Journal Pre-proof

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PII: S0013-9351(23)02194-1

DOI: https://doi.org/10.1016/j.envres.2023.117390

Reference: YENRS 117390

To appear in: *Environmental Research*

Received Date: 4 April 2023

Revised Date: 24 August 2023

Accepted Date: 11 October 2023

Please cite this article as: Campbell, C.E., Cotter, D.L., Bottenhorn, K.L., Burnor, E., Ahmadi, H., Gauderman, W.J., Cardenas-Iniguez, C., Hackman, D., McConnell, R., Berhane, K., Schwartz, J., Chen, J.-C., Herting, M.M., Air pollution and age-dependent changes in emotional behavior across early adolescence in the U.S., *Environmental Research* (2023), doi: https://doi.org/10.1016/j.envres.2023.117390.

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Abstract

Recent studies have linked air pollution to increased risk for behavioral problems during development, albeit with inconsistent findings. Additional longitudinal studies are needed that consider how emotional behaviors may be affected when exposure coincides with the transition to adolescence – a vulnerable time for developing mental health difficulties. This study investigates if annual average $PM_{2.5}$ and NO_2 exposure at ages 9-10 years moderates age-related changes in internalizing and externalizing behaviors over a 2-year follow-up period in a large, nationwide U.S. sample of participants from the Adolescent Brain Cognitive Development (ABCD) Study®. Air pollution exposure was estimated based on the residential address of each participant using an ensemble-based modeling approach. Caregivers answered questions from the Child Behavior Checklist (CBCL) at the baseline, 1-year follow-up, and 2-year follow-up visits, for a total of 3 waves of data; from the CBCL we obtained scores on internalizing and externalizing problems plus 5 syndrome scales (anxious/depressed, withdrawn/depressed, rule-breaking behavior, aggressive behavior, and attention problems). Zero-inflated negative binomial models were used to examine both the main effect of age as well as the interaction of age with each pollutant on behavior while adjusting for various socioeconomic and demographic characteristics. Against our hypothesis, there was no evidence that greater air pollution exposure was related to more behavioral problems with age over time.

Keywords: air pollution; internalizing; externalizing; adolescence; neurodevelopment

1. Introduction

Mental health conditions remain a global health challenge for all age groups (World Health Organization, 2018), but the risk for onset of psychopathology is highest in childhood and adolescence. Both internalizing and externalizing symptoms typically emerge during adolescence (Achenbach et al., 1991). Moreover, up to approximately 20% of children and adolescents are affected by mental health problems worldwide (Polanczyk et al., 2015) with half of all lifetime mental health conditions diagnosed by age 14 years (Kessler et al., 2005). To reduce societal costs and improve quality of life for affected individuals, research on modifiable risk and resilience factors holds the promise to potentially uncover new avenues for early prevention and intervention.

Recent evidence indicates that outdoor air pollution may contribute to increased risk for mental health conditions (Braithwaite et al., 2019; Zundel et al., 2022). A growing body of literature has associated ambient exposure to fine particulate matter ($PM_{2.5}$) and nitrogen dioxide (NO_2) with mental health outcomes in children, adolescents, and adults, including symptoms of anxiety, depression, and aggression in children, as well as increased risk for attention deficit and hyperactivity disorder (ADHD) and delinquency problems (Forns et al., 2016; Margolis et al., 2016; Newman et al., 2013; F. Perera et al., 2016; F. P. Perera et al., 2014; Thygesen et al., 2020; Yorifuji et al., 2016, 2017). However, recent comprehensive reviews of how air pollution relates to anxiety and depression (Zundel et al., 2022) and attention problems (Myhre et al., 2018) highlight a number of inconsistencies and important knowledge gaps in the broader air pollution and mental health literature. For example, while most studies found positive associations between air pollution exposure and anxiety and depression, 25% of studies did not find associations or reported mixed effects, and fewer than 10% examined air pollution exposure during the susceptible window of childhood and adolescence. Even within the developmental literature, there are mixed results: some studies suggest prenatal through adolescent exposure is linked to more internalizing problems (Brokamp et al., 2019; Brunst et al., 2019; B. Fan et al., 2019; Margolis et al., 2016; Rasnick et al., 2021; Yolton et al., 2019), where others have failed to find an association (Jorcano et al., 2019; Zhao et al., 2019). Thus, additional research is needed to clarify the relationship between air pollution exposure and mental health behaviors during the developmental periods of childhood and adolescence.

Importantly, most previous studies have been limited to cross-sectional assessment of mental health outcomes and/or are limited in terms of both the geographic and sociodemographic diversity of their study sample. Discrepancies in results may also be due in part to both differences in the window of exposure as well as the timing of the behavioral evaluation, especially given the known developmental patterns in symptom onset. For example, a recent study of 8 European cohorts found that neither prenatal nor early life exposure was related to cross-sectional outcomes of depression, anxiety, or aggression behavior using the Child Behavior Checklist (CBCL) or Strengths and Difficulties Questionnaire (SDQ) when assessed in mid-to-late childhood (Jorcano et al., 2019); however, this study was limited by examining only one time point of internalizing and externalizing behaviors. Given that the frequency and intensity of emotional problems vary across childhood and adolescence (Barch et al., 2021), it is important to consider how air pollution exposure may contribute to mental health problems over time. For example, Roberts and colleagues (Roberts et al., 2019) found that while exposure to higher levels of $PM_{2.5}$ and NO_2 at age 12 years was not associated with concurrent mental health conditions, it did successfully predict a 1.5 fold increased risk for developing major depressive disorder at 18 years of age. Similarly, Reuben and colleagues (2021) found that exposure to nitrous oxides (NO_X) in childhood predicted later onset of internalizing, externalizing, and thought disorder symptoms at age 18 years. The latter two studies suggest that exposure during childhood and adolescence may lead to greater mental health problems overtime, emphasizing the importance in assessing emotional and behavioral problems longitudinally. Thus, additional large-scale longitudinal studies are warranted to further investigate if exposure in late childhood may moderate changes in emotional behavior problems as individuals transition to early adolescence.

Beyond the considerations of timing of the exposure and longitudinal assessment of the outcome, questions also remain as to the potential health effects of air pollution below the current air quality standards. That is, despite significant declines in air pollution, recent epidemiological studies continue to find links between adverse health effects and levels of exposure well below the Environmental Protection Agency (EPA)'s specified annual averages for $PM_{2.5}$ (<= 12 $\mu g/m^3$) and NO_2 (<=53 *parts per billion; ppb*) (Dominici et al., 2019). This emerging body of research showing that negative health effects can be observed at low concentrations of exposure suggests that no observable threshold may be considered "safe" (for review, see Papadogeorgou et al., 2019). As such, the World Health Organization (WHO) updated their regulatory guidelines on ambient air quality in September 2021, recommending that annual averages of $PM_{2.5}$ and NO_2 not exceed 5 $\mu g/m^3$ and 10 $\mu g/m^3$ (equivalent to 5.33 *ppb*) respectively (World Health Organization, 2021). Previous literature linking behavioral problems with ambient air pollution observed relationships with exposure levels that largely exceed both current EPA standards and WHO recommendations. Thus, further research is necessary to investigate to what degree lower levels of exposure seen across the U.S. may influence developmental changes in emotional behavior in today's youth.

Leveraging the large (N=11,876), nationwide, and socio-demographically and geographically diverse Adolescent Brain Cognitive Development (ABCD) Study® cohort (Jernigan et al., 2018), the current study aimed to examine whether air pollution exposure at ages 9-10 years may relate to longitudinal changes in behavioral and emotional problems over a 2-year follow-up period. The ABCD Study® comprises 21 study sites across the United States and implements an identical protocol for recruitment and data collection of all participants (Garavan et al., 2018; Lisdahl et al., 2018). Given the extant literature (Cory-Slechta et al., 2023; Reuben et al., 2021; Roberts et al., 2019; Zundel et al., 2022) and also limited availability of ABCD exposure data (C. C. Fan et al., 2021), our study focused on one-year annual average $PM_{2.5}$ and NO_2 exposures at ages 9-10 years. With relatively low concentrations of $PM_{2.5}$ and NO_2 in the ABCD Study (Cserbik et al., 2020; C. C. Fan et al., 2021), the current study aims to address links between air pollution and mental health in those regularly exposed to concentrations largely below EPA standards. Given previous findings (Brokamp et al., 2019; Brunst et al., 2019; B. Fan et al., 2019; Margolis et al., 2016; Rasnick et al., 2021; Yolton et al., 2019), we *a priori* chose to examine internalizing and externalizing summary scores from the Child Behavior Checklist (CBCL), as well as distinct internalizing syndrome subscales of anxious/depressed and withdrawn/depressed, and externalizing syndrome subscales of rule-breaking and aggressive behavior, and the independent subscale of attention, thus addressing a wide range of internalizing and externalizing behaviors. We hypothesized that higher exposure levels during late childhood would predict more emotional problems over the 2-year follow-up period.

2. Materials and methods

2.1 Study Design and Participants

The current study utilized data from the larger ongoing nationwide ABCD Study® (NDA 4.0 data release 2021, https://abcdstudy.org/scientists/data-sharing/), which enrolled over 11,876 9- and 10-year-old participants across the USA from 2016-2018 with plans to follow subjects for up to 10 years (Garavan et al., 2018; Jernigan et al., 2018; Volkow et al., 2018). The 21 study sites obtained approval from their local Institutional Review Board (IRB) and a centralized IRB approval was obtained from the University of California, San Diego. Written informed consent was provided by each child's parent or legal guardian (hereafter, "caregiver"); each child provided verbal assent. All ethical regulations were complied with during data collection and analysis. Primary inclusion criteria for ABCD Study participants included age (9.0 to 10.99 years at baseline visit), fluency in English, and the ability to complete the baseline visit. For the current analysis, we utilized data from the first 3 waves of annual data collection, with the additional inclusion criteria of having a valid primary residential address at baseline for all subjects. Given both the extant literature on potential neurotoxic and mental health effects (Cory-Slechta et al., 2023; Reuben et al., 2021; Roberts et al., 2019; Zundel et al., 2022) and data availability (C. C. Fan et al., 2021), the current study focused on investigating both $PM_{2.5}$ and NO_2 exposures. Given the distribution of the outcome data and analytic approach required for hypothesis testing (see section 2.5 below), complete predictors were required for each wave of data collection. A flowchart of our target population for our analyses can also be found in **Supplemental Figure 1**. We also selected data collected before March 1, 2020, to avoid any potential confounding effects of stress on mental health outcomes related to the COVID-19 pandemic (Hamatani et al., 2022; Kiss et al., 2022; Yip et al., 2022). Lastly, we randomly selected one subject per family to reduce the hierarchical structure of our data from 4 levels (time point, subject, family, site) to 3 levels (time point, subject, site). This resulted in a final sample of 9,273 unique participants: 9,271 for baseline, 8,759 for 1-year follow-up, and 5,827 for 2-year follow-up (**Table 1**). A comparison of the overall ABCD cohort with our final analytical sample at baseline, 1-year, and 2-year follow-up can be found in **Supplemental Table 1**, **Supplemental Table 2**, and **Supplemental Table 3**, respectively. All variable names used in the following analyses are documented in **Supplemental Table 4**.

152 **Table 1. Demographics**

	Baseline	1-year follow-up	2-year follow-up
N	9271	8759	5827
Sex assigned at birth			
Female	4413 (47.6%)	4154 (47.4%)	2747 (47.1%)
Male	4858 (52.4%)	4605 (52.6%)	3080 (52.9%)
Age at data collection			
Mean (SD)	9.91 (0.62)	10.91 (0.63)	11.92 (0.64)
Range	8.92 - 11.08	9.75 - 12.42	10.58 - 13.67
Race/ethnicity			
Black	1363 (14.7%)	1221 (13.9%)	678 (11.6%)
Hispanic	1958 (21.1%)	1800 (20.6%)	1198 (20.6%)
Other	1191 (12.8%)	1126 (12.9%)	715 (12.3%)
White	4759 (51.3%)	4612 (52.7%)	3236 (55.5%)
Caregiver education			
< HS Diploma	460 (5.0%)	405 (4.6%)	257 (4.4%)
HS Diploma/GED	899 (9.7%)	800 (9.1%)	460 (7.9%)
Some College	2423 (26.1%)	2247 (25.7%)	1466 (25.2%)
Bachelor	2310 (24.9%)	2217 (25.3%)	1551 (26.6%)
Post Graduate Degree	3179 (34.3%)	3090 (35.3%)	2093 (35.9%)
Caregiver employment			
Employed	6444 (69.5%)	6146 (70.2%)	4139 (71.0%)
Stay at Home Parent	1612 (17.4%)	1516 (17.3%)	1002 (17.2%)
Unemployed	539 (5.8%)	481 (5.5%)	299 (5.1%)
Other	676 (7.3%)	616 (7.0%)	387 (6.6%)
Neighborhood safety			
Mean (SD)	3.873 (0.976)	3.884 (0.971)	3.915 (0.948)
Range	1.000 - 5.000	1.000 - 5.000	1.000 - 5.000
Household income			
<$50k	2564 (27.7%)	2335 (26.7%)	1597 (27.4%)
≥$50K & <$100K	2419 (26.1%)	2312 (26.4%)	1597 (27.4%)
≥$100K	3514 (37.9%)	3418 (39.0%)	2307 (39.6%)
Don’t know or refuse	774 (8.3%)	694 (7.9%)	429 (7.4%)

153 Demographic composition of the final sample across three waves of data collection.

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2.2 Estimation of Annual Air Pollution Exposure

Details regarding the collection of residential addresses and linkage to one-year annual average ambient $PM_{2.5}$ and NO_2 have been previously published in detail by Fan and colleagues (2021). Briefly, daily pollutant estimates were derived at a 1-km^2 resolution using hybrid spatiotemporal models that combine satellite-based aerosol optical depth models, land-use regression, and chemical transport models (Di et al., 2019, 2020). The cross-validation of these models with EPA monitored levels across the U.S. were found to perform well, with R^2 Root Mean Square Error of 0.89 for $PM_{2.5}$ annual averages and 0.84 for NO_2 annual averages (Di et al., 2019, 2020). These daily estimates were then averaged over the 2016 calendar year, when the children were aged 9-10 years-of-age and assigned to the geocoded primary residential address at the baseline ABCD study visit. $PM_{2.5}$ is reported in micrograms per meter cubed ($\mu g/m^3$) and NO_2 is reported in parts per billion (*ppb*). For subjects who have data indicating their time lived at baseline address (N=9,027), the mean was 5.4 years (standard deviation = 3.75). Average yearly consistency of spatial contrast for each pollutant based on daily estimates at the 1-km^2 resolution is also presented in the supplement (**Supplemental Figure 2**), as well as the variability in air pollution estimates across ABCD participants by site (**Supplemental Figure 3**).

2.3 Emotional Behavior

At each annual visit (baseline, 1-year follow-up, 2-year follow-up), the participant's caregiver was asked to report on the child's emotional behavior over the 6 months prior to each study visit using the Child Behavioral Checklist (CBCL) (Achenbach, 2009; Achenbach & Rescorla, 2001). The CBCL within the ABCD Study has 112 different items that each caregiver answers about their child (e.g., "Show little interest in things around him/her") using a 3-point Likert-type scale (0 = Not True, 1 = Somewhat or Sometimes True, 2 = Very True or Often True). These answers are then used to calculate summary scores of internalizing and externalizing behaviors. Based on the prior air pollution and behavioral literature (Brokamp et al., 2019; Brunst et al., 2019; B. Fan et al., 2019; Margolis et al., 2016; Rasnick et al., 2021; Yolton et al., 2019; Zundel et al., 2022), we also chose to examine five additional syndrome subscale scores: anxious/depressed, withdrawn/depressed, rule-breaking behavior, aggressive behavior, and attention problems. Anxious/depressed and withdrawn/depressed subscales fall within the internalizing score, rule-breaking and aggressive behavior subscales fall within the externalizing score, and attention is an independent subscale. Each raw score is a whole number with higher integers indicating increased problem or emotional behaviors, across syndrome scores, such that syndrome score is each on the same scale. While there are age- and sex-normalized scores, we chose to utilize the raw scores to allow us to investigate developmental changes in these behaviors with age, as has been previously done when examining ABCD Study data (Barch et al., 2021). Importantly, the CBCL measures show good test-retest reliability (Pearson's correlations mean = 0.9, min=0.82, max=0.94) and internal consistency was stable over a 12- and 24-month period (Pearson's correlation 12-month mean = 0.74, 24-month mean = 0.70) (Achenbach & Rescorla, 2001). The cross-informant agreement between parent and youth using CBCL items has been found to be strong across multi-cultural societies [Q correlations for U.S.= .84] and similar across internalizing and externalizing behaviors (Rescorla et al., 2013). The raw scores have different ranges by subscale: internalizing [0,64], externalizing [0,70], anxious/depressed [0,26], withdrawn/depressed [0,16], rule-breaking [0,34], aggressive [0,36], and attention [0,20], but all subscales use the same Likert scale units, with higher values indicative of greater problems.

2.4 Confounders and Covariates

We have selected potential confounders based on both prior knowledge and current theories in environmental epidemiology using a directed acyclic graph (Greenland & Brumback, 2002) (**Supplemental Figure 4**). Specifically, we identified confounders that may predict emotional behavior and exposure to ambient air pollutants. All of these variables were reported by the child's caregiver using the PhenX Toolkit (Echeverria et al., 2004; Mujahid et al., 2007). This list includes child's sex, race/ethnicity (non-hispanic white, hispanic, non-hispanic black, other: includes American Indian/Native American, Alaska Native, Native Hawaiian, Guamanian, Samoan, Other Pacific Islander, Asian Indian, Chinese, Filipino, Japanese, Korean, Vietnamese, or Other Race not listed), indicators of family socioeconomic status (e.g., highest caregiver educational attainment, caregiver's employment status, combined total annual household income), as well as perceived neighborhood quality. Highest caregiver educational attainment included <high school diploma, high school diploma or GED, some college, bachelor's degree, or postgraduate degree. Caregiver's employment status included employed (part- or full-time), stay at home parent, unemployed, or other (e.g., temporarily laid off; sick leave; retired; disabled, etc.). Combined total annual household income included less than or equal to $50,000, greater than $50,000 but less than $100,000, greater or equal to $100,000, or don't know/refuse to answer. Perceived neighborhood quality was an average score of three-items assessing parent perspectives of how safe and free from crime and violence they felt their neighborhood is (Mujahid et al. 2007). Each of these variables' baseline values were used in the model, to align with the timing of the available ambient air pollution estimates. To account for potential confounding of co-exposure, we also included the other air pollutant as an additional variable (i.e., when examining the influence of $PM_{2.5}$-by-age on CBCL outcomes, NO_2 is added to the model, and vice versa). Importantly, multicollinearity was not an issue in adjusting for the other pollutant in the model as the Pearson correlation coefficient between the baseline annual pollutant concentrations of $PM_{2.5}$ and NO_2 across all sites was low ($r = 0.22$).

2.5 Analyses

All statistical analyses were implemented in R (version 4.1.2) (R Core Team, 2021). Initial descriptive and exploratory analysis were conducted to check all data for potential errors and outliers, and to assess variable distributions required to satisfy modeling assumptions and understand correlations. To investigate how annual $PM_{2.5}$ and NO_2 moderate emotional development of adolescents over 3 visits spaced 1-year apart, we used a multilevel (i.e., mixed effects) modeling approach to account for the repeated measures. We verified our models were appropriate by checking model assumptions post analyses based on prior published methodology (Cameron & Trivedi, 2013; Garay et al., 2011; Hilbe, 2011).

2.5.1 Reasoning for Modeling Choice

While previous cross-sectional studies examining CBCL outcomes and air pollution have examined the CBCL t-scores (F. P. Perera et al., 2011, 2012), raw CBCL scores are required to better account for developmental changes in emotional behaviors over time when using a repeated measures design (Barch et al., 2021). Furthermore, when multilevel approaches are required, a common modeling approach is to use a linear mixed-effects model, but since CBCL outcomes are naturally zero-inflated (**Supplemental Figure 5**) and thus over-dispersed (over-dispersion quotient ranges from 2.84-17.29), this can lead to artificial inflation of the coefficients' significance (LAND et al., 1996; Stroup, 2016;

Swartout et al., 2015). Thus, we utilized CBCL raw scores as count data and employed a zero-inflated negative binomial (ZINB) model, which adds an extra parameter that accounts for the over-dispersion present (Xu et al., 2017). The *glmm.zinb()* function was used within the NBZIMM package (version 1.0) (https://github.com/nyiuab/NBZIMM); a manuscript detailing the development of this package was also published (Zhang & Yi, 2020). This modeling approach has been used in numerous studies with zero-inflated health data (Preisser et al., 2016; Sheu et al., 2004), and specifically when examining mental health outcomes (Kumagai et al., 2021; Vyas et al., 2020). For even further reading on the ZINB approach, we have cited additional readings (Fang et al., 2016; Stroup, 2012; Yau et al., 2003; Young et al., 2022; Zhang & Yi, 2020).

2.5.2 Final dataset for ZINB model

To implement the ZINB model, complete predictors across timepoints (i.e., no missing values for each subject at each wave of data collection) is required; therefore, listwise deletion was used to remove incomplete data by wave of data collection, making sure at each wave of data collection, each subject had a CBCL outcome score, age at session, race/ethnicity, sex at birth, $PM_{2.5}$ level at year of baseline visit, NO_2 level at year of baseline visit, caregiver's highest level of education at baseline, caregiver's employment status at baseline, perceived neighborhood safety at baseline, and household income at baseline. Since we only had data for our main predictors – $PM_{2.5}$ and NO_2 – at the baseline visit, our environmental covariates and confounders were also only from the baseline visit. Following our initial cleaning steps, creating a dataset across timepoints with complete predictors led to 6%, 5%, and 3% of missing data for the baseline, 1-year, and 2-year follow-up visits, respectively. Bennett (2001) states that greater than 10% missingness could lead to bias within the statistical analysis and prior published literature suggest 5% (on average) missingness is negligible (Jakobsen et al., 2017; Schafer, 1999). Therefore, given the limited amount of missing data, we chose not to perform multiple imputation.

2.5.3 Age-only ZINB models

For the main analysis, the ZINB model combines two models: 1) zero-inflated model, similar to a logistic regression, that evaluates the likelihood of being in the certain-zero (i.e., no problems) as compared to the non-zero category (i.e., exhibits problems), and 2) count model, assuming a negative binomial distribution, that evaluates the non-zero CBCL subscale scores (i.e., magnitude of problems). Initially, age-only models were performed to establish changes in CBCL outcomes from baseline and two 1-year follow-up periods. These models investigated the main effect of age on each CBCL outcome controlling for necessary covariates in both the zero-inflated and count portions of the model (sex-at-birth, race/ethnicity, highest caregiver educational attainment at baseline, caregiver's employment status at baseline, perceived neighborhood safety at baseline, and the combined total annual household income at baseline). For the random effects within the zero-inflated portion of the model, we only included ABCD site since subjects within the certain-zero group were not strongly clustered by subject (low intraclass correlation coefficients (ICC) for all CBCL outcomes: 0.070-0.107). For the random effects within the count model, subject was nested within a random effect of site to account for the within-subject similarities over time in those with non-zero data (ICCs ranging from 0.506-0.710; this medium-high ICC implies a clustering structure of subject within the non-zero data). For ease of interpretation, age was centered at 9 years, the youngest integer age in our cohort.

2.5.4 Age-by-air pollutant ZINB models

To investigate if air pollution modifies emotional problems over time, we added in an interaction between age and each air pollutant ($PM_{2.5}$ or NO_2). For both the zero-inflated model and the count model we utilized the fixed effects of each pollutant ($PM_{2.5}$ or NO_2), age, pollutant-by-age, while adjusting for the same potential confounders as mentioned above; each pollution-by-age model also corrected for the other pollutant (e.g., for the $PM_{2.5}$-by-age model, NO_2 was added as a confounder in addition to the previously mentioned covariates, and vice versa for the NO_2-by-age model). For the random effects within the zero-inflated portion of the model, we again only included ABCD site and for the random effects within the count model, again, subject was nested within a random effect of site. $PM_{2.5}$ and NO_2 were centered to the levels recommended by the WHO, 5 μg/m^3 and 5.33 ppb, respectively, and age was again centered at 9 years. For models where the interaction term between pollution and age was not significant for both the zero-inflated and count portion of the model, the interaction term was dropped, and the model was run to examine the main effect of pollution.

2.5.5 Type-1 error correction

For all above models, to avoid type-1 errors, all *p*-values of interest were corrected for multiple comparisons across the same model type using the false-discovery rate of 5% by utilizing the Benjamini-Hochberg procedure ($p_{FDR} < 0.05$) (Benjamini & Hochberg, 1995), which has been used previously with a ZINB modeling approach (Subramaniyam et al., 2019). All model assumptions post analyses were also conducted based on prior published methodology (Cameron & Trivedi, 2013; Garay et al., 2011; Hilbe, 2011).

2.5.6 Model interpretation

In terms of interpreting our $PM_{2.5}$ results, we focused on displaying the predictions of the EPA annual daily standard ($PM_{2.5}$ = 12 μg/m^3) as compared to the WHO's recommended target level of 5 μg/m^3. For NO_2, our sample's exposure levels were much less than the 53 ppb previously set by EPA in 1971 (US EPA, 2016). Thus, for NO_2 we focused on comparing predictions at 26.1 ppb, based on the 90th percentile of our sample, as compared to the WHO recommended 5.33 ppb. Lastly, given that very large sample sizes tend to identify very small differences as significant, we were sure to also interpret our results in context of effect sizes in order to assess if results were likely to be clinically significant as defined by (Jacobson & Truax, 1991), which requires not only statistical significance, but also a change either in the range of the "dysfunctional population" or "within the range of the functional population".

3. Results

Descriptives of our analytical dataset separated by baseline, 1-year, and 2-year follow-up can be found in **Table 1**. The mean for $PM_{2.5}$ for the total current sample was 7.706 μg/m^3 (range=1.722-15.902 SD=1.571) and for NO_2 it was 18.595 ppb (range=0.729-37.940; SD=5.571), which on average falls significantly below the EPA standards (p's<0.0001) of 12 μg/m^3 and 53 ppb, respectively. Furthermore, descriptives of CBCL outcomes across each collection wave are presented in **Supplemental Table 5**.

3.1 Internalizing Behavior

3.1.1 Changes in internalizing behavior with age

There was a significant main effect of age for the zero-inflated portion of the model, demonstrating a 45% increase in the likelihood of having no internalizing problems (i.e., obtaining a true-zero) with increasing age of the child from 9 to 12 years-old (**Figure 1)**. For individuals who did experience internalizing symptoms (i.e., modeled by the count portion of the model), there was no significant change in the number of internalizing problems reported from 9 to 12 years of age.

3.1.2 Moderating effects of air pollution

The aforementioned age effects in internalizing problems from 9 to 12 years-of-age was significantly moderated by $PM_{2.5}$ and NO_2 **(Figure 1, Supplemental Tables 6 and 8)**. In contrast to our hypothesis, higher levels of exposure tended to relate to decreases in the probability of exhibiting any problems as well as the number of problems over time between the ages of 9-12 years. Specifically, a $PM_{2.5}$ level of 12 µg/m^3 (EPA's standard) predicted a 190% increase in the likelihood of having no internalizing problems, as well as a 13% decrease in the number of internalizing problems if problems were present, from 9 to 12 years of age. A similar pattern was also seen for NO_2, with NO_2 levels of 26.1 ppb (90th percentile of sample) relating to a 106% increased likelihood of having no internalizing problems, as well as a 6% decrease in the number of problems, if internalizing behaviors were present, from 9 to 12 years-of-age. Moreover, exposure to lower $PM_{2.5}$ or NO_2 levels (5 µg/m^3 and 5.33 ppb based on WHO recommendations) predicted a higher likelihood of having internalizing symptoms (e.g., as seen by a relative decrease in the probability of the caregiver reporting no internalizing problems), as well as an increase in number of internalizing problems, from 9 to 12 years of age. Although these results are counterintuitive in that greater exposure levels were linked with less problems over time, it is important to note the effect sizes of these findings, as the detected changes in probability of exhibiting internalizing problems (i.e., true-zero score) ranged from a 1-4% difference and the magnitude of the number of CBCL internalizing problems was a mere 1-point change.

3.1.3 Internalizing subscales: Anxious/Depressed and Withdrawn/Depressed

These subscales both fall within the internalizing score, therefore, unsurprisingly, a similar pattern was seen for age-only and moderating effects of air pollution for the anxious/depressed problems (**Supplemental Table 6 and 8**). A main effect of age was seen showing an increase of 185% in the likelihood of having no anxious/depressed symptoms (i.e., score of 0), and if symptoms were present, an 8% decrease was seen in the number of problems, from 9-12 years-of-age **(Supplemental Figure 6)**. $PM_{2.5}$ and NO_2 both moderated these age effects of anxious/depressed symptom scores with similar patterns as seen with overall internalizing problems.

A noticeably different pattern was seen for both age-only and moderating effects of air pollution of the withdrawn/depressed subscale. More in line with the literature, the likelihood of having no withdrawn/depressed problems decreased over time, as well as a 34% increase in the number of problems, between the ages of 9-12 years, suggesting a slight increase in the probability of exhibiting withdrawn/depressed problems and a greater number of withdrawn/depressed symptoms with age across early adolescence (**Supplemental Figure 6**). Both $PM_{2.5}$ and NO_2 exposure moderated age-related changes in withdrawn/depressed problems. When examining the probability of having withdrawn/depressed symptoms, higher levels of NO_2 exposure was again associated with a greater likelihood of having no withdrawn/depressed symptoms from ages 9-12 years as compared with lower levels of exposure; $PM_{2.5}$ though, did not moderate this age effect. For individuals who exhibited withdrawn/depressed problems, both NO_2 and $PM_{2.5}$ moderated the effect of age, with again lower levels of NO_2 and $PM_{2.5}$ predicting greater increases in the number of withdrawn/depressed problems from ages 9-12 years as compared with higher levels of exposure. However, again, the effect sizes for exposure on both the change in probabilities and the number of problems from 9-12 years-of-age were minimal (i.e., 1-4% change in probability and 1-point increase in number of problems).

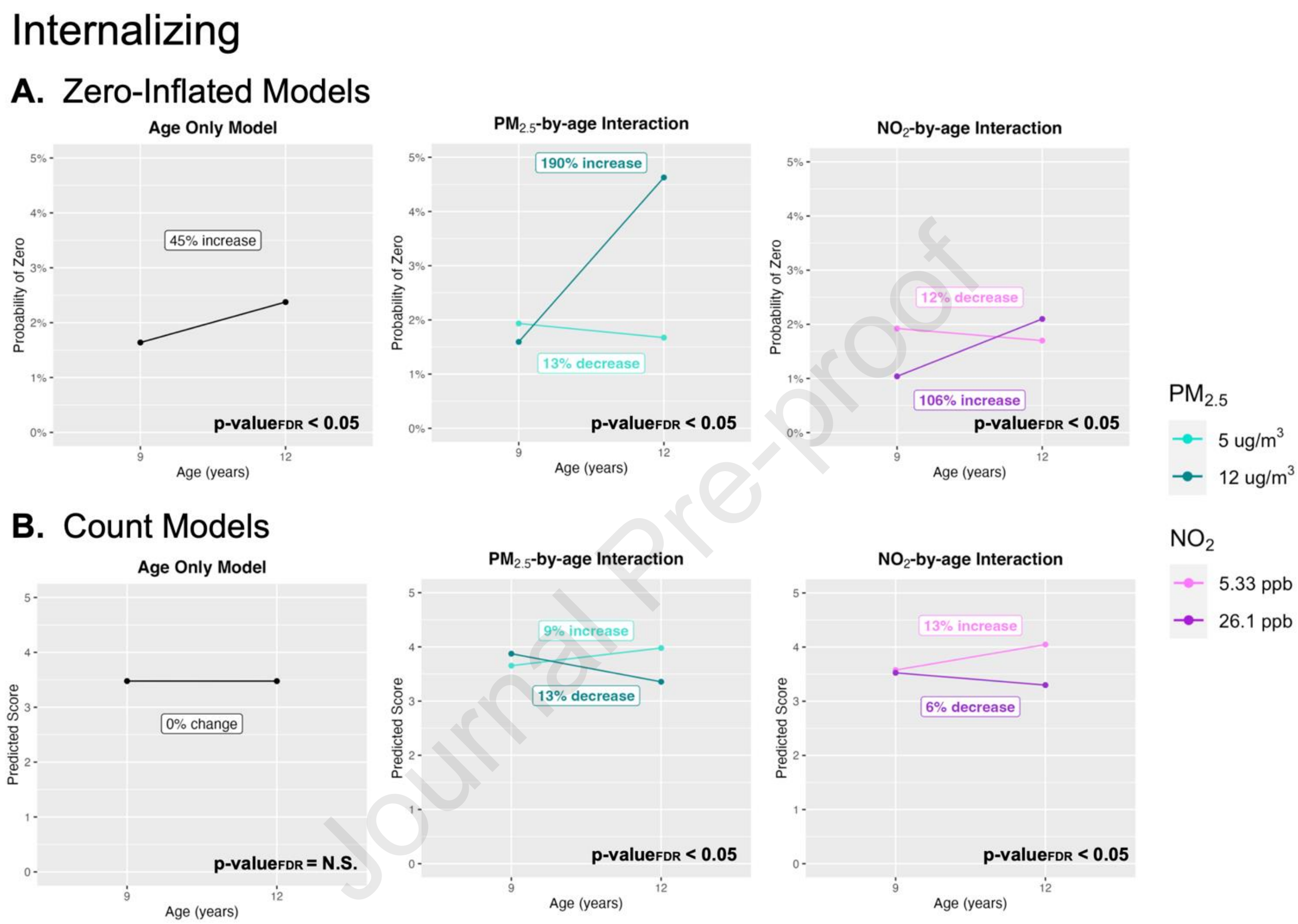

Figure 1 Results for internalizing behavior. ***A)*** Displays the estimated probability of being in the absolute zero category as compared to the non-zero category (i.e., any value for CBCL scores). ***B)*** Displays the estimated CBCL score for subjects whose scores were in the non-zero category. Numerous results are presented which include: ***1)*** **Age only** which displays the main effects of age excluding air pollution with all other variables held constant from 9 to 12 years-of-age; ***2)*** **$PM_{2.5}$-by-age interaction** which displays differences in 9 and 12 years-of-age for the WHO recommended $PM_{2.5}$ levels - 5 $\mu g/m^3$ (light blue) - versus the EPA's - 12 $\mu g/m^3$ (dark blue); ***3)*** **NO_2-by-age interaction** which displays differences in 9 and 12 years-of-age for the WHO recommended NO_2 levels - 5.33 ppb (light purple) - versus the 90th percentile NO_2 level in our sample - 26.1 ppb (dark purple) (The EPA level is 53 ppb which is outside our sample range). All graphs display percent change with age. All covariates held constant at the largest N category (sex = "male", race/ethnicity = 'White', caregiver education = 'Post Graduate Degree', caregiver employment = "Employed", and household income = "≥$100K"), and mean for neighborhood safety ($\bar{x}$ = 3.88); for interaction models, NO_2 is set to the WHO standard (5.33 ppb) for the $PM_{2.5}$-by-age models and $PM_{2.5}$ is set to the WHO standard (5 $\mu g/m^3$) for the Age-only and NO_2-by-age models; p-value$_{FDR}$ = p-value for predictor graphed once FDR corrected for multiple comparisons; N.S. = not significant.

3.2 Externalizing Behavior

3.1.1 Changes in externalizing behavior with age

There was an 88% increase in the likelihood of having no externalizing problems (i.e., obtaining a true-zero) from 9 to 12 years-old. For individuals who did exhibit externalizing problems (count portion of the model), a 12% decrease in the number of externalizing problems was seen from 9-12 years-of-age (**Figure 2**).

3.1.2 Moderating effects of air pollution

$PM_{2.5}$ did not significantly moderate the aforementioned age effects in externalizing behavior from 9-12 years. However, we did find that, regardless of the age of the child, that a main effect of $PM_{2.5}$ was seen, with a 60% increase in the likelihood of no externalizing problems at a $PM_{2.5}$ concentration of 12 as compared to 5 μg/m^3 (**Figure 2 and Supplemental Table 7**). A main effect of $PM_{2.5}$, however, was not seen for the number of externalizing problems. For NO_2, exposure levels did not impact the likelihood of having no externalizing problems (i.e., obtaining a true-zero) from 9 to 12 years-old, but NO_2 did moderate the number of externalizing problems seen with age. Specifically, higher levels of NO_2 were associated with greater decreases in externalizing problems from ages 9-12 years of age as compared to lower levels of NO_2 exposures (**Figure 2 and Supplemental Table 8**). Though, again, the magnitude of these changes equates to less than a 1-point change in the number of problems.

3.1.3 Attention Problems and Externalizing Subscales: Rule-breaking and Aggressive Behavior

There were significant main effects of age for all externalizing subscale behaviors, with an increase in the likelihood of having none of these problems from 9-12 years-of-age. This change in likelihood of problems with age was largest for rule breaking (112%), followed by aggressive behavior (106%), and then attention problems (58%), respectively. For those reporting these problems, a 10% decrease was seen for the number of rule-breaking and attention problems, while a 14% decrease was seen for aggressive behaviors, with age (**Supplemental Figure 7**).

Only NO_2 was found to moderate the effects of age on these types of behaviors, albeit slight differences were seen as to the directionality of these effects (**Supplemental Figure 7 and Supplemental Table 8**). Contrary to our hypotheses, higher levels of NO_2 exposure were related to a greater likelihood of having no rule-breaking behavior from 9-12 years as compared to lower levels of NO_2 exposure. Alternatively, in contrast to all other outcomes, but in line with our hypothesis, a greater likelihood of having no attention problems from 9-12 years was seen at lower as compared to higher levels of NO_2 exposure. Again, higher levels of NO_2 exposure were associated with greater decreases in the number of rule-breaking, aggressive, and attention problems from 9-12 years-of-age as compared to lower levels of NO_2 exposure. Since $PM_{2.5}$ did not moderate age-related changes in these behaviors, we investigated the main effect of $PM_{2.5}$ regardless of age. We found greater likelihood of having no aggressive or attention problems with higher as compared to lower levels of $PM_{2.5}$ exposure (**Supplemental Figure 7 and Supplemental Table 7**). Again, the magnitude of the air pollution effects were marginal, as the differences seen in the probabilities of having problems was on the order of 1% and the number of problems were less than a 1-point change.

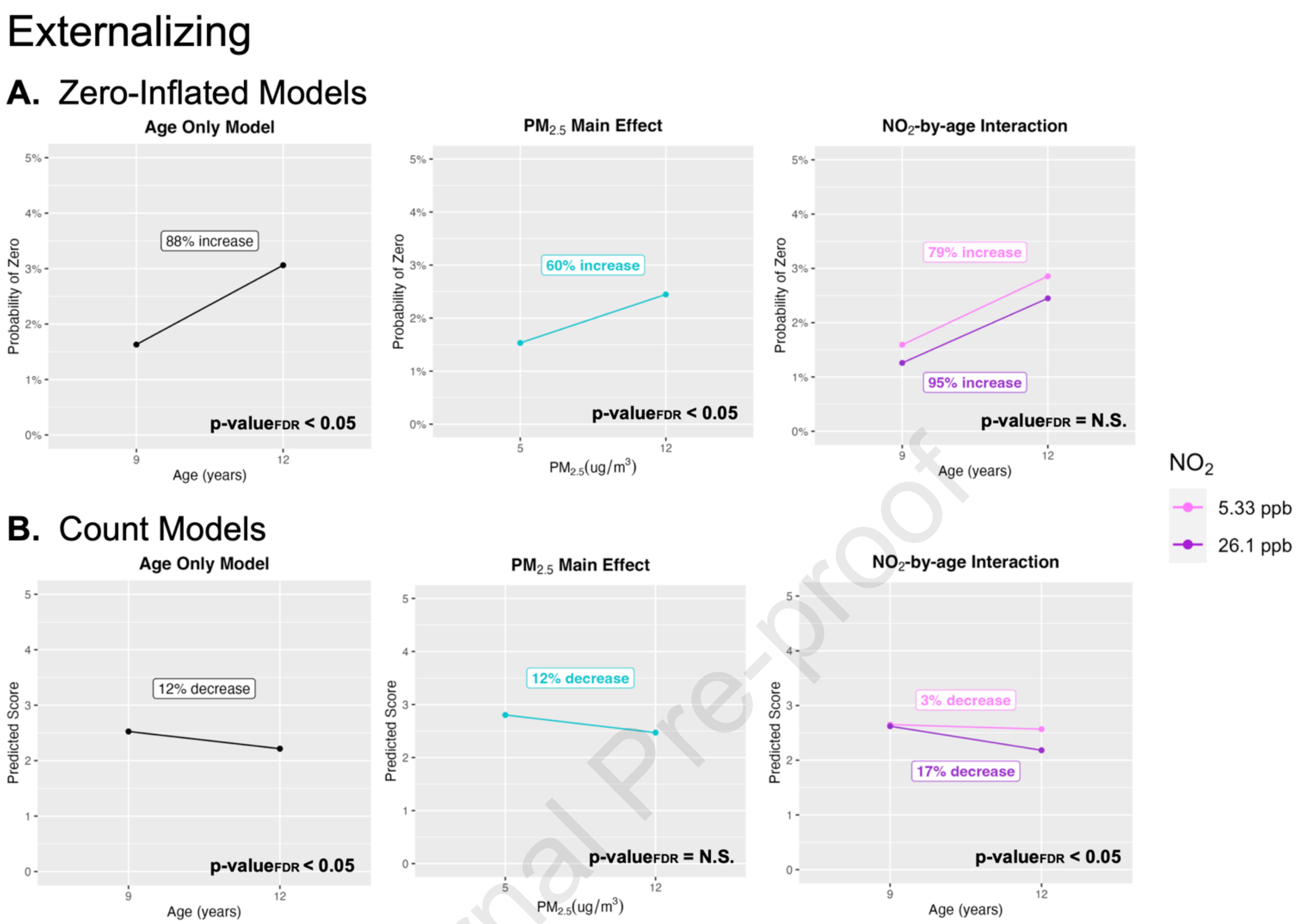

Figure 2 Results for externalizing behavior. ***A)*** Displays the estimated probability of being in the absolute zero category as compared to the non-zero category (i.e., any value for CBCL scores). ***B)*** Displays the estimated CBCL score for subjects whose scores were in the non-zero category. Numerous results are presented which include: ***1)*** **Age only** which displays the main effects of age excluding air pollution with all other variables held constant from 9 to 12 years-of-age; ***2)*** **$PM_{2.5}$-by-age interaction** which displays differences in 9 and 12 years-of-age for the WHO recommended $PM_{2.5}$ levels - 5 µg/m^3 (light blue) - versus the EPA's - 12 µg/m^3 (dark blue); ***3)*** **NO_2-by-age interaction** which displays differences in 9 and 12 years-of-age for the WHO recommended NO_2 levels - 5.33 ppb (light purple) - versus the 90th percentile NO_2 level in our sample - 26.1 ppb (dark purple) (The EPA level is 53 ppb which is outside our sample range). All graphs display percent change with age. All covariates held constant at the largest N category (sex = "male", race/ethnicity = 'White', caregiver education = 'Post Graduate Degree', caregiver employment = "Employed", and household income = "≥$100K"), and mean for neighborhood safety ($\overline{x}$ = 3.88); for interaction models, NO_2 is set to the WHO standard (5.33 ppb) for the $PM_{2.5}$-by-age models and $PM_{2.5}$ is set to the WHO standard (5 µg/m^3) for the Age-only and NO_2-by-age models; p-value$_{FDR}$ = p-value for predictor graphed once FDR corrected for multiple comparisons; N.S. = not significant.

Discussion

In the current longitudinal study, we leveraged a large, nationwide longitudinal cohort of children to examine how exposure to both $PM_{2.5}$ and NO_2 at ages 9-10 years affects age-related changes in behavioral problems as reported on the CBCL over a 2-year follow-up period. To characterize the developmental trajectory of behavioral problems within our sample, as well as aid interpretation of the pollutant effects, we first revealed an age-related decrease in the likelihood of having internalizing and externalizing problems as reported on the CBCL from ages 9-12 years-old (in the zero portion of the model), as well as fewer number of internalizing and externalizing problems over time if behaviors were present (in the count portion of the model). Interestingly, we saw the opposite effect in the withdrawn/depressed syndrome scale, where increasing age was related to an increased likelihood of reporting withdrawn/depressed problems, as well as more problems, when present, from ages 9-12 years old. In contrast to our hypothesis, higher levels of $PM_{2.5}$ and NO_2 exposure did not modify these age-related patterns to result in a greater likelihood or frequency in the number of problems over time. Unexpectedly, higher exposure was linked to lower likelihood of having problems as well as slightly fewer problems over time for most CBCL outcomes. In fact, only the association between NO_2 exposure and attention problems was in the expected direction, with lower NO_2 exposure predicting an increased likelihood of zero attention problems with age as compared with higher exposure. While the directions of the relationships between the pollutants and CBCL outcomes are counterintuitive, it is important to consider the magnitude of the effect sizes in such a large sample, rather than the statistical significance of these findings. This is evident by the largest effect we found, which was the effect of $PM_{2.5}$ on the probability of internalizing symptoms arising at age 12. In children with low $PM_{2.5}$ exposure at ages 9-10 years, the probability of not having problems at age 12 was 1.7%, while in those exposed to high $PM_{2.5}$ at ages 9-10 years the probability of not having problems at age 12 was 4.6%. Not only is the difference in probability only 2.9%, but the likelihood of having any problems regardless of exposure level falls below 5%. Similarly, the effect sizes were extremely small for the quantitative differences in the number of problems, with higher pollution exposure associated with a decrease of less than a single point difference on any given scale. Given that the CBCL uses a 3-point Likert scale (i.e., 0 = Not True, 1 = Somewhat or Sometimes True, 2 = Very True or Often True), a 1-point change is likely clinically negligible, may fall within the range of measurement error, and may not have real-world implications. Thus, against our hypothesis, there was no evidence that low-level exposures to $PM_{2.5}$ and NO_2 at ages 9-10 years resulted in increased emotional problems from ages 9-12 years.

Our study focuses on childhood exposure at ages 9-10 years old – a developmental period currently underrepresented in the literature. About 26% of studies on pollution-related differences in mental health problems cover this age range, despite the high incidence of psychiatric diagnoses in early adolescence (Kessler et al., 2005; Solmi et al., 2022; Zundel et al., 2022). Yet even studies focused on linking $PM_{2.5}$ and NO_2 exposure and emotional behaviors in youth have reported mixed findings. Some of the earliest longitudinal research in this area comes from Columbia Center for Children's Environmental Health (CCCEH) longitudinal cohort study of African American and Dominican women in New York City. These essential studies found that prenatal exposure to airborne polycyclic aromatic hydrocarbons (PAHs), which come from fossil fuel combustion, was linked to greater CBCL reported symptoms of anxious/depressed and attention problems at ages 4-5 and 6-7 years-old children (F. P. Perera et al., 2011, 2012). However, in a more recent study that included using either the Strength and Difficulties Questionnaire or the CBCL in 8 European population-based birth cohorts, prenatal and postnatal air pollution, including $PM_{2.5}$ and NO_2 exposure, were not found to relate to the borderline clinical range of depression, anxiety, and aggression in >13,000 children ages 7-11 years-old (Jorcano et al., 2019). In fact, higher postnatal exposure was linked with overall lower odds of having symptoms in the borderline/clinical range when assessed cross-sectionally with the CBCL; albeit the results did not reach statistical significance. Similar findings were also noted when using the quantitative scores of the symptom scales (Jorcano et al., 2019) as implemented in the current analysis. A similar study assessing ADHD symptoms in children 3-10 years-old using these same 8 European birth cohorts also found no association, or even decreased risk, between prenatal air pollution exposure and ADHD (Forns et al., 2018). Given the positive publication bias, it is likely that more evidence of null associations between exposure and behavior problems exists and has been relegated to the so-called file drawer (Mlinarić et al., 2017). Furthermore, a recent study using similar methodology to our own found that higher childhood and prenatal exposure to $PM_{2.5}$ and NO_2, in addition to other pollutants, was associated with fewer internalizing, externalizing, and attention problems in adolescence regardless if CBCL questionnaire was reported by parent or child (Kusters et al., 2022). Thus, our current findings are in line with these more recent multi-research site-based studies. Similar to these studies, it seems very unlikely that the significant effects found in the current study are in fact reflective of a protective effect given both 1) the absence of any postulated mechanism for a protective element of air pollution exposure, as well as 2) the extremely small magnitude of change detected in part to our large sample size and the resulting statistical power. It is feasible that both the previous findings as well as the current results could be due to residual negative confounding (Forns et al., 2018; Jorcano et al., 2019), although it is important to note that in each case the analyses adjusted for many essential sociodemographic variables (i.e., income, caregiver educational attainment, etc.) that are known to be associated with air pollution exposure and mental health in children. Thus, if residual negative confounding is at play, unexplained factor(s) should be explored that may exist across various cities and within various western populations (e.g., U.S., Germany, Italy, Spain, etc.). Despite the CBCL being a widely used and valid measure in both clinical and research settings (Achenbach & Rescorla, 2001; Wolraich et al., 2008), context and informant differences have been reported in using the CBCL items to assess emotional and behavioral problems in youth (Achenbach et al., 1987). Albeit Kusters et al. (2022) findings suggest air pollution effects on emotional behaviors are consistent regardless of parent or youth (ages 13-16 years) report. Nonetheless, it is feasible that caregiver-report of emotional problems in the current study may contribute to misclassification bias that could contribute towards failing to reject the null hypothesis. Thus, additional studies are warranted using more objective measures, such as clinician-based interviews, of children's mental health and wellbeing.

Putting our current results in the larger context of the literature, the importance of windows of exposure and the timing of behavior continue to prevail as to what role air pollution may play in terms of risk for developing mental health problems. That is, while the current study shows a one-year annual average of air pollution exposure during the transition to adolescence does not substantially increase the age-related clinical risk of mental health problems over a 2-year follow-up period, it is still feasible that exposure during this period of development may ultimately predispose an individual to risk for developing psychopathology later in adolescence or early adulthood. Air pollution, then, may influence ongoing brain development and plasticity across adolescence, due to the protracted development of regions and networks associated with mental health conditions and psychopathology (e.g., hippocampus, amygdala, default mode network, frontoparietal network, and salience network) (Menon, 2011, 2013). A number of MRI studies suggest that exposure to ambient air pollution is linked to differences in brain macro- and microarchitecture as well as functional brain network connectivity (Binter et al., 2022; Burnor et al., 2021; Cotter et al., 2023; Essers et al., 2023; Guxens et al., 2018, 2022; Herting et al., 2019; Lubczyńska et al., 2021; Pérez-Crespo et al., 2022; Sukumaran et al., 2023). Thus, it is feasible that these differences may be early neural biomarkers of $PM_{2.5}$ exposure-related risk prior to any overt changes in behavior. As previously mentioned, the idea that exposure during adolescence may ultimately predispose an individual to later develop mental health disorders parallels the findings that higher levels of air pollution during childhood and adolescence predict later onset of major depressive disorder (Roberts et al., 2019) and other internalizing, externalizing, and thought disorder symptoms at age 18 years (Reuben et al., 2021). In fact, the increased incidence of psychopathology and psychiatric diagnoses seen in adolescence typically occurs in mid-adolescence, around age 14 and a half (Solmi et al., 2022), which is above the upper limit of ages included here. However, consortium efforts to eventually estimate lifetime air pollution exposure (C. C. Fan et al., 2021) in the coming years, in addition to active follow-up of ABCD cohort participants through early adulthood, will soon allow researchers to more formally test this hypothesis. Moreover, the results of the current study may also suggest that while $PM_{2.5}$ and NO_2 exposure at 9-10 years does not meaningfully impact the age-related relative risk of emotional problems at a population-level, it is feasible that exposure during this time may have harmful effects in children who are more susceptible, due to either genetic risk or due to co-exposure to other adverse environmental threats. Thus, more research is warranted taking a more integrated neural exposome approach to understanding adolescent environmental exposures and risk for psychopathology (Tamiz et al., 2022).

The current study has several strengths. Specifically, the statistical approach and data used here contribute to a rigorous assessment of longitudinal, age-related behavioral and emotional problems associated with one-year annual air pollution exposure during the transition to adolescence. While standardized scores are often used to study dimensions of psychopathology and behavior between-subjects, we utilized raw longitudinal CBCL scores in the current study to better capture developmental change (Barch et al., 2021). However, raw CBCL scores are zero-inflated and over-dispersed in normative developmental samples, violating assumptions of general linear models. Our application of a zero-inflated negative binomial (ZINB) model combines the strengths of a logistic regression model with a negative binomial model, allowing robust estimates of associations between air pollution and the emergence of any behavioral or emotional problems (i.e., scores equal to zero vs. scores greater than zero) as children age, and how air pollution is related to the magnitude or number of behavioral or emotional problems (i.e., the range of scores greater than zero). Second, our large, nationwide sample between the ages of 9-12 years provides more geographically diverse estimates of NO_2 and $PM_{2.5}$. This is an improvement over the smaller, localized samples common to air pollution research that pervade the literature, as sources and concentrations of pollutants vary across locations (Snider et al., 2016) and the health effects of $PM_{2.5}$ vary by source (Holguin, 2008; Sarnat et al., 2008). Although the final sample used here is not fully representative of the larger US population (Garavan et al., 2018), it has greater generalizability compared to smaller scale studies of air pollution and mental health. Further, the models were adjusted for numerous socioeconomic and lifestyle variables that are known to be associated with both exposure and emotional behaviors examined in the current study.

A limitation of the current study is that the estimates of air pollution used here only represent a sum across components of $PM_{2.5}$ and capture an average of exposure over one year at the time of study enrollment. Moreover, our study examined exposure levels that are largely below the U.S EPA standards, which may only apply to approximately 50% of high-income countries in North America, Europe, and the Western Pacific, and does not readily apply to existing levels of exposure in many low- and middle-income countries (World Health Organization, 2018). As previously mentioned, different geographical locations have different compositions of $PM_{2.5}$ and the individual components of $PM_{2.5}$ have different effects on human health. It is possible that our results represent an amalgamation of the unique effects of individual components of $PM_{2.5}$ (e.g., elemental carbon, silicon, lead), contributing to our counterintuitive findings. There is also a substantial body of literature quantifying the effects of prenatal air pollution exposure and acute exposure (i.e., days) effects on various mental health outcomes

(Braithwaite et al., 2019; Zundel et al., 2022), which are not available in the 4.0 data release of the ABCD Study. Moving forward, incorporating prenatal exposure, as well as acute estimates, could help elucidate potential nuances that exist in the timing of exposure on the emergence of symptomatology across adolescence, in addition to the prevalence of acute mental health crises (for review, see Heo et al., 2021). Another limitation is that the data included here were collected from 2016 until March 2020, at the beginning of the global COVID-19 pandemic. We chose to exclude data collected after March 2020, to avoid the confounding effect of pandemic-induced emotional and behavioral problems in this sample (Hamatani et al., 2022). The onset of the pandemic complicated data collection, as well, and may have contributed to missingness in data collected at later follow-up visits. For example, although sample demographics in the current study were similar to the larger ABCD cohort (Supplemental Tables 1-3) and our overall missingness was small (≤6%), we cannot rule out the possibility of selection bias influencing our results. Not all participants had complete data at each wave of data collection, and follow-up waves had slightly higher representation of white children, with greater caregiver educational attainment and household income compared to enrollment at baseline. However, due to this small proportion of missing data, that bias is expected to be small or negligible. Moreover, Asian, American Indian/Alaskan Native, and Native Hawaiian/Pacific Islander populations are underrepresented in the ABCD Study, while families with higher total household incomes and highly educated caregivers are over-represented. Thus, additional studies are needed that include children who may be especially susceptible to air pollution related effects because of potential compounding effects of disadvantage due to poverty and minority-related stressors stemming from racism (Hajat et al., 2015). Although both the exposure models used herein as well as the CBCL questionnaire have shown to have both good validity and reliability and the current study adjusted for key confounders, it is feasible that measurement error or residual confounding may have contributed to the current unexpected findings. Lastly, additional studies are also warranted to examine if annual averages to higher levels of exposure experienced in low- and middle-income countries may influence emotional wellbeing in developing children.

Conclusions

There was no evidence that low-level exposures to $PM_{2.5}$ and NO_2 at ages 9-10 years resulted in greater emotional problems from ages 9-12 years. Future research with additional waves of data extending into late adolescence and early adulthood, as well as incorporating cumulative exposure estimates are necessary to further our understanding between air pollution and mental health during adolescence.

Credit authorship contribution statement

Claire E. Campbell: Project Administration, Methodology, Formal Analysis, Visualization, Writing - Original Draft; Devyn L. Cotter: Methodology, Writing - Original Draft; Katherine L. Bottenhorn: Methodology, Visualization, Writing – Original Draft; Elisabeth Burnor: Methodology, Data Curation, Writing – Review & Editing; Hedyeh Ahmadi: Data Curation, Methodology, Writing – Review & Editing; Carlos Cardenas-Iniguez: Writing - Review & Editing; W. James Gauderman: Methodology, Writing - Review & Editing; Rob McConnell: Methodology, Writing - Review & Editing; Kiros Berhane: Methodology, Writing - Review & Editing; Joel Schwartz: Methodology, Data Curation, Resources, Writing - Review & Editing; Jiu-Chiuan Chen: Conceptualization, Methodology, Writing - Review & Editing; Megan M. Herting: Funding Acquisition, Resources, Conceptualization, Methodology, Supervision, Project Administration, Writing - Original Draft.

Acknowledgements

A special thank you to all ABCD cohort participants and their families. Portions of the research described in this article were conducted under contract to the HEI, an organization jointly funded by the US Environmental Protection Agency (EPA) and certain motor vehicle 14 and engine manufacturers. The content of this article does not necessarily reflect the views of HEI or its sponsors, nor does it necessarily reflect the views and policies of the US EPA or motor vehicle and engine manufacturers. Additional support for this research was also provided by the National Institutes of Health [NIEHS R01ES032295 (Herting), R01ES031074 (Herting), P30ES007048-23S1 (Gilliland), 3P30ES000002-55S1 (Weisskopf), NIHP01ES022845 (McConnell), T32 ES013678 (Campbell), F31 MH131347 (Campbell)] and EPA grants [RD-83587201 (Schwartz), RD-83544101 (Schwartz)] and the Rose Hills Foundation (Herting). We would also like to acknowledge and thank Shermaine Abad, MPP, for making the maps shown in Supplemental Figure 2.

Data used in the preparation of this article were obtained from the Adolescent Brain Cognitive DevelopmentSM (ABCD) Study (https://abcdstudy.org), held in the NIMH Data Archive (NDA). This is a multisite, longitudinal study designed to recruit more than 10,000 children aged 9-10 and follow them over 10 years into early adulthood. The ABCD Study® is supported by the National Institutes of Health and additional federal partners under award numbers U01DA041048, U01DA050989, U01DA051016, U01DA041022, U01DA051018, U01DA051037, U01DA050987, U01DA041174, U01DA041106, U01DA041117, U01DA041028, U01DA041134, U01DA050988, U01DA051039, U01DA041156, U01DA041025, U01DA041120, U01DA051038, U01DA041148, U01DA041093, U01DA041089, U24DA041123, U24DA041147. A full list of supporters is available at https://abcdstudy.org/federal-partners.html. A listing of participating sites and a complete listing of the study investigators can be found at https://abcdstudy.org/consortium_members/. ABCD consortium investigators designed and implemented the study and/or provided data but did not necessarily participate in the analysis or writing of this report. This manuscript reflects the views of the authors and may not reflect the opinions or views of the NIH or ABCD consortium investigators. Additional support for this work was made possible from NIEHS R01-ES032295 and R01-ES031074.

Data and Code Availability Statement

Data used in the preparation of this article were obtained from the Adolescent Brain Cognitive Development (ABCD) Study (https://abcdstudy.org), held in the NIMH Data Archive (NDA). This is a multisite, longitudinal study designed to recruit more than 10,000 children aged 9-10 and follow them over 10 years into early adulthood. ABCD consortium investigators designed and implemented the study and/or provided data but did not necessarily participate in analysis or writing of this report. This manuscript reflects the views of the authors and may not reflect the opinions or views of the NIH or ABCD consortium investigators. The ABCD data repository grows and changes over time. The ABCD data used in this report came from 10.15154/1523041.

R analysis code for this project can be found at 10.5281/zenodo.7787017.

Competing Interests

The authors declare no competing interests.

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Highlights:

- We examined one-year air pollution exposure on changes in emotion in 9-12 year-olds
- Concentrations of air pollution exposure were below U.S. EPA standards
- Annual measurements of emotional problems were investigated over 3 years
- Overall, less internalizing and externalizing behavior problems seen over time
- Our results do not support the idea that air pollution increases problems over time

Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: