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# The association between air pollution and childhood asthma: United States, 2010–2015

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## Abstract

**Objective:** The current population-based study examines the association between county-level ambient air pollution and childhood asthma.

**Methods:** Data from the nationally representative 2010–2015 National Health Interview Survey were linked to nationwide fine particulate matter ($PM_{2.5}$) air pollution data at the county-level from the National Environmental Public Health Tracking Network which utilizes air quality monitoring stations and modeled $PM_{2.5}$ measurements (Downscaler model data) and adjusted by county-level socioeconomic characteristics data from the 2010–2015 American Community Survey. Multilevel modeling techniques were used to assess the association between $PM_{2.5}$ annual concentrations (quartiles < 8.11, 8.11–9.50, 9.51–10.59, ≥ 10.60 μg/m$^3$) and current childhood asthma along with two asthma outcomes (episode in the past year, emergency room (ER) visit due to asthma).

**Results:** From 2010–2015, there were significant declines in $PM_{2.5}$ concentrations and asthma outcomes. In unadjusted models, children living in areas with higher $PM_{2.5}$ concentrations were more likely to have current asthma, ≥1 asthma episode in the past year, and ≥1 ER visit due to asthma compared with children living in areas with the lowest quartile (< 8.11 μg/m$^3$). After adjusting for characteristics at the county, geographic, and child and family-level, significant associations remained for asthma episode, and ER visit among children living in areas with $PM_{2.5}$ annual concentrations between 9.51–10.59 μg/m$^3$ (3rd quartile) compared with children living in areas with the lowest quartile.

**Conclusions:** This study adds to the limited literature by incorporating nationally representative county-, child-, and family-level data to provide a multi-level analysis of the associations between air pollution and childhood asthma in the U.S.

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**Keywords**

children; outdoor exposure; modeled data; Downscaler; particulate matter; National Health Interview Survey

## Introduction

Asthma is one of the most common chronic diseases among children (1), and remains a leading cause for childhood hospitalization (2). The costs associated with childhood asthma impose a vast economic burden on the United States health care system (3, 4), with more than 2.4 million physician office visits (5), 545,000 emergency department (ED) visits (6), and 75,000 hospitalizations annually (7) in 2016. Children with asthma also experience 13.8 million missed school days annually (8), as of 2013.

The prevalence of childhood asthma has doubled nonlinearly over the past 40 years (9, 10), despite improvements seen in air pollution over the same time period, as evidenced by a downward shift of criteria pollutants (particulate matter, carbon monoxide, lead, nitrogen dioxide, ozone, sulfur dioxide) (11). Previous studies have demonstrated a clear and consistent association between air pollution and various respiratory diseases due to both short and long term exposures, with asthma being one of the most notable (12–25). However, a standardized approach for exploring the relationship between ambient air pollution and childhood asthma is lacking with inconsistent geographic specificity (e.g. state or local-level pollution data, but rarely national air pollution data) (17–26). Furthermore, although the number of United States Environmental Protection Agency (EPA) monitoring stations are increasing (27), the majority are placed in metropolitan areas, with sporadic locations throughout nonmetropolitan areas, leading to counties without air pollution exposure measurements. Conclusions about air pollution's association with childhood asthma are frequently made while excluding results from rural territories, limiting the ability to generalize nationally (19–22, 24–26).

Recently, the Centers for Disease Control and Prevention (CDC), working with the United States EPA, developed modeled air pollution data (known as Downscaler modeled data) to accompany air monitoring station data (28) at the county-level to create a nationally representative air pollution dataset. Downscaler modeled data, which comes from the National Environmental Public Health Tracking Network, can be utilized to gain a greater understanding of health effects based on a person's county of residence. However, research examining the associations of various health outcomes from a nationally representative health data source to modeled pollution data are lacking. Moreover, few studies have analyzed $PM_{2.5}$ annual concentrations and childhood asthma data using multilevel models (24), which account for the similarity of children living in the same geographical area. Finally, limited studies have modeled socioeconomic county-level characteristics, which have been associated with the availability of medical treatment within and across geographical areas (24, 25). Adjusting for these county-level socioeconomic characteristics has been shown to reduce the magnitude of the association between access to care

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and neighborhood disadvantage by areas (29), and reduce the variance in the estimated prevalence of annual childhood asthma ED visits (30).

The current population-based study combines six years of nationally representative health data from the National Health Interview Survey (NHIS) along with the most recently available air pollution data (31) to explore the association between $PM_{2.5}$ annual concentrations and childhood asthma. This dataset is also linked to county-level American Community Survey (ACS) data to allow for adjustment of county-level socioeconomic characteristics. We hypothesize an association between childhood asthma and air pollution concentrations, but that these associations will be attenuated after adjusting for county- and family-level characteristics.

## Methods

### Data Sources

The current study used data from the 2010–2015 NHIS linked to two external data sources at the county-level, the 2010–2015 National Environmental Public Health Tracking Network (Downscaler modeled data) and the 2010–2015 ACS. These data are linked by United States county. See Figure 1 for more information on how these datasets were linked.

**National Health Interview Survey:** The NHIS is a nationally representative survey of the civilian noninstitutionalized US population conducted by the National Center for Health Statistics (NCHS). Households are sampled and selected to be interviewed in-person by trained United States Census Bureau interviewers, with some follow-ups completed via telephone. The NHIS consists of three components: (a) the family core, with selected demographics and broad health measure questions for each member of the family; (b) the Sample Adult interview, with detailed health measures on a randomly selected adult; and (c) the Sample Child interview, with detailed health measures on a randomly selected child (typically completed by the child's parent). Data for the current analysis come from both the Sample Child interview and the family core. Response rates for the 2010–2015 NHIS Sample Child interview ranged from 63–75% (32). More information about the NHIS, including access to public use datasets can be found at https://www.cdc.gov/nchs/nhis.htm. This study utilizes restricted NHIS data which can be accessed through the CDC Research Data Center: https://www.cdc.gov/rdc/index.htm.

### Measures

***Asthma variables:*** Parents were first asked "Has a doctor or other health professional ever told you that [child's name] had asthma?".

A positive response resulted in three additional asthma questions about the severity of the child's asthma, including its persistence, frequency, and intensity. These questions were not asked if the parent did not affirm a lifetime asthma diagnosis.

Current asthma cases were defined based on an affirmative answer to the follow-up question "Does [child's name] still have asthma?". An asthma episode was captured by an affirmative answer to the question "During the past 12 months, has [child's name] had an episode or an asthma attack?". An asthma-related hospital visit was captured by an affirmative answer to the question "During the past 12 months, did [child's name] have to visit an emergency room or urgent care center because of his/her asthma?" (herein referred to as an "ER visit due to asthma"). For this analysis, these outcomes were examined among all children regardless of lifetime asthma diagnosis. These three variables serve as proxies and could indicate how well a child's asthma may be controlled. Asthma episodes and asthma-related hospital visits have been used as proxies for the frequency and intensity of a child's asthma symptoms (33).

***Child and family-level characteristics:*** Sociodemographic and health characteristics examined have been associated with asthma outcomes (9) and include the child's sex, age group (0–5 years, 6–11 years, 12–17 years), race and ethnicity (non-Hispanic White, non-Hispanic Black, non-Hispanic other, Hispanic), insurance status (only private health insurance, any public health insurance, uninsured), family income recorded as a percentage of the federal poverty level (<100%, 100–199%, 200–399%, ≥400%), educational attainment of the highest educated family member (high school education or less, some college or Associate's degree, Bachelor's degree or more), and housing type (owned, rental, other arrangement). Multiple imputation with the NHIS imputed family income file was used for approximately 8% of the sample (34).

***Geographical household characteristics:*** Geographic region of residence is classified by the United States Census Bureau regions and divisions based on federal information processing standards (FIPS) state codes. Geographic division was categorized into New England, Middle Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain, Pacific (35). Urbanicity of residence was categorized into 6 groups including large central metropolitan, large central metropolitan, medium metropolitan, small metropolitan, micropolitan, and noncore based on the 2013 NCHS Urban-Rural Classification Scheme for Counties (36). Region has been associated with asthma outcomes (8, 9), with mixed findings for urbanicity (9, 37). Both region and urbanicity are included in modeling to account for possible variation at the county-level.

**Environmental Public Health Tracking Network:** The Tracking Network, implemented by the CDC's National Center for Environmental Health combines health and environmental data from national, state, and city sources. In the past, air quality data came primarily from monitoring stations around the country from the EPA. There are approximately 4,000 air pollution monitoring stations located in 20% of US counties, mainly located in urban counties (38). However, recognizing a limitation in the coverage of monitoring stations, as well as the number of available readings at a typical monitoring station, the CDC and the EPA worked together to develop a statistical model, known as Downscaler modeled data, to be able to make Census tract-level estimates of several pollutants, including ozone and fine particulate matter ($PM_{2.5}$) in the contiguous United States (39). These tract-level air pollutant predictions were averaged (40, 41), using tract populations as spatial weights, to generate county-level estimates of $PM_{2.5}$, including an annual average and the number of days above the daily 24-hour National Ambient Air

Quality Standard for $PM_{2.5}$. More information about the Tracking Network can be found at https://ephtracking.cdc.gov.

### Measures

***Air pollution:*** Annual county-level $PM_{2.5}$ values from the contiguous United States are attained via a combination of air quality monitoring stations and modeled $PM_{2.5}$ values, while $PM_{2.5}$ measurements from Hawaii and Alaska only come from air quality monitoring stations (as they were not part of the Tracking Network between 2010–2015). All Hawaii and Alaska counties were assigned the same state-averaged value (calculated from all available monitors within the state) for a given year. $PM_{2.5}$ are atmospheric particulates with a diameter of less than or equal to 2.5 micrometers (μm). The ambient air pollution measurement dataset was scaled into quartiles to provide sufficient power to view meaningful effects between differing annual average levels of $PM_{2.5}$ in $\mu g/m^3$ (< 8.11, 8.11–9.50, 9.51–10.59, ≥ 10.60).

**American Community Survey:** The ACS is a continuous national survey administered by the US Census Bureau, that collects basic demographic, employment, education, housing, and health and disability data from approximately 3.5 million addresses each year. Data are nationally representative, coming from all 50 states as well as the District of Columbia, thereby allowing annual county-level estimates. Response rates for the 2010–2015 ACS ranged from 90–98%. More information about the ACS can be found at https://www.census.gov/programs-surveys/acs/about.html.

### Measures

***County-level characteristics:*** County-level characteristics mirrored the sociodemographic characteristics at the family-level, and include the percentage of individuals who are White, Hispanic, uninsured, living under the federal poverty line, living in owner-occupied housing, and have a high school or higher education. Although similar characteristics are included from the NHIS at the individual or family level, these county-level characteristics are included to be able to adjust for possible variability within and across geographical areas.

## Sample

The 2010–2015 study period includes 75,933 children aged 0–17 years distributed among 850 counties. The analytic sample, which required lifetime asthma status, contains 75,861 children (<0.1% dropped due to missingness). Demographic differences were explored between children with and without current asthma and with and without each asthma outcome (asthma episode, ER visit due to asthma) (Table 1).

## Statistical analysis

Demographic and clinical characteristic differences between children with and without asthma outcomes were tested utilizing a Rao-Scott corrected $\chi^2$ test, and when significant, was followed by bivariate logistic regressions to assess significance of each asthma outcome by specific characteristics (see Table 1). The prevalence of current asthma along with annual air pollution values are presented for each year of the study period in Figure 2.

All estimates and all multilevel models were weighted and accounted for the complex survey design of the NHIS to allow for proper variance estimation. An adjustment was made to the survey weights to account for the six years of data and the number of children in a given sampled county (42–45). Therefore, estimates and results from the multilevel models are nationally representative of the entire child population and designed to reflect all counties in the United States, not just those in-sample. More information about the development of NHIS sample weights can be found elsewhere (46).

Multilevel modeling was employed for current asthma and the two asthma outcomes (asthma episode, ER visit due to asthma) treating air pollution quartiles as a categorical variable with the lowest quartile as the reference group (Table 2). Multilevel modeling adjusts for the similarity of children living in the same county and can establish how much of the variation in asthma outcomes are the result of child and family-level characteristics and how much is related to differences between counties. Each multilevel model contained 2 levels: (1) family (2) county of residence. For each model, an intraclass correlation coefficient (ICC) was calculated to determine the amount of variance in each asthma outcome that can be explained at the county-level. ICCs can range from 0 to 1, with higher numbers representing more variance that can be explained at the county-level. Laplace parameter estimation was utilized for the generalized linear mixed models.

A set of four incremental models were used for each asthma outcome of interest (dependent variable):

1. An unconditional model (Model 0) with no covariates and a random effect for the asthma outcome. This is the baseline model to determine the amount of variance that can be explained at the county-level.

2. A bivariate logistic regression (odds ratios [ORs]) between air pollution quartile (fixed effect) and each asthma outcome (random effect) (Model 1).

3. A multivariate logistic regression (adjusted odds ratios [AORs]) between air pollution quartile and each asthma outcome with the adjustment of select county-level characteristics (percentage of individuals who are White, Hispanic, uninsured, living under the federal poverty line, living in owned housing, and have a high school or higher education) and the geographical household characteristics of region and urbanicity (fixed effects) (Model 2).

4. A multivariate logistic regression (adjusted odds ratios [AORs]) between air pollution quartile and each asthma outcome with the additional adjustment of select child and family-level characteristics (sex, age group, race/ethnicity, insurance status, family income recorded as a percentage of the federal poverty level, educational attainment of the highest educated household member, and housing type) (fixed effects) (Model 3). To account for the possibility of year-to-year fluctuations in air pollution (11), survey year was also included.

Predicted marginals were calculated for each quartile following the logistic regressions in Models 1 and 3 (Figure 3) and differences between quartiles were assessed by examining whether the odds ratios between any two quartiles was significant ($p$<0.05).

# Results

## Demographics

Table 1 presents the child, family, and geographic characteristics of children with and without current asthma and with and without experienced the asthma outcomes of interest (episode in past year, ER visit due to asthma in past year). Consistent patterns emerged where children with the variable of interest were more likely to be male, non-Hispanic Black, and received private or any public health insurance when compared to their respective peers when compared to children without the variable of interest (e.g. children with current asthma vs children not currently diagnosed with asthma). Children who had current asthma or the asthma outcomes were also more likely to live in a family with rented housing, living below the federal poverty line, and with the highest educated family member having some college or an Associate's degree.

## Air pollution and asthma outcomes

During 2010–2015, 8.9% of children had current asthma and the $PM_{2.5}$ annual average was 9.37 μg/m$^3$ for children in the sample. During this time period, there was a significant decrease ($p$<.0001) in the $PM_{2.5}$ annual average from 9.70 μg/m$^3$ in 2010 to 8.99 μg/m$^3$ in 2015 (see Figure 2). In addition, 5.0% of children had had an asthma episode or attack in the past 12 months, and 2.0% of children had an asthma-related emergency room or urgent care visit. There was also a significant decrease from 2010–2015 in the prevalence of current asthma ($p$=.0068), asthma episode ($p$<.0001), and ER visit due to asthma ($p$=.0135) (see Supplemental Table 1 for more details).

## Multilevel models

Unconditional models (Model 0) revealed explainable county-level variance ranging from 5.8% for current asthma to 14.0% for an asthma-related ER visit (Table 2).

In Model 1, children residing in areas with a higher $PM_{2.5}$ air pollution level (Q3: 9.51–10.59) had increased odds of having current asthma, an asthma episode, and visited an ER due to asthma, compared to children residing in areas with the lowest pollution concentrations (Q1: <8.11 μg/m$^3$). In addition, children living in the most polluted areas (Q4: ≥10.60 μg/m$^3$) were more likely to have current asthma, and an ER visit due to asthma compared to children living in the lowest polluted areas (Q1: <8.11 μg/m$^3$). Finally, children were also more likely to have current asthma living in the 2$^{nd}$ least polluted areas (Q2: 8.11–9.50 μg/m$^3$) relative to the least polluted areas (Q1: <8.11 μg/m$^3$).

In Model 2, with adjustments for socioeconomic county-level characteristics, children living in areas with higher $PM_{2.5}$ air pollution concentrations (Q3: 9.51–10.59 continued to more likely to have current asthma, an asthma episode in the past year, and have visited an ER due to asthma compared to children living in areas with the lowest air pollution (Q1: <8.11 μg/m$^3$). However, children living in the most polluted areas (Q4: ≥10.60 μg/m$^3$) were more likely to have visited an ER due to asthma as well as an asthma episode compared to children living in the lowest polluted areas (Q1: <8.11 μg/m$^3$).

In Model 3, after adjusting for characteristics at the county, geographic, and child and family-level, significant associations remained for children residing in the third most polluted quartile (Q3: 9.51–10.59 μg/$m^3$) for asthma episode, and ER visit due to asthma compared to children living in areas with the lowest air pollution quartile (Q1: <8.11 μg/$m^3$). However, no significant difference remained for current asthma among the highest polluted quartile when compared to the lowest polluted quartile (despite a similar adjusted odds ratio seen in the 3rd quartile to 1st quartile comparison), potentially due to reduced statistical power for this comparison.

Figure 3 presents the marginal probabilities of the current asthma and the two asthma outcomes in each $PM_{2.5}$ quartile for Models 1 (unadjusted) and 3 (adjusted). It should be noted that the unadjusted prevalence of current asthma (9.5% vs. 8.8%), asthma episode (5.5% vs. 4.8%) and an ER visit due to asthma (2.2% vs. 2.1%) (Model 1) is higher in the 3rd quartile compared to the 4th quartile, although these differences are not significant. After adjusting for socioeconomic county-level and child and family-level characteristics (Model 3), non-significant differences remained for each asthma outcome when comparing the 3rd and 4th quartiles.

## Discussion

The current study was designed to estimate associations between $PM_{2.5}$ annual concentrations and childhood asthma outcomes using a nationally representative data source in the National Health Interview Survey, linked to datasets with national coverage at the county-level including the Tracking Network (Downscaler Model), and the American Community Survey. Many of the previous studies that investigated ambient air pollution and childhood asthma associations were geographically limited or suffered from limited coverage due to EPA monitoring stations. This study attempts to fill this gap by supplementing a nationally representative survey with county-level socioeconomic characteristics and modeled air concentration data. Using multilevel modeling helps account for the similarity of children living in the same county and speaks to how much variability can be explained by the child's geographic location.

In the first series of models, higher pollution was associated with increased odds of current asthma, having an asthma episode in the past year, or an ER visit due to asthma in the past year. Previous research supports this finding with asthma prevalence and ED visits increasing with greater air pollution rates (47). When accounting for socioeconomic county-level characteristics and geographical household characteristics (Model 2), an association between air pollution remained for all asthma outcomes.

Although the magnitude of the odds ratios throughout the study were small, an association remained among asthma episode, and ER visit due to asthma, for children living in areas with the third highest polluted quartile (9.51–10.59 μg/$m^3$) compared with children living in areas with the lowest air pollution quartile (<8.11 μg/$m^3$) after accounting for county, geographic, and child and family-level characteristics. The final model was designed to explore the potential influence a family's socioeconomic status may play in understanding the impact of air pollution on a child's health. Yet, the characteristics included in the final model could not fully explain the association between $PM_{2.5}$ air pollution quartiles and asthma episode, or ER visit due to asthma. It is unclear if this is a result of unmeasured confounding or a true association between air pollution and the asthma outcomes. In addition, although all children in the same county were assigned the same outdoor air pollution value and same socioeconomic county characteristics, there was likely variability between households. The lack of a significant association between air pollution and current asthma in the final model may be shaped by a parent's perception of the child's asthma status, which could be considered to be a more subjective measure ("Does [child's name] *still* have asthma?") than current asthma, asthma episode, and an ER visit due to asthma.

## Limitations

**National Health Interview Survey—**The cross-sectional nature of NHIS does not allow for causal inference. Moreover, the NHIS does not collect how long the child has lived at the current address or how many times they have moved in their lifetime. Therefore, it is not possible to know if the child's asthma preceded their current air pollution exposure or not. The current study assumes that children have lived in the same geographic county their entire lives, which may prove to be untrue for a portion of the sample, leading to spurious associations. The fact that current asthma had the lowest amount of variance explained at the county-level, could reflect children moving from a given county. It is important to note in some counties that there may be large fluctuations in air pollution year to year, and even within a given year, due to natural disasters (e.g. wildfires).

In addition, NHIS does not include indoor air pollution measures, a potential unmeasured confounder. Developing counties have discovered that indoor air pollution is predicted to be associated with 1.6 million premature deaths worldwide annually with nearly 250,000 children dying before age 14 (48), along with increased risks for developing asthma (49). However, research investigating indoor air pollution is lacking within the United States, with limited generalizability (mostly focusing on populations in inner cities) (50, 51).

Our study implemented a population-based framework with scaled weights to account for the child population at the county-level. The population-based framework incorporates the full NHIS child sample in a given year, and scaling the sampling weights, allowed for nationally representative conclusions with the incorporation of other county-level data from the ACS and Downscaler.

While there is notable value to a risk-based framework (e.g. focusing only on children with a current asthma diagnosis), such an analysis was not feasible with scaled weights, given the potential for both underpowered associations and nonrepresentative conclusions.

Finally, reported asthma cases from NHIS are subject to misclassification due to parent report where recall or social desirability biases may exist. Responses to NHIS are not subject to clinical verification, and as asthma can be difficult to diagnose in younger children, especially children under the age of 5 (26, 52, 53). However, many previous studies analyzing childhood asthma include a full age range of children (8–10, 54–56). In addition, the incorporation of two county-level data sources for the full childhood population (Downscaler modeled data and ACS) and the modification of NHIS final weights to account for the number of children in a given county, requires using children of all ages in the analytic sample.

**Air pollution—**The modeled air pollution dataset had county-level coverage across the contiguous United States, and despite error existing in the model, validation studies of the Downscaler modeled data found high comparability between monitoring stations and modeled data, but with potential underestimation in highly polluted areas (>35 ug/m$^3$) (40, 41). In addition, since the Tracking Network only models air pollution among the contiguous United States and District of Columbia, values had to be derived from $PM_{2.5}$ air pollution monitor readings via the EPA for both Hawaii and Alaska (38).

In addition, the data used in this analysis are between 5 and 10 years old, which does not reflect changes in air pollution and asthma prevalence seen in recent years (9, 10, 38). However, the current paper analyzes the most recent available nationally modeled air pollution data linked with nationally representative health data. While it can be hypothesized that similar associations between $PM_{2.5}$ annual concentrations and childhood asthma continue to exist, additional research is needed as newer air pollution data become available.

## Conclusions

This population-based study provides a multi-level analysis of $PM_{2.5}$ annual concentrations and childhood asthma by using a nationally representative health data source linked to modeled air pollution data and nationally representative socioeconomic county-level data. Future studies may benefit from following children longitudinally (56) while also exploring the potential impact of the child's home environment (including exposure to indoor air pollution) as well as multipollutant effects.

## Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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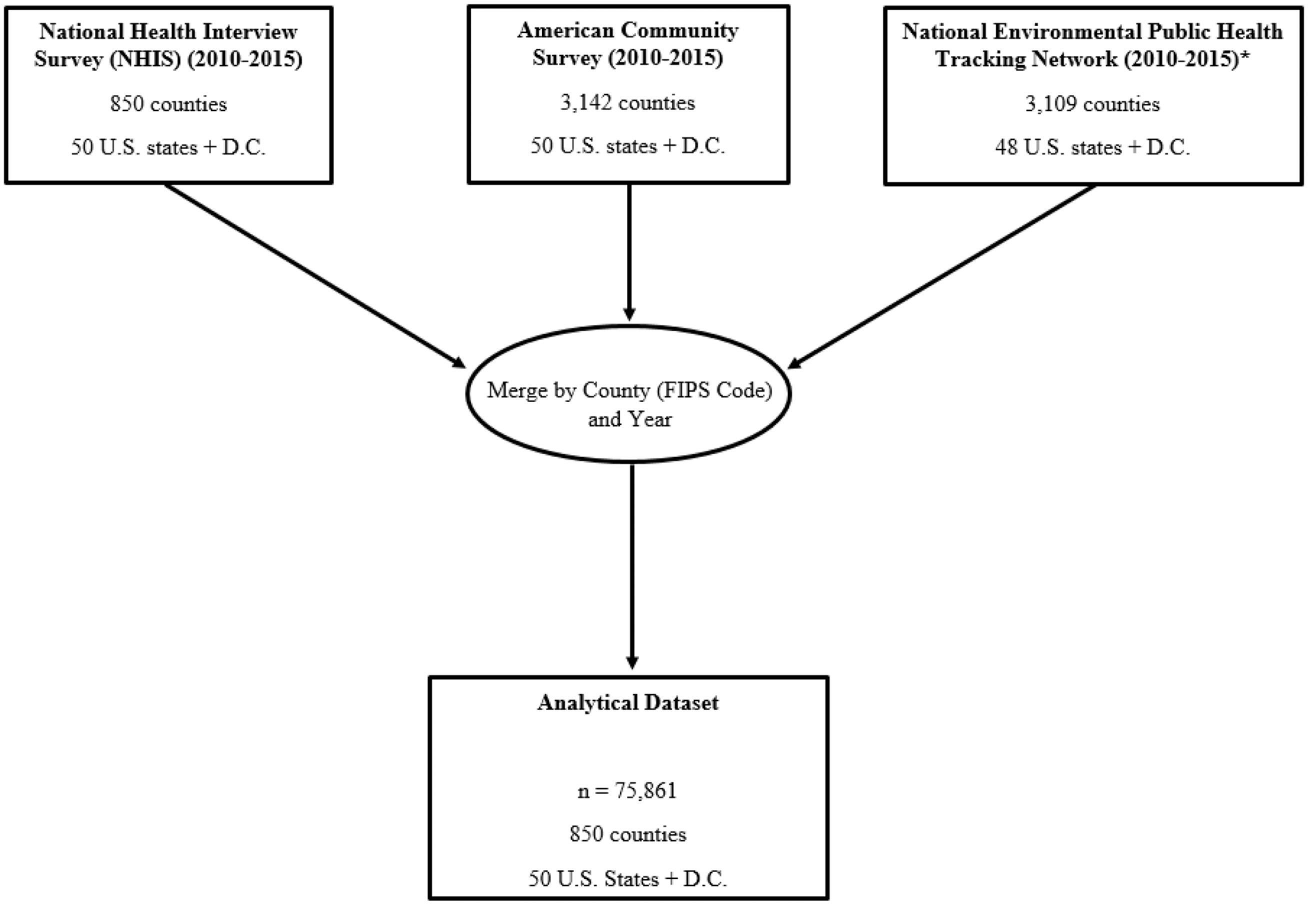


**Figure 1.**

Forming of analytical dataset and merging of datasets

*County-level air pollution was not available for Hawaii and Alaska and was averaged across available US EPA monitoring stations during this time frame.

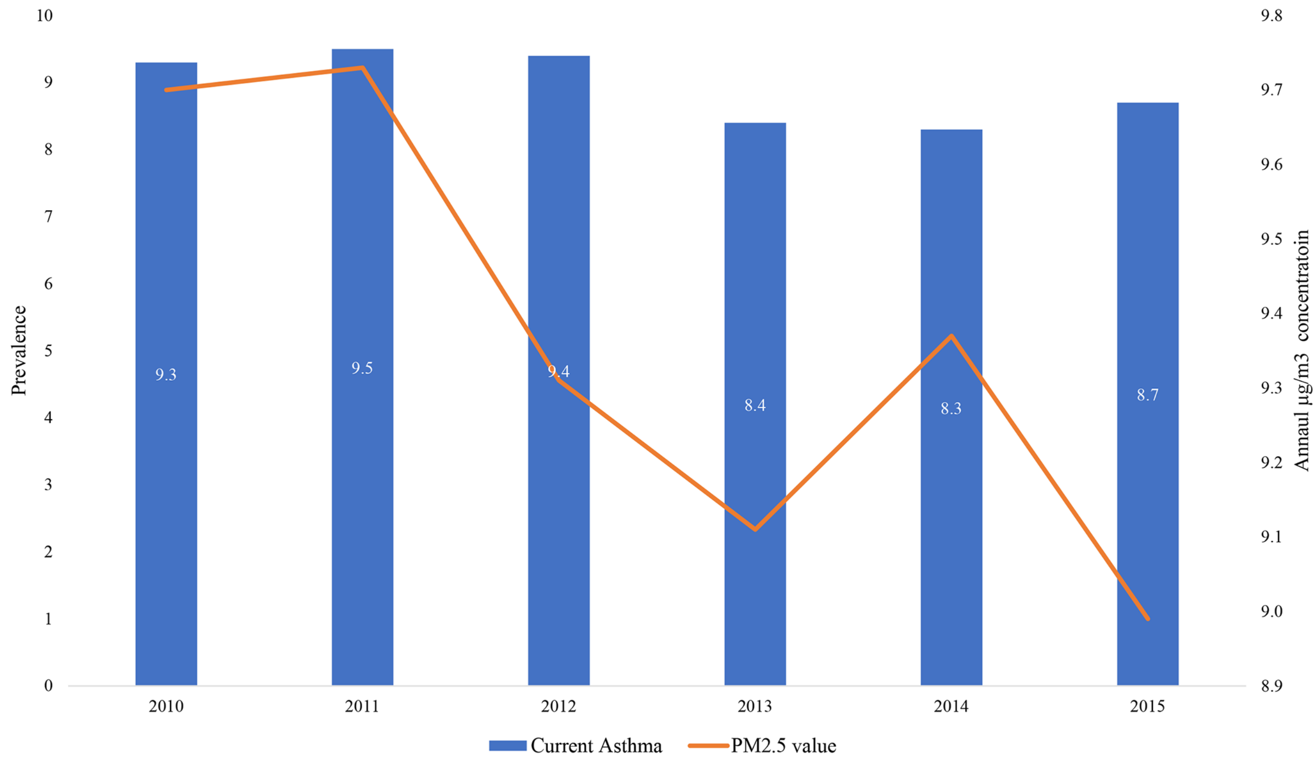


**Figure 2.**

Prevalence of current asthma among children and annual $PM_{2.5}$ concentration*: United States, 2010–2015

*Significant linear trend for annual $PM_{2.5}$ concentration as calculated by linear regression ($p<.01$).

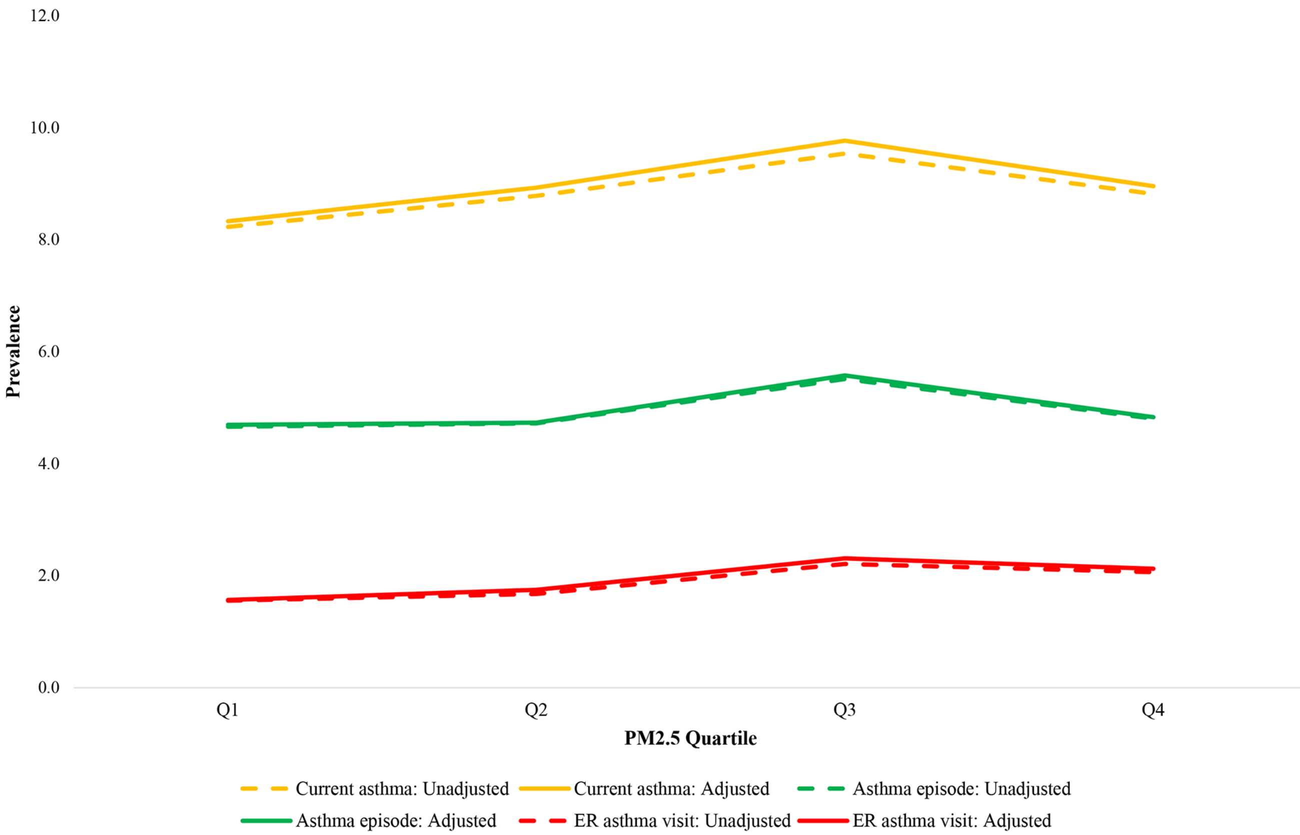


**Figure 3.**

Adjusted vs. unadjusted prevalence of each asthma outcome, by air pollution quartile: United States, 2010–2015

NOTES: Unadjusted percentages are calculated using National Health Interview Survey asthma outcomes, by $PM_{2.5}$ air pollution concentration quartiles (Model 1). Adjusted percentages include American Community Survey (ACS) county-level characteristics, geographical household characteristics, and National Health Interview Survey (NHIS) child and family-level characteristics (Model 3) from the multilevel multivariate logistic regression models. Differences between quartiles were determined by examining whether the adjusted odds ratios between two quartiles were significant (p<.05).

**Table 1 –**

Child, family, and geographic characteristics, by asthma status: United States, 2010–2015

| | **Current asthma (n=7,025) % (SE)** | **No current asthma (n = 68,779) % (SE)** | **Asthma episode (n=3,815) % (SE)** | **No asthma episode (n = 72,036) % (SE)** | **Asthma ER visit (n=1,548) % (SE)** | **No asthma ER visit (n = 74,302) % (SE)** |
|---|---|---|---|---|---|---|
| Youth characteristics | | | | | | |
| Sex | | | | | | |
| Male | 57.5[x] (0.7) | 50.5 (0.2) | 58.8[y] (1.0) | 50.7 (0.2) | 60.1[z] (1.7) | 50.9 (0.2) |
| Female | 42.5[x] (0.7) | 49.5 (0.2) | 41.2[y] (1.0) | 49.3 (0.2) | 39.9[z] (1.7) | 49.1 (0.2) |
| Age group | | | | | | |
| 0–5 years | 22.5[x] (0.7) | 34.6 (0.2) | 27.1[y] (1.0) | 33.8 (0.2) | 41.6[z] (1.7) | 33.3 (0.2) |
| 6–11 years | 38.5[x] (0.8) | 32.7 (0.2) | 40.6[y] (1.1) | 32.8 (0.2) | 36.3[z] (1.6) | 33.1 (0.2) |
| 12–17 years | 39.9[x] (0.7) | 32.8 (0.2) | 32.3 (1.0) | 33.4 (0.2) | 22.1[z] (1.3) | 33.5 (0.2) |
| Race | | | | | | |
| Non-Hispanic White | 43.7[x] (1.0) | 51.6 (0.5) | 45.0[y] (1.2) | 51.2 (0.5) | 30.9[z] (1.7) | 51.3 (0.5) |
| Non-Hispanic Black | 22.6[x] (0.8) | 12.7 (0.3) | 21.7[y] (0.9) | 13.2 (0.3) | 30.2[z] (1.6) | 13.3 (0.3) |
| Non-Hispanic other | 9.3 (0.7) | 9.7 (0.3) | 9.7 (0.8) | 9.6 (0.3) | 10.6 (1.4) | 9.6 (0.3) |
| Hispanic | 24.3[x] (0.7) | 25.9 (0.5) | 23.5[y] (0.9) | 25.9 (0.5) | 28.2 (1.5) | 25.8 (0.5) |
| Health insurance coverage status | | | | | | |
| Private only | 44.0[x] (0.8) | 52.2 (0.4) | 42.5[y] (1.1) | 51.8 (0.4) | 31.0[z] (1.6) | 51.8 (0.4) |
| Any public | 52.3[x] (0.8) | 41.4 (0.4) | 52.6[y] (1.1) | 41.8 (0.4) | 65.1[z] (1.6) | 41.9 (0.4) |
| Uninsured | 4.8[x] (0.3) | 6.5 (0.1) | 4.9[y] (0.4) | 6.4 (0.1) | 4.0[z] (0.6) | 6.4 (0.1) |
| Family characteristics | | | | | | |
| Housing type | | | | | | |
| Owned | 51.6[x] (0.9) | 60.4 (0.4) | 51.5[y] (1.1) | 60.0 (0.4) | 39.8[z] (1.7) | 60.0 (0.4) |
| Rental | 46.2[x] (0.9) | 37.8 (0.4) | 46.1[y] (1.1) | 38.2 (0.4) | 57.1[z] (1.7) | 38.2 (0.4) |
| Other arrangement | 2.1 (0.3) | 1.8 (0.1) | 2.3 (0.5) | 1.8 (0.1) | 3.1 (1.3) | 1.8 (0.1) |
| Federal poverty level | | | | | | |
| <100% | 26.4[x] (0.7) | 21.3 (0.3) | 27.1[y] (1.0) | 21.5 (0.3) | 34.4[z] (1.7) | 21.5 (0.3) |
| 100–199% | 23.6 (0.7) | 23.1 (0.2) | 23.6 (1.0) | 23.1 (0.2) | 23.8 (1.5) | 23.1 (0.2) |
| 200–399% | 26.4[x] (0.7) | 28.6 (0.3) | 25.2[y] (0.9) | 28.6 (0.3) | 23.3[z] (1.5) | 28.5 (0.3) |
| ≥400% | 23.6[x] (0.7) | 27.0 (0.3) | 24.1[y] (0.9) | 26.8 (0.3) | 18.5[z] (1.3) | 26.8 (0.3) |
| Highest education family member | | | | | | |
| High school or less | 32.6[x] (0.8) | 29.5 (0.4) | 30.5 (1.0) | 29.7 (0.4) | 38.0[z] (1.7) | 29.6 (0.4) |

| | Current asthma (n=7,025) % (SE) | No current asthma (n = 68,779) % (SE) | Asthma episode (n=3,815) % (SE) | No asthma episode (n = 72,036) % (SE) | Asthma ER visit (n=1,548) % (SE) | No asthma ER visit (n = 74,302) % (SE) |
|---|---|---|---|---|---|---|
| Some college or Associate of Arts (AA) degree | $37.4^{x}$ (0.7) | 32.4 (0.3) | $38.5^{y}$ (1.0) | 32.5 (0.3) | $39.2^{z}$ (1.6) | 32.7 (0.3) |
| Bachelor's degree or more | $30.0^{x}$ (0.8) | 38.2 (0.5) | $31.0^{y}$ (1.0) | 37.8 (0.5) | $22.8^{z}$ (1.4) | 37.8 (0.5) |
| Region | | | | | | |
| New England | $7.0^{x}$ (0.6) | 5.7 (0.5) | $7.3^{y}$ (0.7) | 5.8 (0.5) | 7.2 (0.9) | 5.8 (0.5) |
| Middle Atlantic | $10.4^{x}$ (0.5) | 9.4 (0.3) | 10.2 (0.6) | 9.4 (0.2) | $11.4^{z}$ (1.0) | 9.4 (0.2) |
| East North Central | 11.3 (0.5) | 11.6 (0.3) | 10.9 (0.7) | 11.6 (0.3) | 10.8 (1.0) | 11.6 (0.3) |
| West North Central | $7.0^{x}$ (0.6) | 8.5 (0.4) | $7.0^{y}$ (0.6) | 8.4 (0.3) | 7.2 (1.0) | 8.4 (0.4) |
| South Atlantic | $18.7^{x}$ (0.7) | 17.4 (0.4) | 18.9 (0.8) | 17.4 (0.4) | $21.0^{z}$ (1.4) | 17.4 (0.4) |
| East South Central | 6.3 (0.5) | 5.3 (0.2) | 6.6 (0.7) | 5.4 (0.2) | 6.7 (1.1) | 5.4 (0.2) |
| West South Central | 14.0 (0.6) | 12.9 (0.3) | 13.7 (0.8) | 13.0 (0.3) | 12.0 (1.0) | 13.0 (0.3) |
| Mountain | 9.1 (0.7) | 10.0 (0.4) | 9.0 (0.9) | 9.9 (0.4) | $7.5^{z}$ (1.2) | 9.9 (0.4) |
| Pacific | $16.3^{x}$ (0.8) | 19.2 (0.5) | $16.4^{y}$ (1.0) | 19.0 (0.5) | 16.3 (1.6) | 19.0 (0.5) |
| Urbanicity | | | | | | |
| Large Central Metropolitan | 32.8 (0.9) | 32.1 (0.5) | 32.4 (1.1) | 32.1 (0.5) | $38.7^{z}$ (1.8) | 32.0 (0.5) |
| Large Fringe Metropolitan | 21.4 (0.9) | 21.8 (0.6) | 22.2 (1.0) | 21.7 (0.6) | $18.9^{z}$ (1.3) | 21.8 (0.6) |
| Medium Metropolitan | 20.9 (1.1) | 21.3 (1.0) | 20.2 (1.2) | 21.3 (1.0) | $17.7^{z}$ (1.5) | 21.3 (1.0) |
| Small Metropolitan | 9.3 (1.0) | 9.5 (0.9) | 9.6 (1.1) | 9.5 (0.9) | 8.4 (1.4) | 9.5 (0.9) |
| Micropolitan | 8.8 (1.1) | 9.0 (1.0) | 8.4 (1.2) | 9.0 (1.0) | 9.4 (1.8) | 9.0 (1.0) |
| Noncore | 6.8 (0.9) | 6.3 (0.8) | 7.1 (1.1) | 6.3 (0.8) | 6.9 (1.2) | 6.3 (0.8) |

NOTE: Differences in the distributions of a given demographic characteristic were first tested using Rao-Scott corrected $\chi^2$ tests comparing children who had experienced a given asthma outcome to those who had not (e.g. children with lifetime asthma vs children never diagnosed with asthma). If significant, bivariate associations (through unadjusted logistic regressions) were run between groups to see if differences existed by subgroup for a given demographic characteristic.

[x] Significantly different from children without a current asthma diagnosis (p<.05).

[y] Significantly different from children who did not have an asthma episode in the past 12 months (p<.05).

[z] Significantly different from children who did not visit an ER in the past 12 months (p<.05).

## Table 2 –

Conditional, unadjusted, and adjusted models

| Outcomes | | Model 0[a] | Model 1[b] OR (95% CI) | Model 2[c] AOR (95% CI) | Model 3[d] AOR (95% CI) |
|---|---|---|---|---|---|
| Current asthma | Q1 | --- | Reference | Reference | Reference |
| | Q2 | --- | 1.111 (1.014–1.217) * | 1.056 (0.957–1.164) | 1.043 (0.945–1.151) |
| | Q3 | --- | 1.190 (1.079–1.313) * | 1.141 (1.020–1.277) * | 1.118 (0.998–1.253) |
| | Q4 | --- | 1.168 (1.047–1.303) * | 1.125 (0.991–1.277) | 1.073 (0.941–1.223) |
| | (ICC) | (0.048) | (0.047) | (0.041) | (0.037) |
| Asthma episode | Q1 | --- | Reference | Reference | Reference |
| | Q2 | --- | 1.080 (0.962–1.213) | 1.100 (0.970–1.247) | 0.998 (0.881–1.131) |
| | Q3 | --- | 1.252 (1.108–1.414) * | 1.297 (1.125–1.495) * | 1.158 (1.004–1.335) * |
| | Q4 | --- | 1.137 (0.992–1.303) | 1.217 (1.036–1.429) * | 1.046 (0.888–1.233) |
| | (ICC) | (0.057) | (0.057) | (0.051) | (0.047) |
| Asthma ER visit | Q1 | --- | Reference | Reference | Reference |
| | Q2 | --- | 1.144 (0.944–1.386) | 1.090 (0.889–1.335) | 1.055 (0.859–1.296) |
| | Q3 | --- | 1.395 (1.142–1.704) * | 1.308 (1.044–1.639) * | 1.270 (1.009–1.599) * |
| | Q4 | --- | 1.397 (1.122–1.739) * | 1.326 (1.032–1.705) * | 1.234 (0.950–1.603) |
| | (ICC) | (0.140) | (0.135) | (0.107) | (0.101) |

* $p<.05$

NOTES: ICC is intraclass correlation coefficient; OR is odds ratio; CI is confidence interval; AOR is adjusted odds ratio; ER is emergency room; Q is quartile.

The annual average concentrations of $PM_{2.5}$ in μg/m$^3$ in Quartile 1: < 8.11; Quartile 2: 8.11–9.50; Quartile 3: 9.51–10.59; Quartile 4: ≥ 10.60).

[a] Model 0 is a multilevel analysis with only the outcome of interest.

[b] Model 1 is a multilevel bivariate logistic regression of the outcome of interest and $PM_{2.5}$ air pollution concentration (broken into quartiles).

[c] Model 2 is a multilevel multivariate logistic regression of the outcome of interest and $PM_{2.5}$ air pollution concentration (broken into quartiles), further adjusted by American Community Survey (ACS) county-level characteristics, and geographical household characteristics.

[d] Model 3 is a multilevel multivariate logistic regression of the outcome of interest and $PM_{2.5}$ air pollution concentration (broken into quartiles), further adjusted by American Community Survey (ACS) county-level characteristics, geographical household characteristics, National Health Interview Survey (NHIS) child and family-level characteristics, and survey year.