SupplementalOnline Content

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eMethods. Supplemental Methods

eFigure 1. Flowchart of Final Sample

eFigure 2. Distribution of PM2.5 Annual Average Exposure by ABCD Site

eFigure 3. Directed Acyclic Graph

eFigure 4. Associations Between PM2.5 Exposure and Mean Diffusivity

eTable 1. Description of Covariates Used in Statistical Analyses

eTable 2. Comparison of Population Characteristics Across Data Sets

eTable 3. Distributions of Population Characteristics at Baseline in Relation to Annual Average $PM_{2.5}$

eTable 4. PM2.5-by-Hemisphere Analyses for RSI Outcomes

eTable 5. Percent Change in RSI rN0 Across Values of PM_{2.5} and Sociodemographic Characteristics for Significant Hemisphere-Specific Models

eTable 6. PM2.5-by-Hemisphere Analyses for DTI Outcomes

eTable 7. Percent Change in DTI MD Across Values of PM_{2.5} and Sociodemographic Characteristics for Significant Hemisphere-Specific Models

This supplemental material has been provided by the authors to give readers additional information about their work.

eMethods. Supplemental Methods

ABCD study design and sample characteristics: Sample recruitment at the ABCD study sites and schematic overview of the ACBD study has been reported previously in detail ¹⁻⁷. Participants were enrolled via school-based recruitment system in which any children at selected schools were invited to participate. Inclusion criteria for the ABCD study were: 1) age 9.00 to 10.99 years at the time of baseline assessment; 2) able to validly and safely complete the baseline visit including MRI; 3) Fluent in English. The ABCD study population is intended to represent a population-based, nonclinical sample; thus exclusion criteria included severe sensory, intellectual, medical, and neurological disorders (such as cerebral palsy, brain tumor, stroke, brain aneurysm, brain hemorrhage, subdural hematoma, multiple sclerosis, sickle cell disease, Lennox-Gastaut syndrome, Dravet syndrome, and Landau Kleffner syndrome), a history of traumatic brain injury, a diagnosis of schizophrenia, moderate or severe autism spectrum disorder, intellectual disability, gestational age less than 28 weeks and birthweight less than 1.2 kilograms, birth complications (besides those associated with prematurity) that resulted in hospitalization for more than a month, and a diagnosis of alcohol/substance abuse ⁸. Additionally, exclusion criteria included conditions that would prevent children from completing ABCD study protocols, including MRI contraindications and non -correctable vision, hearing, or sensorimotor impairments⁹.

Study sites obtained approval from their local institutional review boards (IRBs) and centralized IRB approval was obtained from the University of California, San Diego. All parents or caregivers provided written informed consent; each child provided written assent.

MRI scans performed during the baseline study visit were reviewed by neuroradiologists and classified according to the following categorical scoring system in order to identify and flag incidental findings: 0, image artefacts prevent radiology read; 1, no abnormal findings; 2, normal anatomic variant or common incidental finding, no referral necessary; 3, consider referral; 4, consider immediate referral 10 . During data cleaning for this analysis, only subjects with scans in categories 1 or 2 were retained, and subjects in ca tegories 0, 3, or 4 were excluded. A previous study investigating the rates of incidental findings brain MRIs of the ABCD study cohort did not find systematic differences in the study population with respect to the MRI categorical scoring system ¹⁰. Within the study dataset used in this analyses, a total of 2,412 subjects were removed on the bases of serious incidental MRI findings, poor quality MRI scans (see below), or missing MRI data.

Further data cleaning involved removing subjects with nonva lid addresses (i.e. no estimate for average annual $PM_{2.5}$ exposure); we also randomly selected only one sibling from each family (eFigure 1). For most demographic variables, the children included in the final analytic sample were statistically similar to th e overall ABCD population, with the exception of the 'race/ethnicity' variable (eTable1); children in the final sample were slightly more likely to be parent-identified as white or Hispanic and slightly less likely to be parent-identified as Black or Other ($p = 0.03$). The children in the final sample were also more likely to have been scanned in an MRI machine produced by Siemens, and less likely to have been scanned in a machine produced by GE Medical systems or Philips Medical Systems ($p < 0.001$). They also had lower overall frame displacement (mm) during MRI scanning $(p < 0.001)$; this was to be expected, as removing subjects with high frame displacement was a step in the data cleaning process. For a full breakdown of subjects removed during data cleaning and a comparison between the baseline dataset and the final analytic dataset, see eTable 2.

Imaging pulse sequences, and image processing methods: T1-weighted anatomical acquisition was a 3D T1 weighted inversion prepared RF-spoiled gradient echo scan using prospective motion correction when possible, at the resolution of 1mm isotropic. The diffusion weighted acquisition utilized a multi-shell, multiband Echo Planar Imaging (EPI) with a slice acceleration factor of 3 at the resolution of 1.7mm isotropic a nd 96 gradient directions, including: 7 b0s and 4 b-values (6 directions with $b=500 \text{ s/mm}^2$; 15 direction with $b=1000 \text{ s/mm}^2$; 15 directions with $b=2000$ s/mm²; and 60 directions with $b=3000$ s/mm²).

Quality Control: Automated quality control procedures include the calculation of metrics such as signal-to-noise ratio (SNR) and head motion statistics. For DWI series, head motion was estimated by registering each frame to a corresponding image synthesized from a tensor fit, accounting for variation in image contrast across diffusion orientations. An overall head motion is quantified as the average of an estimated frame-to-frame displacement (FD; mm) from head motion. ¹¹. At the central ABCD Data Analysis, Informatics, and Resource Center (DAIRC), all images underwent quality control $(QC)^{-12}$. Trained technicians at the DAIRC then inspect images for quality control (see 12 for details). Only image types with motion < 2mm and images that passed a rigorous QC for all categories (i.e. imgincl dmri include $= 1$) were included in our final analyses. These QC categories include the following: the images had no serious MRI findings requiring clinical referral, the imaging series passed a raw quality control inspection, the total number of repetitions for all 'OK' scans was 103 or more, the T1 series passed a raw QC inspection, the B0 unwarp data was available, the FreeSurfer QC did not fail, the imaging passed a manual post-processing QC test, the maximal dorsal cutoff score was less than 47, and that maximal ventral cutoff score was less than 54.

Preprocessing: Preprocessing of the diffusion weighted images included: eddy current correction ¹³; head motion correction ¹¹; adjustment of gradients for head motion 11,14; robust tensor fit to identify and exclude dark frames due to abrupt head motion¹⁵; B₀ distortion and gradient distortion correction using opposite phase encoding pairs of b=0s $16,17$; b0 registration to T1-weighted structural images using mutual information 18 ; and cubic interpolation to resample at the 1.7 isotropic resolution.

Fiber tractography: Details regarding fiber tract segmentation have been previously published (see 12 for details). A probabilistic atlas-based method was utilized via AtlasTrack ¹¹. This fiber atlas contains prior probabilities and orientation information for specific projection fibers. For each subject, sMRI images were nonlinearly aligned to the atlas using discrete cosine transforms ¹⁹, and diffusion derived orientation were compared to the atlas fiber orientation in order to refine *a priori* tract locations to create individualized fiber tract regions of interest. Voxels primarily comprised on gray matter or cerebral spinal fluid as derived by FreeSurfer's automated brain segmentation 20 , are excluded from analysis.

Restriction spectrum imaging (RSI): RSI modeling was implemented for separate fiber orientation density (FOD) functions to model, as fourth order spherical harmonic functions, two volume fractionsincluding intracellular and extracellular diffusion within a single voxel 2^{1-23} . Longitudinal diffusion parameter was held constant for both fractions at $1x10^{-3}$ mm²/s and for the intracellular fraction the transverse diffusion parameter was modeled as 0, whereas the extracellular fraction set the transverse parameter to $0.9x10^{-3}$ mm²/s. Measures of interest derived from the RSI model included the directional (rND) and isotropic (rN0) intra -cellular diffusion (e.g. restricted water bounded by membrane of cells) and total hindered extra -cellular diffusion (hD; e.g. hindered space around the neurites) spaces ¹². Each of these measures is normalized and is defined as the Euclidean norm (square root of the sum of squares) for the corresponding model coefficients divided by the norm of all model coefficients. As such, these measures are unitless and range from 0 to 1 and the square of each measure is equivalent to the signal fraction for their respective model components. N0 is derived from the 0th order spherical harmonic coefficients of the restricted fraction and is the contribution of intracellular space to isotropic diffusion in a given voxel. ND is calculated from the 2nd order spherical harmonic coefficients of the restricted fraction and reflects oriented diffusion. ND is thought to be similar to FA except is less affected by crossing fivers. hD is calculated from the norm of the

 $0th$, $2nd$, and $4th$ order coefficients of the hindered fractions, and reflects the overall contribution of diffusion from the extracellular space ¹².

Diffusion tensor image (DTI): DTI outcomes were calculated using a standard, linear estimation approach 24 using the 6 directions at $b=500 \text{ s/mm}^2$, 15 directions at $b=1000 \text{ s/mm}^2$.

Covariates: A full description of each covariate used in statistical analyses can be found in eTable 1. The inclusion of each covariate was decided upon using a directed acyclic graph (DAG) 25 to identify confounders that may predict white matter development and exposure to ambient air pollutants (eFigure 3). Selection of potential confounders were based on both prior knowledge and empirical data 26 . Specifically, race and ethnicity and socioeconomic status were included in this analysis due to abundant previous evidence that large disparities in magnitude and severity of air pollution exposure exist along racial and socioeconomic lines $27-29$. As previously reported 9 , distribution of annual $PM_{2.5}$ exposures are associated with both demographic and social covariates in the ABCD sample (see eTable 3). Therefore, all models in the main analysis were adjusted for sociodemographic covariates, including: a) child's sex, age and race/ethnicity; b) family socioeconomic status (SES): highest education (of any household member), total household income, parental employment status; c) neighborhood quality: average score of three-items assessing parent perspectives of neighborhood safety ³⁰, and for MRI covariates, including an indicator of the imaging device manufacturer, subject's hand dominance, and average framewise displacement to account for MRI motion.

PM_{2.5} exposure estimates capture both local and regional sources of air pollution, and the urban built environment is likely to impact $PM_{2.5}$ exposure. In sensitivity analyses, we assessed additional confounding effects of population density and distance to road. Specifically, residentially derived United Nations population density was measured as persons per km² (based on population counts of the 2010 national census tract adjusted for potential underreporting across the world) 31 as a proxy for urbanicity, and distance to major roads and highways in meters 32 was treated as a categorical variable reflecting those living <150, 150-300m, 300-600m, or > 600m based on previous studies showing that near-roadway pollutants decay to background levels by approximately 115-570m 33 . An exploratory analysis was also conducted to assess whether interaction exists between annual ambient PM $_{2.5}$ exposure and sex at birth.

Statistical analysis:

Statistical models: Based on a directed acyclic graph (DAG) approach ²⁵, we identified potential confounders of interest and then examined potential differences in socio-demographic factors across PM2.5 quintiles using analysis of variance (ANOVA) for continuous variables and Pearson's Chi-square test for categorical variables. We employed hierarchical mixed effects models in R to analyze the associations between annual average residential PM2.5 exposure and tract-specific RSI and DTI measures. An exploration of the shapes of the association highlighted potential non-linearity in most, but not all, of the associations; thus, we opted to use a natural spline function with two knots (PM_{2.5} = 7.05 ug/m³ and 8.31 ug/m³) to allow for flexibility in the associations between annual PM_{2.5} exposure and white matter microstructure. Knots were selected according to tertiles of the overall $PM_{2.5}$ exposure distribution. Knot selection was performed by fitting a series of models with increasing numbers of knots (starting with one), until we determined that model fit was not improved by the addition of new knots. Due to the large number of tracts and outcomes to evaluate, we chose to retain the same natural spline structure for all models – even when there was not strong evidence for non-linearity – in order to simplify interpretations of results and comparisons between outcomes and tracts. As previous studies have found hemispheric differences in brain imaging outcomes, we examined a cross-product term of $PM_{2.5}$ by hemisphere to assess whether an interaction between PM_{2.5} exposure and hemisphere exists (Equ 1). We then examined the associations between PM_{2.5} exposure and RSI and DTI measures in hemisphere-stratified models (Equ 2). For all models, we included a random intercept for ABCD sites (*j*) in order to account for between-site variability (Equ 1 and 2). For models with a cross-product term by hemisphere, we included a nested random effect for subject (*i*) in order to account for within-subject variability in MRI readings in two hemispheres (Equ 1). In a sensitivity analysis, we explored the possibility of geographic variability in the associations between PM2.5 exposure and our outcomes by fitting Equ. 2 models with random slopes by site. All models were also adjusted for the sociodemographic covariates described above (denoted W_i) and the MRI covariates described above (denoted Z_i). In Equations 1 and 2, y_{ij} denotes the measured outcome of interest (e.g. DTI or RSI outcome) for participant *i*, from study site *j* at baseline (ages 9-10). x_i denotes a personalized summary of PM_{2.5} exposure (e.g., assigned to residential address of the 9-10 year old participant i). S_m denotes the mth spline term and δ_m denote the parameter estimate for the S_m spline. M indicates the total number of spline terms in the model. Finally, random effects at the level of study site, and, in Equation 1, at the subject level, are denoted.

$$
Y_{ij} = \beta_0 + \sum_{m=1}^{M} [\delta_m S_m(x_j)] \times Hemisphere + \beta_1 W_i + \beta_2 Z_i + U_{[i]j} + \varepsilon_{ij}
$$
 Equ. 1

$$
Y_{ij} = \beta_0 + \sum_{m=1}^{M} [\delta_m S_m(x_j)] + \beta_1 W_i + \beta_2 Z_i + U_j + \varepsilon_j
$$
 Equ. 2

Statistical Model Interpretation

Spline models do not allow for a straightforward interpretation of model coefficients. Therefore, in order to quantify the magnitude of associations between $PM_{2.5}$ exposure and RSI/DTI outcomes and to capture shifts in the direction and magnitude of associations across the range of $PM_{2.5}$ exposure, we calculated percent change in modelpredicted values for RSI and DTI outcomes across increments in $PM_{2.5}$ exposure as follows. All spline models were fit to the entire analytic dataset, with PM_{2.5} exposures ranging from 1.72 to 15.90 μ g/m³. Percent change estimates are only reported to allow for easier interpretation and quantification of associations. Model-predicted estimates, or marginal means,(denoted *E*) with standard errors for outcome variables were obtained at three levels of PM2.5 exposure $(4 \mu g/m^3, 8 \mu g/m^3,$ and $12 \mu g/m^3$) with all other covariates held constant. $8 \mu g/m^3$ was chosen as a central inflection point by visual inspection of our spline plots (Figures 2 and 3), most of which demonstrate a shift in the slope of association at around 8 µg/m³. We opted to exclude model-predicted marginal means below 4 µg/m³ and above $12 \mu g/m^3$ from our percent change calculations due to the high uncertainty associated with these exposure levels; relatively few datapoints (less than 3% of the dataset) exist at these levels of exposure ($n = 165$). Percent change in outcome was then calculated across 4 µg increments of PM2.5 exposure (Equ. 3). Percent change in DWI outcomes was also calculated across levels of two other model predictors: household income and across a 6-month increase in age. These were calculated as reference points to compare age- and sociodemographic-related differences in white matter outcomes with our main findings related to air pollution-associated differences in our outcomes. The standard errors for the percent change calculations (denoted *SE*) was estimated using the approach outlined in the U.S. Census Bureau's documentation for calculating percent change within the American Community Survey Data ³⁴, using standard errors obtained from model-predicted estimates (Equ. 4).

$$
Percent Change = \frac{E_{\text{upper}} - E_{\text{lower}}}{E_{\text{lower}}} * 100
$$
 Equ. 3

$$
SE = \left| \frac{E_{\text{upper}}}{E_{\text{lower}}} \right| * \sqrt{\frac{SE_{\text{upper}}^2}{E_{\text{upper}}^2} + \frac{SE_{\text{lower}}^2}{E_{\text{lower}}^2}} * 100
$$
 Equ. 4

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eFigure 2. Distribution of PM2.5 annual average exposure by ABCD site

eFigure 3. Directed acyclic graph

Directed Acyclic Graph of potential confounders that may predict white matter neurodevelopment and exposure to ambient air pollutants

eFigure 4. Associations between PM2.5 Exposure and Mean Diffusivity

Annual average PM_{2.5} exposure relates to decreases in mean diffusivity (MD) in 8 tracts of interest. Spline plots reflect modelpredicted values of MD in relation to annual average PM_{2.5} exposure, with all other model covariates held constant. Sagittal and coronal illustrations of relevant white matter tracts are provided in main Figure 3 for reference and colored to match spline plots. Abbreviations: ATR = anterior thalamic radiations (green); CC = corpus callosum (red); CGH = cingulum hippocampal portion (yellow); FX = fornix (magenta); IFO = inferior fronto-occipital (lime green); ILF = inferior longitudinal fasciculus (purple); UNC = $uncinate$ (blue); $SLF = superior$ longitudinal fasciculus (turquoise).

eTable 1. Description of covariates used in statistical analyses

eTable 2. Comparison of population characteristics across datasets

^a P-value from the Pearson *χ-squared* test comparing the distributions of categorical variables between the full ABCD baseline dataset and the final analytic dataset *or* P-value from the ANOVA test comparing means of continuous variables between the full ABCD baseline dataset and the final analytic dataset.

Columns represent the full baseline ABCD dataset, the final analytic dataset, and sub-datasets representing subjects that were removed during data cleaning.

eTable 3. Distributions of population characteristics at baseline in relation to annual average PM2.5.

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Note: Percentages are indicated row-wise.
ª The "Other" race/ethnicity category includes subjects who were parent-identified as American Indian/Native American, Alaska

Native, Native Hawaiian, Guamanian, Samoan, Other Pacific Islander, Asian Indian, Chinese, Filipino, Japanese, Korean,

Vietnamese, Other Asian, or Other Race
^b P-value from the Pearson *χ-squared* test comparing the quintile distribution of PM_{2.5} across categorical variables.

P-value from the ANOVA test comparing means of continuous variables across the quintiles of PM_{2.5}.

		rN0			rND			hD	
	Marginal		p-	Marginal			Marginal		
Tracts	R ²	Conditional R ²	value	R ²	Conditional R ²	p-value	R^2	Conditional R ²	p-value
			$\,<\,$						
ATR	0.1596	0.8859	0.000	0.381	0.8142	< 0.000	0.2283	0.8082	< 0.000
CGC	0.1897	0.8236	0.014	0.4175	0.7176	< 0.000	0.3327	0.7549	< 0.000
			$\,<\,$						
CGH	0.1662	0.784	0.000	0.3628	0.7786	< 0.000	0.2983	0.8052	< 0.000
			$\,<\,$						
CST	0.2692	0.9005	0.000	0.2869	0.8392	0.0026	0.1887	0.8727	< 0.000
			$\,<\,$						
FX	0.1496	0.8357	0.000	0.1736	0.7895	0.1906	0.0939	0.7745	0.0804
			$\,<\,$						
IFO	0.1248	0.869	0.000	0.4453	0.8832	< 0.000	0.3097	0.8903	< 0.000
			$\,<\,$						
ILF	0.083	0.8401	0.000	0.2808	0.833	< 0.000	0.1556	0.8565	< 0.000
			$\,<\,$						
SLF	0.1323	0.8924	0.000	0.3585	0.8791	< 0.000	0.1875	0.8902	< 0.000
			$\,<\,$						
UNC	0.0627	0.8221	0.000	0.417	0.834	< 0.000	0.3131	0.8349	< 0.000
All			$\,<\,$						
Fibers	0.1127	0.9563	0.000	0.4695	0.9686	< 0.000	0.2683	0.9696	< 0.000

eTable 4. PM2.5-by-hemisphere Analyses for RSI outcomes.

 R^2 values and FDR-corrected P-values resulting from Type III Analysis of variance (Satterthwaite Method) for RSI measures

eTable 5. Percent change in RSI rN0 across values of PM2.5 and sociodemographic characteristics for significant hemisphere-specific models

		FA		MD			
	Marginal R^2	Conditional R ²	p-value	Marginal R^2	Conditional R ²	p-value	
ATR	0.4944	0.8724	< 0.000	0.5400	0.9147	< 0.000	
CGC	0.5050	0.774	< 0.000	0.4559	0.8394	< 0.000	
CGH	0.5336	0.8282	< 0.000	0.6355	0.9221	< 0.000	
CST	0.4082	0.8677	0.003	0.6673	0.9662	< 0.000	
FX	0.5033	0.8665	< 0.000	0.6280	0.948	< 0.000	
IFO	0.5663	0.9111	< 0.000	0.4814	0.9406	< 0.000	
ILF	0.4515	0.8377	0.02	0.2934	0.9057	< 0.000	
SLF	0.4900	0.8751	< 0.000	0.1998	0.9132	< 0.000	
UNC	0.5181	0.8638	< 0.000	0.4008	0.8951	< 0.000	
All Fibers	0.6404	0.9788	< 0.000	0.5133	0.9841	< 0.000	

eTable 6. PM2.5-by-hemisphere Analyses for DTI outcomes.

 R^2 values and FDR-corrected P-values resulting from Type III Analysis of variance (Satterthwaite Method) for DTI measure

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