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This study advances research at the intersection of environmental degradation, social stratification, and population health in the United States. Expanding the theoretical principles of power, proximity, and physiology, we hypothesize that the harmful effect of fine particulate matter on life expectancy is greater in states with higher levels of income inequality and larger black populations. To test our hypothesis, we use two-way fixed effects regression analysis to estimate the effect of a three-way interaction between fine particulate matter, income share of the top ten percent, and the percent of the population that is black on state-level average life expectancy for all US states and the District of Columbia (2000–2014). The findings support our hypothesis: the estimated effect of the three-way interaction on average life expectancy is negative and statistically significant, net of various socioeconomic and demographic controls. Using post-estimation techniques, we visually illustrate that the harmful effect of fine particulate matter on life expectancy is especially pronounced in states with both very high levels of income inequality and very large black populations. We conclude by summarizing the theoretical and substantive implications of our findings, the limitations of the study, and potential next steps in this evolving area of interdisciplinary research.

Introduction

Social science scholarship on environmental inequality and environmental justice has long argued that unequal economic conditions and the racial composition of populations often work together to amplify the health implications of environmental degradation, particularly in the United States (e.g. Downey 1998, 2005, Downey and Hawkins 2008, Faber 2008, Mohai *et al* 2009, 2011, Grant *et al* 2010, Taylor 2014, Ard 2015, 2016, Mohai

and Saha 2015, Lynch *et al* 2017). As Brulle and Pellow (2006:117) note, the social distribution of environmental harms has always involved class *and* race and the ‘...social production of environmental inequality cannot be understood through a singularly focused framework that emphasizes one form of inequality to the exclusion of others.’

Recently, Hill and colleagues (2019) conducted a longitudinal analysis of US states and the District of Columbia to formally test whether income inequality

exacerbates the population health impacts of air pollution. They find that the negative association between fine particulate matter (PM_{2.5}) levels and average life expectancy is intensified 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 ten percent. They sketch out and apply the theoretical principles of *power*, *proximity*, and *physiology* to help explain how income inequality can exacerbate the population health impacts of air pollution (see also Charafeddine and Boden 2008, Curran and Mahutga 2018, Hill and Jorgenson 2018).

Briefly, the Power principle focuses on how income inequality exacerbates power differences that may result in certain populations being more vulnerable to air pollution. The Proximity principle highlights how inequality contributes to forms of segregation that increase the vulnerability of certain groups to pollution. The Physiology principle illuminates how inequality can undermine the physiological conditions of economically disadvantaged groups, which makes them more vulnerable to the health impacts of pollution (Hill *et al* 2019).

We engage and expand on this previous research, as we suggest that the theoretical principles of power, proximity, and physiology are also likely to be contingent on the racial/ethnic composition of populations. Thus, we expect to find that air pollution is more harmful to life expectancy in US states when inequitable income distributions are combined with larger minority populations—a three-way interaction of air quality, income inequality, and race/ethnic composition. In other words, we hypothesize that the inverse association between state-level PM_{2.5} and average life expectancy will be *more pronounced* in states with higher levels of income inequality *and* larger racial/ethnic minority populations, and, in particular, relatively larger black populations.

To evaluate our proposition, we conduct a longitudinal analysis of average life expectancy for all fifty US states and the District of Columbia for the 2000 to 2014 period. We estimate two-way fixed effects elasticity models of state-level average life expectancy that include measures of PM_{2.5}, income inequality, and racial/ethnic minority composition as well as multiple socioeconomic and sociodemographic controls. In line with our hypothesis, we primarily focus on the estimated effects of the three-way interaction between PM_{2.5}, income inequality, and percent of the population that is black. The importance of this research is clear. As highlighted by leading media sources⁹, including the *Washington Post*, *New York Times*, and

the *Public Broadcasting Service*, recent research shows that PM_{2.5} levels throughout the United States are on the rise, and the population health impacts are potentially devastating (Clay and Muller 2019).

In the next section we provide a background discussion of the three theoretical principles, and we expand each of them by highlighting the ways in which racial/ethnic minority populations in general and black populations in particular are structurally disadvantaged in terms of power, proximity, and physiology. Prior to the presentation of the findings, we describe the data included in the study as well as the model estimation techniques that we use to conduct the analysis. Following the results section, we conclude by summarizing the theoretical and substantive implications of our findings, the limitations of the study, and potential next steps in this evolving area of interdisciplinary research.

Background

The Power principle proposes that income inequality increases the vulnerability of specific populations to a given level of air pollution (Hill *et al* 2019). In part, this disproportionate exposure takes place because the concentration of political and economic power among a small percentage of the population often undermines environmental regulations and protections, of which the negative consequences are experienced by other segments of the population. Jorgenson and colleagues (2016, 2017, 2018) argue that those with higher incomes are often the owners of energy-producing enterprises and polluting firms. To protect their assets, those with higher incomes are more likely to influence political power and to direct the policy environment in their favor. These actions may manifest in existing environmental regulations not being enforced, the deregulation of industry, and pressure to not consider or adopt new environmental regulations, all of which can negatively affect the health and quality of life for the most vulnerable groups in society (see also Boyce *et al* 1994, 1999, 2007, Faber 2008, Downey 2015).

These overall arguments are consistent with propositions of neo-material theory, which we also treat as part of the Power principle. According to this theory, the concentration of income and political influence among elites weakens broader obligations to the general interests of society. For example, elites often exert political pressure to deregulate polluting industries, reduce taxes, and cut investments in social services and public resources that are intended to improve public health, such as consumer protections, education programs, and health care infrastructure (Kaplan *et al* 1996, Kawachi and Kennedy 1999, Lynch *et al* 2000, Clarkwest 2008, Neumayer and Plümper 2016, Truesdale and Jencks 2016).

⁹ See <https://washingtonpost.com/business/2019/10/23/air-pollution-is-getting-worse-data-show-more-people-are-dying/>, <https://nytimes.com/interactive/2019/10/24/climate/air-pollution-increase.html?action=click&module=Top%20Stories&pgtype=Homepage>, and <https://pbs.org/newshour/nation/u-s-air-quality-is-getting-worse-here-are-the-costs>.

In further expanding this principle, it is important to recognize how racial/ethnic minority populations in the United States, especially black populations, have long been structurally disadvantaged in terms of power (e.g. Du Bois 1992, Peña 1998, Dunbar-Ortiz 2014, Melamed 2015, Dawson 2016, Fraser 2018). Through various forms of expropriation and exploitation, minority populations have been extensively marginalized, resulting in a lack of financial assets, legal resources, and political influence. These conditions contribute to increased vulnerabilities to environmental risks from industry, transportation systems, waste sites, military testing, and other hazardous activities (Evans and Kantrowitz 2002, Hooks and Smith 2004, Brulle and Pellow 2006, Downey and Hawkins 2008, Taylor 2014, Brailsford *et al* 2019). For these reasons, Evans and Kantrowitz (2002:323) argue that nonwhite populations 'bear a disproportionate burden of exposure to sub-optimal, unhealthy environmental conditions in the United States.'

The Proximity principle indicates that income inequality increases the vulnerability of specific populations to a given level of air pollution by contributing to the segregation of vulnerable groups in geographic space (Hill *et al* 2019). Further, when there is a higher concentration of income, it allows the wealthy to live in areas with less industrial-based pollution, which reduces their exposure to environmental degradation. In a related vein, past research suggests that income inequality is associated with higher levels of residential segregation by class and race (Jargowsky 1996, Lobmayer and Wilkinson 2002, Cheshire *et al* 2003, Reardon and Bischoff 2011, Wen *et al* 2003). The concern is that segregated populations are especially vulnerable to industrial-based pollution and other specific forms of environmental degradation.

Environmental justice and public health research suggest that segregation produces and reinforces structural inequities in the context of residential proximity to emitters of industrial pollution (Boyce and Pastor 2013, Mohai and Saha 2015, Ard 2016, Pulido 2016, Brailsford *et al* 2018, Mikati *et al* 2018). For example, Mikati and colleagues (2018) find that socioeconomically disadvantaged groups and neighborhoods are exposed to higher levels of PM_{2.5} from facilities than wealthier communities, and this pattern is especially pronounced for black communities that are often socioeconomically disadvantaged. The health consequences of such environmental harms, according to scholars addressing questions associated with social capital, are compounded by widespread status competition generated by income inequality, which undermines cohesion, trust, cooperation, and, as a consequence, shared attempts to support the most at-risk populations (Kawachi *et al* 1997, Kawachi and Kennedy 1999, Elgar and Aitken 2010, Bell 2013, Truesdale and Jencks 2016).

It is important to underscore that racial/ethnic minority populations are often disadvantaged in terms of proximity. A substantial body of research shows that racial/ethnic minority populations in the United States, especially black populations, tend to live close to harmful sources of pollution because they are more likely to reside in neighborhoods that are segregated and socially isolated due to historical and structural inequalities, race-based discrimination, and racialized housing practices (e.g. Gee and Payne-Sturges 2004, Downey 2005, Brulle and Pellow 2006, Downey and Hawkins 2008, Taylor 2014, Ard 2016, Pulido 2016). As Brulle and Pellow (2006:109) explain, 'racial segregation is a major contributor to the creation and maintenance of environmental inequality because governments and corporations often seek out the path of least resistance when locating polluting facilities'.

The Physiology principle suggests that income inequality escalates the health impacts of air pollution by undermining the physiological conditions of specific human populations (Hill *et al* 2019). Psychosocial theory argues that the stress of relative deprivation, often the consequence of income inequality, exacerbates emotional distress, negative self-appraisals, unhealthy coping behaviors, and, through time, physiological dysregulation or allostatic load (Wilkinson 1996, 2005, Kawachi and Kennedy 1999, Lynch *et al* 2000, Wilkinson and Pickett 2009, Truesdale and Jencks 2016). In other words, income inequality leads to chronic social stressors that overwhelm the physiological stress response or allostatic systems of the human body (Charafeddine and Boden 2008). If stress is short-term or acute, allostatic systems can efficiently manage the physiological consequences of stress. However, when stress is long-term or chronic, the result is allostatic load or significant 'wear and tear' on the major physiological systems of the human body (McEwen 1998:171).

Diminished lung function is a primary sign of allostatic load (McEwen 2002, Crimmins *et al* 2003, Seeman *et al* 2004). Stress and related hormones lead to the physiological dysregulation of the lungs through bronchodilation and increased respiration, airway inflammation and difficulty breathing, and the immune system being comprised, which increases vulnerability to respiratory infections (Lehrer 2006, Kullowatz *et al* 2008). These processes are especially relevant for specific forms of air pollution that can be inhaled deeply into the lungs, including PM_{2.5}.

Racial/ethnic minority populations are especially vulnerable to physiological dysregulation and allostatic load because they are disproportionately exposed to stressful conditions, including the accumulation of structural constraints like racism, income inequality and poverty, and environmental exposures like crime and pollution (e.g. Gee and Payne-Sturges 2004, Geronimus *et al* 2006, Krieger, 2012, Bailey *et al* 2017, Brailsford *et al* 2019). Along these lines,

Krieger's (2012: 941) ecosocial theory of race/ethnic health disparities emphasizes the 'cumulative embodiment of multiple types of discrimination, deprivation, and other harmful exposures,' including racism. Thus, racial/ethnic minority populations in the United States are often disadvantaged in terms of physiology.

Although previous research has not empirically tested the three-way interaction we are proposing, at least two studies have considered the two-way interaction between state-level income inequality and individual-level race/ethnicity. Using pooled data from the 1995 and 1997 Current Population Surveys, Subramanian and Kawachi (2006) find that the positive association between state-level income inequality and fair or poor self-rated health is more pronounced for white respondents than for black respondents. These findings are inconsistent with our racialized model of air quality and income inequality, but we note the study uses a subjective measure of self-rated health rather than more objective measures of chronic illness or life expectancy.

More recently, Vilda and colleagues (2019) use data from the National Center for Health Statistics and American Community Survey (2011–2015) to examine the association between state-level income inequality and pregnancy-related mortality. The study shows that income inequality is positively associated with pregnancy-related mortality among black women, but not among white women. These results are generally consistent with the arguments of our refined theoretical principles of power, proximity, and physiology.

Overall, our primary argument, which we evaluate in the subsequent analysis, is that the interaction between state-level air pollution and income inequality that contributes to reduced life expectancy is likely to be further amplified in states with relatively larger black populations. This three-way interaction (air pollution * income inequality * percent black) and our corresponding theoretical refinements are important extensions of previous studies of environment, social stratification, and health (e.g. Hill *et al* 2019). Building on prior research, we also estimate models with two-way interactions to assess whether (1) the magnitude of the harmful effect of air pollution on population health is higher in states with greater levels of income inequality, (2) the population health impacts of pollution are elevated in states with larger black populations, and (3) the harmful impact of income inequality on life expectancy is higher in states with larger black populations (and vice versa).

Data and methods

Sample

The analyzed sample consists of each of the fifty US states and the District of Columbia for the 2000–2014 period. These are the states and years in which data are

readily available for the dependent variable and the independent variables. We have perfectly balanced panels of 15 observations for all cases except Florida (14 observations), Hawaii (14 observations), Illinois (13 Observations), Maine (3 observations), and Mississippi (12 observations). The missing observations are due to limited availability of data for the PM_{2.5} measure. Since our findings are substantively consistent if we exclude these five states and their unbalanced panels, for broader coverage we choose to include them in the reported analysis. Overall, the analyzed dataset consists of 746 total observations and is available from the lead author upon request.

Model estimation technique

We use Stata to estimate Prais–Winsten time-series cross-sectional regression models with panel-corrected standard errors, allowing for disturbances that are heteroskedastic and contemporaneously correlated across panels (Beck and Katz 1995). We correct for first-order autocorrelation (AR1 disturbances) within panels, and we treat AR1 disturbances as common to all panels because we have no reason for assuming panel-specific autocorrelation. To correct for heterogeneity bias, we control for both state-specific and year-specific effects by including dummy variables for cases and years. Heterogeneity bias, in this context, is the confounding effect of unmeasured variables omitted from regression models.

Our general model is as follows:

$$y_{it} = \beta x_{it} + u_i + w_t + e_{it}.$$

Subscript i represents each state, subscript t represents the year, and y_{it} is the dependent variable for each state at each year. β represents the vector of coefficients for predictor variables that vary over time, x_{it} is the matrix of independent variable values for each year and state, u_i is the state-specific term that is constant over time, w_t is the year-specific term that is constant across all states, and e_{it} is the disturbance term unique to each state at each point in time.

The inclusion of year-specific intercepts is equivalent to modeling temporal fixed effects, and including both year-specific intercepts and case-specific fixed effects is analogous to estimating a two-way fixed effects model, which often lead to relatively conservative hypothesis testing since these intercepts tend to explain a substantial amount of variation in the dependent variable (Allison 2009, Wooldridge 2010). Including year-specific intercepts also lessens the likelihood of biased model estimates resulting from outcomes and predictors with similar time trends. We note that this technique controls out between-case variation in favor of estimating within-case effects, the standard approach in most panel analyses.

With the exception of the dummy variables for the case-specific and temporal fixed effects, all variables are converted into logarithmic form (base 10),

Table 1. Descriptive statistics.

	Mean	Std Dev	Minimum	Maximum
Average life expectancy	77.854	1.758	72.070	81.420
PM _{2.5}	10.552	2.996	3.370	19.024
Income share of top ten percent	44.081	5.048	33.562	62.259
Percent black	12.018	11.105	1.260	61.000
Total population	5953 405	6619 074	490 000	38 625 139
Median household income	57.869	8.877	40.116	82.948
Median age in years	36.866	2.225	27.100	42.500
Percent college degree or higher	30.220	7.545	17.000	70.000
Average life expectancy (log base 10)	1.891	0.010	1.857	1.911
PM _{2.5} (log base 10)	1.005	0.131	0.527	1.279
Income share of top ten percent (log base 10)	1.641	0.048	1.525	1.794
Percent black (log base 10)	0.896	0.418	0.100	1.785
Total population (log base 10)	6.558	0.449	5.690	7.587
Median household income (log base 10)	4.757	0.066	4.603	4.919
Median age in years (log base 10)	1.565	0.027	1.432	1.628
Percent college degree or higher (log base 10)	1.468	0.099	1.230	1.845

Notes. $N = 746$; 15 annual observations per state except for Florida (14 obs.), Hawaii (14 obs.), Illinois (13 obs.), Maine (3 obs.), and Mississippi (12 obs.).

allowing for the estimation of elasticity models, a relatively common technique in longitudinal research in the environmental social sciences and population health. In these models, the elasticity coefficient for an independent variable is the estimated net percentage change in the dependent variable associated with a 1% increase in the independent variable.

Dependent variable

The dependent variable is average life expectancy at birth, one of the most widely studied indicators of population health. These data are obtained from the United States Mortality Data Base, University of California, Berkeley (usa.mortality.org, accessed 5/14/19).

Independent variables

We measure air pollution by using average annual small particulate matter (PM_{2.5}) concentrations from EPA's Air Quality System (AQS) database (<https://epa.gov/aqs>, accessed 5/31/19). Most particulate matter is a combination of chemicals emitted from power plants, transportation vehicles, and various kinds of industrial facilities. Particles of this small size can enter the bloodstream when inhaled, potentially contributing to serious health complications with mortality implications, including atherosclerosis, asthma, and acute heart and lung problems. To calculate state average PM_{2.5} concentrations, and consistent with prior research, we take annual mean concentrations at the county level, weighted by the product of the population and proportion of actual to potential observations in each county (Heutel and Ruhm 2016, Hill *et al* 2019). We obtain data on county populations from this period from the US Census Bureau's intercensal population estimates. We define potential observations as the total number of observations required by EPA (available through the AQS database), since this can vary by county. This

weighting procedure helps adjust for the uneven distribution of monitors across counties and over the study period.¹⁰

We measure income inequality as income share of the top ten percent, which is common in prior state-level research on both population health and environmental outcomes (e.g. Jorgenson *et al* 2017, 2018, Hill and Jorgenson 2018, Hill *et al* 2019). We obtain these data from the World Wealth and Income Database (<http://wid.world/#Database>, accessed 3/2/19), developed by Frank *et al* (2015). There are multiple measures of income inequality, such as the widely used Gini coefficient. Considering our theoretical framework in general, and our arguments about power and proximity in the context of income inequality in particular, our selected measure is quite appropriate for the present study since it explicitly focuses on the top end of the income distribution. Future research could use alternative inequality measures, especially if they are justified on theoretical or substantive grounds.

We include percent of the population that is black as our measure of racial/ethnic minority composition. We obtain these data from the US Census Bureau's online database (accessed 4/3/19). Since a small number of cases for this variable have a value less than 1, and we estimate elasticity models (and therefore all data are transformed into base 10 logarithmic form), we add a constant of 1.0 to each observation for this measure.

We calculate and use the following three-way interaction: PM_{2.5} * income share of top ten percent * percent black. In line with the primary arguments provided in the background section, we expect that when values

¹⁰ While our approach to measuring state-level PM_{2.5} is consistent with past research, we acknowledge that it is not ideal since all other variables included in the estimated models are more direct state-level measures.

Table 2. Elasticity coefficients for the regression of life expectancy on PM_{2.5}, income inequality, percent black, and other predictors: two-way fixed effects model estimates for all US States and the District of Columbia, 2000–2014.

	Model 1	Model 2	Model 3	Model 4	Model 5
PM _{2.5}	−0.005*** (0.001)	−0.007*** (0.001)	−0.008*** (0.001)	−0.005*** (0.001)	−0.007*** (0.001)
Income share of top ten percent	−0.012*** (0.003)	−0.018*** (0.003)	−0.016*** (0.003)	−0.012*** (0.003)	−0.008* (0.003)
Percent black	−0.020*** (0.004)	−0.020*** (0.004)	−0.009* (0.004)	−0.019*** (0.004)	−0.006 (0.004)
PM _{2.5} * income share of top ten percent		−0.109*** (0.012)			−0.105*** (0.012)
PM _{2.5} * percent black			−0.025*** (0.003)		−0.023*** (0.003)
Income share of top ten percent * percent black				0.004 (0.006)	0.012 (0.008)
PM _{2.5} * income share of top ten percent * percent black					−0.255*** (0.044)
Total population	0.019*** (0.003)	0.020*** (0.006)	0.026*** (0.006)	0.019*** (0.006)	0.024*** (0.006)
Median household income	0.004 (0.003)	0.001 (0.003)	0.006* (0.003)	0.004 (0.003)	0.005 (0.003)
Median age in years	−0.035 (0.021)	−0.037 (0.020)	−0.023 (0.019)	−0.037 (0.020)	−0.017 (0.022)
Percent college degree or higher	0.002 (0.002)	0.002 (0.002)	0.002 (0.002)	0.002 (0.002)	0.001 (0.002)
Constant	1.827*** (0.064)	1.812*** (0.068)	1.736*** (0.064)	1.791*** (0.065)	1.715*** (0.070)
R-sq	0.999	0.999	0.999	0.999	0.999

Notes. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ (two-tailed); all variables are in logarithmic form (base 10); panel corrected standard errors in parentheses; $N = 746$; 15 annual observations per state except for Florida (14 obs.), Hawaii (14 obs.), Illinois (13 obs.), Maine (3 obs.), and Mississippi (12 obs.); PM_{2.5} and income share of top ten percent are mean centered in Model 2; PM_{2.5} and percent black are mean centered in Model 3; income share of top ten percent and percent black are mean centered in Model 4; PM_{2.5}, income share of top ten percent, and percent black are mean centered in Model 5.

on each of these are greater, and thus the value of the three-way interaction is higher, that it will lead to reduced average life expectancy. We also calculate and use the following two-way interactions: PM_{2.5} * income share of top ten percent, PM_{2.5} * percent black, and income share of top ten percent * percent black. For ease of interpretation of main effects, we calculate and use the mean-centered versions for these variables (PM_{2.5}, income share of top ten percent, percent black) in the estimated models that consist of any interactions that include them.

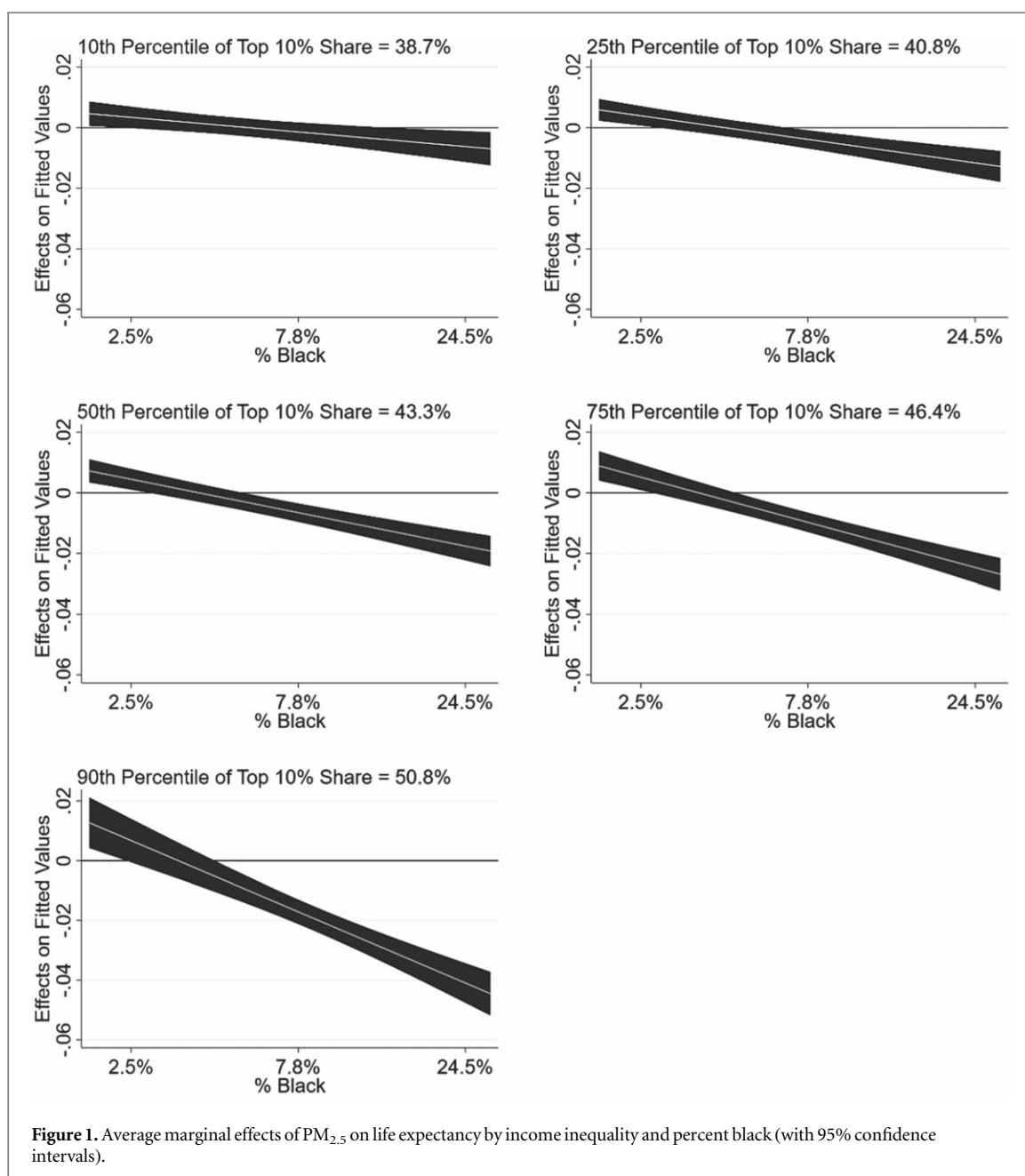
As control variables, we include state-level measures of total population size, median household income (in thousands of constant 2017 US dollars), median age in years, and the percent of the population holding a bachelor's degree or higher for ages 25–34. The data for these four variables are obtained from the US Census Bureau's online database (accessed 4/5/19).

Table 1 reports descriptive statistics for the substantive variables included in the study in their original metrics and in logarithmic form (base 10). Descriptive statistics for all two-way and three-way interactions as well as the mean-centered variables are available from the lead author upon request.

Results

Table 2 presents the findings for the analysis. The close to perfect r -squared statistics are largely due to the state-specific and year-specific intercepts, which serve as the two-way fixed effects in the models. Model 1 includes only the direct effects of the predictors. As expected, we find that PM_{2.5}, income share of the top ten percent, and percent black all exhibit negative and statistically significant effects on average life expectancy. We also find that total population has a positive and statistically significant effect on average life expectancy, and this significant positive effect holds across all reported models. We now turn to the estimated effects of the two-way and three-way interactions in Models 2 through 5.

The results of Model 2 suggest that the two-way interaction between PM_{2.5} and income share of the top ten percent has a negative effect on life expectancy. This finding indicates that PM_{2.5} levels are more detrimental to life expectancy in states with higher levels of income inequality, which replicates prior research (Hill *et al* 2019). Model 3 includes the two-way interaction between PM_{2.5} and percent black, which yields a negative and statistically significant effect on life



expectancy. This suggests that the impact of $PM_{2.5}$ on population health is more detrimental in states with relatively larger black populations. These findings are consistent with longstanding arguments in environmental justice scholarship (e.g. Mohai *et al* 2009). Model 4 introduces the two-way interaction between income share of the top ten percent and percent of population that is black, and its estimated effect on life expectancy is not statistically significant. Overall, the results for Models 2–4 indicate that income inequality and percent of the population that is black both act as moderators that exacerbate the impact of $PM_{2.5}$ on average life expectancy, while percent black does not appear to moderate the impact of income inequality on life expectancy (and vice versa), at least for US states.

Model 5 includes the three-way interaction for $PM_{2.5}$ * income share of the top ten percent * percent black, the primary focus of this study, which is found to have a negative and statistically significant effect on life expectancy¹¹. This result confirms our hypothesis and is consistent with our refined theoretical principles of power, proximity, and physiology. To provide a more nuanced assessment of the relationship, we graphically present the estimated effect of the three-way interaction in figure 1, which we generate using Stata's

¹¹ It is common for models to have very high multicollinearity when they include three-way and two-way interactions (Jaccard *et al* 1990), which likely applies to the present analysis. However, given our relatively large sample size and especially the consistency in findings across the estimated models that include interactions (York 2012), we are reasonably confident in the reliability and validity of the reported findings.

'margins' suite of commands. While there are several ways to illustrate the three-way interaction, we choose to focus on how the slope of $PM_{2.5}$ changes at various levels of the percentage black and income inequality. The plotted line in each graph represents the slope for $PM_{2.5}$ at its mean-centered value, along with the 95% confidence intervals of the point estimates. The graphs plot out the $PM_{2.5}$ slope from low to high percentages of the population that is black, separated by the 10th, 25th, 50th, 75th, and 90th percentiles of the income share of the top ten percent. The results show that the $PM_{2.5}$ slope varies across both levels of percent of the population that is black and percent income of the top ten percent, and the $PM_{2.5}$ slope tends to become more negative in magnitude as both the percentage of the population that is black and income inequality increase.

For each level of income inequality, $PM_{2.5}$ is weakly associated with increases in life expectancy when the percentage of the population that is black is very small. The $PM_{2.5}$ slope coefficient decreases and begins to have a negative effect on life expectancy as the percent of the population that is black increases. The deleterious effect of $PM_{2.5}$ on life expectancy amplifies as income inequality increases as well. For example, when income inequality is at the 10th percentile (top 10% share = 38.7%) and is at the 90th percentile for the percentage black (29.5%), the $PM_{2.5}$ slope coefficient is -0.01 and statistically significant. However, at the 90th percentile of income inequality (top 10% share = 50.8%) and the 90th percentile of percentage black (28.5%), the $PM_{2.5}$ slope coefficient decreases to -0.04 and is statistically significant. Overall, $PM_{2.5}$ has its largest harmful effect on life expectancy in US states that have both a relatively high level of income inequality and a large percent of the population that is black.

Conclusion

This study contributes to interdisciplinary research on environmental degradation, social stratification, and health. More specifically, we built on, and simultaneously refined, the theoretical principles of power, proximity, and physiology, initially formulated by Hill and colleagues (2019) to help explain how income inequality amplifies the population health impacts of air pollution. We argued that these theoretical principles are also very likely to be contingent on the racial/ethnic composition of states, and thus we hypothesized that air pollution, measured as $PM_{2.5}$, is more devastating to life expectancy in US states with both inequitable income distributions and larger minority populations, particularly larger black populations.

To evaluate our hypothesis, we calculated a three-way interaction between $PM_{2.5}$, income inequality (income share of the top ten percent), and the percent of population that is black. We then treated this

three-way interaction as a predictor in longitudinal elasticity models of state-level average life expectancy at birth for all fifty states and the District of Columbia. The results of the analysis for the 2000–2014 period support our hypothesis: the three-way interaction has a negative effect on state-level average life expectancy, net of various covariates as well as state-specific and year-specific fixed effects. Using post-estimation techniques, we graphically illustrated that the harmful effects of $PM_{2.5}$ on life expectancy are especially exacerbated in US states with both high levels of income inequality and larger black populations.

Additional findings indicated that when the three-way interaction is decomposed into its constituent subcomponents, the impacts of $PM_{2.5}$ on life expectancy are more pronounced in states with higher levels of income inequality and in states with larger black populations (modeled with two-way interactions). Furthermore, the direct effects of $PM_{2.5}$, income share of the top ten percent, and the percent of the population that is black on life expectancy are all negative. The stability and consistency of the additional results when the three-way interaction is decomposed suggest that our finding of interest is not a statistical artifact. They also provide additional evidence that economic inequality and racial/ethnic inequality both directly affect population health as well as work in tandem to exacerbate the health impacts of air pollution.

Like all research, this study has limitations, which could be addressed in future analyses. Here we briefly describe four. First, it is possible that there is heterogeneity within states that our study does not capture. This could be considered through pursuing analogous research questions at smaller scales, ideally at the individual level while also taking into account broader contextual factors at the county level or state level, if or when the necessary data for all predictors and the outcome become available. Second, it is unclear if our findings are generalizable outside the United States, which therefore suggests the importance for future research to ask similar questions in other sub-national contexts. Third, while the use of our key predictors and outcome in the present study are justified on theoretical grounds and are consistent with rich bodies of prior population health research and environmental justice scholarship, future investigations would do well to consider alternative measures of pollution, income inequality, and certainly other categories of racial/ethnic population as well as additional objective measures of population health and perhaps subjective measures of health. And fourth, future research would do well to consider other socio-demographic factors that might moderate the impact of $PM_{2.5}$ on population health, such as the age composition of populations or industrial labor conditions. Such analyses could lead to a more comprehensive understanding of the relationships between population health and various socio-environmental inequities.

In conclusion, this study advances theory and interdisciplinary research on pollution, inequality, and health. The results indicate that income inequality and racial/ethnic composition can simultaneously amplify the health impacts of PM_{2.5} in the United States. Specifically, air pollution is most devastating to life expectancy in states with higher levels of income inequality and larger black populations. We hope this research encourages others to pursue related questions concerning the intersections of air quality and other environmental harms, social stratification, and population health.

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Data availability statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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