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EdWorkingPaper No. 26-1381

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Air pollution is one of the most pressing global public health challenges of the 21st century. This article presents a systematic review and meta-analysis of the best available evidence of the effect of air pollution on student achievement. A meta-analysis of 28 causal studies around the world yielding 62 effect sizes estimates that air pollution, across many contexts and pollutants, decreases student achievement by 0.022 standard deviations (SD). One μg/m3 unit increase and one standard deviation increase in pollutant concentration decrease student achievement by 0.011 SD and 0.042 SD respectively. The effect of pollution is about 33% larger for males than females. There are, however, direct and cost-effective solutions that can mitigate pollution's detrimental effects.

VERSION: January 2026

Suggested citation: Nguyen, Tuan D. . (2026). The Effect of Air Pollution on Student Achievement: A Systematic Review and Meta-Analysis of the Causal Evidence. (EdWorkingPaper: 26-1381). Retrieved from Annenberg Institute at Brown University: https://doi.org/10.26300/qekg-t772

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Abstract

Air pollution is one of the most pressing global public health challenges of the 21st century. This article presents a systematic review and meta-analysis of the best available evidence of the effect of air pollution on student achievement. A meta-analysis of 28 causal studies around the world yielding 62 effect sizes estimates that air pollution, across many contexts and pollutants, decreases student achievement by 0.022 standard deviations (SD). One $\mu g/m^3$ unit increase and one standard deviation increase in pollutant concentration decrease student achievement by 0.011 SD and 0.042 SD respectively. The effect of pollution is about 33% larger for males than females. There are, however, direct and cost-effective solutions that can mitigate pollution's detrimental effects.

Keywords: air pollution, student achievement, educational effects, systematic review, meta-analysis

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Acknowledgement: I thank Kate Nelson for the stimulating conversations that led to this paper and for her feedback on the draft. All errors remain my own.

Air pollution is one of the most pressing global public health challenges of the 21st century, responsible for millions of premature deaths annually and associated with an extensive range of chronic diseases, including respiratory, cardiovascular, and neurological disorders (World Health Organization, 2025a). Over the past thirty years, the scientific community has documented the physical health consequences of air pollution, particularly for children and students, resulting in several systematic reviews and meta-analyses (An et al., 2021; Clifford et al., 2016; Currie et al., 2014; Shah et al., 2013). However, the effects of air pollution on student achievement have not garnered as much attention. As educational outcomes, particularly student achievement, are critical to social mobility and long-term economic productivity, it is important to understand how air pollution may affect student achievement in addition to the physical tolls that it has on children and students.

Towards this end, I conduct a systematic review and meta-analysis of the causal effects of air pollution on student achievement, specifically on K-12 students as they are most at risk of the short and long-term effects of air pollution. Since air pollution is ubiquitous, it is critical that we use the most rigorous evidence in order to isolate the effects of air pollution on student achievement and account for a host of factors that may bias the estimates of the effects of air pollution, such as nonrandom assignment of pollution concentrations or environmental confounders that may influence both pollution levels and student achievement (e.g., school locations; district resources). Synthesizing the causal evidence of air pollution and student achievement in a systematic review and meta-analysis, I am able to answer the following research question: What are the effects of air pollution on K-12 student achievement?

The rest of the article is structured as follows. I begin by providing a brief discussion on the composition and sources of air pollution, a summary of the consequences of air pollution on physical health, particularly for young children, and how air pollution can potentially affect student achievement. Next, I explain my methodological approach, including eligibility criteria, literature search, coding of primary studies, and analytical strategy. In discussing the results, I pay careful attention to heterogeneity effects, how effects may vary by study characteristics, and publication bias. I end with a discussion of the findings and implications for policy and practice as well as directions for future research.

To briefly preview the results, I find that air pollution, on average across many contexts and pollutants, decreases student achievement, broadly measured, by 0.022 standard deviations (SD). When I examine only the composite test score results, air pollution decreases student test scores by 0.025 SD. With respect to language and math test scores, pollution decreases language and math achievement by 0.026 SD and 0.014 SD respectively. The effects of air pollution seem to be larger for male than female students. Lastly, I also find that the meta-analytic summary estimates from the high-quality causal studies are slightly larger than the summary estimates using all available studies. Overall, the results clearly indicate that air pollution has negative effects on student achievement, and these effects are also practically meaningful.

Background on Air Pollution

Composition and Sources of Air Pollution

Air pollution, broadly defined, is the presence of high concentrations of one or more contaminants (gas, liquid, or solid) in the atmosphere that would be harmful to human health and ecosystems (Vallero, 2025; World Health Organization, 2025a). While air pollution is not new, the scale and global reach of air pollution have expanded quickly over the last several decades due to rapid industrialization, urbanization, population growth, and increased energy consumption (Pearson & Derwent, 2022). The major gaseous pollutants include carbon monoxide (CO), nitrogen oxides (NO and NO_2, collectively known as NO_x), ozone (O_3), sulfur oxide (SO_2), and volatile organize compound (VOC). NO_2 and SO_2 emitted from vehicles and power plants contribute to acid rain, smog formation, and secondary particulate matter, while O_3 is formed through photochemical reactions between NO_x and VOC. Solid and liquid pollutants are known as particular matter (PM) and are categorized based on the size of the matter. PM_{10} are particles less than 10 micrometers in diameter, and $PM_{2.5}$ are particles with diameters less than 2.5 micrometers. Major contributors to $PM_{2.5}$ include fossil fuel combustion, industrial processes, residential heating, and open burning of agricultural residues, while major contributors of PM_{10} include traffic-related sources, construction and road dust, industrial sources, and natural dust and soil (Vallero, 2025). In general, the smaller the particle, the more it is able to penetrate deeper into the respiratory system, causing more severe health effects (Pearson & Derwent, 2022; Vallero, 2025).

While exposure to air pollution is universal as over 99 percent of the global population lives in places where air quality exceeds the recommended WHO guidelines, the higher concentrations of pollutants are found in rapidly urbanizing regions of Asia, particularly in megacities such as Delhi and Beijing where the annual $PM_{2.5}$ levels are often several times above international guidelines (Cheng et al., 2016; Wang et al., 2020; World Health Organization, 2025b). Marginalized and low-income populations, even within wealthier nations and economies, are disproportionately affected as they often reside near highways, industrial zones, or contaminated sites (Bell & Ebisu, 2012; Jbaily et al., 2022). These disparities illustrate how air pollution is not only an ecological problem but also a profoundly social one.

Physical Health Effects of Air Pollution

The health effects of air pollutions are well-documented. Air pollution affects virtually every organ in the body, and the severity of the effects depends on the concentration and type of pollutants, exposure duration, and individual health conditions (e.g., Bates, 1995; Vallero, 2025). Broadly speaking, air pollution affects respiratory systems and cardiovascular systems, and it has neurological effects as well as reproductive and developmental effects.

With respect to respiratory systems, air pollution can cause inflammation, reduce lung function, and damage airways, and children are particularly vulnerable because they spent more time outside and breathe faster than adults (Bates, 1995). A systematic review and meta-analysis finds that traffic-related air pollutants around schools, including $PM_{2.5}$ and PM_{10}, have significant impact on students' respiratory systems (An et al., 2021). In particular, when concentrations are high, the risks of respiratory infection, asthma, and tracheitis are elevated, and allergic symptoms also increase (An et al., 2021). Air pollution also affects the heart and blood vessels causing a range of cardiovascular diseases including hypertension and atherosclerosis (Vallero, 2025). Even short-term exposure to high pollution levels can increase risk of hospitalization for cardiovascular problems.

Additionally, and more importantly with respect to educational outcomes, air pollution also affects fetal development and neurological development. Pregnant women who are exposed to high levels of pollutants have higher risks of having preterm birth, low birth weight, and congenital abnormalities, which can then cause physical disability as well as intellectual and developmental disorders (Dutheil et al., 2021; Lopuszanska & Samardakiewicz, 2020). Air pollutants can also affect the brain directly, leading to cognitive decline in adults and neurodevelopmental delays in children (e.g., Clifford et al., 2016). In particular, Clifford and colleagues (2016) in their systematic review linking air pollution to cognitive functioning find that air pollution is significantly associated with impairment of brain development in the young (and cognitive decline in the elderly).

Mechanisms Linking Air Pollution to Student Achievement

While early research on air pollution has focused mainly on health outcomes (Bates, 1995), a growing body of interdisciplinary research has examined its subtle but detectable effect on brain development, cognitive processes, and learning outcomes (An et al., 2021; Clifford et al., 2016; Dutheil et al., 2021). This shift reflects a broader understanding that while air pollution can affect well-being by inducing health issues that persist over time, but it can also affect student achievement in multiple ways and through multiple mechanisms. In particular, researchers have posited that air pollution affects student achievement through two main paths: 1) neurobiological and cognitive mechanisms, and 2) physical and behavioral mechanisms (Amanzadeh et al., 2020; Austin et al., 2019; Chung et al., 2025).

First, air pollutants directly impair brain development and function. Exposure to air pollutants, such as $PM_{2.5}$ and ozone, has been associated with inflammation, reduced lung function, and impaired brain development, all of which can lower cognitive performance and academic achievement (e.g., Calderón-Garcidueñas et al., 2015). For instance, children exposed to high air pollutants in Poland have reduced non-verbal intelligence by age 5, even after adjusting for confounders (Edwards et al., 2010). Comparing cohorts of mothers and newborns before and after a power plant closure in Tongliang, China, Tang et al. (2014) find there are differences in biological and neurodevelopment for the newborns. Similarly, there are reductions in developmental milestones and IQ for kids borne to women exposed to higher pollutants in the United States (Perera et al., 2006; Perera et al., 2009). Distance of residence to the nearest major roads has also been linked to cognition (Harris et al., 2015). Globally, students who are exposed to higher concentrations of air pollutants have worse attention and concentration, reduced growth in working memory, and reduced problem-solving ability (An et al., 2021). In other words, students who are exposed to higher concentrations of air pollution are systematically at a disadvantage compared to their peers who are less exposed, even before they set foot in the classroom.

Second, air pollution can affect student behaviors once they are in school. To start, it can increase school absenteeism by worsening illnesses like asthma and other chronic respiratory and cardiovascular illnesses (e.g., Calderón-Garcidueñas et al., 2015). Student attendance is a significant determinant of academic learning and achievement, so it is worrisome that air pollution may induce student absences by making them sick. To this point, previous work has found that an increase in PM_{10} exposure in Utah was associated with increase elementary absenteeism (Random & Pope, 1992), and more recently, Currie et al. (2009) find that carbon monoxide exposure was associated with increased student absences in Texas. School absenteeism was also elevated for Chinese students who were exposed to higher levels of particular matter and ozone (Zhang et al., 2022). Not only would students miss classes when they are ill, but potentially they may also need to make up the work whilst they are still sick.

Furthermore, recent work has also demonstrated that air pollution contributes to more consequential behavioral issues, including disruptive and aggressive behavior (e.g., Berman et al., 2019; Burkhardt et al., 2020). In particular, air pollution has been linked with a host of factors, such as cellular inflammation and oxidative stress, contributing to aggressive behaviors and criminal activities that can lead to school suspension or incarceration (e.g., Calderon-Garciduenas et al., 2015; Hernstadt et al., 2021; Lu et al., 2018; Rammal et al., 2008). For instance, students in Minnesota who are exposed to high level of air pollutants, particularly CO,

NO_x, and $PM_{2.5}$, are more likely to have more violent disciplinary incidents (Rau et al., 2024). Using microdata in Chicago, Illinois, Hernstadt et al. (2021) find that air pollution increases violent crime on the downwind sides of interstate roads, and using administrative data from London, Bondy et al. (2020) find that air pollution has a positive relationship with overall crime and several major crime categories.

Overall, prior works have demonstrated that there are several mechanisms through which air pollution can affect student achievement before and during their time in school.

Study Contributions

While there is extensive literature on the relationship between air pollution and health outcomes, including multiple systematic reviews and meta-analyses, there are currently no systematic reviews or meta-analyses on the relationship between air pollution and student achievement. This work is intended to address this gap by synthesizing the literature on the link between air pollution and student achievement. Moreover, by focusing on causal studies, I am able to more firmly establish the effects of air pollution and not simply how air pollution is correlated with student achievement. In addition to being the first systematic review and meta-analysis on this important topic, I am also able conduct several heterogeneity analyses, including how the effects may differ for male and female students and by different measures of achievement. In short, I make several notable contributions showing the effects of air pollution on student achievement across the globe.

Data and Method

This study is designed to examine the causal estimates of pollution on student achievement by conducting a systematic review and meta-analysis of the literature. To define the eligibility criteria, literature search, data analysis, and reporting conventions, I followed the

Preferred Reporting Items for Systematic Reviews and Meta-Analysis standards as defined by Moher et al. (2009) and Alexander (2020). This process outlined in this framework provided us with a reproducible method to systematically search, assess, and report on the causal evidence of the effects of pollution on students. Figure 1 provides a PRISMA flow diagram illustrating the stages of the study selection process.

Eligibility Criteria

Primary studies eligible for inclusion in this meta-analysis need to meet the following criteria: (a) the sample is comprised of PK-12 students; (b) the study reports quantitative results of student achievement; and (c) the study provides plausibly causal estimates of the effects of pollution on student achievement by employing experimental or rigorous quasi-experimental estimation strategies. Studies that do not provide empirical plausibly causal quantitative results or summarize existing evidence are not included. Some specific examples of excluded studies are quantitative reports that did not provide plausibly causal estimates (e.g., Chen et al., 2000), studies that provided collegiate outcomes (e.g., Xu et al., 2024), studies that provided health outcomes (e.g., Bergstra et al., 2018), or studies that summarize other studies (e.g., Gartland et al., 2022).

Literature Search

Given the topic of this systematic review and meta-analysis, I obtained primary studies from searching commonly used economic and general social science databases, including JSTOR, ERIC, WorldCat, Google Scholar, ProQuest, NBER and Taylor and Francis. I also searched for “grey” literature using Dissertation and Thesis Repositories in WorldCat and ProQuest. I engaged in an iterative process to find an inclusive search string that would capture the keywords associated with the research questions and provide a reasonable number of records that can be screened and analyzed thoroughly. At the end of the process, I employed the following search string: “pollution AND (achievement OR academic OR student OR child*),” which returned a little over 21,000 studies using the databases listed above. Appendix Table 1 provides the number of studies found in each database. In addition to searching databases, my literature search also included ancestral searches where I identified potentially eligible studies using the reference lists of included studies. The official search ended the first week of August 2025. I did not limit the search on publication date, location, or language. As pollution affects people and students all over the world, I did not limit my search by country. As such, the evidence provided below represents the effects of pollution on students globally.

Identifying Studies for Final Inclusion

Starting with the results returned from the search of databases and previous reviews, I screened for primary studies that meet all eligibility criteria, as illustrated in Figure 1. I retained a study if the title, abstract, or introduction mentioned that the study contained empirical results pertaining to pollution and student achievement or academic outcomes. In all, I screened over 21,000 records during the search. This initially large number of studies represents the substantial literature on pollution and student outcomes. However, the vast majority of these studies are not estimating the causal effects of pollution on student achievement or academic outcomes.

In phase two, I was left with 103 studies for full text reading. From these fully reviewed studies, I excluded studies that did not provide causal estimates of pollution on student achievement. When there are multiple reports or publications from the same study, such as a working paper and a peer reviewed article for the same evaluation, I kept only the most current publication, which is most often the published version.

In phase three, I emailed the authors of these reports to see if there are additional studies that the search has missed. From this process, I obtained five additional studies. This step represents additional efforts beyond the standard systematic review process to ensure that I have the most complete set of causal studies on the effects of pollution on student achievement.

At the end of phase three, I was left with a sample of 28 primary studies, 16 from the United States and 12 from a broad range of other countries including Brazil, Chile, England, India, Iran, Israel, and Vietnam. This set of studies serves as the analytic sample for the meta-analysis.

Coding Reports

I coded relevant information for each of the eligible studies using a coding schema (Appendix Table 2). For instance, I coded the following information: publication type, whether the study was peer reviewed, the country of origin, identification strategy, type of pollutant analyzed, the estimate effect, associated standard error, and sample size. I specifically note that I reverse coded a handful of studies that estimate the effect of a treatment, such as bus retrofitting, air filter, or heating-ventilation-and-air-conditioning (HVAC), on student achievement (i.e., Austin et al., 2019; Gilraine, 2025; Persico & Fuller, 2025). In these studies, the positive effects of treatment (treatment to mitigate the detrimental effects of air pollution) are coded as negative to represent the negative effect of air pollution. To reduce any potential coding error, I recoded each of the studies two to three weeks after coding them the first time. No discrepancies or mistakes were made between the two rounds of coding.

Estimating the effects of air pollution. Since air pollution is everywhere, meaning that we are all exposed to it to some extent, it is not trivial to estimate its effects. Moreover, there are other factors that make it difficult to provide causal estimates of the effects of air pollution. First, where people live are not randomly distributed, leading to nonrandom assignment of pollution concentrations. Second, environmental confounding is the second source of endogeneity where the factors that influence pollution may also affect outcomes, such as temperature, humidity, or proximity to industrial sites. Third, there are measurement errors of the concentrations of air pollutants that individuals are exposed to since most measures of air pollution consist of an inverse-distanced weighted average of several monitors that are kilometers or miles away from an individual, or more recently, using satellite data to estimate the concentrations of air pollutants. As such, it is difficult to 1) isolate the effects of air pollution, and 2) use a singular method to provide plausibly causal effects of air pollution. This leads to researchers needing to use different quasi-experimental approaches to estimate the effects of air pollution. For instance, Amanzadeh et al. (2020) use student fixed effects in a panel data to estimate the effect of one standard deviation increase of air pollution on test scores. Austin et al. (2019) use variation in the timing and location of bus retrofits to estimate the effect of the percent of retrofitted bus on language and math scores. Balakrishnan and Tsaneva (2021) use thermal inversions as an instrument to estimate the effect of one unit change in air pollutant concentrations on language and math scores. Using a spatial regression discontinuity design, Gilraine (2025) estimates the effect of installing air filter on test scores. The different estimates and interpretations of the effects of air pollution on student achievement represent an additional complication to synthesizing the results across the studies. I approach this complication in two different ways. First, in the main analysis I use the original estimates from these primary studies to provide a summary estimate of the general effects of air pollution on student achievement. These estimates represent the authors' original intent of their work. In auxiliary analysis, I convert the estimates, whenever possible, so that the interpretation of each estimate is the effect of one $\mu g/m^3$ unit or one standard deviation unit change in the independent variable (e.g., one SD change in $PM_{2.5}$) on a standardized measure of student achievement (e.g., SD change in math or language score). I note some studies do not provide enough information to make this comparison possible. For instance, Dang et al. (2025) and Gilraine and Zheng (2024) do not include the standard deviation measure of $PM_{2.5}$ exposure, so I am unable to compare their unit change estimate to a standard deviation change. Some studies examine the effect of a treatment so it is not possible to estimate a one standard deviation change in pollution. Stafford (2015) estimates the effects of mold and ventilation treatment on test scores and Persico and Fuller (2025) estimate the effects of air filtration, neither of which cannot be converted to a standard deviation interpretation. Using these two approaches allows me to provide 1) the overall effects of air pollution (answering the question of does air pollution affect student achievement) and 2) the effect of one unit change or one standard deviation unit change in the pollutant on a standardized measure of student achievement (with some loss to sample size but providing a more direct interpretation, particularly for researchers and policymakers).

Dependent variable. The main outcomes of interest are causal estimates of the effects of pollution on student achievement as well as the associated standard errors of those estimates (Lipsey & Wilson, 2001). From all the primary studies, there are three types of outcomes that have been examined: composite student test scores, language-specific test scores, and Math-specific test scores. An example composite student test score includes exam scores of student performance (e.g., Ebenstein et al., 2016), and high-stake high-school matriculation exam or university entrance exam in Iran and Brazil respectively (Amanzadeh et al., 2020; Carneiro et al., 2021). I consider composite test scores, language test scores, and Math test scores as student achievement generally in my analysis, but recognizing that these measures are different, I also separate the results by their own category. Some studies also made separate estimates by gender and/or by particulate size ($PM_{2.5}$, PM_{10}). Whenever possible, I also conducted separate meta-analyses using these subgroup estimates.

For ease of interpretations, all estimates have been converted to effect sizes, or changes in standard deviations of each outcome. Consequently, all the meta-analytic results should be interpreted as effect size increases or decreases.

Moderating variables. I coded a series of a priori moderators to examine how the effects of pollution on student achievement may vary by study characteristics. Specifically, I coded for the publication year, publication type, peer-review status, study quality, and country of origin. These moderators were selected based on my reading of the literature and prior systematic reviews and meta-analyses I have conducted. Overall, due to the nature of the retained articles where the vast majority of the studies were peer-reviewed publications published in the last 10 years, there are limited moderators I can employ to examine how effects vary by study characteristics. Specifically, I was able to examine two moderators: 1) study quality, and 2) country of origin (where the data were collected).

Analytic Strategy

Following best meta-analytic practices, I first describe the decision between fixed-effect and random-effects models, selecting causal estimates, and assessing risk of bias from differences in study quality (Borenstein et al., 2021). A fixed-effect meta-analytic approach assumes a true effect size across all studies whereas a random-effects model allows the real treatment effect to vary across populations and programs (Riley et al., 2011). Stated differently, the fixed-effect model assumes all studies estimate the same treatment effect where a random-effects model assumes there are differences in the treatment effect (Borenstein et al., 2009).

Mechanically, the fixed-effect model assigns weights (W_i) to each study (*i*) using the inverse of each within-study variance (V_{y_i}):

$$W_{i,Fixed} = \frac{1}{V_{y_i}} \quad (1)$$

In contrast, the random-effects model weights studies using both the within-study variance and the estimated between-study variance (T^2):

$$W_{i,Random} = \frac{1}{V_{y_i}+T^2} \quad (2)$$

Given the variation across exposure to different pollutants in different countries as well as variations across studies and study quality, the effects of pollution should not be expected to be homogenous across different populations of students. As such, conceptually I prefer the random-effects model in the analysis. Moreover, I also rely on heterogeneity statistics to inform my decisions to use random-effects models.

In terms of selecting the causal estimates, most modern studies provide several plausibly causal estimates to show that the results are robust to alternative specifications. However, most studies state their preferred specification or spend the most time discussing specific estimates. As such, I use the preferred estimates of the primary authors. If the primary authors did not explicitly state their preferred estimate or if there is no clear preference based on the discussion, then I use my professional judgment and select the most rigorous causal estimate based on the extent to which it is able to addressed internal validity issues.

Study Quality

Following best practices, I choose to use an inclusive approach that included all studies satisfying the eligibility criteria. This approach is intended to capture the range of available evidence of the effects of pollution on student achievement and academic outcomes. However, a potential challenge is that this inclusivity may introduce bias from poorly designed or low-quality studies. I address this potential issue by examining study quality specifically (Appendix Table 3). I assess the quality of each study in the spirit of what Alexander (2020) suggests, using a modified quality rating suggested by Lipsey and Wilson (2001). Specifically, using my professional judgment and expertise in quantitative causal analysis, I rated study quality on a scale of 1 to 5 where 1 has high risk of bias and 5 has low risk of bias. For instance, to assess the internal validity of studies employing fixed effects, I consider the extent to which the researchers explain how the fixed effects precisely address which source of bias and the extent to which the results are robust to different modelling specification. For regression discontinuity studies I would consider evidence of non-manipulation of the forcing variable, smoothness of the forcing variable around the threshold, covariate balance checks on either side of the threshold, robustness of findings across various bandwidths, and falsification tests. See Shadish et al. (2002) and Murnane and Willett (2010) for more information on issues of causal inference for a variety of quasi-experimental designs.

I employ this quality rating through two different ways. First, in subgroup analysis, I limit the analysis to high-quality causal studies, studies that have ranking of four or five out of five. Second, I use meta-regression to examine whether study quality is associated with the effect estimate.

Results

Table 1 provides the descriptive information and characteristics of the primary studies included in systematic review and meta-analysis. Primary study characteristics are provided in Appendix Table 4. First, my search reveals 28 causal studies examining the effects of pollution on student academic outcomes. These studies are conducted between 2012 and 2025. Of these 28 studies, 22 are peer reviewed publications and 6 are working papers. The majority of these causal studies, 54 percent, can be considered high-quality, studies with ratings of 4 or 5 out of 5. Slightly more than half, 16 of these studies, are conducted in the United States. Twelve studies are conducted in various countries, including Brazil, Chile, England, India, Iran, Israel, and Vietnam. In terms of the number of treatment estimates, there are a total of 62 total estimates of student achievement, consisting of 15 composite test score estimates, 22 language estimates, and 25 math estimates. With respect to subgroup estimates, there are two general subgroups, one based on gender and one on the size of the particulate. Specifically, there are 12 estimates on female students and 12 estimates on male students. There are 23 estimates of the effects of $PM_{2.5}$ on student achievement and 4 estimates of the effects of PM_{10} on student achievement.

When I consider only the 15 high-quality causal studies, 93 percent are peer reviewed, and 60 percent are based in the United States. From these studies, there are 27 estimates on student achievement, 10 estimates each on gender, and 14 estimates on $PM_{2.5}$. Overall, Table 1 illustrates that the causal studies examining the effects of pollution on student academic outcomes are mostly high-quality studies, have gone through the rigorous peer review process, and have been conducted from all over the world. Next, I provide the meta-analytic results of the effects of pollution on student academic outcomes.

In Panel A of Table 2, I first provide the meta-analytic results when we consider all measures of student achievement, then by composite test scores, language, and math scores. In terms of student achievement, the summary estimate from 62 estimates indicates that pollution decreases student achievement by 0.022 standard deviation (SD) with a standard error of 0.002, with a lower bound of -0.025 and an upper bound of -0.018 SD. This result is statistically significant and clearly indicates that pollution has negative effects on student achievement. When I consider only the composite test score results, the summary estimate from 15 studies indicates that pollution decreases student test score by 0.025 SD, with a lower bound of -0.034 and an upper bound of -0.017 SD. The summary estimates for language and math tests scores are similarly negative, with the estimate for math smaller in magnitude. Specifically, pollution decreases language and math achievement by 0.026 SD and 0.014 SD respectively. In the Discussion section, I contextualize these negative effects compare to experimental evidence on education interventions.

In Panel B of Table 2, I disaggregate the results by gender and size of the particulate. The summary estimate from twelve studies indicates that pollution decrease female student achievement by 0.024 SD and male student achievement by 0.032 SD with both results being statistically significant. These results suggest that pollution may have a more outsize effect on boys than on girls. The summary estimate on male achievement is about an 33% increase than the summary estimate on girls. In terms of the size of the particulate, the summary estimates on $PM_{2.5}$ and PM_{10} are -0.011 SD and -0.059 SD, respectively. These results provide weak but suggestive evidence that PM_{10} may have more negative effects on student achievement than $PM_{2.5}$.

As discussed previously, conceptually I do not expect the effects of pollution to be homogenous across different populations of students, and as such, I rely on the random-effects meta-analysis model. However, I also present empirical evidence that the random-effects models are more appropriate than the fixed-effect models in the last three columns of Table 2. For each summary estimate, I present a set of standard heterogeneity statistics. For instance, for the main student achievement analysis, across these studies the true heterogeneity in effect sizes (I^2) is 98.5, suggesting that less than 1.5 percent of the total variation in effect sizes can be attributed to random error. The Cochrane's Q statistics tests the null hypothesis of homogeneity across studies, and P_Q for student achievement is less than 0.001, indicating that there is strong evidence to reject the null hypothesis that the true dispersion of effect sizes is zero. These heterogeneity statistics present empirical evidence of heterogeneity in effect sizes, which justifies the use of random-effects models. I find similar evidence of heterogeneity across the different subgroups except for PM_{10}, but this is due to the small sample size of four estimates. I explore these differences graphically below with forest plots.

Heterogeneity of Effects

Figure 2 shows the forest plot of the effects of air pollution on student achievement. Each row represents an effect size from a primary study in the meta-analysis, plotted alphabetically by author order. For each row, I also provide the specific outcome (i.e., composite test score, language, or Math) as well as the specific pollutant associated with the outcome. For instance, the first estimate provides the effect of $PM_{2.5}$ on composite test score from the Amanzadeh (2020) study, which is that pollution lowers student test score by 0.03 SD. This estimate contributes to 2 percent of the weight to the summary estimate. Moreover, each figure presents the 95% confidence interval numerically and as lines extending from the point estimates along with the weight that each study contributes to the summary estimate. The overall summary estimate across the studies for that outcome is located at the bottom of the figure. Figure 2 clearly shows that the vast majority of the effect estimates are negative and statistically significant. The vast majority of estimates are between -0.20 and -0.00 SD with a couple of estimates that are less than -0.20 SD (more negative). These estimates, however, are imprecisely estimated, having large standard errors, and they each contribute a very small percent to the overall summary estimate. I note that dropping these imprecisely estimates does not substantively change any of the conclusions. Appendix Figures 1-3 present the forest plots for composite test scores, language scores, and Math scores. Overall, these forest plots show substantial heterogeneity.

Study quality

Even though I have limited this systematic review and meta-analysis to just causal studies, there may still be concerns about the quality of the studies themselves. To address this, I limit the meta-analysis to only high-quality causal studies, studies that are rated at least 4 out of 5 on the quality rating scale. As noted, using these high-quality studies reduces the overall number to 15 studies and 27 estimates on student achievement. Replicating the analysis in Table 2, Panel A of Table 3 shows the summary estimates for student achievement, composite test scores, language scores, and math scores. The summary estimate from 27 high-quality causal estimates indicates that pollution decreases student achievement by 0.029 SD with a lower bound of -0.038 and an upper bound of -0.021 SD. Similar to the main estimates, the summary estimates for composite test scores, language scores, and math scores indicate pollution decrease student scores by 0.031 SD, 0.033 SD, and 0.022 SD respectively. The summary estimates from these high-quality studies are slightly larger than the summary estimates from the main analysis. For instance, the summary estimate changes from -0.022 SD to -0.029 SD for student achievement. In Panel B of Table 3, the summary estimates from the subgroup analysis remain negative and are comparable to the summary estimates from Panel B of Table 2. Overall, these high-quality studies confirm that pollution has negative effects on student achievement.

USA results

As there are substantially more studies examining the effects of air pollution in the United States, I am able to provide meta-analytic results specifically to the United States. The summary estimates from Table 4 indicate that, similar to before, pollution negatively affects student learning. In particular, the summary estimate from 38 U.S.-specific estimates indicate that pollution decreases student achievement by 0.018 SD. The summary estimates for composite test scores, language scores, and math scores indicate pollution decrease student scores by 0.016 SD, 0.030 SD, and 0.013 SD respectively.

Meta-regression results

While the analyses using only high-quality studies and USA-only studies can provide evidence for how the meta-analytic results may change when I limit the sample, another approach would be to use meta-regression analysis, a meta-analytic approach that uses regression analysis to account for available covariates. Using meta-regression will allow me to analyze how high-quality studies or USA-studies may change the summary estimate. Table 5 shows the meta-regression results using a high-quality dichotomous variable where a 1 is equal to studies with ratings of 4 or 5 and a 0 indicates studies of ratings 3 or less (Panel A). Similarly, I use a USA indicator in Panel B.

The meta-regression results for high-quality studies suggest that high-quality causal studies do not find more negative effects of pollution on student achievement as the estimates on high-quality are statistically insignificant except for Math (Panel A of Table 5). Similarly, the estimates on USA studies are insignificant (Panel B). Panel C similarly shows insignificant relationships when we consider both high-quality studies and USA studies.Overall, these meta-regression results are substantively similar to the meta-analytic results using only high-quality and USA-only studies.

Publication Bias

Another concern in meta-analyses relates to potential primary studies that are not published because the outcomes of the studies might have biased the decision to publish or distribute them. This publication bias threat would then systematically underrepresent the true populations of the completed studies (Banks et al., 2012). Most often, these studies are not published or distributed because they have non-significant findings. To explore this possibility, I include Appendix Figure 4 showing the contoured enhanced funnel plot for student achievement, which is designed to help detect publication bias. If studies are missing in the areas of non-significance (the inner most funnel), that would suggest non-significant results are not being published. Asymmetry to the left or right of the center indicates that studies are systematically more likely to have found negative or positive results respectively.

I note that there are many non-significant results in the analysis, which reduces the risk of publication bias. Stated otherwise, the possibility of non-significant findings that are not published or distributed is minimal. In terms of asymmetry, I observe that there are no studies with significant positive effect estimates (right side of zero on the x-axis). This is perfectly reasonable as I would not expect pollution to cause students to learn more. Given these results, I do not suspect that publication bias is a serious threat to the findings.

Standardizing the Effects of Air Pollution

As noted in the Method section, a different way to synthesize the effects of air pollution is to have comparable estimates of the changes in the concentration of air pollutants. However, conversion of overall air pollution effects to $\mu g/m^3$ unit increase or standard deviation increase comes with a non-trivial loss to sample size as some studies estimate the effect of a treatment (e.g., Austin et al., 2019) and others do not provide enough information to estimate a one unit increase or one standard deviation increase (e.g., Lu et al., 2021).

In Table 6, I replicate Table 2 by converting all estimates from primary studies to a comparable one standard deviation change in the pollutant. Using 37 estimates, the summary effect estimate for student achievement is that a one standard deviation change in air pollution causes a decrease of 0.042 SD in student achievement. Similarly, a one standard deviation increase in air pollution decreases composite test scores, language scores, and math scores by 0.038 SD, 0.048 SD, and 0.035 SD respectively. In Table 7, I similarly replicate Table 2 but for a one $\mu g/m^3$ unit increase. I find that a one $\mu g/m^3$ unit increase of pollutant decreases student achievement by 0.011 SD.

Limitations and Future Research

There are a few main limitations with research in this area. First, since air pollution is everywhere, the estimates on the effects of air pollution are sometimes measured in different ways in terms of the concentration of air pollutant exposed to children and students. Specifically, there are many ways to think about dosage: it could be the amount of air pollutants ($\mu g/m^3$), by one Interquartile Range (IQR), above or below a certain threshold (e.g., 200 $\mu g/m^3$), or by one standard deviation of the pollutant. Future research should provide multiple estimates (or interpretations) based on different dosage measurement. It would, for instance, be easiest for policymakers and the public to understand that a standard deviation increase (or a unit increase) of a pollutant has a range of effects on student achievement (my approach in Tables 6 and 7).

Relatedly, measurement error is also a threat to validity to many of the primary studies included in this current work (and in air pollution studies generally). Specifically, there is difficulty in measuring exposure to air pollution as there are limited monitoring data in many parts of the world, the difference between indoor and outdoor exposure, and spatial and temporal variability in short- and long-term exposure to pollutants. Having more indoor and outdoor pollution monitors would make it more possible to estimate how much people are exposed to pollutants on a regular basis.

Another limitation is that there are different components to air pollution, such as CO, NO_x, ozone, and particulate matters. It is not always possible to simultaneously separate out the differential effects of each pollutant, so it is difficult to determine if there is one type or category of pollutants that may be more harmful than others, at least for school-age children. While I am able to conduct some subgroup analysis of $PM_{2.5}$ and PM_{10}, there are not enough studies to clearly say that one or the other is more harmful for student achievement, and there are definitely not enough studies of other types of pollutants to suggest if one is worse than another. I would note, however, that it may not be necessary to fully isolate or tease out the individual effects and harms to children and students if the policy solutions to fix them are similar (e.g., indoor air filters are designed to filter out all of these pollutants). In a similar vein, it would be very useful if more studies provided subgroup estimates, particularly by gender, by socioeconomic status, and by race/ethnicity. The subgroup analysis that I am able to conduct suggests that air pollution may have larger effects on boys than on girls, and it would be important to confirm this and examine the extent to which this type of differential effect may exist by socioeconomic status or by race/ethnicity.

Discussion

By focusing on studies that provide plausibly causal estimates of the effects of air pollution on student achievement, I am able to synthesize the most rigorous evidence on this important issue and examine how the effects of air may differ for male and female students and by different measures of achievement. The majority of the primary studies include in this systematic review and meta-analysis can be considered high-quality causal studies, and includes evidence from a range of countries from Brazil, Iran, Vietnam to the United States. Overall, the evidence indicates that air pollution, broadly measured, negatively affects student achievement globally by about 0.02 standard deviations (SD). Students who are exposed to higher concentrations of air pollution consistently score lower on a variety of tests than students who are not, and this difference is caused by air pollutants. Air pollution causes students to do worse on language and math tests by 0.026 SD and 0.014 SD respectively. On composite tests, the summary effect is about 0.025 SD. Moreover, the effects of air pollution are about 33% larger for boys (0.032 SD) than for girls (0.024 SD). Additionally, the summary estimates tend to be even larger when only the high-quality causal studies are used. Lastly, one unit and one standard deviation increase in air pollution decrease student achievement by 0.011 SD and 0.042 SD respectively.

While the evidence clearly indicates that air pollution is detrimental to student achievement, it is also important to provide some practical interpretation of these results. While a decrease of 0.02 SD to 0.04 SD in student achievement may seem small, it is actually practically meaningful and is comparable to a number of education interventions. First, a 0.042 SD decrease is about a 1.6 percentile point decrease in student achievement (von Hippel, 2025). Second, across 139 effect sizes from 49 preregistered randomized controlled trials (RCTs) of education interventions funded by the Department of Education, the median effect size is 0.03 SD (Kraft, 2020). Examining education interventions in low- and middle-income countries, Evans and Yuan (2022) find that the 25th percentile of effect size is 0.01 SD. Examining interventions in disadvantaged schools specifically, Boulay et al. (2018) find that the median effect of RCTs is 0.03 SD even when these interventions cost several thousand dollars per student. Huillery et al. (2025) find that a four-year mindset intervention had a 0.05 SD increase in grade point average. The average scores for students in districts receiving more than $8,000 per student with the Elementary and Secondary School Emergency Relief (ESSER) federal grants provided to K-12 schools in response to the Covid-19 pandemic increased by 0.047 SD and 0.055 SD in language and math respectively (Dewey et al., 2024). In other words, a decrease of 0.02-0.04 SD in student achievement represents a non-trivial effect and is on par with a median effect size in education interventions.

In sum, the negative effects of air pollution on student achievement are significant and practically meaningful, they may have an outsize effect on male than female students, and they can be observed all over the world, even in wealthier countries like the United States. After I discuss the mechanisms through which air pollution may affect student achievement, I further contextualize these detrimental effects of air pollution and the implications for policy and practice, particularly with respect to the potential economic lost due to student achievement and the cost-effectiveness of interventions to mitigate the effects of air pollution.

Potential Mechanisms of Air Pollution on Student Achievement

While this current work clearly establishes that air pollution undoubtedly negative affects student achievement, it is also important to consider the potential mechanisms through which air pollutants affect K-12 students. As discussed previously, there are two main mechanisms: 1) neurobiological and cognitive mechanisms, and 2) physical and behavioral mechanisms.

In terms of neurobiological and cognitive mechanisms, the health literature has demonstrated over and over again that air pollutants contribute to brain development and function (An et al., 2021; Bates, 1995; Dutheil et al., 2021; Lopuszanska & Samardakiewicz, 2020; Vallero, 2025). Multiple systematic reviews and meta-analyses have shown that children and kids who are exposed to higher concentrations of air pollution are systematically affected by the pollutants and have worse neurobiological and cognitive development. These findings have direct implications for policy and practice that I will turn to in the next section.

With regards to physical and behavioral mechanisms, there has also been substantial evidence that air pollution is associated with increased absenteeism as well as behavioral issues. While there is not enough causal evidence for a formal meta-analysis, there are a handful of recent causal studies that examine how air pollution affects attendance and student behavior. Chen et al. (2018) finds that a one standard deviation increase in pollutant increases the probability of being absent by 7%. Liu and Salvo (2018) find that the occurrence of severe $PM_{2.5}$ in China increase the probability of being absent by 0.88 percentage point, a 14% increase relative to the sample mean. Heissel et al. (2022) find that attending a school downwind of a major highway increases absence rate by 0.54 percentage points and having a behavioral incident by 4.10 percentage points. Similarly, Persico and Venator (2021) find that, in Florida, United States, students exposed to air pollution are more likely to be suspended from school and more likely to be absent. Using daily administrative data in California, United States, Chung et al. (2025) find that a 10 $\mu g/m^3$ increase in daily $PM_{2.5}$ leads to a 5.7% increase in full-day student absences and a 28% increase in office referrals in a three-day window. Moreover, these effects are driven by marginalized students, specifically low-income, Black, and Hispanic students in the California context.

In sum, there is substantial evidence that air pollution can and does negatively impact students' neurobiological and cognitive development as well as their attendance and behaviors in school. Both sets of mechanisms can explain how air pollution ultimately affects student achievement.

Implications for Policy and Practice

What do we do when the air we breathe is poisoning us? Not only is air pollution an ecological phenomenon that negatively affects almost all of us, it also affects our youngest and most vulnerable populations, children and students. The evidence on student achievement that is synthesized in this study along with the broader evidence of the effects of air pollution on physical health and neurobiological development strongly suggests that we need to meet this challenge head on. With respect to students and student achievement specifically, there are two main ways that policymakers can take actions to address this problem.

First, policymakers and citizenries need to do more to improve the ambient air pollution that exists ubiquitously. Air pollution has such detrimental effects on numerous fronts, including education and economics, that it is difficult to think we are not doing more to reduce air pollution everywhere. In the Second Global Conference on Air Pollution and Health, the WHO has put forth the shared objective of reducing health impacts of air pollution by half by 2040 (World Health Organization, 2025b). Forty-seven million people from the health community have argued that clean air is a human right and have urgently called for bold evidence-based actions on air pollution (World Health Organization, 2025c). Similarly, environment ministers worldwide through the United Nations Environment Programme and the "Beat Pollution" campaign have reaffirmed political commitment to reduce all forms of pollution, including air pollution (UNEP, 2025).

While these shared initiatives and commitments at the global level are critical, it is also important to recognize that regional and national policies can also aim to directly affect air pollution. For instance, the revised European Union's Ambient Air Quality Directive (2024), in alignment with the WHO guidelines, has set stricter standards to ensure Europeans enjoy healthier air by updating air quality standards and setting target values for the major air pollutants including NO_x, ozone, PM_{10}, and $PM_{2.5}$ (in the case of $PM_{2.5}$ specifically, the goal is to cut the annual limit by more than half). Their previous goals and standards have resulted in substantial improvement in air quality. For instance, the percent of urban population exposed to $PM_{2.5}$ and NO_2 fell between 2000 and 2023, and by 2023, less than 1% was exposed to concentrations above the annual limit (EEA, 2025).

The United States through the Environmental Protection Agency (EPA) has made similar efforts in the past to reduce pollution throughout the country, and substantial gains were made. Specifically, the EPA estimated that the Clean Air Act reduced traffic emissions by 70% between 1970 and 2015 (EPA, 2015). Based on their work and some back of the envelope calculation, Heissel et al. (2022) estimated that this reduction in traffic pollution has raised test scores by 0.11 SD, which should be considered a medium effect size educational intervention (Kraft, 2020). In sum, we have evidence that major policy actions can and have made positive impacts on air pollutions and that policymakers and society at large, particularly in developed and wealthy nations, should continue to make these investments that would benefit their citizens at home and the global populations at large.

Second, while country-level and global-level efforts are absolutely needed, policymakers and educators at more local level can also take actions to mitigate the detrimental effects of air pollutions for children and students. For instance, education policymakers can retrofit bus engines to reduce children exposure to high levels of air pollution from diesel emissions and high-emission engines. Austin et al. (2019) find that, in addition to health benefits, retrofitting buses (i.e., installing diesel particulate filter, diesel oxidation catalyst, flow-through filter, or a closed crankcase filter) taking students to school increases language and math scores by 0.009 SD and 0.005 SD respectively, which has an estimated monetary value of $2.57 million for students' lifetime earnings and represents more than 25 times the cost of retrofitting.

Schools can also carry out mold and ventilation improvement projects to improve air quality for students at school. Stafford (2015) estimated that the average mold remediation project ($500,000) would improve math and reading scores by 0.15 SD and 0.14 SD respectively, and the average ventilation improvement ($300,000) would similarly improve math and reading scores by 0.07 SD and 0.11 SD. These improvements would then be considered to have medium effect sizes in education interventions (Kraft, 2020), and the costs would be low, particularly when we consider that the improvements would affect thousands of students each year. For example, a mold remediation project costing $500,000 for a school serving 1,000 students would cost $500 per student (this is assuming the cost distributed over just a single year, and the cost is potentially a lot less if spread out over a longer period of time) and have minimal maintenance costs on a per student basis.

In another study that examines the effects of air filters at a school setting, there was a gas leak that occurred in a wealthy Los Angeles neighborhood (California, U.S), and a gas company placed air filters in every classroom within five miles of the leak to remediate this problem. Using a spatial regression discontinuity design, Gilraine (2025) finds that installing air filters increased math and language scores by about 0.10-0.20 SD. Gilraine (2025) estimates that, assuming air filters reduce indoor particular matters by ninety percent, each $\mu g/m^3$ removed was responsible for 0.02-0.03 SD increase in test score. More importantly, the per-year cost to install and maintain air filters in schools is around $1,000 per class, which is perhaps one of the most cost-effective educational interventions available relative to many other well-known interventions such as high dosage tutoring, class size reduction, and Head Start (Brewer et al., 1999; Guryan et al., 2023; Ludwig & Phillips, 2007). It should be further noted that air filters can mitigate poor indoor air quality even more for the most underprivileged or low-income students in high pollution areas.

In conclusion, air pollution affects almost all of us from the moment we are born, all through our formative years, even to our old age. We absolutely need to do more at the local level, national level, and global level to combat this issue that not only affects our physical health and our neurobiological development but also our learning and achievement. The evidence synthesized here clearly indicates that air pollution negatively impacts student achievement, but more importantly, there are direct and cost-effective actions that can be taken to mitigate these detrimental effects.

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* indicates studies included in the systematic review and meta-analysis

Tables and Figures

Table 1. Descriptive information on the primary studies by study characteristics

	Full sample of causal studies	High-quality causal studies
Study characteristics		
Publication year	2012-2025	2016-2025
Publication type	22 articles 6 working papers	12 articles 3 working papers
Peer review	89%	93%
High-quality	54%	100%
USA-based	57%	60%
Other countries (# of studies)	Brazil (2), Chile (3), England, India, Iran (2), Israel (2), Vietnam	Brazil, England, India, Iran, Israel, Vietnam
Number of treatment estimates		
Student achievement	62	27
Composite test scores	15	9
Language	22	9
Math	25	9
Subgroup estimates		
Female students	12	10
Male students	12	10
$PM_{2.5}$	23	14
PM_{10}	4	2
Number of studies	28	15

Note. High-quality studies include studies with scores of 4 or 5 out of 5 based on my rating. Student achievement include estimates on any composite test score, language, or Math. $PM_{2.5}$ and PM_{10} are two pollutants most studied.

Table 2. Meta-analytic results of the effect of air pollution on student achievement

Outcomes	Main effect estimates					Heterogeneity of study effects		
	N	Effect Estimate	Standard Error	Lower Bound	Upper Bound	I^2	Q	P_Q
Panel A: Main analysis								
Student achievement	62	-0.022	0.002	-0.025	-0.018	98.468	3981.053	<.001
Composite test score	15	-0.025	0.004	-0.034	-0.017	99.596	3463.780	<.001
Language	22	-0.026	0.004	-0.034	-0.018	88.210	178.114	<.001
Math	25	-0.014	0.002	-0.017	-0.010	83.913	149.186	<.001
Panel B: Subgroup analysis								
Female achievement	12	-0.024	0.004	-0.031	-0.016	98.788	907.783	<.001
Male achievement	12	-0.032	0.005	-0.042	-0.022	99.131	1265.573	<.001
$PM_{2.5}$	23	-0.019	0.003	-0.024	-0.014	98.949	2093.627	<.001
PM_{10}	4	-0.059	0.009	-0.078	-0.041	34.698	4.594	0.204

Note. Student achievement, test score, language, and Math scores are measured in standard deviations units. N reflects the number of effect sizes.

Table 3. Meta-analytic results of the effect of air pollution on student achievement with high-quality causal studies

Outcomes	Main effect estimates					Heterogeneity of study effects		
	N	Effect Estimate	Standard Error	Lower Bound	Upper Bound	I^2	Q	P_Q
Panel A: Main analysis								
Student achievement	27	-0.029	0.004	-0.038	-0.021	96.728	794.548	<.001
Composite test score	9	-0.031	0.008	-0.046	-0.016	98.343	482.697	<.001
Language	9	-0.033	0.006	-0.045	-0.020	85.758	56.172	<.001
Math	9	-0.022	0.004	-0.029	-0.015	53.253	17.113	0.029
Panel B: Subgroup analysis								
Female achievement	10	-0.025	0.006	-0.038	-0.013	96.279	241.864	<.001
Male achievement	10	-0.033	0.008	-0.049	-0.017	96.637	267.589	<.001
$PM_{2.5}$	14	-0.021	0.004	-0.030	-0.013	94.494	236.107	<.001
PM_{10}	2	-0.050	0.009	-0.067	-0.033	13.099	1.151	0.283

Note. Student achievement, composite test score, language, and Math scores are measured in standard deviations units. N reflects the number of effect sizes. High-quality causal studies have ratings of 4 or 5 out of 5 on the quality rating scale.

Table 4. Meta-analytic results of the effect of air pollution on student achievement in the United States

Outcomes	Main effect estimates					Heterogeneity of study effects		
	N	Effect Estimate	Standard Error	Lower Bound	Upper Bound	I^2	Q	P_Q
Panel A: Main analysis								
Student achievement	38	-0.018	0.002	-0.021	-0.014	93.020	530.101	<.001
Composite test score	7	-0.016	0.006	-0.028	-0.004	97.444	234.780	<.001
Language	14	-0.030	0.006	-0.042	-0.018	89.649	125.592	<.001
Math	17	-0.013	0.002	-0.017	-0.009	86.317	116.930	<.001
Panel B: Subgroup analysis								
Female achievement	4	-0.026	0.002	-0.030	-0.022	5.804	3.185	0.364
Male achievement	4	-0.033	0.003	-0.039	-0.026	16.197	3.580	0.311
$PM_{2.5}$	14	-0.018	0.003	-0.024	-0.012	91.894	160.371	<.001
PM_{10}	4	-0.059	0.009	-0.078	-0.041	34.698	4.594	0.204

Note. Student achievement, composite test score, language, and Math scores are measured in standard deviations units. N reflects the number of effect sizes.

Table 5. Meta-regression results

	(1) Student achievement	(2) Composite test score	(3) Language	(4) Math
Panel A: High Quality Studies				
High quality	-0.009	-0.007	-0.010	-0.016**
	(0.006)	(0.014)	(0.013)	(0.004)
Constant	-0.019**	-0.024*	-0.024*	-0.007**
	(0.004)	(0.010)	(0.009)	(0.002)
N	62	15	22	25
Panel B: USA Studies				
USA	0.006	0.017	-0.006	0.004
	(0.006)	(0.012)	(0.014)	(0.008)
Constant	-0.027**	-0.036**	-0.025*	-0.019**
	(0.005)	(0.008)	(0.011)	(0.006)
N	62	15	22	25
Panel C: USA and High Quality Studies				
High quality	-0.010	-0.008	-0.009	-0.014**
	(0.006)	(0.013)	(0.014)	(0.005)
USA	0.007	0.018	-0.004	0.002
	(0.006)	(0.013)	(0.014)	(0.005)
Constant	-0.023**	-0.032*	-0.022^{+}	-0.010^{+}
	(0.005)	(0.011)	(0.012)	(0.005)
N	62	15	22	25

Note. Standard errors in parentheses
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 6. Meta-analytic results of the effect of one standard deviation increase of air pollution on student achievement

Outcomes	Main effect estimates					Heterogeneity of study effects		
	N	Effect Estimate	Standard Error	Lower Bound	Upper Bound	I^2	Q	P_Q
Panel A: Main analysis								
Student achievement	37	-0.042	0.005	-0.052	-0.032	98.222	2025.144	<.001
Composite test score	11	-0.038	0.007	-0.051	-0.026	99.273	1374.632	<.001
Language	13	-0.048	0.009	-0.065	-0.030	84.633	78.088	<.001
Math	13	-0.035	0.008	-0.052	-0.019	72.871	44.233	<.001
Panel B: Subgroup analysis								
Female achievement	8	-0.039	0.008	-0.055	-0.023	98.626	509.420	<.001
Male achievement	8	-0.065	0.006	-0.077	-0.053	96.662	209.689	<.001
$PM_{2.5}$	18	-0.044	0.006	-0.055	-0.032	97.631	717.639	<.001
PM_{10}	4	-0.067	0.015	-0.096	-0.038	64.252	8.392	0.039

Note. Student achievement, test score, language, and Math scores are measured in standard deviations units. N reflects the number of effect sizes.

Table 7. Meta-analytic results of the effect of one μg/m^3 unit increase of air pollution on student achievement

Outcomes	Main effect estimates					Heterogeneity of study effects		
	N	Effect Estimate	Standard Error	Lower Bound	Upper Bound	I^2	Q	P_Q
Panel A: Main analysis								
Student achievement	39	-0.011	0.002	-0.015	-0.008	99.443	6819.934	<.001
Composite test score	11	-0.011	0.003	-0.017	-0.005	99.851	6729.216	<.001
Language	14	-0.010	0.002	-0.014	-0.006	74.165	50.318	<.001
Math	14	-0.009	0.002	-0.013	-0.005	64.740	36.869	<.001
Panel B: Subgroup analysis								
Female achievement	8	-0.011	0.002	-0.016	-0.006	99.537	1511.649	<.001
Male achievement	8	-0.018	0.006	-0.029	-0.006	99.907	7529.294	<.001
$PM_{2.5}$	20	-0.014	0.003	-0.019	-0.009	99.446	3429.759	<.001
PM_{10}	4	-0.006	0.002	-0.010	-0.002	85.916	21.300	<.001

Note. Student achievement, test score, language, and Math scores are measured in standard deviations units. N reflects the number of effect sizes.

Figures

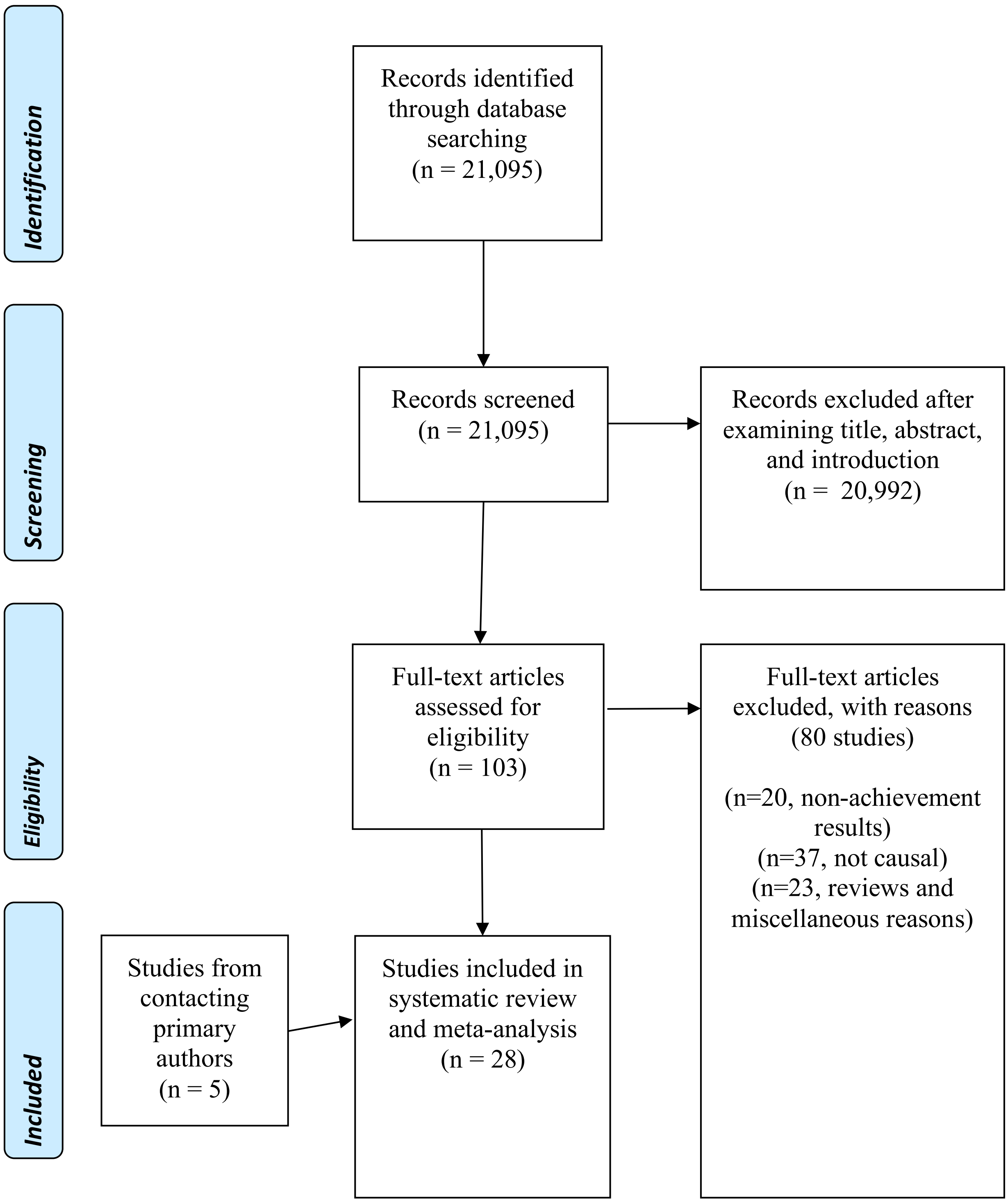


Figure 1. Flow diagram of the literature screening process. Adapted from Moher et al. (2009).

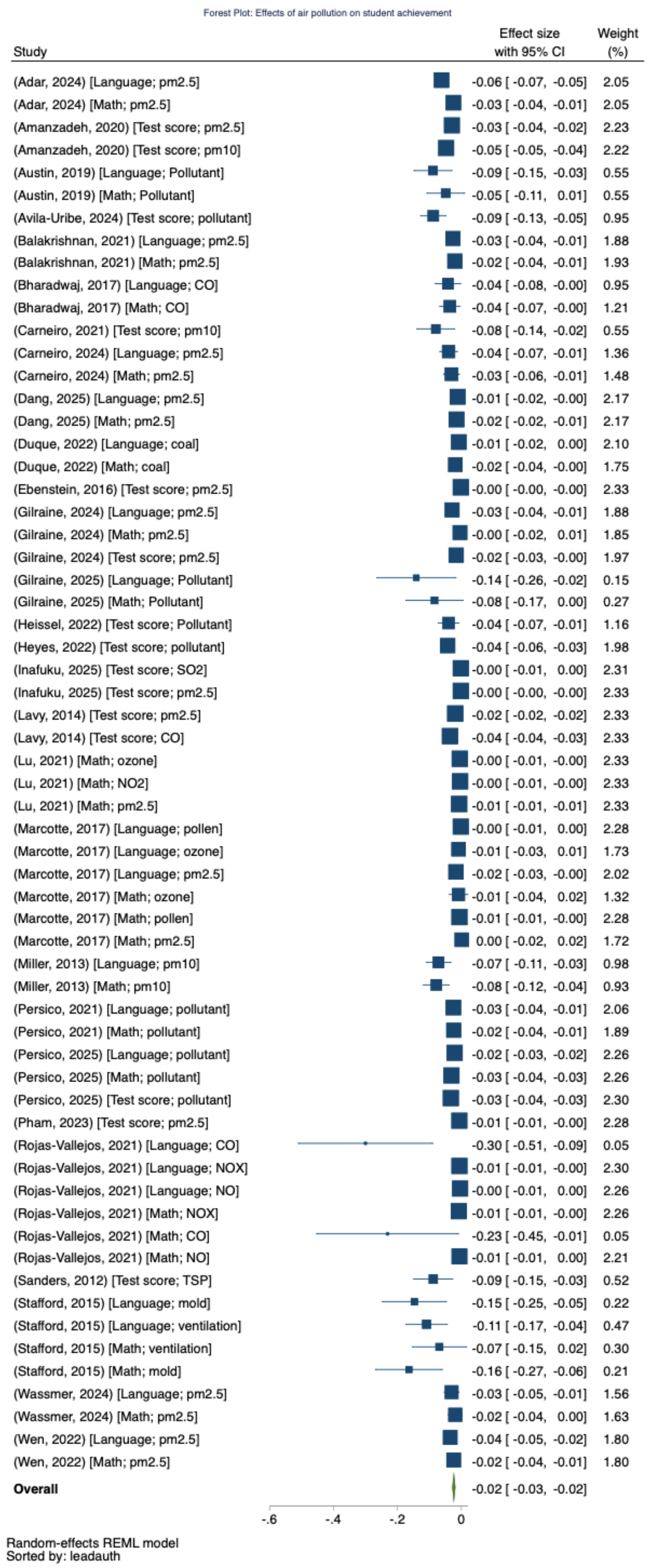


Figure 2. Forest plot for overall effect estimates of air pollution on student achievement

Appendix Tables

Appendix Table 1. Results by database

Database	Results
JSTOR (abstract)	543
JSTOR (title)	245
ERIC	2674
WorldCat	10372
Google scholar	1000
ProQuest	3878
NBER	2026
Taylor and Francis Online (title)	900
Total	21,095

Appendix Table 2. Coding schema

Variable	Description	Level of measurement
Study and Program Characteristics		
Variable	**Description**	**Level of measurement**
Id	ID Number assigned to study	Continuous
Leadauth	Name of lead author	Nominal
Title	Title of paper	Nominal
Yearpub	Year paper was published	Continuous
Pubtype	Type of publication (academic journal, policy report, conference paper, etc.)	Nominal
Peer review	Is the study a peer-reviewed publication?	Binary
Method	Identification strategy (RD, DiD, IV, RCT, fixed effects)	Nominal
Conditional	Are the estimates conditional or unconditional on enrollment?	Nominal
USA	Is the study based in the U.S.?	Binary
State	Name of state (if U.S.=1)	Nominal
Otherctry	Name of the country where the study was conducted if not the U.S.	Nominal
Outcome	The dependent variable(s) of the study: composite test score, language score, math score,	Nominal
Sensi_robust_falsi	Does the study provide sensitivity and robust estimates? Does it provide falsification test?	Nominal
Study_quality	The author's professional judgment of the study's quality from 1-5 (1-poor, 3-average, 5-excellent)	Ordinal
Summary	Qualitative note of the study	Qualitative
Misc_note	Miscellaneous notes	Qualitative
Study Outcomes		
Variable	**Description**	**Level of measurement**
Outcometype	Test score, language, math	Nominal
Pollutant type	Pollutant, mold, particulate matter, NOx, CO, O3, coal, etc.	Nominal
Gender	Gender indicator (male, female, pooled)	Nominal
Main_ana	The main estimate (not subgroup) indicator	Binary
Beta	Regression coefficient of the causal estimate of air pollution on outcome	Continuous
SE	The standard error of the beta	Continuous
Tstat	T-statistics of the beta coefficient estimate	Continuous
Samplesize	Sample size of the estimate	Continuous
Dosage	The difference in air pollutant concentration used in causal estimate	Continuous
Note	Additional notes about the estimates or study	Qualitative

Appendix Table 3. Quality Criteria for Assessing Risk of Bias

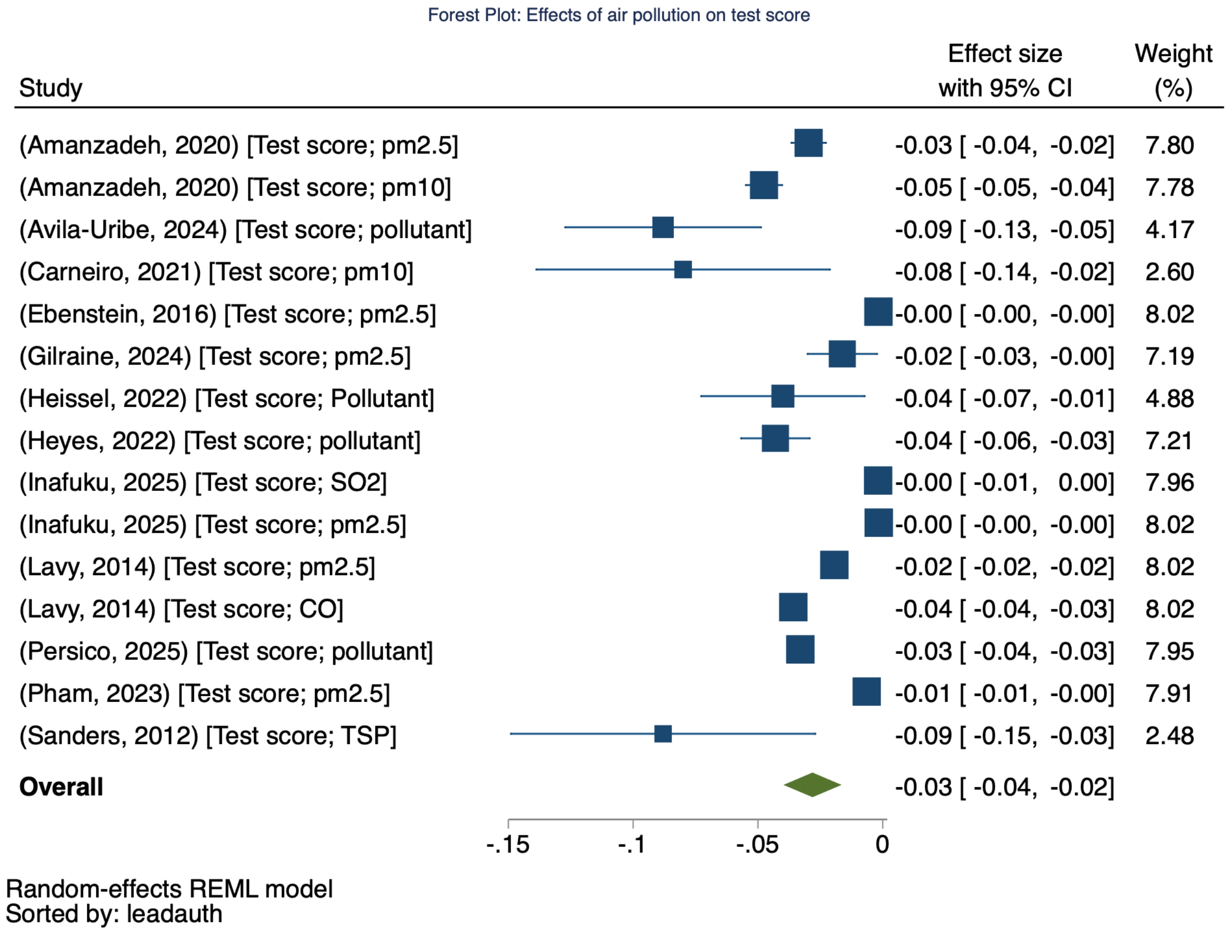
Quality Rating Considerations
Was the study a randomized control trial?
Was implementation fidelity measured and adequately described, and what are the implications of implementation fidelity on outcomes?
What are the relative strengths of the study design?
Was the analytic approach adequately described, and what are the relative merits of the approach used?
Was the comparison condition adequately described, and does the comparison group provide a reasonable counterfactual?
Were threats to internal and external validity considered and addressed?
Were findings robust to different analytical decisions and model specifications?
Was baseline equivalence established between treatment and comparison groups? (This is unnecessary for some approaches such as the difference-in-difference design.)
What sampling decisions were made by the authors and did the analytic sample present any concerns to internal or external validity?

Note: Studies with a rating of four or five out of five were considered high quality studies.

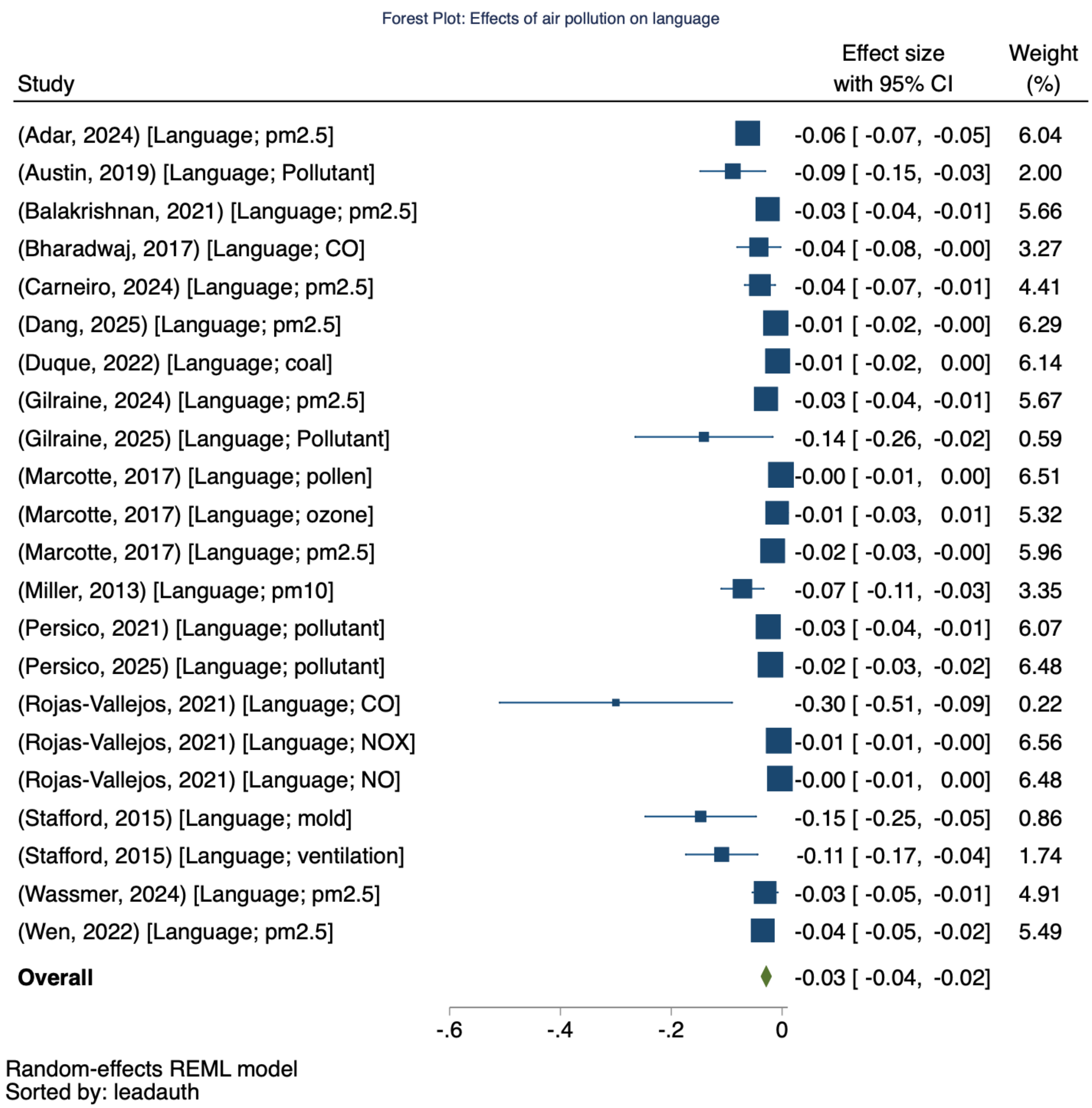
Appendix Table 4. Primary study's characteristics

Lead author	Year	Pub type	Peer review	USA	State	Other country
Adar	2024	Working paper	Yes	Yes	National	
Amanzadeh	2020	Article	Yes	No		Iran
Austin	2019	Article	Yes	Yes	Georgia	
Avila-Uribe	2024	Working paper	Yes	No		England
Balakrishnan	2021	Article	Yes	No		India
Bharadwaj	2017	Article	Yes	No		Chile
Carneiro	2021	Article	Yes	No		Brazil
Carneiro	2024	Article	Yes	No		Brazil
Dang	2025	Article	Yes	No		Vietnam
Duque	2022	Article	Yes	Yes	North Carolina	
Ebenstein	2016	Article	Yes	No		Israel
Gilraine	2024	Article	Yes	Yes	National	
Gilraine	2025	Article	Yes	Yes	California	
Heissel	2022	Article	Yes	Yes	Florida	
Heyes	2022	Working paper	No	No		Iran
Inafuku	2025	Article	Yes	Yes	Hawaii	
Lavy	2014	Working paper	Yes	No		Israel
Lu	2021	Article	Yes	Yes	National	
Marcotte	2017	Article	Yes	Yes	National	
Miller	2013	Working paper	No	No		Chile
Persico	2021	Article	Yes	Yes	Florida	
Persico	2025	Working paper	No	Yes	North Carolina	
Pham	2023	Article	Yes	Yes	National	
Rojas-Vallejos	2021	Article	Yes	No		Chile
Sanders	2012	Article	Yes	Yes	Texas	
Stafford	2015	Article	Yes	Yes	Texas	
Wassmer	2024	Article	Yes	Yes	National	
Wen	2022	Article	Yes	Yes	National	

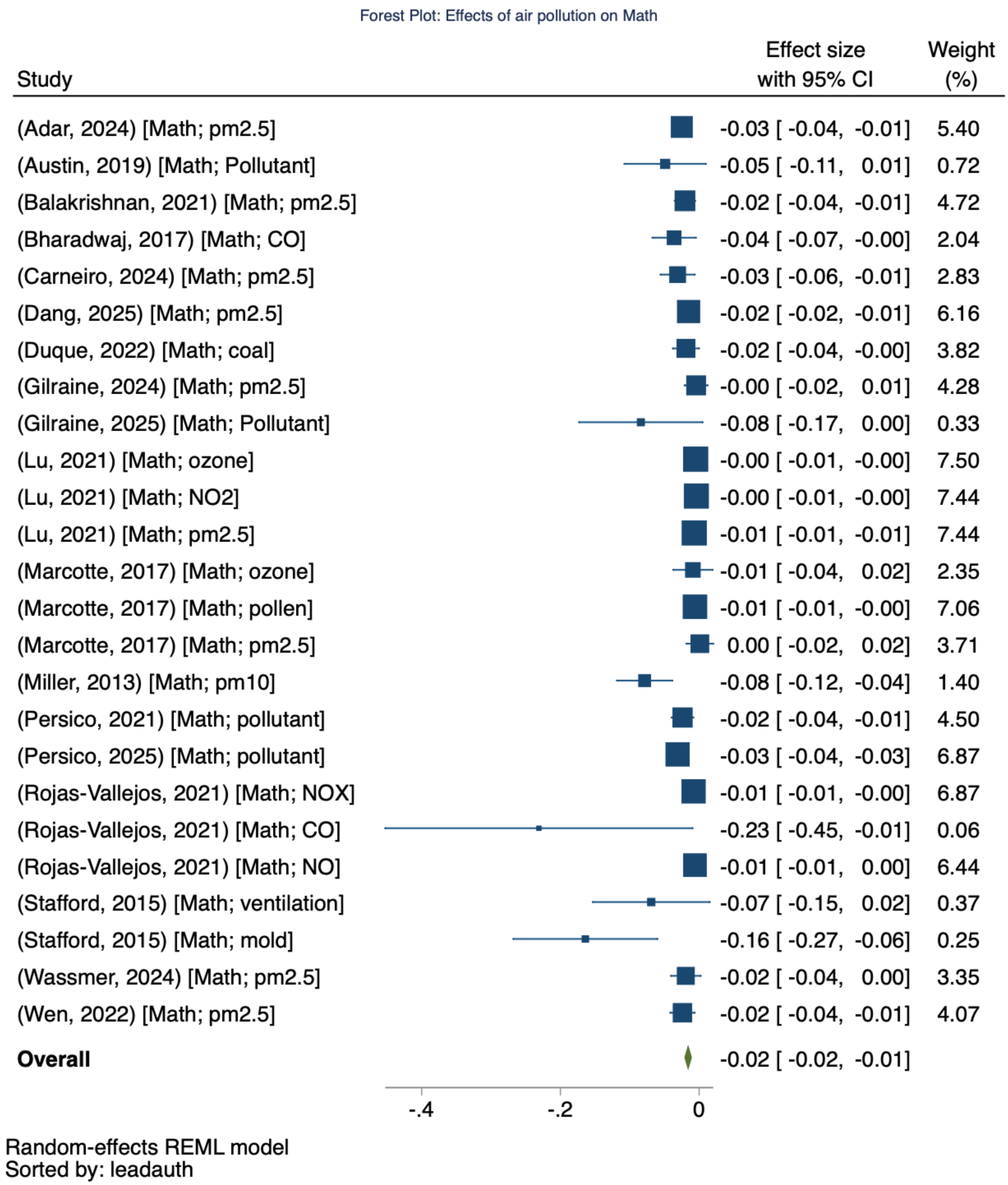
Appendix Figures



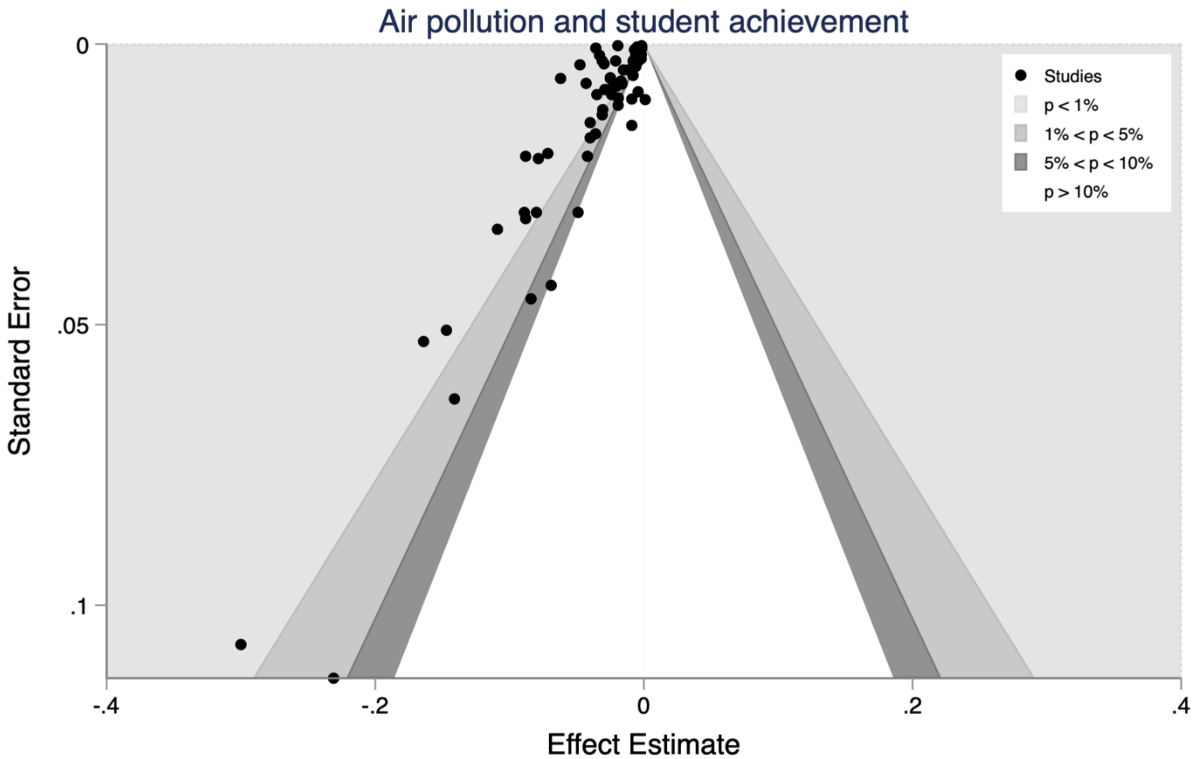
Appendix Figure 1. Forest plot for overall effect estimates of air pollution on test score



Appendix Figure 2. Forest plot for overall effect estimates of air pollution on language



Appendix Figure 3. Forest plot for overall effect estimates of air pollution on Math



Appendix Figure 4. Contoured enhanced funnel plots of air pollution on student achievement