

Mediating effect of pubertal stages on the family environment and neurodevelopment: A
conceptual replication and multiverse analysis of an ABCD Study®

Michael I. Demidenko¹, Dominic P. Kelly¹, Felicia Hardi¹, Ka I Ip², Sujin Lee¹, Sunghyun
Hong¹, Hannah Becker¹, Sandra Thijssen^{3,4}, Monica Luciana⁴, & Daniel P Keating^{1,5}

Author's Note

¹ Department of Psychology, University of Michigan, Ann Arbor, Michigan, USA

² Department of Psychology, Yale University, New Haven, Connecticut, USA

³ Behavioral Science Institute, Radboud University, Nijmegen, the Netherlands

⁴ Department of Psychology, University of Minnesota, Minneapolis, MN, USA

⁵ Institute for Social Research, University of Michigan, Ann Arbor, Michigan, USA

Corresponding Author Information: Correspondence concerning this article should be addressed
to Michael Demidenko, Department of Psychology, University of Michigan, 530 Church St.
2036, Ann Arbor, MI 48109. E-mail: demidenm@umich.edu

Abstract

Increasing evidence demonstrates that environmental factors meaningfully impact the development of the brain (Hyde et al., 2020; McEwen & Akil, 2020). Recent work from the Adolescent Brain Cognitive Development (ABCD) Study® suggests that puberty may indirectly account for some association between the family environment and brain structure and function (Thijssen et al., 2020). However, a limited number of large studies have evaluated what, how, and why environmental factors impact neurodevelopment. When these topics are investigated, there is typically inconsistent operationalization of variables between studies which may be measuring different aspects of the environment and thus different associations in the analytic models. Multiverse analyses (Steege et al., 2016) are an efficacious technique for investigating different operationalizations of the same construct on underlying interpretations. While one of the assets of Thijssen et al. (2020) was its large sample from the ABCD data, the authors used an early release that contained 38% of the full ABCD sample. The analyses used several ‘researcher degrees of freedom’ (Gelman & Loken, 2014) to operationalize key independent, mediating and dependent variables, including but not limited to, the use of a latent factor of preadolescents’ environment comprised of different subfactors, such as parental monitoring and child family conflict. While latent factors can improve reliability of constructs, the nuances of each subfactor and measure that comprise the environment may be lost, making the latent factors difficult to interpret in the context of individual differences. Therefore, this study extends the work of Thijssen et al. (2020) by evaluating the extent that the analytic choices in their study affected their conclusions using multiverse analyses. In Aim 1, using the same variables and models, we extend findings from the original study using the full sample in Release 3.0. Then, in Aim 2, we employ a multiverse analysis to consider nine alternative operationalizations of family, three of puberty, and five of brain measures (total of 135 models) to evaluate the impact on conclusions from Aim 1. We then demonstrate and discuss how different environmental and demographic measures intended to capture stressful experiences in the ABCD data may differentiate findings and interpretations as they relate to puberty and the brain and make recommendations for the future studies using large open datasets, such as the ABCD study.

Introduction

Over the last decade, advances in developmental neuroscience have increased our understanding of the effects of stressful experiences on cognitive and emotional development. Empirical evidence from both animal and human literatures (Bick & Nelson, 2016; Farah, 2017; Hackman et al., 2010; Hanson et al., 2013; McEwen & Akil, 2020; Pizzagalli, 2014) demonstrate that developmental changes in the brain reflect responses and adaptations to stressful environmental conditions. These changes have implications for psychopathology (Hyde et al., 2020), health risk behaviors (Duffy et al., 2018) and public policies relating to poverty (Farah, 2018). However, the measurement of environmental stress (e.g., developmental adversities) has contributed to debates on whether broad characterizations of environmental stressors by researchers meaningfully relate to conclusions about the neural mechanisms (Smith & Pollak, 2020). For example, broad characterizations of a family environment may conceal individual differences in brain-behavior mechanisms that are apparent in specific characterizations, such as parental warmth. Understanding the convergence between broad and specific characterizations in large datasets, such as the Adolescent Brain Cognitive Development (ABCD) Study®, is especially important due large number of environmental, demographic and brain measures that are accessible (Barch et al., 2018; Casey et al., 2018; R. Gonzalez et al., 2021; Zucker et al., 2018). Combining these rich assessments with methods that assess reasonable variations, such as multiverse analysis (Steege et al., 2016), would provide critical insights about the overlap between theoretically valid decisions for future research of environmental experiences.

One way to evaluate the associations between theoretically valid decisions of environmental stressors and conclusions regarding individual differences in neurodevelopment is by thoughtfully extending previously published work. Thijssen et al. (2020) provided much needed evidence of the associations between environmental experiences, puberty, and neurodevelopment in a large sample ($N = 3,183$) of preadolescents from the ABCD study. The authors grounded their work in a strong theoretical framework of a) how stressful family environments have implications for neurodevelopment, and b) how stressful family environments may increase the pace of pubertal development, which may in turn affect changes in the brain. In this work, the family environment is characterized using a higher order factor that is composed of subfactors and subscales. Common to most research studies (Gelman & Loken, 2014), the authors had to make important decisions in how they operationalized this variable of

the family environment, as well as the parental reported puberty scale and different gray matter, white matter tracts and functional coactivation brain measures. These can be considered as ‘researcher degrees of freedom’ (Simmons et al., 2011). While the decisions in Thijssen et al. (2020) were consistent with the theory that motivated the study, other studies measuring environmental adversities in the ABCD study (as we, Demidenko et al. (2021), and others have done (Gonzalez et al., 2020; Petrican et al., 2021; Taylor et al., 2020)) may reasonably impose different decisions and result in different results and conclusions. Thus, given the rich higher order model in Thijssen et al. (2020), we evaluate their core analyses using the multiverse (Steege et al., 2016) and specification curve analyses (Simonsohn et al., 2020) to investigate how the use of different reported environmental and puberty variables in the ABCD study data may impact interpretations and conclusions pertaining to the neural mechanisms.

Measurements of Family Environmental, Puberty and Brain

As discussed above and in Smith & Pollak (2020), there are complex and equally plausible ways to define a stressful environment. This is especially true given the ecological context in which development occurs (Bronfenbrenner & Morris, 2007; Oshri et al., 2020) and how environmental stressors are linked to the developing brain (Hyde et al., 2020). Research studies may impose broad constructs or individual measures of the environment whereas individual measures may strongly reflect single latent factors, understanding the associations of individual measures in a more nuanced way may be valuable to the meaningful interpretation and comparison of findings.

One way to evaluate environmental adversities is to study the quality of a child’s family environment and its potential, associated stressors. Within the ABCD study design, Thijssen et al. (2020) define family environment as a construct encapsulating interactions between family members, socioeconomic status, and psychopathology in the home. It is based on the evolutionary theory of psychosocial acceleration (Belsky et al., 1991), whereby children adapt their development based on their environment, such as caregiving, availability of resources and interpersonal relationships. The latent measure of the family environment used in Thijssen et al. (2020) consisted of child-report of parental conflict, monitoring and acceptance, parent-report of conflict and psychopathology variables, and several demographic questionnaires from the ABCD study. This conceptualization of stressful experiences in the environment, which combines a

variety of factors into a single measure of family environment, is comparable to the cumulative risk approach (Evans et al., 2013; Smith & Pollak, 2020). Given that children often encounter a constellation of risk factors and that the cumulative effect of multiple risks is greater than any singular risk combined (Evans et al., 2013; Gach et al., 2018), examining the aggregated impact of multiple risk factors has been a prominent way to study the impact of stressful family environments.

Contemporary dimensional approaches have examined the impact of environmental stressors as distinct types of adverse events (McLaughlin et al., 2014, 2017, 2021). Dimensions of threat versus deprivation may confer risk for maladaptive outcomes through differential mechanistic pathways (McLaughlin et al., 2021). Importantly, there are high degrees of freedom for researchers on how to operationalize children's environment, depending on one's theoretical perspectives. It is unclear, however, whether various operational approaches (e.g., lumping or splitting) of understanding the same family environment factors may be associated with divergent outcomes (Smith & Pollak, 2020). In fact, Smith & Pollak (2020) argue that by combining a number of variables one may lose information about individuals and critical caregiving factors (Pollak & Smith, 2021) that may be meaningful for understanding mechanistic associations between the family environment and neurodevelopment.

The quality of parenting and resources within an environment are reported as important contributors to socioemotional development, but their associations with neurodevelopment remain unclear. Experiences such as parental separation (Corrás et al., 2017), parent-child and family conflicts (Repetti et al., 2002), or growing up in impoverished environments (Conger et al., 2002; McLoyd, 1998) have been found to increase risks for child behavioral problems (Flouri et al., 2014) and poor functioning in academic settings (Hair et al., 2015). It is proposed that such adversities may accelerate maturation of subcortical structures that are implicated in emotion regulation processes such as the amygdala (Whittle et al., 2014) and anterior cingulate cortex (ACC; Thijssen et al., 2020; Zuo et al., 2019), in addition to their corresponding functional coactivation (Gee et al., 2013; Park et al., 2018; Thijssen et al., 2017). However, there is nuanced variation among the associations between the family environment and neural structures and function. Many studies, for instance, report that brain volume and surface areas are smaller in children of low socioeconomic status (Farah, 2017) or those who were exposed to childhood trauma (De Bellis et al., 1999), but larger in other cases (Tooley et al., 2021). This poses the

question of how broad (e.g., latent factors) and individual measures (e.g., parental conflicts or income) relate to neurodevelopment. In fact, work by Rakesh et al. (2021) using the ABCD study data reported that different constructs of stressful experiences (i.e., neighborhood disadvantage, parental education and high household income-to-needs ratios) were uniquely related to specific functional networks.

The subtleties of the family environment may be especially important as they relate to the effects of environmental adversities and pubertal onsets. For example, adverse family environments have been reported to cause earlier pubertal onset (Belsky, 2019; Ellis & Garber, 2000; Kim & Smith, 1998; Moffitt et al., 1992); however, there are also reports that the effects of early stress on puberty (may) depend on specific experiences (Colich et al., 2020) and child sensitivity to environmental contexts (Ellis et al., 2011). These inconsistencies may in part be attributed to challenges in measuring pubertal development. For instance, parents and children may have differing accounts of child pubertal development. This lack of concordance may be more pronounced at younger ages, including critical prepubertal stages (Clawson et al., 2020; Kapetanovic & Boson, 2020; Yi-Frazier et al., 2016). For boys, physical changes may be less readily apparent to parents (Dorn et al., 2003). These factors suggest that how pubertal development is measured may introduce bias that could produce differing conclusions about the relations between puberty and behavior.

To date, studies using ABCD study data have drawn upon different measures of family environment and puberty when studying neurodevelopment. For instance, studies focused on neurodevelopment have used *latent factors* of family environment (Thijssen et al., 2020), bio-psycho-social ecologies (Gonzalez et al., 2020), neighborhood and family income/stress (Demidenko et al., 2021; Sripada et al., 2021; Taylor et al., 2020) and material deprivation/threat/social support (DeJoseph et al., 2022; Petrican et al., 2021), or *individual scales* of family-to-needs ratios (Gonzalez et al., 2020; Rakesh, Zalesky, et al., 2021), poverty levels (Ellwood-Lowe et al., 2021), parental education (Rakesh, Zalesky, et al., 2021), area deprivation indices (Rakesh, Seguin, et al., 2021; Rakesh, Zalesky, et al., 2021) and parental acceptance (Rakesh, Seguin, et al., 2021). As for measures of pubertal development (see reviews regarding measures and correspondence of pubertal scales: Cheng et al. (2021) and Herting et al. (2021)), published works using ABCD data have used parent-reported pubertal development (Demidenko et al., 2021; McNeilly et al., 2021; Thijssen et al., 2020) and youth/parent reported

averages of pubertal development (Petrican et al., 2021). Given variations in the analytic choices regarding measures of the family environment and puberty, the overall goal of the current analysis is to use a multiverse approach to understand the nuanced associations among stressful family environmental experiences, puberty and neurodevelopment when using broad measures (i.e., latent factors) that are comprised of multiple scales as well as specific measures (i.e., individual scales) that are based on individual scales.

Evaluating Robustness using Multiverse

Multiverse analyses (Steege et al., 2016) have emerged in psychology in response to the replication crisis (Loken & Gelman, 2017; Open Science Collaboration, 2015). In its simplest form, multiverse analyses capture all possible results of analytic choices stemming from reasonable variations of data preparation and variable selections. For example, decisions by researchers to use a median split or latent factor to operationalize a variable, such as measures of environmental adversities. These decisions may at times be considered as ambiguous and thus categorized as a researcher's degrees of freedom in the analytic process (Simmons et al., 2011). For instance, decisions may comprise broad or specific operationalizations of constructs intended to capture different forms of stressful environment experiences (Smith & Pollak, 2020). As the observed data for individuals for different variables varies and our models leverage this variability to make statistical inferences, the multiverse allows the comparison of “*many worlds*” of data (Steege et al., 2016, p. 703) and draws inferences from the *many statistical results*.

The multiverse technique can be used to explore and aggregate how robust an effect is across different measures and model permutations. One approach used to aggregate the results from the multiverse analysis is to use a specification curve (Simonsohn et al., 2020). The specification curve analysis runs all specified model permutations, reporting the range of effects for each model in one panel and the associated variables included in the model for the respective effect in a second panel. This technique provides a visual representation of the variation of positive, negative and neutral effects and their significance across the range of variables that may have *reasonably* been specified in a model.

Multiverse analyses have been used in behavioral and neurodevelopmental work. Orben et al. (2019) evaluated the association between social media use and life satisfaction, reporting inconsistencies that were dependent on how sex was modeled and which analytical method used.

Bloom et al. (2021) used a multiverse analysis to evaluate the robustness of age-related changes in functional activation and brain connectivity in their longitudinal cohort of 4-22 year olds. Across their model permutations, they reported that age-related associations in functional activation in the amygdala to be relatively robust to model permutations but amygdala-medial prefrontal cortex connectivity to be inconsistent across model permutations. Relevant to our study, Rijnhart et al. (2021) used a multiverse analysis to examine indirect, direct and total effects of models evaluating whether fat mass mediated the association between weight change and bone mineral density. Across their models, they observed effects that were consistent and in agreement with existing work, which suggested that association between weight change and bone mineral density was overall robust across alternative analytic decisions in their sample. This demonstrates the feasibility of multiverse analyses to provide nuanced information regarding how key variables and statistical decisions relate to the consistency of evidence relating to prevailing hypotheses.

Current Study

The ABCD Consortium study is longitudinal. Data are released based on a predefined schedule (<https://abcdstudy.org/scientists/data-sharing/>). In the current study we attempt to replicate and extend the findings from primary analyses in Thijssen et al. (2020) that used the Release 1.1 data. The focus is on the association between the (a) environmental variables and (b) preadolescent structural (T1 and diffusion tensor imaging) and resting state coactivations within amygdala-mPFC circuits, and how (c) reported puberty mediates this association. Given that the focus here is on the primary analysis in Thijssen et al. (2020) and the limited variability on the pubertal scale in baseline release of the ABCD study sample (9-10 years old, we do not evaluate the probe the stratified differences of sex.

Our study consists of two aims. For Aim 1, we use identical variables for the Family Environment factor (e.g., parent and youth reported family conflict scale, youth reported parental monitoring and parental acceptance, and parent reported income/education), parent reported puberty measure and five brain measures: Bilateral Amygdala Subcortical, Bilateral Anterior Cingulate Cortex (ACC) Cortical Thickness, Bilateral ACC Cortical Area, Cingulo-Opercular Network and Left Amygdala functional connectivity, and Cingulo-Opercular Network and Right Amygdala functional connectivity, as were used in Thijssen et al. (2020). Part of the results in

Thijssen et al. (2020) were later updated due to changes that were announced by the ABCD consortium regarding the preprocessing of rsfMRI preprocessing data (Thijssen et al., 2021). For Aim 2 we extend Aim 1 findings using a multiverse analysis. Some reasonably assert that, like the definitions in an analysis pipeline, defining the multiverse is often arbitrary (Del Giudice & Gangestad, 2021). Hence, we use alternative derivations of the variables that are modeled in the Family Environment factor, such as sub-factors (i.e., Parent, Child and Demographic factors) and individual scales (e.g., Parental monitoring and Parental Income/Education) which have been and may be used in the ABCD study using theoretical frameworks to obtain numerical representations of stressful experiences in the environment, and identify differences between the use of parent and youth reported pubertal development. With the exception of the Bilateral ACC Fractional Anisotropy variable, the remaining outcome measures of the brain are unchanged. The ACC Fractional Anisotropy was excluded in these analyses as a result of meaningful differences between preprocessing of diffusion weighted data between release 2 and release 3.

In Aim 1, we conduct a *hybrid-replication* of the core overarching family environmental factor mediation results from the original study (using the partial release, 37%, of the baseline ABCD data) in the full release of the baseline data. By the definition of reproducibility and replicability in the literature (Artner et al., 2021), we refer to this as hybrid replication because the baseline ABCD data used here comprises part of the original and 63% new data. We evaluate whether the results replicate by considering two metrics: 1) consistency in direction and significance of the indirect and direct effects in these analyses and the original published work, 2) evaluate whether the estimates from this original study overlapped with the 95% confidence interval for the replication study and 3) a subjective rating of reproducibility of effects (Open Science Collaboration, 2015).

In Aim 2, we extend the core mediation results from Aim 1 by conducting a multiverse analysis that varies along the independent variable (different measures of the family environment) and the mediator (parent reported, youth reported, and youth/parent reported average puberty). Within the constraints of the ABCD study design, we consider the theoretically plausible subfactors and individual scales that may be used in future research to evaluate the family environment, as well as the parent and youth reported variable of pubertal development. We report the results of the multiverse analysis of the mediation model using specification

curves for the direct, indirect and total effects. These results will have important implications for replication and variability of effects using different measures.

Methods

Participants

The ABCD study is composed of 11,878 9- and 10-year-old preadolescents across 21 ABCD research sites (Garavan et al., 2018; Volkow et al., 2018). The analyses in Thijssen et al. (2020) utilized Data Release 1.1 of the ABCD Study, which represented approximately 38% of those preadolescents. For this data replication and extension study, data will be drawn from the Data Release 3.0 (see preregistered **Part1_AggregateData** for specifics¹). Consistent with Thijssen et al. (2020), several exclusion criteria are applied. Participants were excluded if the structural gray matter data was moderately/severely impacted by (1) motion, (2) intensity inhomogeneity, (3) white matter underestimate, (4) pial overestimation, or if the resting state fMRI (5) average framewise displacement value was greater than .55mm and (6) a fieldmap was not collection within two scans. Then, also consistent with the original work, participants were excluded if (1) the guardian completing the survey at the visit was not a biological parent (i.e., biological mother or father), (2) participant is a twin/triplet, and (3) if participants were siblings, one sibling was randomly excluded. This resulted in a sample of 6,658 participants of which N= 2,482 (37%) were represented in the first partial release. The distinction between the first and subsequent releases is based on the August 30, 2017, data cut-off provided by the ABCD Analytics and Resource Center. For more details about the exclusion criteria, please refer to the Part2_Descriptives¹ associated with this OSF preregistration.

Measures

Environmental Measures

Child Items/Factor

¹ The code and more detailed explanations are available for the Stage 1 registered content on GitHub: github.com/demidenm/ABCD_EnvBrainPubert_ReplicateExtend/tree/main/Stage1_Preregistration/Code

An abbreviated measure of maternal acceptance of the *Child Report of Parent Behavior Inventory* (CRPBI; Schaefer, 1965) is used. The 5-item CRPBI is used to assess children's perception of the parent-child dyadic relationship, with a strong emphasis on emotional support from parents. It includes statements such as "Makes me feel better after talking about my worries with him/her" and "Is able to make me feel better when I am upset" which were rated on a 3-point Likert scale ranging from (1) "Not like him/her" to (3) "A lot like him/her". For the individual item scale, items are averaged such that higher scores indicate higher perceptions of parental acceptance.

The youth reported *Family Environment Scale* (FES-Y; Moos & Moos, 1976) is a youth self-report measure that assesses family social environment as perceived by the family member. The FES-Y is a 9-item questionnaire that ascribes the level of conflict within the family using statements such as "We fight a lot in our family" or "Family members often criticize each other" which the participant either responds to as true or false. For the individual item scale, items are averaged such that higher scores indicate higher perceptions of family conflict.

The *Parental Monitoring Survey* (PMON; Chilcoat & Anthony, 1996) is a youth self-report measure that assesses parental monitoring/supervision. The 5 item PMON measures how much the youth believes the parent monitors their whereabouts and includes statements such as "How often do your parents know who you are with when you are not at school and away from home" or "How often do your parents/guardians know where you are?", which were rated on a 5-point likert scale ranging from (1) "Never" to (5) "Always or Almost Always". For the individual item scale, items are averaged such that higher scores indicate higher parental monitoring.

For the current study, the Child Factor is composed of the CRPBI, FES-Y and PMON scales. To account for the reliability of each scale, the confirmatory factor analysis was submitted to `lavaan::cfa()` (Rosseel et al., 2021) in R version 4.0.3 (R Core Team, 2020) with each measure's items loading onto their respective scales (i.e., CRPBI, FES-Y and PMON) and these subfactors were then loaded onto a main Child Factor. Given the ordinal scales, each item was labeled as 'categorical' and all factor variances were constrained to '1'. While there are extensive discussions regarding appropriate fit criteria for Confirmatory Factor Analysis (CFA) models (McNeish & Wolf, 2021), here we use thresholds that are comparable to those in the original paper (Thijssen et al., 2020, p. 689). For the Child Factor, in the current sample the fit

criteria was reasonable: $\chi^2(149) = 1092.6, p < .001$; Comparative Fit Index (CFI) = .97; Tucker-Lewis Index (TLI) = .97; Root Mean Square Error of Approximate (RMSEA) = .03; Standardized Root Mean Square Residual (SRMR) = .05. The loadings of each subscale on the Child Factor were .82 for CRPBI, -.54 for FES-Y and .77 for PMON, which indicated that the Child factor measured positive aspects of the environment. Factor scores were extracted and used in subsequent analyses.

For more details about the variables and code covered in this section, please refer to the files associated with this OSF preregistration on GitHub².

Parent Items/Factor

Similar to the FES-Y, the parent-reported *Family Environment Scale* (FES-P) is a measure that assesses family social environment as perceived by the family member. The FES-P is a 9-item questionnaire that ascribes the level of conflict within the family using statements such as “We fight a lot in our family” or “Family members often criticize each other”, which the participant either responds to as true or false. For the individual item scale, items are averaged such that higher scores indicate higher perceptions of family conflict.

One item measuring conflict from the Kiddie Schedule for Affective Disorders and Schizophrenia (KSADS; Kaufman et al., 1997) was used to assess parental-child conflict. This one item measured the dynamic relationship with the question “In general, how do you and your child get along?”, using a 3-point Likert scale ranging from (1) “Very Well” to (3) “A lot of conflict”. High scores on this item indicate a more negative relationship between the child and parent.

For the current study, the Parent Factor is composed of the FES-P and KSADS scales. To maintain the item/factor structure from Thijssen et al. (2020), two items from the FES-P (Q7 & Q9) were excluded. Like the Child Factor, a CFA was submitted to `lavaan::cfa()` in R with each measure’s items loading onto the Parent Factor. Given the ordinal scales, each item was labeled as ‘categorical’. Using the fit criteria from the original paper, in the current sample the fit criteria for this factor were reasonable, $\chi^2(20) = 947.6, p < .001$, CFI = .93, TLI = .90, RMSEA = .08, SRMR = .10. The positive loadings onto the Parent Factor, indicated that the Parent Factor

² Part3_ExtractFactorScores (Section 3.2) file in the associated Stage 1 code:
https://github.com/demidenm/ABCD_EnvBrainPubert_ReplicateExtend

measured negative aspects of the environment. Factor scores were extracted and used in subsequent analyses.

For more details about the variables and code covered in this section, please refer to the associated files with this OSF preregistration on GitHub³.

Demographic Items/Factor

Youths self-reported their age in months, their sex at birth using options “Male”, “Female”, “Other”, and race/ethnicity, (1) “White, (2) “Black”, (3) “Hispanic”, (4) “Asian”, (5) “Other”. These variables were used as covariates in the all mediation models consistent with Thijssen et al. (2020).

Parents self-reported on income, education, separation and pregnancy variables. For combined household income, parents selected an income category for the past 12 months ranging from (1) “less than \$5,000” to (10) “\$200,000 and greater”, with the option to select “refuse to answer” or “don’t know”. Parents reported on their or their partner's highest level of education by selecting an education category that ranged from (0) “Never Attended” to (21) “Doctoral Degree”, with the option to “refuse to answer” and “don’t know”. Parents reported on their marital status, such as (1) “Married” or (6) “Living with partner” and whether their pregnancy with the child was a planned pregnancy (Yes/No).

Parental psychopathology was assessed using the comprehensive measure from the Achenbach System of Empirically Based Assessment Adult Self-Report (ASRS; Achenbach & Rscorla, 2003). The ASRS assesses different levels of psychopathology, such as anxiety, depression, withdrawal, thought problems and somatic complaints. Here, the t-scored (related to gender at ages 18-35 and 36-59 based on national probability samples) total problems score is used (range 25 to 100), whereby higher values relate to higher problems.

For the current study, the Demographic Factor is composed of income, education, separation, pregnancy and the parental psychopathology variables. Like the Parent and Child Factors, confirmatory factor analysis was submitted to `lavaan::cfa()` in R with each measure’s items loading onto the Parent Factor. Given the ordinal scales, each item except for parental psychopathology was labeled as ‘categorical’. Using the fit criteria from the original paper, in the

³ Part3_ExtractFactorScores (Section 3.2) file in the associated Stage 1 code: https://github.com/demidenm/ABCD_EnvBrainPubert_ReplicateExtend

current sample the fit criteria for this factor were reasonable, $\chi^2(5) = 195.4$, $p < .001$, CFI = .98, TLI = .96, RMSEA = .08, SRMR = .05. The loadings indicate that the Demographic Factor measured negative aspects of the environment. Factor scores were extracted and used in subsequent analyses.

For more details about the variables and code covered in this section, please refer to the associated files with this OSF preregistration⁴.

Family Environment Factor

Similar to the original paper, the Family Environment Factor is a confirmatory factor that is composed of the Child, Parent and Demographic variables. The confirmatory factor analysis was submitted to `lavaan::cfa()` in R. In a single model, the youth reported items representing the family environment (i.e., CRPBI, FES-Y, PMON) loaded onto a Child subfactor, the Parent reported items representing the family environment (i.e. FES-P and KSADS) loaded onto the Parent subfactor, and the demographic items representing the family environment (i.e., Income, Education, Planned Pregnancy, Parental Separation and Parent ASRS) loaded onto the Demographic Subfactors. All subfactors were then loaded onto the overarching Family Environment factor. All factor variances were constrained to '1'. In the model, excluding parental income and parental psychopathology, all categorical items were entered as categorical under the 'ordered' option in `lavaan::cfa`. Using the fit criteria from the original paper, the fit criteria for this factor were reasonable for this sample, $\chi^2(458) = 7079.2$, $p < .001$, CFI = .89, TLI = .89, RMSEA = .05, SRMR = .07. The standardized loadings are Child (Loading: -.56; 95% CI: -.59 to -.54), Parent (Loading: .55; 95% CI: .53 to .58) and Demographic (Loading: .47; 95% CI: .45 to .49). For ease of interpretation, we inverted our family factor scores to ensure it is consistent with the previous study. Higher scores on the Family Environment factor indicate a more positive family environment.

For more details about the variables and code covered in this section, please refer to the associated files with this OSF preregistration on GitHub⁴.

⁴ Part3_ExtractFactorScores (Section 3.2) file in the associated Stage 1 code: : https://github.com/demidenm/ABCD_EnvBrainPubert_ReplicateExtend

Pubertal Stage

The Pubertal Development Scale (PDS; Petersen et al., 1988) assesses the child's pubertal stage. The PDS is a non-invasive measure that assesses current pubertal status in females and males. For females, items assess changes in 1) body hair, 2) breast development and 3) menstruation. For males, items assess changes in 1) body hair, 2) hair on the face and 3) deepening voice. In the ABCD study, there are both youth and parent reported PDS scores. For the individual item scale, items are averaged such that the pubertal category score provides a 1-5 reference for whether a participant is: 1 = "pre puberty"; 2 = "early puberty"; 3 = "mid puberty"; 4 = "late puberty"; or 5 = "post puberty", whereby higher scores indicate further progression in puberty. Here we use the (1) youth self-reported average scores to assess youth reported pubertal development, (2) parent reported average scores that assess parent reported pubertal development and (3) as used in prior ABCD studies (Petrican et al., 2021) the average of parent and youth reported average pubertal development scores.

MRI

Consistent with the original paper, we used the tabulated summary statistics of MRI data concerning the amygdala-anterior cingulate cortex (ACC), provided by the ABCD consortium's data analytic core through their neuroimaging processing algorithm and subject-level analysis plans noted in the Hagler et al. (2019). Our study also examined the MRI data associated with (1) Bilateral Amygdala Subcortical, (2) Bilateral ACC Cortical Thickness, (3) Bilateral ACC Cortical Area, (4) Cingulo-Opercular Network and Left Amygdala functional connectivity, and (5) Cingulo-Opercular Network and Right Amygdala functional connectivity (see Thijssen et al. (2020) study for more details, including the rationale for choosing the brain areas of interest). We do not use the Bilateral ACC Fractional Anisotropy variable, due to the fact that the preprocessing for diffusion weighted imaging data was significantly changed between the first and second release. Data were acquired from T1-weighted anatomical scans, diffusion tensor imaging, and resting-state fMRI (see Casey et al. (2018) for more details). Prior to scanning, participants were invited to experience mock scanners to familiarize themselves with MRI procedures. Head motion was monitored while participants were in the MRI scanners and was corrected for as part of the analyses. MRI preprocessing and analyses information, which were

conducted by the ABCD consortium's data analytic core is in part summarized in the original publication (Thijssen et al., 2020, 2021) and provided in Hagler et al. (2019).

Analytic Plan

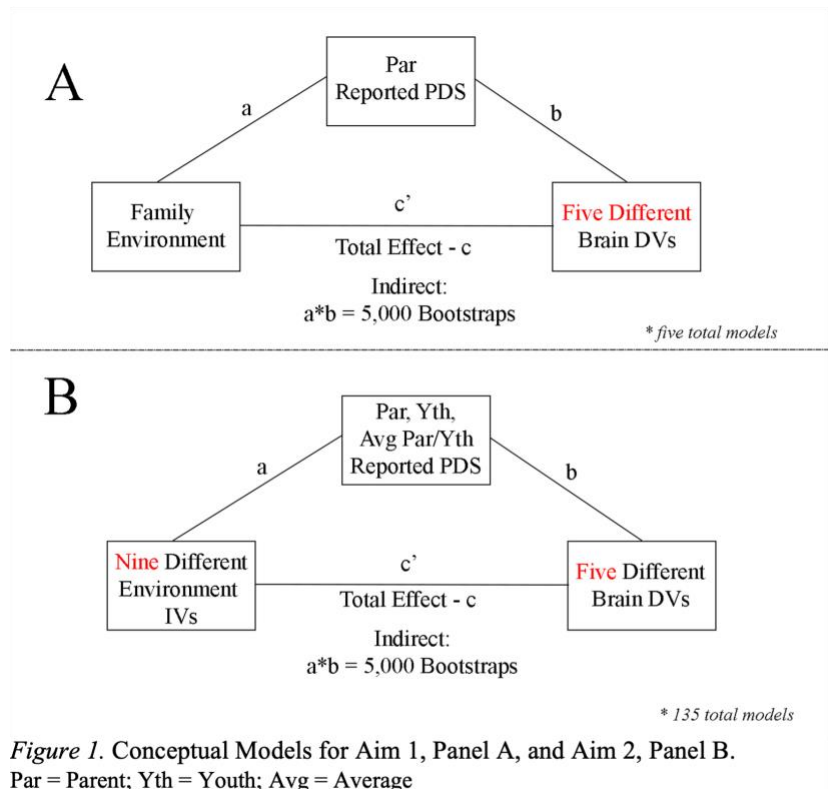
Descriptive statistics were calculated for key demographic variables for this study. Bivariate Pearson correlations (r) are provided for the relations between variables of interest, the subfactors and overarching factors. Distribution plots for each variable are also provided to represent the normality of these variables. Descriptive statistics and the Pearson's correlation tables among the demographic and factor variables are not provided as part of the pre-registration as they are not central to the conceptual replication (Aim 1) and multiverse analyses (Aim 2); see conceptual Figure 1.

The core analyses in this pre-registration are to test the indirect effect of reported pubertal development on the association between the environment on the structure and function of the brain (Thijssen et al., 2020). The mediation model is composed of several parts: path-c, path-a, path-b, path-c' and the indirect effect, as illustrated in traditional mediation analyses (Baron & Kenny, 1986; Mackinnon & Dwyer, 1993) and shown in Figure 1. Path-c is the total effect of the independent variable (IV) exerted onto the dependent variable (DV); path-a is the effect of the IV on the mediator; path-b is the effect of the mediator on the DV adjusted for the IV; and path-c', or the direct effect, is the effect of the IV on the DV adjusted for the effects of path-a and path-b, respectively. The effect of the mediator, or the effect of the IV on DV through the mediator M, is the product of path-a and path-b. For each given model, the total effect (c) is equal to the combination of the direct effect (c') and indirect effect (ab). Given the skew and kurtosis of the indirect effect, R implements bootstrapping to obtain bias-corrected confidence

intervals and p-values (Hayes, 2009). For each of the below models, bootstrapping is held constant at 5,000 sample permutations.

In Aim 1, we replicate the core Mplus mediation results from the Thijssen et al. (2020) study using structural equation modeling in lavaan (Rosseel, 2012) in R version 4.0.3 (R Core Team, 2020). We re-analyze mediation analyses using the IV (Family Environment Factor), the mediator (parent self-reported pubertal development), and the five brain DVs ((1) Bilateral Amygdala Subcortical, (2) Bilateral ACC Cortical Thickness, (3)

Bilateral ACC Cortical Area, (4) Cingulo-Opercular Network and Left Amygdala functional connectivity, and (5) Cingulo-Opercular Network and Right Amygdala functional connectivity, see conceptual Figure 1A). The replication of estimates, specifically indirect and direct coefficients, from the original study and replication in Aim 1 are evaluated using three metrics. First, similar to reports in Open Science Collaboration (2015), for each of the six mediation models in Aim 1, the consistency in a) direction and b) significance of the indirect and direct effects in these analyses and the original published study. Second, acknowledging the sample and measure variability that contribute to our confidence in effects (Patil et al., 2016), for each of the six mediation models, we plot the overlap between the a-path, b-path, indirect, direct, total effects from the original study with their 95% confidence interval (CI) for this replication study, similar to reports of replication in Open Science Collaboration (2015). As a supplementary analysis, we also do the inverse, whereby we overlap the estimate from the replication with the original studies 95% CI. For the original work, we estimate the upper bound 95% CI by adding $1.96 \times \text{Standard Error}$ to β and the lower bound 95% CI by subtracting $1.96 \times \text{Standard Error}$ from β that are published in Figure 1 and Table 4-6 in the original paper. In cases where we could not



calculate this from the original paper, such as for indirect and total effects, we received standard error terms from the original study's authors. Third, out of the list of eight authors on this project that were not part of the original publication, five authors are randomly selected to subjectively rate whether the effect was (1) or was not (0) replicated. The authors inspect the sample size, beta estimates, 95% CI, and p -values from both the original and replication study to derive their conclusion. Based on these ratings, we calculate the fraction of authors, e.g. $n/5$, that concluded whether each effect was replicated from the original to the current study.

In Aim 2, we extend the mediation results in Aim 1 by evaluating the effects across the theoretically plausible multiverse of the *independent* family environment variables and *mediating* pubertal variables (See Table 1 and Figure 1B). Specifically, we consider the theoretically plausible independent variables: Child Factor, Parent Factor, Demographic Factor, and frequently used scales measuring parental acceptance, parental monitoring and family conflict, as reported by the youth and parents, and given their large correlation ($r = .62$) the z-scored average of parent report income and education. Given the nuance in the pubertal scale and dissimilarity discussed above, we consider the theoretically plausible mediator of youth self-reported, parent reported, and the average of youth/parental reported pubertal development.

Similar to the multiverse mediation analyses in Rijnhart et al. (2021), in Aim 2 the mediation results across our 135 mediation model permutations are reported using specification curves (Simonsohn et al., 2020). A specification curve is reported independently for the direct, indirect and total effect, respectively. This is used to represent the distribution of estimated effects across the variable permutations. This is reported in two panels. **Panel A** represents the ordered estimated beta coefficients and their associated significance (null hypothesis is 0) colored based on no significance (gray), negative (red) or positive (blue) significance. **Panel B** represents the analytic decisions (i.e., IV, DV and mediator) that were in the model that produced these ordered estimates. To draw inferences across the specification curve, we report several results. First, like Rijnhart et al. (2021), we report the frequency and direction of the effect across the multiverse compared to the effects in Aim 1. Second, we consider the proportion of effects from Aim 1 that overlap with the 95% CI in Aim 2 for each brain outcome. Finally, we consider the proportion of values that are significant in the direction that is consistent with Aim 1 results. The latter is solely for reporting the percentage of effects that may go unnoticed given the traditional null-hypothesis testing framework and the $p < .05$ threshold that is often used in

psychology research. We set the alpha cut-off ($p < .05$) for the mediation analyses. This is consistent with recent perspectives on multiple comparison corrections in exploratory work (e.g., Rubin, 2021; Thompson et al., 2020). To provide context for deviations across our models, we consider within/between category variation. For instance, we may observe greater similarity in effects across the overarching Family Environment and Parent, Demographics, and Child subfactors than the Family Environment factor and individual scales, as the factors may capture more signal and less noise (Hodson, 2021).

For more details about the variables and code associated with Aim 1 and Aim 2 described in this section, please refer to the associated files with this OSF preregistration on GitHub⁵.

Table 1

Aim 2 Variables for Multiverse Analyses: **IV*M*DV = 135** Total Mediation Models

Environment (IV)	Puberty Scale (M)	Brain (DV)	Covariates (constant)
(1) Family Environment Factor	(1) Par Reported PDS	(1) Bilat. Amygdala SV	Age, Race/Ethnicity, Sex
(2) Parent Factor	(2) Yth Reported PDS	(2) Bilat. ACC CT	
(3) Child Fact	(3) Averaged Par/Yth PDS	(3) Bilat. ACC CA	
(4) Demographic Factor		(4) Left Amygdala-CON rsfMRI	
(5) FES Youth		(5) Left Amygdala-CON rsfMRI	
(6) FES Parent			
(7) Parental Monitoring			
(8) Parental Acceptance			

⁵ Part4_MediationSpecificationCurve file in the associated Stage 1 code:
https://github.com/demidenm/ABCD_EnvBrainPubert_ReplicateExtend

(9) z-scored Parental Income/Education			
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PDS = Pubertal Development Scale; Yth = Youth; Par = Parent; FES = Family Environment Scale; Bilat = Bilateral

Average; ACC = Anterior Cingulate Cortex (rostral/caudal average); CON = Cingulo-Opercular Network; SV =

Subcortical Volume; CT = Cortical Thickness; CA = Cortical Area; IV = Independent Variable; M = Mediator; DV =

Dependent Variable

Results

For this pre-registration, we have populated descriptive statistics for some key demographic variables (Table 2), distributions (Figure 2) and correlations (Figure 3) for several key variables.

Table 2.

Sample Descriptives Across Different Releases and for Final Sample

	Total Release	Release Pre Aug 8, 2018	Release Post Aug 8, 2018	Final Sample
	N=11878	N=4743	N=7135	N=6658
	<i>Mean (SD)</i>			
Age (Months)	119 (7.50)	120 (7.33)	118 (7.53)	119 (7.46)
Parent Report - PDS	1.76 (0.868)	1.72 (0.850)	1.78 (0.880)	1.78 (0.876)
Missing, <i>N</i> (%)	472 (4.0%)	136 (2.9%)	336 (4.7%)	261 (3.9%)
Youth Report - PDS	2.08 (0.834)	2.08 (0.833)	2.08 (0.834)	2.09 (0.828)
Missing, <i>N</i> (%)	2336 (19.7%)	415 (8.7%)	1921 (26.9%)	1312 (19.7%)
	<i>N</i> (%)			
Sex				
F	5682 (47.8%)	2262 (47.7%)	3420 (47.9%)	3291 (49.4%)
M	6196 (52.2%)	2481 (52.3%)	3715 (52.1%)	3367 (50.6%)
Family Income				

Less than \$5,000	417 (3.5%)	104 (2.2%)	313 (4.4%)	253 (3.8%)
\$5,000 through \$11,999	421 (3.5%)	133 (2.8%)	288 (4.0%)	235 (3.5%)
\$12,000 through \$15,999	274 (2.3%)	79 (1.7%)	195 (2.7%)	155 (2.3%)
\$16,000 through \$24,999	524 (4.4%)	186 (3.9%)	338 (4.7%)	296 (4.4%)
\$25,000 through \$34,999	654 (5.5%)	237 (5.0%)	417 (5.8%)	399 (6.0%)
\$35,000 through \$49,999	934 (7.9%)	363 (7.7%)	571 (8.0%)	519 (7.8%)
\$50,000 through \$74,999	1499 (12.6%)	634 (13.4%)	865 (12.1%)	820 (12.3%)
\$75,000 through \$99,999	1572 (13.2%)	692 (14.6%)	880 (12.3%)	906 (13.6%)
\$100,000 through \$199,999	3315 (27.9%)	1382 (29.1%)	1933 (27.1%)	1800 (27.0%)
\$200,000 and greater	1250 (10.5%)	556 (11.7%)	694 (9.7%)	683 (10.3%)
Refuse to answer	512 (4.3%)	192 (4.0%)	320 (4.5%)	289 (4.3%)
Don't Know	504 (4.2%)	185 (3.9%)	319 (4.5%)	301 (4.5%)

Education

Never attended/Kindergarten only	0 (0%)	0 (0%)	0 (0%)	0 (0%)
1st grade	2 (0.0%)	0 (0%)	2 (0.0%)	1 (0.0%)
2nd grade	1 (0.0%)	1 (0.0%)	0 (0%)	1 (0.0%)
3rd grade	10 (0.1%)	3 (0.1%)	7 (0.1%)	7 (0.1%)

4th grade	8 (0.1%)	1 (0.0%)	7 (0.1%)	5 (0.1%)
5th grade	3 (0.0%)	0 (0%)	3 (0.0%)	2 (0.0%)
6th grade	62 (0.5%)	21 (0.4%)	41 (0.6%)	41 (0.6%)
7th grade	21 (0.2%)	7 (0.1%)	14 (0.2%)	13 (0.2%)
8th grade	61 (0.5%)	22 (0.5%)	39 (0.5%)	36 (0.5%)
9th grade	136 (1.1%)	39 (0.8%)	97 (1.4%)	82 (1.2%)
10th grade	107 (0.9%)	38 (0.8%)	69 (1.0%)	62 (0.9%)
11th grade	193 (1.6%)	56 (1.2%)	137 (1.9%)	118 (1.8%)
12th grade	182 (1.5%)	55 (1.2%)	127 (1.8%)	106 (1.6%)
High school graduate	992 (8.4%)	339 (7.1%)	653 (9.2%)	555 (8.3%)
GED or equivalent	268 (2.3%)	77 (1.6%)	191 (2.7%)	156 (2.3%)
Some college	1950 (16.4%)	753 (15.9%)	1197 (16.8%)	1087 (16.3%)
Associate: Occup	874 (7.4%)	335 (7.1%)	539 (7.6%)	466 (7.0%)
Associates: Academic	664 (5.6%)	258 (5.4%)	406 (5.7%)	370 (5.6%)
Bachelor's degree	3333 (28.1%)	1452 (30.6%)	1881 (26.4%)	1849 (27.8%)
Master's degree	2280 (19.2%)	984 (20.7%)	1296 (18.2%)	1259 (18.9%)
Professional School (MD)	334 (2.8%)	147 (3.1%)	187 (2.6%)	205 (3.1%)
Doctoral degree	380 (3.2%)	149 (3.1%)	231 (3.2%)	228 (3.4%)

Refuse to Answer	17 (0.1%)	6 (0.1%)	11 (0.2%)	9 (0.1%)
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Race

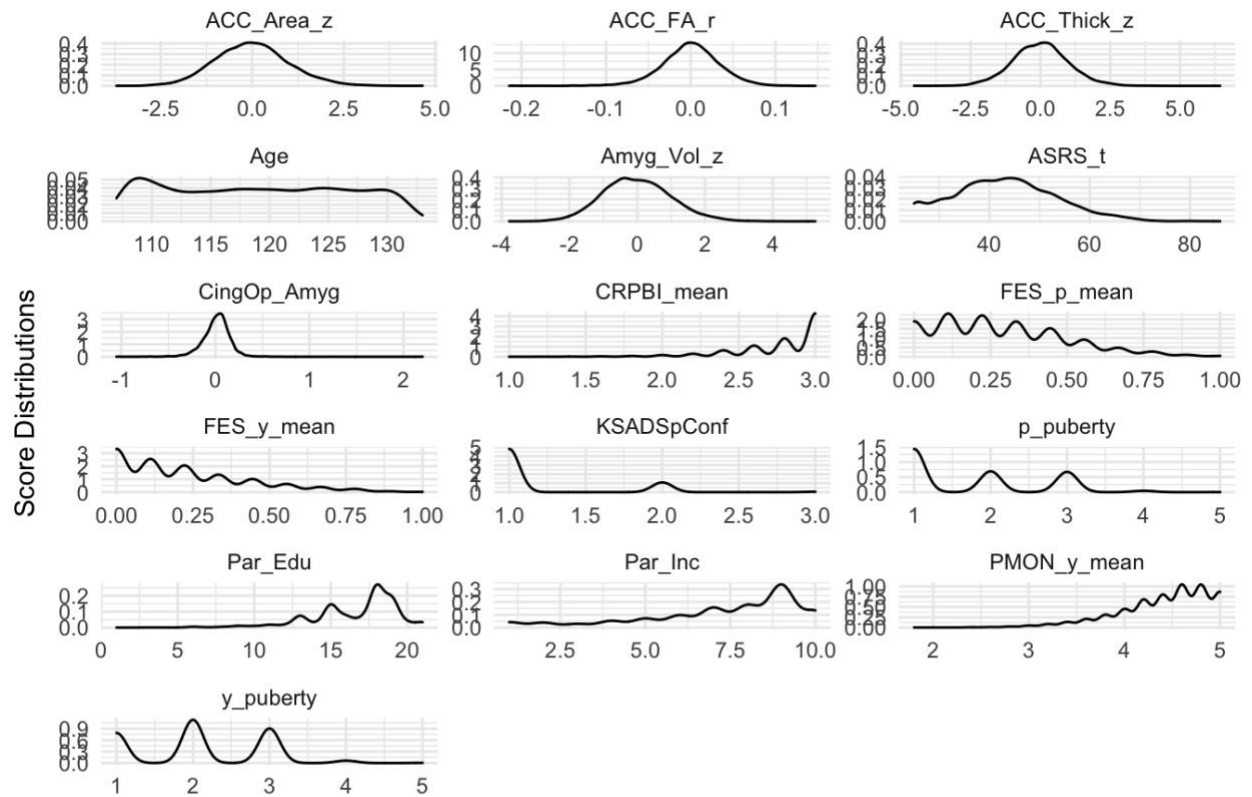
White	6182 (52.0%)	2777 (58.5%)	3405 (47.7%)	3427 (51.5%)
Black	1784 (15.0%)	468 (9.9%)	1316 (18.4%)	897 (13.5%)
Hispanic	2411 (20.3%)	934 (19.7%)	1477 (20.7%)	1536 (23.1%)
Asian	252 (2.1%)	106 (2.2%)	146 (2.0%)	148 (2.2%)
Other	1247 (10.5%)	458 (9.7%)	789 (11.1%)	650 (9.8%)

Parents' Marital Status

Married	7991 (67.3%)	3349 (70.6%)	4642 (65.1%)	4506 (67.7%)
Widowed	97 (0.8%)	49 (1.0%)	48 (0.7%)	40 (0.6%)
Divorced	1082 (9.1%)	470 (9.9%)	612 (8.6%)	567 (8.5%)
Separated	464 (3.9%)	152 (3.2%)	312 (4.4%)	262 (3.9%)
Never Married	1460 (12.3%)	449 (9.5%)	1011 (14.2%)	808 (12.1%)
Living with Partner	688 (5.8%)	253 (5.3%)	435 (6.1%)	411 (6.2%)
Refused to Answer	94 (0.8%)	21 (0.4%)	73 (1.0%)	62 (0.9%)

Before/After Aug 30, 2017 Cut-off

Release 1	4743 (39.9%)	-	-	2482 (37.3%)
Release 2	7135 (60.1%)	-	-	4176 (62.7%)



_y = youth, _p = parental; FES, CRPBI, PMON are averages of items.

Figure 2. Distributions for several key variables

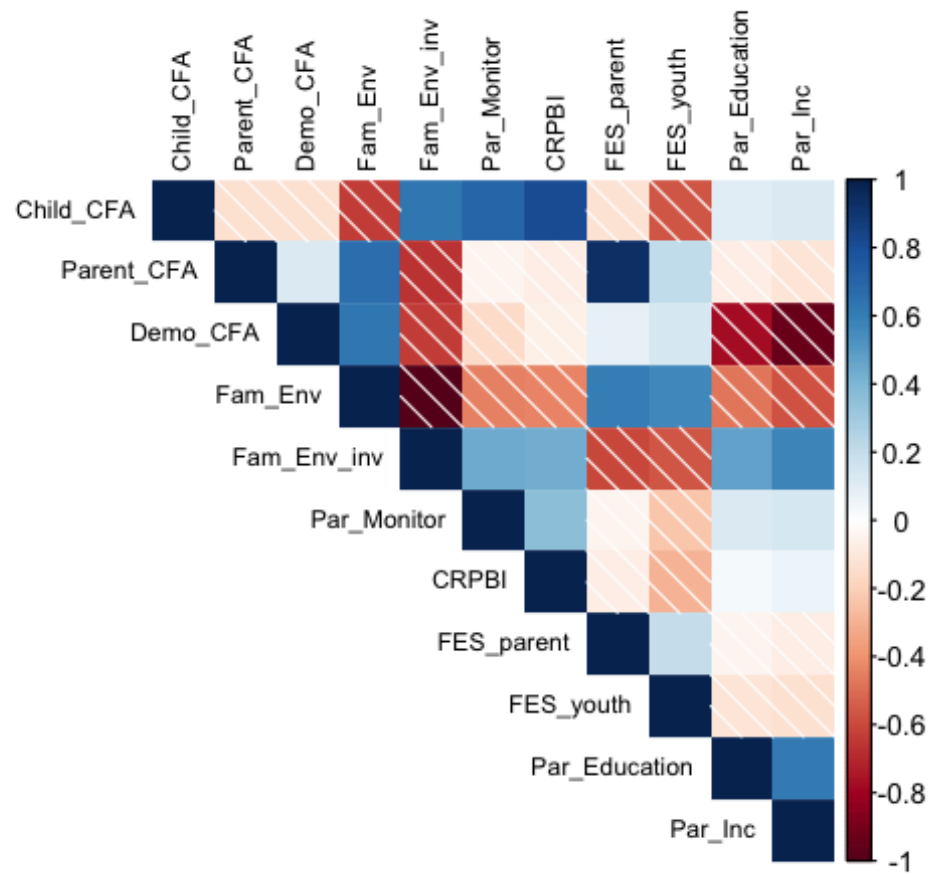


Figure 3. Correlation for several key variables and factors proposed in Aim 2

Aim 1: Conceptual Replication

[TBD]

Aim 2: Multiverse Analyses

[TBD]

Discussion

[TBD]

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