Disparities in air pollution exposure in the United States by race-ethnicity and income, 1990 – 2010

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Abstract

Background: Few studies have investigated air pollution exposure disparities by race-ethnicity and income across criteria air pollutants, locations, or time.

Objectives: To quantify exposure disparities by race-ethnicity and income, throughout the contiguous US, for six criteria air pollutants, during 1990 to 2010.

Methods: We quantified exposure disparities among racial-ethnic groups (non-Hispanic White, non-Hispanic Black, Hispanic (any race), non-Hispanic Asian) and by income for multiple spatial units (contiguous US, states, urban vs. rural areas) and years (1990, 2000, 2010) for carbon monoxide [CO], nitrogen dioxide [NO_2], ozone [O_3], particulate matter [$PM_{2.5}$ excluding year-1990; PM_{10}], and sulfur dioxide [SO_2]. We used census data for demographic information and a national empirical model for ambient air pollution levels.

Results: For all years and pollutants, the racial-ethnic group with the highest national average exposure was a racial-ethnic minority group. In 2010, the disparity between the racial-ethnic group with the highest versus lowest national-average exposure was largest for NO_2 (54% [4.6 ppb]), smallest for O_3 (3.6% [1.6 ppb]), and intermediate for the remaining pollutants (13%-19%). The disparities varied by US state; for example, for $PM_{2.5}$ in 2010, exposures were at least 5% higher-than-average in 63% of states for non-Hispanic Black populations, in 33% and 26% of states for Hispanic and for non-Hispanic Asian populations, respectively, and in no states for non-Hispanic White populations. Absolute exposure disparities were larger among racial-ethnic groups than among income categories (range among pollutants: between 1.1 and 21 times larger). Over the period studied, national absolute racial-ethnic exposure disparities declined by between 35% (0.66 μg m^{-3}; $PM_{2.5}$) and 88% (0.35 ppm; CO); relative disparities declined to between 0.99× ($PM_{2.5}$; i.e., nearly zero change) and 0.71× (CO; i.e., a ~29% reduction).

Discussion: As air pollution concentrations declined during 1990 to 2010, absolute (and to a lesser extent, relative) racial-ethnic exposure disparities also declined. However, in 2010, racial-ethnic exposure disparities remained across income levels, in urban and rural areas, and in all states, for multiple pollutants.

Introduction

Air pollution is associated with ~100,000 annual premature deaths in the United States (US) in 2017 (Stanaway et al. 2018) and has been linked to cardiovascular disease, respiratory disease, cancers, adverse birth outcomes, cognitive decline, and other health impacts (Cohen et al. 2017; Darrow et al. 2019; Lelieveld et al. 2015; Paul et al. 2019; Pope et al. 2009; Rivas et al. 2019; Stieb et al. 2012; Underwood 2017). Air pollution, and its associated health impacts, is not equitably distributed by race-ethnicity or income. Previous research has documented higher-than-average air pollution exposures for racial-ethnic minority populations and lower-income populations in the US (Brulle and Pellow 2006; Evans and Kantrowitz 2002; Mohai et al. 2009), leading to disparities in attributable health impacts (Bowe et al. 2019; Fann et al. 2019; Gee and Payne-Sturges 2004). Most investigations of disparities in air pollution exposure involve a single pollutant, location, and/or time-point (see, e.g., literature reviews by Hajat et al. (2015) and Marshall et al. (2014 – see Table S2)). Evidence from broader investigations suggests that exposure disparities by race-ethnicity and/or income can vary by pollutant (Rosofsky et al. 2018), location (e.g., by state (Bullock et al. 2018; Salazar et al. 2019), urbanicity (Mikati et al. 2018), metropolitan area (Zwickl et al. 2014; Downey et al. 2008)), and time-point (Ard 2015; Clark et al. 2017; Kravitz-Wirtz et al. 2016; Colmer et al. 2020). However, to our knowledge, broad patterns in exposure disparities have not yet been investigated, using consistent methods, across pollutants, locations, and time-points, for the contiguous US population.

The objective of our research was to comprehensively and consistently investigate disparities in exposure to Environmental Protection Agency (EPA) criteria air pollutants for the two decades following the 1990 Clean Air Act Amendments in the US. Specifically, we investigated the following questions regarding disparities in exposure to six criteria air pollutants: (1) How do exposures vary by race-ethnicity and income? (2) How do racial-ethnic exposure disparities vary by pollutant? (3) How do racial-ethnic exposure disparities vary by location (state, urban vs. rural areas)? (4) How have racial-ethnic exposure disparities changed over time? To address these questions, we combined demographic data from the US Census (Manson et al. 2019) with predictions of outdoor average levels of six criteria air pollutants from a publicly-available national empirical model derived from satellite, measurement and other types of data (Kim et al. 2020) at the spatial scale of census block groups and census tracts spatial scales. We then analyzed disparities in exposure to six criteria air pollutants (all criteria air pollutants except lead [Pb]; i.e., carbon monoxide [CO], nitrogen dioxide [NO_2], ozone [O_3], fine and respirable suspended particulate matter [$PM_{2.5}$, PM_{10}], and sulfur dioxide [SO_2]) by race-ethnicity (four racial-ethnic groups: non-Hispanic White, non-Hispanic Black, Hispanic (any race), non-Hispanic Asian) and income (16 household income categories) across time-points (decennial census years: 1990, 2000, and 2010) and spatial units (contiguous US, state, urban vs. rural areas).

Methods

Demographic and Air Pollution Datasets

We obtained demographic data (i.e., population estimates by race-ethnicity, household income, and household income disaggregated by race-ethnicity) and map boundaries (e.g., states, census tracts, and census block groups) for the contiguous US from the 1990, 2000, and 2010 decennial census from the IPUMS National Historic Geographic Information System (NHGIS) (Manson et al. 2019).

NHGIS provides, for each census block group, and for 1990, 2000, and 2010 (standardized to 2010 spatial boundaries), population estimates for six census self-reported racial groups: (i) White alone, (ii) Black or African American alone, (iii) American Indian and Alaska Native alone, (iv) Asian and Pacific Islander alone, (v) some other race alone, and (vi) two or more races. NHGIS reports population estimates for two census self-reported ethnic groups: (i) Hispanic or Latino and (ii) not Hispanic or Latino. Thus, there are a total of 12 combined racial-ethnic groups in NHGIS (six racial groups, two ethnic groups). Our main analyses of racial-ethnic exposure disparities included the four largest racial-ethnic groups, which in total covered 307 million people (97.2% of the population) in the contiguous US in 2010: (i) not Hispanic or Latino, White alone (64% of the population; hereafter, "non-Hispanic White"), (ii) Hispanic or Latino of any race(s) (16%; hereafter, "Hispanic"), (iii) not Hispanic or Latino, Black or African American alone (12%; hereafter, "non-Hispanic Black"), and (iv) not Hispanic or Latino, Asian and Pacific Islander alone (4.6%; hereafter, "non-Hispanic Asian").

For analyses by income in 2010, we used 2010 NHGIS household income estimates. For each block group, NHGIS reports the number of households in 16 annual household income categories (total covered in 2010: 114 million households): <10k, 10k–15k, 15k–20k, 20k–25k, 25k–30k, 30k–35k, 35k–40k, 40k–45k, 45k–50k, 50k–60k, 60k–75k, 75k–100k, 100k–125k, 125k–150k, 150k–200k, and >200k (2010 inflation-adjusted US dollars).

For analyses by income disaggregated by race-ethnicity in 2010, data from the 2010 NHGIS were available at the census tract level. For each census tract, NHGIS reports householder data for eight pre-defined race and/or ethnicity categories within each of the 16 census income groups, including one category based on both race and ethnicity (non-Hispanic White), one based on ethnicity regardless of race (Hispanic or Latino), and six based on race regardless of ethnicity (Black or African American alone, American Indian and Alaska Native alone, Asian alone, Native Hawaiian or Other Pacific Islander alone, some other race alone, and two or more races.). To best match demographic variables used in race-ethnicity analysis at the census block group level, we reported results for four largest race-ethnicity groups (total covered in 2010: 113 million census householders, 98.5% of householders with data on income by race-ethnicity): not Hispanic or Latino, White alone (71% of householders; hereafter, "non-Hispanic White"), Hispanic or Latino (12%; hereafter, "Hispanic"), Black or African American alone (12%; hereafter, "Black"), and Asian alone (3.8%; hereafter, "Asian"). Thus, for the data used for the household income by race-ethnicity analysis (but not for other analyses), Black and Asian categories included both Hispanic and non-Hispanic individuals; for these analyses (but not others), Hispanic Black populations (~0.40% of the population) would be included in results for Hispanic and for Black populations, and Hispanic Asian populations (~0.08%) would be included in results for Hispanic and for Asian populations. Additionally, for the data used for the household income by race-ethnicity analysis (but not for other analyses), the Asian category does not also include Pacific Islander populations.

The US Census Bureau defined census blocks as "urban" or "rural", based on population density and other characteristics (Ratcliffe et al. 2016). We used 2010 census urban/rural block definitions to define a 2010 census block group for all three years (1990, 2000, and 2010) as rural if all blocks inside it were rural, and we defined the remaining block groups as urban (i.e. each census block groups and rural/urban designations were the same in 1990, 2000, and 2010).

Average estimates of ambient air pollution levels for US EPA criteria pollutants were obtained from Center for Air, Climate, and Energy Solutions (CACES) empirical models for the contiguous US (www.caces.us/data). These models incorporate satellite-derived estimates of air pollution, satellite-derived land cover data, land use data, EPA monitoring station data, and universal Kriging (Kim et al. 2020); estimated pollution levels were available by census block at block centroids based on 2010 census boundaries for years from 1990 to 2010 for all pollutants except $PM_{2.5}$ (for which monitoring data and exposure models were only available starting in 1999). Estimated levels of O_3 from the CACES empirical model are 5-month summer averages (specifically, the average during May through September of the daily maximum 8-hour moving average level); for remaining pollutants, estimated levels are annual averages.

CACES model performance during the years studied here (2000, 2010 for $PM_{2.5}$; 1990, 2000, 2010 for the other pollutants), as measured by cross-validated R^2, was 0.84–0.89 for NO_2, 0.85 for $PM_{2.5}$, 0.62–0.82 for O_3, 0.56–0.62 for PM_{10}, 0.32–0.66 for SO_2, and 0.34-0.57 for CO (Kim et al. 2020). Mean error (ME) across the census years studied was between -0.02 and 0 ppm for CO, -0.04 to 0 ppb for O_3, -0.09 to -0.06 ppb for NO_2, -0.17 to -0.13 ppb for SO_2, -0.31 to -0.26 $\mu g\ m^{-3}$ for PM_{10}, and -0.05 to -0.02 $\mu g\ m^{-3}$ for $PM_{2.5}$. Mean bias (MB) was 13% - 22% for SO_2, and <10% for the other pollutants (Table S1); further details about the models and model-performance are in Kim et al. (2020) and Liu (2021).

Combining Demographic and Air Pollution Data

We matched the CACES empirical model results and the Census demographic data using the 2010 census spatial boundary definitions (from finest to coarsest spatial resolution: block, block group and tract boundaries) for the three census years (1990, 2000, 2010). We matched census block–level CACES model predictions for criteria air pollutants (blocks in 2010 in the contiguous US: n = ~7 million; average: ~44 residents per block) to census block group–level demographic data (block groups: n = ~220,000; ~1400 residents per block group) by calculating population-weighted mean air pollution levels for all census block centroids in that census block group using census block population data. Similarly, to match census tract-level demographic data (tracts: n = ~74,000; ~4200 residents per tract), we calculated the population-weighted mean air pollution levels for all census block groups located within that tract.

Estimating Exposures to Pollutants

We estimated annual pollutant-specific exposures for 1990 (excluding $PM_{2.5}$), 2000, and 2010 based on population-weighted mean predicted ambient air pollution levels for each demographic group (race-ethnicity, income, and income by race-ethnicity; results for additional groups [income poverty ratio, age, language, mobility, travel time] are described in the Supplemental Material [SM]). The data for the five additional groups (income poverty ratio, age, language, mobility, travel time) were extracted from NHGIS (i.e., we are directly employing values calculated by NHGIS; the values employed do not reflect our own data or calculations) (Manson et al. 2019). For all five additional groups, the rationale for including them is to explore whether exposures vary univariately for that demographic attribute. For all five additional groups, the categories used follow NHGIS categories and/or natural breaks in the data (e.g., for a ratio, separating values at, e.g., one-half, one, 1.5, two; for age, separating young children as 4 years or below, other children [who, typically, attend K12 education] as 5-17 years, adults as 18-64 years, and older adults as 65+ [reflecting an assumed retirement age]). Income poverty ratio is defined by the U.S Census as the ratio of income to poverty level in the past 12 months (Manson et al. 2019). The poverty level varies by number of people in the family and their ages; poverty level does not vary geographically (i.e., the same threshold is used throughout the US) (US Census Bureau 2021). In results shown in the SM for income poverty ratio, we bin this ratio into five categories: <0.5, 0.5-1, 1-1.5, 1.5-2, >2. The motivation for this analysis is to investigate income relative to the Census-defined poverty level. Age is binned into four categories: <5 years old, 5-17 years old , 18-64 years old , 65+ years old. Language refers to language(s) spoken in the home. For households in which language(s) other than English are spoken, the Census sub-divides household counts into (1) households in which no one 14 and over speaks English only, and (2) households in which one or more people 14 and over speaks English 'very well'. We bin the NHGIS household language data into nine categories: English only, Spanish language and no English, English and a Spanish language, Asian language and no English, English and an Asian language, European language and no English, English and a European language, other language and no English, English and other language. Mobility refers to geographical mobility in the past year for current residence, based on metropolitan statistical areas (MSA) . We bin them into six categories: (1) same house 1 year ago, (2) different house: moved from same metropolitan, (3) different house: moved from different metropolitan, (4) different house: moved from micropolitan, (5) different house: moved from not metropolitan nor micropolitan, and (5) abroad 1 year ago. Travel time refers to travel time to work for workers 16 years and over who did not work at home. We divided the data into seven categories: <10 minutes, 10-20 minutes, 20-30 minutes, 30-40 minutes, 40-60 minutes, 60-90 minutes, >90 minutes. This approach (average ambient air pollution level at residential census block group or tract) is broadly consistent with many examples in research and practice, including EPA monitors (Office of Air Quality Planning and Standards 2008), the National Ambient Air Quality Standards (e.g., Clean Air Scientific Advisory Committee 2010; Independent Particulate Matter Review Panel 2020; US EPA 2019, 2020), many influential epidemiological studies (e.g., Di et al. 2017; Laden et al. 2006; Pope et al. 2009, 2020; Shi et al 2016; Zanobetti and Schwartz 2009), and national empirical models for air pollution in the US (e.g., Bechle et al. 2015; Di et al. 2020; Goldberg et al. 2019; Kim et al. 2020; Novotny et al. 2011; US EPA 2016; Van Donkelaar et al. 2019; Young et al. 2016). We used the finest publicly available census spatial boundary data to estimate exposures for each analysis (income by race-ethnicity: tracts; all other analyses: block groups) based on availability of census demographic data.

The national annual (for O_3, 5-month average; for remaining pollutants, annual-average) exposure (e_i) for demographic group *i* was calculated for a given pollutant and year as:

$$e_i = \frac{\sum_{j=1}^{n} c_j p_{ij}}{\sum_{j=1}^{n} p_{ij}}, \qquad [1]$$

where c_j is the predicted average ambient pollution level for census block group or census tract *j* (here and after, we use *c* to represent ambient pollution level [observed or predicted] and *e* to represent population-weighted value for c), p_{ij} is the population of demographic group *i* in census block group or census tract *j*, and *n* is the number of census block groups or census tracts in the analyzed spatial level (the contiguous US, each of the 49 "states" [including the District of Columbia plus the 48 contiguous states], and urban vs. rural areas).

National Exposure Disparities Analyses

Our primary exposure disparity metrics are based on absolute and relative differences in population-weighted mean air pollution exposures. We selected metrics based on mean pollution levels for consistency with our focus on broad national average patterns in exposure disparities among multiple pollutants. Absolute disparity metrics are often connect to pollutant-specific health impacts (Harper et al. 2013) (this article focuses on pollution level disparities rather than health outcomes). Relative disparity metrics (e.g., ratios, relative percent differences) are relevant for quantifying disproportionality in exposure burdens, in a way that can be compared or summarized among different pollutants. An important limitation of these metrics (based on differences in mean exposures) is that they do not include information about disparities across the full exposure distributions (Harper et al. 2013). To address this limitation, we conducted supplemental analyses using inequality metrics accounting for full exposure distributions (Gini Coefficient and between-group Atkinson Index), as described in the SM, as well as sensitivity analyses comparing metrics based on other specific points of the exposure distribution (i.e., comparing specific exposure percentiles) as described below**.**

We calculated the absolute and relative exposure disparity metrics using two different approaches nationally: (1) by race-ethnicity group and/or income category (i.e., the unit of analysis is a national subpopulation defined by race-ethnicity and/or income), and (2) by local demographic characteristics (i.e., the unit of analysis is a set of census block groups defined based on proportion of racial-ethnic minority residents).

National Exposure Disparity Metrics Based on Racial-Ethnic Group and/or Income Category

Our primary absolute disparity metric for quantifying national racial-ethnic exposure disparities is the pollutant-specific absolute difference in population-weighted average pollution level, as calculated using **Equation (1)** with block group level data, between the racial-ethnic group with the highest national mean exposure ("most-exposed group") and the racial-ethnic group with the lowest national mean exposure ("least-exposed group") among the four racial-ethnic groups (non-Hispanic White, non-Hispanic Black, non-Hispanic Asian, Hispanic); here, the unit of analysis is a racial-ethnic group. In addition, we derived the percent difference relative to the model-predicted national mean exposure level for that pollutant {[(population-weighted mean in most exposed – population-weighted mean in least exposed)/national mean exposure]*100}. We also included relative exposure disparity metric as the pollutant-specific exposure ratio (i.e., population-weighted mean in most exposed / population-weighted mean in least exposed). Both the absolute and relative exposure disparity metrics are constructed based on differences between most and least exposed racial-ethnic groups, to provide a measure of overall racial-ethnic disparities that avoids pre-selecting two specific groups for comparison and accounts for exposure disparities across multiple groups, in a consistent way for each pollutant (accounting for potential differences in the most- and least-exposed racial-ethnic groups by pollutant). We also report averages in relative disparities across pollutants as a representation of overall average inequalities in exposure to multiple pollutants; not as a representation of inequalities in health risks, which are pollutant-specific and depend on absolute levels of pollution exposure. Lastly, as a supplemental comparison among pollutants, we also calculated inequality metrics that account for the full exposure distributions: Gini coefficients by race-ethnicity and between-group Atkinson Indices.

To quantify national income-based exposure disparities we calculated the pollutant-specific absolute difference in population-weighted average pollution level, using **Equation (1)** with block group level data, between the lowest (<$10,000) and the highest (>$200,000) household income categories (of the 16 census categories). Additionally, as a relative disparity metric, we calculated the relative percent difference in mean exposures between the lowest and highest income categories. As a supplementary analysis, we calculated similar absolute and relative exposure disparity metrics between the income category containing the 25th percentile ($20,000-25,000) and the 75th percentile ($75,000-100,000) of the income distribution.

To quantify national exposure disparities by race-ethnicity and income, we first calculated the absolute difference in population-weighted average pollution level between the most- and least-exposed racial-ethnic group (among the four racial-ethnic groups, not mutually exclusive with four racial-ethnic groups in racial-ethnic disparity, as described in **Demographic and Air Pollution Datasets (Methods section**) within each of the 16 census income categories, and then averaged that income category-specific racial-ethnic exposure disparity across all 16 income categories, for each pollutant. In the analyses for both race-ethnicity and income, we used census data for householders to calculate exposures for the four racial-ethnic groups using **Equation (1)** with tract level data. Reflecting publicly available census data for racial-ethnic groups by income category, for this section only, the Black and Asian groups include Hispanic and non-Hispanic individuals, and the Asian group does not include Pacific Islander individuals. As a relative disparity metric, we divided the absolute exposure disparity metric by the national mean pollution level, for each of the pollutants.

National Exposure Disparity Metrics Based on Local Demographic Characteristics (i.e., Block Group Bins by Proportion of Racial-Ethnic Minority Residents)

We also investigated exposure disparities based on racial-ethnic minority resident percentages; here, the unit of analysis is bin of census block groups. Each block group bin was defined as single percentile (i.e., 1%) of all block groups stratified by the proportion of racial-ethnic minority residents. There were approximately 215,000 block groups in 2010, so each block group bin contained approximately 2,150 block groups. To investigate racial-ethnic disparities among block group bins, we rank ordered all census block group bins based on percent of a racial-ethnic minority residents (i.e., people self-reporting any race-ethnicity other than non-Hispanic White alone). For example, the first block group bin was the first percentile, and consisted of all block groups with between 0% and 0.67% racial-ethnic minority residents; the second block group bin was the second percentile, consisting of all block groups with 0.67% – 0.97% racial-ethnic minority residents; the third block group bin consisted of all block groups with 0.97% – 1.2% racial-ethnic minority residents, and so on through all 100 block group bins. The last block group bin consisted of all block groups with 99% – 100% racial-ethnic minority residents. The annual exposure (e_{ig}) for demographic group i for the g^{th} percentile census block group bin (i.e., the average exposure across all block groups in the g^{th} percentile for proportion of residents that belong to a racial-ethnic minority group) was calculated for a given pollutant and year as:

$$e_{ig} = \frac{\sum_{j=1}^{n_g} c_j \mathrm{p_{ij}}}{\sum_{j=1}^{n_g} p_{ij}}, \qquad [2]$$

where c_j is the predicted average ambient pollution level for census block group j, p_{ij} is the population of demographic group i in census block group j, and n_g is the number of census block groups in the g^{th} percentile block group bin. The absolute disparity is calculated as the exposure difference between block groups with the highest- versus lowest- deciles of proportion racial-ethnic minority residents, and, similarly, the relative disparity is calculated as the exposure ratio between block groups with the highest- versus lowest- deciles of proportion racial-ethnic minority residents.

Sensitivity Analysis on Robustness of National Exposure Disparity Estimates

We conducted three sensitivity tests to investigate the robustness of conclusions based on estimated exposure disparities. First, as a sensitivity test for conclusions based on comparisons of mean values' rank order for exposures between groups, we calculated disparities using different metrics of the exposure distribution (10th, 25th, 50th, 75th, 90th percentiles).

The remaining two sensitivity tests investigated whether conclusions here are robust to uncertainty in exposure model predictions. Specifically, in the second sensitivity test, we repeated the analysis of national mean exposures by racial-ethnic group, but for only the population living in a census block group with an EPA monitor in 2010. In this sensitivity test, we used the monitor observations directly as the exposure level, rather than modeling exposures. We then calculated Spearman rank-order correlation of relative disparities by pollutant (between the most- and least- exposed group) between base case and sensitivity test.

In the third sensitivity test, we compared the magnitude of uncertainties in the estimated racial-ethnic exposure disparities with the magnitude of the estimated racial-ethnic exposure disparities. To assess the potential impact of model error on racial-ethnic disparities, we first calculated population-weighted mean error (ME_i) for each racial-ethnic group, i, using **Equation (3)**:

$$ME_i = \frac{\sum_{j=1}^{no}(c_{jm} - c_{jo})p_{ij}}{\sum_{j=1}^{no} p_{ij}}, \qquad [3]$$

where c_{jm} is the predicted average ambient pollution level for census block group j, c_{jo} is the measured average ambient pollution level across all reporting EPA monitors within census block group j, p_{ij} is the population of demographic group i in block group j, and n_o is the total number of census block groups with EPA monitors. For each pollutant, the ME of disparity between two racial-ethnic groups i_1 and i_2 induced by the model was calculated as the difference between populated-weighted ME for the most- and least-exposed racial-ethnic groups i_1 and i_2. Calculated uncertainties are based on comparison with EPA measured pollution level in 2010. We then derived the ratio between the uncertainty due to exposure model error (i.e., the difference in population-weighted mean errors between racial-ethnic groups) and the estimated disparity in mean annual exposures between the most- and least-exposed racial-ethnic groups.

National Analysis of High-End Exposure Disparities in 2010

To quantify racial-ethnic disparities at the highest exposure levels, we analyzed the racial-ethnic composition of census block groups above the 90th percentiles of the average pollution level among all census block groups. This was done seperately for each pollutant. First, for each of the four largest racial-ethnic groups, we estimated the proportion of that group's national population that lived in a high exposure block group; here, our unit of analysis is a racial-ethnic group. This calculation reflects the proportion of a racial-ethnic group's total US population that lived in heavily polluted (above the 90th percentile) block groups. We performed this calculation for each pollutant and each racial-ethnic group, using **Equation (4)**.

$$a_i = \frac{\sum_{j=1}^{n90} p_{ij}}{p_{total\_national_i}} * 100\%. \qquad [4]$$

Where a_i is the percent of racial-ethnic group i living in a block group with concentration above the 90th percentile for that pollutant, p_{ij} is the population of group i in census block group j, $p_{total\_national_i}$ is the total population for demographic group i in the United States, and n_{90} is the number of census block groups with mean pollutant concentration > 90th percentile.

In the second analysis, which was the converse of the first, we investigated the racial-ethnic composition of block groups above the 90th percentile for average pollution level. Here, our unit of analysis is all block groups above the 90th percentile. This calculation reflects the demographics of only people that lived in heavily polluted block groups. We completed this calculation for each pollutant and each racial-ethnic group using **Equation (5)**.

$$\mathrm{b_i} = \frac{\sum_{j=1}^{n90} p_{ij}}{p_{total\_block\,group}} * 100\%. \qquad [5]$$

Where b_i is (when considering only the people counted towards $P_{total\_block\,group}$) the percent of people who are in demographic group *i*, and $p_{total\_\mathrm{block\,group}}$ is the total population of census block groups above the 90th percentile in the United States for that pollutant.

In addition, we explored differences in exposures to multiple pollutants by race-ethnicity by using data for 2010 and **Equation (3)** to estimate the proportion of each major race-ethnicity group's total US population living in block groups with mean exposure levels above the 90th percentile for 0, 1, 2, 3, and ≥4 pollutants, respectively.

Counterfactual Analysis of Migration

We investigated whether changes in racial-ethnic exposure disparities over time were mainly attributable to changes in air pollution levels ("air pollution") or changes in where people lived (abbreviated as "migration", but also including immigration and other shifts in demographic patterns) as a sensitivity analysis. To do so, we employed two counterfactual scenarios (Clark et al. 2017) during two decades (1990 to 2000; 2000 to 2010). For each scenario and year, we calculated exposures for the four largest racial-ethnic groups for the contiguous US population using **Equation (1)** based on census block group data. We then calculated the absolute racial-ethnic exposure disparity between the most- and least-exposed racial-ethnic groups (referred to in this section as "disparity") for all pollutants with available data (i.e., all except $PM_{2.5}$ in 1990). To analyze 1990 to 2000, we calculated the change in disparity attributable to air pollution changed from 1990 to 2000 levels, with demographics remained constant at 1990 values (counterfactual scenario A), and used 1990 air pollution levels with demographic data changed from 1990 to 2000 values (counterfactual scenario B). To estimate the separate contribution of changes in *air pollution* during 1990 to 2000, we divided the disparity-changes from counterfactual scenario A by the "true" calculated disparity-change between 1990 and 2000 (i.e., using 1990 air pollution levels with 1990 demographic data, and using 2000 air pollution levels with 2000 demographic data). Similarly, to estimate the separate contribution of *migration* during 1990 to 2000, we divided the disparity-changes from counterfactual scenario B by the "true" calculated disparity change between 1990 and 2000. Lastly, we used an analogous approach to analyze the next decade: 2000 to 2010.

Exposure Disparities Comparison Metrics for States

We investigated patterns in absolute exposure disparities among the 48 states of the contiguous US plus the District of Columbia (DC) (hereafter, "states" refers to 48 states and DC, a total of 49 geographic units in state-level related calculations) using two metrics for racial-ethnic exposure disparity. First, for each state, pollutant, and race-ethnicity group, we calculated the normalized population-weighted disparity ($d1_i$) as the absolute difference in the annual exposure for racial-ethnic group *i* in the state (e_i) and the annual exposure for the state population as a whole (e_{state}) relative to the annual exposure across the contiguous US ($e_{national}$):

$$d1_i = \frac{e_i - e_{state}}{e_{national}}. \qquad [6]$$

Second, for each state, we used **Equation (7)** to calculate a normalized population-weighted disparity ($d2_m$) between the annual exposure for all non-Hispanic Black, non-Hispanic Asian, and Hispanic people combined (e_m), and for non-Hispanic White population (e_{NHW}). This metric has the advantage of consistently comparing, for each state, exposures between racial-ethnic minority populations and the majority racial-ethnic group population (non-Hispanic White, 64% of the population).

$$d2_m = \frac{e_m - e_{NHW}}{e_{national}}. \qquad [7]$$

Lastly, for each state, we averaged both metrics across the six pollutants.

Results

National Exposure Disparities by Race-Ethnicity and Income in 2010

By Race-Ethnicity

To investigate national disparities in exposure to criteria air pollution by race-ethnicity, we first compared national population-weighted mean exposures by US census self-reported race-ethnicity in 2010, the most recent decennial census year with available data. We first present results for differences among subpopulations (unit of analysis: racial-ethnic group), then we present differences among locations, depending on the proportion of each racial-ethnic group residents in that location (unit of analysis: census block groups binned by proportion of racial-ethnic minority residents).

Estimated national mean air pollution exposures for 2010 were higher for all three racial-ethnic minority groups than for the non-Hispanic White group for four of the six criteria pollutants (CO, NO_2, $PM_{2.5}$, and PM_{10}) (**Table 1, Table S2-S3** and **Fig. 1**). For all six pollutants, the most-exposed group was a racial-ethnic minority group: for $PM_{2.5}$ and SO_2, national mean exposures were highest for the non-Hispanic Black population; for CO, NO_2, and O_3, the non-Hispanic Asian population; and for PM_{10}, the Hispanic population. For CO, NO_2, $PM_{2.5}$, and PM_{10}, national mean exposures were lowest for non-Hispanic White population; for O_3, Hispanic population; and for SO_2, non-Hispanic Asian population. Disparities between the most- and least-exposed racial-ethnic groups were largest (based on the relative disparity ratio) for NO_2 (absolute disparity: 4.6 ppb (54%), relative disparity [ratio]: 1.6); intermediate for SO_2 (0.29 ppb (19%), 1.2), PM_{10} (3.0 μg m^{-3} (17%), 1.2), CO (0.044 ppm (16%), 1.1), and $PM_{2.5}$ (1.2 μg m^{-3} (13%), 1.1); and lowest for O_3 (1.6 ppb (3.6%), 1.0) (Table S4). Across the five pollutants, normalized disparities were also largest for NO_2 and smallest for O_3 for all the additional demographic groups considered (income poverty ratio, age, language, mobility, and travel time) (Table S5). Disparities that stand out as comparatively larger are income poverty ratio (NO_2), mobility (NO_2, CO), and travel time (NO_2) (see Fig. S1, Table S5).

Sensitivity test on robustness of conclusions based on mean values showed that, for all pollutants, the rank-order (i.e., most- to least-exposed racial-ethnic group, among the four racial-ethnic groups) was consistent throughout the exposure distributions (**Fig. 1**). Results for the supplemental inequality metrics (Gini coefficient; between-group Atkinson Index) indicate that exposure inequality was largest for NO_2 and smallest for O_3 (Table S6 and S7). This finding is consistent with the findings based on our primary metrics. The remaining two sensitivity tests investigated whether conclusions here are robust to uncertainty in exposure model predictions. Results reveal that the conclusions are robust to exposure model uncertainty. Results for analyzing only the population living in a census block group with an EPA monitor in 2010 were essentially the same as results using exposure model predictions: the non-Hispanic White group was the least-exposed group on average for most pollutants (CO, NO_2, $PM_{2.5}$, PM_{10}, and O_3), and the relative disparities by pollutant (between the most- and least- exposed group on average) were highly-correlated (Spearman rank-order correlation between base case and sensitivity test:

0.89) (Table S8 and S9). The ratio between the uncertainties in estimated racial-ethnic exposure disparities and the estimated racial-ethnic disparities between the most- and least-exposed racial-ethnic groups were small: on average across the six pollutants, 0.0073 (if using absolute values of the ratio, 0.083). The largest absolute ratio was -0.17 [O_3]. That result indicated that the uncertainty in the exposure model predictions was always small compared to the predicted racial-ethnic exposure disparities (Table S10 and S11).

We also performed an analysis to determine whether average air pollution levels varied based on the racial-ethnic composition of a given census block group. For CO, NO_2, $PM_{2.5}$, and PM_{10}, average pollution levels were higher in census block groups with higher proportions of racial-ethnic minority residents (**Fig. 2**). For O_3, estimated average levels were approximately equal across census block group bins, regardless of census block group racial-ethnic characteristics (**Fig. 2**). For SO_2, estimated average levels were generally higher in census block group bins with the highest and lowest proportions of racial-ethnic minority residents (i.e., higher in more racially segregated census block groups) (**Fig. 2**). This approach also reveals that the disparities were much larger for NO_2 than for other pollutants. The disparity in average air pollution levels between block groups with the highest- versus lowest- deciles of proportion racial-ethnic minority residents (block groups with >88% vs. <4% racial-ethnic minority residents) was larger for NO_2 (absolute disparity: 9.4 ppb, relative disparity [ratio]: 3.1) than for other pollutants (relative disparity [ratio] range: 0.8 – 1.4, median: 1.1) (Table S12).

Lastly, we investigated racial-ethnic disparities in exposure to the highest air pollution levels. First, for each racial-ethnic group we calculated the proportion of people nationally who lived in a block group with air pollution levels above the 90th percentile for each pollutant. Averaged across all pollutants, the proportion of people nationally who lived in those highest-exposure block groups was: 9.6% for the overall population, 17% for the Hispanic population, 15% for the non-Hispanic Asian population, 12% for the non-Hispanic Black population, and 7.2% for the non-Hispanic White population. Racial-ethnic minority populations were more likely than non-Hispanic White populations to live in a census block group with air pollution levels above the 90th percentile for all pollutants (range: 1.0× to 4.1×, median: 2.1×) except SO_2 (0.88×) (Fig. S2 and Table S13). Next, we calculated the racial-ethnic composition of the block groups with air pollution levels above the 90th percentile for each pollutant. Non-Hispanic White populations decomposed less proportion above the 90th percentile block groups than that of national for all pollutants besides SO_2 (Fig. S3 and Table S14). Racial-ethnic minority populations were also disproportionately likely to live in a census block group having *multiple* pollutants with levels above the 90th percentile. For example, the proportion of population living in a census block group with levels above the 90th percentile for four or more criteria pollutants was 5.2% for the Hispanic population (3.6× the national population average proportion), 2.2% for the non-Hispanic Asian population (1.5× the average), 1.9% for the non-Hispanic Black population (1.3× the average), and 0.36% for the non-Hispanic White population (0.25× the average) (for comparison: 1.4% for the overall US population) (Table S14). The ratio of the non-Hispanic White population relative to the national population average in each block group category declined monotonically as the number of pollutants above the 90th percentile increased from 0 to ≥4 (ratios from 1.1 to 0.25), while corresponding ratios increased monotonically for non-Hispanic Black (from 0.88 to 1.3) and Hispanic populations (from 0.84 to 3.6), and increased non-monotonically for non-Hispanic Asian populations (from 0.88 for 0 pollutants to 2.3 and 1.5 for 3 and ≥4 pollutants >90th percentile, respectively.) (Fig. S4 and Table S15).

By Income

To investigate national exposure disparities by income, we first compared national mean exposures to criteria air pollution by census income category in 2010. For all pollutants except O_3, national mean exposures were higher for lowest-income (<$10,000; 7.2% of the households with income data) than for highest-income (>$200,000; 4.2%) households, with all pollutants except NO_2 (and, to a lesser extent, CO and O_3) exhibiting a monotonic trend (Fig. S5). (Consistent with those findings, we also find that for the remaining three pollutants [SO_2, $PM_{2.5}$, PM_{10}], but not for O_3, NO_2, and CO, the most-exposed income category is the lowest-income category and the least-exposed income category is the highest-income category; see Table S16.) Relative to the overall population-weighted mean exposure for all households in 2010, the absolute difference between mean exposures among those in the lowest versus highest-income category households were 16% (relative to national mean exposure) higher for SO_2, 6.6% higher for $PM_{2.5}$, and 5.2% higher for PM_{10}. For NO_2, CO, and O_3, exposures for lowest- and highest-income households were similar (~±2%) (Table S17). (For comparison, for NO_2, CO, O_3, exposure differences between the most- and least-exposed income categories were 2.5% to 9.4%; see Table S16.)

Based on differences in average exposures between the approximate 25th and 75th percentiles for income ($20,000-25,000 [midpoint: $22,500] and $75,000-100,000 [midpoint: $87,500]), a $10,000 increase in income was associated with an average reduction in concentration (expressed as a percent of the national mean concentration) of 0.90% for SO_2, 0.41% for $PM_{2.5}$, 0.36% for NO_2, and 0.22% for PM_{10} and CO, and an increase of 0.16% for O_3. For NO_2, the change in average exposure per $10,000 increase in income was 0.59% between the 25th and 50th ($40,000-45,000 [midpoint: $42,500]) percentiles, and 0.26% between the 50th and 75th percentile (Table S18).

By Both Race-Ethnicity and Income

In this section, we present exposure disparities accounting for both race-ethnicity and income together for census householders (hereafter, "households"). For all six pollutants, the absolute exposure disparity between the most- and least-exposed racial-ethnic groups was larger (on average, ~6× larger; 1.1× for SO_2, 21× for NO_2, 1.4×-6.8× for the remaining pollutants) than the absolute exposure disparity between the lowest- and highest-income categories in 2010 (relative disparity: on average, ~ 1.2× larger). The absolute exposure disparity between the most- and least-exposed racial-ethnic groups is 5.8× for NO_2 (1.1× for SO_2, and 1.4×-4.4× for remaining pollutants) than the absolute exposure disparity between the most- and least-exposed income categories (Table S19). For all income levels and pollutants, the most-exposed racial-ethnic group was a racial-ethnic minority group (**Fig. 3** and Table S20). For five of the six pollutants (not SO_2; **Fig. 3**), average exposures were higher on average for Black households at the approximate 75th percentile for income (income category midpoint: $87,500) than for non-Hispanic White households at the approximate 25th percentile for income (midpoint: $22,500). Racial-ethnic exposure disparities tended to be comparatively smaller at higher incomes than at lower incomes (except for O_3), but the size of that effect was modest. For example, the absolute exposure disparity between the most- and least-exposed racial-ethnic groups (**Fig. 3**) was, on average, 9.5% lower for households at the approximate 75th percentile than at the approximate 25th percentile of income.

Income distributions varied by racial-ethnic group. For example, non-Hispanic White households represented 61% of the lowest income category (<$10,000) and 85% of the highest income category (>$200,000), versus 23% and 3.5%, respectively, for Black households, 13% and 4.3% for Hispanic households, and 3.5% and 6.9% for Asian households (Table S21). To quantify racial-ethnic exposure disparities after accounting for racial-ethnic income distribution variation, we calculated the absolute exposure disparity between the most- and least- exposed racial-ethnic groups within each income category in 2010 and then averaged across all 16 income categories. The resulting national absolute exposure disparity between most- and least-exposed racial-ethnic groups averaged across income categories and normalized to national mean exposure (i.e., expressed as a percent of the national mean concentration) was 58% for NO_2, 4.5% for O_3, 12% to 17% for the remaining pollutants. Conversely, to quantify income exposure disparities after accounting for race-ethnicity, we calculated the absolute income disparity within each racial-ethnic group and averaged across the four racial-ethnic groups. The resulting national absolute exposure disparity between lowest and highest income categories normalized to national mean exposure was 15% for SO_2, -2.9% for O_3, and 2.7% to 6.3% for the remaining pollutants (Table S22). In conclusion, the results given here, consistent with Liu (2021), indicate that racial-ethnic exposure disparities were distinct from, and larger than, exposure disparities by income.

Racial-ethnic Exposure Disparities by State and by Urbanicity in 2010

By State

We explored how exposures varied by state, pollutant, and racial-ethnic group in 2010 (**Fig. 4**). The analysis separately considers the District of Columbia (DC) plus the 48 states of the contiguous US (hereafter, “states” refers to 48 states and DC, a total of 49 geographic units in state-level related calculations). There are 294 pollutant-state combinations (6 pollutants × 49 units and 1176 pollutant-state-groups (294 pollutant-states × 4 racial-ethnic groups). For this section, we define ±5% (all percentages used in this section were expressed as a percent of the national mean exposure in 2010) as “similar to”, and therefore report examples where exposures differ from the average by >5% (or, in a sensitivity test, >20%). For example, “>5% lower-than-average” means the exposure is lower-than-state average by an amount greater than 5% of the pollutant’s national mean.

Overall, several spatial patterns emerge across states. First, racial-ethnic exposure disparities were ubiquitous among US states. In all 48 states and DC, one or more racial-ethnic groups experienced exposures >5% of the state average exposure in 2010. Second, racial-ethnic minority populations within states were much more likely to have been more-exposed versus less-exposed than the state average; in contrast, none of the non-Hispanic White populations within states experienced exposures >5% above the state average. Third, having exposures >5% lower-than-average within a state was much more likely to happen for non-Hispanic White populations than for racial-ethnic minority (non-Hispanic Black, non-Hispanic Asian, and Hispanic populations combined) populations (**Fig. 4**, right column). Fourth, racial-ethnic exposure disparities were most pronounced (in magnitude and with regard to the number of states affected) for NO_2, while mean O_3 exposures were similar among all racial-ethnic groups in all states.

Those findings reflect underlying trends across states, pollutants, and racial-ethnic groups. For example, for the non-Hispanic White group, 87% of the 294 pollutant-states had exposures that were similar (±5%) to the average, 13% had exposures >5% less than average, and none were >5% greater than average. In contrast, for exposures for the three racial-ethnic minority groups, 42% (of 882 pollutant-state-groups) were >5% greater than average, 55% were

±5% of the average, and only 4% were >5% less than average. Thus, within individual states, the non-Hispanic White group was exposed to pollution levels that were similar to or cleaner than average, whereas the three racial-ethnic minority groups were more likely to be exposed to dirtier rather than cleaner pollution levels. For example, averaged across pollutants, the proportion of the states for which exposures were >5% greater than average is 73% for non-Hispanic Black populations, 57% for Hispanic populations, 35% for non-Hispanic Asian populations, and zero for non-Hispanic White populations.

The three racial-ethnic minority groups were disproportionately *likely* to be the *most*-exposed group, and disproportionately *unlikely* to be the *least*-exposed group of the four racial-ethnic groups across states. For example, the most-exposed group (for all cases, not just cases >5% greater than average) was the non-Hispanic Black group for 45% of the 294 pollutant-areas, the Hispanic group for 29%, the non-Hispanic Asian group for 18%, and non-Hispanic White group for 7.5%. In contrast, the least-exposed group was rarely a racial-ethnic minority group (~8% of all 294 pollutant-states for the non-Hispanic Black and for Hispanic group, 15% for the non-Hispanic Asian group) and was usually (70% of 294 pollutant-states) the non-Hispanic White group.

Changed the analysis threshold to exposures >20% greater than average (rather than 5%) found that the air pollution disproportionately impacted racial-ethnic minority groups. For example, exposure disparities >20% of national mean exposure for one or more pollutant-groups occurred for 67% of states (**Fig. 4**, left four columns for six pollutants), further emphasizing that disparities were widespread across states in 2010.

Fig. 4 reveals differences among states. For example, the four most populous states (California, Florida, New York, Texas), all have large, racially/ethnically diverse urban areas. However, average disparities between racial-ethnic minority populations and non-Hispanic White populations (**Fig. 4** bottom right) were notably larger (on average, 6× larger) for California and New York than for Florida and Texas (Excel Table S1). Some small, relatively rural states also had substantial exposure disparities. Examples include NO_2 in Nebraska (19%) and $PM_{2.5}$ in Nebraska (8.1%).

By Urbanicity

We investigated racial-ethnic and income-based exposure disparities in 2010 separately for block groups that were defined as urban (89% of the population) versus rural (11% of the population). Overall, urban population experienced larger exposure than that of rural population for all pollutants (Table S23).

The most- and least-exposed of the four racial-ethnic groups differed between urban and rural areas for SO_2 and for O_3. For SO_2, the most-exposed racial-ethnic group was the non-Hispanic Black group in urban areas and the non-Hispanic White group in rural areas. For O_3, the most-exposed racial-ethnic group was the non-Hispanic Asian group in urban areas and non-Hispanic White group in rural areas. For the remaining four pollutants, the most-exposed group was a racial-ethnic minority group in both urban and rural areas (Table S24).

The racial-ethnic exposure disparities were generally larger for urban than for rural block groups. Specifically, the average exposure disparity between the most- and least-exposed racial-ethnic group was 5.5× larger for absolute disparity (1.2× for relative disparity [ratio between relative disparity in urban areas and relative disparity in rural areas]) for urban block groups than for rural block groups for NO_2, 3.1× (1.0×) larger for O_3, 2.4× (1.1×) larger for CO, 1.3× (1.0×) larger for SO_2, and 1.2× (1.0×) larger for PM_{10}. In contrast, for $PM_{2.5}$, the average racial-ethnic exposure disparity was 1.2× (1.0×) larger for rural block groups than for urban block groups (Table S24).

Exposure disparities by income category were also larger in urban than in rural areas. Absolute exposure disparities between lowest and highest income category were 1.1× [$PM_{2.5}$] to 25× [O_3] (median: 3.5×) greater (for relative disparity [ratio], range: 0.98× to 1.1×, median: 1.0×) in urban than in rural areas (Table S25). Of the 12 pollutant-urbanicity categories (6 pollutants × 2 urbanicities), exposures were higher for the lowest-income category than for the highest-income category in all cases except for O_3 in urban areas and for NO_2 in rural areas (Table S25).

Changes in National Exposures and Exposure Disparities from 1990 – 2010

Criteria air pollution levels have declined in the US in the decades following the 1990 Clean Air Act amendments (US EPA 2020) (Table S26). To investigate if these reductions have led to reductions in racial-ethnic exposure disparities, we compared average exposures by racial-ethnic group from 1990 to 2010, for five of the pollutants. Exposure model results for $PM_{2.5}$ were only available from 2000 to 2010, so those results are presented separately.

National mean pollution levels of all six pollutants fell over the study period. For example, from 1990 to 2010, the national mean exposures decreased for all five pollutants by an average of 40% relative to national mean exposures in 1990 (range: -6% [O_3] to -71% [SO_2]; -34% to -55% for remaining three pollutants). $PM_{2.5}$ exposures decreased 29% from 2000 to 2010 (Table S27).

The average racial-ethnic exposure disparities also declined from 1990 – 2010. The amount of change depends in part on whether one considers *absolute* or *relative* disparities. In terms of *absolute* disparities, the disparities between the most- and least-exposed racial-ethnic groups decreased on average by 69% relative to absolute disparity in 1990 across the five pollutants. The largest change was an 88% decrease for CO disparities (0.40 ppm in 1990, 0.044 ppm in 2010, a 0.35 ppm [i.e., 88%] change) and the smallest change was a 54% decrease for NO_2 (9.8 ppb [1990], 4.6 ppb [2010], a 5.3 ppb [54%] change). From 2000 to 2010, $PM_{2.5}$ disparities decreased by 35% (1.9 $\mu g\ m^{-3}$ [2000], 1.2 $\mu g\ m^{-3}$ [2010], a 0.66 $\mu g\ m^{-3}$ change) (Table S28).

In terms of *relative* disparities, the greatest change during 1990 – 2010 was a decrease for CO (disparities: 1.63 [1990], 1.15 [2010], 0.71× [i.e., 29% reduction]) and the smallest was a decrease for O_3 (1.10 [1990], 1.04 [2010], 0.95× [i.e., 5% reduction]); remaining three pollutants (NO_2, PM_{10}, SO_2) were between 0.94× and 0.95× (i.e., 5%–6% reduction in relative disparity). $PM_{2.5}$ relative disparity remained nearly constant (0.99×) during 2000 to 2010 (Table S28).

Absolute disparities between census block group bins with the highest versus lowest deciles of proportions of racial-ethnic minority residents (90^{th} - 100^{th} versus 1^{st} - 10^{th} percentiles in **Fig. 2**) decreased for CO, NO_2, PM_{10}, and SO_2 (by 10%[SO_2] to 164%[CO]) and decreased by 17% from 2000 to 2010 for PM2.5 (Table S29). For O_3, absolute disparities increased slightly, from -1.7 ppb in 1990 to -1.3 ppb (which is 0.74% of the national mean exposure) in 2010.

In addition to national changes, we investigated changes in absolute racial-ethnic exposure disparities from 1990 to 2010 by state and by urban versus rural areas. Most states (>75%) experienced a reduction in racial-ethnic exposure disparities for pollutants except for PM_{10} (and, except for $PM_{2.5}$ during 2000-2010) (Fig. S6, Table S30). Urban areas experienced larger reductions in racial-ethnic exposure disparities than did rural areas for NO_2 and PM_{10} (13× larger reductions in urban areas, for both pollutants), CO (2.4×), and SO_2 (1.2×). Conversely,

$PM_{2.5}$ (during 2000-2010) and O_3 (during 1990-2010) had larger reductions in absolute racial-ethnic disparities for rural than for urban (2.4× and 3.4× larger in rural areas, respectively) (Fig. S7, Table S31).

Finally, we investigated whether the changes in absolute racial-ethnic exposure disparities from 1990 to 2010 were more attributable to changes in air pollution levels or to changes in demographic patterns (migration, immigration, and other factors). Based on a counterfactual analysis, reductions in racial-ethnic exposure disparities between the most- and least- exposed racial-ethnic groups were mainly attributable to changes in air pollution levels rather than to changes in demographic patterns. On average across all pollutants, 87% of the reduction in the absolute racial-ethnic disparity metric was attributable to changes in air pollution levels from 1990 to 2000 (excluding $PM_{2.5}$ based on lack of available data), and 97% from 2000 to 2010 (Table S32 and S33).

Discussion

Our research provides the first national investigation of air pollution exposure disparities by income and race-ethnicity for all criteria pollutants (except lead). Our results reveal trends by pollutant and across time and space.

In 2010, on average nationally, racial-ethnic minority populations were exposed to higher average levels of transportation-related air pollution (CO, NO_2) and particulate matter ($PM_{2.5}$, PM_{10}) than non-Hispanic White populations. This finding, which holds even after accounting for uncertainties in the predictions from exposure models, is consistent with prior national studies of NO_2, $PM_{2.5}$, and PM_{10} (Clark et al. 2017; Kravitz-Wirtz et al. 2016; Mikati et al. 2018; Tessum et al. 2019; Colmer et al. 2020). Disparities for the remaining pollutants (CO, O_3 and SO_2) had not been previously studied in detail for the national population, and few studies have considered how disparities for any pollutant have changed across 20 years (Kravitz-Wirtz et al. 2016; Bullard et al. 2008).

Our findings on "which group was most-exposed over time?" (on average, nationally) varied by pollutant, but in all six cases the most exposed group was a racial-ethnic minority group. That result is consistent with prior national studies, which have reported, for example, highest average NO_2 exposures for Hispanic Black and non-Hispanic Asian populations (Clark et al. 2017), and highest average proximities to industrial $PM_{2.5}$ emissions (Mikati et al. 2018) and highest average exposures to industrial air toxins (Ard 2015) for non-Hispanic Black populations.

We found that racial-ethnic minority populations were more than two times as likely than non-Hispanic white populations to live in a census block group with highest air pollution levels (above 90^{th} percentile) on average. Those results are consistent with existing literature on disproportionate environmental risks for racial-ethnic minority populations (Collins 2016) and on groups or locations with higher risks for one environmental factor having higher risks for other factors too (Morello-Frosch and Lopez 2006; Su et al. 2012).

We found that air pollution exposures were generally higher for lower-income than for higher-income households (for all pollutants except O_3). This finding is consistent with previous national research (e.g., for industrial $PM_{2.5}$ emissions (Mikati et al. 2018), industrial air toxins (Ard 2015), and $PM_{2.5}$ and NO_2 (Clark et al. 2014; Kravitz-Wirtz et al. 2016)). Additionally, we found that, in 2010, absolute racial-ethnic exposure disparities were distinct from, and were larger than (on average, ~6× larger than), absolute exposure disparities by income. The findings here are *inconsistent* with the idea that racial-ethnic exposure disparities can be explained by, or are "merely" a reflection of, income disparities among racial-ethnic groups (Liu, 2021).

The findings from this study can be used to compare relative exposure disparities for different criteria air pollutants in a consistent way, providing additional context for previous studies of single pollutants. We found that in 2010, relative racial-ethnic exposure disparities (i.e., ratios of average exposures between the most- and least-exposed groups) were largest for NO_2 and smallest for O_3. Relative income-based exposure disparities (i.e., ratios of average exposures between the lowest and highest income groups), although smaller than racial-ethnic exposure disparities for each pollutant, were largest for SO_2 and smallest (and similar) for NO_2, CO, and O_3. (These results provide information on the rank-order of relative disparities in air pollution levels by pollutant; information on the rank-order of relative disparities in associated health impacts by pollutant would require further analysis, as discussed next).

Exposure disparities often connect with health disparities. Based on the magnitude of exposure disparities (e.g., 2010 national average $PM_{2.5}$ exposures for non-Hispanic Black people were 1.0 μg m^{-3} higher-than-average), the resulting health disparities may be substantial (Liu 2021). Future research could usefully extend our exposure disparity results to provide rigorous, comprehensive investigation of the associated health impacts.

State-level results may be especially useful given the important role that states play in air pollution and environmental policy making (Abel et al. 2015). Exposures >5% greater than the national mean exposure within states were common for racial-ethnic minority populations, but not for non-Hispanic white populations. This finding reflects disparity in exposure as well as non-Hispanic White populations representing a large percentage of states' populations. Exposure disparities varied substantially among states, even among states with similar characteristics (e.g., urbanicity, population, region). Our results emphasize differences among states in the level and makeup of exposure disparities, yet also demonstrate that exposure disparities were ubiquitous, including both large and small states, and states in all regions of the US, in 2010.

Our analyses by urbanicity were in part motivated by, and reflect, urban-rural differences in demographics and air pollution levels (Clark et al. 2017; Mikati et al. 2018; Rosofsky et al. 2018). Racial-ethnic disparities were larger for urban block groups for all pollutants except $PM_{2.5}$. Of the six pollutants, the largest ratio between urban and rural racial-ethnic absolute disparity (5.5× larger) was for NO_2 (Table S24). The NO_2 results are consistent with prior research (Clark et al. 2017). Over our study period, reductions in absolute racial-ethnic exposure disparity for $PM_{2.5}$ and O_3 were larger for rural than for urban areas. Analyzing urban and rural block groups separately, exposures were mostly higher for the lowest income category than the highest. Absolute income-based exposure disparities were also 7.5 times larger on average in urban than in rural areas.

The results by state and by urbanicity reflect that exposure disparities differ by spatial units (e.g., urban/rural, and by state); future research could explore these aspects further, for example, through a spatial decomposition of national exposure disparities.

Regulations such as the 1990 Clean Air Act Amendments have achieved substantial reductions in the concentrations of many pollutants. Our analysis reveals that, as a co-benefit, falling pollution levels have reduced absolute exposure disparities among racial-ethnic groups. These findings are consistent with previous national research for NO_2, $PM_{2.5}$, and industrial air toxins (Ard 2015; Clark et al. 2017; Kravitz-Wirtz et al. 2016; Colmer et al. 2020). We found that a larger share of the racial-ethnic exposure disparity reduction was attributable to air pollution level reduction rather than changes in demographic and residential patterns.

Our study described patterns in exposure disparities but did not investigate aspects such as underlying causes or ethical or legal aspects. Systemic racism and racial segregation are two major causes discussed in multiple previous studies (Jones et al. 2014; Morello-Frosch and Lopez 2006; Schell et al. 2020). Future longitudinal research could further investigate the underlying causes of exposure disparities. One important dimension not considered here is responsibility for generating pollution. Recent analysis suggests that Hispanic and Black populations have disproportionately lower consumption of goods and services whose emissions lead to $PM_{2.5}$ air pollution (Tessum et al. 2019).

Our study has several limitations. The finest spatial scale of publicly-available Census demographic data for race-ethnicity and income is at Census block group level; race-ethnicity across income data is at Census tract level with slightly different categories (see Methods); we were unable to assess disparities at finer spatial scales than what the Census provides; we only included the four main racial-ethnic groups. Our analysis of exposures by income is based on national-level income distribution data and does not account for spatial variations in income distributions (e.g., among states). Our disparity estimates do not account for (1) daily mobility for work, shopping, recreation, and other activities, (2) direct indoor exposure to indoor sources such as cigarette smoke, cooking emissions, or incense, (3) indoor-outdoor relationships in pollution levels, such as particle losses during airflow in ducts or ozone losses to indoor surfaces, or (4) occupational exposures. Our exposure disparity estimates were limited by uncertainties in the CACES exposure model predictions and in Census demographic data. Our uncertainty analysis (but not our main analysis) was limited to US EPA monitoring locations; we were not able to test potential exposure errors at locations without monitors on the national scale.

To our knowledge, our study provides the first national analysis of air pollution exposure disparities among income and racial-ethnic groups, for all criteria pollutants (except lead), including trends across time (by decade, 1990–2010) and spatial location (by state and for urban versus rural areas). On average, exposures were generally higher for racial-ethnic minority populations than for non-Hispanic White populations. Among pollutants, national racial-ethnic exposure disparities were largest for NO_2 and smallest for O_3. Exposures were also, on average, higher for the lowest-income households than for the highest-income households. However, exposure disparities by race-ethnicity were not explained by disparities in income. Racial-ethnic exposure disparities declined from 1990 to 2010 (on an absolute basis, and to a lesser extent, on a relative basis), but still existed in all states in 2010.

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Tables

Table 1. Population distribution and population-weighted exposure distribution for six criteria pollutants for four main racial-ethnic groups in year 2010.

Demographic	Non-Hispanic White	Non-Hispanic Black	Hispanic	Non-Hispanic Asian	Entire Population
Proportion of population	64%	12%	16%	4.6%	100%
$PM_{2.5}$ (μg m^{-3})					
10th percentile	6.1	7.9	6.5	6.7	6.3
25th percentile	7.7	9.2	7.7	8.2	7.9
50th percentile	9.3	10	9.6	9.7	9.5
Mean (SD)	9.1 (2.2)	10 (1.8)	9.4 (2.2)	9.4 (1.9)	9.3 (2.2)
75th percentile	11	11	11	11	11
90th percentile	12	13	12	12	12
NO_2 (ppb)					
10th percentile	3.1	3.8	4.6	5.4	3.4
25th percentile	4.3	5.8	6.6	7.5	4.9
50th percentile	6.2	8.7	9.5	10	7.4
Mean (SD)	7.2 (4.1)	9.7 (5.3)	11 (6.1)	12 (5.9)	8.7 (5.1)
75th percentile	8.9	12	15	15	11
90th percentile	12.5	18	21	21	16
O_3 (ppb)					
10th percentile	38	39	33	39	38
25th percentile	43	43	42	44	43
50th percentile	47	47	46	47	47
Mean (SD)	46 (6.0)	46 (6.1)	45 (7.2)	46 (5.9)	46 (6.2)
75th percentile	50	50	49	50	50
90th percentile	52	53	52	53	52
SO_2 (ppb)					
10th percentile	0.91	1.0	0.83	0.79	0.95
25th percentile	1.1	1.2	1.0	1.0	1.2
50th percentile	1.5	1.6	1.3	1.2	1.5
Mean (SD)	1.6 (0.65)	1.7 (0.63)	1.4 (0.55)	1.4 (0.58)	1.6 (0.64)
75th percentile	1.9	2.1	1.7	1.7	2.0
90th percentile	2.4	2.5	2.2	2.3	2.5
PM_{10} (μg m^{-3})					
10th percentile	12	14	15	14	13
25th percentile	14	16	17	16	15
50th percentile	17	19	20	19	18
Mean (SD)	18 (4.4)	19 (3.7)	21 (4.9)	20 (4.5)	18 (4.6)
75th percentile	21	21	23	22	22
90th percentile	23	23	28	25	24
CO (ppm)					
10th percentile	0.23	0.25	0.26	0.27	0.24

25th percentile	0.27	0.29	0.30	0.30	0.28
50th percentile	0.31	0.32	0.34	0.34	0.31
Mean (SD)	0.30 (0.057)	0.32 (0.067)	0.35 (0.079)	0.35 (0.071)	0.31 (0.066)
75th percentile	0.33	0.35	0.39	0.38	0.35
90th percentile	0.37	0.40	0.45	0.45	0.39

Figure captions

Fig. 1. Distribution of exposure to pollutants in years 1990, 2000, and 2010, stratified by racial-ethnic group, for (A) $PM_{2.5}$, (B) NO_2, (C) O_3, (D) SO_2, (E) PM_{10}, and (F) CO. For all panels, the highest/lowest bound represents the $90^{th}/10^{th}$ percentile value, the box shows the 25^{th} and 75^{th} percentiles, and the horizontal line in the box represents the median. Color circles indicate the national population-weighted mean. $PM_{2.5}$ has no estimates in 1990 because of a lack of monitoring data prior to 1999. Note: CO=carbon monoxide, NO_2=nitrogen dioxide, O_3=ozone, $PM_{2.5}$=particulate matter with diameters that are generally 2.5 micrometers and smaller, PM_{10}=particulate matter with diameters that are 10 micrometers and smaller, and SO_2=sulfur dioxide. “NH” refers to non-Hispanic. “Hispanic” refers to Hispanic people of any race(s).

Fig. 2. Relationship between the proportion of racial-ethnic minority residents in census block groups and average criteria air pollution concentrations in the years 1990, 2000, and 2010 for A) $PM_{2.5}$, (B) NO_2, (C) O_3, (D) SO_2, (E) PM_{10}, and (F) CO. For each panel, the bold portion of the line indicates the 25^{th} to 75^{th} percentile of census block groups, the thin line indicates the 10^{th} and 90^{th} percentiles, the dashed line indicates the 1^{th} and 99^{th} percentiles, and the diamond icon indicates the median. Note: CO=carbon monoxide, NO_2=nitrogen dioxide, O_3=ozone, $PM_{2.5}$=particulate matter with diameters that are generally 2.5 micrometers and smaller, PM_{10}=particulate matter with diameters that are 10 micrometers and smaller, and SO_2=sulfur dioxide. “NH” refers to non-Hispanic. “Hispanic” refers to Hispanic people of any race(s).

Fig. 3. Population-weighted criteria air pollution concentration in 2010 for 16 household income groups, stratified by race-ethnicity, for (A) $PM_{2.5}$, (B) NO_2, (C) O_3, (D) SO_2, (E) PM_{10}, and (F) CO. For all panels, each data point represents pollution exposure for one income category and racial-ethnic group. Values plotted for household income are, for values below \$200k (i.e., for the first 15 income categories), the midpoint value; for the highest income category (">\$200k"), the value plotted is the low end of the range (\$200k). Note: CO=carbon monoxide, NO_2=nitrogen dioxide, O_3=ozone, $PM_{2.5}$=particulate matter with diameters that are generally 2.5 micrometers and smaller, PM_{10}=particulate matter with diameters that are 10 micrometers and smaller, and SO_2=sulfur dioxide. “NH White” refers to non-Hispanic White people. “Hispanic” refers to Hispanic people of any race(s). “Asian” refers to Hispanic and non-Hispanic Asian people. “Black” refers to Hispanic and non-Hispanic Black people.

Fig. 4. **State racial-ethnic disparities in average pollution exposure in 2010, showing the difference between (1) NH White vs. state average, (2) NH Black vs. state average, (3) Hispanic vs. state average, (4) NH Asian vs. state average, and (5) Minority vs. NH White for the six pollutants (A) $PM_{2.5}$, (B) NO_2, (C) O_3, (D) SO_2, (E) PM_{10}, and (F) CO, and (G) average across the six pollutants.** Columns 1-4: exposure disparity relative to state average; calculated as mean exposure for a racial-ethnic group in that state minus the overall mean for that state, then divided by the national overall mean. Column 5: exposure disparity for racial-ethnic minorities relative to the racial-ethnic majority group; calculated as mean exposure for racial-ethnic minorities minus mean exposure for non-Hispanic White people, then divided by the national overall mean. Mean values are population-weighted. States displayed in white indicate

that the disparity is within ±5% of the national overall mean. Purple shading indicates that mean exposures are higher-than-average by more than 5% of the national overall mean (columns 1-4) or that mean exposures are higher for racial-ethnic minorities than for the racial-ethnic majority, by more than 5% of the national overall mean (column 5). Orange shading indicates the reverse: mean exposures are lower-than-average for that group (columns 1-4) or mean exposures are lower for racial-ethnic minorities than for non-Hispanic White people (column 5), and the disparity is greater than 5% of the national overall mean. See Excel Table S1 for corresponding numeric data. Note: CO=carbon monoxide, NO_2=nitrogen dioxide, O_3=ozone, $PM_{2.5}$=particulate matter with diameters that are generally 2.5 micrometers and smaller, PM_{10}=particulate matter with diameters that are 10 micrometers and smaller, and SO_2=sulfur dioxide. "NH" refers to non-Hispanic. "Hispanic" refers to Hispanic people of any race(s).

Supplemental Material

Supplementary material are available online.

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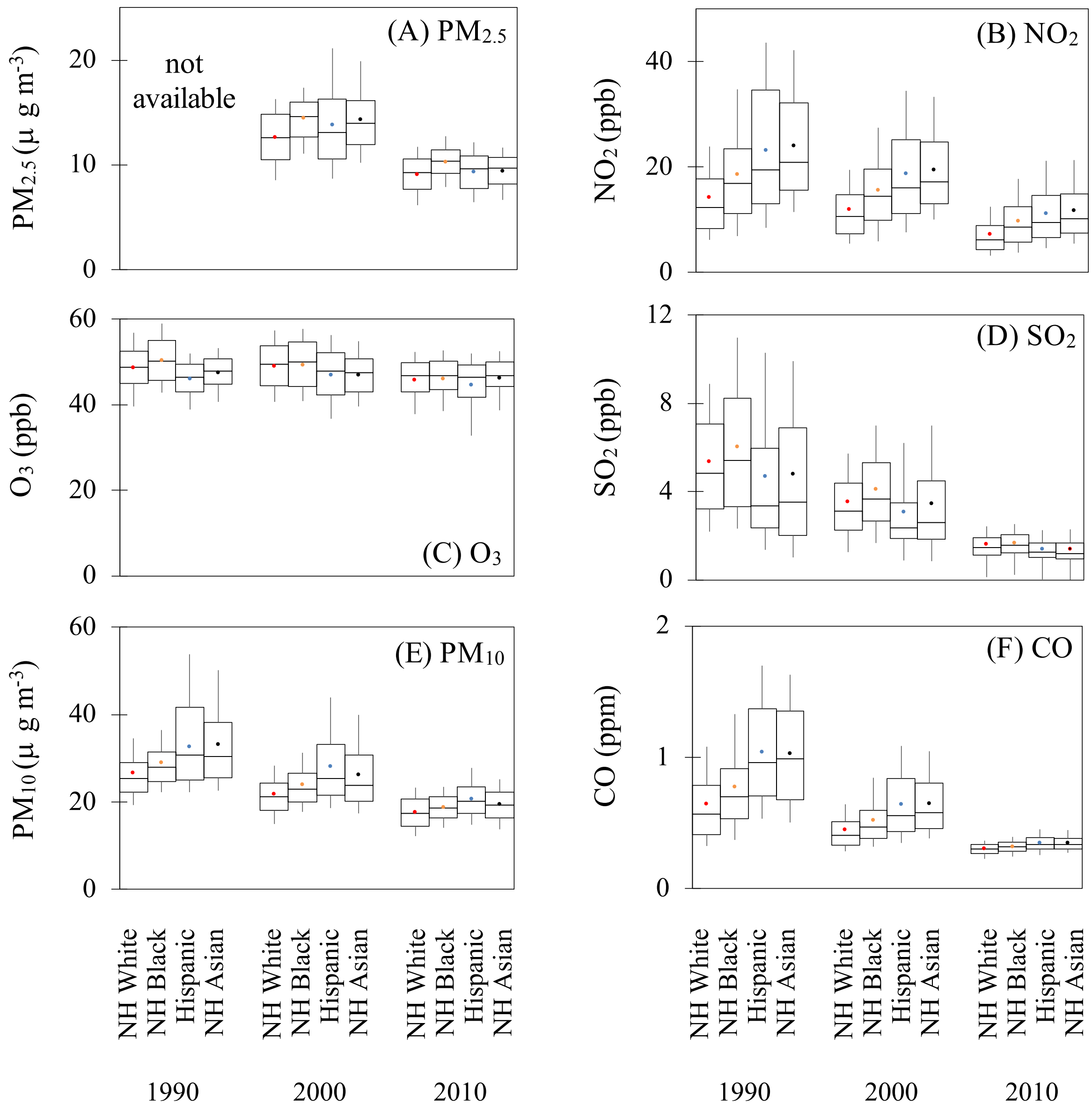
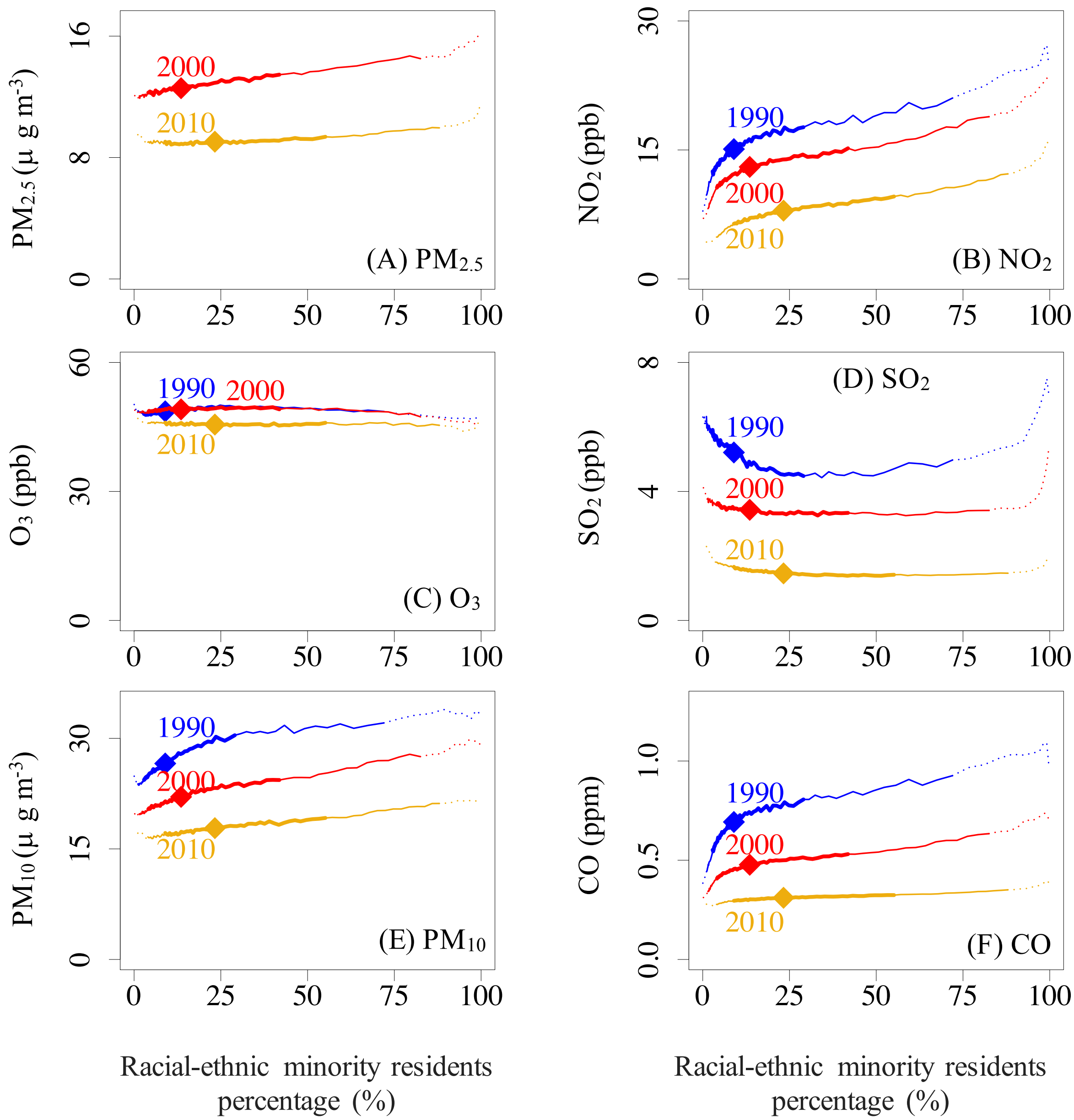
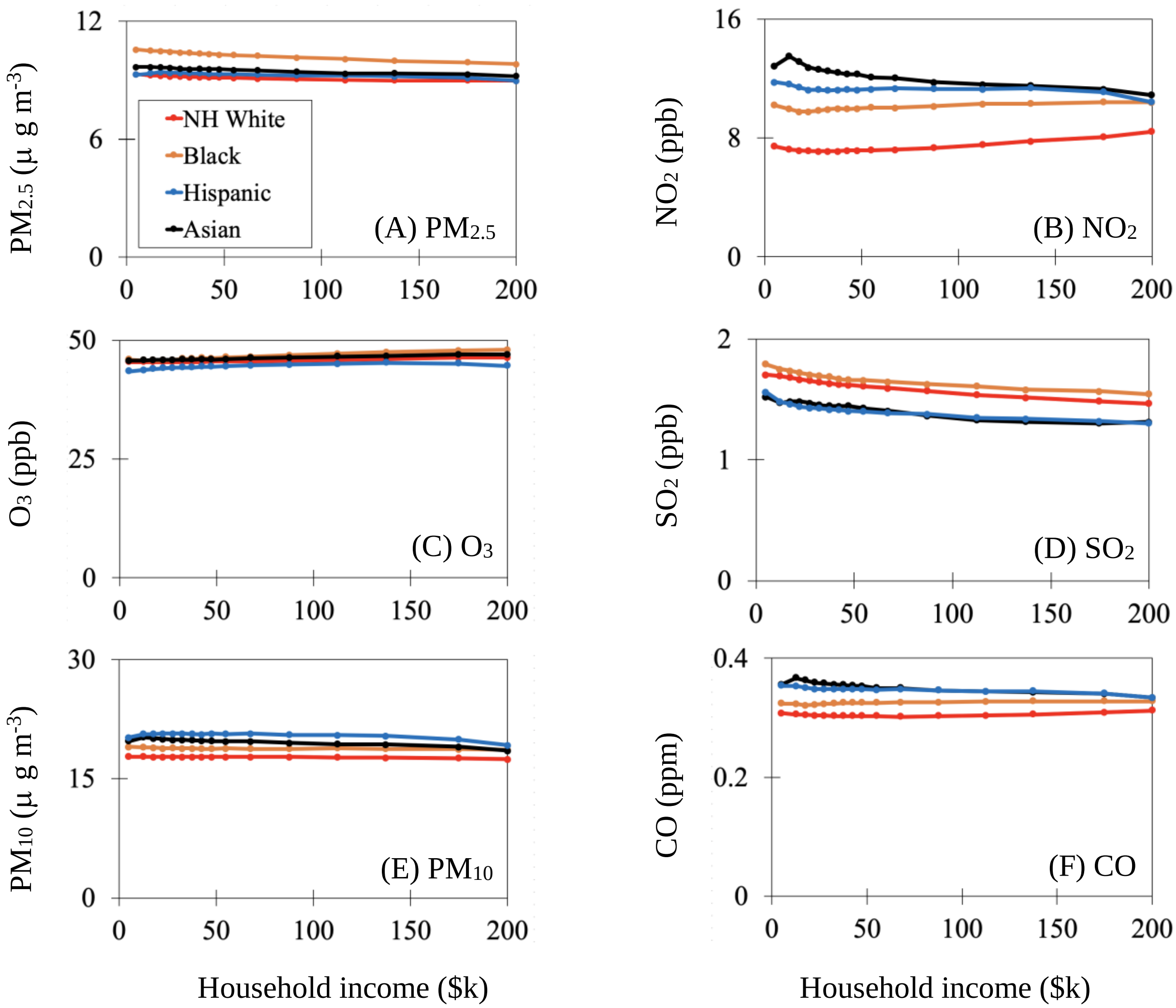
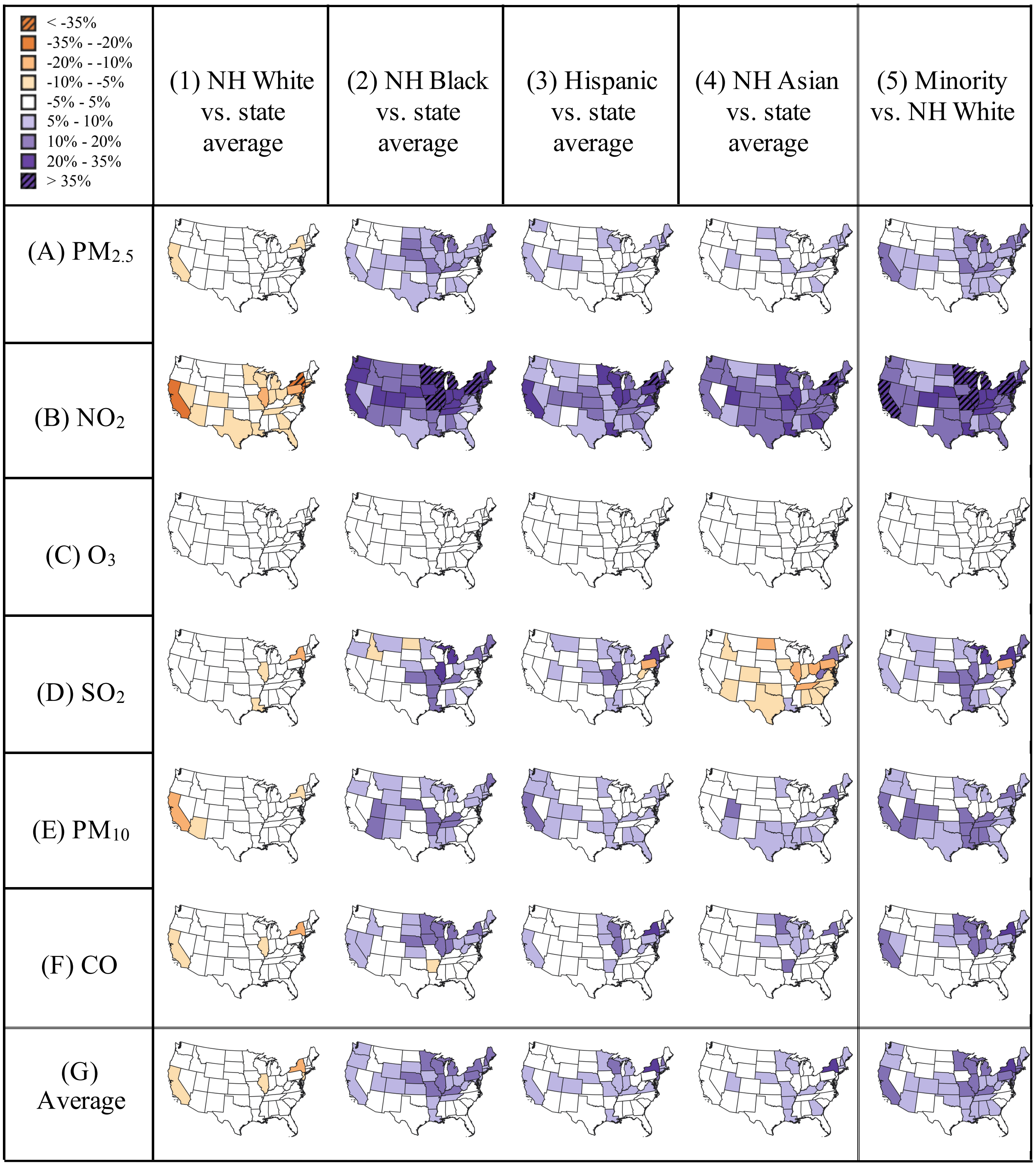

(A) $PM_{2.5}$
not available
$PM_{2.5}$ (μ g m^{-3})
0
10
20
(B) NO_2
NO_2 (ppb)
0
20
40
(C) O_3
O_3 (ppb)
0
20
40
60
(D) SO_2
SO_2 (ppb)
0
4
8
12
(E) PM_{10}
PM_{10} (μ g m^{-3})
0
20
40
60
(F) CO
CO (ppm)
0
1
2
NH White
NH Black
Hispanic
NH Asian
1990
2000
2010



(A) PM2.5
PM2.5 (μ g m-3)
(B) NO2
NO2 (ppb)
(C) O3
O3 (ppb)
(D) SO2
SO2 (ppb)
(E) PM10
PM10 (μ g m-3)
(F) CO
CO (ppm)
1990
2000
2010
Racial-ethnic minority residents percentage (%)



(A) $PM_{2.5}$
(B) NO_2
(C) O_3
(D) SO_2
(E) PM_{10}
(F) CO
NH White
Black
Hispanic
Asian
$PM_{2.5}$ (μ g m^{-3})
NO_2 (ppb)
O_3 (ppb)
SO_2 (ppb)
PM_{10} (μ g m^{-3})
CO (ppm)
Household income ($k)
Household income ($k)



< -35%
-35% - -20%
-20% - -10%
-10% - -5%
-5% - 5%
5% - 10%
10% - 20%
20% - 35%
> 35%
(1) NH White vs. state average
(2) NH Black vs. state average
(3) Hispanic vs. state average
(4) NH Asian vs. state average
(5) Minority vs. NH White
(A) $PM_{2.5}$
(B) NO_2
(C) O_3
(D) SO_2
(E) PM_{10}
(F) CO
(G) Average