Air Quality and Life Expectancy in the United States:

An Analysis of the Moderating Effect of Income Inequality

Terrence D. Hill, School of Sociology, University of Arizona[a]

Andrew K. Jorgenson, Department of Sociology, Boston College[b]

Peter Ore, School of Sociology, University of Arizona[a]

Kelly S. Balistreri, Department of Sociology, Bowling Green State University[c]

Brett Clark, Department of Sociology, University of Utah[d]

Corresponding Author: Terrence D. Hill, The University of Arizona, School of Sociology, Social Sciences Building, Room 427, 1145 E. South Campus Drive, Tucson, AZ 85721. E-mail: tdhill@email.arizona.edu. Phone: 520-621-3804. Fax: 520-621-9875.

[a]University of Arizona, School of Sociology, Social Sciences Building, Room 427, 1145 E. South Campus Drive, Tucson, AZ 85721. E-mail: peterore@email.arizona.edu.

[b]Boston College, Department of Sociology, McGuinn Hall 426, 140 Commonwealth Avenue, Chestnut Hill, MA 02467. E-mail: andrew.jorgenson@bc.edu.

[c]Bowling Green State University, Department of Sociology, 218 Williams Hall, Bowling Green, OH 43403. E-mail: kellyba@bgsu.edu.

[d]University of Utah, Department of Sociology, 380 S 1530 E RM 301, Salt Lake City, UT 84112. E-mail: brett.clark@soc.utah.edu.

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ABSTRACT

Although studies have shown that air pollution can be devastating to population health, little is known about 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 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 in years, 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, net of various controls. We discuss the implications of our results for future research in social epidemiology and environmental justice.

Keywords: air quality; particulate matter; income inequality; life expectancy; social epidemiology

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 and Holgate, 2002; Chay and Greenstone, 2003; Clancy et al., 2002; Currie and Neidell, 2005; Currie et al., 2009; Franklin et al., 2007; Graff Zivin and Neidell, 2013; Greenstone and Hanna, 2014; Heutel and Ruhm, 2016; Knittel et al., 2016; Künzli et al., 2000; Mikati et al., 2018; Mustafić et al., 2012; Pope and Dockery, 2006; Wellenius et al., 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 and Pastor, 2013; Currie et al., 2009; Devlin et al., 2003; Heutel and Ruhm, 2016; Mikati et al., 2018; Mohai and Saha, 2015).

In this study, we expand on previous health and environmental justice research by exploring the intersection of air pollution and income inequality in the US context. Although previous scholarship has shown that greater income inequality is associated with poorer population health (Clarkwest, 2008; Diez-Roux et al., 2000; Hill and Jorgenson, 2018; Lynch et al., 2001; Kaplan et al., 1996; Kawachi and Kennedy, 1999; Neumayer and Plümper, 2016; Pickett and Wilkinson, 2015; Rambotti, 2015; Wen et al., 2003; Wilkinson and 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 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 the political-economy approach developed by Boyce and colleagues (1994, 1999, 2007), Jorgenson and colleagues (2016, 2017, 2018) point out that those with higher incomes and wealth are often the owners of polluting firms and energy producing enterprises (see also Schor and Jorgenson, in press). 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 findings are further supported by Neo-Material theory, which suggests that income inequality concentrates wealth and power among elites and weakens broader commitments to the general interests of society among lower classes, which 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; Jorgenson et al., 2017; Kaplan et al., 1996; Kawachi and Kennedy, 1999; Lynch et al., 2000; Neumayer and Plümper, 2016; Truesdale and Jencks, 2016).

<Figure 1 about here>

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 et al., 2003; Jargowsky, 1996; Lobmayer and Wilkinson, 2002; Reardon and 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 and Pastor, 2013; Mikati et al., 2018; Mohai and Saha, 2015). For example, a recent study by Mikati and colleagues (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, 2010; Kawachi et al., 1997; Kawachi and Kennedy, 1999; Truesdale and 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. 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 and Kennedy, 1999; Lynch et al., 2000; Truesdale and Jencks, 2016; Wilkinson, 1996, 2005; Wilkinson and 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 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 et al., 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 in regard to specific forms of air pollution, most notably fine particulate matter, which can be inhaled deeply into the lungs.

In this study, we directly assess the multiplicative impact of income inequality on the association between fine particulate matter and life expectancy 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 intensified in states with higher levels of income inequality.

METHODS

Data

This study involves two sources of data. The first data source includes annual observations for average life expectancy at birth from 2000 to 2010 for 49 US states and the District of Columbia. Our final analytic sample for our first source of data includes 550 observations. The second data source 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, leading to 150 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 data source is restricted to three years due to data availability limitations for our sex-specific life expectancy measures.

Measures

Life Expectancy. Our regression 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 et al., 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 monitor. 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 either the weighted or unweighted versions of $PM_{2.5}$.

Income Inequality. Following recent research (e.g., Hill and Jorgenson 2018; Jorgenson et al., 2017, 2018), we measure income inequality as income shares for the top 10%. Our income share data were obtained from the World Wealth and Income Database (WWID). Income shares are constructed from individual tax filing data available from the Internal Revenue Service and are measured in percentages (see Frank et al., 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 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 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 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%.

<Table 1 about here>

Regression Analyses

Tables 2, 3, and 4 present two-way fixed-effects models for total average life expectancy (Table 2), female life expectancy (Table 3), and male life expectancy (Table 4). Across all outcomes and 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.

<Tables 2-4 about here>

To formally assess whether the association between air quality and life expectancy varies as a function of income inequality levels, we tested six interaction terms in Tables 2, 3, and 4. Across 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 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. Figure 1 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%.

<Table 5 about here>

<Figure 2 about here>

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. Thus, 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 employed 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-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 and Holgate, 2002; Chay and Greenstone, 2003; Clancy et al., 2002; Currie and Neidell, 2005; Currie et al., 2009; Franklin et al., 2007; Graff Zivin and Neidell, 2013; Greenstone and Hanna, 2014; Heutel and Ruhm, 2016; Knittel et al., 2016; Künzli et al., 2000; Mikati et al., 2018; Mustafić et al., 2012; Pope and 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 (Ard, 2016; Boyce and Pastor, 2013; Currie et al., 2009; Devlin et al., 2003; Heutel and Ruhm, 2016; Mikati et al., 2018; Mohai and 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 (Clarkwest, 2008; Diez-Roux et al., 2000; Hill and Jorgenson, 2018; Lynch et al., 2001; Kaplan et al., 1996; Kawachi and Kennedy, 1999; Neumayer and Plümper, 2016; Pickett and Wilkinson, 2015; Rambotti, 2015; Wen et al., 2003; Wilkinson and Pickett, 2006, 2009). We provide additional evidence to suggest that income inequality can also amplify the 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 to 2010). Second, we examine only one indicator of air quality (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, it is possible that our state-level analyses could overlook important heterogeneity 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 within 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 formal mediated moderation 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 neo-liberalism continue to drive the deregulation of economic systems, healthcare, and environmental protections (Coburn, 2004; Harvey, 2006).

REFERENCES

Allison, P. (2009). *Fixed effects regression models*. Thousand Oaks, CA: SAGE.

Ard, K. (2016). By all measures: An examination of the relationship between segregation and health risk from air pollution. *Population and Environment*, *38*, 1-20.

Beck, N., & Katz, J. (1995). What to do (and not to do) with time-series cross-section data. *American Political Science Review*, *89*, 634-647.

Boyce, J. (1994). Inequality as a cause of environmental degradation. *Ecological Economics*, *11*, 169-178.

Boyce, J., Klemer, A., Templet, P., & Willis, C. (1999). Power distribution, the environment, and public health: A state-level analysis. *Ecological Economics*, *29*, 127-140.

Boyce, J. (2007). Inequality and environmental protection. In J. Baland, P. Bardhan, & S. Bowles (Eds.), *Inequality, Collective Action, and Environmental Sustainability* (pp. 314-348). Princeton: Princeton University Press.

Boyce, J., & Pastor, M. (2013). Clearing the air: incorporating air quality and environmental justice into climate policy. *Climatic Change*, *120*, 801-814.

Brook, R., Rajagopalan, S., Pope, C., Brook, J., Bhatnagar, A., Diez-Roux, A., ... & Peters, A. (2010). Particulate matter air pollution and cardiovascular disease: An update to the scientific statement from the American Heart Association. *Circulation*, *121*, 2331-2378.

Brunekreef, B., & Holgate, S. (2002). Air pollution and health. *The Lancet*, *360*, 1233-1242.

Chay, K., & Greenstone, M. (2003). The impact of air pollution on infant mortality: evidence from geographic variation in pollution shocks induced by a recession. *The Quarterly Journal of Economics*, *118*, 1121-1167.

Cheshire, P., Monastiriotis, V., & Sheppard, S. (2003). Income inequality and residential segregation: Labour market sorting and the demand for positional goods. In R. Martin and P. Morrison (Eds.), *Geographies of Labour Market Inequality* (pp. 67-85). London: Routledge.

Clancy, L., Goodman, P., Sinclair, H., & Dockery, D. (2002). Effect of air-pollution control on death rates in Dublin, Ireland: An intervention study. *The Lancet*, *360*, 1210-1214.

Clarkwest, A. (2008). Neo-materialist theory and the temporal relationship between income inequality and longevity change. *Social Science & Medicine*, *66*, 1871-1881.

Coburn, D. (2004). Beyond the income inequality hypothesis: class, neo-liberalism, and health inequalities. *Social Science & Medicine*, *58*, 41-56.

Crimmins, E., Johnston, M., Hayward, M., & Seeman, T. (2003). Age differences in allostatic load: An index of physiological dysregulation. *Experimental Gerontology*, *38*, 731-734.

Currie, J., & Neidell, M. (2005). Air pollution and infant health: What can we learn from California's recent experience? *The Quarterly Journal of Economics*, *120*, 1003-1030.

Currie, J., Neidell, M., & Schmieder, J. (2009). Air pollution and infant health: Lessons from New Jersey. *Journal of Health Economics*, *28*, 688-703.

Devlin, R., Ghio, A., Kehrl, H., Sanders, G., & Cascio, W. (2003). Elderly humans exposed to concentrated air pollution particles have decreased heart rate variability. *European Respiratory Journal*, *21*, 76s-80s.

Diez-Roux, A., Link, B., & Northridge, M. (2000). A multilevel analysis of income inequality and cardiovascular disease risk factors. *Social Science & Medicine*, *50*, 673-687.

Elgar, F., & Aitken, N. (2010). Income inequality, trust and homicide in 33 countries. *European Journal of Public Health*, *21*, 241-246.

Frank, M., Sommeiller, E., Price, M., & Saez, E. (2015). Frank-Sommeiller-Price Series for top income shares by US states since 1917. Methodological Notes, The World Top Incomes Database. Available at: http://www.wid.world/.

Franklin, M., Zeka, A., & Schwartz, J. (2007). Association between PM 2.5 and all-cause and specific-cause mortality in 27 US communities. *Journal of Exposure Science and Environmental Epidemiology*, *17*, 279-287.

Graff Zivin, J., & Neidell, M. (2013). Environment, health, and human capital. *Journal of Economic Literature*, *51*, 689-730.

Greenstone, M., & Hanna, R. (2014). Environmental regulations, air and water pollution, and infant mortality in India. *American Economic Review*, *104*, 3038-72.

Harvey, D. (2006). Neo-Liberalism as creative destruction. *Geografiska Annaler: Series B, Human Geography*, *88*, 145-158.

Heutel, G., & Ruhm, C. J. (2016). Air pollution and procyclical mortality. *Journal of the Association of Environmental and Resource Economists*, *3*, 667-706.

Hill, T., & Jorgenson, A. (2018). Bring out your dead!: A study of income inequality and life expectancy in the United States, 2000–2010. *Health & Place*, *49*, 1-6.

Jackson, J. (1986). “The Pleasure Principle.” Santa Monica, CA: A&M Records

Jargowsky, P. A. (1996). Take the money and run: Economic segregation in US metropolitan areas. *American Sociological Review*, *61*, 984-998.

Jorgenson, A., Schor, J., Knight, K., & Huang, X. (2016). Domestic inequality and carbon emissions in comparative perspective. *Sociological Forum*, 31, 770-786.

Jorgenson, A., Schor, J., & Huang, X. (2017). Income inequality and carbon emissions in the United States: a state-level analysis, 1997-2012. *Ecological Economics 134*, 40-48.

Jorgenson, A., Dietz, T., & Kelly, O. (2018). Inequality, poverty, and the carbon intensity of human well-being in the United States: a sex-specific analysis. *Sustainability Science*, *13*, 1167–1174.

Kaplan, G. A., Pamuk, E. R., Lynch, J. W., Cohen, R. D., & Balfour, J. L. (1996). Inequality in income and mortality in the United States: analysis of mortality and potential pathways. *BMJ*, *312*, 999-1003.

Kawachi, I., Kennedy, B., Lochner, K., & Prothrow-Stith, D. (1997). Social capital, income inequality, and mortality. *American Journal of Public Health*, *87*, 1491-1498.

Kawachi, I., & Kennedy, B. P. (1999). Income inequality and health: pathways and mechanisms. *Health Services Research*, *34*, 215-227.

Knittel, C., Miller, D., & Sanders, N. (2016). Caution, drivers! Children present: Traffic, pollution, and infant health. *Review of Economics and Statistics*, *98*, 350-366.

Kullowatz, A., Rosenfield, D., Dahme, B., Magnussen, H., Kanniess, F., & Ritz, T. (2008). Stress effects on lung function in asthma are mediated by changes in airway inflammation. *Psychosomatic Medicine*, *70*, 468-475.

Lehrer, P. (2006). Anger, stress, dysregulation produces wear and tear on the lung. *Thorax*, *61*, 833-834

Leigh, A., & Jencks, C. (2007). Inequality and mortality: Long-run evidence from a panel of countries. *Journal of Health Economics*, *26*, 1-24.

Lobmayer, P., & Wilkinson, R. (2002). Inequality, residential segregation by income, and mortality in US cities. *Journal of Epidemiology & Community Health*, *56*, 183-187.

Lynch, J., Smith, G., Kaplan, G., & House, J. (2000). Income inequality and mortality: importance to health of individual income, psychosocial environment, or material conditions. *BMJ*, *320*, 1200-1204.

Lynch, J., Smith, G., Hillemeier, M., Shaw, M., Raghunathan, T., & Kaplan, G. (2001). Income inequality, the psychosocial environment, and health: Comparisons of wealthy nations. *The Lancet*, *358*, 194-200.

Künzli, N., Kaiser, R., Medina, S., Studnicka, M., Chanel, O., Filliger, P., ... & Schneider, J. (2000). Public-health impact of outdoor and traffic-related air pollution: A European assessment. *The Lancet*, *356*, 795-801.

Mellor, J., & Milyo, J. (2001). Reexamining the evidence of an ecological association between income inequality and health. *Journal of Health Politics, Policy and Law*, *26*, 487-522.

McEwen, B. (1998). Protective and damaging effects of stress mediators. *The New England Journal of Medicine*, *338*, 171-179.

McEwen, B. (2002). The end of stress as we know it. Washington, DC: Joseph Henry Press.

Mikati, I., Benson, A., Luben, T., Sacks, J., & Richmond-Bryant, J. (2018). Disparities in distribution of particulate matter emission sources by race and poverty status. *American Journal of Public Health*, *108*, 480-485.

Mohai, P., & Saha, R. (2015). Which came first, people or pollution? Assessing the disparate siting and post-siting demographic change hypotheses of environmental injustice. *Environmental Research Letters*, *10*, 115008.

Mustafić, H., Jabre, P., Caussin, C., Murad, M., Escolano, S., Tafflet, M., ... & Jouven, X. (2012). Main air pollutants and myocardial infarction: a systematic review and meta-analysis. *JAMA*, *307*, 713-721.

Neumayer, E., & Plümper, T. (2016). Inequalities of income and inequalities of longevity: A cross-country study. *American Journal of Public Health*, *106*, 160-165.

Peters, A., Von Klot, S., Heier, M., Trentinaglia, I., Hörmann, A., Wichmann, H., & Löwel, H. (2004). Exposure to traffic and the onset of myocardial infarction. *New England Journal of Medicine*, *351*, 1721-1730.

Pope, C., & Dockery, D. (2006). Health effects of fine particulate air pollution: Lines that connect. *Journal of the Air & Waste Management Association*, *56*, 709-742.

Rambotti, S. (2015). Recalibrating the spirit level: An analysis of the interaction of income inequality and poverty and its effect on health. *Social Science & Medicine*, *139*, 123-131.

Reardon, S., & Bischoff, K. (2011). Income inequality and income segregation. *American Journal of Sociology*, *116*, 1092-1153.

Schor, J., & Jorgenson, A. (in press). Is it too late for growth? *Review of Radical Political Economics*.

Seeman, T., Crimmins, E., Huang, M., Singer, B., Bucur, A., Gruenewald, T., ... & Reuben, D. B. (2004). Cumulative biological risk and socio-economic differences in mortality: MacArthur studies of successful aging. *Social Science & Medicine*, *58*, 1985-1997.

Truesdale, B., & Jencks, C. (2016). The health effects of income inequality: Averages and disparities. *Annual Review of Public Health*, *37*, 413-430.

Wang, H., Schumacher, A., Levitz, C., Mokdad, A., & Murray, C. (2013). Left behind: widening disparities for males and females in US county life expectancy, 1985–2010. *Population Health Metrics*, *11*, 8.

Wellenius, G., Schwartz, J., & Mittleman, M. (2005). Air pollution and hospital admissions for ischemic and hemorrhagic stroke among Medicare beneficiaries. *Stroke*, 36, 2549-2553.

Wen, M., Browning, C., & Cagney, K. (2003). Poverty, affluence, and income inequality: neighborhood economic structure and its implications for health. *Social Science & Medicine*, *57*, 843-860.

Wilkinson, R. (1996). Unhealthy societies: Afflictions of inequality. New York: Routledge.

Wilkinson, R. (2005). The impact of inequality: How to make sick societies healthier. New York: The New Press.

Wilkinson, R., & Pickett, K. (2006). Income inequality and population health: A review and explanation of the evidence. *Social Science & Medicine*, *62*, 1768-1784.

Wilkinson, R., & Pickett, K. (2009). *The spirit level: Why greater equality makes societies stronger*. New York: Bloomsbury Press.

Wooldridge, J. (2010). Econometric analysis of cross section and panel data. Cambridge, MA: MIT Press.

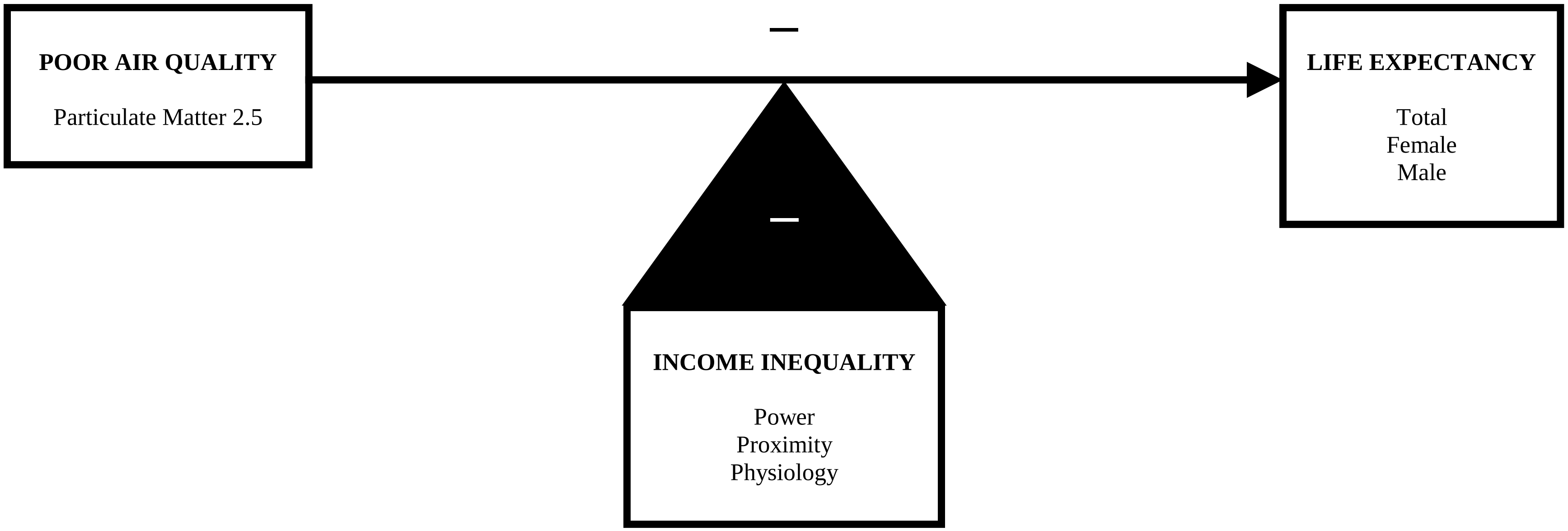


Figure 1: Income Inequality as a Moderator of the Association between Air Quality and Life Expectancy

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	490000	37350000	5887127	6494525
GDP Per Capita	26644	151257	42467.61	15938.14
Median Household Income	39182	81018	56953.45	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	.26	60	11.09	11.30
Percent Hispanic/Latino	.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.

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	Raw Particulate Matter	Raw Particulate Matter	Raw Particulate Matter	Weighted Particulate Matter	Weighted Particulate Matter	Weighted Particulate Matter	Weighted Particulate Matter
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**
Particulate Matter 2.5	-.026**		-.030**	.196***	-.023*		-.028**	.168**
	(.010)		(.011)	(.064)	(.010)		(.011)	(.061)
Income Share of Top 10%		-.024*	-.027**	.028*		-.024*	-.026**	.022*
		(.010)	(.010)	(.011)		(.010)	(.010)	(.011)
Particulate Matter 2.5 * Income Share of Top 10%				-.006***				-.005**
				(.001)				(.002)
Total Population (log 10)	.265	-.186	.432	.867	.116	-.186	.268	.438
	(1.018)	(.960)	(.974)	(.973)	(1.004)	(.960)	(.948)	(.925)
GDP Per Capita (log 10)	-.281	-.666	-.144	-.356	-.351	-.666	-.204	-.470
	(.737)	(.671)	(.703)	(.658)	(.731)	(.671)	(.693)	(.653)
Median Household Income	-.001	.001	.001	.001	-.001	.001	.001	.001
	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)
Median Age in Years	-.042	-.038	-.047	-.038	-.042	-.038	-.048	-.041
	(.033)	(.031)	(.032)	(.032)	(.034)	(.031)	(.032)	(.032)
Percent College Degree or Higher (log 10)	.356	.119	.235	.181	.307	.119	.184	.121
	(.345)	(.319)	(.343)	(.362)	(.339)	(.319)	(.339)	(.350)
Percent Black (log 10)	-1.601*	-1.786**	-1.685**	-1.479*	-1.568*	-1.786**	-1.638*	-1.434*
	(.681)	(.713)	(.662)	(.637)	(.690)	(.713)	(.672)	(.650)
Percent Hispanic/Latino (log 10)	-1.973*	-1.606#	-2.036*	-1.414#	-1.874*	-1.606#	-1.941*	-1.248
	(.952)	(.918)	(.862)	(.747)	(.953)	(.918)	(.672)	(.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 2000-2010 for all US States (except Maine) and District of Columbia. All models include AR1 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	Raw Particulate Matter	Raw Particulate Matter	Raw Particulate Matter	Weighted Particulate Matter	Weighted Particulate Matter	Weighted Particulate Matter	Weighted Particulate Matter
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**
Particulate Matter 2.5	-.107***		-.098***	.252**	-.094**		-.083***	.245**
	(.031)		(.022)	(.079)	(.029)		(.023)	(.091)
Income Share of Top 10%		-.064***	-.061***	.024		-.064***	-.061***	.017
		(.127)	(.010)	(.019)		(.127)	(.011)	(.021)
Particulate Matter 2.5 * Income Share of Top 10%				-.008***				-.007***
				(.001)				(.002)
2005	.571**	.587***	.594***	.482***	.553**	.587***	.577***	.480***
	(.184)	(.161)	(.125)	(.124)	(.196)	(.161)	(.137)	(.140)
2010	1.366***	1.542***	1.362***	1.133***	1.330***	1.542***	1.337***	1.162***
	(.318)	(.282)	(.210)	(.205)	(.333)	(.282)	(.229)	(.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 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	-.158**		-.147***	.302*	-.142**		-.129**	.253*
	(.054)		(.043)	(.115)	(.050)		(.044)	(.124)
Income Share of Top Ten Percent		-.081**	-.076***	.033		-.081**	-.075***	.015
		(.026)	(.021)	(.034)		(.026)	(.022)	(.036)
Particulate Matter 2.5 * Income Share of Top 10%				-.010***				-.008**
				(.002)				(.003)
2005	1.003**	1.021**	1.031***	.887***	.976**	1.021**	1.005***	.892**
	(.335)	(.333)	(.273)	(.262)	(.345)	(.333)	(.285)	(.288)
2010	2.087***	2.350***	2.081***	1.787***	2.025***	2.350***	2.034***	1.830***
	(.545)	(.587)	(.429)	(.416)	(.558)	(.587)	(.450)	(.461)

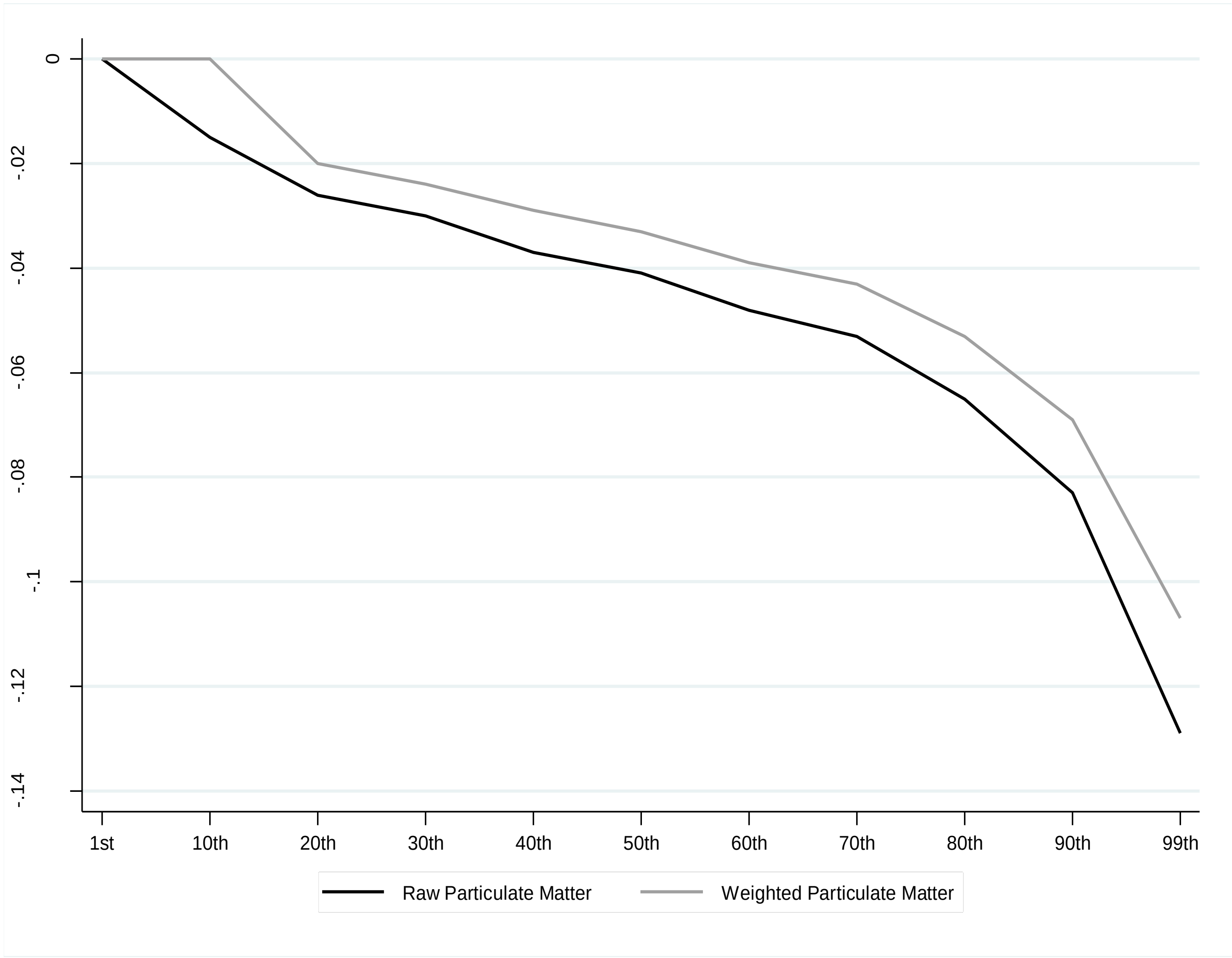
Notes: N = 150. * p<.05, ** p<.01, *** p<.001 (two-tailed), #p<.05 (one-tailed). Clustered robust standard errors appear in parentheses. Observations for years 2000, 2005 and 2010 for all US States (except Maine) and the District of Columbia. All models include unreported case-specific fixed effects. All models include 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 Particulate Matter

Percentiles for Income Share of Top 10%	Raw Particulate Matter	Weighted Particulate Matter
1st Percentile [34.43704]	.004	.005
	(.010)	(.010)
10th Percentile [38.02291]	-.015#	-.010
	(.008)	(.008)
20th Percentile [40.01854]	-.026**	-.020*
	(.009)	(.008)
30th Percentile [40.90752]	-.030***	-.024**
	(.009)	(.008)
40th Percentile [42.03272]	-.037***	-.029**
	(.010)	(.009)
50th Percentile [42.81685]	-.041***	-.033***
	(.011)	(.010)
60th Percentile [43.98028]	-.048***	-.039***
	(.012)	(.011)
70th Percentile [45.03413]	-.053***	-.043***
	(.014)	(.013)
80th Percentile [47.13808]	-.065***	-.053***
	(.017)	(.015)
90th Percentile [50.45599]	-.083***	-.069***
	(.022)	(.020)
99th Percentile [58.59861]	-.129***	-.107***
	(.035)	(.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. All estimates are based on models reported in Table 2.

Figure 2: Slope Coefficients for Particulate Matter 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%.