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# Temporal Trends in Air Pollution Exposure Inequality in Massachusetts

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## Abstract

Mounting evidence over the past several decades has demonstrated inequitable distribution of pollutants of ambient origin between sociodemographic groups in the United States. Most environmental inequality studies to date are cross-sectional and used proximity-based methods rather than modeled air pollution concentrations, limiting the ability to examine trends over time or the factors that drive exposure inequalities. In this paper, we use 1 $km^2$ modeled $PM_{2.5}$ and $NO_2$ concentrations in Massachusetts over an 8-year period and Census demographic data to quantify inequality between sociodemographic groups and to develop a more nuanced understanding of the drivers and trends in longitudinal air pollution inequality. Annual-average population-weighted $PM_{2.5}$ and $NO_2$ concentrations were highest for urban non-Hispanic black populations (11.8 μg/$m^3$ in 2003 and 8.4 μg/$m^3$ in 2010, vs. 11.3 μg/$m^3$ and 8.1 μg/$m^3$ for urban non-Hispanic whites) and urban Hispanic populations (15.9 ppb in 2005 and 13.0 ppb in 2010, vs. 13.0 ppb and 10.2 ppb for urban non-Hispanic whites), respectively. While population groups experienced similar absolute decreases in exposure over time, disparities in population-weighted concentrations increased over time when quantified by the Atkinson Index, a relative inequality measure. Exposure inequalities were approximately one order of magnitude greater for $NO_2$ compared to $PM_{2.5}$, were more pronounced in urban compared to rural geographies, and between racial/ethnic groups compared to income and educational attainment groups. Our results also revealed similar longitudinal $PM_{2.5}$ and $NO_2$ inequality trends using Census 2000 and Census 2010 data, indicating that spatio-temporal shifts in air pollution may best explain observed trends in inequality. These findings enhance our understanding of factors that contribute to persistent inequalities and underscore the importance of targeted exposure reduction strategies aimed at vulnerable populations and neighborhoods.

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Conflicts of interest
None

### Keywords

air pollution; environmental inequality; environmental justice; longitudinal analysis; inequality index

## 1. Background

Ambient exposure to nitrogen dioxide ($NO_2$) and fine particulate matter ($PM_{2.5}$) have been associated with a range of adverse health effects including increased risk of asthma and respiratory infections (Brauer et al., 2002; O'Connor et al., 2008; Xing et al., 2016), adverse birth outcomes such as early gestational age and low birth weight (Brauer et al., 2008; Stieb et al., 2012; Zheng et al., 2016), increased risk of autism spectrum disorders (Raz et al., 2015; Volk et al., 2013), and all-cause mortality (Franklin et al., 2008; Shi et al., 2016). Mounting evidence over the past several decades has demonstrated inequitable distribution of exposure to $PM_{2.5}$ and $NO_2$ in the United States among children and older adults, non-Hispanic black and Hispanic populations, low educational attainment and low income populations, potentially contributing to environmental health disparities (Bell and Ebisu, 2012; Brugge et al., 2015; Clark et al., 2014; Morello-Frosch and Lopez, 2006; Su et al., 2009).

However, there are three key limitations in the exposure inequality literature to date. First, much of the environmental inequality (EI) research is cross-sectional, examining environmental inequalities at one point in time. This limits the ability to examine longitudinal trends or the causal mechanisms that drive inequality (Legot et al., 2012; Mohai et al., 2011; Pastor et al., 2004). In particular, there is limited insight about whether disparities are driven by population shifts subsequent to siting of hazardous facilities or roadways, disparate siting practices in poor communities and communities of color, or policies focused on decreasing ambient pollution that simply do not examine distributional consequences. Investigators in both the sociological and environmental health literature argue that residential segregation is a main driver of environmental health disparities (Mohai and Saha, 2015; Morello-Frosch and Lopez, 2006), so demographic shifts over time could have an influence on land use practices, declining social capital and local economies and ultimately, community-level environmental exposures (Mohai and Saha, 2015a; Pastor et al., 2004, 2001). Further, demographic change over time could modify inequalities even in the absence of changes in air quality. Therefore, it is imperative to incorporate demographic time trends in air pollution exposure inequality studies.

Second, a limited number of studies have used quantitative metrics to assess EI over space and time. Quantifiable measures of exposure inequality allow regulators to formally assess patterns of EI and to maximize efficiency in exposure reduction policies that seek to reduce environmental exposures, while simultaneously incorporating social equity into distributional assumptions (Boyce et al., 2016; Harper et al., 2013; Levy et al., 2007, 2006). A handful of environmental studies to date have incorporated formal inequality indices to assess geographic and social distribution of environmental hazards (Boyce et al., 2016; Clark et al., 2014; Levy et al., 2007, 2006; Post et al., 2011; Su et al., 2009). These previous studies have adopted welfare-based or health-based measures of inequality to assess sociodemographic distributions of exposure to a single hazard (Boyce et al., 2016; Clark et al., 2014; Fann et al., 2011; Levy et al., 2006; Post et al., 2011) or cumulative environmental hazards (Su et al., 2009). This paper employs the Atkinson Index (AI) (Atkinson, 1970), a relative measure of inequality, discussed in further detail below. Although some previous studies have used the AI to quantify exposure inequality (Clark et al., 2014; Levy et al., 2009, 2006; Post et al., 2011), these studies focused to a greater extent on understanding the inequality implications of air pollution control strategies, and not on longitudinal patterns of inequality.

Most EI studies examine inequitable distributions of hazardous facilities among population subgroups (Mohai and Saha, 2015a, 2015b). A limited, but growing number of EI studies have examined inequalities with respect to both hazardous facilities and traffic-related air pollution using modeled or measured ambient concentrations. However, many are at coarse geographic resolutions, ignore chemical fate and transport and local meteorological conditions, and do not address longitudinal trends in EI (Clark et al., 2014; Hajat et al., 2015; Kravitz-Wirtz et al., 2016; Mohai and Saha, 2015b; Morello-Frosch and Jesdale, 2006; Pope et al., 2016). Pollutants such as $NO_2$ and $PM_{2.5}$ have significant public health burdens but are not typically dominated by local emissions from hazardous facilities, reinforcing the importance of an exposure-based analytical approach to identify EI occurring at smaller spatial scales.

In this paper, we quantify inequality in modeled ambient $PM_{2.5}$ and $NO_2$ concentrations between racial, ethnic, income and education groups across Massachusetts between 2003 and 2010 using methods to address the three major limitations in this area of research. The work applies a formal inequality index to examine patterns of exposure among rural and urban populations as a means to identify populations most vulnerable to air pollution exposure within the state. The availability of demographic data from the decennial 2000 and 2010 Census at the block group level and modeled ambient air pollution at a 1 $km^2$ resolution over an eight-year period provides us the unique opportunity to examine inequalities over time and develop a more nuanced understanding of whether $PM_{2.5}$ and $NO_2$ exposure inequalities are driven by demographic shifts or longitudinal pollution source distribution.

## 2. Methods

### 2.1 Data Sources

**2.1.1 Ambient air pollution for Massachusetts, 2003–2010—**Daily surface $PM_{2.5}$ at a 1 $km^2$ resolution was modeled from 2003–2010 using a 3-stage statistical modeling approach (Kloog et al., 2014). This modeling approach used a combination of aerosol optical depth (AOD) satellite data retrieved using the multi-angle implementation of atmospheric correction (MAIAC) algorithm, land use and meteorological predictors of variation in surface-$PM_{2.5}$, and monitored $PM_{2.5}$ concentrations (Kloog et al., 2014). This produced an overall “out-of-sample” $R^2$ for daily values of 0.88, and cross validation results produced a slope of observed versus predicted of 0.99. Details of the $PM_{2.5}$ prediction models can be found in in Kloog et al. (2014).

We used daily ground $NO_2$ concentrations that were estimated for the New England region from 2005–2010 at a 1 $km^2$ resolution from a combination of ground-level $NO_2$ data at monitoring sites, satellite Ozone Monitoring Instrument $NO_2$ vertical column density data, and land use regression (Lee and Koutrakis, 2014). Predictors in mixed effects models included population density, distance to major highways, percent developed area, $NO_2$ source emissions, elevation, and temperature data. This model produced an $R^2$ of 0.79 and cross validation results produced a slope of observed versus predicted of 0.98, demonstrating high predictive reliability. $NO_2$ model details can be found in Lee and Koutrakis (2014).

**2.1.2 Demographic Data—**We gathered geographic distributions of race/ethnicity, income, and educational attainment from the US Census and American Community Survey (ACS) at the block group unit of analysis. Measures of educational attainment and income were not collected in the decennial 2010 Census. Therefore, we obtained race/ethnicity data from Census 2010, and measures of income and educational attainment from ACS 2006–2010 5-year estimates. We categorized block groups as rural and urbanized centers according to Census classifications, which rely on population density (Ratcliffe et al., 2016). We utilize Census data at two distinct time periods, 2000 and 2010, rather than at 1-year intervals over the decade under study because the non-decennial 1-year summaries from the ACS are less-reliable, constitute a smaller sample size, and were only collected starting in 2005.

We categorized population characteristics into the following groups:

- Race/ethnicity: individuals in each block group that self-identify as non-Hispanic white, non-Hispanic Black, non-Hispanic Asian, Hispanic or other
- Income: 1999 and 2010 inflation-adjusted median household income as < $20,000/year, $20–35,000/year, $35–50,000/year, $50–75,000/year, and > $75,000/year
- Educational Attainment: individuals in each block group ≥25 years of age with less than a high school degree, high school graduate, postsecondary degree, bachelors and graduate degree

We aggregated daily $PM_{2.5}$ and $NO_2$ concentrations to average annual concentrations. Annual $PM_{2.5}$ (years 2003–2010) and $NO_2$ (years 2005–2010) concentrations were assigned to each block group centroid using the closest 1 $km^2$ grid cell centroid for each year over the study period. This exposure assignment method was performed separately for Census 2000 and ACS/Census 2010 block groups using ArcGIS 10.3 (ESRI, Inc.).

## 2.2 Statistical Analysis

**2.2.1 Summary Statistics—**We calculated summary statistics for Massachusetts of the number and percentage of individuals and households within each racial/ethnic and education group and the percentage change between 2000 and 2010 stratified by urban (densely developed territories with 50,000 or more people (Census 2000, n=4277; Census and ACS 2010, n=4308)) and rural (any territory not defined as urban (Census 2000, n=654; Census and ACS 2010, n=596)) block groups (Table 1). Median household income in 2010 dollars is also presented for both time points. Due to the small number of block groups categorized by the Census Bureau as "urban clusters," territories containing between 2,500 and 50,000 residents (Census 2000, n=116; Census and ACS 2010, n=75), these block groups were excluded from stratified analyses.

**2.2.2 Calculating Population-Weighted Concentrations across Subpopulations—**We calculate block group population-weighted $PM_{2.5}$ concentrations for each year from 2003 to 2010, and population-weighted $NO_2$ concentrations for each year from 2005 to 2010. As corresponding annual population data are not available, we calculate separately using each of Census 2000, Census 2010 and ACS 2006–2010, and we evaluate the influence of using alternative population data. Population-weighted concentrations were calculated for each population demographic group stratified by urban and rural classifications. Block-group $PM_{2.5}$ and $NO_2$ ($PM_{2.5i}$, $NO_{2i}$) were multiplied by the number of people in each population subgroup ($p_i$). The subgroup block group values were summed for the state and divided by the total population in each subgroup:

$$\frac{\sum PM_{2.5_i}pi}{\sum pi} \text{ or } \frac{\sum NO_{2_i}pi}{\sum pi} \quad (1)$$

**2.2.3 Quantifying Inequality Using the AI—**We formally quantify air pollution exposure inequality between population subgroups using the Atkinson Index (AI) (Atkinson, 1970). The AI has been traditionally used as a welfare-based measure of income inequality (Kawachi and Kennedy, 1997), but has since been adopted in the environmental inequality literature (Clark et al., 2014; Levy et al., 2007, 2006). The AI can be decomposed into between-group, within-group and total inequality measures (Lasso de la Vega and Urrutia, 2003; Levy et al., 2006). This feature allows investigators to compare distributions of pollutants between population subgroups, and determine whether total inequality in a population can be explained by disproportionate pollution burden between population subgroups (Harper et al., 2013).

For the purposes of the current analysis, we present only "between-group" inequality, as the focus of this paper is examining trends in environmental inequality between population subgroups given the environmental justice implications. The AI ranges from zero to one, zero indicating no inequality and one indicating complete inequality.

The Between-Group AI can be expressed as:

$$1-\left(\sum_{j=1}^{n} f_i\left[\frac{\overline{y}_j}{\overline{y}}\right]^{1-\varepsilon}\right)^{\frac{1}{1-\varepsilon}} \quad (2)$$

where $n$ represents the number of individuals in the population, $f_j$ represents the fraction of the total population in each subgroup, $\overline{y}_j$ represents mean exposure of each subgroup, $\overline{y}$ represents the mean exposure over the full population within a given geographic boundary (state, rural or urban) and ε represents an explicit inequality aversion parameter, explained below (Atkinson, 1970). The AI is therefore a relative (as opposed to absolute) measure of inequality, so that proportional changes in exposure across the population would not influence the AI, but additive changes would have an effect. By comparing each subgroup's weighted exposure to the overall population average exposure within a defined geography, the between-group AI represents the magnitude, in relative terms, of exposure disparities between population subgroups. This is an overall measure of inequality between defined subgroups- it does not explicitly provide information about which of those subgroups are most inequitably exposed.

The inequality aversion parameter is a measure of societal concern about inequality. It determines where relative weights should be placed across the exposure distribution. The parameter ranges from zero to infinity, with increasing values reflecting greater weight on the bottom of the distribution. Unlike income, environmental exposures are worse at higher levels, so we perform all AI calculations with the inverse of the pollution concentrations to allow for interpretable calculations (Harper et al., 2013). All calculations presented here apply an aversion parameter of 0.75, consistent with the literature (Clark et al., 2014; Fann et al., 2011; Levy et al., 2009, 2007, 2006; Post et al., 2011). As a sensitivity analysis, we report the AI for multiple alternative inequality aversion parameters (0.25–2) in the Appendix (Figure A4).

Applying the AI ($\varepsilon$ =0.75), we quantified between-group $PM_{2.5}$ and $NO_2$ exposure inequality by applying average annual $PM_{2.5}$ concentrations for each year between 2003 and 2010 and average annual $NO_2$ concentrations for each year between 2005 and 2010, keeping the demographic data constant.

## 3. Results

### 3.1 Population Characteristics

State-wide demographic characteristics by block group in 2000 and 2010 are presented in Table 1. Overall, the Massachusetts state population grew by 3.1% between 2000 and 2010. The state contained 81.9% Non-Hispanic white in 2000 and 76.1% in 2010. The Hispanic population increased by 47% from 2000 to 2010, growing from 6.7% of the population to 9.6%. The percent of the population with less than a high school education decreased 3.9 percentage points from 2000 to 2010. Average inflation-adjusted median household income among all Massachusetts block groups was essentially unchanged, although the $10^{th}$ percentile value decreased by $3,383 (9.8%) and the 95th percentile value increased by $4,407 (3.4%), indicating growing income inequality.

We observe distinct population distribution changes between block groups categorized as rural or urban. The size of the population grew by 5.3% in urban block groups and decreased by 4.1% in rural block groups. Overall, a higher percentage of racial/ethnic minorities live in urban than in rural block groups. Urban non-Hispanic whites experienced the greatest change of any population group between 2000 and 2010, decreasing by 6.2%. Educational attainment distributions are similar between rural and urban block groups in both 2000 and 2010, and both experienced a decrease in the population with less than a high school education. In general, median household incomes were higher in rural than in urban block groups, and the growing income inequality was more pronounced in urban areas.

### 3.2 Population Weighted Concentrations

Based on modelled $PM_{2.5}$ and $NO_2$, we find that average annual $PM_{2.5}$ concentrations across the state decreased by 35% between 2003 and 2010, and that average annual $NO_2$ concentrations decreased by 24% between 2005 and 2010. Concentrations were consistently lower in rural than urban areas, but patterns of change remained the same between the two strata (Figures 1a and 1b).

Tables 2 and 3 display snapshots of subgroup population-weighted $PM_{2.5}$ and $NO_2$ concentrations, along with absolute and relative (percent) change in exposure over the study period for the full state and rural/urban classifications. Population-weighted concentrations for $PM_{2.5}$ in 2003 and $NO_2$ concentrations in 2005 were calculated using the Census 2000 population, approximating the spatial and demographic distributions of the population in those years. For $PM_{2.5}$ and $NO_2$ population-weighted concentrations in 2010, the Census 2010 and ACS 2006–2010 populations were used to characterize the population distribution (Tables 2 and 3). Figures 2a–f display population weighted trends in $PM_{2.5}$ and $NO_2$ concentration for each year between 2003 and 2010 using demographic data from Census 2010 and ACS 2006–2010, allowing us to isolate the effects of changing concentrations from any sociodemographic shifts. Longitudinal changes in population-weighted concentrations using demographic data from Census 2000 can be found in the Appendix (Figures A1a–A1f).

**3.2.1 $PM_{2.5}$—**Overall, weighted $PM_{2.5}$ exposures in 2003 across the state ranged from 11.1 to 11.7 μg/m$^3$ across racial/ethnic groups, with ranges in urban block groups from 11.3 to 11.8 μg/m$^3$ and in rural block groups from 10.1 to 10.8 μg/m$^3$ (Table 2). In 2010, weighted $PM_{2.5}$ exposures ranged across racial/ethnic groups ranged from 7.8 to 8.4 μg/m$^3$, 8.1 to 8.5 μg/m$^3$ and 6.8 to 7.0 μg/m$^3$ across the state and among urban and rural populations, respectively. Across the state in 2003, $PM_{2.5}$ concentrations were highest for the non-Hispanic black (11.7 μg/m$^3$) population among racial/ethnic groups, those with less than a high school education (11.3 μg/m$^3$) among education groups, and those with incomes less than $20,000 per year (11.4 μg/m$^3$) among income groups. Among racial/ethnic groups in 2003, the greatest difference in population weighted concentration was between non-Hispanic whites (11.1 μg/m$^3$) and non-Hispanic blacks (11.7 μg/m$^3$), and in 2010 the greatest difference was between non-Hispanic whites (7.8 μg/m$^3$) and both Hispanic and non-Hispanic black (8.4 μg/m$^3$) populations. These patterns were present in urban but not rural block groups. The absolute decrease in $PM_{2.5}$ over time was relatively homogenous across all population groups.

Figures 2a–c display population weighted trends in $PM_{2.5}$ exposures from 2003 to 2010, holding Census 2010 and ACS 2006–2010 data constant. Among racial and ethnic groups, non-Hispanic Asian populations experienced the largest decrease in $PM_{2.5}$ exposures between 2003 and 2010 in both urban (28.8%) and rural (33.6%) locations, whereas the urban Hispanic population experienced the lowest percentage decrease (27.3%). Among rural income groups, the greatest decrease in $PM_{2.5}$ was observed for median incomes above \$75,000 per year (33.5%), a pattern that differed from urban income groups. In general, the population groups with the highest exposures in 2003 experienced lower relative decreases in exposures over time, consistent with similar absolute reductions across populations. Holding the Census 2000 population constant over annual $PM_{2.5}$ concentrations reveals similar results (Figures A1a–A1c).

**3.2.2 $NO_2$—**Table 3 displays population weighted $NO_2$ concentrations, absolute and percent decrease in exposure for the full state, and patterns of exposure stratified by sociodemographic characteristics and rural/urban status. Across the state in both 2005 and 2010, $NO_2$ concentrations were highest for Hispanic populations (15.8 ppb in 2005 and 12.8 ppb in 2010), those with less than a high school education (14.5 ppb in 2005 and 11.9 ppb in 2010) and households in the lowest income bracket (14.4 ppb in 2005 and 11.7 ppb in 2010). Patterns were identical in urban block groups. However, in rural block groups, the non-Hispanic Asian population experienced the highest exposure in 2005 (11.6 ppb), while non-Hispanic whites (7.9 ppb) had the highest $NO_2$ burden in 2010. Those in the highest income bracket in rural block groups also experienced the highest $NO_2$ concentrations in both 2005 and 2010.

Figures 2d–f display trends in population-weighted $NO_2$ concentrations from 2005 to 2010 using demographic data from Census 2010 and ACS 2006–2010. In general, the rate of $NO_2$ concentration decrease was greater in rural than urban block groups. Similar to $PM_{2.5}$, population-weighted $NO_2$ exposure inequality existed for urban, but not rural, sociodemographic groups. Trends in population-weighted $NO_2$ exposure make clear that patterns of inequalities persisted from 2005 to 2010, and that urban racial/ethnic minorities, low income and education groups remained the highest exposure groups. Results are similar when applied to the Census 2000 population (Figures A1d–A1f).

### 3.3 Atkinson Index

**3.3.1 $PM_{2.5}$—**We estimate the AI for each year, separately using Census 2000 and Census 2010/ACS 2006–2010, to determine how exposure inequality has evolved over time and whether this is related to concentration patterns or changing demographics. Overall, AI trends and values are relatively insensitive to the choice of population data (Figure 3). The principal difference between the two demographic years is demonstrated in modestly higher rural exposure inequality trends among racial/ethnic and income groups for the Census 2000 compared to the Census 2010 population. These results indicate that both population mobility and shifting $PM_{2.5}$ distributions contribute to rural exposure inequality trends. Exposure inequality trends among all subgroups living in urban block groups are nearly identical between 2000 and 2010, indicating that shifting $PM_{2.5}$ distributions (and not population mobility) are likely driving observed exposure inequality trends in urban areas.

Between-sociodemographic group $PM_{2.5}$ inequality using the AI reveals peaks of increased and decreased inequality over time as a result of $PM_{2.5}$ concentration distributions in urban block groups, and a slight decreasing trend among rural block groups (Figure 3a). We additionally find that inequality is generally greater in magnitude, especially after 2005, in urban block groups. Although the AI values are generally low, they are consistently higher for racial/ethnic groups compared to inequality among income and education groups. The AI results seen here are explained by non-Hispanic black and Hispanic populations, low-income, and low educational attainment populations consistently experiencing a greater $PM_{2.5}$ burden than the other racial/ethnic, income and education groups (Table 2). As all sociodemographic groups experience a similar absolute decrease in exposure, the lowest exposed groups, such as non-Hispanic whites, undergo greater relative rates of exposure decline over time.

**3.3.2 $NO_2$—**We observe distinctly different patterns in quantified $NO_2$ inequality as compared to $PM_{2.5}$ inequality (Figure 3). AI values are generally low but approximately one order of magnitude greater for $NO_2$ compared to $PM_{2.5}$. Between 2005 and 2010 there is a slight increase in $NO_2$ inequality among all population strata located in urban block groups. Inequality was greatest for racial/ethnic subpopulations in urban block groups, which also experienced the greatest rate of increase in AI over time. AI results were similar between when using Census 2000 and Census 2010/ACS 2006–2010 population data.

## 4. Discussion

Our study builds on previous environmental inequality analyses that use measures of proximity or coarsely-resolved measures of air pollution exposure and investigate inequality at one point in time by incorporating longitudinal Census data and pollution concentrations. This work additionally builds on the current literature by employing a novel application of the AI to formally quantify inequality between population groups over time.

Although modeled and monitored air pollution data have demonstrated longitudinal reductions in concentrations, our highly-resolved and stratified analyses provided some novel insights with respect to exposure inequalities. For example, we found distinct differences in population-weighted concentration patterns and trends over time between $PM_{2.5}$ and $NO_2$ and between urban and rural geographic areas. Urban areas contain greater densities of low-income, non-white and low-educational attainment populations and $PM_{2.5}$ and $NO_2$ pollution sources, contributing to some exposure heterogeneity and potential inequalities. Greater concentration of urban air pollution sources is reflected in our findings of non-Hispanic blacks, individuals with lower educational attainment, and households with an annual income of <$20K as the most burdened population groups for both $NO_2$ and $PM_{2.5}$ concentrations throughout the state.

That said, $PM_{2.5}$ concentrations are more regional than local in nature because they are derived from a wide variety of sources, with a strong contribution from secondary pollutant formation and long-range transport (Zheng et al., 2002). $NO_2$ is strongly linked to automobiles and other mobile sources and tends to exhibit high intra-urban variability. As such, it has greater potential for exposure inequalities in urban settings. $PM_{2.5}$ is a regionally-based pollutant, exhibiting less spatial variability in urban areas, leading to smaller exposure disparities compared to $NO_2$ (Clougherty et al., 2008). These pollutant-specific characteristics are reflected in our finding of $NO_2$ inequality that is greater in magnitude than $PM_{2.5}$ inequality. Higher $NO_2$ inequality growth rates within urban areas, especially between racial/ethnic groups, may further be explained by increased local source emissions, such as higher traffic counts over time or increased transportation infrastructure in Boston neighborhoods containing high proportions of non-Hispanic black and Hispanic populations (Brugge et al., 2015; Levy et al., 2001).

In rural settings, $NO_2$ exposures were disproportionately higher for Hispanic populations, individuals with lower educational attainment, and households with lower income in urban block groups, but higher for non-Hispanic Asians and the wealthiest population groups in rural block groups. This could reflect the fact that roadway proximity tends to decrease property value in urban areas, but may potentially increase them in rural areas (Bateman et al., 2001; Lake et al., 1998). Analyses that did not stratify by urban/rural status would not appropriately characterize exposure inequality or capture key between-group differences.

We additionally found fluctuations in $PM_{2.5}$ inequality and increasing trends in between-group $NO_2$ inequality, despite similar absolute rates of $PM_{2.5}$ and $NO_2$ decline across population groups. Uniform absolute reductions are beneficial to all but do not decrease exposure inequalities, and in fact, tend to increase them for metrics such as the AI given growing relative differences. Similar AI trends using Census 2000 and Census 2010 populations indicates that sociodemographic mobility is not the main driver of urban $PM_{2.5}$ and statewide $NO_2$ inequality trends, although it could remain a contributing factor. It would be informative for future studies to examine inequality trends using annual demographic data where available, holding ambient concentrations constant.

Because most environmental inequality studies rely on cross-sectional data, they do not inform our understanding of the components that contribute to changing inequality over time (Bell and Ebisu, 2012; Lopez, 2002; Miranda et al., 2011; Pastor et al., 2004; Rosofsky et al., 2014). Our application of the AI to characterize exposure inequality addresses this literature gap by separately examining population and air pollution patterns, to determine which best explains changing inequality. To our knowledge, only one study to date has applied the AI to describe spatial patterns of pollution across sociodemographic characteristics and between rural and urban areas (Clark et al., 2014). Clark et al. (2014) findings of population-weighted racial/ethnic and income disparity for $NO_2$ exposure nationwide were similar to our results: nonwhite and low-income populations experienced the greatest burden of $NO_2$ exposure, and these disparities were more pronounced in large urban areas than rural areas.

A handful of studies within the environmental inequality literature have also moved to address this gap (Kravitz-Wirtz et al., 2016; Mohai and Saha, 2015b; Pastor et al., 2001). One recent study by Kravitz-Wirtz et al. (2016) examined trends in racial and ethnic disparities in exposure to neighborhood air pollution across the U.S., while controlling for individual and neighborhood-level changes over time. The authors found that black and Hispanic participants were disproportionately exposed to higher concentrations of $NO_2$, $PM_{2.5}$ and $PM_{10}$ compared to white participants, and that concentrations decreased for all racial and ethnic groups over time. In contrast to our findings, rate of decline in $PM_{2.5}$ and $NO_2$ exposure among black and Hispanic participants were more pronounced than for white participants. The authors hypothesized that these findings are explained by more rapid decreases in pollution in urban areas, where black and Hispanic participants of the study reside. However, our study found the opposite effect, with concentrations of $PM_{2.5}$ and $NO_2$ falling more rapidly in rural areas, and for the non-Hispanic white population.

In general, our AI values are quite small, and we observed small absolute differences in $PM_{2.5}$ and $NO_2$ concentrations between population groups. However, AI values cannot be reasonably compared across contexts (i.e., income spans many orders of magnitude, whereas ambient air pollution has a narrower range within a state), and are most meaningful for comparisons over time or between pollutants analyzed similarly. In addition, the exposure differences may be large enough to contribute to health disparities (Atkinson et al., 2014; Brauer et al., 2008; Clark et al., 2014; Shi et al., 2016). For instance, in a recent study by Shi et al. (2016), all-cause mortality increased by 0.9% per μg/$m^3$ increase in long-term $PM_{2.5}$ concentrations even when restricted to ambient concentrations below 10 μg/$m^3$. The 0.6 μg/$m^3$ difference in exposure in urban areas in 2010 for non-Hispanic whites versus Hispanics would therefore translate into a 0.5% increase in mortality rates, all else being equal. Further, the population subgroups found to have the highest population-weighted $PM_{2.5}$ and $NO_2$ concentrations also tend to have higher baseline rates of asthma and cardiovascular disease, leaving them more vulnerable to persistent, longitudinal air pollution exposure (Crain et al., 1994; Jones et al., 2009; O'Neill et al., 2003).

Our findings demonstrating inequitable pollution exposure by SES and race/ethnicity are supported by evidence of environmental inequality that is firmly established in the academic literature (Lopez, 2002; Mohai and Bryant, 1992; Mohai and Saha, 2015a; Morello-Frosch and Lopez, 2006). Further, a growing number of studies have demonstrated environmental inequality specific to $PM_{2.5}$ and $NO_2$ in Massachusetts and nationwide using Census data (Clark et al., 2014; Miranda et al., 2011; Yanosky et al., 2008). For instance, Miranda et al. (2011) used an air quality ranking approach to assess environmental justice dimensions of air pollution exposure, finding that the proportion of non-Hispanic black residents in the 20% of counties in the United States with the poorest air quality was twice that in those counties with the most favorable air quality. Yanosky et al. (2008) evaluated whether predicted $NO_2$ concentrations are associated with socioeconomic position, after controlling for spatial autocorrelation in Worcester, Massachusetts. They found that block group $NO_2$ concentrations exhibit a significant negative association with median household income, and that rates of poverty and low educational attainment populations rose by 3.1% and 3.4%, respectively, with every one standard deviation increase in block group mean $NO_2$.

Despite employing novel inequality-based methods using data of high temporal and geographic resolution, there are some limitations that merit discussion. The use of Census data restricts our ability to examine disparities at the individual/household level. Using personal monitors is not feasible at this scale, so we assigned modeled $PM_{2.5}$ and $NO_2$ concentrations to each block group to approximate individual exposure, thereby limiting potential variability in exposure across the population. Our results consequently do not incorporate individual mobility or characteristics that may provide a more comprehensive understanding of the drivers of inequality. However, the inputs used to assign block-group level exposures are advantageous over proximity-based and aggregation methods that ignore chemical fate and transport and local meteorological conditions (Chakraborty et al., 2011;

Lucier et al., 2011; Mohai et al., 2011; Pastor et al., 2001). These predictions are also an improvement over EI studies that use predicted concentrations over coarse geographic and temporal resolutions (Hajat et al., 2015; Kravitz-Wirtz et al., 2016; Mohai and Saha, 2015b; Morello-Frosch and Jesdale, 2006; Pope et al., 2016). A 1 $km^2$ resolution is adequate for regionally-based pollutants, such as $PM_{2.5}$, but may ignore local hotspots for locally-based pollutants such as $NO_2$. Conversely, smaller geographic resolutions may introduce bias related to individual mobility (Setton et al., 2011)

We acknowledge that the temporal misalignment of $PM_{2.5}$ (years 2003–2010) and $NO_2$ (years 2005–2010) with Census data for the year 2000 or 2010 prevents a precise characterization of exposure patterns over time. However, as discussed above, the relative stability of our inequality measures across different population data indicates that this is a minor source of error.

As a final overall limitation, we only studied inequalities in outdoor ambient air pollution exposures; low socioeconomic status groups may be disproportionately exposed to indoor-generated exposures or from indoor exposure to outdoor pollutants due to older, leakier housing stock (Adamkiewicz et al., 2011). Taking into account the full exposure profile of both indoor and outdoor-generated air pollutants may reveal a more striking characterization of exposure inequality between population groups.

## 5. Conclusion

Despite overall reductions in ambient air pollution concentrations and decreased industrialization, we found that air pollution inequalities have slightly increased over time when measured on a relative scale, and that group-specific concentrations are most disparate between racial/ethnic groups. Greater inequalities in urban areas, where there is often substantial segregation, reinforces the importance of targeted exposure reduction strategies within vulnerable populations and neighborhoods. Ultimately, there is a complex dynamic wherein changing sociodemographics over time may impact land use decisions, enforcement policy measures, and other factors influencing emissions. To complement these findings, more studies that utilize longitudinal, individual-level data are needed to understand population mobility and individual factors that affect exposure disparities.

## Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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## Highlights

- We characterized longitudinal $PM_{2.5}$ and $NO_2$ inequality trends across Massachusetts
- Exposure inequality increased in urban, but not rural areas
- $NO_2$ exposure inequality was greater in magnitude than $PM_{2.5}$ inequality
- Observed inequality trends likely driven by spatiotemporal pollution shifts

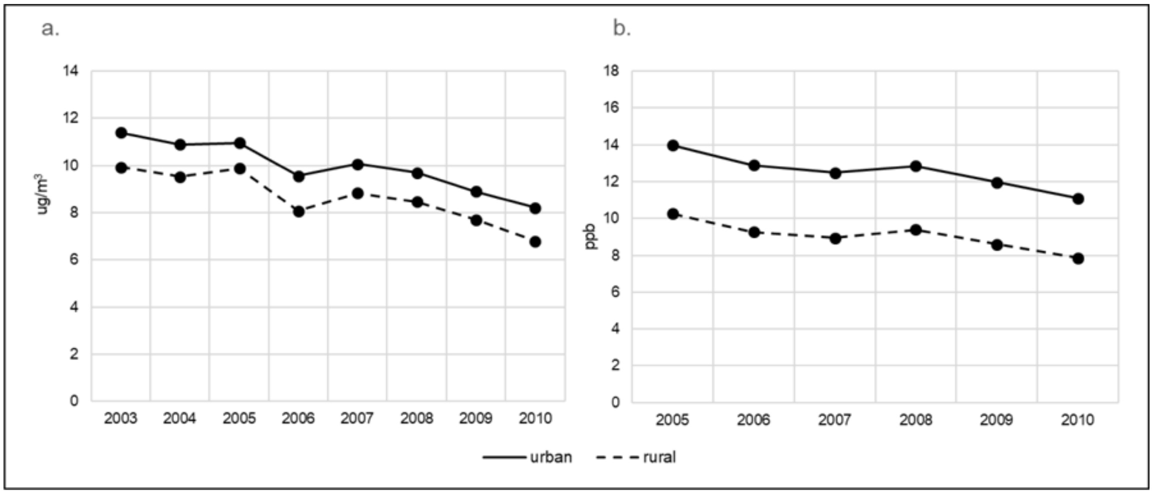


**Figure 1.**

a. Annual Average $PM_{2.5}$ Concentrations in Massachusetts, 2003–2010. b. Annual Average $NO_2$ Concentrations in Massachusetts, 2005–2010

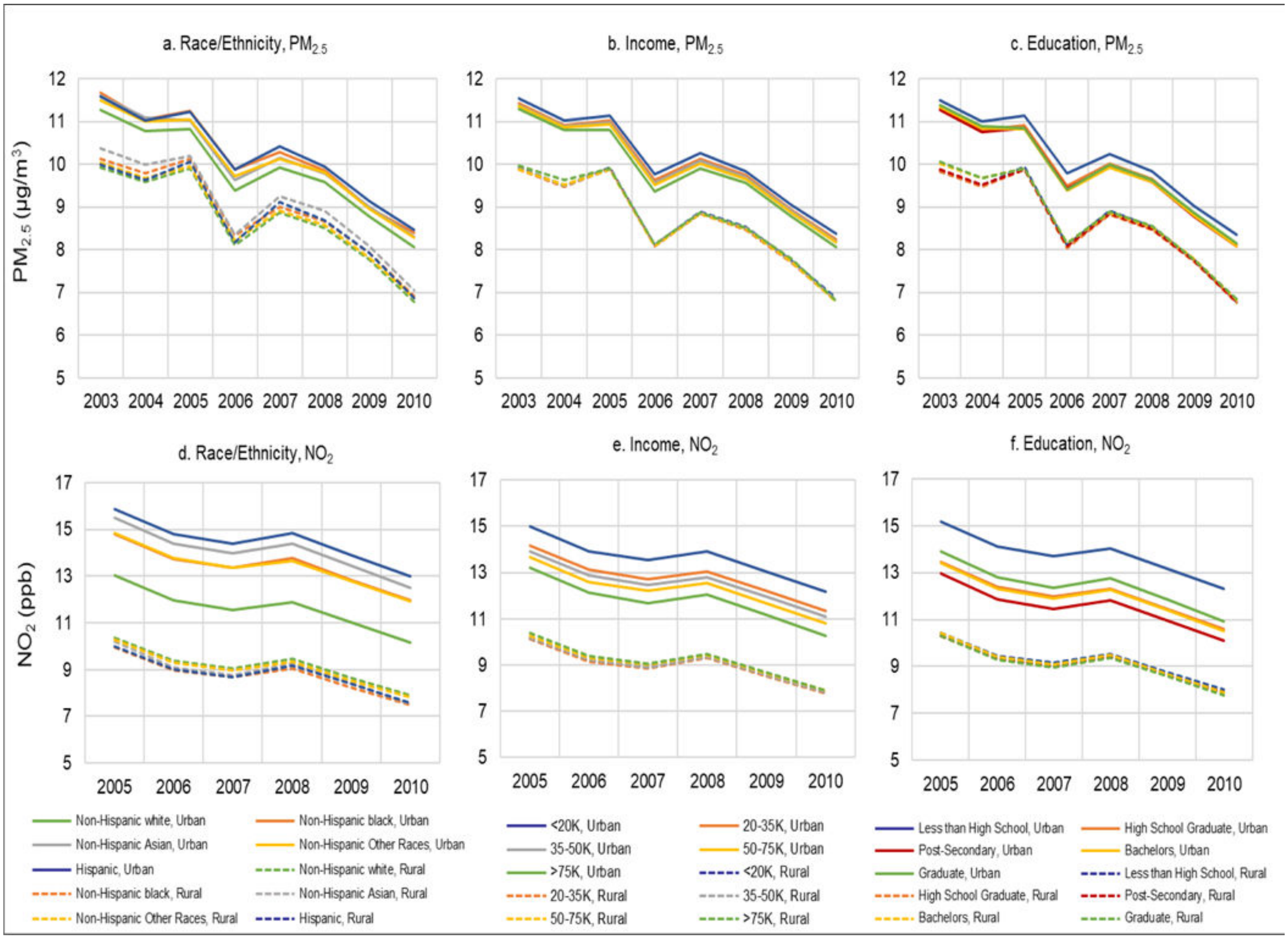


**Figure 2.**

a–f. Population-Weighted Annual Average $PM_{2.5}$ (a–c) and $NO_2$ (d–f) concentrations by Census 2010 and ACS 2006–2010 Demographic and Geographic Subpopulations

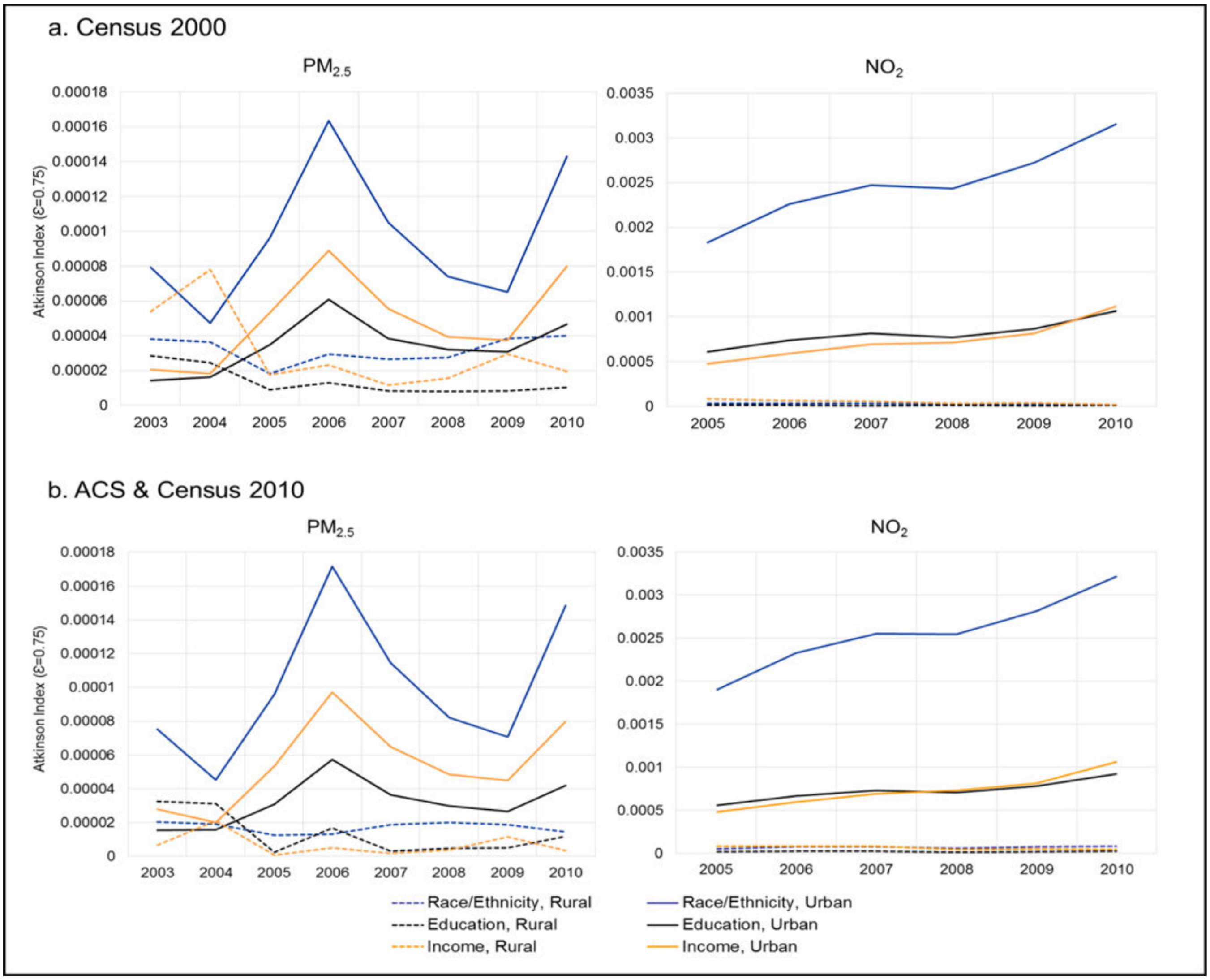


**Figure 3.**

Between-Group Inequality in Population-Weighted Annual Average $PM_{2.5}$ and $NO_2$ Concentrations. **a** displays results for $PM_{2.5}$ and $NO_2$ inequality for the Census 2000 Demographic and Geographic Subpopulations. **b** displays results for $PM_{2.5}$ and $NO_2$ inequality for the Census 2010 and ACS 2006–2010 Demographic and Geographic Subpopulations.

**Table 1**

Massachusetts Census 2000, Census 2010 and ACS 2006–2010 demographic and geographic subpopulation characteristics

| | Full State | | | | | Urban | | | | | Rural | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **2000** | | **2010** | | **% Change**$^{b}$ | **2000** | | **2010** | | **% Change**$^{b}$ | **2000** | | **2010** | | **% Change**$^{b}$ |
| | **#** | **%** | **#** | **%** | | **#** | **%** | **#** | **%** | | **#** | **%** | **#** | **%** | |
| Race/Ethnicity | | | | | | | | | | | | | | | |
| Total | 6349097 | | 6547629 | | | 5337451 | | 5620943 | | 5.3 | 885599 | | 849293 | | |
| Non-Hispanic White | 5197124 | 81.9 | 4984800 | 76.1 | −5.7 | 4248651 | 79.6 | 4126251 | 73.4 | −6.2 | 836963 | 94.5 | 790098 | 93.0 | −1.5 |
| Non-Hispanic Black | 314472 | 5.0 | 391693 | 6.0 | 1.0 | 301276 | 5.6 | 380308 | 6.8 | 1.1 | 9923 | 1.1 | 9625 | 1.1 | 0.0 |
| Non-Hispanic Asian | 237006 | 3.7 | 347495 | 5.3 | 1.6 | 223262 | 4.2 | 331479 | 5.9 | 1.7 | 10159 | 1.1 | 15010 | 1.8 | 0.6 |
| Non-Hispanic Other | 173155 | 2.7 | 195987 | 3.0 | 0.3 | 156707 | 2.9 | 178692 | 3.2 | 0.2 | 12936 | 1.5 | 14843 | 1.7 | 0.3 |
| Hispanic | 427340 | 6.7 | 627654 | 9.6 | 2.9 | 407555 | 7.6 | 604213 | 10.7 | 3.1 | 15618 | 1.8 | 19717 | 2.3 | 0.6 |
| Educational Attainment | | | | | | | | | | | | | | | |
| Total | 4273275 | | 4382378 | | | 3598210 | | 3745562 | | 2.8 | 600501 | | 583138 | | |
| Less than High School | 651093 | 15.2 | 495822 | 11.3 | −3.9 | 575286 | 16.0 | 448584 | 12.0 | −4.0 | 64965 | 10.8 | 41550 | 7.1 | −3.7 |
| High School | 1165489 | 27.3 | 1171725 | 26.7 | −0.5 | 978895 | 27.2 | 996370 | 26.6 | −0.6 | 163986 | 27.3 | 157267 | 27.0 | −0.3 |
| Graduate Post-Secon dary | 1038398 | 24.3 | 1036622 | 23.7 | −0.6 | 859029 | 23.9 | 867966 | 23.2 | −0.7 | 160918 | 26.8 | 153673 | 26.4 | −0.4 |
| Bachelors | 834554 | 19.5 | 961563 | 21.9 | 2.4 | 695403 | 19.3 | 817500 | 21.8 | 2.5 | 126717 | 21.1 | 134937 | 23.1 | 2.0 |
| Graduate | 583741 | 13.7 | 716646 | 16.4 | 2.7 | 489597 | 13.6 | 615142 | 16.4 | 2.8 | 83915 | 14.0 | 95711 | 16.4 | 2.4 |
| | Full State | | | | | Urban | | | | | Rural | | | | |
| | Mean | SD | 5th | 95th | | Mean | SD | 5th | 95th | | Mean | SD | 5th | 95th | |
| Median Household Income | | | | | | | | | | | | | | | |
| Census 2000, 2010 inflation- adjusted $ | 70,169 | 32,225 | 27,152 | 127,964 | | 69,110 | 32,221 | 26,535 | 126,745 | | 80,098 | 31,413 | 42,402 | 14,2350 | |

| | **Full State** | | | | | **Urban** | | | | | **Rural** | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **2000** | | **2010** | | **% Change**[b] | **2000** | | **2010** | | **% Change**[b] | **2000** | | **2010** | | **% Change**[b] |
| | **#** | **%** | **#** | **%** | | **#** | **%** | **#** | **%** | | **#** | **%** | **#** | **%** | |
| Census 2010, 2010 inflation-adjusted $ | 70,114 | 34,262 | 31,125 | 132,371 | | 69,070 | 34,785 | 20,543 | 132,197 | | 80,172 | 29,315 | 42,024 | 13,9853 | |

[a]Includes all block groups classified as urbanized, urban cluster, or rural by the U.S. Census. Due to the small number of block groups categorized as “urban cluster,” stratified results for this category are not presented.

[b]Change in percent of total population

**Table 2**

Population-weighted annual average $PM_{2.5}$ ($\mu g/m^3$) Concentrations by Census 2000, Census 2010 and ACS 2006–2010 demographic and geographic subpopulations

| | Full State | | | | Urban | | | | Rural | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $PM_{2.5}$ 2003, Census 2000 | $PM_{2.5}$ 2010, Census 2010 | Absolute Change[a] | Relative Change[b] | $PM_{25}$ 2003, Census 2000 | $PM_{25}$ 2010, Census 2010 | Absolute Change[a] | Relative Change[b] | $PM_{25}$ 2003, Census 2000 | $PM_{25}$ 2010, Census 2010 | Absolute Change[a] | Relative Change[b] |
| Race/Ethnicity | | | | | | | | | | | | |
| Total | 11.2 | 8.0 | −3.2 | −28.7 | 11.4 | 8.1 | −3.2 | −28.3 | 10.1 | 6.8 | −3.3 | −32.7 |
| non-Hispanic white | 11.1 | 7.8 | −3.2 | −29.2 | 11.3 | 8.1 | −3.2 | 28.6 | 10.1 | 6.8 | −3.3 | −32.7 |
| non-Hispanic black | 11.7 | 8.4 | −3.4 | −28.6 | 11.8 | 8.4 | −3.4 | −28.6 | 10.4 | 6.9 | −3.5 | −33.6 |
| non-Hispanic Asian | 11.6 | 8.2 | −3.4 | −29.0 | 11.7 | 8.3 | −3.4 | −28.8 | 10.8 | 7.0 | −3.8 | −35.0 |
| non-Hispanic other | 11.4 | 8.2 | −3.3 | −28.6 | 11.6 | 8.3 | −3.3 | −28.4 | 10.2 | 6.9 | −3.3 | −32.6 |
| Hispanic | 11.6 | 8.4 | −3.2 | −27.4 | 11.6 | 8.5 | −3.2 | −27.3 | 10.5 | 6.9 | −3.6 | −34.4 |
| | $PM_{2.5}$ 2003 Census 2000 | $PM_{2.5}$ 2010, ACS 2010 | Absolute Change[a] | Relative Change[b] | $PM_{2.5}$ 2003, Census 2000 | $PM_{2.5}$ 2010 ACS 2010 | Absolute Change[a] | Relative Change[b] | $PM_{2.5}$ 2003, Census 2000 | $PM_{2.5}$ 2010, ACS 2010 | Absolute Change[a] | Relative Change[b] |
| Educational Attainment | | | | | | | | | | | | |
| Total | 11.2 | 7.9 | −3.2 | −28.8 | 11.4 | 8.1 | −3.2 | −28.4 | 10.1 | 6.8 | −3.3 | −32.8 |
| < High School | 11.3 | 8.2 | −3.1 | −27.6 | 11.5 | 8.3 | −3.1 | −27.3 | 10.1 | 6.8 | −3.4 | −33.2 |
| High School Grad | 11.1 | 7.9 | −3.2 | −28.7 | 11.3 | 8.1 | −3.2 | −28.2 | 10.0 | 6.8 | −3.3 | −32.7 |
| Post-Secondary | 11.1 | 7.9 | −3.2 | −28.9 | 11.3 | 8.1 | −3.2 | −28.5 | 10.0 | 6.8 | −3.3 | −32.5 |
| Bachelors | 11.2 | 7.9 | −3.3 | −29.3 | 11.3 | 8.1 | −3.3 | −28.8 | 10.2 | 6.8 | −3.4 | −33.1 |
| Masters | 11.2 | 8.0 | −3.3 | −29.0 | 11.4 | 8.2 | −3.3 | −28.6 | 10.2 | 6.8 | −3.4 | −33.0 |
| Median Household Income | | | | | | | | | | | | |
| Total | 11.2 | 8.0 | −3.2 | −28.7 | 11.4 | 8.2 | −3.2 | −28.3 | 10.1 | 6.8 | −3.3 | −32.6 |
| <20,000 | 11.4 | 8.2 | −3.1 | −27.6 | 11.5 | 8.4 | −3.2 | −27.4 | 10.2 | 6.9 | −3.3 | −32.4 |
| 20–35,000 | 11.2 | 8.1 | −3.2 | −28.1 | 11.4 | 8.2 | −3.2 | −27.8 | 10.0 | 6.8 | −3.2 | −32.0 |
| 35–50,000 | 11.2 | 8.0 | −3.2 | −28.3 | 11.4 | 8.2 | −3.2 | −28.0 | 10.0 | 6.8 | −3.2 | −31.7 |
| 50–75,000 | 11.1 | 8.0 | −3.2 | −28.3 | 11.3 | 8.2 | −3.2 | −28.1 | 10.0 | 6.8 | −3.2 | −32.1 |
| >75,000 | 11.1 | 7.9 | −3.3 | −29.3 | 11.3 | 8.1 | −3.2 | −28.7 | 10.2 | 6.8 | −3.4 | −33.5 |

[a] Absolute change in concentrations ($\mu g/m^3$)

[b] Percentage change in concentrations

**Table 3**

Population-weighted annual average $NO_2$ (ppb) Concentrations by Census 2000, Census 2010 and ACS 2006–2010 demographic and geographic subpopulations

| | Full State | | | | Urban | | | | Rural | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $NO_2$ 2005, Census 2000 | $NO_2$ 2010, Census 2010 | Absolute Change[a] | Relative Change[b] | $NO_2$ 2005, Census 2000 | $NO_2$ 2010, Census 2010 | Absolute Change[a] | Relative Change[b] | $NO_2$ 2005, Census 2000 | $NO_2$ 2010, Census 2010 | Absolute Change[a] | Relative Change[b] |
| Race/Ethnicity | | | | | | | | | | | | |
| Total | 13.2 | 10.4 | −2.8 | −21.4 | 13.7 | 10.8 | −2.9 | −21.2 | 10.5 | 7.9 | −2.6 | −24.8 |
| non-Hispanic white | 12.7 | 9.8 | −2.9 | −23.0 | 13.0 | 10.2 | −2.9 | −22.2 | 10.4 | 7.9 | −2.5 | −24.4 |
| non-Hispanic black | 14.9 | 11.8 | −3.1 | −20.8 | 14.8 | 12.0 | −2.9 | −19.3 | 10.9 | 7.5 | −3.3 | −30.8 |
| non-Hispanic Asian | 15.8 | 12.3 | −3.5 | −22.2 | 15.5 | 12.5 | −3.0 | −19.2 | 11.6 | 7.5 | −4.0 | −35.0 |
| non-Hispanic other | 14.9 | 11.5 | −3.3 | −22.5 | 14.8 | 11.9 | −2.9 | −19.6 | 10.6 | 7.8 | −2.8 | −26.3 |
| Hispanic | 15.8 | 12.8 | −3.0 | −19.2 | 15.9 | 13.0 | −2.9 | −18.0 | 11.2 | 7.6 | −3.6 | −32.0 |
| | $NO_2$ 2005 Census 2000 | $NO_2$ 2010, ACS 2010 | Absolute Change[a] | Relative Change[b] | $NO_2$ 2005, Census 2000 | $NO_2$ 2010, ACS 2010 | Absolute Change[a] | Relative Change[b] | $NO_2$ 2005, Census 2000 | $NO_2$ 2010, ACS 2010 | Absolute Change[a] | Relative Change[b] |
| Educational Attainment | | | | | | | | | | | | |
| Total | 13.1 | 10.3 | −2.8 | −21.7 | 13.7 | 10.7 | −3.0 | −21.7 | 10.4 | 7.9 | −2.6 | −24.5 |
| < High School | 14.5 | 11.9 | −2.7 | −18.3 | 15.1 | 12.3 | −2.8 | −18.5 | 10.6 | 8.0 | −2.6 | −24.4 |
| High School Grad | 13.0 | 10.2 | −2.8 | −21.5 | 13.5 | 10.6 | −2.9 | −21.5 | 10.4 | 7.9 | −2.5 | −23.8 |
| Post-Secondary | 12.5 | 9.7 | −2.8 | −22.4 | 13.0 | 10.1 | −2.9 | −22.4 | 10.4 | 7.9 | −2.5 | −24.0 |
| Bachelors | 12.9 | 10.1 | −2.9 | −22.0 | 13.5 | 10.5 | −3.0 | −22.1 | 10.5 | 7.9 | −2.6 | −24.7 |
| Masters | 13.3 | 10.5 | −2.8 | −21.2 | 13.9 | 10.9 | −2.9 | −21.1 | 10.5 | 7.8 | −2.8 | −26.2 |
| Total | 13.3 | 10.5 | −2.8 | −21.4 | 13.9 | 10.9 | −3.0 | −21.4 | 10.4 | 7.9 | −2.6 | −24.5 |
| Median Household Income | | | | | | | | | | | | |
| <20,000 | 14.4 | 11.7 | −2.7 | −18.5 | 15.0 | 12.2 | −2.8 | −18.8 | 10.5 | 7.8 | −2.6 | −24.4 |
| 20–35,000 | 13.6 | 10.9 | −2.7 | −20.1 | 14.2 | 11.3 | −2.9 | −20.1 | 10.3 | 7.8 | −2.5 | −23.8 |
| 35–50,000 | 13.4 | 10.6 | −2.7 | −20.3 | 13.9 | 11.1 | −2.8 | −20.4 | 10.3 | 7.8 | −2.5 | −24.0 |
| 50–75,000 | 13.0 | 10.4 | −2.6 | −20.2 | 13.6 | 10.8 | −2.8 | −20.3 | 10.4 | 7.9 | −2.6 | −24.7 |
| >75,000 | 12.7 | 9.9 | −2.8 | −22.1 | 13.2 | 10.3 | −2.9 | −21.9 | 10.6 | 7.9 | −2.8 | −26.2 |

[a]Absolute change in concentrations (ppb)

[b]Percentage change in concentrations