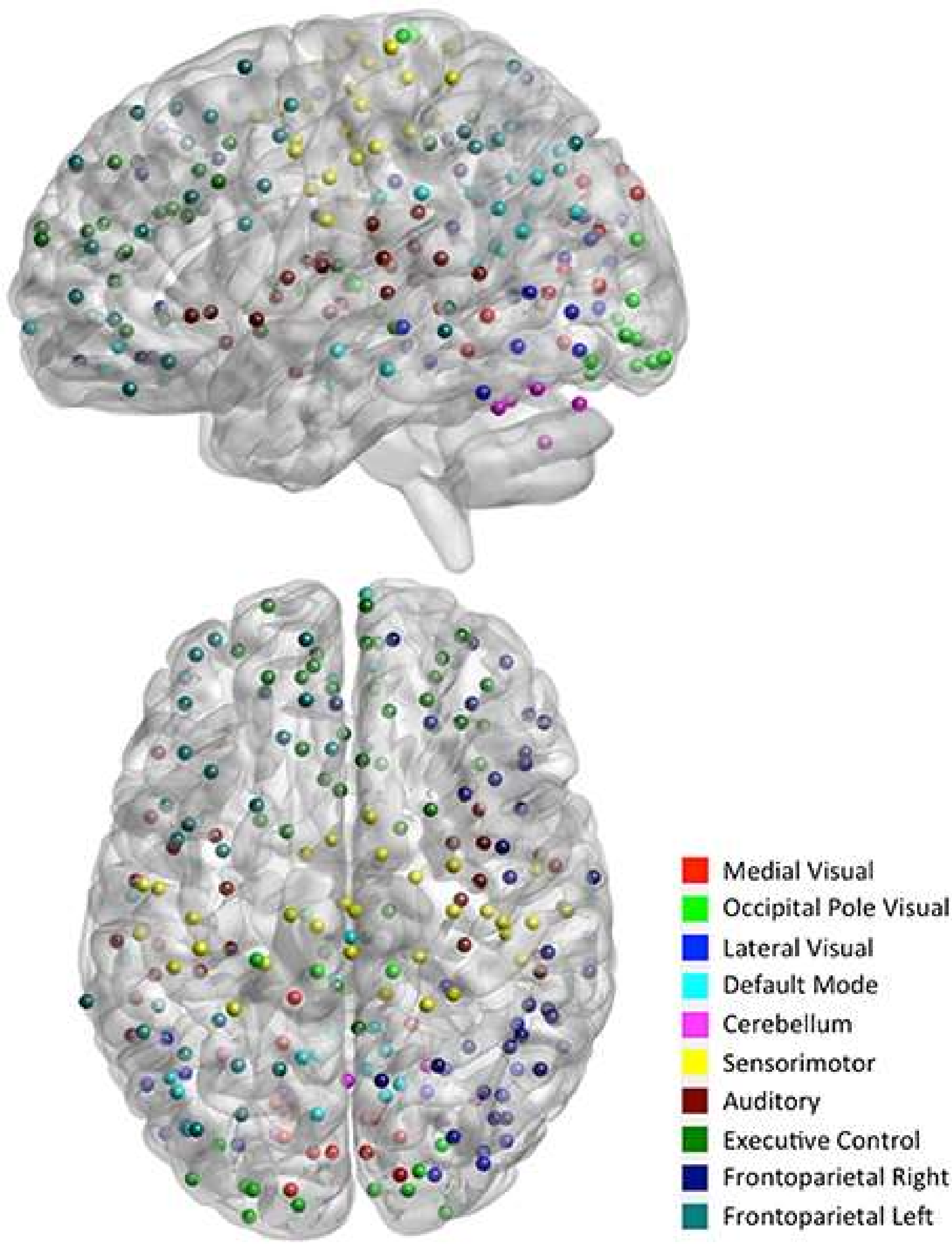
Note. Higher weighted averages reflect more material hardship; SAND: Study of Neural Development; Material hardship reports for youth who were included in the distinct connectome-based analyses relative to the full sample.

Figure 2.3 SAND Sample: Family material hardship frequency count of reports plotted by item over the 5 waves of data collection.



Note. SAND: Study of Neural Development; Eight material hardship items used for composite score are plotted over 5 waves of data collection. Data Collection Years: Age 1(2000-2001);Age 3(2002-2003);Age 5(2004-2005); Age 9(2008-2009); Age 15 (2014-2015)

Figure 2.4 Illustration of Power et al's (2011) 13 large-scale network brain parcellation.



Note. Uses 264 MNI ROIs; Three Networks not shown in figure are Salience, Ventral and Dorsal Attention Networks not shown, Regions of Interest are MNI Space; Image originally published in Yang et al. (2016). Doi: 10.3389/fnins.2016.00123/full

Figure 2.5 Procedure for conducting network contingency analysis.

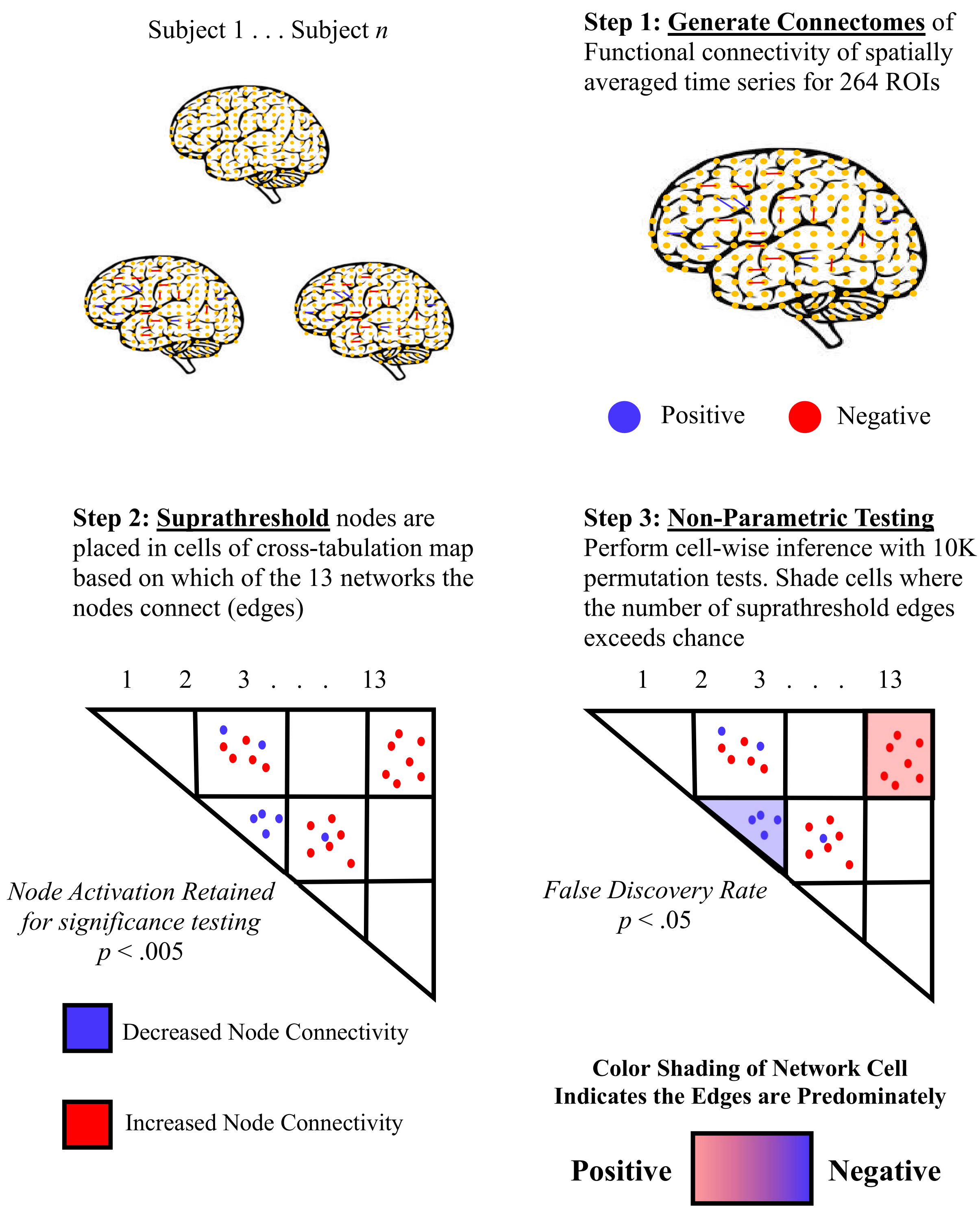
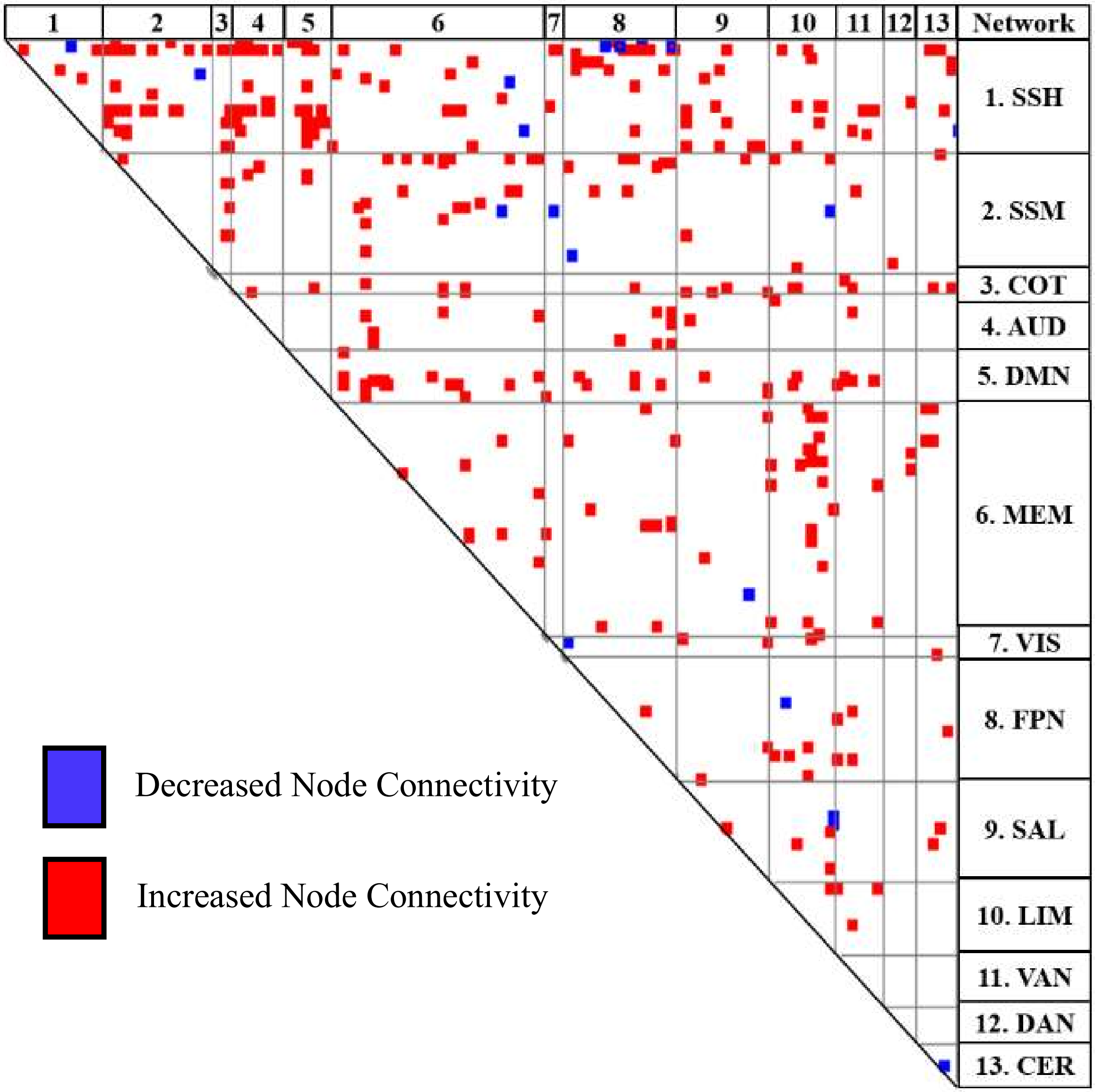


Figure 2.6 Suprathreshold (p<.005) cross-tabulation network map displaying the node activation associated with material hardship during ages 1 to 3 and at-rest connectivity.



Note. Networks: SSH: Somato Sensory Hand; SSM: Somato Sensory Mouth; COT: Cingular Opercular Task Control; AUD: Auditory; DMN: Default Mode; MEM: Memory Retrieval; VIS: Visual; FPN: Frontoparietal Task Control; SAL: Salience; LIM: Limbic; VAN: Ventral Attention; DAN: Dorsal Attention; CER: Cerebellum

Figure 2.7. Suprathreshold (p<.005) cross-tabulation network maps of at rest-connectivity displaying node activation by individual material hardship wave.

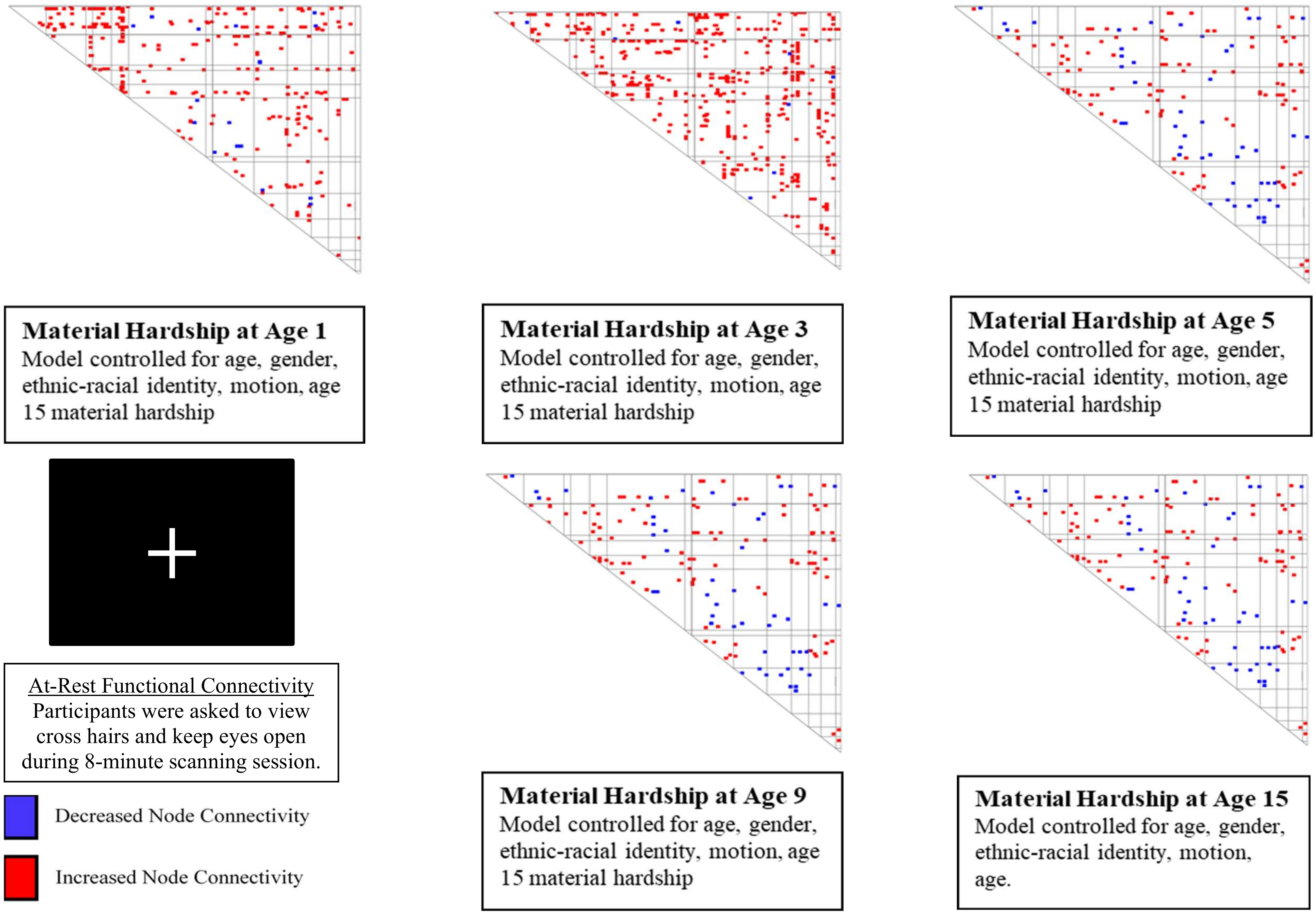


Figure 2.8. Suprathreshold (*p*<.005) cross-tabulation network maps of at rest-connectivity displaying node activation by incremental material hardship waves.

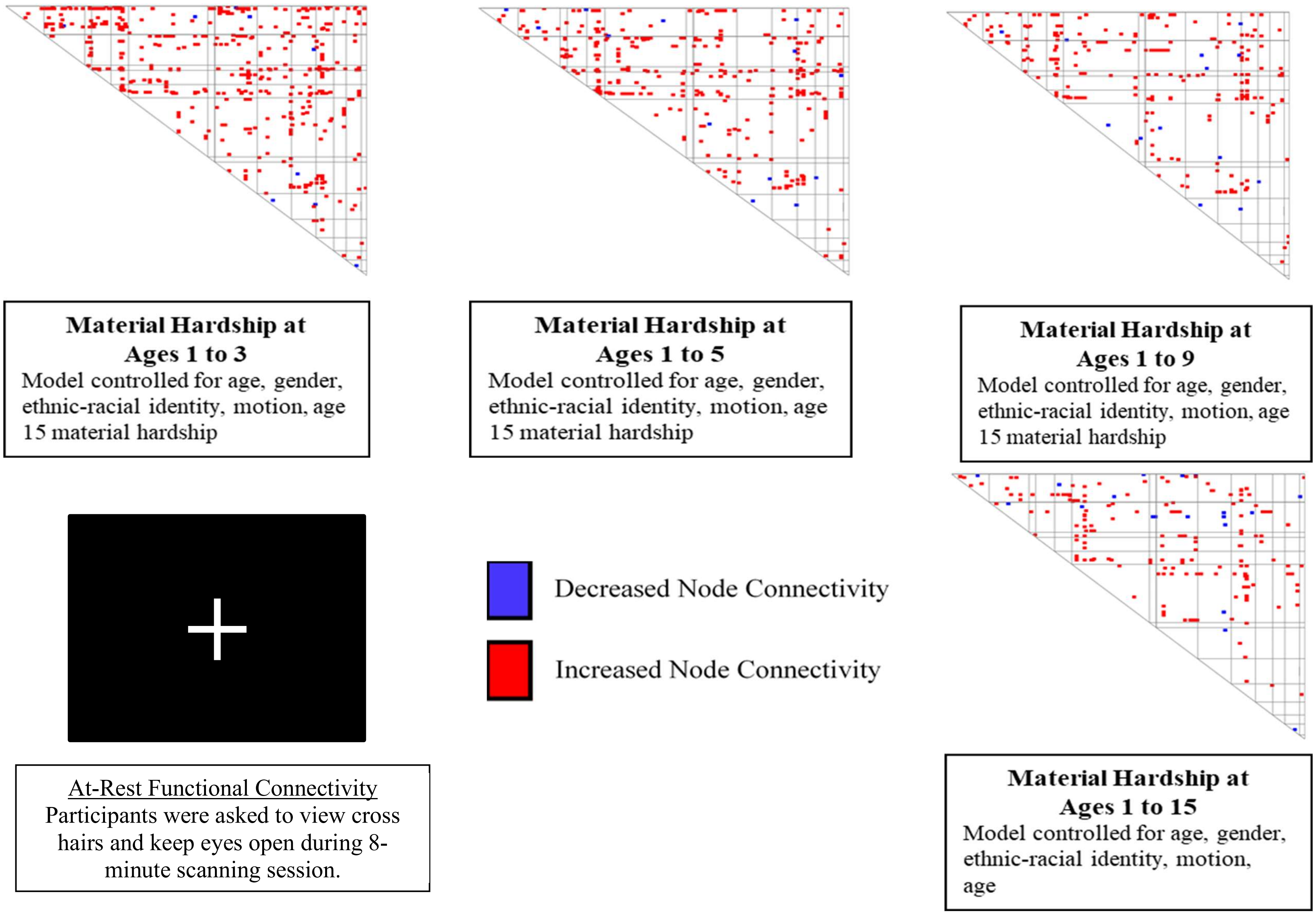


Figure 3.1 Gender identification task during scanning session.

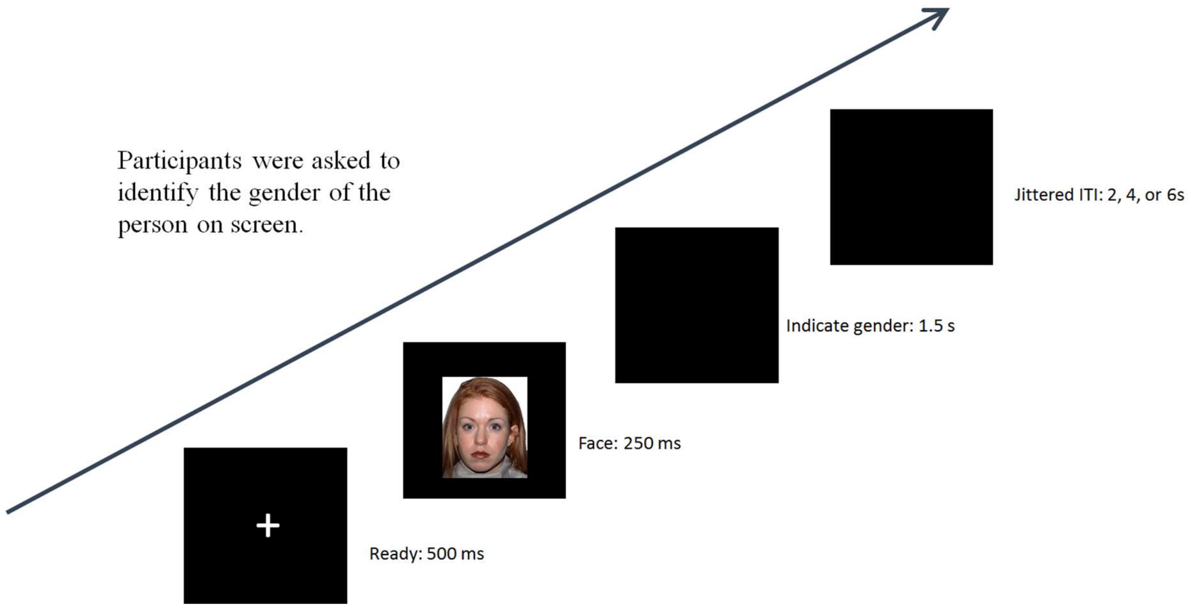


Figure 3.2. Suprathreshold (*p*<.005) cross-tabulation network maps of node activation of task-based connectivity by condition versus baseline contrasts for material hardship during ages 1 to 3.

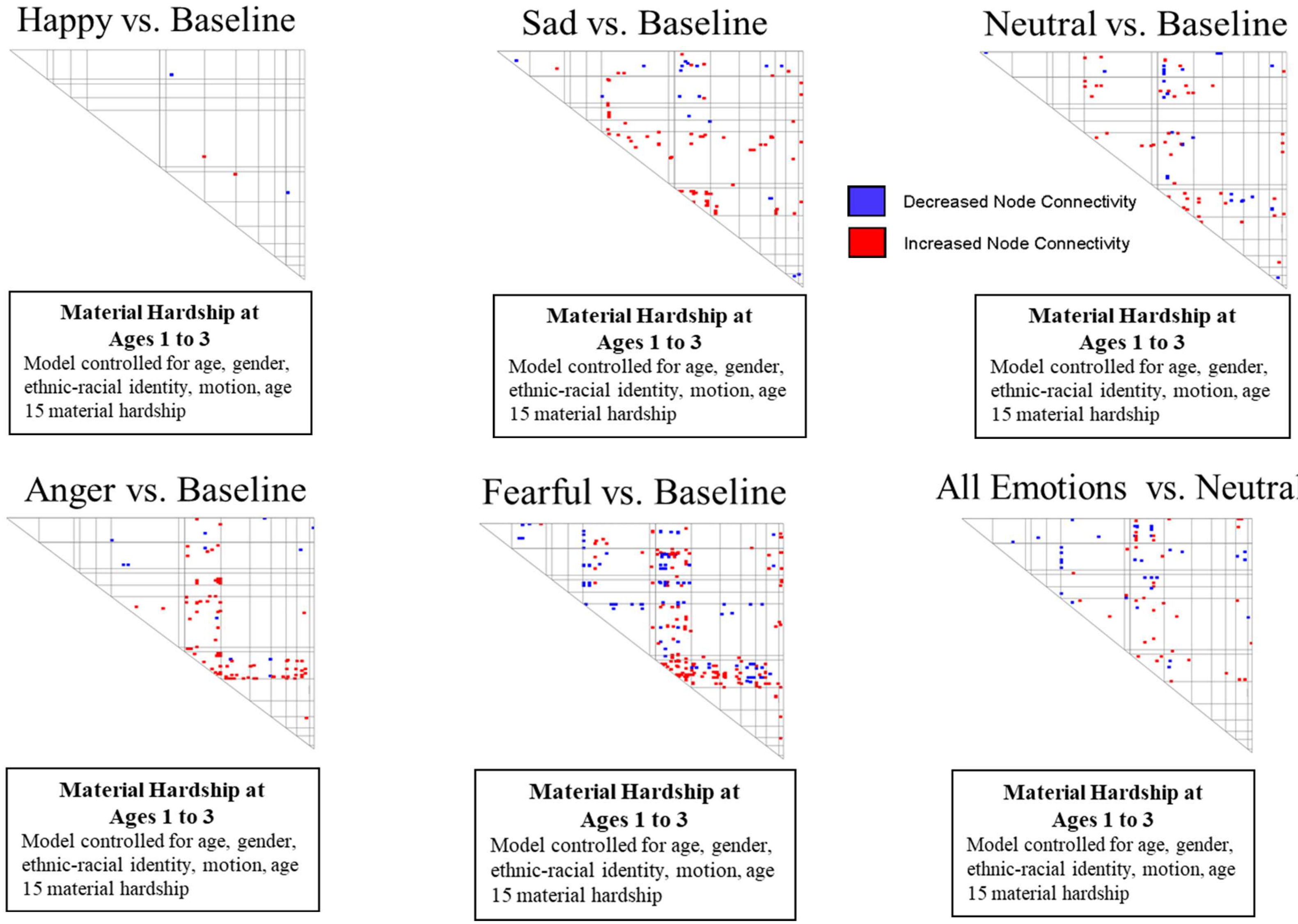


Figure 3.3. Suprathreshold (p<.005) cross-tabulation network maps of task-based connectivity displaying node activation by individual material hardship wave for "Fearful" condition.

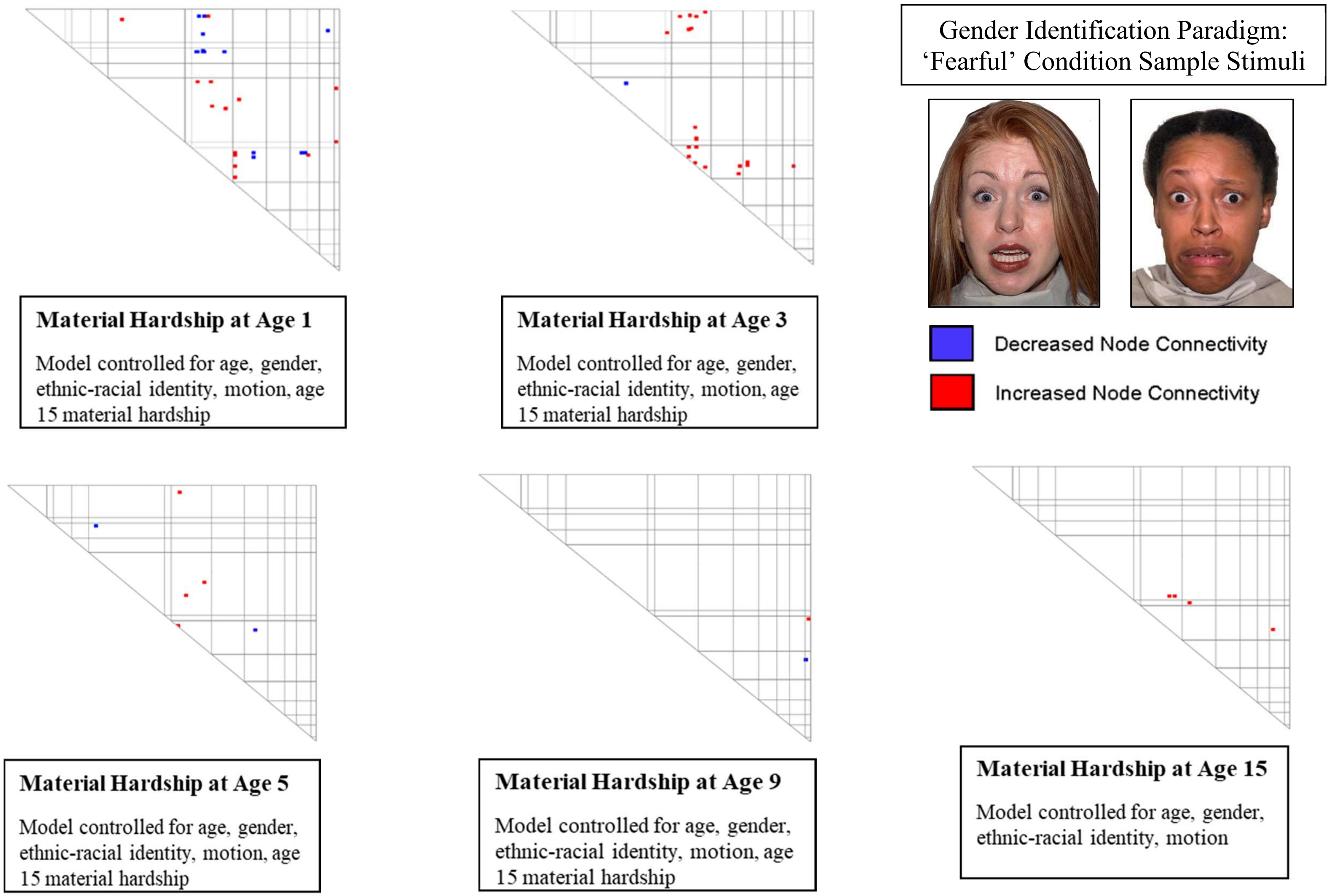


Figure 3.4. Suprathreshold (*p*<.005) cross-tabulation network maps of node activation evoked while viewing "Fearful" faces by incremental material hardship waves

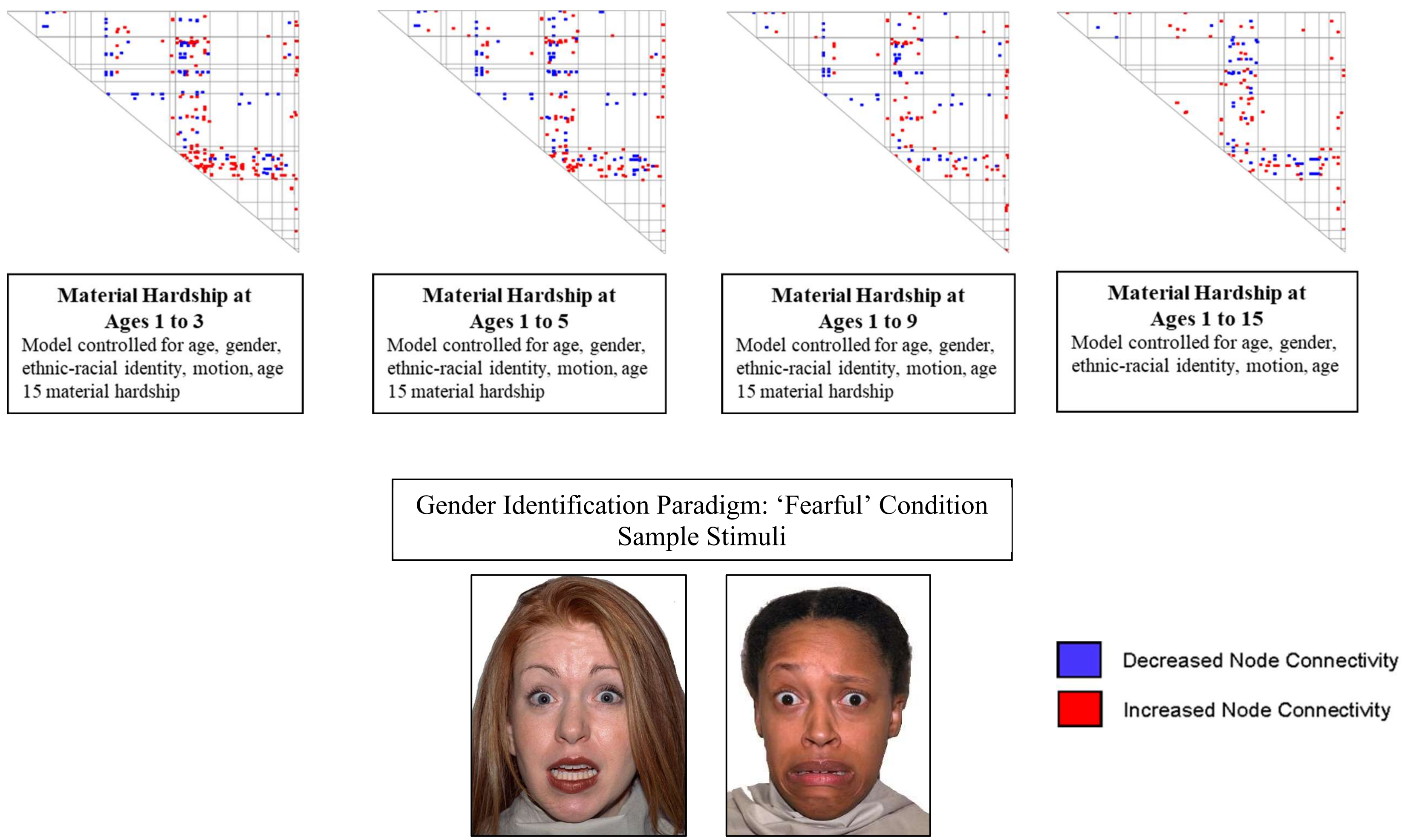
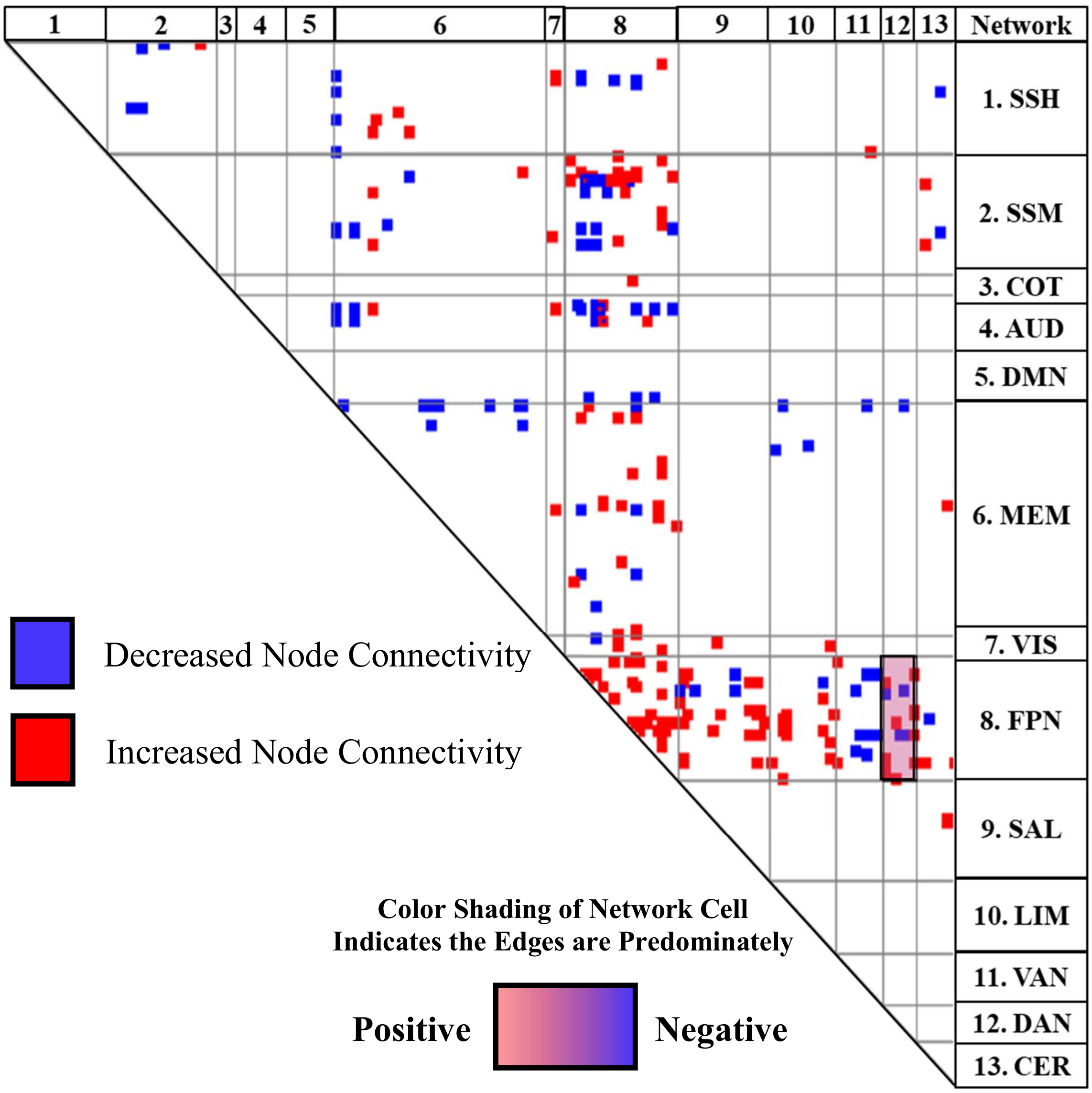


Figure 3.5 Shaded contingency cross-tabulation network map displaying non-parametric significance testing results for network activation observed during the "Fearful" faces condition



Note. Non-parametric significance testing used adjusted False Discovery Rate p-values generated from a 10K permutation distribution ($p<.05$); Networks: SSH: Somato Sensory Hand; SSM: Somato Sensory Mouth; COT: Cingular Opercular Task Control; AUD: Auditory; DMN: Default Mode; MEM: Memory Retrieval; VIS: Visual; FPN: Frontoparietal Task Control; SAL:Salience; LIM: Limbic; VAN: Ventral Attention; DAN: Dorsal Attention; CER: Cerebellum; FPN-DAN, adjusted FDR p=.03, *Cohen's d* = 0.01, 95% CI [-0.51,0.48].

REFERENCES

Ahmed, S. P., Bittencourt-Hewitt, A., & Sebastian, C. L. (2015). Neurocognitive bases of emotion regulation development in adolescence. *Developmental Cognitive Neuroscience*, 15, 11–25. doi: 10.1016/j.dcn.2015.07.006

Alkire, S. (2007). The missing dimensions of poverty data: Introduction to the special issue. *Oxford Development Studies*, *35*(4), 347–359. doi: 10.1080/13600810701701863

Althoff, R. R., Ametti, M., & Bertmann, F. (2016). The role of food insecurity in developmental psychopathology. *Preventive Medicine*, *92*, 106–109. doi: 10.1016/j.ypmed.2016.08.012

American Psychological Association. (2019). *Guidelines for psychological practice for people with low-income and economic marginalization*. Retrieved from www.apa.org/about/policy/guidelines-lowincome.pdf.

Ananat, E. O. (2011). The wrong sides(s) of the tracks: The causal effects of racial segregation on urban poverty and inequality. *American Economic Journal: Applied Economics*, *3*(2), 34–66.

Anand, S., & Sen, A. (1997). Concepts of human development and poverty: A multidimensional perspective. In *United Nations Development Programme, Poverty and human development: Human development papers*.

Anderson, S. F., & Maxwell, S. E. (2017). Addressing the "Replication Crisis": Using original studies to design replication studies with appropriate statistical power. *Multivariate Behavioral Research*, *52*(3), 305–324. doi: 10.1080/00273171.2017.1289361

Angelini, V., Howdon, D. D. H., & Mierau, J. O. (2019). Childhood socioeconomic status and late-adulthood mental health: Results from the survey on health, ageing and retirement in Europe. *Journals of Gerontology: Social Sciences*, *74*(1), 95–104. doi: 10.1093/geronb/gby028

Arnsten, A. F. T., & Rubia, K. (2012). Neurobiological circuits regulating attention, cognitive control, motivation, and emotion: Disruptions in neurodevelopmental psychiatric disorders. *Journal of American Academy of Child & Adolescent Psychiatry*, *51*(4), 356–367. doi: 10.1016/j.jaac.2012.01.008

Ashiabi, G. S., & O'Neal, K. K. (2007). Children's health status: Examining the associations among income poverty, material hardship, and parental factors. *PLoS ONE*, *2*(9). doi: 10.1371/journal.pone.0000940

Astle, D., Johnson, A., Bathelt, J., Akarca, D., & Team, T. R. (2020). Far and wide: Associations between childhood socio-economic status and brain connectomics. *Developmental Cognitive Neuroscience*. doi: 10.1016/j.dcn.2020.100888

Atkinson, A. B. (2003). Multidimensional deprivation: Contrasting social welfare and counting approaches. *Journal of Economic Inequality*, *1*(1), 51–65. doi: 10.1023/A:1023903525276

Baek, E., & DeVaney, S. A. (2010). How do families manage their economic hardship? *Family Relations*, *59*(4), 358–368. doi: 10.1111/j.1741-3729.2010.00608.x

Bao, Z., Chen, C., Zhang, W., Zhu, J., Jiang, Y., & Lai, X. (2016). Family economic hardship and Chinese adolescents' sleep quality: A moderated mediation model involving perceived economic discrimination and coping strategy. *Journal of Adolescence*, *50*(55), 81–90. doi: 10.1016/j.adolescence.2016.04.005

Barch, D. M. (2017). Resting state functional connectivity in the Human Connectome Project: Current status and relevance to understanding psychopathology. *Havard Review Psychiatry*, *25*(5), 209–217. doi: 10.1097/HRP.0000000000000166.Resting

Bashat, D. Ben, Sira, L. Ben, Graif, M., Pianka, P., Hendler, T., Cohen, Y., & Assaf, Y. (2005). Normal white matter development from infancy to adulthood: Comparing diffusion tensor and high b value diffusion weighted MR images. *Journal of Magnetic Resonance Imaging*, *21*(5), 503–511. doi: 10.1002/jmri.20281

Bassett, D. S., & Sporns, O. (2017). Network neuroscience. *Nature Neuroscience*, *20*(3), 353–364. doi: 10.1038/nn.4502

Batty, M., & Taylor, M. J. (2006). The development of emotional face processing during childhood. *Developmental Science*, *9*(2), 207–220. doi: 10.1111/j.1467-7687.2006.00480.x

Bauman, K. J. (2002). Welfare, work and material hardship in single parent and other households. *Journal of Poverty*, *6*(1), 21–40. doi: 10.1300/J134v06n01

Bell, M. A., & Wolfe, C. D. (2004). Emotion and cognition: An intricately bound developmental process. *Child Development*, *75*(2), 366–370. doi: 10.1111/j.1467-8624.2004.00679.x

Bellair, P. E., Mcnulty, T. L., Roscigno, V. J., Kit, M., Lei, K., … Karlo, M. K. (2019). Childhood material hardship and externalizing behavior. *Justice Quarterly*, 1–25. doi: 10.1080/07418825.2019.1584326

Benjamini, Y., & Hochberg, Y. (1995). Controlling the False Discovery Rate : A practical and powerful approach to multiple testing. *Journal of the Royal Statistical Society. Series B (Methodological)*, *57*(1), 289–300. Retrieved from https://www.jstor.org/stable/2346101%0AJSTOR

Benjet, C., Borges, G., & Medina-Mora, M. E. (2010). Chronic childhood adversity and onset of psychopathology during three life stages: Childhood, adolescence and adulthood. *Journal of Psychiatric Research*, *44*(11), 732–740. doi: 10.1016/j.jpsychires.2010.01.004

Berger, L. M., Paxson, C., & Waldfogel, J. (2009). Income and child development. *Children and Youth Services Review*, *31*(9), 978–989. doi: 10.1016/j.childyouth.2009.04.013

Bertini, C., & Elisabetta, L. (2021). Fear-related signals are prioritised in visual, somatosensory and spatial systems. *Neuropsychologia*, *150*(107698), 1–9. doi: 10.1016/j.neuropsychologia.2020.107698

Beverly, S. G. (2001). Measures of material hardship: Rationale and recommendations. *Journal of Poverty*, *5*(1), 23–41. doi: 10.1300/J134v05n01_02

Birmaher, B., Khetarpal, S., Brent, D., Cully, M., Balach, L., Kaufman, J., & McKenzie Neer, S. (1997). The screen for child anxiety related emotional disorders (SCARED): Scale construction and psychometric characteristics. *Journal of the American Academy of Child and Adolescent Psychiatry*, *36*(4), 545–553. doi: 10.1097/00004583-199704000-00018

Biswal, B. B., Yetkin, F. Z., Haughton, V. M., & Hyde, J. S. (1995). Functional connectivity in the motor cortex of resting human brain using. *Magn Reson Med*, *34*(9), 537–541. doi: 10.1002/mrm.1910340409

Black, M. M., Walker, S. P., Fernald, L. C. H., Andersen, C. T., DiGirolamo, A. M., Lu, C., … Grantham-McGregor, S. (2017). Early childhood development coming of age: science through the life course. *The Lancet*, *389*(10064), 77–90. doi: 10.1016/S0140-6736(16)31389-7

Blair, C., Raver, C., Granger, D., Mills-Koonce, R., Hibel, L., & Investigators, F. L. P. K. (2011). Allostasis and allostatic load in the context of poverty in early childhood. *Developmental Psychopathology*, *23*(3), 845–857. doi: 10.1017/S0954579411000344.Allostasis

Blank, R. M. (2008). Presidential address: How to improve poverty measurement in the United States. *Journal of Policy Analysis and Management*, *27*(2), 233–254. doi: 10.1002/pam.20323

Bøe, T., Øverland, S., Lundervold, A. J., & Hysing, M. (2012). Socioeconomic status and children's mental health: Results: from the Bergen Child Study. *Social Psychiatry and Psychiatric Epidemiology*, *47*(10), 1557–1566. doi: 10.1007/s00127-011-0462-9

Bolger, K. E., Patterson, C. J., Thompson, W. W., & Kupersmidt, J. B. (1995). Psychosocial adjustment among children experiencing persistent and intermittent family economic hardship. *Child Development*, *66*(4), 1107–1129. Retrieved from https://www.jstor.org/stable/1131802

Boltvinik, J. (1999). Poverty mesurement methods- An overview. In *UNDP Social Development & Poverty Elimination Division. k*., 1-39. Retrieved from http://www.julioboltvinik.org/wp-content/uploads/PAG_ELECTRO/2.1_Poverty_Measurement_Methods_an_overview.pdf

Bor, J., Cohen, G. H., & Galea, S. (2017). America: Equity and equality in health 5, Population health in an era of rising income inequality: USA, 1980-2015. *Lancet*, *389*, 1475–1490. doi: 10.1016/S0140-6736(17)30571-8

Boushey, H., & Gundersen, B. (2001). *When work just isn't enough: Measuring hardships faced by families after moving from welfare to work*. Retrieved from http://search.proquest.com/docview/62261809?accountid=13042

Bradley, R. H., & Corwyn, R. F. (2002). Socioeconomic status and child development. *Annual Review of Psychology*, *53*(1), 371–399. doi: 10.1146/annurev.psych.53.100901.135233

Bradshaw, J., & Finch, N. (2003). Overlaps in dimensions of poverty. *Journal of Social Policy*, *32*(4), 513–525. doi: 10.1017/S004727940300713X

Bressler, S. L., & Menon, V. (2010). Large-scale brain networks in cognition: emerging methods and principles. *Trends in Cognitive Sciences*, *14*(6), 277–290. doi: 10.1016/j.tics.2010.04.004

Brito, N. H., Piccolo, L. R., & Noble, K. G. (2017). Associations between cortical thickness and neurocognitive skills during childhood vary by family socioeconomic factors. *Brain and Cognition*, *116*, 54–62. doi: 10.1016/j.bandc.2017.03.007

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

Brooks-Gunn, J., Warren, M. P., Rosso, J., & Gargiulo, J. (1987). Validity of self-report measures of girls ' pubertal status. *Child Development*, *58*(3), 829–841.

Brown, L. K., Tolou-Shams, M., Lescano, C., Houck, C., Zeidman, J., Pugatch, D., & Lourie, K. J. (2006). Depressive symptoms as a predictor of sexual risk among African American adolescents and young adults. *Journal of Adolescent Health*, *39*(3). doi: 10.1016/j.jadohealth.2006.01.015

Bullmore, E., & Sporns, O. (2009). Complex brain networks: graph theoretical analysis of structural and functional systems. *Nat Rev Neurosci.*, *10*(3), 186–198. doi: 10.1038/nrn2575

Burke, H. M., Fernald, L. C., Gertler, P. J., & Adler, N. E. (2005). Depressive symptoms are associated with blunted cortisol stress responses in very low-income women. *Psychosomatic Medicine*, *67*(2), 211–216. doi: 10.1097/01.psy.0000156939.89050.28

Butterworth, P., Cherbuin, N., Sachdev, P., & Anstey, K. J. (2012). The association between financial hardship and amygdala and hippocampal volumes: Results from the PATH through life project. *Social Cognitive and Affective Neuroscience*, *7*(5), 548–556. doi: 10.1093/scan/nsr027

Callan, T., Nolan, B., & Whelan, C. T. (1993). Resources, deprivation and the measurement of poverty. *Journal of Social Policy*, *22*(2), 141–172. doi: 10.1017/s0047279400019280

Campbell, F. A., Pungello, E. P., Miller-Johnson, S., Burchinal, M., & Ramey, C. T. (2001). The development of cognitive and academic abilities: growth curves from an early childhood educational experiment. *Developmental Psychology*, *37*(2), 231–242. doi: 10.1037/0012-1649.37.2.231

Cancian, M., & Meyer, D. R. (2004). Alternative measures of economic success among TANF participants: Avoiding poverty, hardship, and dependence on public assistance. *Journal of Policy Analysis and Management*, *23*(3), 531–548. doi: 10.1002/pam.20025

Cao, W., Li, C., Zhang, J., Dong, D., Sun, X., Yao, S., … Liu, J. (2019). Regional homogeneity abnormalities in early-onset and adolescent-onset conduct disorder in boys: A resting-state fMRI study. *Frontiers in Human Neuroscience*, *13*(February), 1–8. doi: 10.3389/fnhum.2019.00026

Casey, B. J., Giedd, J. N., & Thomas, K. M. (2000). Structural and functional brain development and its relation to cognitive development. *Biological Psychology*, *54*(1–3), 241–257. doi: 10.1016/s0301-0511(00)00058-2

Cauthen, N. K. (2007). *Testimony on measuring poverty in America*. doi: https://doi.org/10.7916/d8-nqp5-2t15

Cellini, S. R., McKernan, S. M., & Ratcliffe, C. (2008). The dynamics of poverty in the United States: A review of data, methods, and findings. *Journal of Policy Analysis and Management*, *27*(3), 577–605. doi: 10.1002/pam

Chantiluke, K., Halari, R., Simic, M., Pariante, C. M., Papadopoulos, A., Giampietro, V., & Rubia, K. (2012). Fronto-striato-cerebellar dysregulation in adolescents with depression during motivated attention. *Biological Psychiatry*, *71*(1), 59–67. doi: 10.1016/j.biopsych.2011.09.005

Chattopadhyay, S., Tait, R., Simas, T., van Nieuwenhuizen, A., Hagan, C. C., Holt, R. J., … Suckling, J. (2017). Cognitive behavioral therapy lowers elevated functional connectivity in depressed adolescents. *EBioMedicine*, *17*, 216–222. doi: 10.1016/j.ebiom.2017.02.010

Chaudry, A., & Wimer, C. (2016). Poverty is not just an indicator: The relationship between income, poverty, and child well-being. *Academic Pediatrics*, *16*(3), S23–S29. doi: 10.1016/j.acap.2015.12.010

Chen, E., Miller, G. E., Brody, G. H., & Lei, M. K. (2015). Neighborhood poverty, college attendance, and diverging profiles of substance use and allostatic load in rural African American youth. *Clinical Psychological Science*, *3*(5), 675–685. doi: 10.1177/2167702614546639

Chen, Q., Kong, Y., Gao, W., & Mo, L. (2018). Effects of socioeconomic status, parent-child relationship, and learning motivation on reading ability. *Frontiers in Psychology*, *9*(1297), 1–12. doi: 10.3389/fpsyg.2018.01297

Chen, S., & Ravallion, M. (2007). Poverty and hunger special feature: Absolute poverty measures for the developing world, 1981- 2004. *Proceedings of the National Academy of Sciences*, *104*(43), 16757–16762. doi: 10.1073/pnas.0702930104

Chetty, R., Stepner, M., Abraham, S., Lin, S., Scuderi, B., Turner, N., … Cutler, D. (2016). The association between income and life expectancy in the United States, 2001-2014. *Journal of the American Medical Association*, *315*(16), 1750–1766. doi: 10.1001/jama.2016.4226

Chiang, J. J., Bower, J. E., Almeida, D. M., Irwin, M. R., Seeman, T. E., & Fuligni, A. J. (2015). Socioeconomic status, daily affective and social experiences, and inflammation during adolescence. *Psychosomatic Medicine*, *77*(3), 256–266. doi: 10.1097/PSY.0000000000000160

Cohen, S., Janicki-Deverts, D., Chen, E., & Matthews, K. A. (2010). Childhood socioeconomic status and adult health. *Ann. N.Y. Acad. Sci*, *1186*, 37–55. doi: 10.1111/j.1749-6632.2009.05334.x

Cole, P. M., Marin, S. E., & Dennis, T. A. (2004). Emotion regulation as a scientific construct: methodological challenges for child development research. *Child Development*, *75*(2), 317–333. doi: 10.1111/j.1467-8624.2004.00673.x

Collin, G., & Van Den Heuvel, M. P. (2013). The ontogeny of the human connectome: Development and dynamic changes of brain connectivity across the life span. *Neuroscientist*, *19*(6), 616–628. doi: 10.1177/1073858413503712

Córdova-Palomera, A., Tornador, C., Falcón, C., Bargalló, N., Brambilla, P., Crespo-Facorro, B., … Faanás, L. (2016). Environmental factors linked to depression vulnerability are associated with altered cerebellar resting-state synchronization. *Scientific Reports*, *6*, 1–11. doi: 10.1038/srep37384

Coste, C. P., & Kleinschmidt, A. (2016). Cingulo-opercular network activity maintains alertness. *NeuroImage*, *128*, 264–272. doi: 10.1016/j.neuroimage.2016.01.026

Cullen, K. R., Westlund, M. K., Klimes-Dougan, B., Mueller, B. A., Houri, A., Eberly, L. E., & Lim, K. O. (2014). Abnormal amygdala resting-state functional connectivity in adolescent depression. *JAMA Psychiatry*, *71*(10), 1138–1147. doi: 10.1001/jamapsychiatry.2014.1087

Currie, J., & Lin, W. (2007). Chipping away at health: More on the relationship between income and child health. *Health Affairs*, *26*(2), 331–344. doi: 10.1377/hlthaff.26.2.331

de Mestral, C., & Stringhini, S. (2017). Socioeconomic status and cardiovascular disease: An update. *Current Cardiology Reports*, *19*(11). doi: 10.1007/s11886-017-0917-z

Dennis, E. L., & Thompson, P. M. (2013). Mapping connectivity in the developing brain. *International Journal of Developmental Neuroscience*, *31*(7), 525–542. doi: 10.1016/j.ijdevneu.2013.05.007

DeWitt, S. J., Aslan, S., & Filbey, F. M. (2014). Adolescent risk-taking and resting state functional connectivity. *Psychiatry Research: Neuroimaging*, *222*(3), 157–164. doi: https://doi-org.proxy.lib.umich.edu/10.1016/j.pscychresns.2014.03.009

Dixon, M. L., De La Vega, A., Mills, C., Andrews-Hanna, J., Spreng, R. N., Cole, M. W., & Christoff, K. (2018). Heterogeneity within the frontoparietal control network and its relationship to the default and dorsal attention networks. *Proceedings of the National Academy of Sciences of the United States of America*, *115*(7), E1598–E1607. doi: 10.1073/pnas.1715766115

Dolcos, F., Wang, L., & Mather, M. (2014). Current research and emerging directions in emotion-cognition interactions. *Frontiers in Integrative Neuroscience*, *8*(November), 83. doi: 10.3389/fnint.2014.00083

Domènech-Abella, J., Mundó, J., Miret, M., Ayuso-Mateos, J. L., Sánchez-Niubò, A., Abduljabbar, A. S., … Olaya, B. (2019). From childhood financial hardship to late-life depression: socioeconomic pathways. *Aging and Mental Health*, 1–8. doi: 10.1080/13607863.2019.1671313

dos Santos, T. M. (2017). Poverty as a lack of capabilities: An analysis of the definition of poverty of Amartya Sen. *PERI*, *9*(2), 125–148.

Duh-Leong, C., Messito, M. J., Katzow, M. W., Tomopoulos, S., Nagpal, N., Fierman, A. H., & Gross, R. S. (2020). Material hardships and infant and toddler sleep duration in low-income Hispanic families. *Academic Pediatrics*, *20*(8), 1184–1191. doi: 10.1016/j.acap.2020.07.003

Duncan, G. J., Brooks-Gunn, J., & Klebanov, P. K. (1994). Economic deprivation and early childhood development. *Child Development*, *65*(2), 296–318. Retrieved from http://dx.doi.org/10.1111/j.1467-8624.1994.tb00752.x

Duncan, G. J., Magnuson, K., Kalil, A., & Ziol-Guest, K. (2012). The importance of early childhood poverty. *Social Indicators Research*, *108*(1), 87–98. doi: 10.1007/s11205-011-9867-9

Duncan, G. J., Ziol-Guest, K. M., & Kalil, A. (2010). Early-childhood poverty and adult attainment, behavior, and health. *Child Development*, *81*(1), 306–325. doi: 10.1111/j.1467-8624.2009.01396.x

Dutta, I., Foster, J., & Mishra, A. (2011). On measuring vulnerability to poverty. *Social Choice and Welfare*, *37*(4), 743–761. doi: 10.1007/s00355-011-0570-1

Eckman, P. (1973). Cross-cultural studies of facial expression. In P. Ekman (Ed.), *Darwin and Facial Expression*. New York, NY: Academic Press Inc.

Eisenmann, J. C., Gundersen, C., Lohman, B. J., Garasky, S., & Stewart, S. D. (2011). Is food insecurity related to overweight and obesity in children and adolescents ? A summary of studies , 1995 - 2009. *Obesity Reviews Revision*, *12*, e73–e83. doi: 10.1111/j.1467-789X.2010.00820.x

Engen, H. G., Kanske, P., & Singer, T. (2017). The neural component-process architecture of endogenously generated emotion. *Social Cognitive and Affective Neuroscience*, *12*(2), 197–211. doi: 10.1093/scan/nsw108

Erhart, A., Dmitrieva, J., Blair, R. J., & Kim, P. (2019). Intensity, not emotion: The role of poverty in emotion labeling ability in middle childhood. *Journal of Experimental Child Psychology*, *180*, 131–140. doi: 10.1016/j.jecp.2018.12.009

Evans, G. W. (2016). Childhood poverty and adult psychological well-being. *Proceedings of the National Academy of Sciences of the United States of America*, *113*(52), 14949–14952. doi: 10.1073/pnas.1604756114

Evans, G. W., & Cassells, R. C. (2014). Childhood poverty, cumulative risk exposure, and mental health in emerging adults. *Clinical Psychological Science*, *2*(3), 287–296. doi: 10.1177/2167702613501496

Evans, G. W., & Fuller-Rowell, T. E. (2013). Childhood poverty, chronic stress, and young adult working memory: The protective role of self-regulatory capacity. *Developmental Science*, *16*(5), 688–696. doi: 10.1111/desc.12082

Evans, G. W., Li, D., & Whipple, S. S. (2013). Cumulative risk and child development. *Psychological Bulletin*, *139*(6), 1342–1396. doi: 10.1037/a0031808

Evans, G. W., & Schamberg, M. A. (2009). Childhood poverty, chronic stress, and adult working memory. *Proceedings of the National Academy of Sciences of the United States of America*, *106*(16), 6545–6549. Retrieved from www.pnas.orgcgidoi10.1073pnas.0811910106

Facer-Childs, E. R., Campos, B. M., Middleton, B., Skene, D. J., & Bagshaw, A. P. (2019). Circadian phenotype impacts the brain's resting-state functional connectivity, attentional performance, and sleepiness. *Sleep*, *42*(5), 1–12. doi: 10.1093/sleep/zsz033

Fair, D. A., Cohen, A. L., Power, J. D., Dosenbach, N. U. F., Church, J. A., Miezin, F. M., … Petersen, S. E. (2009). Functional brain networks develop from a "local to distributed" organization. *PLoS Computational Biology*, *5*(5), 14–23. doi: 10.1371/journal.pcbi.1000381

Fass, S. (2009). *Measuring poverty in the United States*, 1-4. Retrieved from https://www.nccp.org/wp-content/uploads/2020/05/text_876.pdf

Fass, S., & Cauthen, N. K. (2008). *Who are America's poor Children?: The official story*, 1-4. Retrieved from https://doi.org/10.7916/d8-f6q9-je34.

Fernald, A., Marchman, V. A., & Weisleder, A. (2013). SES differences in language processing skill and vocabulary are evident at 18 months. *Developmental Science*, *16*(2), 234–248. doi: 10.1111/desc.12019

Fernández, C. R., Yomogida, M., Aratani, Y., & Hernández, D. (2018). Dual food and energy hardship and associated child behavior problems. *Academic Pediatrics*, *18*(8), 889–896. doi: 10.1016/j.acap.2018.07.002

Fine, S. E., Izard, C. E., Mostow, A. J., Trentacosta, C. J., & Ackerman, B. P. (2003). First grade emotion knowledge as a predictor of fifth grade self-reported internalizing behaviors in children from economically disadvantaged families. *Development and Psychopathology*, *15*(2), 331–342. doi: 10.1017/S095457940300018X

Fox, L. (2018). *The Supplemental Poverty Measure: 2017*. Retrieved from https://www.census.gov/content/dam/Census/library/publications/2018/acs/acsbr17-02.pdf

Frank, D. A., Casey, P. H., Black, M. M., Rose-Jacobs, R., Chilton, M., Cutts, D., … Cook, J. T. (2010). Cumulative hardship and wellness of low-income, young children: Multisite surveillance study. *Pediatrics*, *125*(5), e1115–e11123. doi: 10.1542/peds.2009-1078

Freedman, D., & Lane, D. (1983). A nonstochastic interpretation of reported significance levels. *Journal of Business and Economic Statistics*, *1*(4), 292–298. doi: 10.1080/07350015.1983.10509354

Freeman, A., Tyrovolas, S., Koyanagi, A., Chatterji, S., Leonardi, M., Luis Ayuso-Mateos, J., … Haro, J. M. (2016). The role of socio-economic status in depression: results from the COURAGE (aging survey in Europe). *BCM Public Health*, *16*(1098), 1–8. doi: 10.1186/s12889-016-3638-0

Friston, K. (2013). Life as we know it. *Journal of the Royal Society Interface*, *10*(86). 1-12. doi: 10.1098/rsif.2013.0475

Fuller, A., Messito, M. J., Mendelsohn, A. L., Oyeku, S. O., & Gross, R. S. (2018). Prenatal material hardships and infant regulatory capacity at 10 months old in low-income Hispanic mother-infant pairs. *Academic Pediatrics*, *18*(8), 897–904. doi: 10.1016/j.acap.2018.04.134

Gagnon, S. A., & Wagner, A. D. (2016). Acute stress and episodic memory retrieval: Neurobiological mechanisms and behavioral consequences. *Annals of the New York Academy of Sciences*, *1369*(1), 55–75. doi: 10.1111/nyas.12996

Gale, C. R., O'Callaghan, F. J., Godfrey, K. M., Law, C. M., & Martyn, C. N. (2004). Critical periods of brain growth and cognitive function in children. *Brain*, *127*(2), 321–329. doi: 10.1093/brain/awh034

Gao, W., Alcauter, S., Elton, A., Hernandez-Castillo, C., Smith, J. K., Ramirez, J., & Lin, W. (2015). Functional network development during the first year: Relative sequence and socioeconomic correlations. *Cerebral Cortex*, *25*, 2919–2928. doi: 10.1093/cercor/bhu088

Gao, W., & Lin, W. (2012). Frontal parietal control network regulates the anti-correlated default and dorsal attention networks. *Human Brain Mapping*, *33*(1), 192–202. doi: 10.1002/hbm.21204

Garcia, F. (2018). Resting-state functional connectivity in youth with gender dysphoria. *CUNY Academic Works*. Retrieved from https://academicworks.cuny.edu/gc_etds/2781

Gay, C. W., Robinson, M. E., Lai, S., O'shea, A., Craggs, J. G., Price, D. D., & Staud, R. (2016). Abnormal resting-state functional connectivity in patients with chronic fatigue syndrome: Results of seed and data-driven analyses. *Brain Connectivity*, *6*(1), 48–56. doi: 10.1089/brain.2015.0366

Geronimus, A. T., Hicken, M., Keene, D., & Bound, J. (2006). "Weathering" and age patterns of allostatic load scores among Blacks and Whites in the United States. *American Journal of Public Health*, *96*(5), 826–833. doi: 10.2105/AJPH.2004.060749

Gershoff, E. T., Aber, J. L., Raver, C. C., & Lennon, M. C. (2007). Income is not enough: Incorporating material hardship into models of income associations with parenting and child development. *Child Development*, *78*(1), 70–95. doi: 10.1111/j.1467-8624.2007.00986.x

Gilman, S. E., Kawachi, I., Fitzmaurice, G. M., & Buka, S. L. (2002). Socioeconomic status in childhood and the lifetime risk of major depression. *International Journal of Epidemiology*, *31*(2), 359–367. doi: 10.1093/intjepid/31.2.359

Gong, Q., & He, Y. (2015). Depression, neuroimaging and connectomics: A selective overview. *Biological Psychiatry*, *77*(3), 223–235. doi: 10.1016/j.biopsych.2014.08.009

Goosby, B. J. (2007). Poverty duration, maternal psychological resources, and adolescent socioemotional outcomes. *Journal of Family Issues*, *28*(8), 1113–1134. doi: 10.1177/0192513X07300712

Goto, M., Abe, O., Miyati, T., Yamasue, H., Gomi, T., & Takeda, T. (2016). Head motion and correction methods in resting-state functional MRI. *Magnetic Resonance in Medical Sciences*, *15*(2), 178–186. doi: 10.2463/mrms.rev.2015-0060

Gottlieb, G. (1991). Experiential canalization of behavioral development: Results. *Developmental Psychology*, *27*(1), 35–39. doi: 10.1037/0012-1649.27.1.35

Grose-Fifer, J., Rodrigues, A., Hoover, S., & Zottoli, T. (2013). Attentional capture by emotional faces in adolescence. *Advances in Cognitive Psychology*, *9*(2), 81–91. doi: 10.2478/v10053-008-0134-9

Gross, R. S., Mendelsohn, A. L., & Messito, M. J. (2018). Prenatal material hardship and the internal locus of control over the prevention of child obesity: A progress report. *Academic Pediatrics*, *18*(6), 603–604. doi: 10.1016/j.acap.2018.01.016

Grusky, D. B., & Hill, J. (2018). Poverty and Inequality in the 21st Century. In D. B. Grusky & J. Hill (Eds.), *Inequality in the 21st Century* (1st Ed, pp. 1–7). doi: 10.4324/9780429499821-1

Guyer, A. E., Choate, V. R., Grimm, K. J., Pine, D. S., & Keenan, K. (2011). Emerging depression is associated with face memory deficits in adolescent girls. *Journal of the American Academy for Child Adolescent Psychiatry*, *50*(2), 180–190. doi: 10.1036/j.jaac.2010.11.008

Hackman, D. A., & Farah, M. J. (2009). Socioeconomic status and the developing brain. *Trends in Cognitive Sciences*, *13*(2), 65–73. doi: 10.1016/j.tics.2008.11.003

Haimovici, A., Tagliazucchi, E., Balenzuela, P., & Chialvo, D. R. (2013). Brain organization into resting state networks emerges at criticality on a model of the human connectome. *Physical Review Letters*, 178101, 1-4, doi: 10.1103/PhysRevLett.110.178101

Hair, N. L., Hanson, J. L., Wolfe, B. L., & Pollak, S. D. (2015). Association of child poverty, brain development, and academic achievement. *JAMA Pediatrics*, *169*(9), 822–829. doi: 10.1001/jamapediatrics.2015.1475

Haller, S. P., Kircanski, K., Stoddard, J., White, L. K., Chen, G., Sharif-Askary, B., … Brotman, M. A. (2018). Reliability of neural activation and connectivity during implicit face emotion processing in youth. *Developmental Cognitive Neuroscience*, *31*, 67–73. doi: 10.1016/j.dcn.2018.03.010

Hamilton, W. L., Cook, J. T., Thompson, W. W., Buron, L. F., Frongillo, Jr., E. A., Olson, Christine, M., & Wehler, C. A. (1997). *Household food security in the United States in 1995: Technical report of the food security measurement project*, 1-95. Retrieved from http://handle.nal.usda.gov/10113/36556

Hanson, J. L., Adluru, N., Chung, M. K., Alexander, A. L., Davidson, R. J., & Pollak, S. D. (2013). Early neglect is associated with alterations in white matter integrity and cognitive functioning. *Child Development*, *84*(5), 1566–1578. doi: 10.1111/cdev.12069

Hanson, J. L., Albert, W. D., Skinner, A. T., Shen, S. H., Dodge, K. A., & Lansford, J. E. (2019). Resting state coupling between the amygdala and ventromedial prefrontal cortex is related to household income in childhood and indexes future psychological vulnerability to stress. *Development and Psychopathology*, *31*(3), 1053–1066. doi: 10.1017/S0954579419000592

Hanson, J. L., Hair, N., Shen, D. G., Shi, F., Gilmore, J. H., Wolfe, B. L., & Pollak, S. D. (2013). Family poverty affects the rate of human infant brain growth. *PLoS ONE*, *8*(12), 1-9. doi: 10.1371/journal.pone.0080954

Hardaway, C. R., & Cornelius, M. D. (2014). Economic hardship and adolescent problem drinking: Family processes as mediating influences. *Journal of Youth and Adolescence*, *43*(7), 1191–1202. doi: 10.1007/s10964-013-0063-x

Hauser, R. M. (1994). Measuring socioeconomic status in studies of child development. *Child Development*, *65*(6), 1541–1545. doi: 10.1111/j.1467-8624.1994.tb00834.x

Hazzouri, A. Z. A., Elfassy, T., Sidney, S., Jacobs, D., Pérez Stable, E. J., & Yaffe, K. (2017). Sustained economic hardship and cognitive function: The Coronary Artery Risk Development in Young Adults Study. *American Journal of Preventive Medicine*, *52*(1), 1–9. doi: 10.1016/j.amepre.2016.08.009

Heflin, C. M. (2006). Dynamics of material hardship in the Women's Employment Study. *Social Service Review*, *80*(3), 377–397. doi: 10.1086/505289

Heflin, C. M. (2014). Family instability and the risk of material hardship. *Focus*, *31*(1), 1–9. Retrieved from https://www.irp.wisc.edu/publications/focus/pdfs/foc311c.pdf

Heflin, C. M., & Iceland, J. (2009). Poverty , material hardship , and depression. *Social Science*, *90*(5), 1052–1071. Retrieved from https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1540-6237.2009.00645.x

Heflin, C., Sandberg, J., & Rafail, P. (2009). The structure of material hardship in U.S. households: An examination of the coherence behind common measures of well-being. *Social Problems*, *56*(4), 746–764. doi: 10.1525/sp.2009.56.4.746

Helms, J. E., Jernigan, M., & Mascher, J. (2005). The meaning of race in psychology and how to change it: A methodological perspective. *The American Psychologist*, *60*(1), 27–36. doi: 10.1037/0003-066X.60.1.27

Hitchcock, C., Werner-Seidler, A., Blackwell, S. E., & Dalgleish, T. (2017). Autobiographical episodic memory-based training for the treatment of mood, anxiety and stress-related disorders: A systematic review and meta-analysis. *Clinical Psychology Review*, *52*, 92–107. doi: 10.1016/j.cpr.2016.12.003

Ho, T. C., Connolly, C. G., Blom, E. H., Lewinn, K. Z., Strigo, I. A., Paulus, M. P., … Yang, T. T. (2015). Emotion-dependent functional connectivity of the default mode network in adolescent depression. *Biological Psychiatry*, *78*, 635–646. doi: 10.1016/j.biopsych.2014.09.002

Ho, T. C., Yang, G., Wu, J., Cassey, P., Brown, S. D., Hoang, N., … Yang, T. T. (2014). Functional connectivity of negative emotional processing in adolescent depression. *Journal of Affective Disorders*, *155*(1), 65–74. doi: 10.1016/j.jad.2013.10.025

Hoff, G. E. A.-J., Van den Heuvel, M. P., Benders, M. J. N. L., Kersbergen, K. J., & De Vries, L. S. (2013). On development of functional brain connectivity in the young brain. *Frontiers in Human Neuroscience*, *7*, 650, 1-7. doi: 10.3389/fnhum.2013.00650

Hosokawa, R., & Katsura, T. (2018). Effect of socioeconomic status on behavioral problems from preschool to early elementary school – A Japanese longitudinal study. *PLoS ONE*, *13*(5:e019761), 1–23. doi: 10.1371/journal.pone.0197961

Huang, J., Kim, Y., & Sherraden, M. (2017). Material hardship and children's social-emotional development: Testing mitigating effects of child development accounts in a randomized experiment. *Child: Care, Health and Development*, *43*(1), 89–96. doi: 10.1111/cch.12385

Huang, J., Nam, Y., Sherraden, M., & Clancy, M. M. (2016). Improved financial capability can reduce material hardship among mothers. *Social Work*, *61*(4), 313–320. doi: 10.1093/sw/sww052

Huang, J., Sherraden, M., Kim, Y., & Clancy, M. (2014). Effects of child development accounts on early social-emotional development: An experimental test. *JAMA Pediatrics*, *168*(3), 265–271. doi: 10.1001/jamapediatrics.2013.4643

Huang, Y., Heflin, C. M., & Validova, A. (2021). Material hardship, perceived stress, and health in early adulthood. *Annals of Epidemiology*, *53*, 69–75. doi: 10.1016/j.annepidem.2020.08.017

Huberty, T. J. (2012). *Anxiety and depression in children and adolescents: Assessment, intervention, and prevention*, Springer Press, NY. doi: 10.1017/CBO9781107415324.004

Hung, G. C. L., Hahn, J., Alamiri, B., Buka, S. L., Goldstein, J. M., Laird, N., … Gilman, S. E. (2015). Socioeconomic disadvantage and neural development from infancy through early childhood. *International Journal of Epidemiology*, *44*(6), 1889–1899. doi: 10.1093/ije/dyv303

Iceland, J. (2005). Measuring poverty : Theoretical and empirical considerations. *Measurement: Interdisciplinary Research and Perspectives*, *3*(4), 199–235. doi: 10.1207/s15366359mea0304

Iceland, J. (2019). Racial and ethnic inequality in poverty and affluence, 1959–2015. *Population Research and Policy Review*, *38*(5), 615–654. doi: 10.1007/s11113-019-09512-7

Iceland, J., & Bauman, K. (2004). *Income poverty and capability deprivation how strong is the association?* Retrieved from https://www.census.gov/content/dam/Census/library/working-papers/2004/demo/income-poverty-and-material-hardship-how-strong-is-the-association.pdf

Izard, C., Fine, S., Schultz, D., Mostow, A., Ackerman, B., & Youngstrom, E. (2001). Emotion knowledge as a predictor of social behavior and academic competence in children at risk. *Psychological Science*, *12*(1), 18–23. doi: 10.1111/1467-9280.00304

Jacobs, R. H., Barba, A., Gowins, J. R., Klumpp, H., Jenkins, L. M., Mickey, B. J., … Langenecker, S. A. (2016). Decoupling of the amygdala to other salience network regions in adolescent-onset recurrent major depressive disorder. *Psychological Medicine*, *46*, 1055–1067. doi: 10.1017/S0033291715002615

Javanbakht, A., King, A. P., Evans, G. W., Swain, J. E., Angstadt, M., Luan Phan, K., & Liberzon, I. (2015). Childhood poverty predicts adult amygdala and frontal activity and connectivity in response to emotional faces. *Frontiers in Behavioral Neuroscience*, *9*(154), 1-8. doi: 10.3389/fnbeh.2015.00154

Johnson, S. B., Riis, J. L., & Noble, K. G. (2016). State of the art review: Poverty and the developing brain. *Pediatrics*, *137*(4), 1-16. doi: 10.1542/peds.2015-3075

Joinson, C., Kounali, D., & Lewis, G. (2017). Family socioeconomic position in early life and onset of depressive symptoms and depression: a prospective cohort study. *Social Psychiatry and Psychiatric Epidemiology*, *52*(1), 95–103. doi: 10.1007/s00127-016-1308-2

Jotterand, F. (2018). Childhood brain development, the educational achievement gap, and cognitive enhancement. *Frontiers in Pharmacology*, *9*(1142), 1-8. doi: 10.3389/fphar.2018.01142

Karpman, M., Gonzalez, D., Zuckerman, S., & Adams, G. (2018). *What explains the widespread material hardship among low-income families with children?* Retrieved from https://www.urban.org/sites/default/files/publication/99521/what_explains_the_widespread_material_hardship_among_low-income_families_with_children_0.pdf

Katz, J., Crean, H. F., Cerulli, · Catherine, & Poleshuck, E. L. (2018). Material hardship and mental health symptoms among a predominantly low income sample of pregnant women seeking prenatal care. *Maternal and Child Health Journal*, *22*, 1360–1367. doi: 10.1007/s10995-018-2518-x

Kelly, C., & Castellanos, F. X. (2014). Strenthening connections: Functional connectivity and brain plasticity. *Neuropsychology Review*, *24*(1), 63–76. doi: 10.1016/j.surg.2006.10.010.Use

Kim, D. J., Davis, E. P., Sandman, C. A., Glynn, L., Sporns, O., O'Donnell, B. F., & Hetrick, W. P. (2019). Childhood poverty and the organization of structural brain connectome. *NeuroImage*. doi: 10.1016/j.neuroimage.2018.09.041

Kim, P., Evans, G. W., Angstadt, M., Ho, S. S., Sripada, C. S., Swain, J. E., … Phan, K. L. (2013a). Effects of childhood poverty and chronic stress on emotion regulatory brain function in adulthood. *Proceedings of the National Academy of Sciences of the United States of America*, *110*(46), 18442–18447. doi: 10.1073/pnas.1308240110

Kim, P., Evans, G. W., Angstadt, M., Ho, S. S., Sripada, C. S., Swain, J. E., … Phan, K. L. (2013b). Effects of childhood poverty and chronic stress on emotion regulatory brain function in adulthood. *Proceedings of the National Academy of Sciences of the United States of America*, *110*(46), 18442–18447. doi: 10.1073/pnas.1308240110

Kim, P., Evans, G. W., Angstadt, M., Ho, S. S., Sripada, C. S., Swain, J. E., … Phan, K. L. (2013c). Effects of childhood poverty and chronic stress on emotion regulatory brain function in adulthood. *Proceedings of the National Academy of Sciences of the United States of America*, *110*(46), 18442–18447. doi: 10.1073/pnas.1308240110

Kitayama, S., & Uskul, A. K. (2011). Culture, mind, and the brain: Current evidence and future directions. *Annual Review of Psychology*, *62*, 419–449. doi: 10.1146/annurev-psych-120709-145357

Knudsen, E. I. (2004). Sensitive periods in the development of the brain and behavior. *Journal of Cognitive Neuroscience*, *16*(8), 1412–1425. doi: 10.1162/0898929042304796

Koball, H., & Jiang, Y. (2018). *Basic facts about low-income children: Children under 18 years, 2016*. New York: National Center for Children in Poverty, Columbia University Mailman School of Public Health.

Kovacs, M. (1992). *Children's Depression Inventory*. North Tonawanda: NY: Multi-Health Systems, Inc.

Lagioia, A., van de Ville, D., Debbané, M., Lazeyras, F., & Eliez, S. (2010). Adolescent resting state networks and their associations with schizotypal trait expression. *Frontiers in Systems Neuroscience*, *4*, 1–12. doi: 10.3389/fnsys.2010.00035

Lawson, G. M., Hook, C. J., & Farah, M. J. (2018). A meta-analysis of the relationship between socioeconomic status and executive function performance among children. *Developmental Science*, *21*(2), 1–22. doi: 10.1111/desc.12529

Lebel, C., Walker, L., Leemans, A., Phillips, L., & Beaulieu, C. (2008). Microstructural maturation of the human brain from childhood to adulthood. *NeuroImage*, *40*(3), 1044–1055. doi: 10.1016/j.neuroimage.2007.12.053

Lee, Y. J., Guell, X., Hubbard, N. A., Siless, V., Frosch, I. R., Goncalves, M., … Anteraper, S. A. (2020). Functional alterations in cerebellar functional connectivity in anxiety disorders. *Cerebellum*, 1–11. doi: 10.1007/s12311-020-01213-8

Leijser, L. M., Siddiqi, A., & Miller, S. P. (2018). Imaging evidence of the effect of socio-economic status on brain structure and development. *Seminars in Pediatric Neurology*, 26-34. doi: 10.1016/j.spen.2018.03.004

Levit-binnun, N., Davidovitch, M., & Golland, Y. (2013). Sensory and motor secondary symptoms as indicators of brain vulnerability. *Journal of Neurodevelopmental Disorders*, *5*(26), 1-21. doi: 10.1186/1866-1955-5-26

Levy, H. (2015). Income, poverty, and material hardship among older Americans. *RSF: The Russell Sage Foundation Journal of the Social Sciences*, *1*(1), 55–77. doi: 10.7758/rsf.2015.1.1.04

Lewis, O. (1966). The culture of poverty. *Scientific American*, *215*(4), 19–25. doi: 10.4324/9781351319447-2

Li, K., Guo, L., Nie, J., Li, G., & Liu, T. (2009). Review of methods for functional brain connectivity detection using fMRI. *Computerized Medical Imaging and Graphics*, *33*(2), 131–139. doi: 10.1016/j.compmedimag.2008.10.011

Li, S., Hu, N., Zhang, W., Tao, B., Dai, J., Gong, Y., … Lui, S. (2019). Dysconnectivity of multiple brain networks in schizophrenia: A meta-analysis of resting-state functional connectivity. *Frontiers in Psychiatry*, *10*, 1–11. doi: 10.3389/fpsyt.2019.00482

Li, X., Zhang, M., Li, K., Zou, F., Wang, Y., Wu, X., & Zhang, H. (2019). The altered somatic brain network in state anxiety. *Frontiers in Psychiatry*, *10*, 1–9. doi: 10.3389/fpsyt.2019.00465

Liberzon, I., Ma, S. T., Okada, G., Shaun Ho, S., Swain, J. E., & Evans, G. W. (2015). Childhood poverty and recruitment of adult emotion regulatory neurocircuitry. *Social Cognitive and Affective Neuroscience*, *10*(11), 1596–1606. doi: 10.1093/scan/nsv045

Lichter, D. T., Parisi, D., & Taquino, M. C. (2012). The geography of exclusion: Race, segregation, and concentrated poverty. *Social Problems*, *59*(3), 364–388. doi: 10.1525/sp.2012.59.3.364

Lichtin, R. D., Merz, E. C., He, X., Desai, P. M., Simon, K. R., Melvin, S. A., … Noble, K. G. (2020). Material hardship, prefrontal cortex–amygdala structure, and internalizing symptoms in children. *Developmental Psychobiology*, 1–14. doi: 10.1002/dev.22020

Lillard, A. S., & Erisir, A. (2011). Old dogs learning new tricks: Neuroplasticity beyond the juvenile period. *Developmental Review*, *31*(4), 207–239. doi: 10.1016/j.dr.2011.07.008

Lindquist, M. a, & Gelman, A. (2009). Correlations and multiple comparisons in functional imaging: A statistical perspective (Commentary on Vul et al., 2009). *Perspectives in Psychological Science*, *4*, 1–12. doi: 10.1111/j.1745-6924.2009.01130.x

Lino, M., Kuczynski, K., Rodriguez, N., & Schap, T. (2017). Expenditures on children by families, 2015. *Miscellaneous Publication No. 1528-2013*, p. 37. Retrieved from http://www.cnpp.usda.gov/familyeconomicsandnutritionreview.htm%5Cnhttp://search.ebscohost.com/login.aspx?direct=true&db=ecn&AN=0616896&site=ehost-live

Lipina, S. J., & Evers, K. (2017). Neuroscience of childhood poverty: Evidence of impacts and mechanisms as vehicles of dialog with ethics. *Frontiers in Psychology*, *8*, 1–13. doi: 10.3389/fpsyg.2017.00061

Lipina, S. J., & Posner, M. I. (2012). The impact of poverty on the development of brain networks. *Frontiers in Human Neuroscience*, *6*, 1–12. doi: 10.3389/fnhum.2012.00238

Lipowicz, A., Koziel, S., Hulanicka, B., & Kowalisko, A. (2007). Socioeconomic status during childhood and health status in adulthood: The Wroclaw Growth Study. *Journal of Biosocial Science*, *39*, 481–491. doi: 10.1017/S0021932006001799

Lledo, P. M., Alonso, M., & Grubb, M. S. (2006). Adult neurogenesis and functional plasticity in neuronal circuits. *Nature Reviews Neuroscience*, *7*(3), 179–193. doi: 10.1038/nrn1867

Lopez, K. C., Luby, J. L., Belden, A. C., & Barch, D. M. (2018). Emotion dysregulation and functional connectivity in children with and without a history of major depressive disorder. *Cognitive, Affective and Behavioral Neuroscience*, *18*(2), 232–248. doi: 10.3758/s13415-018-0564-x

Luo, Y., & Waite, L. J. (2005). The impact of childhood and adult SES on physical, mental, and cognitive well-being in later life. *Journal of Gerontology: Social Sciences*, *60B*(2), S93–S101. doi: 10.1093/geronb/60.2.S93

Mani, A., Mullainathan, S., Shafir, E., & Zhao, J. (2013). Poverty impedes cognitive function. *Science*, *341*(6149), 976–980. doi: 10.1126/science.1238041

Markant, J., Ackerman, L. K., Nussenbaum, K., & Amso, D. (2016). Selective attention neutralizes the adverse effects of low socioeconomic status on memory in 9-month-old infants. *Developmental Cognitive Neuroscience*, *18*, 26–33. doi: https://doi-org.proxy.lib.umich.edu/10.1016/j.dcn.2015.10.009

Markett, S., Jawinski, P., Kirsch, P., & Gerchen, M. F. (2020). Specific and segregated changes to the functional connectome evoked by the processing of emotional faces: A task-based connectome study. *Scientific Reports*, *10*(1), 1–15. doi: 10.1038/s41598-020-61522-0

Mayer, S. E., & Jencks, C. (1989). Poverty and the distribution of material hardship. *The Journal of Human Resources*, *24*(1), 88–114. Retrieved from https://www.jstor.org/stable/145934

McConnell, D., Breitkreuz, R., & Savage, A. (2011). From financial hardship to child difficulties: Main and moderating effects of perceived social support. *Child: Care, Health and Development*, *37*(5), 679–691. doi: 10.1111/j.1365-2214.2010.01185.x

McEwen, C. A., & McEwen, B. S. (2017). Social Structure, Adversity, Toxic Stress, and Intergenerational Poverty: An Early Childhood Model. *Annual Review of Sociology*, *43*(1), 445–472. doi: 10.1146/annurev-soc-060116-053252

McLaughlin, K. A., Costello, E. J., Leblanc, W., Sampson, N. A., & Kessler, R. C. (2012). Socioeconomic status and adolescent mental disorders. *American Journal of Public Health*, *102*(9), 1742–1750. doi: 10.2105/AJPH.2011.300477

McLaughlin, K. A., Green, J. G., Alegría, M., Jane Costello, E., Gruber, M. J., Sampson, N. A., & Kessler, R. C. (2012). Food insecurity and mental disorders in a national sample of U.S. adolescents. *Journal of the American Academy of Child and Adolescent Psychiatry*, *51*(12), 1293–1303. doi: 10.1016/j.jaac.2012.09.009

McLaughlin, K. A., Hilt, L. M., & Nolen-Hoeksema, S. (2007). Racial/ethnic differences in internalizing and externalizing symptoms in adolescents. *Journal of Abnormal Child Psychology*, *35*(5), 801–816. doi: 10.1007/s10802-007-9128-1

McLoyd, V. C. (1998). Socioeconomic disadvantage and child development. *American Psychologist*, *53*(2), 185–204. doi: 10.1037/0003-066X.53.2.185

McLoyd, V. C. (2011). How money matters for children's socioemotional adjustment: Family processes and parental investment. In G. Carlo, L. J. Crockett, & M. A. Carranza (Eds.), *Health Disparitiess in Youth and Families: Research and Applications. Nebraska Symposium on Motivation* (Vol. 57, pp. 33–72). New York, NY: Springer.

McRae, K., Gross, J. J., Weber, J., Robertson, E. R., Sokol-Hessner, P., Ray, R. D., … Ochsner, K. N. (2012). The development of emotion regulation: An fMRI study of cognitive reappraisal in children, adolescents and young adults. *Social Cognitive and Affective Neuroscience*, *7*(1), 11–22. doi: 10.1093/scan/nsr093

Menon, V. (2011). Large-scale brain networks and psychopathology: A unifying triple network model. *Trends in Cognitive Sciences*, *15*(10), 483–506. doi: 10.1016/j.tics.2011.08.003

Meyer-Lindenberg, A. (2009). Neural connectivity as an intermediate phenotype: Brain networks under genetic control. *Human Brain Mapping*, *30*(7), 1938–1946. doi: 10.1002/hbm.20639

Meyer, B. D., & Sullivan, J. X. (2004). The effects of welfare and tax reform: The material well-being of single mothers in the 1980s and 1990s. *Journal of Public Economics*, *88*(7–8), 1387–1420. doi: 10.1016/S0047-2727(02)00219-0

Meyer, B. M., Huemer, J., Rabl, U., Boubela, R. N., Kalcher, K., Berger, A., … Pezawas, L. (2016). Oppositional COMT Val158Met effects on resting state functional connectivity in adolescents and adults. *Brain Structure and Function*, *221*(1), 103–114. doi: 10.1007/s00429-014-0895-5

Mezulis, A. H., Priess, H. A., & Hyde, J. S. (2011). Rumination mediates the relationship between infant temperament and adolescent depressive symptoms. *Depression Research and Treatment*, 1–9. doi: 10.1155/2011/487873

Mill, R. D., Ito, T., & Cole, M. W. (2017). From connectome to cognition: The search for mechanism in human functional brain networks. *NeuroImage*, *160*, 124–139. doi: 10.1016/j.neuroimage.2017.01.060

Millar, P. R., Petersen, S. E., Ances, B. M., Gordon, B. A., Benzinger, T. L. S., Morris, J. C., & Balota, D. A. (2020). Evaluating the sensitivity of resting-state BOLD variability to age and cognition after controlling for motion and cardiovascular influences: A network-based approach. *Cerebral Cortex*, *30*(11), 5686–5701. doi: 10.1093/cercor/bhaa138

Miller, A. L., Gouley, K. K., Seifer, R., Zakriski, A., Eguia, M., & Vergnani, M. (2005). Emotion knowledge skills in low-income elementary school children: Associations with social status and peer experiences. *Social Development*, *14*(4), 637–651. doi: 10.1111/j.1467-9507.2005.00321.x

Mirowsky, J., & Ross, C. E. (1999). Economic hardship across the Life course. *American Sociological Review*, *64*(4), 548–569. doi: 10.2307/2657255

Mode, N. A., Evans, M. K., & Zonderman, A. B. (2016). Race, neighborhood economic status, income inequality and mortality. *PLoS ONE*, *11*(5:e0154535), 1–14. doi: 10.1371/journal.pone.0154535

Mohamed, S., & Toran, H. (2018). Family socioeconomic status and social-emotional development among young children in Malaysia. *Journal of Applied Sciences*, *18*(3), 122–128. doi: 10.3923/jas.2018.122.128

Monk, C. S., McClure, E. B., Nelson, E. E., Zarahn, E., Bilder, R. M., Leibenluft, E., … Pine, D. S. (2003). Adolescent immaturity in attention-related brain engagement to emotional facial expressions. *NeuroImage*, *20*(1), 420–428. doi: 10.1016/S1053-8119(03)00355-0

Monk, C. S., Telzer, E. H., Mogg, K., Bradley, B. P., Mai, X., Louro, H. M. C., … Pine, D. S. (2008). Amygdala and ventrolateral prefrontal cortex activation to masked angry faces in children and adolescents with generalized anxiety disorder. *Archives of General Psychiatry*, *65*(5), 568–576. doi: 10.1016/S0084-3970(08)79329-0

Moulson, M. C., Fox, N. A., Zeanah, C. H., & Nelson, C. A. (2009). Early adverse experiences and the neurobiology of facial emotion processing. *Developmental Psychology*, *45*(1), 17–30. doi: 10.1037/a0014035

Mueller, S. C. (2011). The influence of emotion on cognitive control: Relevance for development and adolescent psychopathology. *Frontiers in Psychology*, *2*(NOV), 1–21. doi: 10.3389/fpsyg.2011.00327

Muffels, Ruud, J. A., & Fouarge, Didier, J. A. G. (2001). *Do European welfare regimes matter in explaining social exclusion? Dynamic analyses of the relationship between income poverty and deprivation: A … Managing social risks through transitional labour markets View project Philips WGP View project Do European*. Retrieved from https://www.researchgate.net/publication/228743614

Mukherjee, P., Miller, J. H., Shimony, J. S., Conturo, T. E., Lee, B. C. P., Almli, C. R., & McKinstry, R. C. (2001). Normal brain maturation during childhood: Developmental trends characterized with diffusion-tensor MR imaging. *Radiology*, *221*(2), 349–358. doi: 10.1148/radiol.2212001702

Mulders, P. C., van Eijndhoven, P. F., Schene, A. H., Beckmann, C. F., & Tendolkar, I. (2015). Resting-state functional connectivity in major depressive disorder: A review. *Neuroscience and Biobehavioral Reviews*, *56*, 330–344. doi: 10.1016/j.neubiorev.2015.07.014

National Academies of Sciences Engineering and Medicine. (2019). *A Roadmap to Reducing Child Poverty*. doi: 10.17226/25246

Neckerman, K. M., Garfinkel, I., Teitler, J. O., Waldfogel, J., & Wimer, C. (2016). Beyond income poverty: Measuring disadvantage in terms of material hardship and health. *Academic Pediatrics*, *16*(3), S52–S59. doi: 10.1016/j.acap.2016.01.015

Nelson, G. (2011). Measuring poverty: The official U.S. measure and material hardship. *Poverty & Public Policy*, *3*(3), 1–35. doi: 10.2202/1944-2858.1077

Noble, K. G., Houston, S. M., Brito, N. H., Bartsch, H., Kan, E., Kuperman, J. M., … Sowell, E. R. (2015). Family income, parental education and brain structure in children and adolescents. *Nature Neuroscience*, *18*(5), 773–778. doi: 10.1038/nn.3983

Noble, K. G., Houston, S. M., Kan, E., & Sowell, E. R. (2012). Neural correlates of socioeconomic status in the developing human brain. *Developmental Science*, *15*(4), 516–527. doi: 10.1111/j.1467-7687.2012.01147.x

Nord, C. L., Gray, A., Robinson, O. J., & Roiser, J. P. (2019). Reliability of fronto-amygdala coupling during emotional face processing. *Brain Sciences*, *9*(89), 1–12. doi: 10.3390/brainsci9040089

Ochsner, K. N., & Gross, J. J. (2005). The cognitive control of emotion. *Trends in Cognitive Sciences*, *9*(5), 242–249.

Oh, A. (2019). Characterizing relationships between resource insecurity, internalizing symptoms, and functional brain connectivity in children (Yale University). Retrieved from https://psychology.yale.edu/sites/default/files/files/Alice-Thesis-FINAL.pdf

Orr, C., Morioka, R., Behan, B., Datwani, S., Doucet, M., Ivanovic, J., … Garavan, H. (2013). Altered resting-state connectivity in adolescent cannabis users. *The American Journal of Drug and Alcohol Abuse*, *39*(6), 372–381. doi: 10.3109/00952990.2013.848213

Orshansky, M. (1963). Children of the poor. *Social Security Bulletin*, *26*(7), 3–13. Retrieved from https://heinonline-org.proxy.lib.umich.edu/HOL/P?h=hein.journals/ssbul26&i=237.

Orshansky, M. (1965). Counting the poor: Another look at the poverty profile. *Social Security Bulletin*, *28*(1), 3–29. Retrieved from https://heinonline-org.proxy.lib.umich.edu/HOL/P?h=hein.journals/ssbul28&i=5.

Ouellette, T., Burstein, N., Long, D., & Beecroft, E. (2004). *Measures of material hardship: Final report*. Retrieved from https://aspe.hhs.gov/system/files/pdf/73366/report.pdf

Palmer, C. A., Oosterhoff, B., Bower, J. L., Kaplow, J. B., & Alfano, C. A. (2018). Associations among adolescent sleep problems, emotion regulation, and affective disorders: Findings from a nationally representative sample. *Journal of Psychiatric Research*, *96*, 1–8. doi: 10.1016/j.jpsychires.2017.09.015

Park, S. S., Wiemers, E. E., & Seltzer, J. A. (2019). The family safety net of Black and White multigenerational families. *Population and Development Review*, *45*(2), 351–378. doi: 10.1111/padr.12233

Parkes, L., Fulcher, B., Yu¨cel, M., & Fornitod, A. (2017). An evaluation of the efficacy, reliability, and sensitivity of motion correction strategies for resting-state functional MRI. *NeuroImage*. doi: 10.1016/j.neuroimage.2017.12.073

Parkinson, T. D., Kornelsen, J., & Smith, S. D. (2019). Trait mindfulness and functional connectivity in cognitive and attentional resting state networks. *Frontiers in Human Neuroscience*, *13*. doi: 10.3389/fnhum.2019.00112

Paus, T., Collins, D. L., Evans, a. C., Leonard, G., Pike, B., & Zijdenbos, a. (2001). Maturation of white matter in the human brain: A review of magnetic resonance studies. *Brain Research Bulletin*, *54*(3), 255–266. doi: 10.1016/S0361-9230(00)00434-2

Perry, R. E., Finegood, E. D., Braren, S. H., Dejoseph, M. L., Putrino, D. F., Wilson, D. A., … Key, F. L. P. (2019). Developing a neurobehavioral animal model of poverty: Drawing cross-species connections between environments of scarcity-adversity, parenting quality, and infant outcome. *Developmental Psychopathology*, *31*(2), 399–418. doi: 10.1016/j.physbeh.2017.03.040

Pessoa, L. (2018). Understanding emotion with brain networks. *Current Opinion in Behavioral Sciences*, *19*, 19–25. doi: 10.1016/j.cobeha.2017.09.005

Pessoa, L., & Adolphs, R. (2010). Emotion processing and the amygdala: From a "low road" to "many roads" of evaluating biological significance. *Nature Reviews Neuroscience*, *11*(11), 773–782. doi: 10.1038/nrn2920

Pessoa, L., & McMenamin, B. (2017). Dynamic networks in the emotional brain. *Neuroscientist*, *23*(4), 383–396. doi: 10.1177/1073858416671936

Petersen, A. C., Crockett, L., Richards, M., & Boxer, A. (1988). A self-report measure of pubertal status: Reliability, validity, and initial norms. *Journal of Youth and Adolescence*, *17*(2), 117–133. doi: 10.1007/BF01537962

Pfeffer, F. T., & Killewald, A. (2019). Intergenerational wealth mobility and racial inequality. *Socius: Sociological Research for a Dynamic World*, *5*, 237802311983179. doi: 10.1177/2378023119831799

Pietras, S. A., & Goodman, E. (2013). Socioeconomic status gradients in inflammation in adolescence. *Psychosomatic Medicine*, *75*(5), 442–448. doi: 10.1097/PSY.0b013e31828b871a

Ponnet, K. (2014). Financial stress, parent functioning and adolescent problem behavior: An actor–partner interdependence approach to family stress processes in low-, middle-, and high-income families. *Journal of Youth and Adolescence*, *43*(10), 1752–1769. doi: 10.1007/s10964-014-0159-y

Poulton, R., Caspi, A., Milne, B. J., Thomson, W. M., Taylor, A., Sears, M. R., & Moffitt, T. E. (2002). Association between children's experience of socioeconomic disadvantage and adult health: A life-course study. *Lancet*, *360*(9346), 1640–1645. doi: 10.1016/S0140-6736(02)11602-3

Power, J. D., Fair, D. A., Schlaggar, B. L., & Petersen, S. E. (2010). The development of human functional brain networks. *Neuron*, *67*(5), 735–748. doi: 10.1016/j.neuron.2010.08.017

Power, J. D., Schlaggar, B. L., & Petersen, S. E. (2014). Studying brain organization via spontaneous fMRI signal. *Neuron*, *84*(4), 681–696. doi: 10.1016/j.neuron.2014.09.007

Power, J. D., Schlaggar, B. L., & Petersen, S. E. (2015). Recent progress and outstanding issues in motion correction in resting state fMRI. *NeuroImage*, *105*, 536–551. doi: 10.1016/j.neuroimage.2014.10.044

Pruim, R. H. R., Mennes, M., Buitelaar, J. K., & Beckmann, C. F. (2015). Evaluation of ICA-AROMA and alternative strategies for motion artifact removal in resting state fMRI. *NeuroImage*, *112*, 278–287. doi: 10.1016/j.neuroimage.2015.02.063

Pruim, R. H. R., Mennes, M., van Rooij, D., Llera, A., Buitelaar, J. K., & Beckmann, C. F. (2015). ICA-AROMA: A robust ICA-based strategy for removing motion artifacts from fMRI data. *NeuroImage*, *112*, 267–277. doi: 10.1016/j.neuroimage.2015.02.064

Rainisch, B. K. W., & Upchurch, D. M. (2013). Sociodemographic correlates of allostatic load among a national sample of adolescents: Findings from the National Health and Nutrition Examination Survey, 1999-2008. *Journal of Adolescent Health*, *53*(4), 506–511. doi: 10.1016/j.jadohealth.2013.04.020

Ratcliffe, C. (2015). Child poverty and adult success. *Urban Institute Low-Income Working Families Initiative*, pp. 1–15. Retrieved from http://www.urban.org/sites/default/files/publication/65766/2000369-Child-Poverty-and-Adult-Success.pdf

Raver, C., Blair, C., & Willoughby, M. (2013). Poverty as a predictor of 4-year-olds' executive function: New perspectives on models of differential susceptibility. *Developmental Psychology*, *49*(2), 292–304. doi: 10.1037/a0028343

Raver, C. C. (2004). Placing emotional self-regulation in sociocultural and socioeconomic contexts. *Child Development*, *75*(2), 346–353. doi: 10.1111/j.1467-8624.2004.00676.x

Raver, C. C., Roy, A. L., Pressler, E., Ursache, A. M., & McCoy, D. C. (2017). Poverty-related adversity and emotion regulation predict internalizing behavior problems among low-income children ages 8-11. *Behavioral Sciences*, *7*(1). doi: 10.3390/bs7010002

Rector, R. E., Johnson, K. A., & Youssef, S. E. (1999). The extent of material hardship and poverty in the United States. *Review of Social Economy*, *57*(3), 351–387. doi: 10.1080/00346769900000007

Reichman, N. E., Teitler, J. O., Garfinkel, I., & McLanahan, S. S. (2001). Fragile Families: Sample and Design. *Children and Youth Services Review*, *23*(4–5), 303–326.

Reiss, F. (2013). Socioeconomic inequalities and mental health problems in children and adolescents: A systematic review. *Social Science and Medicine*, *90*, 24–31. doi: 10.1016/j.socscimed.2013.04.026

Reiss, F., Meyrose, A. K., Otto, C., Lampert, T., Klasen, F., & Ravens-Sieberer, U. (2019). Socioeconomic status, stressful life situations and mental health problems in children and adolescents: Results of the German BELLA cohort-study. *PLoS ONE*, *14*(3), 1–16. doi: 10.1371/journal.pone.0213700

Rivas-drake, D., Seaton, E. K., Markstrom, C., Quintana, S., Syed, M., Lee, R. M., … French, S. (2014). Ethnic and racial identity in adolescence : Implications for psychosocial , academic , and health outcomes. *Child Development*, *85*(1), 40–57. doi: 10.1111/cdev.12200

Rodems, R., & Luke Shaefer, H. (2020). Many of the kids are not alright: Material hardship among children in the United States. *Children and Youth Services Review*, 104767. doi: 10.1016/j.childyouth.2020.104767

Rogers, B. P., Morgan, V. L., Newton, A. T., & Gore, J. C. (2007). Assessing functional connectivity in the human brain by fMRI. *Magnetic Resonance Imaging*, *25*(10), 1347–1357. doi: 10.1016/j.mri.2007.03.007

Rousselet, G. A., & Pernet, C. R. (2012). Improving standards in brain-behavior correlation analyses. *Frontiers in Human Neuroscience*, *6*(119), 1-11. doi: 10.3389/fnhum.2012.00119

Rushton, J. L., Forcier, M., & Schectman, R. M. (2002). Epidemiology of depressive symptoms in the National Longitudinal Study of Adolescent Health. *Journal of the American Academy of Child and Adolescent Psychiatry*, *41*(2), 199–205. doi: 10.1097/00004583-200202000-00014

Saarni, C., Campos, J. J., Camras, L. A., & Witherington, D. (2008). Principles of emotion and emotional competence. In D. Kuhn, R. S. Siegler, & N. Eisenberg (Eds.), *Child and Adolescent Development: An Advanced Course* (pp. 361–393). New York, NY: John Wiley & Sons.

Sacchet, M. D., Ho, T. C., Connolly, C. G., Tymofiyeva, O., LeWinn, K. Z., Han, L. K. M., … Yang, T. T. (2016). Large-scale hypoconnectivity between resting-state functional networks in unmedicated adolescent major depressive disorder. *Neuropsychopharmacology*, *41*(12), 2951–2960. doi: 10.1038/npp.2016.76

Sato, J. R., Biazoli, C. E., Salum, G. A., Gadelha, A., Crossley, N., Vieira, G., … Jackowski, A. P. (2016). Connectome hubs at resting state in children and adolescents: Reproducibility and psychopathological correlation. *Developmental Cognitive Neuroscience*, *20*, 2–11. doi: 10.1016/j.dcn.2016.05.002

Schwartz, S. J., Syed, M., Yip, T., Knight, G. P., Umaña-Taylor, A. J., Rivas-Drake, D., … Sellers, R. M. (2014). Methodological issues in ethnic and racial identity research with ethnic minority populations: Theoretical precision, measurement issues, and research designs. *Child Development*, *85*(1), 58–76. doi: 10.1111/cdev.12201

Seeley, W. W., Menon, V., Schatzberg, A. F., Keller, J., Gary, H., Kenna, H., … Greicius, M. D. (2007). Dissociable intrinsic connectivity networks for salience processing and executive control. *Journal of Neurosciences*, *27*(9), 2349–2356. doi: 10.1523/JNEUROSCI.5587-06.2007.Dissociable

Semega, J., Kollar, M., Crearmer, J., & Mohanty, A. (2019). *Income and poverty in the United States: 2018 current population reports*. Retrieved from U.S. Government Printing Office website: https://www.census.gov/library/publications/2019/demo/p60-266.html

Sen, A. (1985). A sociological approach to the measurement of poverty: A reply to Professor Peter Townsend. *Oxford Journals*, *37*(4), 669–676. Retrieved from https://www.jstor.org/stable/2663049

Sen, A. (2005). Human rights and capabilities. *Journal of Human Development*, *6*(2), 151–166. doi: 10.1080/14649880500120491

Sha, Z., Wager, T. D., Mechelli, A., & He, Y. (2019). Common dysfunction of large-scale neurocognitive networks across psychiatric disorders. *Biological Psychiatry*, *85*(5), 379–388. doi: 10.1016/j.biopsych.2018.11.011

Shaw, B. (1988). Poverty: absolute or relative? *Journal of Applied Philosophy*, *5*(1), 27–36. doi: 10.1111/j.1468-5930.1988.tb00226.x

Sherman, L. E., Rudie, J. D., Pfeifer, J. H., Masten, C. L., McNealy, K., & Dapretto, M. (2014). Development of the Default Mode and Central Executive Networks across early adolescence: A longitudinal study. *Developmental Cognitive Neuroscience*, *10*, 148–159. doi: 10.1016/j.dcn.2014.08.002

Shonkoff, J. P., Boyce, W. T., & McEwen, B. S. (2009). Neuroscience, molecular biology, and the childhood roots of health disparities. *JAMA*, *301*(21), 2252. doi: 10.1001/jama.2009.754

Short, K. S. (2005). Material and financial hardship and income-based poverty measures in the USA. *Journal of Social Policy*, *34*(1), 21–38. doi: 10.1017/S0047279404008244

Short, K. S., & Garner, T. I. (2002). *A decade of experimental poverty thresholds 1990 to 2000* (pp. 1–32). pp. 1–32. Retrieved from www.census. gov/hhes/poverty/povmeas/papers

Shrout, P. E., & Rodgers, J. L. (2018). Psychology, science, and knowledge construction: Broadening perspectives from the replication crisis. *Annual Review of Psychology*, *69*, 487–510. doi: 10.1146/annurev-psych-122216-011845

Sidor, A., Fischer, C., & Cierpka, M. (2017). The link between infant regulatory problems, temperament traits, maternal depressive symptoms and children's psychopathological symptoms at age three: A longitudinal study in a German at-risk sample. *Child and Adolescent Psychiatry and Mental Health*, *11*(1), 1–17. doi: 10.1186/s13034-017-0148-5

Sirin, S. R. (2005). Socioeconomic status and academic achievement: A meta-analytic review of research. *Review of Educational Research*, *75*(3), 417–453.

Skinner, M. L., Elder, G. H., & Conger, R. D. (1992). Linking economic hardship to adolescent aggression. *Journal of Youth and Adolescence*, *21*(3), 259–276. doi: 10.1007/BF01537018

Slack, K. S., & Yoo, J. (2005). Food hardship and child behavior problems among low-income children. *Social Service Review*, *79*(3), 511–536. doi: 10.1086/430894

Slopen, N., Fitzmaurice, G., Williams, D. R., & Gilman, S. E. (2010). Poverty, food insecurity, and the behavior for childhood internalizing and externalizing disorders. In *Journal of the American Academy of Child & Adolescent Psychiatry* (Vol. 49). doi: 10.1016/j.jaac.2010.01.018

Smedley, A., & Smedley, B. D. (2005). Race as biology is fiction, racism as a social problem is real: Anthropological and historical perspectives on the social construction of race. *The American Psychologist*, *60*(1), 16–26. doi: 10.1037/0003-066X.60.1.16

Smith, S. M., Beckmann, C. F., Andersson, J., Auerbach, E. J., Bijsterbosch, J., Douaud, G., … Glasser, M. F. (2013). Resting-state fMRI in the Human Connectome Project. *NeuroImage, 80,* 144-168. doi: 10.1016/j.neuroimage.2013.05.039

Sommet, N., Morselli, D., & Spini, D. (2018). Income inequality affects the psychological health of only the people facing scarcity. *Psychological Science*, *29*(12), 1911–1921. doi: 10.1177/0956797618798620

Sonik, R. A., Parish, S. L., Akobirshoev, I., Son, E., & Rosenthal, E. (2017). Population estimates, health care characteristics, and material hardship experiences of U.S. children with parent-reported speech-language difficulties: Evidence from three nationally representative surveys. *Language, Speech, and Hearing Services in Schools*, *48*(4), 286–293. doi: 10.1044/2017_LSHSS-16-0072

Spicker, P., Gordon, R., & Scotland, A. (2009). *Poverty, democratic governance and poverty reduction strategies*.

Sporns, O. (2013). The human connectome: Origins and challenges. *NeuroImage*, *80*, 53–61. doi: 10.1016/j.neuroimage.2013.03.023

Sporns, O. (2014). Contributions and challenges for network models in cognitive neuroscience. *Nature Neuroscience*, *17*(5), 652–660. doi: 10.1038/nn.3690

Spreng, R. N., Sepulcre, J., Turner, G. R., W. Dale, S., & Schacter, D. L. (2013). Intrinsic architecture underlying the relations among the default, dorsal attention, and frontopareital control networks of the human brain. *Journal of Cognitive Neuroscience*, *25*(1), 74–86.

Sripada, C., Angstadt, M., Kessler, D., Luan Phan, K., Liberzon, I., Evans, G. W., … Swain, J. E. (2014). Volitional regulation of emotions produces distributed alterations in connectivity between visual, attention control, and default networks. *Neuroimage*, *89*, 110–121. doi: 10.1016/j.neuroimage.2013.11.006

Sripada, C., Kessler, D., Fang, Y., Welsh, R. C., Prem Kumar, K., & Angstadt, M. (2014). Disrupted network architecture of the resting brain in attention-deficit/hyperactivity disorder. *Human Brain Mapping*, *35*(9), 4693–4705. doi: 10.1002/hbm.22504

Sripada, C., Rutherford, S., Angstadt, M., Thompson, W. K., Luciana, M., Weigard, A., … Heitzeg, M. (2020). Prediction of neurocognition in youth from resting state fMRI. *Molecular Psychiatry*, *25*, 3413–3421. doi: 10.1038/s41380-019-0481-6

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

Steinlin, M. (2007). The cerebellum in cognitive processes : Supporting studies in children. *The Cerebellum*, *6*, 237–241. doi: 10.1080/14734220701344507

Stevens, M. C. (2016). The contributions of resting state and task-based functional connectivity studies to our understanding of adolescent brain network maturation. *Neuroscience and Biobehavioral Reviews*, *70*, 13–32. doi: 10.1016/j.neubiorev.2016.07.027

Sullivan, J. X., Turner, L., & Danziger, S. (2008). The relationship between income and material hardship. *Journal of Policy Analysis and Management*, *27*(1), 63–81. doi: 10.1002/pam

Sun, W., Li, D., Zhang, W., Bao, Z., & Wang, Y. (2015). Family material hardship and Chinese adolescents' problem behaviors: A moderated mediation analysis. *PLoS ONE*, *10*(5), 1–22. doi: 10.1371/journal.pone.0128024

Sylvester, C. M., Corbetta, M., Raichle, M. E., Rodebaugh, T. L., Schlaggar, B. L., Sheline, Y. I., … Lenze, E. J. (2012). Functional network dysfunction in anxiety and anxiety disorders. *Trends in Neurosciences*, *35*(9), 527–535. doi: 10.1016/j.tins.2012.04.012

Taylor, M. J., Batty, M., & Itier, R. J. (2004). The faces of development: A review of early face processing over childhood. *Journal of Cognitive Neuroscience*, *16*(8), 1426–1442. doi: 10.1162/0898929042304732

Thomason, M. E., Hamilton, J. P., & Gotlib, I. H. (2011). Stress-induced activation of the HPA axis predicts connectivity between subgenual cingulate and salience network during rest in adolescents. *Journal of Child Psychology and Psychiatry and Allied Disciplines*, *52*(10), 1026–1034. doi: 10.1111/j.1469-7610.2011.02422.x

Tottenham, N., Tanaka, J. W., Leon, A. C., McCarry, T., Nurse, M., Hare, T. A., … Nelson, C. (2009). The NimStim set of facial expressions: Judgments from untrained research participants. *Psychiatry Research*, *168*(3), 242–249. doi: 10.1016/j.psychres.2008.05.006

Townsend, P. (1979). *Poverty in the United Kingdom: A survey of household resources and standards of living*. doi: 10.1086/227691

Troy, A. S., Ford, B. Q., McRae, K., Zarolia, P., & Mauss, I. B. (2017). Change the things you can: Emotion regulation is more beneficial for people from lower than from higher socioeconomic status. *Emotion*, *17*(1), 141–154. doi: 10.1037/emo0000210

Tsui, K.-Y. (2002). Multidimensional poverty indices. *Social Choice and Welfare*, *19*(1), 69–93. Retrieved from https://link.springer.com/content/pdf/10.1007/s355-002-8326-3.pdf

Twenge, J. M., & Nolen-Hoeksema, S. (2002). Age, gender, race, socioeconomic status, and birth cohort differences on the Children's Depression Inventory: A meta-analysis. *Journal of Abnormal Psychology*, *111*(4), 578–588. doi: 10.1037/0021-843X.111.4.578

Vaidya, C. J., & Gordon, E. M. (2013). Phenotypic variability in resting-state functional connectivity: Current status. *Brain Connectivity*, *3*(2), 99–120. doi: 10.1089/brain.2012.0110

VanTieghem, M. R., & Tottenham, N. (2018). Neurobiological programming of early life stress: Functional development of amygdala-prefrontal circuitry and vulnerability for stress-relted psychopathology. *Current Topics in Behavioral Neurosciences*, *38*, 117–136. doi: 10.1007/7854_2016_42

Voss, P., Thomas, M. E., Cisneros-Franco, J. M., & de Villers-Sidani, É. (2017). Dynamic brains and the changing rules of neuroplasticity: Implications for learning and recovery. *Frontiers in Psychology*, *8*(OCT), 1–11. doi: 10.3389/fpsyg.2017.01657

Wang, Z., Dai, Z., Gong, G., Zhou, C., & He, Y. (2015). Understanding structural-functional relationships in the human brain: a large-scale network perspective. *Neuroscientist*, *21*(3), 290–305. doi: 10.1177/1073858414537560

Weaver, A., Taylor, R. J., Chatters, L. M., & Himle, J. A. (2018). Depressive symptoms and psychological distress among rural African Americans: The role of material hardship and self-rated health. *Journal of Affective Disorders*, *236*, 207–210. doi: 10.1016/j.jad.2018.04.117

Weissman, D. G., Conger, R. D., Robins, R. W., Hastings, P. D., & Guyer, A. E. (2018). Income change alters default mode network connectivity for adolescents in poverty. *Developmental Cognitive Neuroscience*, *30*(January), 93–99. doi: 10.1016/j.dcn.2018.01.008

Williamson, A., Steven Witzel, B., & Steven, B. (2016). Instilling resilience in children of poverty. *The Winthrop McNair Research Bulletin*, *2*, Article 13. Retrieved from http://digitalcommons.winthrop.edu/wmrb%5Cnhttp://digitalcommons.winthrop.edu/wmrb/vol2/iss1/13

Wimer, C., Nam, J., Waldfogel, J., & Fox, L. (2016). Trends in child poverty using an improved measure of poverty. *Academic Pediatrics*, *16*(3), S60–S66. doi: 10.1016/j.acap.2016.01.007

Winston, J. S., O'Doherty, J., & Dolan, R. J. (2003). Common and distinct neural responses during direct and incidental processing of multiple facial emotions. *NeuroImage*, *20*(1), 84–97. doi: 10.1016/S1053-8119(03)00303-3

Yeo, B. T. T., Krienen, F. M., Sepulcre, J., Sabuncu, M. R., Lashkari, D., Hollinshead, M., … Buckner, R. L. (2011). The organization of the human cerebral cortex estimated by intrinsic functional connectivity. *Journal of Neurophysiology*, *106*, 1125–1165. doi: 10.1152/jn.00338.2011.

Yoo, J. P., Slack, K. S., & Holl, J. L. (2009). Material hardship and the physical health of school-aged children in low-income households. *American Journal of Public Health*, *99*(5), 829–836. doi: 10.2105/AJPH.2007.119776

Yoo, J. P., Slack, K. S., & Holl, J. L. (2010). The impact of health-promoting behaviors on low-income children's health: A risk and resilience perspective. *Health and Social Work*, *35*(2), 133–143. Retrieved from https://academic.oup.com/hsw/article/35/2/133/567853

Zanto, T. P., & Gazzaley, A. (2013). Fronto-parietal network: flexible hub of cognitive control. *Trends in Cognitive Sciences*, *17*(12), 602–603. doi: 10.1016/j.tics.2013.10.001

Zhang, F. (2017). Resting-state functional connectivity abnormalities in adolescent depression. *EBioMedicine*, *17*, 20–21. doi: 10.1016/j.ebiom.2017.02.028

Zilanawala, A., & Pilkauskas, N. V. (2012). Material hardship and child socioemotional behaviors: Differences by types of hardship, timing, and duration. *Children and Youth Services Review*, *34*(4), 814–825. doi: 10.1016/j.childyouth.2012.01.008

APPENDICES

A. Aggregated sample characteristics table

Table 3.8 Aggregated sample characteristics table

Measure	Full Sample	Resting-State fMRI Sample	Task-Based fMRI Sample
Sample Size	237	186	168
Age in Years (Mean, SD)	15.41(.54)	15.41(.55)	15.43(.55)
Gender (%, Count)			
Female	52% (124)	55% (102)	54% (91)
Male	48% (113)	45% (84)	46% (77)
Ethnic Racial Identity (Count, %)			
Black/African American (Non-Hispanic)	76% (181)	77% (144)	76% (128)
White/Caucasian	13% (30)	11% (21)	10% (17)
Hispanic/ Latino	4% (10)	5% (9)	5% (9)
Other Non-Hispanic Groups (Asian, Native Americans, Arabs)	2% (5)	2% (4)	3% (5)
Multi-Ethnic/Race	5% (11)	4% (8)	5% (9)
Household Poverty Ratio (Mean, SD)			
Age 1 Wave (n=225)	1.80(1.96)	1.81(1.95)	1.81(1.93)
Age 3 Wave (n=224)	1.83(1.97)	1.79(1.97)	1.85(2.02)
Age 5 Wave (n=226)	1.68(1.74)	1.60(1.64)	1.63(1.65)
Age 9 Wave (n=219)	1.77(1.69)	1.67(1.68)	1.76(1.63)
Age 15 Wave (n=236)	1.95(2.12)	1.98(2.24)	2.06(2.27)
Material Hardship (Mean, SD)			
Age 1 Wave (n=225)	.12(.16)	.12(.16)	.12(.16)
Age 3 Wave (n=224)	.13(.16)	.14(.17)	.13(.16)
Age 5 Wave (n=226)	.15(.17)	.16(.17)	.15(.17)
Age 9 Wave (n=220)	.19(.18)	.20(.19)	.19(.18)
Age 15 Wave (n=236)	.15(.19)	.16(.19)	.15(.19)
Internalizing Sxs Scales			
Depression-CDI	8.42(6.52)	8.73 (6.68)	8.57(6.46)
Anxiety-SCARED	21.51(20.46)	19.68(16.75)	19.48(16.63)
Total N in Connectome Analyses	-	174	134

Note. CDI: Children's depression inventory, score range 0-54, SCARED: Screen for Child Anxiety Related Disorder, score range 0-76; household income poverty ratio drawn from Fragile Families Child Wellbeing Study Longitudinal Data; SD: Standard Deviation

B. Measures: Child Depression Inventory (CDI)

Directions: Kids sometimes have different feeling and ideas. Pick one sentence that describes you ***best*** for the past 2 weeks.		
Item 1. I am sad once in a while. (0) I am sad many times. (1) I am sad all the time. (2)	Item 10. I feel like crying every day. (2) I feel like crying many days. (1) I feel like crying once in a while.(0)	Item 19 Most days I do not feel like eating. (2) Many days I do not feel like eating. (1) I eat pretty well. (0)
Item 2. Nothing will ever work out for me. (2) I am not sure if things will work out for me. (1) Things will work out for me O.K. (0)	Item 11. Things bother me all the time. (2) Things bother me many times. (1) Things bother me once in a while. (0)	Item 20 I do not worry about aches and pains.(0) I worry about aches and pains many times. (1) I worry about aches and pains all the time. (2)
Item 3. I do most things O.K. (0) I do many things wrong. (1) I do everything wrong. (2)	Item 12. I like being with people. (0) I do not like being with people many times. (1) I do not like being with people at all. (2)	Item 21 I do not feel all alone. (0) I feel all alone many times. (1) I feel alone all the time. (2)
Item 4. I have fun in many things. (0) I have fun in some things. (1) Nothing is fun at all (2)	Item 13. I cannot make up my mind about things. (2) It is hard to make up my mind about things. (1) I make up my mind about things easily. (0)	Item 22 I never have fun at school. (2) I have fun in school once in a while. (1) I have fun at school many times. (0)
Item 5. I am bad all the time. (2) I am bad sometimes. (1) I am bad once in a while. (0)	Item 14. I cannot make up my mind about things. (2) It is hard to make up my mind about things. (1) I make up my mind about things easily. (0)	Item 23. I have plenty of friends. (0) I have some friends but I wish I had more. (1) I do not have any friends. (2)
Item 6. I think about bad things happening to me once in a while. (0) I worry that bad things will happen to me. (1) I am sure that terrible things will happen to me.(2)	Item 15. I look O.K. (0) There are some bad things about my looks. (1) I look ugly. (2)	Item 24. My schoolwork is all right. (0) My schoolwork is not as good as before. (1) I do very badly in subjects I used to be good in. (2)
Item 7. I hate myself. (2) I do not like myself. (1) I like myself. (0)	Item 16. I have to push myself all the time to do my schoolwork. (2) I have to push myself many times to do my schoolwork. (1) Doing schoolwork is not a big problem (0)	Item 25. I can never be as good as other kids. (2) I can be as good as other kids if I want to. (1) I am just as good as other kids. (0)
Item 8. All bad things are my fault. (2) Many bad things are my fault. (1) Bad things are not usually my fault. (0)	Item 17 I have trouble sleeping every night. (2) I have trouble sleeping many nights. (1) I sleep pretty well. (0)	Item 26 Nobody really loves me. (2) I am not sure if anybody loves me. (1) I am sure that somebody loves me. (0)
Item 9. I want to kill myself (2) I think about killing myself, but I would not do it (1) I do not think about killing myself (0)	Item 18 I am tired once in a while. (0) I am tired many days. (1) I am tired all the time. (2)	Item 27. I usually do what I am told. (0) I do not do what I am told most times. (1) I never do what I am told. (2)
		Item 28. I get along with people. (0) I get into fights many times. (1) I get into fights all the time. (2)
Source: (Kovacs, 1992)		

C. Measures: Screen for Child Anxiety Related Disorders (SCARED)

Item	Almost Never	Sometimes	Often
1. When frightened, it is hard to breathe	0	1	2
2. I get headaches or stomach aches when I am at school	0	1	2
3. I don't like to be with people I don't know	0	1	2
4. I get scared when I sleep away from home	0	1	2
5. I worry about others not liking me	0	1	2
6. When frightened, I feel like passing out	0	1	2
7. I am nervous	0	1	2
8. I follow my parents wherever they go	0	1	2
9. People tell me that I look nervous	0	1	2
10. I feel nervous with people I don't know well	0	1	2
11. I don't like going to school	0	1	2
12. When frightened, I feel like going crazy	0	1	2
13. I worry about sleeping alone	0	1	2
14. I worry about being as good as other kids	0	1	2
15. When frightened, I feel that things are not real	0	1	2
16. I have nightmares about my parent	0	1	2
17. I worry about going to school	0	1	2
18. When frightened, my heart beats fast	0	1	2
19. I feel weak and shaky	0	1	2
20. I have nightmares about bad things happening to me	0	1	2
21. I worry about things working out for me	0	1	2
22. I am a worrier	0	1	2
23. When frightened, I sweat a lot	0	1	2
24. I get really frightened for no reason	0	1	2
25. I am afraid to be alone at home	0	1	2
26. I find it hard to talk with people I don't know	0	1	2
27. When frightened, I feel like I am choking	0	1	2
28. People tell me I worry too much	0	1	2
29. I don't like being away from my family	0	1	2
30. I am afraid of having anxiety attacks	0	1	2
31. I worry that bad things happen to my parents	0	1	2
32. I am shy with people I don't know well	0	1	2
33. I worry about the future	0	1	2
34. When frightened, I feel like throwing up	0	1	2
35. I worry about how well I do things	0	1	2
36. I am scared to go to school	0	1	2
37. I worry about things that happened in the past	0	1	2
38. When frightened, I feel dizzy	0	1	2
Source: (Birmaher et al., 1997)			