Article

Air quality and life expectancy in the United States: An analysis of the moderating effect of income inequality

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ABSTRACT

Although studies have shown that air pollution can be devastating to population health, little is known about the health implications of the intersection of air pollution and income inequality. We investigate if air pollution is especially detrimental to the health of US state populations characterized by more inequitable distributions of income. In other words, are the populations of states with higher levels of income inequality especially vulnerable to similar levels of air pollution? We use two-way fixed-effects panel regression techniques to analyze longitudinal data for 49 US states and the District of Columbia (2000–2010) to model state-level life expectancy as a function of fine particulate matter, income inequality, and other state-level factors. We estimate models with interaction terms to formally assess whether the association between fine particulate matter and life expectancy varies by level of state income inequality. Across multiple life expectancy outcomes and additive models, states with higher $PM_{2.5}$ levels tend to exhibit lower average life expectancy. This general pattern is observed with our specifications for raw and weighted $PM_{2.5}$ and with adjustments for income share of the top 10%, total population, GDP per capita, median household income, median age, percent college degree or higher, percent black, and percent Hispanic/Latino. We also find that the association between state $PM_{2.5}$ levels and average life expectancy intensifies in states with higher levels of income inequality. More specifically, $PM_{2.5}$ levels are more detrimental to population life expectancy in states where a higher percentage of income is concentrated in the top 10% of the state income distribution. We discuss the implications of our results for future research in social epidemiology and environmental justice.

Introduction

Air pollution is devastating for population health. Over the past two decades, studies have shown that various forms of air pollution (e.g., particulate matter, carbon monoxide, and ozone) increase the risk of heart disease, cerebrovascular disease, all-cause mortality across the life course, cause-specific adult mortality linked to respiratory diseases, cardiovascular diseases, malignant neoplasms, and unintentional injuries (Brook et al., 2010; Brunekreef & Holgate, 2002; Chay & Greenstone, 2003; Clancy, Goodman, Sinclair, & Dockery, 2002; Currie & Neidell, 2005; Currie, Neidell, & Schmieder, 2009; Franklin, Zeka, & Schwartz, 2007; Graff Zivin & Neidell, 2013; Greenstone & Hanna, 2014; Heutel & Ruhm, 2016; Knittel, Miller, & Sanders, 2016; Künzli et al., 2000; Laden, Schwartz, Speizer, & Dockery, 2006; Mikati, Benson, Luben, Sacks, & Richmond-Bryant, 2018; Mustafić et al., 2012; Pope & Dockery, 2006; Wellenius, Schwartz, &

Mittleman, 2005). Although air pollution potentially harms all segments of society, environmental justice research in the United States (US) has found distinct inequities regarding its impacts, such as in relation to the health of younger, older, poorer, and non-white populations (Ard, 2016; Boyce & Pastor, 2013; Currie et al., 2009; Devlin, Ghio, Kehrl, Sanders, & Cascio, 2003; Heutel & Ruhm, 2016; Mikati et al., 2018; Mohai & Saha, 2015).

In this study, we expand on previous health research and environmental justice research by exploring the health implications of the intersection of air pollution and income inequality in the US context (Charafeddine & Boden, 2008). Although previous scholarship has shown that greater income inequality is associated with poorer population health (Anderson, Bjorklund, & Rambotti, in press; Clarkwest, 2008; Curran & Mahutga, 2018; Diez-Roux, Link, & Northridge, 2000; Hill & Jorgenson, 2018; Lynch et al., 2001; Kaplan, Pamuk, Lynch, Cohen, & Balfour, 1996; Kawachi & Kennedy, 1999; Neumayer & Plümper, 2016; Pickett & Wilkinson, 2015; Rambotti,
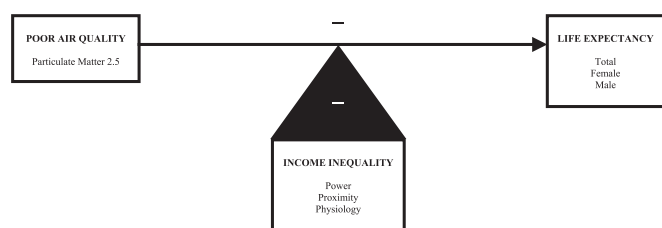
Fig. 1. Income inequality as a moderator of the association between air quality and life expectancy.

2015; Wen, Browning, & Cagney, 2003; Wilkinson & Pickett, 2006, 2009), in this study we are less interested in the direct effects of income inequality on health. Instead, we consider whether air pollution is especially detrimental to the health of US states' populations characterized by the inequitable distribution of income. In other words, are the populations of US states with higher levels of income inequality especially vulnerable to *similar* levels of air pollution?

Our assessment of the multiplicative impact of income inequality, as illustrated in Fig. 1, is supported by three theoretical principles: Power, Proximity, and Physiology. The *Power* principle suggests that income inequality could increase the vulnerability of populations to a given level of air pollution due to the undermining of environmental regulations and protections (e.g., public discussions and warnings, working conditions, living standards, and other resources) through the concentration of wealth and political power. Drawing on a political-economy approach initially developed by Boyce (1994, 2007) and Boyce, Klemer, Templet, and Willis (1999), Jorgenson, Schor, Knight, and Huang (2016), Jorgenson, Schor, and Huang (2017), and Jorgenson, Dietz, and Kelly (2018) point out that those with higher incomes and wealth are often the owners of polluting firms and energy producing enterprises. To protect these assets, they are more likely to use their economic resources to influence political power and to dominate the policy environment in their favor (Boyce et al., 1999). These arguments are consistent with Neo-Material theory, which suggests that income inequality concentrates wealth and power among elites and weakens broader commitments to the general interests of society. This creates political pressure to cut taxes, deregulate industries (including less environmental regulations), and limit investments in public resources and social services that promote public health, including, for example, education, consumer protections, and health care infrastructure (Clarkwest, 2008; Kaplan et al., 1996; Kawachi & Kennedy, 1999; Lynch, Smith, Kaplan, & House, 2000; Neumayer & Plümper, 2016; Truesdale & Jencks, 2016).

The *Proximity* principle suggests that income inequality could increase the vulnerability of populations to a given level of air pollution by contributing to the segregation of vulnerable populations in geographic space. Several studies show that income inequality is associated with higher levels of residential segregation by race and class (Cheshire, Monastiriotis, & Sheppard, 2003; Jargowsky, 1996; Lobmayer & Wilkinson, 2002; Reardon & Bischoff, 2011). Reardon and Bischoff (2011: 1140) explain that "income inequality appears to be responsible for a specific aspect of income segregation—the large scale separation of the affluent from lower-income households and families." From public health and environmental justice perspectives, segregation contributes to social inequalities in residential proximity to sources of harmful pollution (Ard, 2016; Boyce & Pastor, 2013; Mikati et al., 2018; Mohai & Saha, 2015). For example, a recent study by Mikati et al. (2018) shows that impoverished and non-white communities are disproportionately exposed to particulate matter emitting facilities. Social Capital theory proposes that these concerns may be compounded, given that income inequality generates widespread status competition, which undermines interpersonal trust, social cohesion, cooperation, and, as consequence, collective political efforts to support vulnerable populations (Elgar & Aitken, 2010; Kawachi, Kennedy, Lochner, & Prothrow-Stith, 1997; Kawachi & Kennedy, 1999; Truesdale & Jencks, 2016).

Finally, the *Physiological* principle suggests that income inequality could increase the vulnerability of populations to a given level of air pollution by

undermining the physiological health of human populations (Charafeddine & Boden, 2008). Psychosocial theory contends that the stress of relative deprivation, from the unequal distribution of income, contributes to negative self-appraisals (e.g., low self-esteem), emotional distress (e.g., anxiety and anger), risky coping behaviors (e.g., heavy alcohol consumption and smoking), and, over time, physiological dysregulation or allostatic load (Kawachi & Kennedy, 1999; Lynch et al., 2000; Truesdale & Jencks, 2016; Wilkinson, 1996, 2005; Wilkinson & Pickett, 2009). More simply, income inequality creates a wide range of chronic social stressors that in turn overwhelm the physiological stress response or allostatic systems of the human body. When stress is acute or short-term, allostatic systems can efficiently manage the physiological consequences of stress. When stress is chronic or long-term, such as under the enduring economic conditions of heightened income inequality, the result is allostatic load. According to McEwen (1998: 171), allostatic load is "the wear and tear that results from chronic overactivity or underactivity of allostatic systems." A key indicator of allostatic load is lung function (Crimmins, Johnston, Hayward, & Seeman, 2003; McEwen, 2002; Seeman et al., 2004). Stress and related hormones can contribute to the physiological dysregulation of the lungs through bronchodilation and increased respiration (lungs take in more air), airway inflammation and difficulty breathing (lungs take in less air), and suppression of the immune system, which leads to increased vulnerability to respiratory infections (Kullowatz et al., 2008; Lehrer, 2006). These processes are especially relevant for specific forms of air pollution, most notably fine particulate matter, which can be inhaled deeply into the lungs.

In our review of the research literature, we could find only one quantitative study of the health implications of the intersection of air pollution and income inequality. Using data from the 2001 Behavioral Risk Factor Surveillance System, Charafeddine and Boden (2008) found that the association between county-level fine particular matter and individual-level fair or poor *self-rated* health was moderated by state-level income inequality, measured as a Gini coefficient. However, the association between fine particular matter and individual-level self-rated health was most pronounced at low levels of income inequality. The authors concluded that their analyses could be limited by the "subjective nature" of their dependent variable and recommended that future research explore more "objective outcomes" like "mortality or hospitalization."

Building on the work of Charafeddine and Boden (2008), we use longitudinal statistical modeling techniques to directly assess the multiplicative impact of income inequality on the association between fine particulate matter and life expectancy, a well-established *objective measure* of population health, at the US state level. In accordance with previous research, which does not consider additional moderating effects, we expect that states with higher levels of fine particulate matter will tend to exhibit lower average life expectancy. Drawing on the theoretical principles of Power, Proximity, and Physiology, we anticipate that the inverse association between particulate matter and average life expectancy will be greater in states with higher levels of income inequality.

Methods

Data

This study involves the analyses of two datasets. The first dataset includes annual observations for average life expectancy at birth from 2000 to 2010 for 49 US states and the District of Columbia (550 total observations). The second dataset is restricted to three annual observations (2000, 2005, and 2010) for sex-specific average life expectancy for 49 US states and the District of Columbia (150 total observations). These specific years were selected to include all available comparable data for our focal independent and dependent variables. Maine is excluded from all analyses due to data limitations for our particulate matter measures. The second dataset is restricted to the three yearly observations five years apart due to data availability limitations for our sex-specific life expectancy measures.

Measures

Life expectancy

Our analyses include three dependent variables: (1) average life expectancy at birth, (2) average female life expectancy at birth, and (3) average male life expectancy at birth. These data were obtained from the Institute for Health Metrics and Evaluation's (IHME) Global Burden of Disease database. IHME provides these data for all states and the District of Columbia (see Wang, Schumacher, Levitz, Mokdad, & Murray, 2013).

Air quality

Our focal indicator of air quality is particulate matter 2.5 ($PM_{2.5}$). $PM_{2.5}$ refers to fine inhalable chemical particles in the air. Most particulate matter is a combination of chemicals (e.g., sulfur dioxide and nitrogen oxides) emitted from transportation vehicles, power plants, and other industrial sites. Because these chemical particles are 30 times smaller than a single strand of hair, they can contribute to a host of health problems by travelling through the respiratory tract into the lungs and bloodstream. We obtained $PM_{2.5}$ concentration data from Environmental Protection Agency's Air Quality System (AQS) database. AQS provides, among other measures, annual average arithmetic mean $PM_{2.5}$ concentrations by air quality monitors. Following Heutel and Ruhm (2016), we weighted state average particulate matter concentrations in order to compensate for the uneven distribution of monitors across space and time by the product of the monitor's county population and the proportion of actual to potential observations. County populations were obtained from the U.S. Census Bureau's intercensal population estimates. Potential observations were defined as the total number of observations required by Federal law for each monitor. As robustness checks, in the analyses we estimate separate models with the weighted and unweighted versions of $PM_{2.5}$.

Income inequality

Following recent research (e.g., Hill & Jorgenson 2018; Jorgenson et al., 2017, 2018), we measure income inequality as income share of the top 10%. We gathered these state-level inequality data from the World Wealth and Income Database (WWID), developed by Mark Frank et al. (http://www.wid.world/#Database). These data are measured in percentages. The inequality measures are constructed from individual tax filing data available from the Internal Revenue Service. For in-depth information on the creation of the state-level income inequality measures, see Frank, Sommeiller, Price, and Saez (2015).

Control variables

Consistent with previous studies of air quality and income inequality, our analyses include a range of state-level time-varying control variables, including median age (in years), percent black, percent Hispanic/Latino, percent with a four-year college degree or higher, median household income (in constant 2016 US dollars), GDP per capita (in chained 2007 dollars), and total population size. Our GDP data were obtained from the United States Department of Commerce Bureau of Economic Analysis database. Data for all other control variables were drawn from the U.S. Census Bureau's online databases. Because several control variables were positively skewed, the subsequent regression analyses employ a base 10 logarithmic transformation for the state-level measures of percent black, percent Hispanic/Latino, percent with a four-year college degree or higher, GDP per capita, and total population.

Model estimation techniques

In our analysis of average life expectancy (annual observations for 2000–2010), we use the "xi:xtpcse" commands in Stata to estimate time-series cross-sectional Prais-Winsten regression models with panel-corrected standard errors, allowing for disturbances that are heteroskedastic and contemporaneously correlated across panels (Beck & Katz, 1995). We correct for first-order autocorrelation (AR1 disturbances) within panels. Since we have no theoretical basis for assuming panel-specific autocorrelation, we

treat AR1 disturbances as common to all panels. We control for both year-specific and state-specific effects by including dummy variables for years and cases. This approach is one of the most commonly used longitudinal methods because it addresses the problem of heterogeneity bias. Heterogeneity bias in this context refers to the confounding effect of unmeasured time-invariant variables that are omitted from our regression models. To correct for heterogeneity bias, fixed-effects models control for omitted variables that are time-invariant by examining variability within states rather than between states. To control for potential unobserved heterogeneity that is cross-sectionally invariant within periods, we include dummy variables for our annual observations (i.e., period-specific intercepts) with the year 2000 serving as the reference category. The inclusion of period-specific intercepts is equivalent to modeling temporal fixed effects, and including both period-specific intercepts and case-specific fixed effects is analogous to estimating a two-way fixed-effects model (Wooldridge, 2010).

For our analysis of sex-specific average life expectancy (annual observations for 2000, 2005, and 2010), we use the "xtreg" commands in Stata to estimate two-way fixed-effects panel regression models with robust standard errors clustered by state and the District of Columbia. The time fixed effects are accounted for by the inclusion of the year-specific intercepts. With the xtreg suite of commands in Stata, the case-specific fixed effects are estimated using the within estimator, which involves a mean deviation algorithm for the dependent variable and each time-varying independent variable (Allison, 2009).

In our moderation analyses, we calculate and use interaction terms ($PM_{2.5}$*Income Share of Top 10%) to formally assess whether the association between air quality and life expectancy varies as a function of income inequality. We also estimate partial slope coefficients for the effect of $PM_{2.5}$ on life expectancy at percentile levels of the moderator variable, income share of the top 10%. These slope coefficients are estimated using the "margins" commands in Stata.

Results

Descriptive analyses

Table 1 provides univariate descriptive statistics for all substantive variables included in our analyses. Although some variables are converted to logarithmic form for the panel regression analyses, we report descriptive statistics for each variable in their original metrics. The mean for total average life expectancy is nearly 78 years. Average life expectancy is closer to 80 years for females and 75 years for males. Average raw (i.e., unweighted) and weighted air quality estimates indicate moderate levels of $PM_{2.5}$. Our income inequality estimates indicate an average income share of the top 10% of nearly 44%.

Regression analyses

Tables 2–4 present the two-way fixed-effects models for total average life expectancy (Table 2), female life expectancy (Table 3), and male life expectancy (Table 4). The same 8 models are estimated for each dependent variable. Model 1 includes all control variables as well as the raw form of $PM_{2.5}$, while Model 2 includes the controls and income share of the top 10%. Model 3 includes both raw $PM_{2.5}$ and income share of the top 10% as well as the controls, while Model 4 also includes the interaction between raw $PM_{2.5}$ and income share of the top 10%. Models 5–8 are structured the same as Models 1–4, but they instead include the weighted form of $PM_{2.5}$.

Across all outcomes and relevant additive models (1, 3, 5, and 7), states with higher $PM_{2.5}$ levels tend to exhibit lower average life expectancy. This general pattern is observed with our specifications for raw and weighted $PM_{2.5}$ and with adjustments for income share of the top 10%, total population, GDP per capita, median household income, median age in years, percent college degree or higher, percent black, and percent Hispanic/Latino. Since the estimated coefficients are unstandardized, comparing the magnitude of the effects across the independent variables is inappropriate.

To formally assess whether the association between air quality and life

Table 1
Descriptive statistics.

	Minimum	Maximum	Mean	SD
Life Expectancy	72.58	81.30	77.61	1.68
Female Life Expectancy	76.20	83.50	79.82	1.48
Male Life Expectancy	68.30	78.20	74.82	1.94
Particulate Matter 2.5 (raw)	3.60	20.18	10.88	2.83
Particulate Matter 2.5 (weighted)	3.60	19.02	11.22	3.03
Income Share of Top 10%	33.56	62.26	43.64	4.98
Total Population	490,000	37,350,000	5887127	6,494,525
GDP Per Capita	26,644	151,257	42,467.61	15,938.14
Median Household Income	39,182	81,018	56,953.45	8648.20
Median Age in Years	27.10	41.50	36.56	2.11
Percent College Degree or Higher	17	66	29.50	7.27
Percent Black	0.26	60	11.09	11.30
Percent Hispanic/Latino	0.57	46.30	9.40	9.39

Notes: N = 550 for all variables except Female Life Expectancy and Male Life Expectancy. N = 150 for Female Life Expectancy and Male Life Expectancy. All measures are state-level.

expectancy varies as a function of income inequality levels, we tested six interaction terms in Tables 2–4. With the incorporation of the continuous interaction term for $PM_{2.5}$ * Top 10% Income Share, the linear coefficients for the two variables are to be interpreted as conditional relationships (Jaccard, Wan, & Turrisi, 1990). In other words, the linear coefficient for $PM_{2.5}$ or for income share of top 10% is the estimated effect on life expectancy when the other variable equals zero, which, like much research across disciplines, does not occur for the analyzed cases. As shown in Table 1, for the analyzed panel data, the minimum value of $PM_{2.5}$ is 3.60, and for income share of the top 10% the minimum value is 33.56.

Across the three life expectancy outcomes and multiplicative models (4 and 8), the negative association between state $PM_{2.5}$ levels and average life expectancy intensifies in states with greater income inequality. In other words, $PM_{2.5}$ levels are more detrimental to population life expectancy in states where a higher percentage of income is concentrated in the top 10%. Table 5 presents partial slopes for the association between $PM_{2.5}$ and total average life expectancy as a function of income shares to the top 10% (based on the analyses reported in Table 2). At low levels of income inequality (1st and 10th percentiles), $PM_{2.5}$ is essentially unrelated to average life expectancy. Around the 20th percentile of the income inequality distribution, we begin to see the expected inverse association between $PM_{2.5}$ and average life expectancy. These partial slopes increase in magnitude through the 99th percentile of the income inequality distribution. Fig. 2 provides a graphic illustration of these patterns. The slope coefficients for the inverse association between $PM_{2.5}$ and average life expectancy clearly increase in magnitude at higher levels of income inequality, measured as income shares of the top 10%.

In a series of unreported sensitivity analyses, we estimated additional models separately that systematically include only one of the control variables as well as all possible combinations of them, which all yield results consistent with the reported findings. We also estimated additional models that instead use measures of the income share of the top 5% and of the top 1%. The results of these unreported analyses are also entirely consistent with the reported findings.

Discussion

Although numerous studies have shown that forms of air pollution can be devastating to population health, little is known about the health consequences of the intersection of air pollution and income inequality (Charafeddine & Boden, 2008). In this study, we asked whether air pollution is especially detrimental to the health of populations characterized by a more inequitable distribution of income. In other words, are populations with higher levels of income inequality especially vulnerable to similar levels of air pollution? To answer this question, we used two-way fixed-effects model estimation techniques to assess the extent to which state-level life expectancy is a function of fine particulate matter and a range of time-

Table 2
Two-way fixed-effects coefficients for the regression of average life expectancy (US States and the District of Columbia, 2000–2010).

	Raw Particulate Matter Model 1	Raw Particulate Matter Model 2	Raw Particulate Matter Model 3	Raw Particulate Matter Model 4	Weighted Particulate Matter Model 5	Weighted Particulate Matter Model 6	Weighted Particulate Matter Model 7	Weighted Particulate Matter Model 8
Particulate Matter 2.5	-0.026(0.010)**		-0.030(0.011)**	0.196(0.064)***	-0.023(0.010)*		-0.028(0.011)**	0.168(0.061)**
Income Share of Top 10%		-0.024(0.010)*	-0.027(0.010)**	0.028(0.011)*		-0.024(0.010)*	-0.026(0.010)**	0.022(0.011)*
Particulate Matter 2.5 * Income Share of Top 10%				-0.006(0.001)***				-0.005(0.002)**
Total Population (log 10)	0.265(1.018)	-0.186(0.960)	0.432(0.974)	0.867(0.973)	0.116(1.004)	-0.186(0.960)	0.268(0.948)	0.438(0.925)
GDP Per Capita (log 10)	-0.281 (0.737)	-0.666 (0.671)	-0.144 (0.703)	-0.356 (0.658)	-0.351 (0.731)	-0.666 (0.671)	-0.204 (0.693)	-0.470 (0.653)
Median Household Income	-0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	-0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)
Median Age in Years	-0.042 (0.033)	-0.038 (0.031)	-0.047 (0.032)	-0.038 (0.032)	-0.042(0.034)	-0.038(0.031)	-0.048(0.032)	-0.041(0.032)
Percent College Degree or Higher (log 10)	0.356 (0.345)	0.119 (0.319)	0.235 (0.343)	0.181 (0.362)	0.307 (0.339)	0.119 (0.319)	0.184 (0.339)	0.121(0.350)
Percent Black (log 10)	-1.601 (0.681)*	-1.786 (0.713)**	-1.685 (0.662)**	-1.479 (0.637)*	-1.568 (0.690)*	-1.786 (0.713)**	-1.638 (0.672)*	-1.434 (0.650)*
Percent Hispanic/Latino (log 10)	-1.973 (0.952)*	-1.606 (0.918)#	-2.036 (0.862)*	-1.414 (0.747)#	-1.874 (0.953)*	-1.606 (0.918)#	-1.941 (0.672)*	-1.248 (0.774)

Notes: N = 550. * p < .05, ** p < .01, *** p < .001 (two-tailed), #p < .05 (one-tailed). Panel corrected standard errors appear in parentheses. Annual observations from 2000 to 2010 for all US States (except Maine) and District of Columbia. All measures are state-level. All models include ARI correction. All models include unreported case-specific and year-specific intercepts.

Table 3

Two-way fixed-effects coefficients for the regression of female life expectancy (US States and the District of Columbia, 2000–2010).

	Raw Particulate Matter Model 1	Raw Particulate Matter Model 2	Raw Particulate Matter Model 3	Raw Particulate Matter Model 4	Weighted Particulate Matter Model 5	Weighted Particulate Matter Model 6	Weighted Particulate Matter Model 7	Weighted Particulate Matter Model 8
Particulate Matter 2.5	-0.107(0.031)***		-0.098(0.022)***	0.252(0.079)**	-0.094(0.029)**		-0.083(0.023)***	0.245(0.091)**
Income Share of Top 10%		-0.064(0.127)***	-0.061(0.010)***	0.024(0.019)		-0.064(0.127)***	-0.061(0.011)***	0.017(0.021)
Particulate Matter 2.5 * Income Share of Top 10%				-0.008(0.001)***				-0.007(0.002)***
2005	0.571(0.184)**	0.587(0.161)***	0.594(0.125)***	0.482(0.124)***	0.553(0.196)**	0.587(0.161)***	0.577(0.137)***	0.480(0.140)***
2010	1.366(0.318)***	1.542(0.282)***	1.362(0.210)***	1.133(0.205)***	1.330(0.333)***	1.542(0.282)***	1.337(0.229)***	1.162(0.231)***

Notes: N = 150. * p < .05, ** p < .01, *** p < .001 (two-tailed), #p < .05 (one-tailed). Clustered robust standard errors appear in parentheses. Observations for years 2000, 2005 and 2010 for all US States (except Maine) and the District of Columbia. All models include unreported case-specific fixed effects. All models include state-level controls for Total Population, GDP Per Capita, Median Household Income, Median Age in Years, Percent College Degree or Higher, Percent Black, and Percent Hispanic/Latino.

Table 4

Two-way fixed-effects coefficients for the regression of male life expectancy (US States and the District of Columbia, 2000–2010).

	Raw Particulate Matter Model 1	Raw Particulate Matter Model 2	Raw Particulate Matter Model 3	Raw Particulate Matter Model 4	Weighted Particulate Matter Model 5	Weighted Particulate Matter Model 6	Weighted Particulate Matter Model 7	Weighted Particulate Matter Model 8
Particulate Matter 2.5	-0.158(0.054)**		-0.147(0.043)***	0.302(0.115)*	-0.142(0.050)**		-0.129(0.044)**	0.253(0.124)*
Income Share of Top Ten Percent		-0.081(0.026)**	-0.076(0.021)***	0.033(0.034)		-0.081(0.026)**	-0.075(0.022)***	0.015(0.036)
Particulate Matter 2.5 * Income Share of Top 10%				-0.010(0.002)***				-0.008(0.003)**
2005	1.003(0.335)**	1.021(0.333)**	1.031(0.273)***	0.887(0.262)***	0.976(0.345)**	1.021(0.333)**	1.005(0.285)***	0.892(0.288)**
2010	2.087(0.545)***	2.350(0.587)***	2.081(0.429)***	1.787(0.416)***	2.025(0.558)***	2.350(0.587)***	2.034(0.450)***	1.830(0.461)***

Notes: N = 150. * p < .05, ** p < .01, *** p < .001 (two-tailed), #p < .05 (one-tailed). Clustered robust standard errors appear in parentheses. Observations for years 2000, 2005 and 2010 for all US States (except Maine) and the District of Columbia. All models include unreported case-specific fixed effects. All models include state-level controls for Total Population, GDP Per Capita, Median Household Income, Median Age in Years, Percent College Degree or Higher, Percent Black, and Percent Hispanic/Latino.

Table 5
Slope coefficients for the association between particulate matter and average life expectancy as a function of income shares.

Percentiles for income share of top 10%	Raw particulate matter	Weighted particulate matter
1st Percentile [34.43704]	0.004(0.010)	0.005(0.010)
10th Percentile [38.02291]	-0.015(0.008)#	-0.010(0.008)
20th Percentile [40.01854]	-0.026(0.009)**	-0.020(0.008)*
30th Percentile [40.90752]	-0.030(0.009)***	-0.024(0.008)**
40th Percentile [42.03272]	-0.037(0.010)***	-0.029(0.009)**
50th Percentile [42.81685]	-0.041(0.011)***	-0.033(0.010)***
60th Percentile [43.98028]	-0.048(0.012)***	-0.039(0.011)***
70th Percentile [45.03413]	-0.053(0.014)***	-0.043(0.013)***
80th Percentile [47.13808]	-0.065(0.017)***	-0.053(0.015)***
90th Percentile [50.45599]	-0.083(0.022)***	-0.069(0.020)***
99th Percentile [58.59861]	-0.129(0.035)***	-0.107(0.032)***

Notes: N = 550. * $p < .05$, ** $p < .01$, *** $p < .001$ (two-tailed), #$p < .05$ (one-tailed). Raw percentile values appear in brackets. Panel corrected standard errors appear in parentheses.
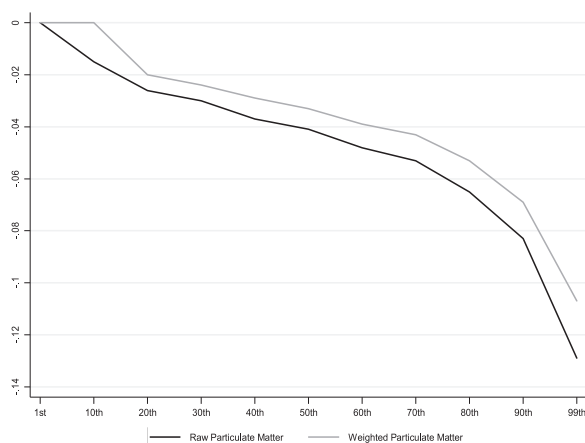

Fig. 2. Slope coefficients for the association between particulate matter and average life expectancy as a function of income shares. *Notes*: Values obtained from Table 5. Y axis includes slope coefficients for particulate matter. X axis includes percentiles for income shares of top 10%.

varying characteristics. We also calculated and used interaction terms to formally assess whether the association between fine particulate matter and life expectancy varies by the level of income inequality within states.

We anticipated that states with higher levels of fine particulate matter would tend to exhibit lower life expectancy. This is what we found. Across all three outcomes and additive models, states with higher $PM_{2.5}$ levels tend to exhibit lower average life expectancy. This general pattern was observed with our specifications for raw and weighted $PM_{2.5}$ and with adjustments for income share of the top 10%, total population, GDP per capita, median household income, median age in years, percent college degree or higher, percent black, and percent Hispanic/Latino. These results are generally consistent with previous research on the population health consequences of air pollution (Brook et al., 2010; Brunekreef & Holgate, 2002; Chay & Greenstone, 2003; Clancy et al., 2002; Currie & Neidell, 2005; Currie et al., 2009; Franklin et al., 2007; Graff Zivin & Neidell, 2013; Greenstone & Hanna, 2014; Heutel & Ruhm, 2016; Knittel et al., 2016; Künzli et al., 2000; Laden et al., 2006; Mikati et al., 2018; Mustafić et al., 2012; Pope & Dockery, 2006; Wellenius et al., 2005).

We also proposed that the inverse association between particulate matter and life expectancy would be intensified in states with greater income inequality. Across our three life expectancy outcomes and multiplicative models, the association between state $PM_{2.5}$ levels and average life expectancy intensified in states with higher levels of income inequality. Put differently, $PM_{2.5}$ levels were more detrimental to population life expectancy in states where a higher percentage of income was concentrated in

the top 10% of the state income distribution. To our knowledge, this is the first study to examine the multiplicative impact of income inequality on the association between air quality and life expectancy within the United States.

Our findings make an important contribution to the environmental justice literature, which among other things, emphasizes that uneven levels of exposure to human-caused pollution are tied to forms of structural inequality (Ard, 2016; Boyce & Pastor, 2013; Currie et al., 2009; Devlin et al., 2003; Heutel & Ruhm, 2016; Mikati et al., 2018; Mohai & Saha, 2015). Although not a direct test, our results are also generally consistent with the noted principles of Power, Proximity, and Physiology. Past research shows that income inequality undermines the health and functioning of populations (Anderson et al., in press; Clarkwest, 2008; Diez-Roux et al., 2000; Hill & Jorgenson, 2018; Lynch et al., 2001; Kaplan et al., 1996; Kawachi & Kennedy, 1999; Neumayer & Plümper, 2016; Pickett & Wilkinson, 2015; Rambotti, 2015; Wen et al., 2003; Wilkinson & Pickett, 2006, 2009). While we observe an inverse relationship between income inequality and life expectancy, we also provide additional evidence to suggest that income inequality can amplify the health risks associated with environmental degradation.

Our analyses should be considered within the context of multiple limitations. First, our data are limited to only one decade (2000–2010). Second, we examined only one indicator of air quality (fine particulate matter), population health (average life expectancy), and income inequality (income shares to the top 10%). We note that our findings are generally the same if we instead use measures of the income share of the top 5% and the top 1% (see also Hill and Jorgenson, 2018; Jorgenson et al., 2017). Third, income inequality stands in as a black box in our analyses. We offer various theoretical explanations for why income inequality might intensify the effects of particulate matter on life expectancy, but in the present study none of these explanations are assessed empirically. Fourth, we acknowledge that our two-way fixed-effects models likely led to the estimation of relatively conservative coefficients, especially since such models account for multiple forms of heterogeneity bias with the use of case-specific and year-specific intercepts, or the equivalent (Allison, 2009; Treiman, 2009; Wooldridge, 2010). Thus, our results could be viewed as conservative estimates of the effects of particulate matter and income inequality on life expectancy. Fifth, it is possible that our state-level analyses overlook important variation within states, such as at the county level. Finally, our analyses focus explicitly on US states. The extent to which air pollution and income inequality impact population health could be quite different in other Global North nations as well as in nations throughout the Global South. With these limitations in mind, the veracity of our analyses is contingent upon replication using data for subnational units for the US and other nations, with longer study periods and lower levels of aggregation (e.g., county-level analyses), more indicators of air pollution, population health (e.g., infant mortality and cause-specific mortality), and income inequality (e.g., Robin Hood, Atkinson, and Theil), and more direct tests of the theoretical principles of Power, Proximity, and Physiology.

Conclusion

Our findings indicate that fine particulate matter is especially detrimental to life expectancy in US states with higher levels of income inequality. One important implication for social epidemiology is moving beyond the direct and indirect effects of income inequality. Reframing income inequality as an effect modifier, as we have done, opens new doors to the seemingly countless ways in which income inequality can make other established risk factors for population health even worse. Further, a notable implication of our results for environmental justice research is the indexing of environmental inequality according to the broader inequitable conditions of states, in this case income inequality. Thus, a next step includes considering additional moderating effects in relation to racial composition and other sociodemographic characteristics of populations, which could provide a more comprehensive environmental justice analysis. Research along these lines will become increasingly important as broader trends toward neoliberalism continue to drive the deregulation of economic systems, healthcare, and environmental protections (Coburn, 2004; Harvey, 2006).

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Conflicts of interest

No conflicts of interest.

Ethical statement

None.

IRB

This study uses de-identified secondary state-level data. Because the current study uses previously collected data that are linked to states, not individuals, it was exempt from review at the University of Arizona.

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