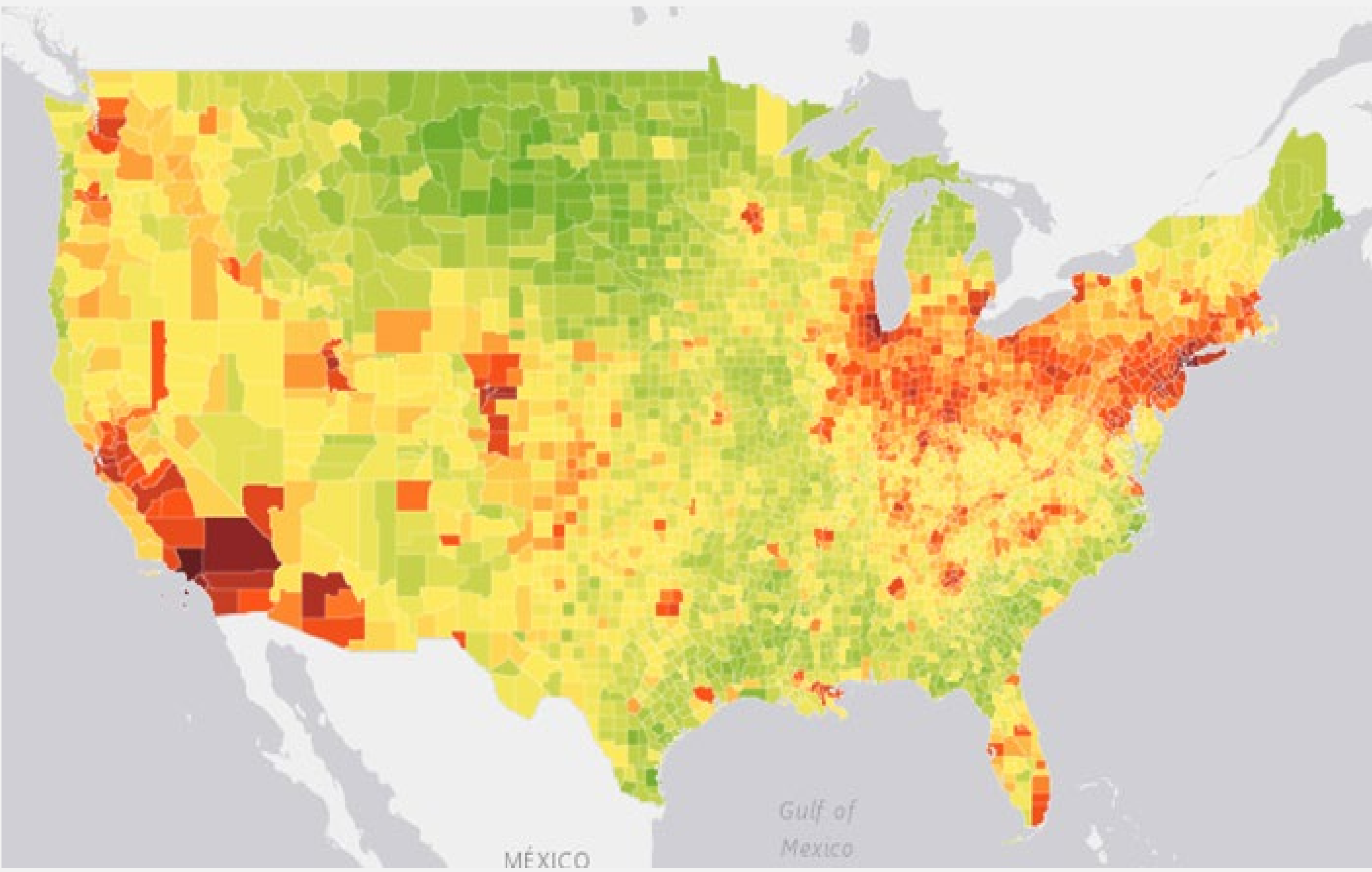
TRAFFIC-RELATED AIR POLLUTION AND CHILDHOOD ASTHMA IN THE UNITED STATES: A BURDEN OF DISEASE



January 2021

Center for Advancing Research in
Transportation Emissions, Energy, and Health
A USDOT University Transportation Center

Texas A&M Transportation Institute
Georgia Tech College of Engineering
Johns Hopkins Bloomberg School of Public Health
College of Engineering, The University of Texas at El Paso
UC Riverside CE-CERT

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TECHNICAL REPORT DOCUMENTATION PAGE

1. Report No.	2. Government Accession No.	3. Recipient's Catalog No.
4. Title and Subtitle Traffic-Related Air Pollution and Childhood Asthma in the United States: A Burden of Disease Assessment		5. Report Date January 2021 6. Performing Organization Code
7. Author(s) Haneen Khreis and Raed Alotaibi		8. Performing Organization Report No. TTI-01-10
9. Performing Organization Name and Address: CARTEEH UTC Texas A&M Transportation Institute 3135 TAMU, College Station, TX 77843		10. Work Unit No. 11. Contract or Grant No. 69A3551747128
12. Sponsoring Agency Name and Address Office of the Secretary of Transportation (OST) U.S. Department of Transportation (USDOT)		13. Type of Report and Period Final January 18, 2018–December 31, 2019 14. Sponsoring Agency Code

15. Supplementary Notes

This project was funded by the Center for Advancing Research in Transportation Emissions, Energy, and Health University Transportation Center, a grant from the U.S. Department of Transportation Office of the Assistant Secretary for Research and Technology, University Transportation Centers Program.

16. Abstract

Asthma is one of the leading chronic airway diseases among children in the United States and across the world. Emerging evidence indicates that traffic-related air pollution leads to the onset of childhood asthma. In this work, the researchers estimated the number of incident asthma cases among children attributable to three common traffic-related air pollutants across the contiguous United States for the years 2000 and 2010, noting changes and trends in the burden of disease over this decade. Because burden of disease assessments typically rely on national-level incidence rates for the health outcomes of interest, the researchers also explored, in a nested sub-study, the impact of using a constant national-level childhood asthma incidence rate versus a more granular spatially varying rate at the state level. In this sub-study, the researchers focused on one pollutant and one year and estimated the burden of incident childhood asthma cases attributable to nitrogen dioxide (NO_2), a criteria pollutant and a good marker of traffic, in the contiguous United States.

This report presents the first study to estimate the childhood asthma burden of disease on a national scale for the contiguous United States and also presents the results for the major 498 cities and every county in an interactive, accessible, and open-access manner. The researchers utilized the best available data sets and state-of-the-art research—using small-scale geographical units for both the census data and air pollution exposure estimation, and meta-analysis-derived exposure-response functions from the most recent and largest study that linked traffic-related air pollution to the onset of childhood asthma. The combination of this effort and using a standard burden of disease assessment framework enabled the researchers to estimate the burden of new childhood asthma cases attributable to NO_2, $PM_{2.5}$, and PM_{10} both separately and over a decade's period. The attributable burden of childhood asthma dropped by 33 percent between 2000 and 2010. However, a significant proportion of cases can still be prevented. The researchers also estimated new state-specific asthma incidence rates for the contiguous United States. Using state-specific incidence rates versus a constant national incidence rate resulted in a small change in the NO_2-attributable burden of disease at the national level but had a more prominent impact at the state level, which may have important implications for monetary evaluation and the regulatory process.

17. Key Words	18. Distribution Statement
Traffic Related, Air Pollution, Burden of Disease, Asthma, Onset, Children, United States, Incidence Rates, National Data, State-Specific Data, Socioeconomic Status, Urban Status, Rural Status, Health Impact Assessment, Policy	No restrictions. This document is available to the public through the CARTEEH UTC website. http://carteeh.org

19. Security Classif. (of this report)	20. Security Classif. (of this page)	21. No. of Pages	22. Price
Unclassified	Unclassified	60	$0.00

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Executive Summary

Asthma is one of the leading chronic airway diseases among children in the United States and across the world. Emerging evidence indicates that traffic-related air pollution, as opposed to ambient air pollution in general, leads to the onset of childhood asthma. In this work, the researchers estimated the number of incident asthma cases among children attributable to three common traffic-related air pollutants across the contiguous United States for the years 2000 and 2010, noting changes and trends in the burden of disease over this decade. Because burden of disease assessments typically rely on national-level incidence rates for the health outcomes of interest, the researchers also explored, in a nested sub-study, the impact of using a constant national-level childhood asthma incidence rate versus a more granular spatially varying rate at the state level. In this sub-study, the researchers focused on one pollutant and one year and estimated the burden of incident childhood asthma cases attributable to nitrogen dioxide (NO_2), a criteria pollutant and a good marker of traffic, in the contiguous United States.

The number of incident childhood asthma cases and the percentage due to traffic-related air pollution were estimated using standard burden of disease assessment methods. The researchers first combined children (<18 years) counts and pollutant exposures at populated United States census blocks with a national asthma incidence rate and meta-analysis-derived exposure-response functions that the researchers obtained from the literature. NO_2, particulate matter with a diameter less than 2.5 micrometers ($PM_{2.5}$), and particulate matter with a diameter less than 10 micrometers (PM_{10}) were used as surrogates of traffic-related air pollution exposures, with NO_2 being the most specific pollutant. Annual average concentrations were obtained from previously published and validated exposure assessment models. The national-level asthma incidence rate and an exposure-response function for each pollutant were obtained from the literature. The researchers also estimated the number of preventable cases among blocks that exceeded the limit for two counterfactual scenarios. The first scenario used the recommended air quality annual averages from the World Health Organization (WHO) as a limit. The second scenario used the minimum modeled concentration for each pollutant, in either year, as a limit. Similar methods were used in the nested sub-study, with the only difference being the use of different asthma incidence rates and a focus on NO_2 in the year 2010 only. In this sub-study, the researchers estimated childhood asthma incidence rates using data from the 2006–2010 Behavioral Risk Factor Surveillance System Survey and the Asthma Call-Back Survey, both conducted by the Centers for Disease Control and Prevention. In both studies, the researchers stratified the estimated burden of disease by urban versus rural status and by median household income.

The researchers found that average concentrations in 2000 and 2010, respectively, were 20.6 and 13.2 $\mu g/m^3$ for NO_2 (36 percent decrease), 12.1 and 9 $\mu g/m^3$ (26 percent decrease) for $PM_{2.5}$, and 21.5 and 17.9 $\mu g/m^3$ (17 percent decrease) for PM_{10}. The attributable number of cases ranged from 209,100 to 331,200 for the year 2000 and 141,900 to 286,500 for 2010, depending on the pollutant. Asthma incident cases due to the studied air pollutants represented 27–42 percent of all cases in 2000 and 18–36 percent in 2010. The percentage of cases due to air pollution were higher in (a) urban areas compared to rural areas, and (b) block groups with the lowest median household income. The researchers created online open-access interactive maps and tables summarizing the findings at the county level and the 498 major cities in the United States, and these tools can be found at https://carteehdata.org/l/s/TRAP-burden-of-childhood-asthma. Assuming that pollutants did not exceed the WHO air quality guideline values, the number of incident cases that could have been prevented ranged between 300 and 53,400, depending on the pollutant and year. Assuming that pollutant levels were limited to the minimum modeled concentration, the number of childhood asthma incident cases that could have been prevented ranged between 127,700 and 317,600, depending on the pollutant and year. In the sub-study exploring the impact of using a constant national-level childhood asthma incidence rate versus a more granular spatially varying rate at the state level, the researchers estimated the national aggregate asthma incidence rate at 11.6 per 1,000 at-risk children, and it ranged from 4.3 (Montana) to 17.7 (D.C.) per 1,000 at-risk children. The 17 states that did not have data to estimate an incidence rate were assigned the national aggregate asthma incidence rate. Using the state-specific incidence rates, the researchers estimated a total of 134,166 (95 percent confidence interval [CI]: 75,177–

193,327) childhood asthma incident cases attributable to NO_2, accounting for 17.6 percent of all childhood asthma incident cases. Using the national-level incidence rate, the researchers estimated a total of 141,931 (95 percent CI: 119,222–163,505) incident cases attributable to NO_2, accounting for 17.9 percent of all childhood asthma incident cases. Using the state-specific incidence rates reduced the attributable number of cases by 7,765 (5.5 percent relative reduction) in comparison to estimates using the national-level incidence rate. Across states, the change in the attributable number of cases ranged from −64.1 percent (Montana) to +33.8 percent (Texas). California had the largest absolute decrease (−6,190) in attributable cases, while Texas had the largest increase (+3,615). Stratifying by socioeconomic status and urban versus rural status produced new trends compared to the previously published burden of disease analysis showing high heterogeneity across the states.

This report presents the first study to estimate the childhood asthma burden of disease on a national scale for the contiguous United States and also presents the results for the major 498 cities and every county in an interactive, accessible, and open-access manner. The researchers utilized the best available data sets and state-of-the-art research—using small-scale geographical units for both the census data and air pollution exposure estimation, and meta-analysis-derived exposure-response functions from the most recent and largest study that linked traffic-related air pollution to the onset of childhood asthma. The combination of this effort and using a standard burden of disease assessment framework enabled the researchers to estimate the burden of new childhood asthma cases attributable to NO_2, $PM_{2.5}$, and PM_{10} both separately and over a decade's period. The attributable burden of childhood asthma dropped by 33 percent between 2000 and 2010. However, a significant proportion of cases can still be prevented. The researchers also estimated new state-specific asthma incidence rates for the contiguous United States. Using state-specific incidence rates versus a constant national incidence rate resulted in a small change in the NO_2-attributable burden of disease at the national level but had a more prominent impact at the state level, which may have important implications for monetary evaluation and the regulatory process.

Acknowledgments

The authors would like to thank Matthew Bechle and Julian Marshall at the University of Washington for providing the air pollution exposure estimates for 2000 and 2010, work that was developed under the Center for Air, Climate and Clean Energy Solutions, which was supported under Assistance Agreement No. R835873 awarded by the U.S. Environmental Protection Agency (EPA). This work has not been formally reviewed by EPA, and the views expressed in this document are solely those of authors and do not necessarily reflect those of the agency. EPA does not endorse any products or commercial services mentioned in this publication. The authors also acknowledge critical feedback and helpful comments received from the following individuals throughout the duration of this project: Tara Ramani (Texas A&M Transportation Institute), Josias Zietsman (Texas A&M Transportation Institute), Mark J. Nieuwenhuijsen (Barcelona Institute for Global Health), Jennifer Horney (University of Delaware), and Rob McConnell (University of Southern California).

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Background and Introduction

Definition of Asthma

Asthma is a chronic airway disease characterized by episodes of shortness of breath, coughing, wheezing, and sputum production. These symptoms are caused by a reversible or partially reversible airway obstruction and hyperresponsiveness, with varying degrees of severity ranging from mild self-resolving to severe episodes resulting in death (National Heart, Lung, and Blood Institute, 2007). In 2015, a global burden of disease (BoD) study estimated that more than 358 million individuals had asthma, making it the most prevalent chronic respiratory disease worldwide (GBD Chronic Respiratory Disease Collaborators, 2017). In the United States, asthma is one of the most common chronic diseases, affecting approximately 5,530,131 children (Centers for Disease Control and Prevention [CDC], 2019, 2020), and 24,753,379 million adults and children combined in 2018 (CDC, 2020). Asthma severity refers to the intensity of the disease process, and it is categorized into two types: intermittent severity and persistent severity (CDC, 2015). The intermittent severity type includes people with asthma that is well controlled without long-term control medication (CDC, 2015). The persistent severity type includes people with well-controlled asthma who are on long-term control medications and people with uncontrolled asthma who are not on long-term control medication (CDC, 2015). Currently, nearly 60 percent of children with asthma have persistent asthma, and 40 percent have intermittent asthma (CDC, 2015).

Economic and Educational Burden of Asthma

Living with asthma can carry a huge financial burden for individuals and families. The economic and educational burden of asthma in the United States is huge. Asthma costs the U.S. economy more than $80 billion annually in medical expenses, missed work and school days, and deaths, according to Nurmagambetov et al. (2018). Financial costs can include direct costs like costs for alternative treatment/medications, primary care consultations, hospital emergency and outpatient attendance, ambulance and other transportation, and hospital admissions; indirect costs like missing school and workdays also contribute to asthma's financial burden (Bahadori et al., 2009). Education burden can mean missing school and workdays for children and their parents. The annual per-person medical cost of asthma is $3,266 total, which includes $1,830 for prescriptions, $640 for office visits, $529 for hospitalizations, $176 for hospital outpatient visits, and $105 for emergency room care. On average, there are 3,168 annual deaths from asthma, with an estimated cost of $29 billion per year. The combined cost for missed work and school days nationally is $3 billion per year, representing 8.7 million workdays and 5.2 million school days lost due to asthma, while the total number of missed school days among children with asthma by state ranges from 9,020 days to 617,980 days, costing a state anywhere from $1.4 million to $116.5 million. When adding workdays, the cost range increases from $4.4 million to $344.9 million (Nurmagambetov et al., 2018; Nurmagambetov et al., 2017). Nurmagambetov et al. (2018) also stated that annual spending on prescription medication, office-based visits, outpatient visits, emergency room visits, and inpatient hospital admissions averages $1,700 more for families with (compared to without) asthmatic children (<18 years).

Causation of Asthma and the Link with Air Pollution

Asthma is a heterogeneous disease with complex causal pathways in which genetic and environmental factors interact, leading to multiple sub-phenotypes with different biological, pathological, and clinical characteristics (Gowers et al., 2012; Wenzel, 2012). The increased understanding of the complex causal pathways of asthma wherein environmental and genetic factors interact has led to the discovery of these multiple sub-phenotypes. However, causal pathways are still not completely understood. It is well established that asthma can be exacerbated by exposure to ambient air pollution of varying concentrations and sources (World Health Organization [WHO], 2005). However, debate has existed over whether air pollution can initiate asthma. Studies have shown that exposure to general ambient air pollution is not associated with the initiation of new cases of asthma (Anderson et al., 2011). However, new evidence indicates that exposure to a more specific mixture of air pollutants, most notably traffic-related air pollution (TRAP), is associated with an increased risk of asthma developing among children (Anderson et al., 2013; Khreis, Kelly, et al., 2017), thereby challenging the prior belief that air pollution does not contribute to asthma development. This new conclusion builds on an existing body of evidence, including an early review conducted by the Health Effects Institute (2010) that included 34 fewer studies than the latest systematic review on the topic (Khreis, Kelly, et al., 2017). At the time, the Health Effects Institute's panel concluded that the evidence for a causal relation between TRAP and the onset of childhood asthma was in a gray zone between *sufficient* and *suggestive but not sufficient*. A subsequent meta-analysis by Bowatte et al. (2015), which included 30 fewer studies than the latest systematic review on the topic (Khreis, Kelly, et al., 2017), concluded that TRAP exposure in early childhood is associated with the development of subsequent asthma. Finally, Khreis, Kelly, et al. (2017) expanded and updated these syntheses and concluded that childhood exposure to TRAP contributes to the development of asthma—a conclusion supported by more recent individual studies and by a synthesis of epidemiological, clinical, and toxicological evidence (Thurston et al., 2020).

Traffic-Related Air Pollution

Traffic is a major source of urban air pollution. TRAP refers to ambient air pollution resulting from the use of motorized vehicles, such as heavy-duty and light-duty vehicles, buses, coaches, passenger cars, and motorcycles. These vehicles emit a variety of air pollutants, including but not limited to black carbon (BC), elemental carbon, carbon monoxide (CO), hydrocarbon (HC), nitrogen oxides (NO_x), nitrogen dioxide (NO_2), particulate matter with a diameter less than 2.5 micrometers ($PM_{2.5}$), particulate matter with a diameter less than 10 micrometers (PM_{10}), and particles with a diameter less than 0.1 micrometers (which are referred to as ultra-fine particles). These pollutants can be directly emitted through the vehicle exhaust, and they are also known as tailpipe emissions (Khreis, 2020). They can also be emitted through non-exhaust mechanisms such as evaporative emissions, the resuspension of dust, the wear of brakes and tires, and the abrasion of road surfaces; emissions through non-exhaust mechanisms are known as non-tailpipe emissions (Khreis, 2020; Askariyeh et al., 2020). Several factors contribute to the type and quantity of pollutants emitted, including vehicle type, age, condition, weight, fuel type, exhaust after-treatment technology, driving conditions, and road type. Vehicle emissions disperse into ambient air based on multiple factors that are highly variable, such as wind speed, wind direction and atmospheric stability, local and regional terrain, and background air pollution concentrations from other sources like industry, agricultural emissions, and coal and wood burning (Khreis, 2020). The result of this dispersion is elevated concentrations of air pollutants through primary emissions or through the formation of secondary pollutants. Humans are exposed to these air pollutants in ambient air or indoors through the infiltration of outdoor air pollutants. Human exposures and their inhaled doses that reach target organs or tissues are also then determined by various dynamic factors such as mobility patterns, distance from the source, height, physical activity, and transport mode choice (Khreis, 2020). Human exposure to TRAP can elicit a wide range of adverse health effects. The full chain of events covering traffic activity, vehicle emissions, dispersion of these emissions, human exposures, and their ultimate health impacts (as described above) is depicted in Figure 1.

Figure 1. The full chain: Linking TRAP to health impacts. Source: Center for Advancing Research in Transportation Emissions, Energy and Health (CARTEEH) (available from https://www.carteeh.org/).

The Burden of Childhood Asthma Attributable to Traffic-Related Air Pollution and Knowledge Gaps

Although convincing evidence now links TRAP with childhood asthma incidence, few studies have examined the burden of asthma attributable to TRAP. A study of 10 European cities, where on average 31 percent of the combined population lived within 75 m of high-traffic-volume roads, reported that proximity to major roadways accounted for an average of 14 percent of all childhood asthma cases, with a range of 7 percent to 23 percent (Perez et al., 2013). A study in Southern California examining exposure to air pollution from major roads and ship emissions used an 8-year average concentration of NO_2 and ozone (O_3) and found that between 6 percent and 9 percent of childhood asthma cases could have been prevented if exposures were reduced to levels found in clean communities (Perez et al., 2009). Both studies used the *proximity to major roadways* measure as a surrogate of TRAP exposures in which children living within a 75-m buffer of main roadways were classified as exposed. In the Los Angeles study (Perez et al., 2009), only 20 percent of the total children's population lived near a main roadway, while in Europe this percentage was higher (31 percent), with a range of 14 percent to 56 percent, depending on the city (Perez et al., 2013). A more recent study by Khreis et al. (2018) using a land-use regression (LUR) exposure assessment model estimated that 24 percent of all new childhood asthma in the city of Bradford, United Kingdom, was attributable to NO_2. In their follow-up study, Khreis, Ramani, et al. (2019) reported that BC, $PM_{2.5}$, and PM_{10} exposures accounted for 15 percent to 33 percent of all new childhood asthma cases in Bradford. Finally, two larger-scale studies—one European and one global—were conducted and published during the performance period of this project. The first study, by Khreis, Cirach, et al. (2019), combined data on country-level childhood asthma incident rates (IRs); LUR model exposure estimates for NO_2, $PM_{2.5}$, and BC pollutants; population counts; and exposure-response functions (ERFs) across 18 European countries and 63,442,419 children to estimate asthma incident cases attributable to the three pollutants. The authors estimated that compliance with the NO_2 and $PM_{2.5}$ WHO air quality guideline values was estimated to prevent 2,434 (0.4 percent) and 66,567 (11 percent) incident cases, respectively. On the other hand, meeting the minimum air pollution levels for NO_2 (1.5 $\mu g.m^{-3}$), $PM_{2.5}$ (0.4 $\mu g \cdot m^{-3}$), and BC ($0.4 \times 10^{-5}\ m^{-1}$) was estimated to prevent 135,257 (23 percent), 191,883 (33 percent), and 89,191 (15 percent) incident cases, respectively. The second study, from Achakulwisut et al. (2019), also combined data on country-level childhood asthma IRs, LUR model exposure estimates for NO_2, and population-count ERFs across 194 countries to estimate asthma incident cases attributable to NO_2. The authors estimated that 4 million new childhood asthma cases may be attributed to NO_2 annually, which on average accounts for 13 percent of the global incidence and ranges from 6 percent to 16 percent depending on country. Estimates by continent and major cities were also provided, and the authors reported that 19 percent of new childhood asthma cases may be attributable to NO_2 in high-income North America (Achakulwisut et al., 2019).

Before the Achakulwisut et al. (2019) publication, no analysis provided BoD estimates for North America, and as yet, no study focuses on the United States specifically. In addition, Achakulwisut et al. (2019) only investigated NO_2 exposures and did not look into particulate matter exposures, for which the biological plausibility case is stronger (Thurston et al., 2020).

Furthermore, many sources of errors and uncertainties exist in such BoD assessments, mainly due to errors and uncertainties in the data inputs to the models, including:

- The air pollution exposure levels and distribution.
- The ERFs.
- The baseline asthma IRs.

The impacts of errors and uncertainties in the input data have not been thoroughly researched in the literature. Some studies investigating the impacts of different input data sets on the final BoD estimates found that different exposure assessment methods, namely dispersion versus LUR modeling, can result in up to a 3 percent absolute difference in the percentage of total annual asthma cases attributable to TRAP (Khreis et al., 2018). Previous studies relied on national-level asthma IRs, which is in line with practice by prominent institutions and studies, such as the global BoD analyses. Childhood asthma, however, can be challenging to diagnose and ascertain. National-level IRs are likely to vary at the subnational level, particularly among urban and rural populations, and between different socioeconomic groups. Numerous studies show that when compared to rural populations, urban populations have a higher risk of asthma (Asher, 2011; Timm et al., 2016; McCormack and Leo, 2018; Rodriguez et al., 2019), regardless of the asthma definition (e.g., current-wheeze, doctor diagnosis, wheeze-ever, self-reported asthma, asthma questionnaire, and exercise challenge) (Rodriguez et al., 2019). However, these studies have been unable to fully identify which characteristics of urbanization may be responsible for this uneven gradient, and a multitude of environmental factors, including air pollution, have been implicated (Hill et al., 2011; Milligan et al., 2016). Similarly, there is evidence that children of lower socioeconomic status have a higher risk of asthma morbidity (Cesaroni et al., 2003; Kozyrskyj et al., 2010; Hill et al., 2011; Uphoff et al., 2015), which results in subnational and sub-city variations, and again may be partly related to environmental factors such as air pollution, which is known to follow a similar socioeconomic gradient (Khreis and Nieuwenhuijsen, 2019). Khreis et al. (2018) and follow-up work by Khreis, Ramani, et al. (2019) showed that using a national versus a local baseline asthma IR can result in up to a 10 percent difference in the number of estimated attributable asthma cases. However, this analysis was limited to one medium-sized city in England (Bradford) and the national (birth to 18 years old) and local (birth to 7 years old) baseline asthma IRs related to different age groups; consequently, it is not directly comparable. The impact of the ERFs and the baseline asthma IRs on the BoD estimates have not been studied beyond in the studies reported above and in this report.

Objectives

In this report, the researchers present a project that aimed to fill the knowledge gaps outlined above by estimating the childhood asthma BoD attributable to three traffic-related pollutants: NO_2, $PM_{2.5}$, and PM_{10}, which are related to traffic activity to different extents, across the entire contiguous United States in two different years (2000 and 2010). Thus, this project highlights changes in air pollution levels and the attributable BoD over a decade's worth of data.

The project also investigated the impacts of uncertainties in the ERFs and the baseline asthma IRs on uncertainties in the final BoD estimates due to the different pollutants. In a detailed sub-study, the researchers reanalyzed the NO_2 and attributable BoD estimates for the year 2010 using newly generated varying state-specific asthma IRs and highlighted the differences between those estimates and estimates made using one (fixed) national-level asthma IR, as is usually practiced. The researchers conducted this comparison at the national level but also show the results separately by state. Using the more granular state-specific asthma IRs, the researchers also explored trends in the BoD estimates by socioeconomic status and urban versus rural status to compare with trends observed in the analysis using one (fixed) national-level asthma IR. Establishing how the pollution-attributable BoD estimates vary depending on baseline childhood asthma IR distinguishes this BoD study from previous ones.

Finally, this report presents the results using interactive tools—namely interactive maps and tables—and a wealth of graphics to raise awareness and present findings in an accessible manner to practitioners, policy makers, and the general public.

Methodology

Study Area and Timeframe

This project was organized into two studies. In the first study, Alotaibi et al. (2019) analyzed data from the years 2000 and 2010 for three pollutants nationally. The second study, Khreis et al. (2020), was a nested sub-study that focused on a subset of the data used in the first study—the year 2010 and one pollutant (NO_2)—to establish the impact of using state-specific versus national-level asthma IRs on the final BoD estimates.

In the Alotaibi et al. (2019) study, the researchers analyzed data for the contiguous United States, which includes 48 states and the District of Columbia (D.C.), for the years 2000 and 2010 for the three pollutants NO_2, $PM_{2.5}$, and PM_{10}. All analyses were conducted at the census block level, which is the smallest geographical unit for which census data are available (see Figure 2). Census blocks are bounded by visible features like roads, streams, and railroad tracks; and non-visible features like property lines with varying sizes (U.S. Census Bureau, 1994). One variable of interest, the median household income, was only available at the census block group level, which is one geographical level higher than the census block (U.S. Census Bureau, 2010).

Only populated census blocks were included in the analyses. The researchers selected years 2000 and 2010 due to the following:

- The availability of full population counts from the decennial census.
- The availability of exposure estimates at a geographical level matching the census block level for the contiguous United States (described in the exposure assessment section).

In the Khreis et al. (2020) study, the researchers also analyzed data for the 48 contiguous United States and D.C. but only for the year 2010 and only for one pollutant: NO_2. All analyses were also conducted at the census block level except for the analysis of the median household income, which again was only available at the census block group level (see Figure 2).

Air pollution data were unavailable for states or territories outside the contiguous United States (Alaska, Hawaii, and Puerto Rico) and thus were excluded from both studies.

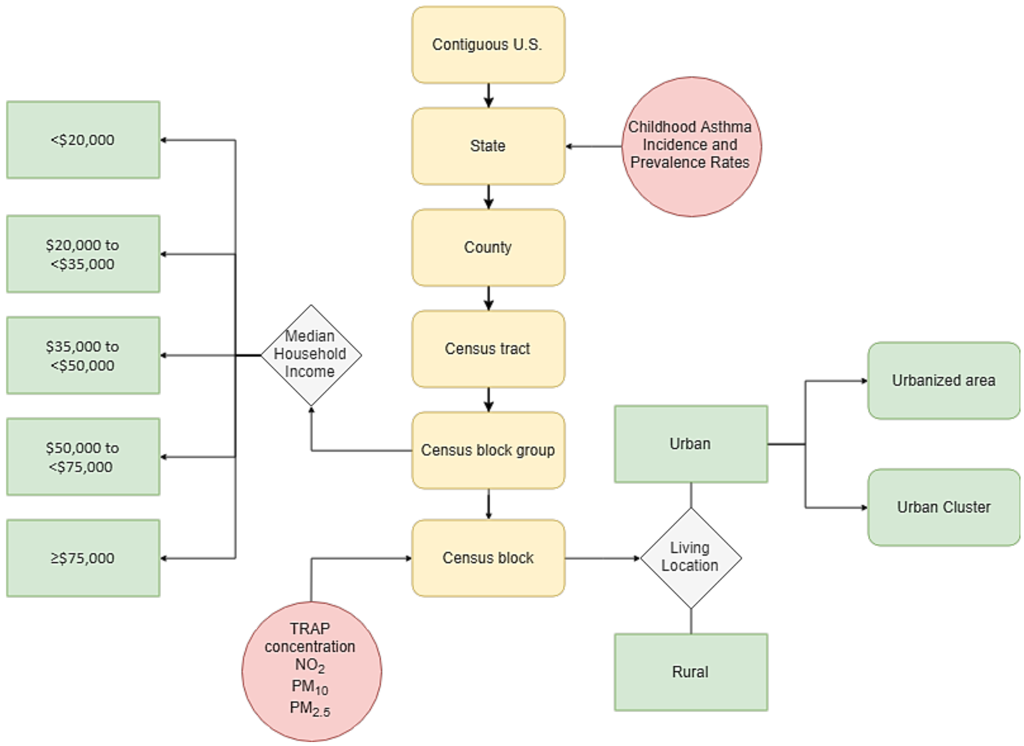


Figure 2. Geographical unit hierarchy.

Census Data

The researchers obtained decennial census data for 2000 and 2010 from the National Historical Geographic Information System (NHGIS) website (Manson et al., 2018). The data included total population counts and total counts of children less than 18 years old living in the contiguous United States at the census block level. The researchers only included populated census blocks. Population counts were stratified into urban or rural at the census block level. Census-designated urban areas were defined by the U.S. Census Bureau using multiple criteria, including total population thresholds, density, nonresidential urban land use (e.g., paved areas and airports), and distance to other urban developed areas (Ratcliffe et al., 2016). Further, census-designated urban areas were classified into two subtypes: urban clusters (≥2,500 to <50,000 people) or urbanized areas (≥50,000 people). Annual median household income was stratified into the following categories (not adjusted for inflation): <$20,000, $20,000 to <$35,000, $35,000 to <$50,000, $50,000 to <$75,000, and ≥$75,000 at the census block group level. Census blocks were assigned the same median household income of the census block group they resided within. There were 2,686 (0.04 percent) census blocks with missing median household income data in 2010. These census blocks were excluded from the analysis in the Alotaibi et al. (2019) study, while they were assigned a *not defined* status in the Khreis et al. (2020) study.

Table 1 summarizes the demographic and geographic characteristics in census blocks for both years. The total number of children in 2000 was 71,807,328 (26 percent of the total population) and in 2010 was 73,690,271 (24 percent of the total population). In regard to living location, 79 percent and 81 percent of children lived in an urban setting in 2000 and 2010, respectively. Concerning median household income, fewer children lived in the lowest median income group (not adjusted for inflation) than in other groups across both years.

Air Pollution Exposure Assessment

For the air pollution exposure assessment in both the Alotaibi et al. (2019) and Khreis et al. (2020) studies, the researchers utilized a previously established and validated LUR model. LUR modeling is a commonly used empirical-statistical method in air pollution epidemiology and BoD and health impact assessment studies. This method has become widely used for estimating within-urban variability in air pollution typically associated with traffic emissions (Bechle et al., 2015; Anderson et al., 2013). The method uses a least squares regression to combine measured pollutant concentrations with geographical information system (GIS)-based predictor variables. These predictor variables often reflect air pollution sources and surrounding land-use characteristics, among others, to build a prediction model applicable to non-measured locations (Khreis and Nieuwenhuijsen, 2017). Traffic variables are often included in the LUR models by describing the road type or traffic density within a fixed distance or buffer of each measurement site and sometimes by splitting the vehicle density by vehicle type. Once the relationship between the measured pollutant concentrations and the predictor variables is established, the LUR model is used to predict air pollution exposures in locations where measurements have not been made. The general pros and cons of LUR models in comparison to other exposure models have been previously described in Khreis and Nieuwenhuijsen (2017).

Table 1. Census Data Description

Data Description	2000	2010	Change (%)
Geographic characteristics			
Total populated census blocks	5,280,214	6,182,882	17%
Total census-designated urban areas	2,970,347 (56%)	3,590,278 (58%)	21%
Demographic characteristics			
Total population	279,583,437	306,675,006	10%
Total population of children (0–18)	71,807,328 (26%)	73,690,271 (24%)	3%
Mean (range) number of children in census blocks	14 (0–4713)	12 (0–2214)	−12%
Population of children by living location			
Urban	56,504,832 (79%)	59,927,088 (81%)	6%
Rural	15,302,496 (21%)	13,763,183 (19%)	−10%
Population of children by median household income			
<20,000	4,055,407 (6%)	2,614,804 (4%)	N/A[a]
20,000 to <35,000	20,694,588 (29%)	12,770,843 (17%)	
35,000 to <50,000	21,974,042 (31%)	18,573,954 (25%)	
50,000 to <75,000	17,350,990 (24%)	21,953,876 (30%)	
≥75,000	7,732,301 (11%)	17,763,239 (24%)	

[a] Not applicable; the researchers could not adjust for inflation.

NO_2 Model and Exposures

The air pollution exposure assessment was based on the annual average pollutant concentration at the centroid of each census block for the years 2000 and 2010. The researchers estimated the BoD due to exposure of three pollutants; NO_2, $PM_{2.5}$, and PM_{10}. Pollutant concentrations were obtained from satellite-based LUR and kriging models (Bechle et al., 2015; Kim et al., 2019). Exposure data were matched with census blocks using a unique identifier for each census block as provided in the NHGIS data set. The following sections present a description of the modeling method used for each pollutant.

To estimate NO_2 exposures for the contiguous United States, the researchers adopted a national LUR model developed by Bechle et al. (2015) that provided annual average NO_2 concentration estimates for 2000 and 2010 at the centroid location of each populated census block. The development of the model incorporated two components, a spatial and a temporal component. For the spatial component, data were sourced using satellite readings, U.S. Environmental Protection Agency (EPA) air quality monitor readings, and multiple GIS-based predictor variables, including impervious surfaces, tree canopies, population count, major road length, minor road length, total road length, elevation, and distance to coast. The model had a spatial resolution typical for urban-scale LURs (~100 m scale) and covered 100 percent of populated census blocks in the contiguous United States. For the temporal component, the monthly NO_2 average concentrations for 11 consecutive years from EPA air quality monitors were used as a scaling factor for the data to increase the predictive ability of the model. Data from air quality monitors were only included when at least 75 percent of the hourly values were available. The validation of the spatial model was satisfactory, with an R^2 ranging from 0.63 to 0.82 using hold-out cross-validation. The R^2 of the model was consistent with other continental-scale NO_2 models documented elsewhere. For example, Novotny et al. (2011) reported on a U.S. national NO_2 LUR model with an R^2 of 0.78. Hystad et al. (2011) reported on a Canadian national NO_2 LUR model with an R^2 of 0.72. Beelen et al. (2009) reported on a European NO_2 LUR model with an R^2 of 0.61, and Vienneau et al. (2013) reported on a Western European NO_2 LUR model with an adjusted R^2 of 0.58. NO_2 concentrations from the Bechle et al. (2015) model were converted from parts per billion (ppb) to ug/m^3 units by multiplying them by 1.88 (WHO, 2005).

$PM_{2.5}$ Model and Exposures

Annual average air pollution concentrations for $PM_{2.5}$ were modeled using 17 years of data (1999–2015) from regulatory air quality monitors. The model was constructed using a universal kriging framework (Kim et al., 2019). The model incorporated hundreds of geographic variables, including land-use, population-count, and satellite data. The validation of the model was performed using a hold-out cross-validation, with satisfactory performance of 10-fold hold-out cross-validation R^2 reaching 0.86 and 0.85 in 2000 and 2010, respectively.

PM_{10} Model and Exposures

Annual average air pollution concentrations for PM_{10} were estimated using 27 years of data (1988–2015) in a method similar to the one used for $PM_{2.5}$ (Kim et al., 2019). The validation of the model was performed using a hold-out cross-validation, with satisfactory performance of 10-fold hold-out cross-validation R^2 reaching 0.60 and 0.57 in 2000 and 2010, respectively.

Table 2 provides a detailed summary of pollutant concentrations for NO_2, $PM_{2.5}$, and PM_{10} across both years. Pollutant data at the state level and across the different strata (urban versus rural and by median household income) are provided in the supplementary materials of the two published papers (Khreis et al., 2020; Alotaibi et al., 2019).

Table 2. Summary of Pollutant Concentrations Using Populated Census Blocks Only

Pollutant	Population-Weighted Average Concentrations								
	NO_2 µg/m^3			$PM_{2.5}$ µg/m^3			PM_{10} µg/m^3		
	2000	2010	Change (%)	2000	2010	Change (%)	2000	2010	Change (%)
Mean	20.6	13.2	−36%	12.1	9.0	−26%	21.5	17.9	−17%
Min	2.2	1.5	−32%	0.6	1.3	117%	2.8	0.7	−75%
25%	12.1	7.9	−35%	9.8	7.4	−24%	18	14.6	−19%
50%	17.9	11.4	−36%	12.2	9.1	−25%	21.3	17.8	−16%
75%	26.3	16.6	−37%	14.5	10.6	−27%	24.2	21.2	−12%
Max	95.9	58.3	−39%	26.4	16.6	−37%	73.7	49.1	−33%

Asthma Incidence and Prevalence Rates

An IR is defined as the number of new cases of a disease within a specified time period among an at-risk population (Mausner and Kramer, 1985). U.S. national-level or state-specific childhood asthma IRs in 2000 and 2010 were not readily available. The estimations of the childhood asthma IRs were conducted differently in the Alotaibi et al. (2019) and the Khreis et al. (2020) studies and are described in detail below.

National-Level Study: National-Level IR

For the Alotaibi et al. (2019) study, the primary objective was to estimate the childhood asthma BoD attributable to three pollutants—NO_2, $PM_{2.5}$, and PM_{10}—across the entire contiguous United States in the years 2000 and 2010.

The researchers relied on an already published childhood asthma IR without reanalyzing any of the underlying health data. The researchers used an aggregated annual average asthma IR of 12.5 (95 percent confidence interval [CI] = 10.5–14.4) per 1,000 at-risk children for the period 2006–2008, as published by Winer et al. (2012). This asthma IR was estimated using the Behavioral Risk Factor Surveillance System (BRFSS) and the Asthma Call-Back Survey (ACBS) data sets extracted from 31 states and D.C., with a total sample size of 200,993 from the BRFSS and 8,437 children from the ACBS (CDC, 2009, 2011). Both surveys were conducted by the CDC and are described next.

The Behavioral Risk Factor Surveillance System

The BRFSS is a continuous national health-related telephone survey conducted in all 50 states, as well as D.C., and three U.S. territories (Guam, Puerto Rico, and the U.S. Virgin Islands). The ACBS is a follow-up survey in select participating states and among select individuals with an affirmative asthma diagnosis, as established during the BRFSS. If states participate in an optional random child selection module, an adult respondent may serve as a proxy for one randomly selected child (<18 years) per household (CDC, 2009).

To estimate the childhood asthma IR, participants were assessed for a lifetime asthma status using the following BRFSS question: "Has a doctor, nurse, or other health professional ever said that [name of child] has asthma?" If the answer was "Yes," the respondent was then asked to participate in the ACBS. If the respondent answered "No," the child was designated by the status *never asthma*.

The Asthma Call-Back Survey

During the follow-up ACBS interview, the respondent was asked the following: "How old was [name of child] when a doctor or other health professional first said [he/she] had asthma? How long ago was that?" If the answer was "within the past 12 months," the child's status was designated as *newly diagnosed asthma case*.

Asthma IR was then estimated as the number of newly diagnosed asthma cases among at-risk children within a specified time period. At-risk children were the sum of never asthma and newly diagnosed asthma cases among children (i.e., excluding prevalent cases in each year). Figure 3 shows a flowchart of how asthma incident cases were ascertained through the BRFSS and ACBS (Winer et al., 2012).

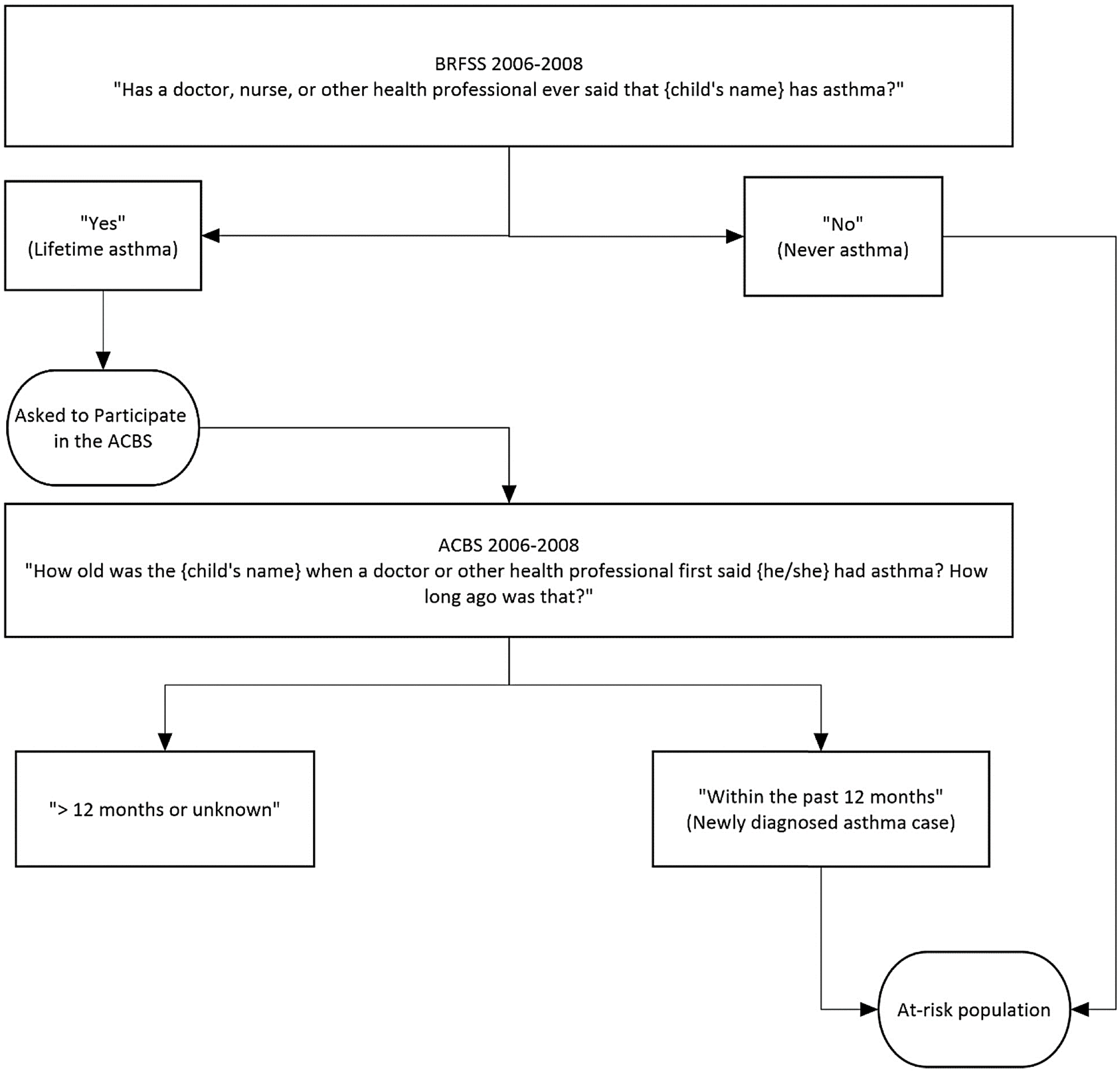


Figure 3. Never asthma, newly diagnosed asthma case, and at-risk population from the BRFSS and ACBS data sets, 2006–2008.

State-Level Study: National-Level versus State-Specific Incidence Rates

For the Khreis et al. (2020) study, the primary objective was to study the impacts of the uncertainties in the baseline asthma IRs on the final BoD estimates. This study focused on one year (2010) and one pollutant (NO_2), and the researchers reran the analyses twice: once using a national-level childhood asthma IR, and the other using a state-specific IR. The year 2010 was selected because it was the more recent year. The pollutant NO_2 was selected because its ERF is well supported by a wealth of literature, and it is the most commonly used pollutant in previous epidemiological and BoD assessments of incident asthma. Furthermore, NO_2 is a relatively specific marker of TRAP, which might be the most relevant air pollution mixture in the context of air-pollution-induced asthma (Khreis, Kelly, et al., 2017).

In the Khreis et al. (2020) study, the raw data from the BRFSS and the ACBS for the years 2006 through 2010 were obtained and reanalyzed to estimate a new national-level and state-specific childhood asthma IR. These data can be found at the CDC website: https://www.cdc.gov/brfss/. The study included multiple years of data rather than only data from the year 2010 to increase the available sample sizes, statistical power, and number of states with available data since some states participated in some years and not others, as shown in Table 3.

Table 3. Available Childhood Asthma IRs by State and Year

State	2006[a]	2007[a]	2008[a]	2009[a]	2010[a]	Aggregate IR[a]	Aggregate PR[b]
Alabama							14.4 (12.2–16.6)
Arizona	23.7	6.8				15.2 (0–30.5)	13.1 (11.5–14.7)
Arkansas							
California	12.1	6.5				9.3 (3.8–14.8)	12.2 (11.4–13)
Colorado							
Connecticut		9.9	14.1	10.8	13.5	12 (6.6–17.5)	16 (14.9–17.1)
Delaware							18.2 (15.4–21.1)
D.C.	5.3	28.8				17.7 (1.2–34.3)	19.9 (18.2–21.5)
Florida							
Georgia	6.4	5.8	9.1	16.6	6.9	9.1 (4.4–13.7)	15.1 (14.1–16.1)
Idaho							9 (8–9.9)
Illinois		4.2		9.2		6.7 (0.3–13)	12.4 (11.3–13.5)
Indiana	25.4	9.3	13.4	9.9	17.6	15.2 (9.6–20.7)	12.8 (12–13.7)
Iowa	5	4	9.9			6.3 (3.2–9.4)	8.4 (7.7–9.1)
Kansas	7.8	9.9	9.9	8.3	9	9 (6.1–11.9)	11.6 (10.9–12.2)
Kentucky							14 (12.7–15.2)
Louisiana				5.8		5.8 (0–12.8)	13 (11.7–14.2)
Maine	13	8.7	5.8			9.2 (3.7–14.8)	13.2 (12.1–14.3)
Maryland	16.2	8.6	11	17.3	2.3	11.2 (6.8–15.5)	14.8 (14–15.7)
Massachusetts							
Michigan	5.3	7.7	5.2	13.4	29.3	12 (7.6–16.5)	13.6 (12.7–14.4)
Minnesota							9.5 (7.8–11.2)
Mississippi		10.8			17.2	14 (4.2–23.9)	14.2 (13.4–15)
Missouri	21.2	10.3	7.2			12.9 (3–22.8)	13.9 (12.6–15.2)
Montana	2.8	2		3.7	8.5	4.3 (1.6–6.9)	9.7 (8.9–10.5)
Nebraska	11.9	8.3	8.9	3.3	12.9	9.1 (5.5–12.7)	9.3 (8.6–10)
Nevada							10.9 (9.6–12.1)
New Hampshire	11.5	13.8	10.4			12 (5.9–18)	12.1 (11.1–13.2)
New Jersey			6.3	12.5	10.5	9.8 (5.5–14.1)	14.3 (13.5–15)
New Mexico		3.2	9.5		7.2	6.7 (3.1–10.3)	12 (10.9–13)
New York	12.9	6.1	28.4	11.2		14.7 (7.7–21.7)	15.8 (14.7–16.9)
North Carolina							
North Dakota							8.9 (7.8–9.9)
Ohio		13.1	17			15.1 (7.4–22.7)	12.3 (11.2–13.4)
Oklahoma		9.2	10.1		12.9	10.8 (5.8–15.8)	14 (13.1–14.8)
Oregon		11.1				11.1 (2.6–19.5)	11.1 (9.9–12.3)
Pennsylvania		21.8			4.3	13.1 (3.7–22.6)	13.9 (13–14.8)
Rhode Island			15.3	13.2		14.3 (4.4–24.1)	16.1 (15–17.2)
South Carolina							
South Dakota							
Tennessee							
Texas	14.4		18.2	12.5	21	16.6 (9–24.2)	13.1 (12.2–14.1)
Utah		15.4	11.9	5.6	9.3	10.4 (6.5–14.3)	10.2 (9.6–10.9)
Vermont	13.5	4.4	8.5	21.2	10.4	11.5 (7.4–15.6)	13.8 (13–14.7)

Virginia							13.6 (12.4–14.8)
Washington				7.9	5.6	6.8 (3.8–9.8)	10.8 (10–11.5)
West Virginia		11.8				11.8 (0.9–22.8)	12.7 (11.6–13.7)
Wisconsin	12.3					12.3 (0–24.5)	10.6 (9.2–11.9)
Wyoming							9.5 (8.6–10.4)

Note: PR = prevalence rate.

[a] IR per 1,000 at-risk children (the ranges in parentheses represent the 95% Confidence Intervals).

[b] PR per 100 children (the ranges in parentheses represent the 95% Confidence Intervals).

The study followed the methods described by Winer et al. (2012) to estimate the childhood asthma IR at both the national and state levels. Both the BRFSS and ACBS defined childhood as birth to 18 years of age, which is in line with the meta-analysis from which the researchers sourced the ERFs, as will be described in the next section. The following variables were extracted from the surveys:

- Asthma status question (from the BRFSS).
- Incident status question (from the ACBS).
- Children sample weights from both surveys.

To determine the asthma status of children, respondents to the BRFSS were asked, “Has a doctor, nurse, or other health professional ever said that the child has asthma?” If the answer was “Yes,” the respondent was designated as *ever asthma*. If the answer was “No,” the respondent was designated as *never asthma*.

Respondents with children designated as *ever asthma* were requested to participate in the ACBS follow-up. To determine the incident status of children, respondents to the ACBS were asked, “How old was [name of child] when a doctor or other health professional first said [he/she] had asthma? How long ago was that?” If the answer to the latter part of this question was “within the past 12 months,” the respondent was designated as *incident asthma*.

The BRFSS/ACBS utilize a complex sample survey design in which each sample (individual) is assigned a weight. Weights are used to convert samples to population estimates of children. For example, if respondent (X) had a weight of 150, her/his response to survey questions represented answers of 150 children within the state. Weights are assigned in complex survey design studies to adjust for the disproportionate population sample selection in comparison to the state’s overall population distribution, the variation in probability of selection, and the actual response/nonresponse of each respondent (Garbe et al., 2011; Korn and Graubard, 2011). The sum of childhood weights for the BRFSS represents the total population of children within each state, while the sum of weights for the ACBS represents the total population of children designated as *ever asthma* within each state.

The number of states participating in the BRFSS/ACBS vary each year, as shown in Table 3. Therefore, the researchers adjusted the state sample weights to account for the varying number of years of participation by dividing the BRFSS and ACBS weights by the number of years each state participated. Results of the state-specific IRs and PRs represent an average estimate from 2006 to 2010 for the states participating in the BRFSS/ACBS. Overall, there were 32 states for which the researchers were able to extract childhood asthma IRs and 41 states with childhood asthma PRs. These data are shown in full in the supplementary material of Khreis et al. (2020).

The step-by-step process for estimating childhood asthma IR, PR, and the number of at-risk children for specific states and nationally is outlined below.

The PR for each state was calculated as the weighted *ever asthma* divided by the sum of the weighted *ever asthma* and weighted *never asthma* across all available years (k), as shown in Equation (1).

$$PR = \sum_{i=1}^{k} \frac{Ever\ asthma_{weighted(w)}}{(Ever\ asthma_w + Never\ asthma_w)} \quad (1)$$

At-risk children were estimated by taking the weighted sum of respondents designated as *incident asthma* and *never asthma*, as shown in Equation (2).

$$At-risk\ children\ =\ Incident\ asthma_w +\ Never\ asthma_w \quad (2)$$

The asthma IR for each state was calculated as the weighted *incident asthma* divided by *at-risk children* across all available years (*k*), as shown in Equation (3).

$$IR = \sum_{i=1}^{k} \frac{Incident\ asthma_w}{At-risk\ children} \quad (3)$$

To estimate the state-specific asthma IR for a given year (*k*), both the ACBS and BRFSS data must be available for the state in the given year *k*. For example, if the ACBS data for a certain state were available during the year 2009 but the BRFSS data were not, the researchers could not estimate the IR. To estimate the PR, only the BRFSS data must be available for the given year *k*. Not all states participated in the surveys during the period 2006–2010 (Table 3). Moreover, data for some states were not publicly available due to technical issues—including too few records (<75) to produce reliable weights, changes in data collection time frame, changes in protocol that affected the weighting procedures, and differences in Institutional Review Board requirements and/or approval—even though they participated in the surveys (Garbe et al., 2011). For states for which the researchers were not able to estimate the asthma IR and PR (n = 17; see Table 3), the researchers assigned the aggregate IR estimated from all other states with available data: IR = 11.6 per 1,000 at-risk children (95 percent CI: 11.646–11.649), and PR = 13.1 per 100 children (95 percent CI: 13.1327–13.1333).

Exposure-Response Functions

The researchers obtained the ERF for the association between exposure to the three pollutants and the subsequent development of childhood asthma from a meta-analysis published by Khreis, Kelly, et al. (2017). The meta-analysis synthesized a total of 41 international studies that examined the association between children's exposure to TRAP metrics from birth to 18 years old and their risk of subsequent asthma incidences or lifetime prevalence. Random-effects meta-analyses were selected to summarize the risk estimates across the range of studies because they account for within-study variance caused by chance and sampling error and also for between-study variance caused by heterogeneity (Riley et al., 2011), a feature that is likely to be present in studies on TRAP and asthma development (Health Effects Institute, 2010). The overall risk estimates from the meta-analyses showed statistically significant associations between NO_2, $PM_{2.5}$, and PM_{10} exposures and risk of asthma development, which were robust in multiple sensitivity analyses (Khreis, Kelly, et al., 2017).

The ERF for NO_2 was 1.05 (95 percent CI = 1.02–1.07) per 4 $\mu g/m^3$, while for $PM_{2.5}$ it was 1.03 (95 percent CI = 1.01–1.05) per 1 $\mu g/m^3$, and for PM_{10} it was 1.05 (95 percent CI = 1.02–1.08) per 2 $\mu g/m^3$. The NO_2 ERF was based on 20 studies, while the $PM_{2.5}$ and PM_{10} ERF were based on 10 and 12 studies, respectively. It is worth noting that the studies included in the underlying meta-analyses did not adjust for co-pollutants. As such, the numbers of asthma cases attributable to NO_2, $PM_{2.5}$, and PM_{10} should not simply be added. Instead, these estimates should be viewed as independent estimates of the potential impact of different traffic-related air pollutants. These ERFs represent data from the most recent and largest meta-analysis of TRAP and onset of childhood asthma and have been used in several published peer-reviewed BoD assessments (Khreis et al., 2018; Khreis, Ramani, et al., 2019; Achakulwisut et al., 2019; Khreis, Cirach, et al., 2019).

Burden of Disease Assessment

To estimate the BoD of incident childhood asthma cases attributable to NO_2, $PM_{2.5}$, and PM_{10} exposures, the researchers followed standard BoD assessment methods that combined child population counts, exposure estimates, asthma IRs, and pollutant-specific ERFs. For the Alotaibi et al. (2019) study, the analysis was conducted for each pollutant in each year separately. For the Khreis et al. (2020) study, the analysis was conducted for NO_2 in 2010 using national-level versus state-specific IRs separately. The steps that were followed are outlined separately for both studies.

Steps for Burden of Disease Assessment in the National-Level Study

First, the researchers estimated the number of new asthma cases for that year (asthma incident cases) by multiplying the number of at-risk children in that year by the IR, as shown in Equations (4) and (5).

$$\textit{At-risk children} = \textit{Total children} - (\textit{Total children} * PR) \tag{4}$$

$$\textit{Asthma incident cases} = \textit{At-risk children} * IR \tag{5}$$

Second, the researchers estimated the relative risk (RR_{diff}) associated with the exposure difference between the current exposure and the counterfactual exposure scenarios of zero air pollution (elimination of air pollution), as shown in Equation (6):

$$RR_{diff} = e^{(\ln(RR)/RR_{unit}) * Exposure} \tag{6}$$

where *RR* is the relative risk obtained from the ERF, and RR_{unit} is the exposure unit of the *RR* as obtained from the ERF.

Third, using the RR_{diff}, the researchers estimated the percentage of asthma incident cases due to each pollutant's exposure, otherwise known as the population attributable function (PAF), as shown in Equation (7).

$$PAF = (RR_{diff} - 1) / (RR_{diff}) \tag{7}$$

Using the *PAF*, the researchers estimated the number of asthma incident cases due to each pollutant's exposure, also known as the attributable number of cases (ACs), as shown in Equation (8).

$$AC = PAF * \textit{Asthma incident cases} \tag{8}$$

Finally, the researchers summed the ACs across all the included census blocks separately for each pollutant and each year.

Note that for the Alotaibi et al. (2019) study analysis, one aggregated annual average asthma IR of 12.5 (95 percent CI = 10.5–14.4) per 1,000 at-risk children for the period 2006–2008 was used, as presented by Winer et al. (2012). This result was used for the analyses in both years 2000 and 2010.

Steps for Burden of Disease Assessment in the State-Level Study

The difference between the BoD assessment in the Khreis et al. (2020) study and the Alotaibi et al. (2019) study is in the IRs used, as referenced above and as next described. The Khreis et al. (2020) study also focused on NO_2 and the year 2010 only.

The total number of at-risk children residing in a census block was estimated for each state. This was done by subtracting the total number of children within the census block multiplied by the state-specific PR from the total number of children within the same census block, as shown in Equation (9).

$$At - risk\ children_{census\ block(c)} = Total\ children_c - (Total\ children_c * PR_{state\text{-}specific(s)}) \tag{9}$$

The researchers then estimated the number of childhood asthma incident cases within each census block by multiplying the state-specific asthma IR by the at-risk children in each census block, as shown in Equation (10).

$$Asthma\ incident\ cases_c = At\text{-}risk\ children\ _c * IR_s \tag{10}$$

The researchers then calculated the relative risk (RR_{diff}) for asthma onset due to the exposure difference between the estimated exposure levels from the LUR model (NO_2 concentration at the centroid of each census block) and the no-exposure counterfactual scenario (zero NO_2 concentration) at each census block, as shown in Equation (11):

$$RR_{diff} = e^{((ln\ (RR)\ /\ RR_{unit}\ *\ Exposure_{census\ block\ (c)})} \tag{11}$$

where *RR* is the NO_2 relative risk obtained from the ERF, and RR_{unit} is the exposure unit of the *RR* as obtained from the ERF (4 ug/m^3).

The *PAF* was then estimated at each census block, as shown in Equation (12).

$$PAF_c = \left(RR_{diff} - 1\right) / RR_{diff} \tag{12}$$

The attributable number of *AC* was estimated by multiplying the *PAF* with the total number of asthma incident cases in each census block, as shown in Equation (13).

$$AC_c = PAF_c * Asthma\ incident\ cases_c \tag{13}$$

The attributable number of asthma incident cases for each census block was then summed across the state to obtain state total AC estimates, and summed across the entire country to obtain the national AC estimates, as shown in Equation (14).

$$Total\ AC = \sum AC_c \tag{14}$$

To run the analysis and estimate the standard errors associated with each IR and PR, the researchers used the open-access statistical software R and the *svyratio* function from the survey package (Lumley, 2004). The package utilizes the Taylor linearization of estimating functions for complex statistics (Lumley, 2011). The 95 percent CIs were obtained directly from the software.

Counterfactual Scenarios in the National-Level Study

In the Alotaibi et al. (2019) study, the researchers also estimated the impact of two more realistic counterfactual scenarios besides the full elimination of air pollution exposures scenario. The analysis was repeated for each of the three pollutants and for each year separately for the following scenarios:

- Air pollution levels did not exceed the WHO air quality guideline values (Krzyzanowski and Cohen, 2008), as shown below:
    - NO_2 was 40 µg/m^3 (annual average).
    - $PM_{2.5}$ was 10 µg/m^3 (annual average).
    - PM_{10} was 20 µg/m^3 (annual average).
- Air pollution levels did not exceed the minimum modeled concentration by the exposure assessment models at any census block in either year (Alotaibi et al., 2019), as shown below:
    - NO_2 was 1.48 µg/m^3 (annual average).

- $PM_{2.5}$ was 0.55 µg/m^3 (annual average).
- PM_{10} was 0.72 µg/m^3 (annual average).

The researchers then reran the analysis following the steps outlined above and estimated the number of incident asthma cases due to TRAP that could have been prevented among census blocks that exceeded annual average limits for the two above scenarios.

Sensitivity Analysis in the National-Level Study

In the national-level study, the researchers examined the range of uncertainty in the BoD estimates resulting from uncertainties in the asthma IR and the ERF. For this purpose, the researchers reran the analysis using all possible combinations of the upper and lower 95 percent CI of both the national asthma IR (fixed value in the first study) and ERFs. The researchers produced a sensitivity analysis matrix summarizing all possible combinations of 95 percent CI bounds for the BoD estimated in association with every possible combination of the IR and the ERF.

Results

Census Description

More than 5 million and 6 million populated census blocks existed in 2000 and 2010, respectively, of which urban designated blocks, encompassing urban clusters and urbanized areas, represented 56 percent and 58 percent. The total population of children was 71,807,328 (26 percent of total population) and 73,690,271 (24 percent) in 2000 and 2010, respectively. Seventy-nine percent and 81 percent of children lived in an urban designated area in 2000 and 2010, respectively. In 2000, most children lived in the \$35,000 to <50,000 median household income category, while in 2010, most children lived in the \$50,000 to <75,000 median household income category. Table 1 provides the geographical and population distribution by median household income group for each year. State-specific geographical and demographic characteristics are detailed in the supplementary material of Alotaibi et al. (2019).

Air Pollution Concentrations and Trends

The means and ranges for the three modeled pollutants across the contiguous United States are shown in Table 2. All pollutants were significantly reduced between the years 2000 and 2010: NO_2 by 36 percent, $PM_{2.5}$ by 26 percent, and PM_{10} by 17 percent, on average. Table 4 shows the exposure estimates by urban versus rural status and by median household income. The highest mean concentrations for the three pollutants were in urban areas, specifically urbanized areas (data not shown), for both years. By median household income group, trends differed across pollutants and years. For NO_2, the highest concentration in 2000 and 2010 was among the highest median household income group of ≥\$75,000, followed by the lowest median household income group of <\$20,000 in 2010 only. For $PM_{2.5}$ and PM_{10}, the highest concentration in 2000 and 2010 was among the lowest median household income group of <\$20,000 (Table 4). In the Khreis et al. (2020) study, the researchers looked in more detail at the trends of 2010 NO_2 levels by both median household income group and urban versus rural status. The study observed that rural areas had an increasing average concentration as income increased, and urban clusters had a decreasing average concentration as income increased, while urbanized areas showed a U-shaped trend, with high average concentrations in the lowest and highest income strata (Figure 4).

The regions with the largest and lowest NO_2 concentrations were D.C. (38.2 µg/m^3) and North Dakota (6.8 µg/m^3) in 2000 and D.C. (26.3 µg/m^3) and South Dakota (5.2 µg/m^3) in 2010. The NO_2 concentration change across all states between 2000 and 2010 ranged from a decrease of 46 percent (Florida) to a decrease of 21 percent (North Dakota). The regions with the largest and lowest $PM_{2.5}$ concentrations were D.C. (15.7 µg/m^3) and New Mexico (5.5 µg/m^3) in 2000 and Indiana (14.9 µg/m^3) and New Mexico (4.5 µg/m^3) in 2010. The $PM_{2.5}$ concentration change across all states between 2000 and 2010 ranged from a 6 percent increase (North Dakota) to a 41 percent decrease (California). The states with the largest and lowest PM_{10} concentrations were Arizona (31.5 µg/m^3) and New Hampshire (10.4 µg/m^3) in 2000 and Iowa (23.7 µg/m^3) and New Hampshire (9.4 µg/m^3) in 2010. The PM_{10}

concentration change across all states between 2000 and 2010 ranged from a 7 percent increase (North Dakota) to a 35 percent decrease (Idaho).

Table 4. Summary of Pollutant Concentrations by Urban versus Rural and by Median Household Income Strata

Strata		Year 2000				Year 2010			
		Mean	Min	Median	Max	Mean	Min	Median	Max
NO_2 ug/m^3									
Total									
By Living Location	Urban	27.0	2.5	24.7	95.9	17.0	1.6	15.4	58.3
	Rural	12.4	2.2	11.7	72.3	8.0	1.5	7.8	37.7
By Median Household Income	<20,000	24.2	2.8	21.7	95.2	16.1	2.0	14.9	56.8
	20,000 to <35,000	18.3	2.7	15.7	95.9	13.2	1.6	11.7	58.3
	35,000 to <50,000	19.1	2.2	16.4	90.8	11.8	1.5	10.0	58.0
	50,000 to <75,000	24.3	3.3	21.4	89.4	12.8	1.6	10.8	55.7
	≥75,000	28.8	3.7	27.2	85.7	16.5	2.1	14.9	55.5
$PM_{2.5}$ ug/m^3									
Total									
By Living Location	Urban	13.0	1.1	12.9	26.3	9.6	2.0	9.8	16.6
	Rural	10.9	0.6	11.0	26.0	8.1	1.3	8.4	15.7
By Median Household Income	<20,000	13.3	0.7	13.7	26.3	10.3	1.7	10.6	16.6
	20,000 to <35,000	11.9	0.6	12.0	26.3	9.5	1.5	9.7	16.3
	35,000 to <50,000	11.9	0.6	11.9	26.0	8.9	1.3	9.0	16.1
	50,000 to <75,000	12.4	0.7	12.3	26.0	8.7	1.3	8.9	16.4
	≥75,000	12.7	1.0	12.6	25.6	8.7	1.4	8.9	15.5
PM_{10} ug/m^3									
Total									
By Living Location	Urban	23.0	3.5	22.2	73.6	19.1	1.8	19.0	46.9
	Rural	19.5	2.8	19.9	71.3	16.3	0.7	15.9	49.1
By Median Household Income	<20,000	23.4	3.7	22.8	73.6	19.2	1.1	19.2	46.6
	20,000 to <35,000	21.5	2.8	21.4	71.3	18.2	1.2	18.0	49.1
	35,000 to <50,000	21.2	2.9	21.2	73.0	17.8	0.9	17.5	46.0
	50,000 to <75,000	21.6	3.0	21.1	59.9	18.0	0.7	17.8	45.5
	≥75,000	21.1	4.0	20.1	57.9	17.7	1.6	17.6	42.7

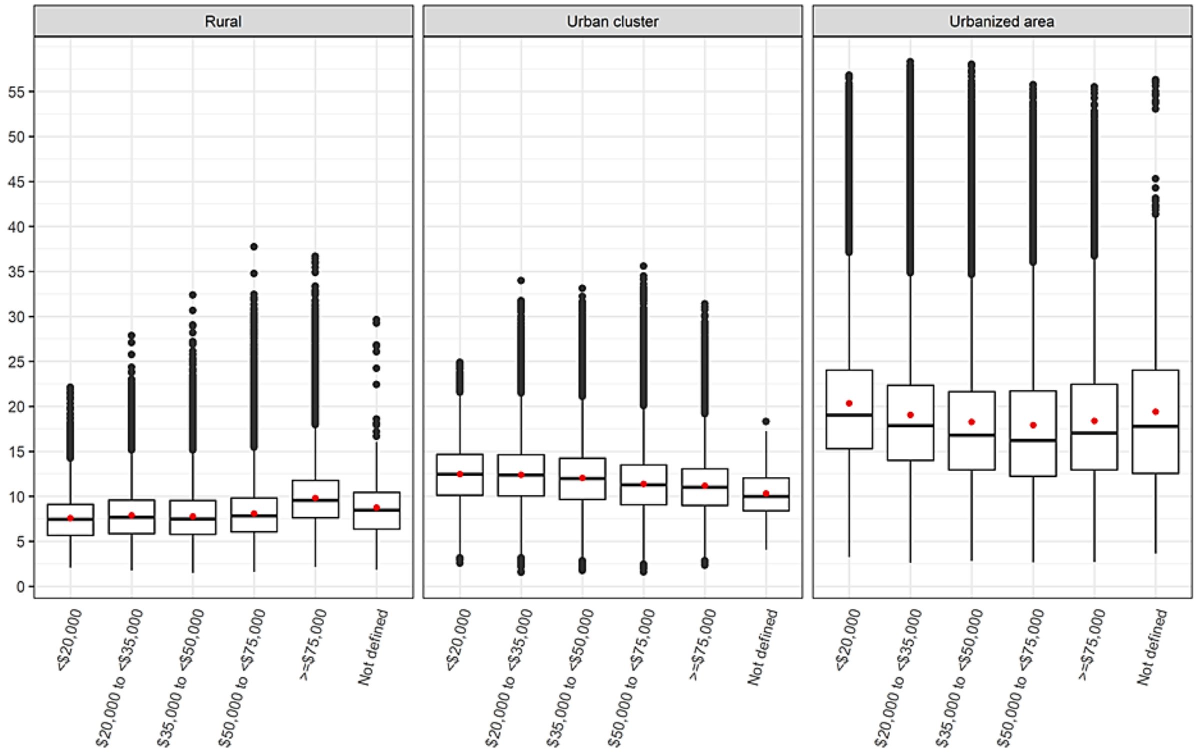


Figure 4. Distribution of NO_2 concentrations (ug/m^3) by median household income group stratified by living location. Red dots represent the mean value, while the midline represents the median value across all census blocks.

Trends across states were also generally consistent, with a few exceptions, as shown in Figure 5 and Figure 6. Overall, the lowest and the highest median household income groups had the highest NO_2 concentrations in 2010. Across all states, urban areas had higher NO_2 concentrations than rural areas.

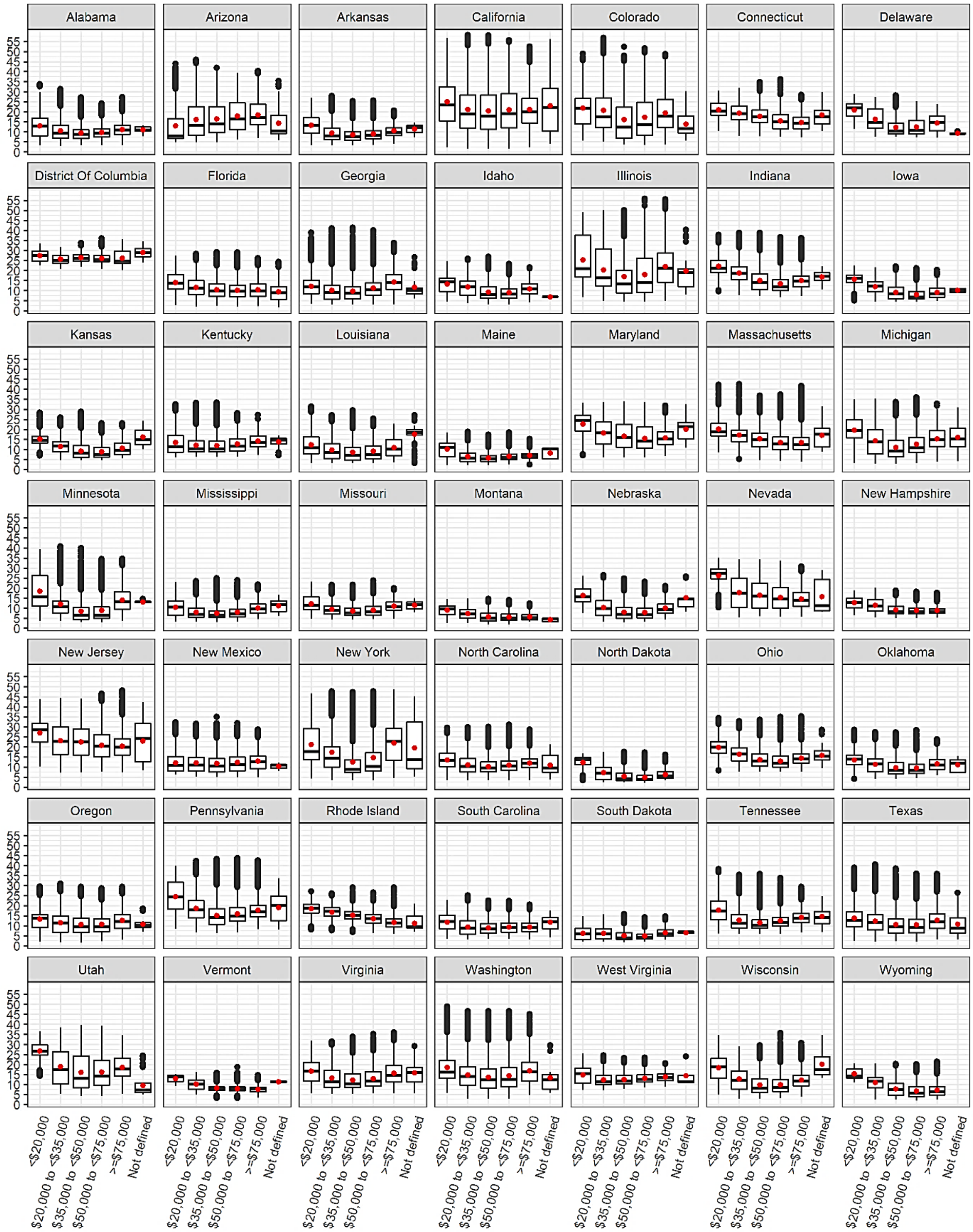


Figure 5. Distribution of NO_2 concentrations (ug/m^3) by state and median household income group. Red dots represent the mean value, while the midline represents the median value.

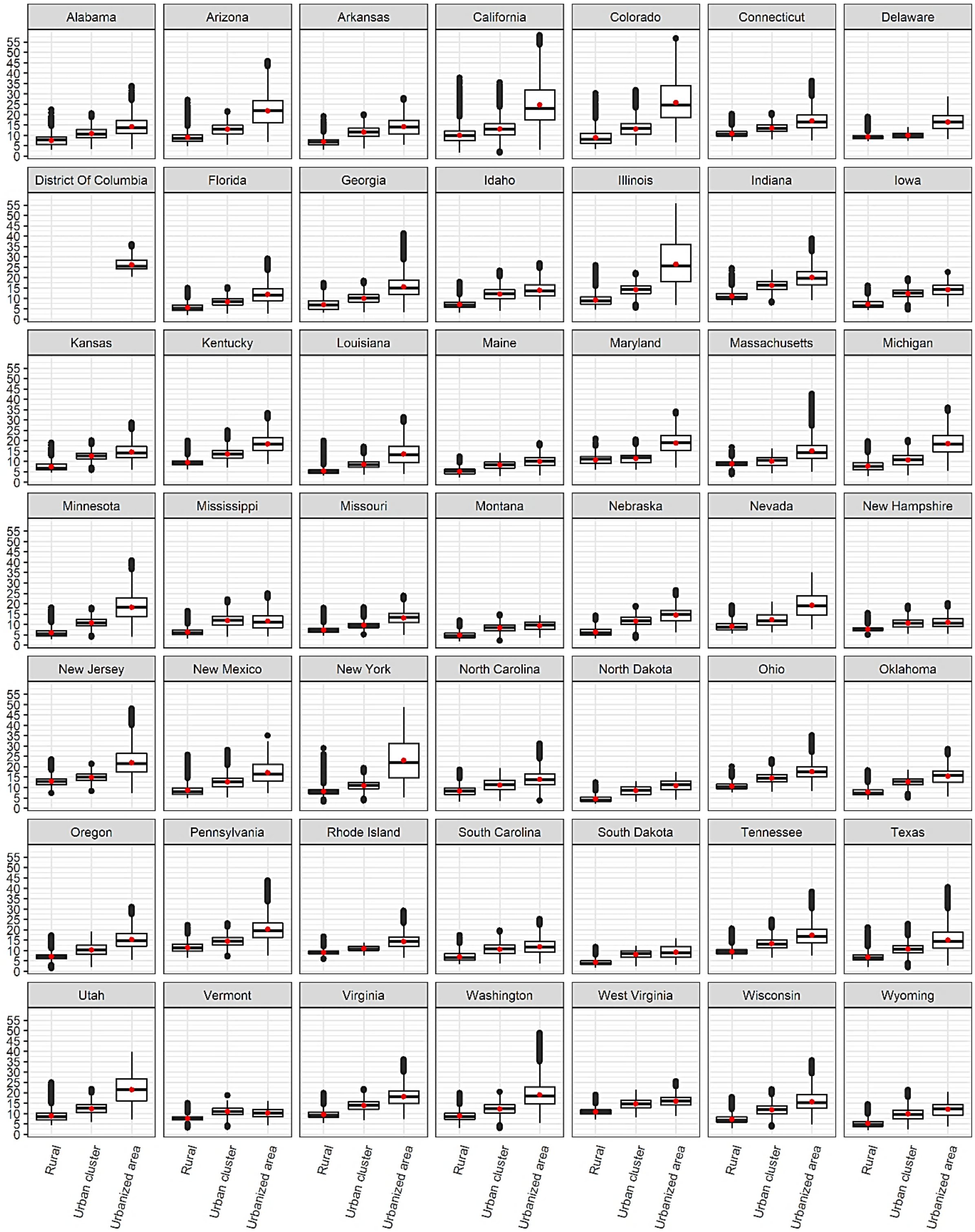


Figure 6. Distribution of NO_2 concentrations (ug/m^3) by state and living location. Red dots represent the mean value, while the midline represents the median value.

Overall Asthma Incident Cases Due to All Causes

National-Level Study Results

For the first analysis in Alotaibi et al. (2019), the researchers used a single childhood asthma IR of 12.5 per 1,000 at-risk children, as presented by Winer et al. (2012), for 2000 and 2010. The asthma IR was an average rate across the years 2006–2008, which included samples of 8,437 children from 31 states and D.C. throughout the time period. Using this IR and the childhood population counts, the researchers estimated that the total number of incident cases was 786,290 and 794,934 in 2000 and 2010, respectively. As shown in Table 5, 79 percent and 81 percent of the total child population, and therefore the estimated incident cases, were living in an urban area in 2000 and 2010, respectively. The largest percentage of total incident cases (31 percent) lived in census block groups with a median household income of $35,000 to <$50,000 in 2000, and 30 percent lived in a census block group with a median household income of $50,000 to <$75,000 in 2010, as shown in Table 5.

Table 5. Estimated Asthma Incident Cases among Children (Due to All Causes, Not Only Attributable to Air Pollutants)

Asthma Incident Cases	2000	2010	Change (%)
Total	786,290	794,934	1.1%
By Living Location (% of Total)			
Urban	618,728 (79%)	646,463 (81%)	4%
Rural	167,562 (21%)	148,470 (19%)	−11%
By Median Household Income			
<20,000	44,407 (6%)	28,207 (4%)	N/A[a]
20,000 to <35,000	226,606 (29%)	137,765 (17%)	
35,000 to <50,000	240,616 (31%)	200,367 (25%)	
50,000 to <75,000	189,993 (24%)	236,827 (30%)	
≥75,000	84,669 (11%)	191,621 (24%)	

[a] Not applicable; the researchers could not adjust for inflation.

State-Level Study Results

For the Khreis et al. (2020) study, the researchers used a state-specific IR estimated using the BRFSS and ACBS data and explained in the study's section titled "Asthma Incidence and Prevalence Rates." The total childhood samples included for the period 2006–2010 were 293,464 samples from the BRFSS and 16,156 samples from the ACBS (Table 6). The BRFSS samples ranged between 55,094 samples (2006) and 61,862 (2008). The ACBS samples ranged between 2,017 (2006) and 4,095 (2009). As explained earlier, the weighted estimates represent the childhood population counts of available states from the BRFSS and the ACBS for the years when the survey was conducted. Not all states participated in the ACBS, while some states participated for only a few years between 2006 and 2010; states with missing data from either the ACBS or BRFSS were excluded, and national-level estimates for IRs were used instead.

Across all available states, the overall aggregate asthma PR for the years 2006–2010 was 13.1 per 100 children (Table 6). Iowa had the lowest aggregate childhood asthma, PR = 8.4 (95 percent CI: 7.7–9.1), per 100 children, while D.C. had the highest aggregate childhood asthma, PR = 19.9 (95 percent CI: 18.2–21.5), per 100 children (see the supplementary material of Khreis et al. [2020]). States that did not have a PR available (n = 8 states: Arkansas, Colorado, Florida, Massachusetts, North Carolina, South Carolina, South Dakota, and Tennessee) were assigned an overall aggregate asthma PR of 13.1 per 100 children.

The overall aggregate asthma IR for the years 2006–2010 was 11.6 per 1,000 at-risk children (Table 6). Montana had the lowest aggregate childhood asthma IR, IR = 4.3 (95 percent CI: 1.6–6.9) per 1,000 at-risk children, followed by Louisiana, IR = 5.8 (95 percent CI: 0–12.8) per 1,000 at-risk children, while D.C. had the highest aggregate childhood asthma IR, IR = 17.7 (95 percent CI: 1.2–34.3) per 1,000 at-risk children, followed by Texas, IR = 16.6

(95 percent CI: 9–24.2), per 1,000 at-risk children (see the supplementary material of Khreis et al. [2020]). States that did not have an IR available (n = 17 states) were assigned the overall aggregate asthma IR of 11.6 per 1,000 at-risk children.

Using state-specific asthma IRs, the estimated number of incident cases of childhood asthma in 2010 were 764,421 (95 percent CI: 451,177–1,079,034). The state with the lowest number of estimated incident cases of childhood asthma was Montana, with 866 (95 percent CI: 333–1,402) cases, while the state with the largest number was Texas, with 99,084 (95 percent CI: 53,820–144,348) cases.

Table 6. Childhood Asthma Survey Summaries

	2006	2007	2008	2009	2010	Total
BRFSS sample (weighted)	55,094 (50,674,742)	59,487 (43,661,381)	61,862 (53,327,550)	59,821 (47,747,373)	57,200 (39,975,264)	293,464
Ever asthma sample (weighted)	7,168 (6,493,224)	7,971 (5,763,409)	8,255 (7,218,400)	8,126 (6,279,938)	7,483 (5,158,455)	39,003
ACBS sample (weighted)	2,017 (4,580,870)	2,797 (5,459,638)	3,924 (4,343,245)	4,095 (4,154,076)	2,196 (3,116,669)	16,156
Incident case sample (weighted)	154 (404,276)	173 (312,917)	169 (385,818)	153 (297,546)	160 (319,743)	809
At-risk sample (weighted)	48,080 (30,825,589)	51,689 (36,050,557)	53,776 (26,491,259)	51,848 (25,942,087)	49,877 (22,900,850)	255,270
IR (95% Confidence Interval)	13.1 (8.9–17.3)	8.7 (6.2–11.1)	14.6 (9.7–19.4)	11.5 (7.4–15.5)	14 (8.7–19.3)	11.6[a] (11.646–11.649)
PR (95% Confidence Interval)	12.8 (12.2–13.4)	13.2 (12.6–13.8)	13.5 (13.1–14)	13.2 (12.7–13.6)	12.9 (12.4–13.4)	13.1[b] (13.1327–13.1333)
Number of states included	18	26	20	17	17	32[c]

[a] Aggregate asthma IR per 1,000 at-risk children.
[b] Aggregate asthma PR per 100 children.
[c] Total number of states included in the aggregate asthma IR estimation.

Attributable Asthma Incidence Cases

National-Level Study Results

Attributable Number of Asthma Incident Cases Due to NO_2, $PM_{2.5}$, and PM_{10}

Rounded to the nearest hundred, the researchers estimated on average 209,100 and 141,900 attributable cases due to NO_2 in 2000 and 2010, respectively, which accounted for 27 percent and 18 percent of all childhood asthma incident cases (see Table 7). For $PM_{2.5}$, the number of estimated attributable cases were 247,100 and 190,200 cases for 2000 and 2010, respectively, which accounted for 31 percent and 24 percent of all childhood asthma incident cases. For PM_{10}, the number of estimated attributable cases were 331,200 and 286,500 in 2000 and 2010, respectively, which accounted for the highest percentage of overall childhood asthma incident cases, at 42 percent and 36 percent.

Attributable Number of Asthma Incident Cases by Living Location (Urban versus Rural)

Most attributable asthma cases were clustered in urban areas (see Table 7), and this clustering was most prominent in the NO_2 analysis. For NO_2, the ACs living in an urban area were 184,500 and 127,500 cases, with 30 percent and 20 percent of all cases being due to NO_2 in 2000 and 2010, respectively. In rural areas, only 15 percent and 10 percent of all cases were due to NO_2 in 2000 and 2010, respectively. For $PM_{2.5}$, the ACs living in an urban area were 200,100 and 158,200, with 32 percent and 24 percent of all cases being due to $PM_{2.5}$ in 2000 and 2010, respectively. In rural areas, only 28 percent and 22 percent of all cases were due to $PM_{2.5}$ in 2000 and 2010, respectively. For PM_{10}, the ACs living in an urban area were 270,100 and 240,800, with 44 percent and 37 percent of cases being due to PM_{10} in 2000 and 2010, respectively. In rural areas, only 36 percent and 31 percent of all cases were due to PM_{10} in 2000 and 2010, respectively.

Attributable Number of Asthma Incident Cases by Median Household Income

The most-deprived median household income group (<$20,000) had the highest percentage of asthma cases due to NO_2 among all cases, at 31 percent and 21 percent for 2000 and 2010, respectively. The second highest percentage of asthma incident cases due to NO_2 was among the highest income group (≥$75,000) for year 2000, at 29 percent of all cases. However, for 2010, the second highest percentage of asthma incident cases due to NO_2 was for the median household income group of $20,000 to <$35,000, the second lowest. For $PM_{2.5}$, the highest percentage of asthma incident cases was among the lowest median household income group for both years, at 33 percent and 26 percent. For PM_{10}, the highest percentage of asthma incident cases was also among the lowest median household income group for both years, at 45 percent and 38 percent (Table 7).

Table 7. Attributable Number of Childhood Asthma Incident Cases and Percentage of Asthma Incident Cases Due to the Three Pollutants in 2000 and 2010

		AC		% of All Asthma Cases		Change (%)	
		2000	2010	2000	2010	AC	AF
NO_2							
Total		209,100	141,900	27%	18%	−32%	−33%
By Living Location	Urban	184,500	127,500	30%	20%	−31%	−33%
	Rural	24,600	14,500	15%	10%	−41%	−33%
By Median Household Income	<20,000	13,700	5,900	31%	21%	N/A[a]	N/A[a]
	20,000 to <35,000	59,600	25,800	26%	19%		
	35,000 to <50,000	60,700	34,600	25%	17%		
	50,000 to <75,000	50,900	40,500	27%	17%		
	≥75,000	24,100	35,100	29%	18%		
$PM_{2.5}$							
Total		247,100	190,200	31%	24%	−23%	−24%
By Living Location	Urban	200,100	158,200	32%	24%	−21%	−24%
	Rural	47,100	32,000	28%	22%	−32%	−23%
By Median Household Income	<20,000	14,600	7,400	33%	26%	N/A[a]	N/A[a]
	20,000 to <35,000	71,600	34,600	32%	25%		
	35,000 to <50,000	74,900	48,300	31%	24%		
	50,000 to <75,000	59,400	55,700	31%	24%		
	≥75,000	26,700	44,100	32%	23%		
PM_{10}							
Total		331,200	286,500	42%	36%	−13%	−14%
By Living Location	Urban	270,100	240,800	44%	37%	−11%	−16%
	Rural	61,100	45,700	36%	31%	−25%	−14%
By Median Household Income	<20,000	19,800	10,700	45%	38%	N/A[a]	N/A[a]
	20,000 to <35,000	98,300	51,300	43%	37%		
	35,000 to <50,000	100,800	72,300	42%	36%		
	50,000 to <75,000	78,700	85,000	41%	36%		
	≥75,000	33,700	67,300	40%	35%		

Note: Numbers are rounded to nearest hundred. AF = attributable fraction.

[a] Not applicable; the researchers could not adjust for inflation.

Preventable Cases in the Counterfactual Scenarios

Table 8 presents a summary of the preventable number of asthma cases in the two counterfactual scenarios, as described below.

1. **Preventable number of asthma incident cases if blocks had not exceeded WHO air quality guideline values**. The estimated preventable asthma incident cases not exceeding the WHO air quality guideline values were as follows. For NO_2, with an annual average concentration of 40 ug/m^3 as a limit, there were an estimated 11,100 (1 percent of all asthma cases) and 300 (<1 percent) preventable asthma incident cases in 2000 and 2010, respectively. For $PM_{2.5}$, with an annual average concentration of 10 µg/m^3 as a limit, there were an estimated 53,400 (7 percent) and 9,500 (1 percent) preventable asthma incident cases in 2000 and 2010, respectively. For PM_{10}, with an annual average concentration of 20 µg/m^3 as a limit, there were an estimated 43,900 (6 percent) and 14,400 (2 percent) preventable asthma incident cases in 2000 and 2010, respectively.
2. **Preventable number of asthma incident cases if pollutant concentrations were reduced to minimum levels**. The estimated preventable asthma incident cases had pollutant concentrations for all census blocks been reduced to the minimum levels modeled were as follows. For NO_2, with a minimum level of 1.48 ug/m^3 as a limit, there were an estimated 188,300 (24 percent of all asthma cases) and 127,700 (16 percent) preventable asthma incident cases in 2000 and 2010, respectively. For $PM_{2.5}$, with a minimum level of 0.55 ug/m^3 as a limit, there were an estimated 234,500 (30 percent) and 177,400 (22 percent) preventable asthma incident cases in 2000 and 2010, respectively. For PM_{10}, with a minimum level of 0.72 ug/m^3 as a limit, there were an estimated 317,700 (40 percent) and 272,700 (34 percent) preventable asthma incident cases in 2000 and 2010, respectively.

Table 8. Preventable Number of Asthma Incident Cases Exceeding the Safe Levels

	2000		2010	
	AC	% of All Asthma Cases	AC	% of All Asthma Cases
WHO guidelines "safe level"				
NO_2	11,100	1%	300	<1%
$PM_{2.5}$	53,400	7%	9,500	1%
PM_{10}	43,900	6%	14,400	2%
Minimum concentration "safe level"				
NO_2	188,300	24%	127,700	16%
$PM_{2.5}$	234,500	30%	177,400	22%
PM_{10}	317,600	40%	272,700	34%

Note: Numbers rounded to nearest hundred.

Results of Sensitivity Analysis

To produce the most conservative and most extreme estimates and explore the impact of uncertainty in the ERFs, the IR used, and the combination thereof on the estimated BoD, the researchers reran multiple sensitivity analyses and reported the results by the year studied (Table 9).

Most Conservative Estimates

For the most conservative estimates, the analysis was repeated using the lower 95 percent CI bound for both the ERF and the IR. The attributable asthma incidence cases due to air pollution decreased by 60–69 percent, depending on the year and pollutant studied (Table 10).

Most Extreme Estimates

For the most extreme estimates, the analysis was repeated using the upper 95 percent CI of both the ERF and the IR. The attributable asthma incidence cases due to air pollution increased by 49–74 percent, depending on the year and pollutant studied (Table 10).

Table 9. Sensitivity Analysis of Attributable Number of Cases

	Exposure-Response Function							
	Year 2000			Year 2010				
NO_2	LL (1.02)	M (1.05)	UL (1.07)	LL (1.02)	M (1.05)	UL (1.07)		
	79,900 *	175,600	227,200	52,000 *	119,200	158,000	LL (10.5)	IR
	95,100	**209,100** **	270,400	61,900	**141,900** **	188,100	M (12.5)	
	109,500	240,900	311,500 ***	71,400	163,500	216,700 ***	UL (14.4)	
$PM_{2.5}$	LL (1.01)	M (1.03)	UL (1.05)	LL (1.01)	M (1.03)	UL (1.05)		
	79,500 *	207,600	304,000	59,000 *	159,800	241,600	LL (10.5)	
	94,700	**247,100** **	361,900	70,300	**190,200** **	287,600	M (12.5)	
	109,100	284,700	416,900 ***	80,900	219,100	331,300 ***	UL (14.4)	
PM_{10}	LL (1.02)	M (1.05)	UL (1.08)	LL (1.02)	M (1.05)	UL (1.08)		
	133,500 *	278,200	377,900	111,700 *	240,700	335,800	LL (10.5)	
	158,900	**331,200** **	449,900	133,000	**286,500** **	399,800	M (12.5)	
	183,010	381,600	518,300 ***	153,200	330,100	460,600 ***	UL (14.4)	

* Represents the most conservative burden estimates using the lower 95% Confidence Intervals of both the ERF and IR.

** Represents the mean burden estimates using the mean values of the ERF and IR, as shown in Table 7.

*** Represents the least conservative burden estimates using the upper 95% Confidence Intervals of both the ERF and IR.

Table 10. Sensitivity Analysis of Attributable Number of Cases by Percentage Change

	Exposure-Response Function						
	Year 2000			Year 2010			IR
NO_2	LL (1.02)	M (1.05)	UL (1.07)	LL (1.02)	M (1.05)	UL (1.07)	
	−62% [*]	−16%	9%	−63% [*]	−16%	11%	LL (10.5)
	−55%	**0%** [**]	29%	−56%	**0%** [**]	33%	M (12.5)
	−48%	15%	49% [***]	−50%	15%	53% [***]	UL (14.4)
$PM_{2.5}$	LL (1.02)	M (1.05)	UL (1.07)	LL (1.02)	M (1.05)	UL (1.07)	
	−68% [*]	−16%	23%	−69% [*]	−16%	27%	LL (10.5)
	−62%	**0%** [**]	46%	−63%	**0%** [**]	51%	M (12.5)
	−56%	15%	69% [***]	−57%	15%	74% [***]	UL (14.4)
PM_{10}	LL (1.02)	M (1.05)	UL (1.07)	LL (1.02)	M (1.05)	UL (1.07)	
	−60% [*]	−16%	14%	−61% [*]	−16%	17%	LL (10.5)
	−52%	**0%** [**]	36%	−54%	**0%** [**]	40%	M (12.5)
	−45%	15%	56% [***]	−47%	15%	61% [***]	UL (14.4)

[*] Represents the most conservative burden estimates using the lower 95% Confidence Intervals of both the ERF and IR.

[**] Represents the mean burden estimates using the mean values of the ERF and IR, as shown in Table 7.

[***] Represents the least conservative burden estimates using the upper 95% Confidence Intervals of both the ERF and IR.

State-Level Study Results

Overall Asthma Incident Cases (Due to All Causes) Using National-Level versus State-Specific IRs

Using state-specific asthma IRs, the number of total incident asthma cases decreased by 30,513 (4 percent relative change) compared to estimates using a national-level asthma IR assigned to all states (Table 11). By living location, the largest relative change was among urban clusters, with a decrease of 3,539 (5 percent) cases, followed by urbanized areas, with a reduction of −22,861 (4 percent) cases. By income group, the largest relative change in the number of total incident cases was among the highest income groups, with a decrease of 11,386 (6 percent) cases, while the smallest relative change was among the lowest income group, with an increase of 213 (1 percent) cases (Table 11). California had the largest decrease in the number of total childhood asthma incident cases (24,441 cases), while Texas had the largest increase in the number of total childhood asthma incident cases (25,019 cases). Montana had the largest relative reduction in total childhood asthma incident cases (64.1 percent). Texas had the largest relative increase (33.8 percent). These data are shown in further detail in the supplementary material of Khreis et al. (2020).

Attributable Number of Asthma Incident Cases by Living Location, Median Household Income, and State

The researchers estimated a total of 134,166 (95 percent CI: 75,177–193,327) childhood asthma incident cases attributable to NO_2 exposure in 2010, thus accounting for 17.6 percent of all childhood asthma incident cases (Table 11). By living location, urbanized areas had the largest number of attributable cases—110,681 (95 percent CI: 61,125–160,369)—and the highest percentage of all asthma incident cases (20.2 percent). Rural areas had a total of 14,112 cases (95 percent CI: 8,661–19,586) and accounted for the lowest percentage of all asthma cases (at 9.8 percent), while urban clusters had 9,373 cases (95 percent CI: 5,391–13,372), representing 13.0 percent of all asthma incident cases (Table 11).

By median household income, census blocks with incomes of $50,000 to <$75,000 had the largest number of cases attributable to NO_2 in 2010, with 37,920 (95 percent CI: 21,110–54,775) cases, accounting for 16.8 percent of all asthma incident cases. However, the income group with the largest proportion of asthma cases attributable to NO_2 in 2010 was the lowest income group, <$20,000, accounting for 20.8 percent of all asthma incident cases (Table 11).

Table 11. Results from the Second Study: Burden of Disease Estimates Using National-Level versus State-Specific Asthma IRs

		Results Using Constant National-Level IR					Results Using State-Specific IR					Difference (absolute)			Difference (%)		
		Incident Cases		AC		AF	Incident Cases		AC		AF	Incident Cases	AC	AF	Incident Cases	AC	AF
	Total	794,934	(667,744–915,764)	141,931	(119,222–163,505)	17.9%	764,421	(451,177–1,079,034)	134,166	(75,177–193,327)	17.6%	-30,513	-7,765	-0.3%	-3.8%	-5.5%	1.9%
By living location (% of total)	**Rural**	148,470 (19%)	(124,715–171,038)	14,466 (10%)	(12,151–16,664)	9.7%	144,357(19%)	(89,962–199,097)	14,112 (11%)	(8,661–19,586)	9.8%	-4,113	-354	0.1%	-2.8%	-2.5%	0.8%
	Urban cluster	75,453 (9%)	(63,380–86,922)	9,844 (7%)	(8,269–11,341)	13.0%	71,914 (9%)	(41,965–102,031)	9,373 (7%)	(5,391–13,372)	13.0%	-3,539	-471	0.0%	-4.7%	-4.8%	0.3%
	Urbanized area	571,011 (72%)	(479,649–657,804)	117,621 (83%)	(98,802–135,500)	20.6%	548,150 (72%)	(319,250–777,906)	110,681 (82%)	(61,125–160,369)	20.2%	-22,861	-6,940	-0.4%	-4.0%	-5.9%	2.0%
By median household income (% of total)	**<$20,000**	28,207 (4%)	(23,694–32,495)	5,892 (4%)	(4,949–6,788)	20.9%	28,420 (4%)	(16,727–40,210)	5,902 (4%)	(3,335–8,484)	20.8%	213	10	-0.1%	0.8%	0.2%	-0.6%
	$20,000 to <$35,000	137,765 (17%)	(115,723–158,706)	25,794 (18%)	(21,667–29,715)	18.7%	136,179 (18%)	(80,728–191,955)	25,202 (19%)	(14,123–36,325)	18.5%	-1,586	-592	-0.2%	-1.2%	-2.3%	-1.0%
	$35,000 to <$50,000	200,367 (25%)	(168,308–230,822)	34,549 (24%)	(29,022–39,801)	17.2%	193,212 (25%)	(115,256–271,569)	32,737 (24%)	(18,414–47,107)	16.9%	-7,155	-1,812	-0.3%	-3.6%	-5.2%	-1.5%
	$50,000 to <$75,000	236,827 (30%)	(198,935–272,825)	40,540 (29%)	(34,054–46,703)	17.1%	226,227 (30%)	(132,720–320,114)	37,920 (28%)	(21,110–54,775)	16.8%	-10,600	-2,620	-0.3%	-4.5%	-6.5%	-2.0%
	≥$75,000	191,621 (24%)	(160,962–220,747)	35,128 (25%)	(29,507–40,467)	18.3%	180,235 (24%)	(105,669–254,967)	32,377 (24%)	(18,182–46,594)	18.0%	-11,386	-2,751	-0.3%	-5.9%	-7.8%	-1.8%

The distribution of the AFs at the census block level showed that the mean value was higher in urbanized areas than in rural areas and followed a U-shape distribution by income group (data are not shown, but they are consistent with trends shown in Figure 5 and Figure 6). When examining the distribution of the AF across income groups and also stratified by living location, the researchers observed that the mean value increased by increasing income group in rural areas, decreased by increasing income group in urban clusters, and appeared as a U-shape in urbanized areas (data are not shown, but they are consistent with trends shown in Figure 4).

The state with the lowest number of estimated attributable cases due to 2010 NO_2 was Montana, with 69 cases (95 percent CI: 26–112), while California had the largest number of estimated attributable cases, at 19,205 (95 percent CI: 7,854–30,555). The state with the lowest AF was South Dakota (7.6 percent), while D.C. had the highest AF (26.9 percent). When examining the distribution of AFs across all census blocks, the researchers observed that the state with the lowest average value was South Dakota, while D.C. had the largest average value (Figure 7).

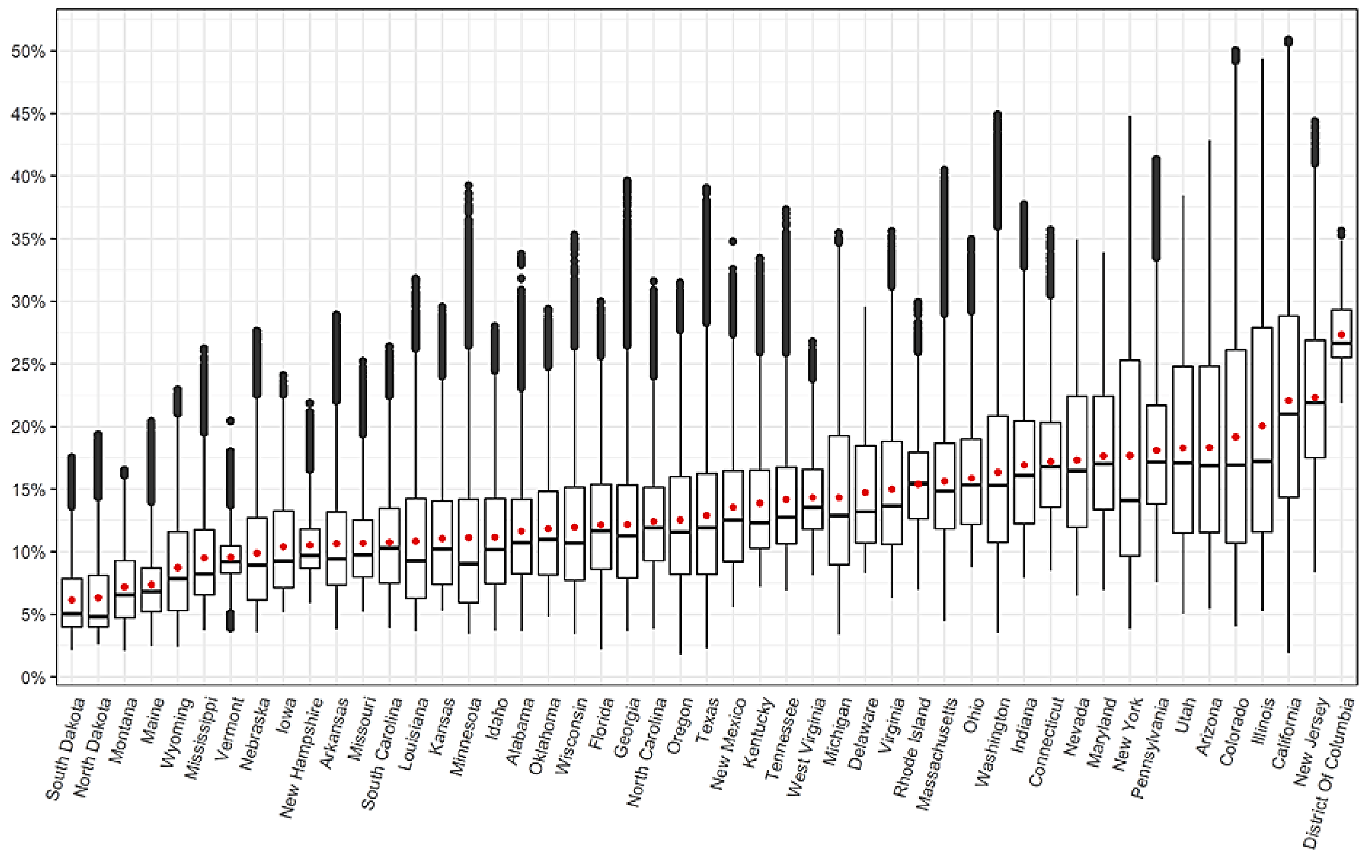


Figure 7. Distribution of AFs by state. Red dots represent the mean value, while the midline represents the median value.

The researchers also investigated the distribution of AFs across all census blocks by living location and median household income group for each state. Most states broadly follow a distribution similar to the national level, with a few exceptions. (By living location, see Delaware, Maryland, Mississippi, and Vermont. By median household income, see Arizona, Connecticut, D.C., Florida, Maine, Massachusetts, Montana, Nevada, New Hampshire, New Jersey, New Mexico, Vermont, West Virginia, Rhode Island, and Wyoming.)

Comparing Attributable Asthma Incident Cases Due to NO_2 Using National-Level versus State-Specific IRs

The number of cases attributable to NO_2 in 2010 was reduced by 7,765 (5.5 percent relative change) when compared to estimates using a national-level asthma IR (Table 11) versus state-specific IRs. By living location, urbanized areas had the largest relative change, with a decrease of 6,940 (5.9 percent) cases, while rural areas had the least relative change, with a decrease of 354 (2.5 percent) cases attributable to NO_2 exposure. By income group, the highest income group had the largest relative change, with a decrease in NO_2-attributable cases by 2,751 (7.8 percent), while the lowest income group had the least relative change, with an increase of 10 (0.2 percent) cases. California had the largest decrease in cases attributable to NO_2 (6,190 cases), while Texas had the largest increase (3,615 cases) (Table 12). As shown in Table 12, differences between the NO_2-attributable number of incident cases estimated using state-specific versus national-level IRs generally fall within the range of uncertainty as expressed by the 95 percent CI. This finding is true for most states, but not all.

Comparing Attributable Asthma Incident Fractions Due to NO_2 Using National-Level versus State-Specific IRs

The overall absolute reduction in the AF was 0.3 percent (a 1.9 percent relative reduction) (Table 11). In terms of living location, urbanized areas had the largest relative reduction (2 percent), while rural areas had the largest relative increase (0.8 percent). In terms of income group, the largest relative reduction was 2 percent for the $50,000 to <$75,000 income strata (Table 11). The AF across states did not differ when using state-specific asthma IRs. The small differences observed across some states in Table 12 are due to rounding.

Table 12. State-Specific Results and Comparison

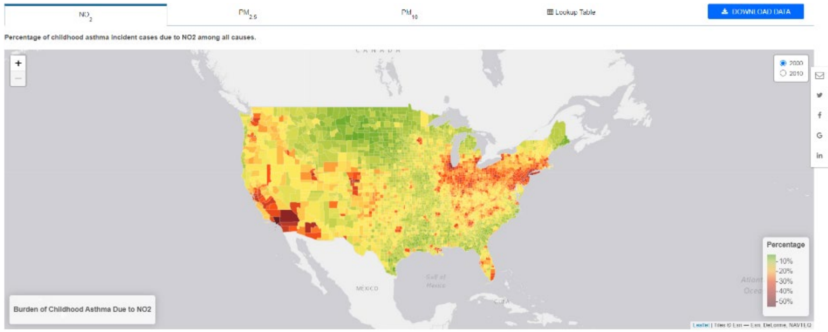
State	Results Using Constant National-Level IR			Results Using State-Specific IR					Difference			Difference (%)		
	Incident Cases	AC	AF	Incident Cases	95% CI	AC	95% CI	AF	Incident Cases	AC	AF	Incident Cases	AC	AF
Alabama	12,216	1,439	11.8%	11,287	(11,286-11,289)	1,330	(1,330-1,330)	11.8%	-929	-109	0.0%	-7.6%	-7.6%	-0.1%
Arizona	17,573	3,772	21.5%	21,538	(0-43,204)	4,623	(0-9,273)	21.5%	3,965	851	0.0%	22.6%	22.6%	-0.2%
Arkansas	7,675	887	11.6%	8,178	(8,177-8,180)	945	(945-945)	11.6%	503	58	0.0%	6.6%	6.5%	-0.4%
California	100,270	25,395	25.3%	75,829	(31,011-120,646)	19,205	(7,854-30,555)	25.3%	-24,441	-6,190	0.0%	-24.4%	-24.4%	0.1%
Colorado	13,221	3,089	23.4%	14,089	(14,087-14,091)	3,292	(3,291-3,292)	23.4%	868	203	0.0%	6.6%	6.6%	-0.1%
Connecticut	8,814	1,601	18.2%	8,265	(4,501-12,029)	1,502	(818-2,186)	18.2%	-549	-99	0.0%	-6.2%	-6.2%	-0.1%
D.C.	1,088	293	26.9%	1,433	(95-2,772)	386	(26-746)	26.9%	345	93	0.0%	31.7%	31.7%	0.1%
Delaware	2,220	355	16.0%	1,960	(1,960-1,960)	313	(313-314)	16.0%	-260	-42	0.0%	-11.7%	-11.8%	-0.2%
Florida	43,173	5,502	12.7%	46,005	(45,998-46,011)	5,863	(5,862-5,864)	12.7%	2,832	361	0.0%	6.6%	6.6%	0.3%
Georgia	26,878	3,887	14.5%	19,165	(9,356-28,973)	2,772	(1,353-4,190)	14.5%	-7,713	-1,115	0.0%	-28.7%	-28.7%	-0.2%
Idaho	4,629	581	12.6%	4,549	(4,548-4,550)	571	(571-571)	12.6%	-80	-10	0.0%	-1.7%	-1.7%	-0.4%
Illinois	33,756	8,333	24.7%	18,264	(753-35,776)	4,509	(186-8,832)	24.7%	-15,492	-3,824	0.0%	-45.9%	-45.9%	0.0%
Indiana	17,350	3,143	18.1%	21,263	(13,522-29,004)	3,852	(2,450-5,254)	18.1%	3,913	709	0.0%	22.6%	22.6%	0.1%
Iowa	7,853	971	12.4%	4,193	(2,102-6,285)	519	(260-777)	12.4%	-3,660	-452	0.0%	-46.6%	-46.5%	-0.2%
Kansas	7,842	1,067	13.6%	5,781	(3,917-7,644)	787	(533-1,040)	13.6%	-2,061	-280	0.0%	-26.3%	-26.2%	0.1%
Kentucky	11,040	1,649	14.9%	10,255	(10,254-10,257)	1,532	(1,532-1,532)	14.9%	-785	-117	0.0%	-7.1%	-7.1%	0.3%
Louisiana	12,061	1,401	11.6%	5,616	(0-12,473)	653	(0-1,449)	11.6%	-6,445	-748	0.0%	-53.4%	-53.4%	0.2%
Maine	2,962	234	7.9%	2,196	(877-3,515)	173	(69-277)	7.9%	-766	-61	0.0%	-25.9%	-26.1%	-0.3%
Maryland	14,595	2,787	19.1%	12,849	(7,862-17,836)	2,454	(1,501-3,406)	19.1%	-1,746	-333	0.0%	-12.0%	-11.9%	0.0%
Massachusetts	15,307	2,539	16.6%	16,311	(16,308-16,313)	2,705	(2,705-2,706)	16.6%	1,004	166	0.0%	6.6%	6.5%	-0.1%
Michigan	25,287	4,211	16.7%	24,356	(15,335-33,377)	4,056	(2,554-5,558)	16.7%	-931	-155	0.0%	-3.7%	-3.7%	-0.3%
Minnesota	13,852	2,093	15.1%	13,540	(13,538-13,542)	2,045	(2,045-2,046)	15.1%	-312	-48	0.0%	-2.3%	-2.3%	0.0%
Mississippi	8,151	832	10.2%	9,101	(2,695-15,507)	929	(275-1,583)	10.2%	950	97	0.0%	11.7%	11.7%	0.1%
Missouri	15,377	1,845	12.0%	15,821	(3,694-27,949)	1,898	(443-3,353)	12.0%	444	53	0.0%	2.9%	2.9%	0.0%
Montana	2,412	192	8.0%	866	(331-1,402)	69	(26-112)	8.0%	-1,546	-123	0.0%	-64.1%	-64.1%	-0.4%
Nebraska	4,954	648	13.1%	3,775	(2,279-5,272)	494	(298-690)	13.1%	-1,179	-154	0.0%	-23.8%	-23.8%	-0.1%
Nevada	7,174	1,431	19.9%	6,904	(6,903-6,905)	1,377	(1,377-1,377)	19.9%	-270	-54	0.0%	-3.8%	-3.8%	0.2%
New Hampshire	3,099	338	10.9%	3,017	(1,491-4,543)	329	(163-496)	10.9%	-82	-9	0.0%	-2.6%	-2.7%	0.0%
New Jersey	22,278	5,357	24.0%	17,281	(9,654-24,908)	4,155	(2,321-5,989)	24.0%	-4,997	-1,202	0.0%	-22.4%	-22.4%	0.2%
New Mexico	5,595	864	15.4%	3,047	(1,393-4,700)	471	(215-726)	15.5%	-2,548	-393	0.1%	-45.5%	-45.5%	0.4%
New York	46,655	11,754	25.2%	53,600	(28,086-79,114)	13,504	(7,076-19,932)	25.2%	6,945	1,750	0.0%	14.9%	14.9%	0.0%
North Carolina	24,613	3,182	12.9%	26,228	(26,224-26,231)	3,390	(3,390-3,391)	12.9%	1,615	208	0.0%	6.6%	6.5%	0.2%
North Dakota	1,617	139	8.6%	1,591	(1,591-1,591)	137	(137-137)	8.6%	-26	-2	0.0%	-1.6%	-1.4%	0.1%
Ohio	29,458	5,036	17.1%	36,060	(17,612-54,508)	6,165	(3,011-9,319)	17.1%	6,602	1,129	0.0%	22.4%	22.4%	0.0%
Oklahoma	10,029	1,342	13.4%	8,619	(4,633-12,605)	1,154	(620-1,687)	13.4%	-1,410	-188	0.0%	-14.1%	-14.0%	-0.1%
Oregon	9,347	1,295	13.9%	8,517	(2,035-15,000)	1,180	(282-2,078)	13.9%	-830	-115	0.0%	-8.9%	-8.9%	-0.3%
Pennsylvania	30,120	6,011	20.0%	31,595	(8,838-54,351)	6,305	(1,764-10,846)	20.0%	1,475	294	0.0%	4.9%	4.9%	-0.2%

Rhode Island	2,416	380	15.7%	2,679	(825-4,533)	422	(130-713)	15.8%	263	42	0.1%	10.9%	11.1%	0.3%
South Carolina	11,656	1,287	11.0%	12,420	(12,418-12,422)	1,371	(1,371-1,372)	11.0%	764	84	0.0%	6.6%	6.5%	0.4%
South Dakota	2,188	165	7.5%	2,331	(2,331-2,332)	176	(176-176)	7.6%	143	11	0.1%	6.5%	6.7%	0.7%
Tennessee	16,138	2,503	15.5%	17,197	(17,194-17,199)	2,667	(2,667-2,667)	15.5%	1,059	164	0.0%	6.6%	6.6%	0.1%
Texas	74,065	10,701	14.4%	99,084	(53,820-144,348)	14,316	(7,776-20,856)	14.4%	25,019	3,615	0.0%	33.8%	33.8%	0.3%
Utah	9,396	1,929	20.5%	8,142	(5,104-11,179)	1,672	(1,048-2,295)	20.5%	-1,254	-257	0.0%	-13.3%	-13.3%	0.2%
Vermont	1,394	136	9.8%	1,285	(827-1,742)	126	(81-171)	9.8%	-109	-10	0.0%	-7.8%	-7.4%	0.1%
Virginia	19,997	3,430	17.2%	18,656	(18,653-18,659)	3,200	(3,200-3,201)	17.2%	-1,341	-230	0.0%	-6.7%	-6.7%	-0.3%
Washington	17,059	3,039	17.8%	9,559	(5,332-13,786)	1,703	(950-2,456)	17.8%	-7,500	-1,336	0.0%	-44.0%	-44.0%	0.1%
West Virginia	4,179	603	14.4%	4,003	(292-7,715)	578	(42-1,114)	14.4%	-176	-25	0.0%	-4.2%	-4.1%	0.3%
Wisconsin	14,450	2,118	14.7%	14,694	(8-29,380)	2,154	(1-4,307)	14.7%	244	36	0.0%	1.7%	1.7%	-0.3%
Wyoming	1,461	141	9.7%	1,427	(1,427-1,427)	138	(138-138)	9.7%	-34	-3	0.0%	-2.3%	-2.1%	-0.3%

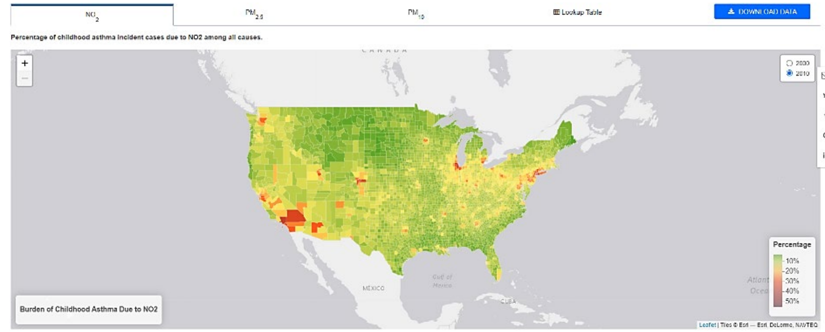
Visualizing the Results and Interactive Tools

To raise awareness and increase the potential for knowledge translation and technology transfer, the researchers present these results in an accessible manner specifically for the use of practitioners, policy makers, and the general public. The researchers developed online open-access interactive maps and tables summarizing the findings at the county level and 498 major U.S. cities. The interactive maps can be accessed at https://carteehdata.org/l/s/TRAP-burden-of-childhood-asthma and are shown in Figure 8 for the years 2000 and 2010 and for the three studied pollutants. For both years, 2000 and 2010, users can click on their county of interest and find the name of the county; how many children lived there; the mean air pollution level for NO_2, $PM_{2.5}$, and PM_{10}; the attributable number of new childhood asthma cases; and the percent compared to all childhood asthma cases. The produced lookup table summarizes the data at the city level for 498 major cities in the United States that the researchers selected from the CDC's 500 cities project, as described in detail at https://www.cdc.gov/places/about/500-cities-2016-2019/index.html. The 500 cities included in the CDC's project are shown in Figure 9. From that list, the researchers had to exclude two cities—Anchorage, Alaska, and Honolulu, Hawaii—because the researchers did not have exposure data for these states. The lookup table can also be accessed at https://carteehdata.org/l/s/TRAP-burden-of-childhood-asthma and lists the following information for each of the 498 cities:

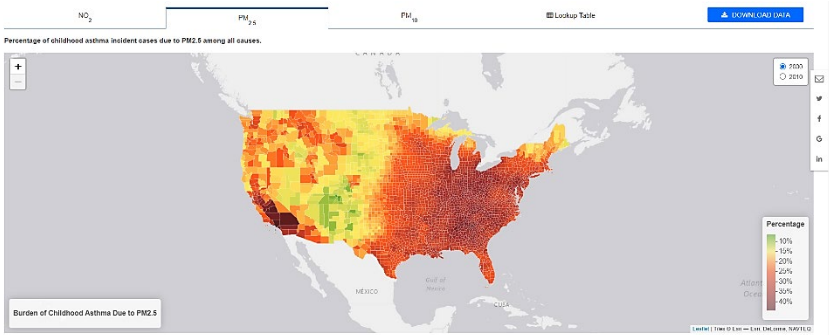
- Name of the city.
- State.
- Total population in 2000.
- Total population in 2010.
- Total child population in 2000.
- Total child population in 2010.
- Total childhood asthma cases in 2000.
- Total childhood asthma cases in 2010.
- Cases attributable to NO_2 in 2000.
- Cases attributable to NO_2 in 2010.
- NO_2 population AF in 2000.
- NO_2 population AF in 2010.
- NO_2 concentration in 2000.
- NO_2 concentration in 2010.
- NO_2 weighted concentration in 2000.
- NO_2 weighted concentration in 2010.
- Cases attributable to $PM_{2.5}$ in 2000.
- Cases attributable to $PM_{2.5}$ in 2010.
- $PM_{2.5}$ population AF in 2000.
- $PM_{2.5}$ population AF in 2010.
- $PM_{2.5}$ concentration in 2000.
- $PM_{2.5}$ concentration in 2010.
- $PM_{2.5}$ weighted concentration in 2000.
- $PM_{2.5}$ weighted concentration in 2010.
- Cases attributable to PM_{10} in 2000.
- Cases attributable to PM_{10} in 2010.
- PM_{10} population AF in 2000.
- PM_{10} population AF in 2010.
- PM_{10} concentration in 2000.
- PM_{10} concentration in 2010.
- PM_{10} weighted concentration in 2000.
- PM_{10} weighted concentration in 2010.



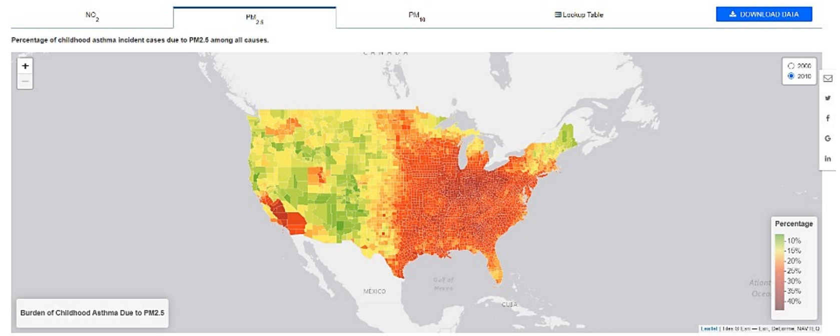
Burden of childhood asthma onset attributable to 2000 NO_2 exposures



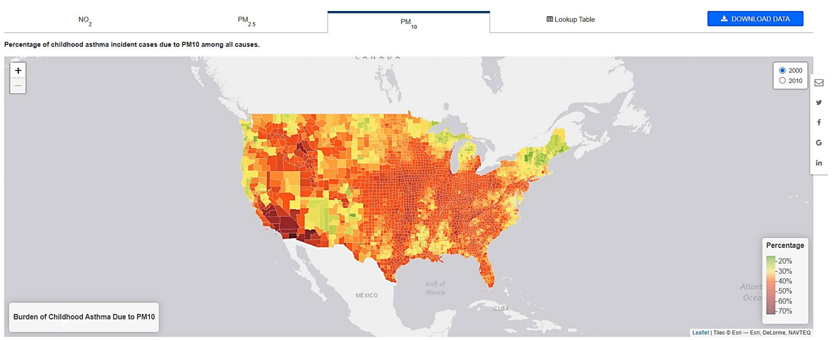
Burden of childhood asthma onset attributable to 2010 NO_2 exposures



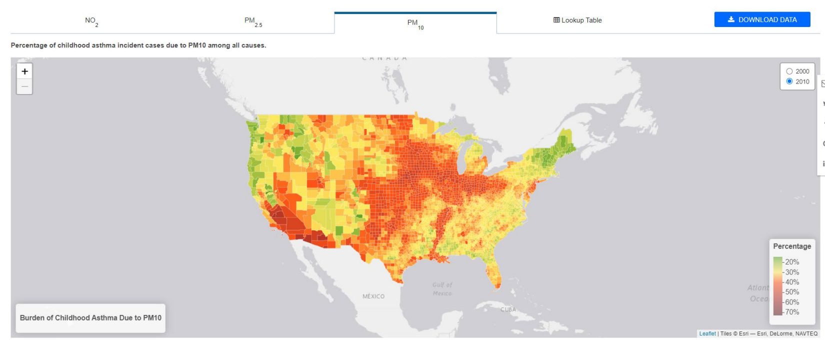
Burden of childhood asthma onset attributable to 2000 $PM_{2.5}$ exposures



Burden of childhood asthma onset attributable to 2010 $PM_{2.5}$ exposures



Burden of childhood asthma onset attributable to 2000 PM_{10} exposures



Burden of childhood asthma onset attributable to 2010 PM_{10} exposures

Figure 8. Interactive maps for 2000 and 2010 for the three studied pollutants.

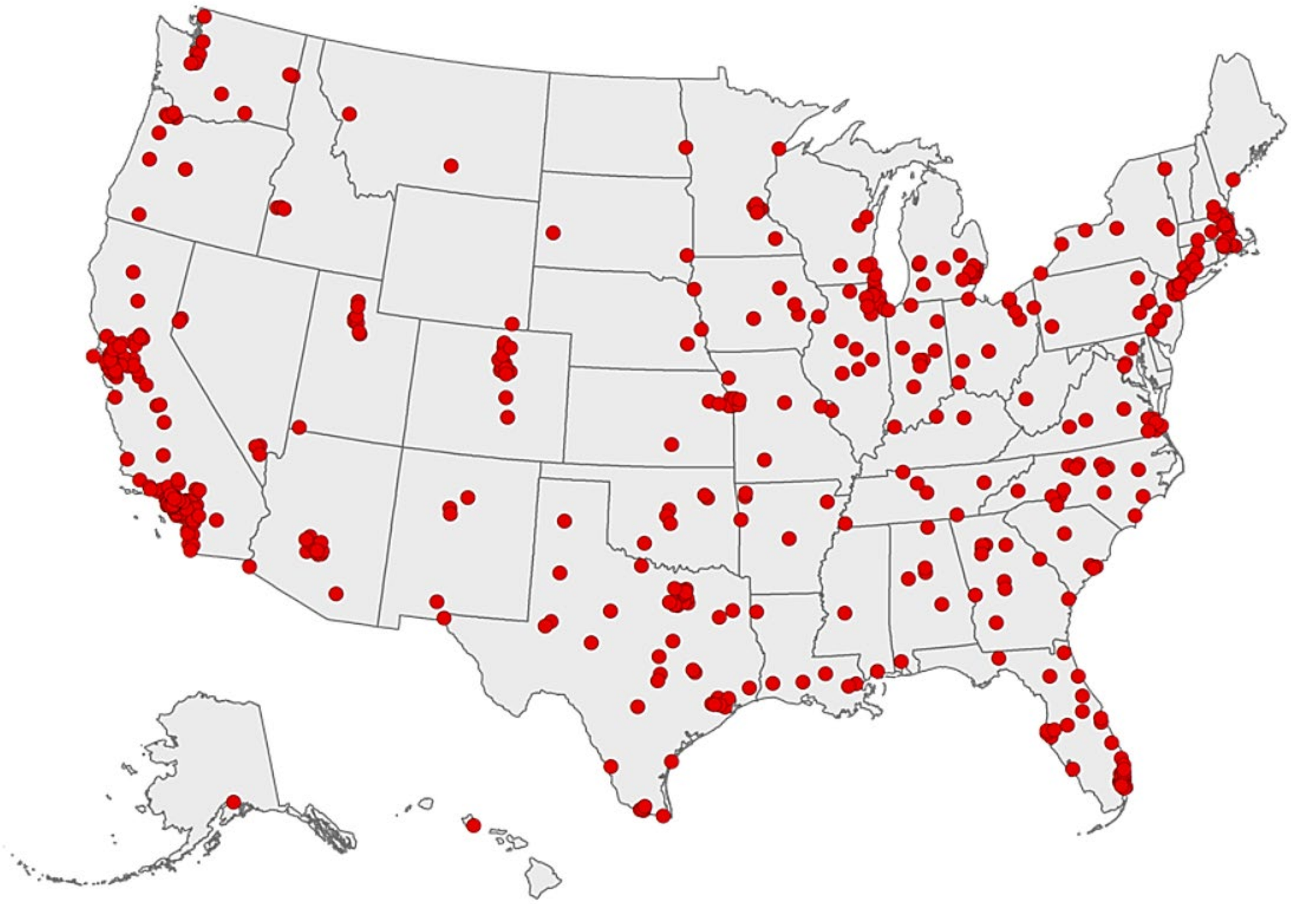


Figure 9. 500 CDC major cities.

Discussion

Summary and Key Findings

The studies documented in this report are the first to examine multiple air pollution exposures related to traffic activity and their relationship with the burden of childhood asthma development in the United States on a national scale—and separately on an individual state scale—by using air pollution exposure levels at the smallest available geographical unit and meta-analysis-derived ERF. The findings, based on emerging evidence that TRAP leads to the onset of asthma among children, suggest that TRAP is responsible for the development of a large portion of preventable childhood asthma cases in the United States, with large variations across and within states.

In the Alotaibi et al. (2019) study, the researchers estimated that between 141,900 (18 percent) and 331,200 (42 percent) (numbers are rounded to the next hundred) of new childhood asthma cases were attributable to air pollution. The BoD varied depending on the pollutant that was selected in the analysis, and the results suggest that NO_2 contributes to the least BoD, while PM_{10} contributes to the most. It is important, however, to note that traffic contributes to these different pollutants in urban air in extremely varying degrees. For example, studies in Europe demonstrated that traffic contributes to over 80 percent of urban NO_2, between 9 percent and 66 percent of $PM_{2.5}$, and between 9 percent and 53 percent of PM_{10} (Sundvor et al., 2012). It is generally accepted that NO_2, which is a more specific surrogate of the TRAP mixture than particulate matter, both coarse and fine, may better represent the burden associated with traffic emissions in particular (Beckerman et al., 2008; Karner et al., 2010). Over the 10-year period of the analysis, the attributable number of incident asthma cases due to all the pollutants decreased. The reduction in NO_2 levels was the most prominent among pollutants and accounted for a 33 percent reduction in the estimated BoD. This finding is mainly due to a reduction in the estimated NO_2 concentrations (Clark et al., 2017) since the asthma IR the researchers used in the 10-year analysis remained unchanged between 2000 and 2010, and the total number of incident cases among children only increased by 1 percent during the same time period due to population changes.

In the Khreis et al. (2020) study, the researchers focused on the year 2010 and NO_2 only and reanalyzed the data using newly generated IRs at both the national and the state level. The researchers conducted this analysis to shed light on the impact of uncertainties in the asthma IRs on the final BoD estimates. The researchers documented the differences in BoD estimates when using state-specific versus a constant national-level asthma IR for the first time. Previous literature only used national-level asthma IRs for BoD assessments, and the impact of this simplification was unknown. At the U.S. level, the difference in the estimated BoD using state-specific versus a national-level asthma IR was relatively small and, for most states, fell within the range of uncertainty, as expressed using the 95 percent CI. Using the state-specific asthma IR, the researchers estimated a total of 134,166 (95 percent CI: 75,177–193,327) childhood asthma incident cases attributable to NO_2, accounting for 17.6 percent of all childhood asthma incident cases. Using the national-level IR, the researchers estimated a total of 141,931 (95 percent CI: 119,222–163,505) incident cases attributable to NO_2, accounting for 17.9 percent of all childhood asthma incident cases (numbers are not rounded to the next hundred and are therefore slightly different than the numbers reported above). Using the state-specific IRs resulted in a 5.5 percent relative reduction (−7,765 attributable cases), which equates to a 1.9 percent relative reduction in the AF. Although a 1.9 percent relative reduction in the AF is relatively small and should be weighed against the effort that was required to produce state-specific IRs, the implication of this reduction may still be important depending on whether and how BoD estimates are used in policy making, including regulatory cost-benefit analysis or EPA risk assessments. For example, according to Perry et al. (2019), the average annual costs of asthma per child in the United States ranged from \$3,076 to \$13,612. In simplistic terms, using the state-specific versus the national-level IR would result in 7,765 fewer attributable cases, which would result in an overall reduction ranging from \$23,885,140 (7,765 x \$3,076) to \$105,697,180 (7,765 x \$13,612) in estimated burden costs per year at the national level. The larger variation across states may also be important for state policy making and priority setting, and for some states, the 95 percent CI of the estimated burden using the state-specific IR did not overlap with the central estimate produced using the national-level IR, as shown in Table 12. Using state-specific IRs, which the researchers expect to better capture between-state variation, resulted in a relative change in the ACs, ranging from −64.1 percent (Montana) to 33.8 percent (Texas), with an average change of 16.3 percent. California had the largest absolute decrease in the number of attributable cases (6,190 cases), while Texas had the largest increase (3,615 cases), followed by New York (1,750), as shown in Table 12.

Stratifying the analyses by socioeconomic status and urban versus rural status, the researchers found that children living in urban areas had twice the percentage of asthma cases attributable to NO_2 exposures as children living in rural areas: 30 percent versus 15 percent in the year 2000, and 20 percent versus 10 percent in the year 2010 (Alotaibi et al., 2019). This result is due to the higher average levels of NO_2 in urban areas than in rural areas, as shown in Table 4. This contrast was not as great for $PM_{2.5}$, which had only a 4 percent and 2 percent absolute difference in percent of asthma incident cases between urban and rural locations, respectively, while PM_{10} had an absolute difference of 8 percent and 6 percent in 2000 and 2010, respectively. Children living in census block groups with a lower median household income had a slightly higher percentage of attributable incident cases than children living in areas with a higher median income. The results are in line with previously published data showing that, on average, households with lower income were more likely to live near high-density traffic (Clark et al., 2017; Rowangould, 2013). The only exception was in NO_2 exposure in 2000, in which the highest median household income group had the second largest percentage of attributable cases.

Using state-specific asthma IRs, the researchers also reexplored trends in BoD estimates stratified by socioeconomic status and urban versus rural status to compare trends observed in the analysis, which relied on a national-level IR, as described above. Most of the relative change in the ACs (−5.9 percent) occurred in urbanized areas and among the highest median household income group of ≥\$75,000 (−7.8 percent) (Table 11). The distribution of the AFs across all census blocks by living location and median household income group showed the following: (a) all states had the highest burden concentrated in urbanized areas and the lowest burden in rural areas; and (b) the majority of states broadly followed the U-shaped distribution observed at the U.S. level, wherein the lowest and the highest median household income groups had the highest burden, thus corresponding to the highest NO_2 exposures modeled in those strata. However, many exceptions existed, including Arizona, Connecticut, D.C., Florida, Maine, Massachusetts, Montana, Nevada, New Hampshire, New Jersey, New Mexico, Vermont, West Virginia, Rhode Island, and Wyoming. On the other hand, in some states, this U-shaped distribution was more prominent, including Illinois and New York, and to a lesser extent, Pennsylvania and Texas. It is worth emphasizing here that these trends, both in the urban versus rural differences and in the differences by median household income, are solely related to differences in NO_2 exposures across those strata. The researchers showed that NO_2 concentrations tend to be higher in census blocks designated as urbanized areas and are generally highest in the most- and least-deprived households (although not all states follow this trend, as indicated earlier). As such, the attributable burden of childhood asthma is higher in those strata. However, the researchers could not account for the sub-state variation in asthma IRs, which may well be different in urban versus rural areas and by socioeconomic status. The researchers had no source of baseline asthma IRs at a spatial resolution finer than the state level, and as such, the results only indicate that the previously documented gradients in asthma prevalence by urbanization and socioeconomic status may be, in part, explained by similar gradients in air pollution.

The finding that the lowest median household income groups had the highest BoD may reflect that low-income populations are in the most polluted census blocks due to the decreased financial costs of housing in more polluted areas. This trend is well established in the environmental justice literature (Hajat et al., 2015). On the other hand, the finding that the highest median household income groups also suffer from a high exposure and BoD may reflect that the highest income populations live in highly polluted census blocks because they prefer to live near the amenities of busy downtowns and central business districts, where TRAP is higher. If this result is the case, this trend does not apply to all states and may differ by rural, urban, and urbanized area status. Previous work suggests that metropolitan areas in particular exhibit considerable heterogeneity when it comes to socioeconomic status and exposure to air pollution. For example, in cities like New York, wealthy neighborhoods have been associated with higher concentrations of pollution (Hajat et al., 2013). Other works support the trends observed in the results. A national study covering all wards in Great Britain showed that the association between NO_2 and poverty was not simply linear but J-shaped, with wards with the highest poverty having the highest average NO_2 concentrations, while wards with the lowest poverty also had higher-than-average NO_2 concentrations but with a less dramatic variation (Mitchell and Dorling, 2003). The 10 percent most-deprived wards in Britain had a mean annual NO_2 concentration that was 17 percent above the national mean, while the 10 percent least-poor wards in Britain had a mean annual NO_2 concentration that was 7 percent above the national mean (Mitchell and Dorling, 2003). These findings warrant further investigation using more refined air pollution and asthma IR estimates at an even more granular spatial resolution that may help highlight heterogeneity between and within neighborhoods and explain why some states do not follow these documented trends.

Comparison with Previous Studies

A few studies estimating the BoD due to air pollution and TRAP have been previously published. In a study of 10 European cities, the burden of asthma attributable to TRAP had an average of 14 percent and ranged from 7 percent to 23 percent (Perez et al., 2013). Another study in Los Angeles, California, reported a range between 6 percent and 9 percent (Perez et al., 2009). Both estimates were lower than the range of 18 percent to 42 percent. However, both studies used a proximity to major roadways measure as the surrogate of TRAP exposures—where children living within a 75-m buffer of main roadways were classified as exposed. In the Los Angeles study by Perez et al. (2009), only 20 percent of the total children's population lived near a main roadway, while in Europe this percentage was higher (31 percent), with a range of 14 percent to 56 percent depending on the city (Perez et al., 2013). In the study, all kids were exposed, albeit to different levels of air pollution, and as such, both studies may have resulted in a large portion of the population being misclassified as non-exposed based on the proximity measure. A study by Ryan et al. (2007) examining associations between infant wheezing and residing within 100 m from stop-and-go bus and truck traffic showed that using a LUR model may reduce exposure misclassification that arises from a proximity model. Using a LUR model, a more recent study by Khreis et al. (2018) estimated that 24 percent of all new childhood asthma in the city of Bradford, United Kingdom, was attributable to NO_2. In their follow-up study, Khreis, Ramani, et al. (2019) reported that $PM_{2.5}$, PM_{10}, and BC exposures accounted for 15 percent to 33 percent of all new childhood asthma cases in Bradford. The results are therefore comparable to estimates reported in the English studies despite being higher.

Also, previous BoD studies on air pollution and new onset asthma identified the use of a constant national-level baseline asthma IR as a gap that may impact final BoD estimates. The results suggested that the impact of using a finer level of asthma IR was smaller at the national level compared to the state level. Changes in the ACs at the state level ranged from

−64.1 percent to +33.8 percent. These results are not directly comparable to previous studies using only a national-level incidence. However, the BoD estimates attributable to NO_2 (AF = 17.6 percent) were very similar to previous reports outlined above, and a new global analysis has estimated the BoD attributable to NO_2 at 19 percent in high-income populations in North America (Achakulwisut et al., 2019).

Strengths and Limitations

The researchers used a meta-analysis derived ERF of continuous pollutant exposures (Khreis, Kelly, et al., 2017) rather than a single ERF using a proximity measure (McConnell et al., 2006). Using a meta-analysis-derived ERF is considered more appropriate when extrapolating to a national scale and different locations. A meta-analysis-derived ERF also overcomes statistical uncertainty associated with a single study and better addresses heterogeneity among different populations. Further, the ERFs were pollutant-specific and are better suited to capture the impact of the spatial variability of the different air pollutants. Although most studies included in the meta-analysis adjusted for major confounders (e.g., socioeconomic status, smoking, parental atopy), there were no specific ERFs based on these variables (e.g., an ERF for low versus high median household income); thus, the researchers could not account for this in the analysis. However, the researchers stratified the results by living location and median household income to simply visualize the BoD estimates without using different ERFs and IRs across these strata since this information is predominantly lacking in the literature. Although this process is a simplification of the analysis, it is still useful to show these stratified estimates, and this approach is in line with wider literature cited earlier. The researchers did not have median household income at the census block level, which was the geographical level at which the researchers assigned exposure and population data. Instead, census blocks were assigned the same median household income of the census block group they resided within. This procedure was the best available option, but it could have resulted in misclassification and therefore biased some of the trends the researchers observed in the stratified socioeconomic status analyses.

In the study, the researchers used a childhood asthma IR instead of a PR. The main advantage is that the researchers were able to estimate the number of preventable cases of childhood asthma had there been reduced or no (zero) exposures to the pollutants the researchers studied. To the researchers' knowledge, this study is the first to investigate the impact of using a spatially varying asthma IR in the context of air pollution and asthma BoD assessment. Further, there is no published material providing state-specific asthma IRs within the United States. The researchers used the best available data from the CDC for the longest period possible that was aligned with the exposure assessment year (2010) to generate state-specific childhood asthma IRs, which have not been readily available until now.

However, the national IR itself had some noteworthy limitations. First, the ACBS aggregated the rates for the years 2006 through 2008, which do not cover the time period of the study (2000 and 2010). Second, not all states participated in the survey for each year (Winer et al., 2012); thus, the IR is not representative of all states. Although these limitations might result in different IRs and therefore different BoD estimates, the researchers believe that the results are robust for two reasons. First, the researchers do not believe that the IR would vary significantly during a relatively short period of time. For example, asthma prevalence for children was 8.7 percent in 2001 and increased to only 9.7 percent in 2010 (Moorman et al., 2012). Second, the sensitivity analysis showed that changing the national IR to the lower (10.5 per 1,000 children per year) and upper (14.4 per 1,000 children per year) CI bounds would change the mean estimate of ACs for all pollutants by no more than 16 percent. Another limitation in the data underlying the calculations of the IRs is that Winer et al. (2012) used self-reported doctor diagnoses to identify asthma cases. This approach will likely lead to an overestimation of the number of cases in the analysis. However, studies or data sets estimating asthma incidence using more specific objective methods, and at local scales, are not available. When future data become available, the models can be reconfigured to more accurately estimate the number of attributable asthma cases. There were also limitations in the data sets the researchers used to estimate the state-specific asthma IRs. The total childhood sample included for the period 2006–2010 was 293,464 samples from the BRFSS and 16,156 samples from the ACBS. These samples were, however, weighted to represent the total number of children within each state with similar characteristics (age, sex, and race) to the sample. In other words, weights were used to convert samples to population estimates of children. A larger sample size in these surveys may have better represented the U.S. childhood population of <73 million, which the researchers included in the analysis, but this element is not established. NO_2 exposures were estimated for the year 2010, while the estimation of the asthma IRs utilized data from 2006 to 2010. The reason why the researchers included earlier years of data in the estimation of the asthma IRs was because many states did not have survey results for the year 2010, and relying on 2010 data only would mean that the researchers would have to exclude those states from the analysis. Furthermore, and importantly, since the estimation of asthma IRs was done at a finer spatial resolution in the Khreis et al. (2020) study (at the state versus the national level), the sample sizes available for this estimation were limited and used the aggregate data from the years 2006–2010 to increase the confidence of the IR estimates. Ideally, enough data would have been available to allow a complete and robust calculation of asthma IRs for the year 2010 specifically, but because the aim of the second study was to establish the potential impact of using different IRs only, this aim was not compromised by the use of aggregate survey data from the years 2006–2010.

Another limitation is related to the air pollution exposure assessment. Using the LUR model to assign exposure values has several limitations. This type of model assumes that pollutant exposure is from ambient air pollution and does not consider indoor air pollution sources. The model is often used to assign exposures at a single location for study subjects, commonly the residential address, and does not consider time-activity patterns—for example, how much of the exposure happens at school or at the playground or during daily commute. Another limitation is exposure misclassification error. The precision of the LUR model varies within urban areas, leading to misclassification of exposure in either direction depending on the direction of the error of the pollutant prediction. If the model is over-predicting, it will lead to overexposure classification; if the model is under-predicting, the opposite might be true. LUR models are limited in their ability to provide detailed source apportionment, unlike, for example, atmospheric dispersion models (Khreis, 2020). LUR models can only reflect the predictors used in the model and are subject to varying uncertainties among different pollutants, and the quality of the data representing meaningful predictors are sensitive to the locations and density of measurement sites. Finally, the models' outputs are also sensitive to the locations and density of measurement sites (Khreis, 2020).

In addition, while the LUR predicts air pollution with fairly high accuracy, it considers all sources of air pollution, and the researchers could not parse out the exact contribution of traffic from other sources in the exposure and attributable BoD. For example, the 2014 National Emissions Inventory Report describes four major sources of air pollution emissions: stationary (e.g., fuel combustion for electricity generations, industrial processes like fertilizer application), fire, biogenic (naturally occurring emissions), and mobile sources. Mobile sources include on-road (traffic) and non-road sources (e.g., aircrafts and marine sources). The report estimated that between 2002 and 2011, around 41 percent of nitrogen oxide emissions were from on-road sources, 21 percent from non-road sources, 37 percent from stationary sources (e.g., fuel combustion), and the remaining from other sources. For $PM_{2.5}$, stationary sources accounted for 70 percent of emissions, and <5 percent of emissions were from on-road sources, while for PM_{10}, stationary sources accounted for 90 percent of emissions, and <2 percent were from on-road sources (EPA, 2014). These ratios are generic from across the United States—both urban and rural emissions combined. For NO_2 and $PM_{2.5}$, the researchers assume that the proportion of total concentrations that are attributable to traffic is higher in urban areas than in rural areas. The approach, therefore, would lead to an overestimation of the burden of asthma due to TRAP; this overestimation would be greater in rural areas than in urban areas. Most of the pediatric population in this analysis lived in an urban setting (≈80 percent).

It is important to note that the Census Bureau categorizes urban areas using several criteria, including population threshold, density, land use, and distance. Urban areas are subdivided into two types: urbanized areas with a population of 50,000 or more, and urban clusters with at least 2,500 but fewer than 50,000 people. In order for a census block to be defined as urban, it must have a population density of at least 1,000 people per square mile (ppsm), or 500 ppsm if the block contains a mix of residential and nonresidential land use (e.g., parks, retail, schools), or contains nonresidential land use with a high amount of impervious surface while distanced within a quarter mile of an urban area. Rural is defined as all population, housing, and territory not included within an urbanized area or urban cluster. TRAP exposure surrogates more correctly relate to an urban setting with high levels of people and traffic since the level of pollution from traffic sources as a ratio of ambient pollution is higher in urban settings than in rural settings. Therefore, the use of pollutant surrogates (NO_2, $PM_{2.5}$, and PM_{10}) as a measure for TRAP would overestimate TRAP exposures and the attributable cases more in rural areas than in urban areas. The LUR models also estimate concentrations at the centroid of census blocks, which could be a farther point from roadways since census blocks are usually delineated by roadways. However, the researchers could not verify how this would affect the direction of exposure since calculating the average concentration at a finer scale within census blocks was not feasible in this project due to the large computational intensity needed to predict values across the contiguous United States. The researchers also assigned exposures at the residential location, while variability in exposure at the indoor, outdoor, and personal levels was not considered. This is in line with the meta-analysis derived ERF the researchers used, which were predominantly based on residential locations. However, previous research suggests that personal exposure to pollutants is usually higher than indoor and outdoor exposure concentrations, which might result in underestimating exposure levels and the associated BoD (Monn, 2001).

Finally, the analysis assumes TRAP is causally associated with the development of childhood asthma. However, there remains some level of uncertainty. First, the studies included in the underlying meta-analysis had different levels of heterogeneity. For example, Khreis, May, et al. (2017) showed that the largest heterogeneity among the pollutants was with NO_2, suggesting that NO_2 may act as a surrogate for other pollutant(s) in the mixture. Possible interactions between pollutants were not considered, and it is uncertain whether pollutants act in single or multiple causal pathways leading to the development of asthma. Second, it is uncertain if there are other confounders that would still cause asthma cases even if the TRAP exposure were eliminated, which may lead to an overestimation of the burden attributable to TRAP. Third, Khreis, May, et al. (2017) indicated that the most common method of identifying asthma between studies underlying the meta-analysis was by using parental reporting of doctor diagnosis. Although this method is in line with how the researchers estimated the national childhood asthma IR, it may lead to classification errors, especially among younger children in which symptoms of respiratory illnesses overlap (Castro-Rodríguez et al., 2000; Werk et al., 2000).

Conclusions and Recommendations

The study contributes to the scarce literature estimating the burden of childhood asthma onset attributable to air pollutants related to traffic activity, especially in urban areas. This report presents the first studies to estimate the childhood asthma BoD on a national scale for the contiguous United States, while also presenting the results for the major 498 U.S. cities and every county in an interactive, accessible, and open-access manner. The researchers utilized the best available data sets and state-of-the-art research, using small-scale geographical units for both the census data and air pollution exposure estimation and meta-analysis derived ERFs from the most recent and largest study that linked TRAP to the onset of childhood asthma. The combination of this effort, while using a standard BoD assessment framework, enabled researchers to estimate the burden of new childhood asthma cases attributable to NO_2, $PM_{2.5}$, and PM_{10} separately.

On average, the estimated percentage of new childhood asthma cases attributable to the three pollutants in the contiguous United States ranged between 18 percent and 42 percent, depending on the year and pollutant selected in the analysis. The reduction in air pollution concentrations over the 10-year study period translated into a reduction of up to 33 percent in the number and percentage of attributable new childhood asthma cases. However, the results still indicate that air pollutants are responsible for a large proportion of preventable childhood asthma cases—up to 286,500 cases in 2010. The number of these cases can be further reduced by more reductions in air pollution levels. For $PM_{2.5}$ and PM_{10}, the results are likely to represent an overestimation of the impact of traffic sources on childhood asthma, mainly because the models the researchers used to estimate exposures reflect all sources of air pollution, which for PM in particular are many and are significant contributors. The researchers also investigated the impacts of two counterfactual scenarios. The researchers estimated that reducing pollutant levels in the United States from the 2010 levels to levels that are compliant with the WHO air quality guideline values would reduce new childhood asthma cases by up to 14,400 cases (2 percent of all asthma cases). Moreover, if pollutant levels are reduced to the lowest modeled levels from the exposure assessment models, the new childhood asthma cases could be reduced by up to 272,700 cases (34 percent of all asthma cases). At the time of the Alotaibi et al. (2019) study, due to the unavailability of asthma incidence studies reporting on spatially varying childhood asthma IR, the researchers were unable to consider the varying spatial distribution of childhood asthma incidence and used an aggregate national-level IR.

In the Khreis et al. (2020) study, using raw data collected from CDC surveys (BRFSS and ACBS), the researchers generated state-specific childhood asthma IRs and repeated the analyses for the year 2010 and NO_2 using state-specific versus national-level IRs. Using a constant U.S. versus state-specific childhood asthma IR resulted in a small reduction in the NO_2-attributable BoD at the national level with overlapping 95 percent CI in comparison to BoD estimates using the national-level IRs. The change in BoD estimates for the individual states, however, was more prominent, and for some states, the range of uncertainty as indicated by the 95 percent CI did not overlap. For example, the relative change in the attributable number of new childhood asthma cases using the state-specific asthma IRs ranged from −64.1 percent (Montana) to +33.8 percent (Texas). The reduction in the NO_2 AF of asthma at the U.S. level when using the state-specific IRs was relatively small and should be weighed against the effort required to produce state-specific IRs, as described in this report. However, the implications of using finer-level IRs might be significant, depending on whether and how the BoD estimates are used in regulatory cost-benefit analyses or EPA risk assessments for policy making. This is specifically relevant if regulatory assessments are conducted at the state level. Otherwise, the findings support using national-level asthma IRs to estimate the burden of new childhood asthma due to air pollution at the national level and when IRs are not available at a finer resolution. To the researchers' knowledge, this study was also the first to analyze the impact of using a spatially varying asthma IR in the context of air pollution and asthma BoD assessment.

These studies provide evidence that air pollution contributes to the development of a substantial proportion of asthma cases in children. The results indicate that the elimination or the reduction of air pollution levels and exposures can potentially prevent a considerable number of childhood asthma cases from developing. The attribution of new childhood asthma cases to air pollution has substantial implications for the burden of asthma-related exacerbations as well, which has not been discussed in this report. Because air pollution increases the risk of developing new asthma cases, then all future acute exacerbations of these cases, regardless of subsequent (immediate) causes of the exacerbations, should be again attributed to air pollution. This conceptualization has been previously followed in the literature, wherein BoD estimates associated with air pollution were revised to account not only for asthma symptoms that are directly triggered by air pollution but also for asthma symptoms triggered by other causes in children who developed asthma because of air pollution (Figure 10). The result has a significantly higher BoD estimate and perhaps paints a more realistic picture of the societal and economic impacts of air pollution (Künzli et al., 2008; Brandt et al., 2012). These impacts are largely preventable, and numerous transport and land-use policy measures at the city level can reduce traffic emissions, air pollution levels, and exposures. These policy measures have been discussed in detail elsewhere (Khreis, May, et al., 2017; Sanchez et al., 2020).

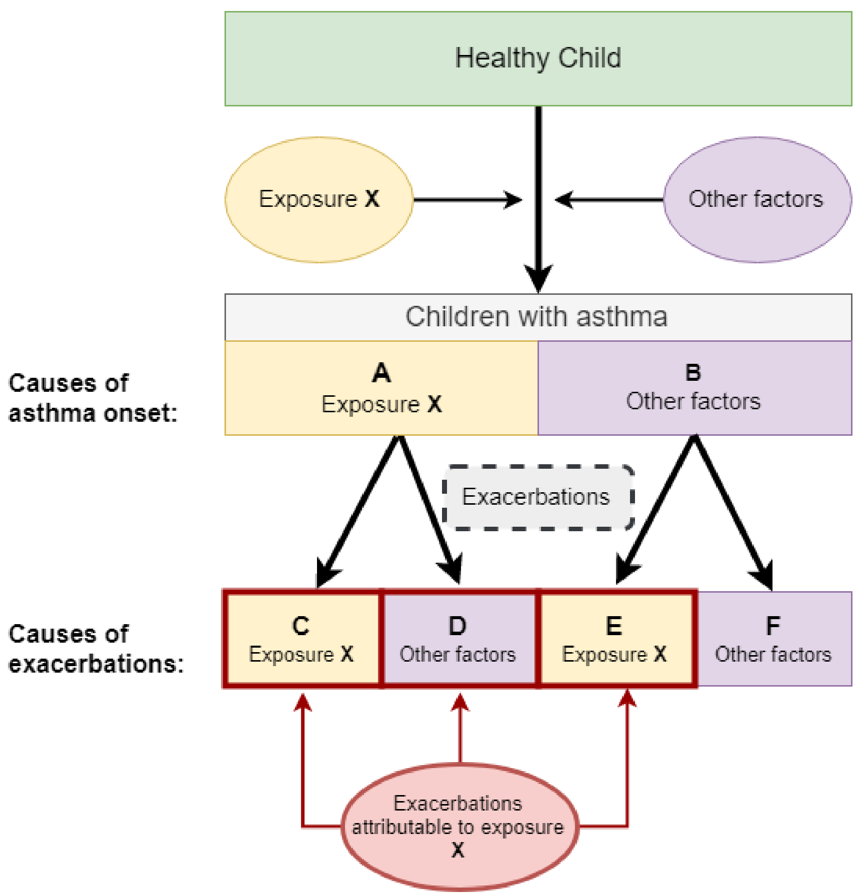


Figure 10. The burden of asthma exacerbations in children attributable to Exposure X assuming a causal role of X in both disease onset and exacerbation. Adapted from Künzli et al. (2008).

Outputs, Outcomes, and Impacts

Outputs

The outputs of this research are as follows:

- The development of the health assessment piece of TEMPO (Transportation and Emissions Modeling Platform for Optimization), available at https://tempo-dashboard.io/home.
- Training aid to replicate analyses and results, including a project repository with all data sets and a project guide, available at https://carteehdata.org/library/dataset/burden-of-disease-due-to--7e53.

Outcomes

None known.

Impacts

None known.

Research Outputs, Outcomes, and Impacts

- Alotaibi, R., Bechle, M., Marshall, J.D., Ramani, T., Zietsman, J., Nieuwenhuijsen, M.J. and Khreis, H., 2019. Traffic Related Air Pollution and the Burden of Childhood Asthma in the Contiguous United States in 2000 and 2010. Environment International, 127, pp. 858–867. ***Peer-reviewed publication.***
- Khreis, H., Alotaibi, R., Horney, J. and McConnell, R., 2020. The Impact of Baseline Incidence Rates on Burden of Disease Assessment of Air Pollution and Onset Childhood Asthma: Analysis of Data from the Contiguous United States. Annals of Epidemiology. ***Peer-reviewed publication.***
- Alotaibi, Raed; Bechle, Mathew; Marshall, Julian D.; Ramani, Tara; Zietsman, Josias (Joe); Nieuwenhuijsen, Mark J.; Khreis, Haneen, 2018. Air Pollution and the Burden of Childhood Asthma in the Contiguous United States in 2000 and 2010. The Joint Annual Meeting of the International Society of Exposure Science and the International Society for Environmental Epidemiology (ISES-ISEE 2018), Ottawa, Canada, 26–30 August 2018. ***Conference presentation.***
- Alotaibi, Raed; Bechle, Mathew; Marshall, Julian D.; Ramani, Tara; Zietsman, Josias (Joe); Nieuwenhuijsen, Mark J.; Khreis, Haneen, 2018. Air Pollution and the Burden of Childhood Asthma in the Contiguous United States in 2000 and 2010. Urban Transitions, Barcelona, Spain, 25–27 November 2018. ***Conference presentation.***
- Alotaibi, Raed; Bechle, Mathew; Marshall, Julian D.; Ramani, Tara; Zietsman, Josias (Joe); Nieuwenhuijsen, Mark J.; Khreis, Haneen, 2018. Air Pollution and the Burden of Childhood Asthma in the Contiguous United States in 2000 and 2010. Transportation, Air Quality and Health Symposium, Austin, Texas, USA, 18–20 February 2019. ***Conference presentation.***
- Alotaibi, Raed; Bechle, Mathew; Marshall, Julian D.; Ramani, Tara; Zietsman, Josias (Joe); Nieuwenhuijsen, Mark J.; Khreis, Haneen, 2019. Traffic Related Air Pollution and the Burden of Childhood Asthma in the Contiguous United States in 2000 and 2010. Southern Transportation Air Quality Summit (STAQS) 2019 meeting, Louisville, Kentucky, USA, 21–22 August 2019. ***Conference presentation.***
- Khreis, Haneen, 2019. Exposure to Traffic-Related Air Pollution and Risk of New Onset Asthma: What Is the Evidence and What Does it Mean? University of Texas at Austin, Dell Medical School: Connecting Environment to Health, a UT Austin environmental health collaborative event, Austin, USA, 21 February 2019. ***Invited presentation.***
- Khreis, Haneen, 2019. Traffic-Related Pollution: Pathways to Healthier Lungs. New York University School of Medicine Continuing Medical Education: Asthma, Airways, and the Environment, New York, USA, 22 March 2019. ***Invited presentation.***
- Khreis, Haneen, 2019. Integrating Human Health into Urban Transport Planning. The Mansueto Institute Lunch Colloquium Series, University of Chicago, Chicago, USA, 15 April 2019. ***Invited presentation.***

Technology Transfer Outputs, Outcomes, and Impacts

- The development of the health assessment piece of TEMPO relied on codes developed in this project; available at https://tempo-dashboard.io/home.
- A project repository with all data sets and a project guide to replicate the analyses and results from this project, available at https://carteehdata.org/library/dataset/burden-of-disease-due-to--7e53.
- R code developed for the analysis, available at https://carteehdata.org/library/dataset/burden-of-disease-due-to--7e53.
- Significant media attention, including the following:
    - Reach/impressions: 75,714,700 → Reach/impressions is the potential number of people who saw the article based on news subscriptions, website visitors to a media outlet, and social media followers of each outlet that shared the article on social media or their website. This is a number calculated by the media monitoring service Meltwater.
    - Twitter shares from media stories: 1,147.
    - Facebook shares from media stories: 2,263.
    - Earned media value: $705,360.98 → Earned media value is a method to calculate the importance of branded content gained through marketing or public relations efforts that is not paid media (not advertising) and not from owned (did not come from one's own media channels). This includes blogs, referrals, social posts, influencer marketing, reviews, and more. This value is calculated by the media monitoring service Meltwater.
- ***Selected*** media articles:
    - Cleveland19 News, Story: "Research shows connection between Cleveland traffic pollution and asthma in kids" https://www.cleveland19.com/2019/09/09/research-shows-connection-between-cleveland-traffic-pollution-asthma-kids/
    - The Rivard Report, Story: "Study estimates San Antonio traffic pollution causes nearly 600 child asthma cases per year" https://therivardreport.com/study-estimates-sa-traffic-pollution-causes-nearly-600-child-asthma-cases-per-year/
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Education and Workforce Development Outputs, Outcomes, and Impacts

Raed Alotaibi, a doctoral student enrolled in the program for Public Health at Texas A&M University, was hired on this project to conduct all data handling and analysis and also assisted with the literature review and the write-up of the two resulting papers. Raed co-authored the two papers and presented the results in numerous internal events, including to his peers and other researchers at the Texas A&M Transportation Institute. Raed used the knowledge and skills he gained from this project to develop his doctoral proposal and dissertation, titled *Air Pollution and Diabetes Mellitus*, for which he was awarded the degree of Doctor of Public Health. In his dissertation, he used the same exposure models, census data, and BoD assessment methods to estimate the diabetes mellitus BoD attributable to air pollution across the contiguous United States. In his dissertation, he found that around 5,978,048 prevalent and 213,641 incident diabetes cases may be attributable to air pollution exposure, thus representing 28.1 percent and 11.0 percent of all diabetes prevalent and incident cases, respectively. The fraction of attributable cases was higher in urban areas than in rural areas and in census blocks with predominantly Asian populations. Similar to this project, he developed an online interactive map and a lookup table to visualize and explore the burden of diabetes due to air pollution at the county level, further expanding and reinforcing the outreach efforts presented here. This project was also the basis for a subsequent project in which the researchers hired an undergraduate public health student, Minaal Farrukh, to monetize the childhood asthma BoD attributable to NO_2 in 2010. This work is currently ongoing and will be published in a white or peer-reviewed journal paper with the title “Monetizing the Burden of Childhood Asthma Due to Traffic-Related Air Pollution in the Contiguous United States.”

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