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Longitudinal Environmental Inequality and Environmental Gentrification: Who Gains From Cleaner Air?

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Abstract

A vast empirical literature has convincingly shown that there is pervasive cross-sectional inequality in exposure to environmental hazards. However, less is known about how these inequalities have been evolving over time. I fill this gap by creating a new dataset, which combines satellite data on ground-level concentrations of fine particulate matter with linked administrative and survey data. This linked dataset allows me to measure individual pollution exposure for over 100 million individuals in each year between 2000 and 2014, a period of time has seen substantial improvements in average air quality. This rich dataset can then be used to analyze longitudinal dimensions of environmental inequality by examining the distribution of changes in individual pollution exposure that underlie these aggregate improvements. I confirm previous findings that cross-sectional environmental inequality has been on the decline, but I argue that this may miss longitudinal patterns in exposure that are consistent with environmental gentrification. I find that advantaged individuals at the beginning of the sample experience larger pollution exposure reductions than do initially disadvantaged individuals.

Keywords: environmental justice, satellite data, air quality

JEL classification: D63, D39, Q53

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1 Introduction

In this paper, I grapple with two broad topics of interest related to the environment. First, the long-term trend in the United States has been towards a substantially lower level of air pollution on average, driven in part by progressively more restrictive emissions policies and in part by long term trends in technology and economic development (Ross et al. (2012), EPA (2016)). Second, a large literature, intertwined with the "environmental justice" movement, has provided convincing evidence that disadvantaged populations (notably ethnic minority and poor households) are exposed to substantially higher levels of exposure to harmful environmental hazards such as toxic waste sites and air pollution (Banzhaf, ed (2012)).

The environmental justice literature has focused on the concept of "environmental gentrification" as a potential mechanism for the persistence of cross-sectional disparities in exposure over time. In the classic version of this mechanism, local environmental improvements result in locational sorting that maintains exposure disparities, as richer, more advantaged households move into newly clean areas, which often lead to rising housing prices, displacing the incumbent poorer, disadvantaged population to other high-pollution areas with lower housing prices. In this paper, I provide the first population-level analysis of how improvements in air quality since 2000 have been distributed across the population. This analysis allows me to synthesize these two topics through the lens of environmental gentrification: have the improvements in average air quality been broadly shared across the population and between groups? Or have these improvements accrued disproportionately to advantaged households?

Answering these questions on a population basis requires longitudinal information on how individual exposure to environmental hazards has evolved across the entire population. Data sufficient to this task have not been previously available. I am able to answer these questions by combining satellite data on ground-level concentrations of fine particulate matter, with linked survey and administrative data which allows me to measure the location, demographic profile, and household income for almost all individuals in the United States annually from 2000-2014. Previous literature (e.g., Voorheis (2016)) has used satellite data to describe how cross-sectional measures of the distribution of pollution exposure have evolved over time. I extend this literature by examining the distribution of individual changes in pollution exposure, which can be thought of as an environmental analogue of intragenerational income mobility.

Previous literature has shown that average exposure to a variety of pollutants (notably particulates) has declined over time, and Voorheis (2016) shows that these declines in average exposure have coincided with declines in the level of environmental inequality. These trends in environmental inequality do not necessarily describe how individuals have experienced improvements in air quality, however. In order to study how air quality has evolved longitudinally for individuals, I introduce a new measurement tool (pollution-reduction profiles) that allows me to measure how individual changes in exposure vary across the initial income and initial exposure distributions. I find that, over the whole period 2000-2014, air quality improvements have been largest for individuals who were initially exposed to high levels of pollution. However, I also find, especially in the latter half of the period (after 2008) that improvements in air quality disproportionately accrue to initially advantaged individuals (whites and individuals in high-income households). These two trends are suggestive of a trend towards environmental gentrification: air quality improvements that are concentrated in gentrifying cities would generate these two sets of pollution-reduction profiles.

The rest of the paper proceeds as follows. Section 2 summarizes the relevant literature and notes the gaps in our knowledge about the distribution of environmental hazards. Section 3 describes the data used in the study and the process for linking satellite data with survey and administrative records. Section 4 considers the normative welfare theory of cross-sectional versus longitudinal environmental inequality (these two concepts can be seen as analogues to income inequality and intragenerational income mobility respectively). Section 5 analyzes how the distribution of pollution exposure has evolved over time and Section 6 concludes.

2 Previous Literature

This project draws on two different sets of literature: first, the literature in atmospheric and environmental science that has focused on the use of remote-sensing data to measure ground-level exposure to various pollutants for the purposes of population-based health and epidemiological analysis; and second, the large literature on the topic environmental justice that has focused on measuring the distribution of exposure to environmental hazards for explicitly normative purposes. This latter literature is itself indebted to the long tradition of formal normative inquiry into the measurement of income inequality. Additionally, the data and trends analyzed in this paper have implications for a third literature: the small but growing group of papers examining the long run impact of pollution exposure on later life outcomes.

Setting up and maintaining networks of ground-level monitors is expensive and labor intensive (and, where air quality monitoring is required by law, this burden can result in political push-back). For this reason, there has long been an interest in leveraging the remote-sensing technology that has been useful in the study of stratospheric phenomena (the ozone layer) and ground level climatological trends (e.g., temperature) for the study of ground-level concentrations of pollution. A variety of satellites housing a number of instruments have been launched in the past two decades with the goal of providing improved remote-sensing observations to allow for improved measurement of air quality from space. As these instruments have proliferated, their use has moved beyond the atmospheric chemistry research community to a variety of applied users. Duncan et al. (2014) and Streets et al. (2013) provide overviews of the current state-of-the-art and best practices for the use of satellite data for air quality measurement.

Remote-sensing instruments can measure two types of pollutants from low earth orbit: trace gases and particulate matter. It is possible to measure the quantity of molecules of a trace gas (e.g., NO_2) in the column of air above a fixed area, the vertical column density (VCD), which can then be related to ground-level concentrations through the use of a chemical air transport model. It is also possible to measure the aerosol optical depth (AOD) of high-resolution images to infer the ground-level concentrations of fine particulate matter. Measuring particulate matter concentrations using AOD retrievals has received substantial attention in the atmospheric science literature, largely because the relationship between AOD and concentrations is less well understood than the VCD-concentration relationship for trace gases. Nonetheless, much progress has been made, first by leveraging high-resolution retrievals from the Moderate-Resolution Imaging Spectroradiometer (MODIS) satellite combined with chemical transport models and calibrated to measurements from ground-level monitors (van Donkelaar et al. (2010)), and then by combining multiple satellite retrievals, and increasingly sophisticated modelling to separate out species of particulates that are the result of natural processes (van Donkelaar et al. (2015), Boys et al. (2014)). These efforts have resulted in the availability of ground-level particulate matter measurements at very fine spatial resolutions ($1km^2$), as in the data used in this study (described in detail below and in van Donkelaar et al. (2016)).

The second literature that informs this project is the broad literature on the topic of environmental justice that has established that substantial disparities in exposure to environmental hazards exist across advantaged and disadvantaged subgroups. This literature is extensive, and is ably reviewed by Mohai et al. (2009) and Brulle and Pellow (2006). The canonical environmental justice concern involves the siting of facilities, such as toxic waste sites, landfills, power plants, and confined animal feeding operations (CAFOS), which impose environmental health hazards on the surrounding community. Indeed, the "founding document" of the Environmental Justice movement, Chavis and Lee (1987), exclusively focusing on fixed toxic sites. This concern was paramount not only in the the early Environmental Justice literature (Bryant and Mohai (1992)), but also continues to be the focus of recent literature (Morello-Frosch and Jesdale (2006), Wolverton (2009)). Less work has been done to examine disparities in exposure, not to fixed toxic sites, but to air or water pollution. This area, the focus of this paper, has been periodically studied (e.g., Zwickl et al. (2014), Boyce and Voirnovytskyy (2010)), with several studies focusing on the formal theory of how to measure environmental inequality (Boyce et al. (2016), Sheriff and Maguire (2014) and Voorheis (2016)), which will inform the dashboard approach to environmental inequality described below. Finally, it should be noted that a single paper unites these two literatures described here — Clark et al. (2014), which, using NO_2 satellite data from Novotny et al. (2011) describes cross-sectional patterns in environmental inequality for a single year.

Additionally, the environmental justice literature in general, and the results of this project in particular, are relevant for a third literature focusing on the effects of pollution exposure at various time-scales. The current state of this literature is reviewed in Currie (2011) and Currie (2013). The focus of this literature is often on how exposure to air pollution in utero or early in life affects early life and potentially later life outcomes, although a small literature has examined how contemporaneous pollution exposure might affect labor supply and worker productivity (Chang et al. (2014), Chang et al. (2016)). The early literature on early life exposure focused on short term effects such as birth outcomes and infant mortality (Currie et al. (2009), Currie and Walker (2011), Currie et al. (2013)). A small but growing number of papers has begun to examine how early life exposure might affect longer-term outcomes such as human capital attainment (Bharadwaj et al. (2014), Lavy et al. (2014),Aizer et al. (2016)) and crime (Reyes (2014)).

3 Data

Any analysis of environmental inequality at a point in time requires information on exposure. Measuring exposure, in turn, requires information on the spatial distribution of both air pollution and individual people. Analysis of longitudinal environmental inequality requires additional information on how pollution levels are changing and how the population is changing. The former requirements are formidable; until now the latter has been insurmountable for population-scale analyses. There are two main data limitations that have limited previous analyses: 1) high-quality data on ground-level pollution concentrations have only been available from ground-level monitoring networks (e.g., the Environmental Protection Agency (EPA)'s Air Quality Monitoring System) and 2) information about population distribution is generally only available at an aggregate level such as Census tracts or block groups.

Air quality monitors provide temporally high resolution information about ground-level air composition (hourly), but only in the immediate spatial neighborhood of the monitor. Thus in order to assess exposure on a population scale, a very dense monitoring network is necessary. Unfortunately, the existing monitoring network in the United States is in fact quite sparse–for PM2.5, the pollutant of interest for this study, there are fewer monitors (2568) than counties (3144). Additionally, the monitoring network is designed to monitor compliance with air quality standards, and not to measure the distribution of pollution per se. As such, the siting of monitors is non-random, and is in fact a function of the local pollution levels. Areas in locations that have been historically out of compliance with air quality standards (e.g., the Los Angeles basin) are more likely to be monitored than are areas which have not received as much regulatory scrutiny from the environmental authorities.

Information about aggregate level population changes for the entire US was available only between decennial Censuses until the introduction of the American Community Survey in 2005, after which population changes for Census tracts and block groups (small geographic entities that are often used as a proxy for neighborhoods) have been available. Using these aggregate population measures to estimate environmental inequality is reasonable for tracking cross-sectional inequality, but misses individual longitudinal features that may be driving trends in cross-sectional inequality over time. Additionally, using tracts or block groups in this manner implicitly assumes no within-neighborhood inequality in exposure, which, given the presence of "hotspots" around point sources of pollution, will understate the true degree of environmental inequality.

In this study, I construct a dataset with novel features that addresses these previously limiting factors. I link satellite-derived remote-sensing data on ground level concentrations of particulate matter smaller than 2.5 micrograms (PM2.5) with data from IRS tax returns and the 2000 and 2010 Censuses. The satellite data provide annual average (from 2000-2014) PM2.5 concentrations at a very fine geographic resolution for most of the globe, although since the coverage is poor above the 69th parallel, I will restrict my attention to the contiguous United States.

3.1 Satellite Data

A satellite in low earth polar orbit has the capacity to observe every location on the globe on a regular basis (most satellites are designed to observe a location at least once every day), and is thus uniquely placed to produce data on air quality for a population-based study. The chief concern in the atmospheric science literature has been in how to use various types of remote-sensing observations (these may include observations of vertical column density of trace gases, or the degree of visual occlusion in high resolution images) to infer the ground-level concentration of pollutants of interest. Most approaches to this problem have in common a reliance on using chemical transport models to define the relationship between ground-level and remotely-sensed pollution levels.

In this study, I use a dataset of ground-level concentrations of PM2.5 that is generated using observations from several satellites, ground-level data from pollution monitors, a state-of-the-art chemical air transport model, and additional modeling to account for seasonal variation and the presence of non-human-generated particulates such as dust or sea salt. This dataset is made publicly available by the Atmospheric Composition Analysis Group (ACAG) at Dalhousie University, and is described in great detail by van Donkelaar et al. (2010) and van Donkelaar et al. (2016). I will briefly describe how the ACAG dataset is produced from raw satellite imaging data, and how the ACAG data is matched to administrative and survey data on the location of individuals.

Several satellites have been launched in the past few decades with the purpose of producing high resolution images of the entire globe at a fine spatial resolution. It is possible to use this imaging data to measure a number of features of the Earth's surface and atmosphere. Relevant to this study, it is possible to measure the aerosol optical depth (AOD), which is a measure of the degree to which radiance from the sun is extinguished by aerosol particles in the troposphere. AOD can be used unmodified as an indirect proxy measure of the amount of particulate matter in the atmosphere; however, to infer ground level concentrations (the measurement of interest for studying exposure), a model of the ground level PM2.5-AOD relationship is necessary. The ACAG dataset utilizes AOD observations from three satellite instruments (MODIS, MISR, and SeaWIFS) and infers ground-level PM2.5 concentrations by the use of GEOS-CHEM (a state-of-the-art chemical air transport model), with ground-level concentration observations from a sample of worldwide PM2.5 monitors serving as the "ground truth" to which the model can be calibrated. Additionally, the air transport modelling attempts to remove the influence of non-anthropogenic particulates, such as sea salt in coastal areas, and airborne dust in desert regions.

The final publicly available ACAG dataset contains annual average measurements of PM2.5 on a fixed 0.01×0.01 degree (about 1 km square at the equator) grid nearly spanning the entire globe for each year between 1998-2014.[1] It is necessary to interpolate over this grid in order to match this gridded concentration data to the locations where individuals reside. I interpolate to two different geographies: to the Census block, and the full nine-digit zip code (sometimes called "zip+4"). Each of these geographies is well defined, and represents a small enough area that it is reasonable to assume all residents in a block or zip+4 have approximately the same pollution exposure. I use inverse distance weighting to perform this interpolation for each year of the ACAG data, using all grid points within 0.1 degree of the target geography's centroid.[2] Figure 1 visualizes one year (2005) of this interpolated data as a choropleth map for the entire country.

[1] The grid-point centroids have a latitude ranging from 54.995°S to 69.995°N, and a longitude range from 179.995°W to 179.995°E

[2] The centroid coordinates for blocks are available from the Census Gazeteer, while the centroid coordinates for 9 digit zip codes are provided by MELISSA, a commercial data provider.

Figure 2 "zooms in" to the Los Angeles Area, which is a particularly striking example of the degree of heterogeneity within metropolitan areas.

3.2 Administrative Records

The satellite data provides a detailed, fine-grained picture of the *spatial* distribution of ground-level PM2.5 concentrations, but is not sufficient to characterize the distribution of PM2.5 *exposure*, especially as it relates to sociodemographic characteristics such as race, ethnicity and household income. To estimate the levels and trends in environmental inequality, and to characterize the distribution of changes in individual exposure, data is required on the identity, sociodemographic characteristics and location of individuals over time, a combination of information has historically been difficult to obtain. I am able to overcome this difficulty by linking data on demographics from the 2000 and 2010 Censuses with information on location and income from IRS Form 1040 tax returns and pollution levels at these locations from the previously described satellite data. This allows me to characterize the yearly exposure for more than 250 million individuals in each year, and allows me to characterize cumulative exposure over the period 2000-2014 for over 100 million individuals.[3]

The linkage between the IRS records and the decennial Census response data is accomplished using the Person Identification Validation System (PVS) developed by the U.S. Census Bureau's Center for Administrative Records Research and Applications. PVS performs person-level probabilistic matching between datasets using information on individuals' name, address, date of birth, and, when available, Social Security Number. Using this information, PVS assigns a Protected Identification Key (PIK) to each individual given there is enough information available for unique identification. These PIKs can then be used to link records between different datasets, allowing for the creation of individual level panel data on location, household income, and, with the pollution data, environmental exposure. The details of the probabilistic matching procedure used in PVS is described in detail by Wagner and Layne (2014).

To track locations over time, I primarily use the IRS Form 1040 data, since Form 1040 requires a valid address, and is available annually. Additionally, since Form 1040 requires filers to fill in their Social Security Number, almost everyone listed on each tax return can be assigned a PIK.[4] The address information available in the form 1040 includes the full 9-digit zip code (zip+4). CARRA has additionally performed address matching to assign a Master Address File ID (MAFID) to most but not all of the 1040 tax returns. I assign PM2.5 exposure to each person with a PIK listed on a tax return according to the following rule:

[3]Note that each individual does not necessarily appear on a tax return in each year, and thus there are fewer individuals who appear on tax returns in every year between 2000-2014 than those who appear on a tax return in a given year.

[4]Note, however, that the 1040 data used here only lists the first 4 dependents of a tax unit.

if they have a MAFID and block-level geographic information, I assume they receive the average annual exposure in their Census block. If they do not have a MAFID, I assume they receive the average exposure of the zip+4 listed on their tax return. I assign to each person the tax unit income (defined as Adjusted Gross Income, adjusted for household size by a square root equivalence scale) for the form 1040 on which they are listed.[5] To obtain demographic information (specifically, race and ethnicity) I link all individuals listed on tax returns to records from the 2000 and 2010 Decennial Census short forms by PIK. For individuals who appear in only one Census, I assign demographic characteristics based on this response. For individuals who appear in both Censuses, I assign characteristics based on the 2000 Census. Table 1 summarizes the number of individuals for which this linkage is successful, as well as the number of individuals for whom I have records in each year 2000-2014 (for whom I can calculate cumulative exposure).

4 Measuring Longitudinal Environmental Inequality

Measuring inequality in the cross-sectional distribution of pollution exposure is a well defined problem, albeit one which is still subject to some disagreement in the literature. The problem of how to measure inequality in exposure longitudinally has received little or no attention, however. I remedy this by adapting a technique from the literature on intra-generational income mobility first introduced by Jenkins and Van Kerm (2006). Jenkins and Van Kerm define "income mobility profiles" and show that first order dominance in these has normative content, and induces a partial social ordering of distributions of income changes, while a weighted average (with ethical weights) induces a complete ordering.

As a metaphor for these measures, I introduce two types of "pollution-reduction profiles" (PRP) which describe the distribution of changes in individual pollution exposure over time. Paralleling Voorheis (2016), these two types of PRPs capture vertical and horizontal equity concerns. Define $\delta(x, y)$ as a "distance function" capturing the change in an individual's pollution exposure between two years. A vertical equity sensitive pollution-reduction profile considers how $\delta(x, y)$ varies across initial levels of pollution exposure x:

$$m_v(x, y) = \int_{z_-}^{z_+} \delta(x, y) dF_{Y|X=x}(y)$$

A horizontal equity sensitive pollution-reduction profile, on the other hand, would consider how $\delta(x, y)$ varies across initial levels of household income I.[6] To clarify the difference, let us define the change in

[5] Some individuals appear both as a dependent on their parent's tax return and as the primary filer on their own return. I assign these individuals to the tax unit in which they are listed as a dependent. Subsequent analysis is robust to assigning them to their primary tax unit, and to dropping these observations.

[6] It is also possible to modify m_v to be sensitive to horizontal equity by computing sub-group specific PRPs, an approach

pollution exposure for an individual as $c = \delta(x, y)$, and the distribution of these changes as $F_C(c)$. Then a horizontal equity pollution profile can be expressed as

$$m_h(i, c) = \int_{z_-}^{z_+} (c) dF_{C|I=i}(c)$$

These pollution-reduction profiles provide useful information in and of themselves about how the distribution of pollution exposures is changing longitudinally. In particular, these profiles are naturally visualized in a manner that allows for judgments about the degree to which environmental improvements are benefiting disadvantaged communities (where disadvantage is defined either in terms of initial pollution exposure or initial income. As with the income mobility profiles m_v and m_h are based upon, the logical way to visualize these pollution-reduction profiles is to graph m_v or m_h against the initial rank in the distribution of exposure (or income). Specifically, for m_v, let $p = F_X(x)$ and $x(p) = F_X^{-1}(p)$ so that

$$m_v(p) = \int_{z_-}^{z_+} \delta(x(p), y) dF_{Y|X=x(p)}(y)$$

Similarly, for m_h, let $q = F_I(i)$ and $i(q) = F_I^{-1}(q)$, so that

$$m_h(q) = \int_{z_-}^{z_+} (c) dF_{C|I=i(q)}(c)$$

Additionally, it is possible to construct indices of pollution-reduction which can be used for social evaluation. Again following Jenkins and Van Kerm (2006), define

$$M_v^w(p) = \int_0^1 w_v(p) \times -1 \times m_v(p) dp$$

and

$$M_h^w(q) = \int_0^1 w_h(q) \times -1 \times m_v(q) dq$$

These social evaluation functions are essentially weighted means of individual pollution reductions. The functional form of the weighting functions $w(p), w(q)$ allows for ethical judgements in the social evaluation function. If $w_v'(p) \geq 0, \forall p$ then larger weight is put on the most exposed populations for social evaluations, which builds in a preference for progressive pollution reduction (in the sense that pollution reductions accruing to disadvantaged individuals are preferred). Likewise, if $w_h'(q) \leq 0, \forall q$, then larger weight is put on

which allows for the comparison of the pollution-reduction experiences across racial groups.

the initially poorest in social evaluations, which again can be seen as a preference for progressive pollution reduction.

These weighting functions differ mainly in that the ordering of the population by initial exposure and initial income imply different directions of disadvantage: individuals with the lowest incomes are the most disadvantaged, while individuals with the highest income are the most advantaged. Since the ordering by income in the horizontal equity social evaluation $M_h^w(q)$ is the same as in the income mobility case studied by Jenkins and Van Kerm (2006), I adopt the generalized Gini weights used there, so that

$$w_h(q) = \nu(1-q)^{\nu-1}, \nu \geq 1$$

However, since the vertical equity social evaluation $M_v^w(q)$ implies an opposite ordering of advantage, it is necessary to modify the generalized Gini weights, so that

$$w_v(p) = \nu(p)^{\nu-1}, \nu \geq 1$$

There is a tight link between the social evaluation functions and the pollution-reduction profiles upon which they are based. Paralleling the well known Atkinson theorem ((Atkinson, 1970)), stochastic dominance in terms of the pollution-reduction profiles implies a complete ordering by the social evaluation functions. For the empirical applications, I will focus on first order dominance. For either of the vertical or horizontal equity measures, if a pollution-reduction profile for one distribution lies everywhere below the pollution-reduction profile for another, then the first distribution is preferred by the social evaluation function:

$$m_v^1(p) \leq m_v^2(p), \forall p \in [0,1] \rightarrow M_v^{w1}(p) \geq M_v^{w2}(p)$$

The proof of this statement is the same as in Jenkins and Van Kerm (2006) with a reversal of the inequality signs.

5 Analysis

With a rich longitudinal dataset on individual-level pollution exposure over a decade and a half, it is possible to perform two distinct types of distributional analyses. First, and most straightforwardly, it is possible to summarize trends in the evolution of the cross-sectional distribution of PM2.5 exposure. I collect these results in an appendix, as they largely provide confirmatory evidence to the previous literature. Second, for summarize trends in the evolution of the cross-sectional distribution of PM2.5 exposure. I collect these results in an appendix, as they largely provide confirmatory evidence to the previous literature. Second, for the subset of individuals who can be linked between a given pair of years (i.e., who appear on tax returns in years i and j), I can analyze the distribution of individual changes in exposure using the pollution-reduction profiles defined above.

Before analyzing this longitudinal environmental inequality, it is worthwhile to set the stage by examining trends in average exposure, and examine visual evidence of how the distribution of PM2.5 exposure has been changing. Figure 3 summarizes how average PM2.5 exposure has changed over the period 2000–2014.[7] Exposure increased on average for the first two years of the sample, and has been largely flat since 2010, but the middle of sample (roughly 2002–2010) saw large decreases in average exposure. From the beginning to end of sample, average PM2.5 exposure declined by more than 4 $\mu g/m^3$. Shi et al. (2016) shows that a $1\mu g/m^3$ increase in annual exposure increases all cause mortality by 0.7 percent; this would suggest a nearly 3 percent decline in mortality is attributable to falling PM2.5 exposure.

Figure 4 provides some suggestive visual evidence for how the average decrease in exposure might be distributed across the population, by plotting the quantile function of annual exposure distributions from 2000-2014. Consistent with the trends in average exposure, the largest declines appear to occur between 2002–2010. Interestingly, the middle of the distribution appears to have received the largest pollution reductions relative to the bottom of the exposure distribution. Note however, that because of differing regional trends in exposure and geographical mobility of individuals, declines in exposure in the middle of the distribution do not necessarily coincide with declines in exposure by any individual in the middle of the distribution.[8] In the next section, I will show results for PRPs, which do summarize individual pollution reductions over time.

5.1 Pollution-Reduction Profiles

The pollution-reduction profiles introduced in Section 4 amount to estimating a conditional mean. As there is no reason to expect any particular functional form, I proceed with this estimation nonparametrically via local regression techniques. Kerm (2009) and Jenkins and van Kerm (2016) suggest the use of LOESS local regression for estimating income mobility profiles, upon which I base the pollution-reduction profiles. LOESS estimation, however, is infeasible for very large datasets, such as the linked records from two years

[7] For this and subsequent calculations comparing cross-sectional trends, all individuals who appear on a tax return and have a PIK are used in the calculation of the distributional statistic (in this case the mean) for a given year.

[8] This divergence in similar to the difference between growth incidence curves and income mobility profiles in the income distribution literature.

of the individual pollution data. As an alternative, I estimate pollution-reduction profiles via Generalized Additive Models (GAM), which have similar local smoothing properties and can scale up to accommodate large datasets.[9]

I compute both the horizontal and vertical equity versions of the PRFs defined above for each pair of years $[i, j], s.t. j > i$. Since these are many more comparisons than can be shown parsimoniously, I will highlight comparisons between the beginning and end of the time period covered by the satellite data, and also compare the "pollution mobility" profiles on either end of the Great Recession, comparing pollution reduction between 2000-2007 to pollution reduction between 2008-2014.[10] However, it will become clear that, especially for the horizontal equity pollution-reduction profiles, the initial distribution of income is important for drawing normative conclusions about the distribution of pollution exposure reductions.

Consistent with the taxonomy of cross-sectional environmental inequality, pollution-reduction profiles (capturing longitudinal environmental inequality) can capture not just horizontal and vertical equity concerns, but can also assess both relative and absolute inequality. The latter distinction boils down to specifying a functional form for $\delta(x, y)$. I will specify $\delta(x, y) = y - x$ to capture absolute inequality concerns, while relative inequality concerns are addressed by the use of $\delta(x, y) = log(y) - log(x)$. PRPs using these two distance functions capture, alternately, the expected change in pollution exposure and the expected percent change in pollution exposure.

Figure 5 begins by showing both types of the relative pollution-reduction profiles on the top panel (horizontal equity on the left, vertical equity on the right) over the whole length of the sample, comparing exposure in 2014 to exposure in 2000 for the sample of individuals with records in both years. Both horizontal and vertical equity measures suggest that the change in exposure has been progressive, in the sense that initially disadvantaged individuals have received larger amounts of pollution reduction than initially advantaged individuals. Graphically, this is merely stating that $m_h(q)$ is upward sloping (so that people who were poor in 2000 received larger air quality improvements than people who were rich in 2000), and that $m_v(p)$ is downward sloping (so that people with the highest exposure in 2000 received the largest air quality improvements).

The bottom panels of Figure 5 shows the absolute pollution-reduction profiles for 2000-2014 (using $\delta(x, y) = y - x$), which exhibit largely similar trends for both the horizontal and vertical equity variants. the chief difference between the absolute and relative PRPs occurs in the top quartile of the pollution exposure

[9]As a robustness check, I compare the estimated PRPs using LOESS and GAM for a small subsample (0.005 percent of linked records from 2000-2001), and find essentially identical results.

[10]The EPA's 2006 NAAQS standards went into full effect at the end of 2007, so this is delineation can additionally be seen as very roughly informing the distributional impacts of this regulation.

distribution. Regardless of whether pollution reduction is viewed in absolute or relative terms, pollution reduction was more evenly distributed across the income distribution than across the initial pollution exposure distribution: individuals at the 90th percentile of the income distribution received a 39 percent decrease in exposure from 2000-2014, compared to a 41 percent decrease for individuals at the 10th percentile of initial income. In contrast, the 10th percentile of initial pollution exposure received a 25 percent decrease in exposure, compared to a 45 percent decrease for the 90th percentile of exposure.

Next, I consider how individual pollution exposure reductions have evolved over the beginning of the sample (2000–2007) and the end (2008–2014). These two periods coincide with two major events which had large implications for the level of PM2.5 pollution. First, the 2006 revisions to the EPA's National Ambient Air Quality Standards for particulate matter started coming into effect by the end of 2007, and second, the global financial crisis of 2007–2009, and subsequent slow recovery, resulted in large decreases in industrial activity, electricity demand, and vehicle miles traveled.

Figure 6 shows the relative and absolute inequality versions of the vertical and horizontal equity PRPs for the period 2000-2007. In general, this earlier subsample suggests that there was largely progressive pollution reduction, as shown by both vertical and horizontal equity PRPs. Both absolute and relative PRPs suggest that disadvantaged individuals (either initially poor or initially highly exposed) received larger amounts of pollution reduction than did more advantaged individuals. However, there is slight disagreement when comparing within disadvantaged communities: the relative vertical equity PRP suggests a relatively flat profile over the upper half of the pollution exposure distribution, suggesting relatively even pollution reductions within the highly exposed, while the absolute vertical equity PRP suggests monotonically increasing pollution reductions across the exposure distribution.

Looking at pollution exposure reduction in the latter period, 2008–2014, tells a much different story. Figure 7 summarizes the relative and absolute, vertical and horizontal equity PRPs over this period. The vertical equity PRPs, both relative and absolute, continue to suggest that pollution exposure reduction has been progressive, with larger pollution reductions accruing to the most exposed individuals. The horizontal equity PRPs, however tell a dramatically different story: individuals who were in the top 1 percent of the income distribution in 2008 received, on average, a 5 percent decrease in PM2.5 exposure, while individuals in the bottom 10 percent of the income distribution in 2008 received pollution exposure decreases less than 2 percent on average. This is our first evidence of environmental gentrification: richer individuals are disproportionately reaping the rewards of improving air quality.

What can account for the stark contrast in the horizontal equity pollution-reduction profiles between

2000–2007 and 2008–2014? One possible driver may be the underlying distribution of incomes: the base year distribution of income determines the ranking of individuals to estimate the PRPs. Thus changes in the income distribution which are otherwise unrelated to pollution exposure might lead to re-ranking and a different, spurious, normative conclusion. To illustrate this, consider the pollution-reduction profiles starting from a base year of 2001 instead of 2000. Figure 8 shows the relative and absolute horizontal equity PRPs for the periods 2001–2007 and 2001–2014. Recall that the horizontal equity PRPs using 2000 as a base year suggested strongly progressive pollution exposure reduction. In contrast, 2001 as a base year reverses the conclusion: pollution exposure reductions disproportionately benefit the rich. On average, individuals in the top 1 percent of the 2001 income distribution experienced 42 percent declines in PM2.5 exposure, while individuals in the bottom 10 percent experienced 40.5 percent declines. As Figure 9 illustrates, however, the vertical equity pollution-reduction profiles imply progressive pollution reduction in terms of initial exposure.

Indeed, it turns out that 2000 is in some ways an outlier in terms of income distributions: using essentially any other year as a base year results in downward-sloping horizontal equity PRPs.[11] There are a number of factors that might be at work in the uniqueness of 2000: it was the last year of the robust job growth oif the recovery between the 1991 recession and the 2001 recession, which resulted in growing incomes at the bottom of the distribution, and also coincided with the dot-com bust, which resulted in large capital losses for top income earners. Regardless, the consistent pattern for non-2000 base years strongly suggests that pollution exposure reduction after 2001 was regressive in terms of income, a fact that is consistent with the environmental gentrification lens observed environmental justice correlations.

The patterns observed using the vertical and horizontal equity pollution-reduction profiles may be complicated by the level and trend of residential segregation across race and ethnicity. To untangle this complication, I next examine how pollution-reduction profiles vary between race groups, focusing on the difference in the pollution-reduction profiles of blacks and whites. Looking at the vertical and horizontal equity versions of the pollution-reduction profiles allows me to examine the degree to which the income-pollution reduction gradients identified above for the whole population are concentrated within specific race groups, and the degree to which similarly exposed individuals of different races receive disparate treatment in terms of pollution reduction.

Figure 10 shows the race-specific horizontal and vertical, relative and absolute pollution-reduction profiles for the full sample period 2000-2014. Vertical equity PRPs suggest that there has been relatively equitable pollution reduction across race groups, with largely similar amounts of pollution reduction across blacks

[11] The full set of PRPs are available upon request.

and whites conditional on initial PM2.5 exposure. Consistent with the full-population results, the vertical equity PRPs suggest progressive pollution reduction for both blacks and whites. The horizontal equity PRPs suggest progressive pollution reduction with respect to income, and in fact this progressivity is more pronounced for blacks. Blacks in the bottom 10 percent of the income distribution experienced 45 percent decreases in PM2.5 exposure 2000-2014, compared to 40 percent for blacks in the top 1 percent of income. Whites in the bottom 10 percent, on the other hand, experienced 41.5 percent declines, compared to 39.5 percent declines for whites in the top 1 percent.

Once again, it is instructive to examine how pollution reductions differ within the beginning and end of the sample. Figures 11 summarizes the pollution-reduction profiles for the early part of the sample, 2000–2007. As in the full-sample results, the period 2000–2007 experienced equitable pollution reduction across race groups (the vertical equity PRPs are similar for blacks and whites), and more progressive pollution reduction with respect to income for blacks (the horizontal equity PRP for blacks has a steeper slope than the white PRP).

However, there is a stark contrast looking at the end of the sample. Figure 12 summarizes the pollution-reduction profiles for the latter part of the sample, 2008–2014. Here there are cleavages between blacks and whites in terms of the pattern of pollution reduction. The race-specific vertical equity PRPs suggest that although initially highly exposed (i.e., the top quartile of pollution exposure) individuals receive equitable treatment across race groups, there is a gap in the pollution exposure reduction between blacks and whites for the bottom 3/4 of the distribution, and in fact, blacks in the bottom quartile of exposure in fact experience higher levels of PM2.5 exposure in 2014 vs. 2008. The horizontal equity PRPs show an even starker pattern of racial inequality. Across the entire income distribution, whites experience larger pollution reductions than do blacks. Blacks at the bottom 10 percent of the income distribution experience a 2 percent increase in PM2.5 exposure, while whites in the top 1 percent experience 4 percent declines in exposure. In this latter period, it is not only the case that pollution reduction is disproportionately accruing to the advantaged (white and higher income individuals), but also, the most disadvantaged (black and lower income individuals) are actually worse off in absolute terms.

6 Conclusion

Due to a combination of policy and changes in patterns of industrial and consumption activity, pollution exposure has, on average, declined dramatically over the last several decades. This decline in average exposure, however, has not been experienced equally by all individuals or groups. Particularly in the period since 2008, there is evidence of an unequal distribution of air quality improvements across race and class lines that is consistent with the "environmental gentrification" explanation for enduring environmental injustice. There is a tension in the various ways of examining how exposure has changed: disadvantaged groups are better off in absolute terms over long time scales (15 years), but in the very recent past, it seems as if they are losing ground to more advantaged individuals.

This study adds important nuance to our understanding of the evolution of the distribution of pollution exposure over the last two decades. By introducing new measurement tools for analyzing longitudinal environmental inequality — the pollution-reduction profiles — it is possible to analyze how trends in average exposure and cross-sectional environmental inequality have played out for individuals. Mirroring the trends in cross-sectional inequality, individual pollution exposure reductions were progressive by income and initial exposure in the early part of the sample (2000-2007), but fissures have emerged post-2008. Reductions in pollution exposure since 2008 have disproportionately benefited advantaged groups (whites and the rich), while some subgroups (poor blacks) have actually seen increasing pollution exposure.

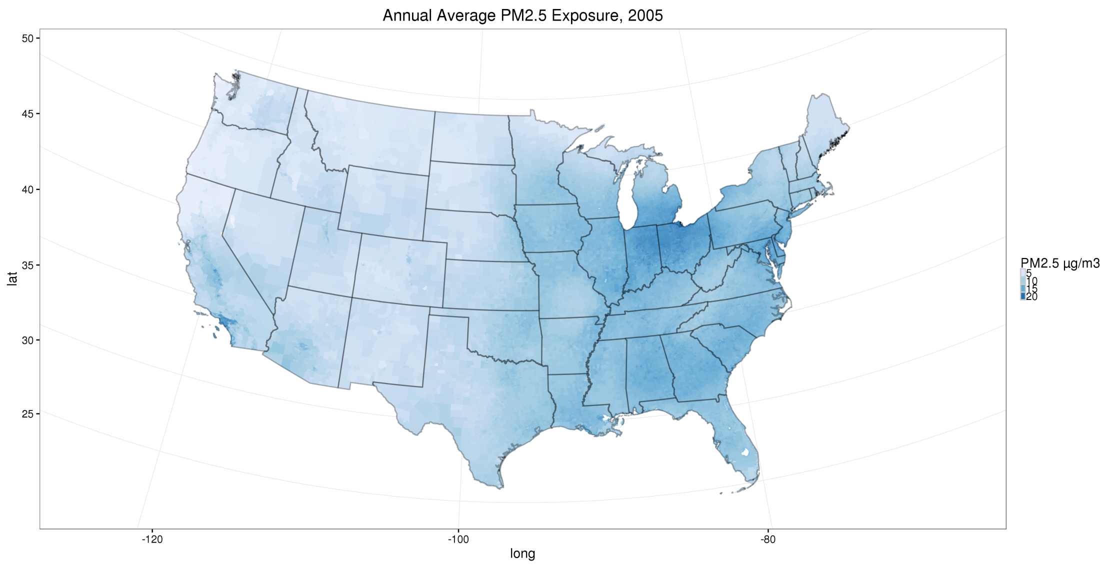
These trends in longitudinal environmental inequality can inform the recent literature on the human capital impacts of pollution exposure. This large literature has suggested that pollution exposure, especially early in life, can have large and negative impacts on future educational attainment and even wages. In light of this literature, the pattern of race-group-specific pollution-reduction profiles after 2008 suggests that the way in which air quality has improved will potentially increase racial gaps in educational attainment and ultimately increase racial income inequality. Studying and more carefully analyzing the effects of the trends in environmental inequality identified in this project will be an important line of inquiry going forward, as will the leveraging of the longitudinal exposure data to better understand how cumulative exposure and not just point-in-time acute exposure might affect outcomes of interest.

7 Tables and Figures

Table 1: Number of Matched Records, IRS 1040 and Decennial Censuses

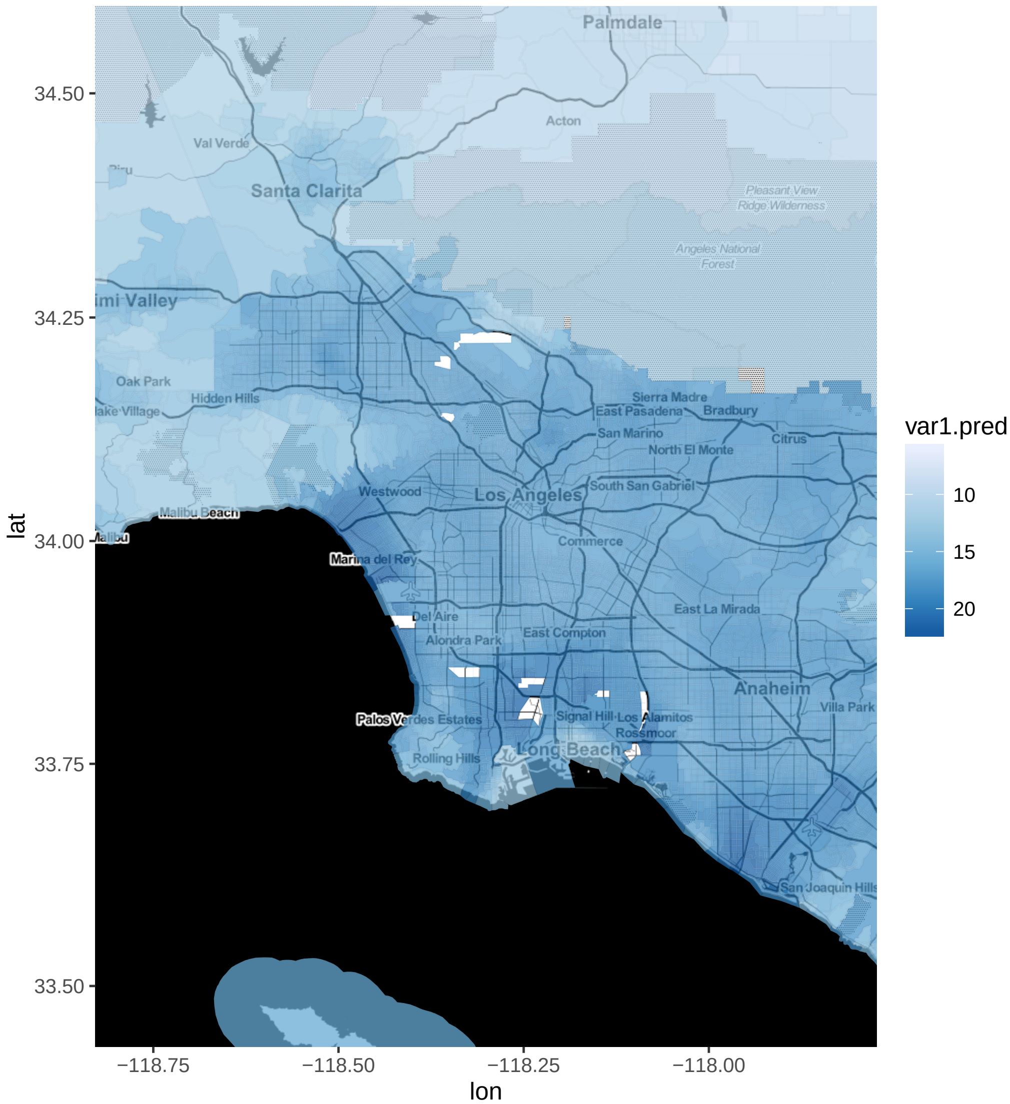
Year	# on 1040	# Linked to 2000 Census	# Linked to 2010 Census	# Linked to 2000 and 2010 Census	# Linked to 2000 or 2010 Census
2000	231, 479, 653	200, 783, 127	194, 636, 704	171, 815, 612	223, 604, 219
2001	233, 616, 258	198, 799, 417	197, 998, 420	171, 305, 387	225, 492, 450
2002	239, 039, 611	198, 899, 295	204, 037, 993	172, 662, 158	230, 275, 130
2003	241, 932, 711	197, 019, 933	207, 985, 399	172, 338, 640	232, 666, 692
2004	240, 593, 888	192, 016, 675	208, 298, 929	169, 232, 415	231, 083, 189
2005	246, 587, 262	192, 342, 995	214, 657, 156	170, 664, 817	236, 335, 334
2006	249, 833, 148	190, 947, 478	218, 698, 825	170, 587, 923	239, 058, 380
2007	269, 512, 453	202, 151, 657	236, 305, 711	181, 092, 710	257, 364, 658
2008	253, 806, 813	181, 566, 327	222, 054, 075	164, 953, 835	238, 666, 567
2009	270, 054, 824	187, 717, 173	237, 056, 467	171, 799, 261	252, 974, 379
2010	273, 922, 321	186, 370, 241	237, 461, 874	171, 120, 491	252, 711, 624
2011	275, 716, 606	183, 899, 167	234, 361, 826	168, 778, 293	249, 482, 700
2012	275, 247, 210	180, 496, 582	230, 171, 744	165, 667, 344	245, 000, 982
2013	275, 538, 098	177, 431, 349	226, 430, 244	162, 843, 894	241, 017, 699
2014	275, 899, 601	174, 302, 503	222, 693, 380	159, 933, 337	237, 062, 546
	Records with matches every year in 2000-2014:				
	115,556,105	104,015,036	108,395,383	98,434,752	113,975,667

Figure 1: National Distribution of PM2.5 Exposure, 2005



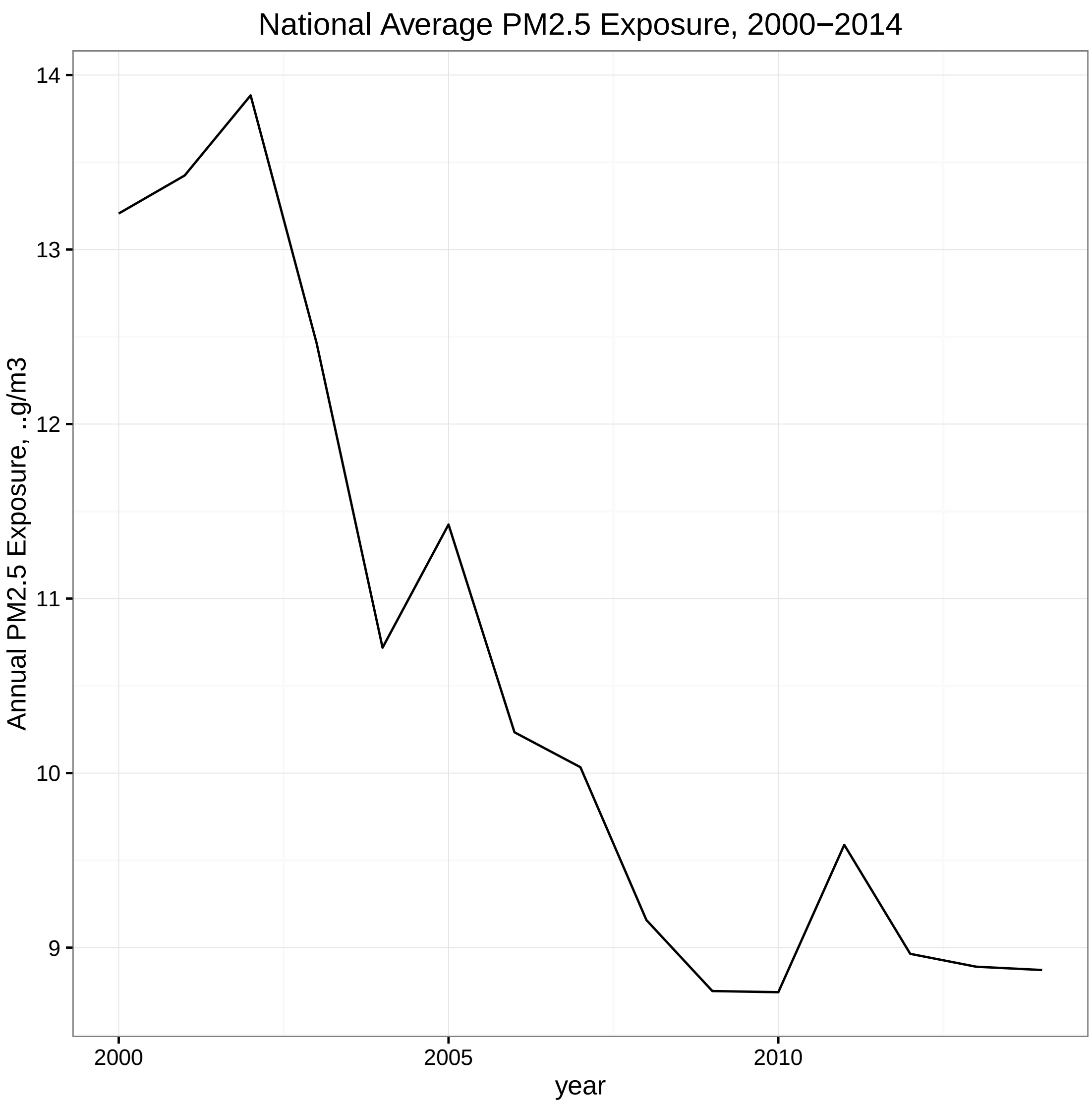
Source: Author's Calculations from ACAG Satellite data

Figure 2: Distribution of PM2.5 Exposure, Los Angeles Area, 2005



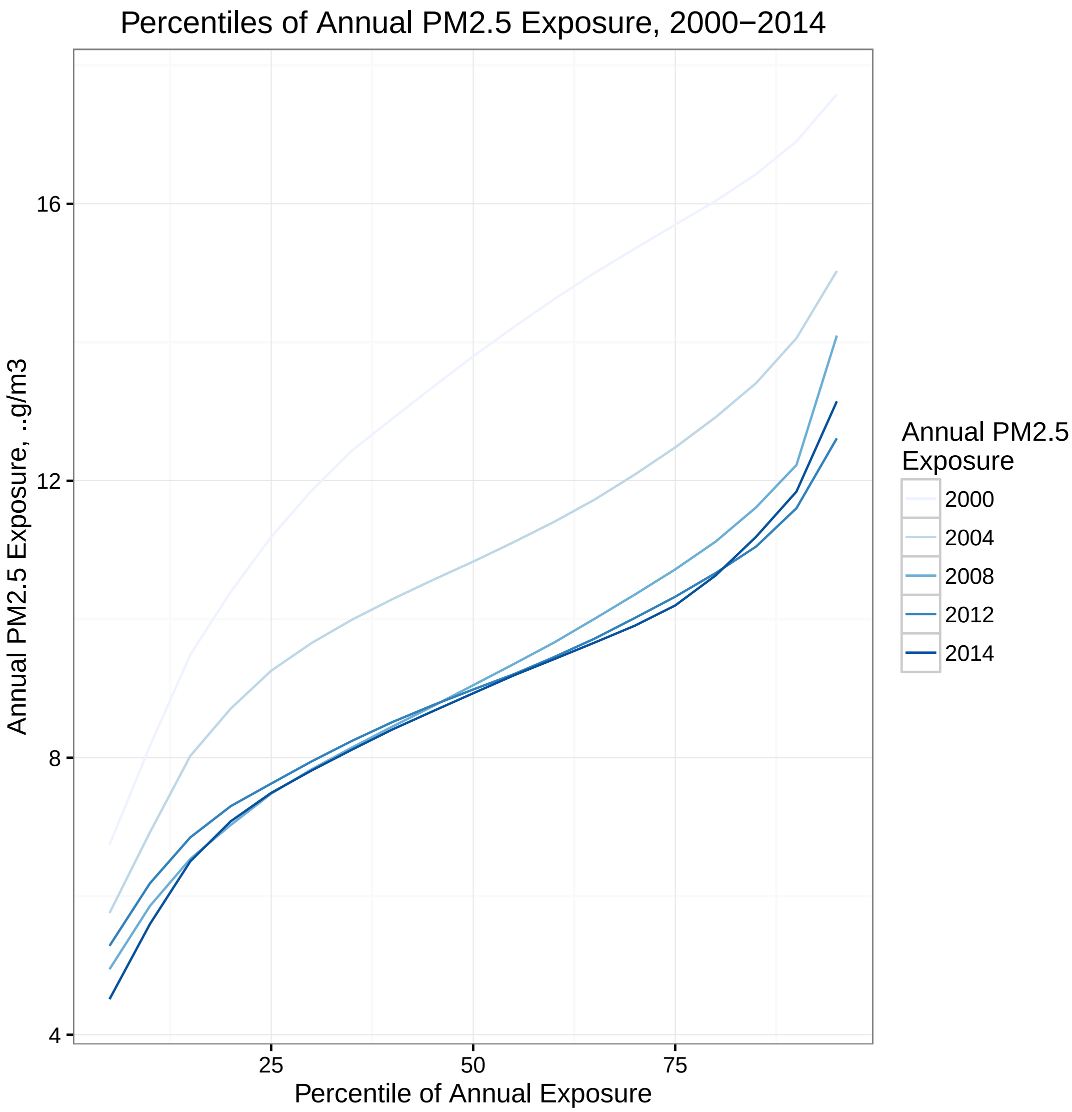
Source: Author's Calculations from ACAG Satellite data

Figure 3: National Average PM2.5 Exposure, 2000-2014



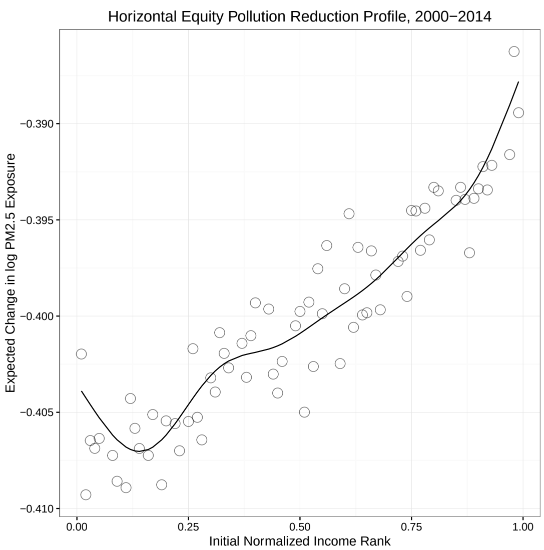
Source: Author's Calculations from IRS 1040, 2000 & 2010 Decennial Census and ACAG Satellite data

Figure 4: National PM2.5 Exposure by Percentile of the Exposure Distribution

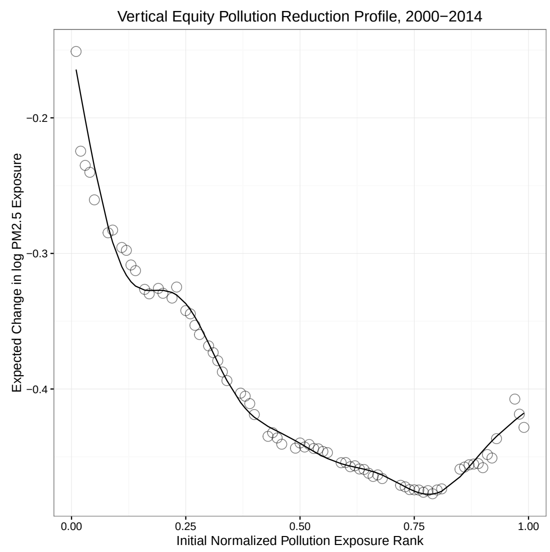


Source: Author's Calculations from IRS 1040, 2000 & 2010 Decennial Census and ACAG Satellite data

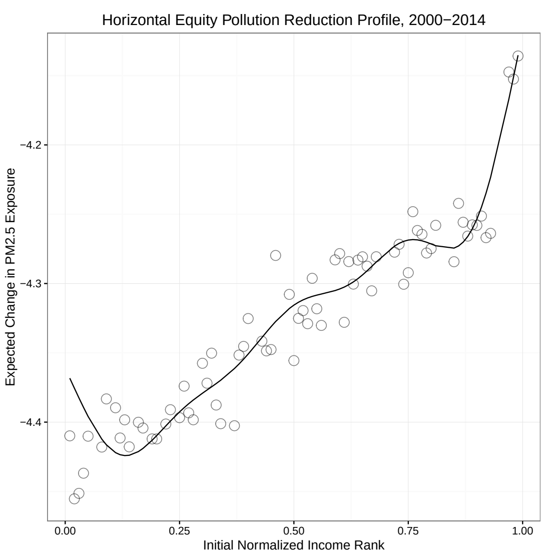
Figure 5: Pollution-Reduction Profiles, 2000-2014



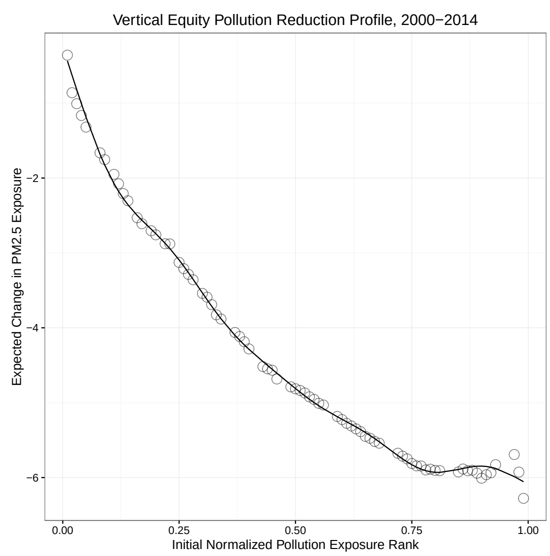
(a) Relative, Horizontal Equity



(b) Relative, Vertical Equity



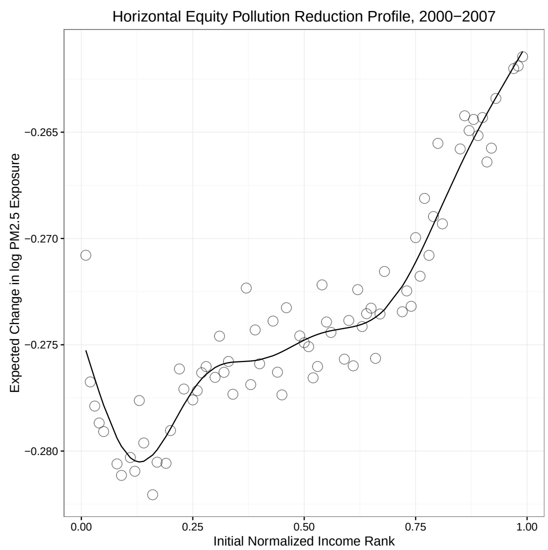
(c) Absolute, Horizontal Equity



(d) Absolute, Vertical Equity

Source: Author's Calculations from IRS 1040, 2000 & 2010 Decennial Census and ACAG Satellite data

Figure 6: Pollution-Reduction Profiles, 2000-2007



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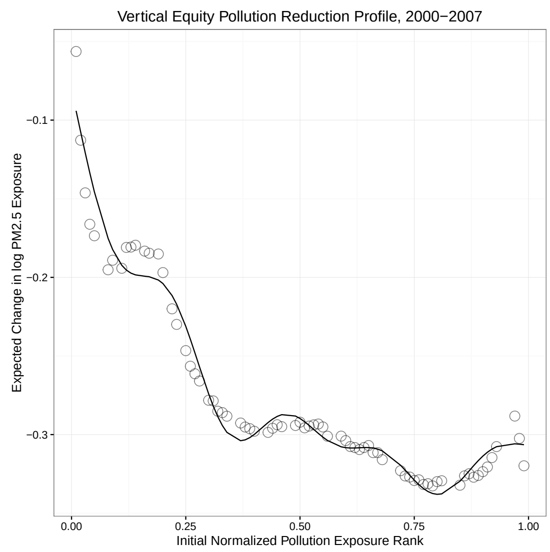

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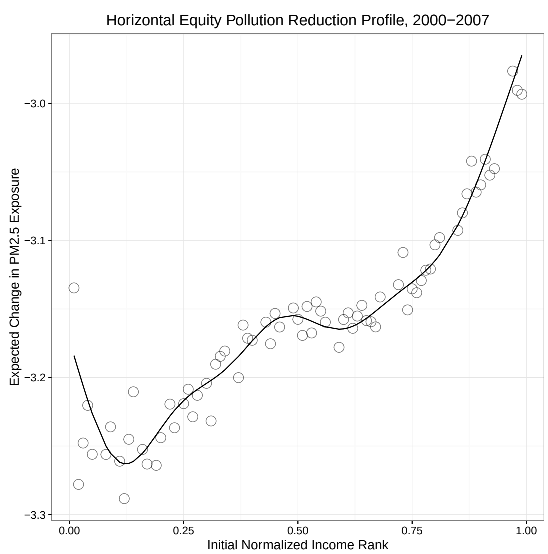

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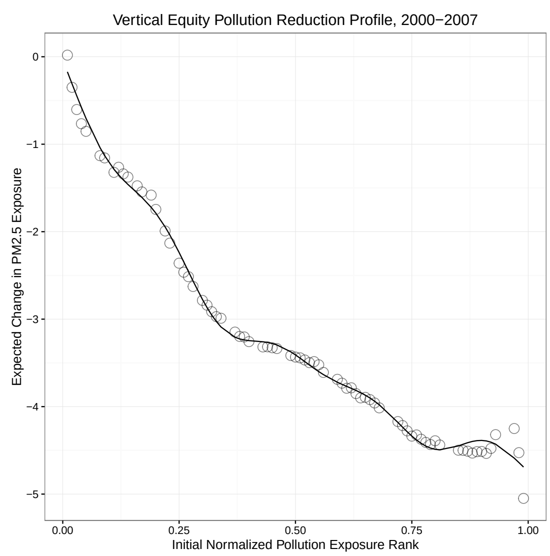
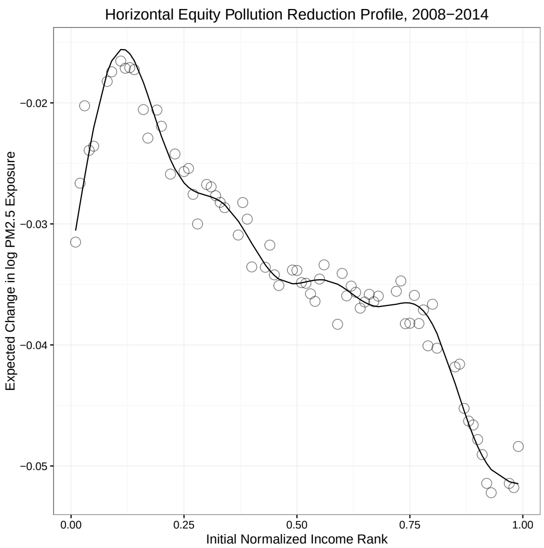


(d) Absolute, Vertical Equity

Source: Author's Calculations from IRS 1040, 2000 & 2010 Decennial Census and ACAG Satellite data

Figure 7: Pollution-Reduction Profiles, 2008-2014



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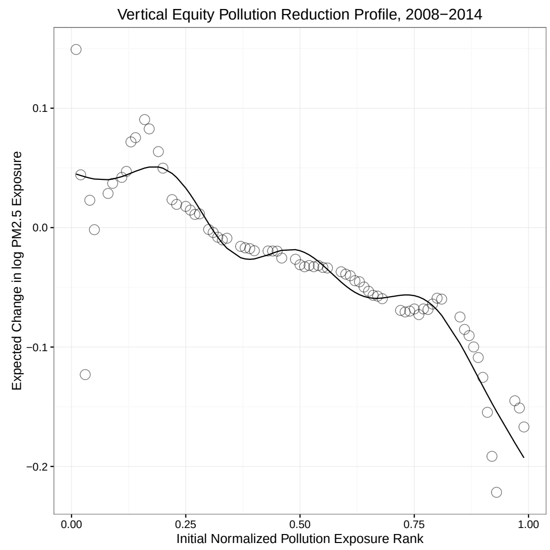

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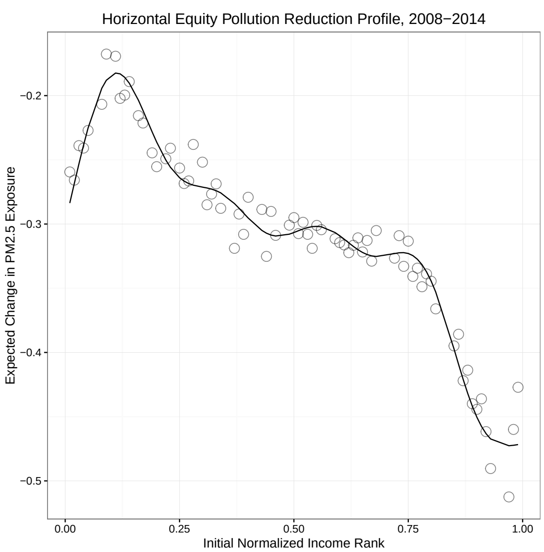

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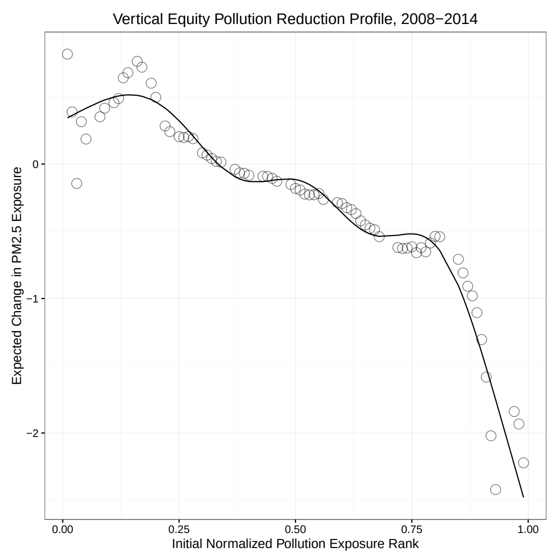
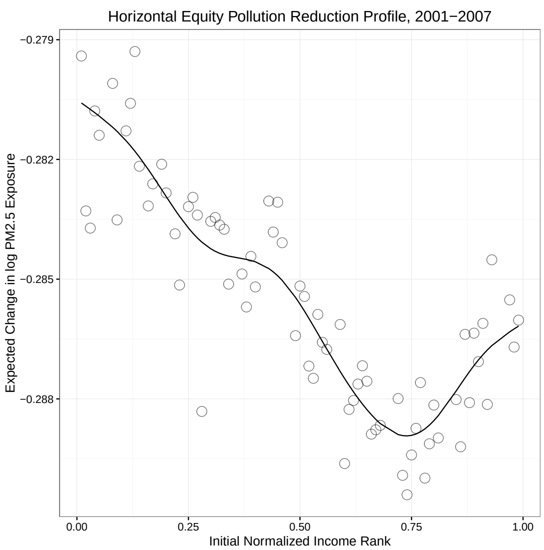


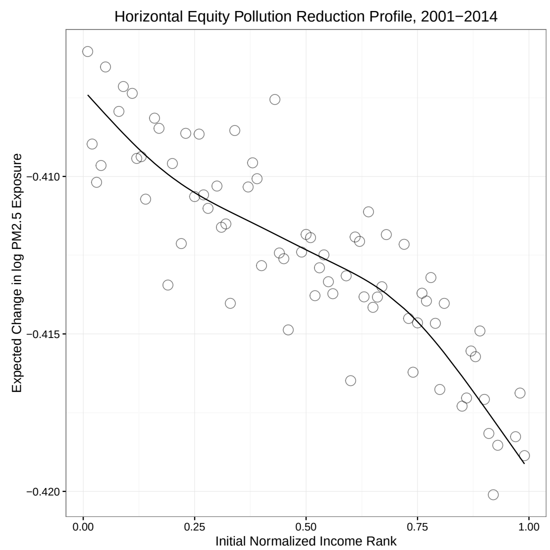
(d) Absolute, Vertical Equity

Source: Author's Calculations from IRS 1040, 2000 & 2010 Decennial Census and ACAG Satellite data

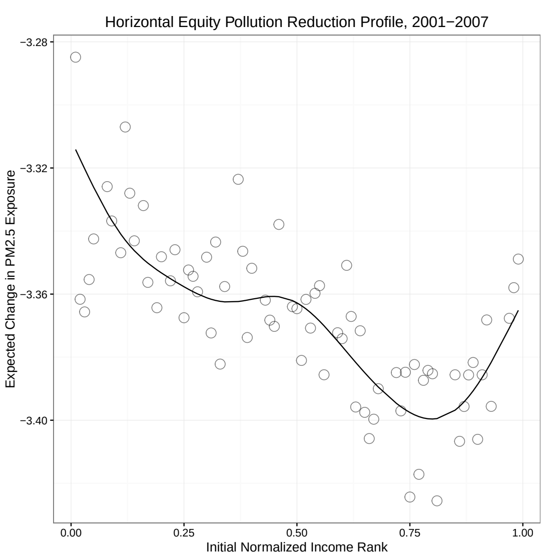
Figure 8: Horizontal Equity Pollution-Reduction Profiles, 2001-2007 and 2001-2014



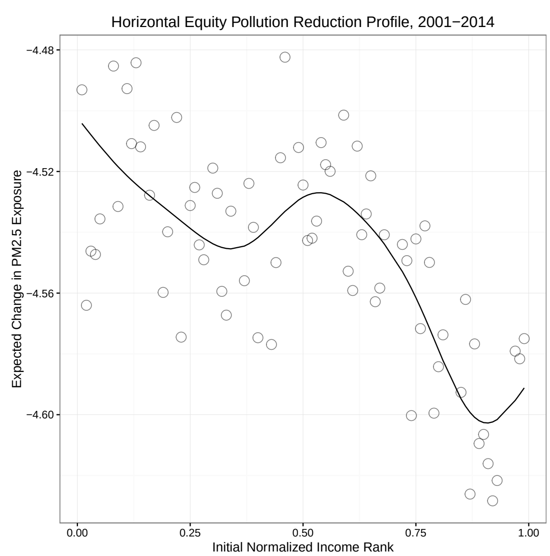
(a) Relative, Horizontal Equity, 2001-2007



(b) Relative, Horizontal Equity, 2001-2014



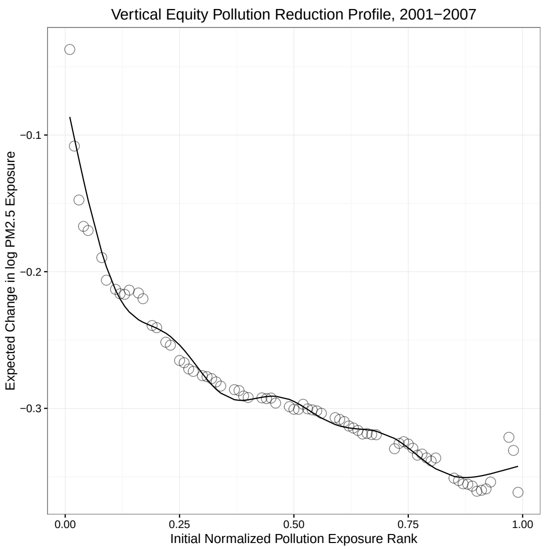
(c) Absolute, Horizontal Equity, 2001-2007



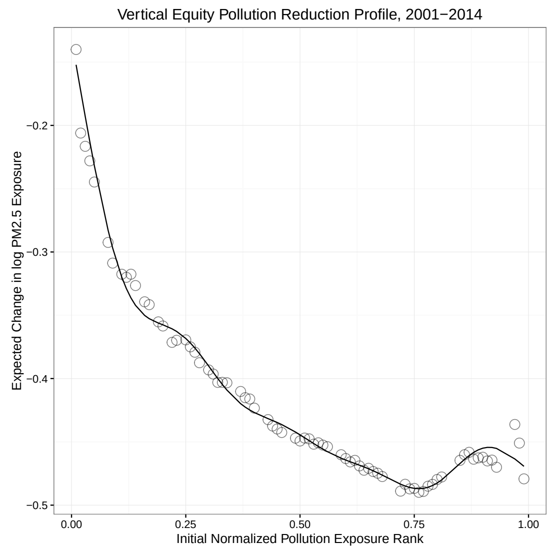
(d) Absolute, Horizontal Equity, 2001-2014

Source: Author's Calculations from IRS 1040, 2000 & 2010 Decennial Census and ACAG Satellite data

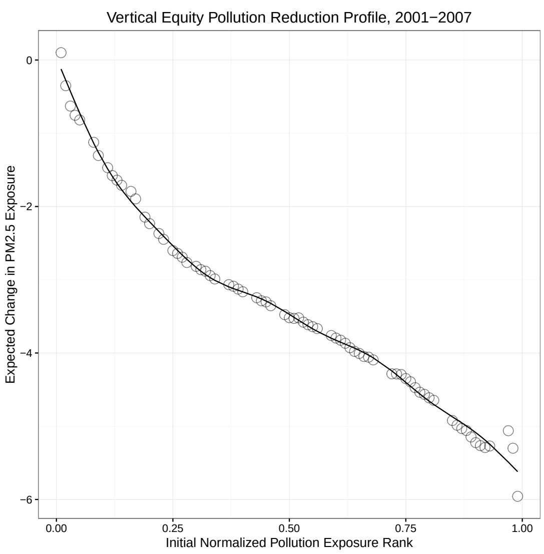
Figure 9: Vertical Equity Pollution-Reduction Profiles, 2001-2007 and 2001-2014



(a) Relative, Vertical Equity, 2001-2007



(b) Relative, Vertical Equity, 2001-2014



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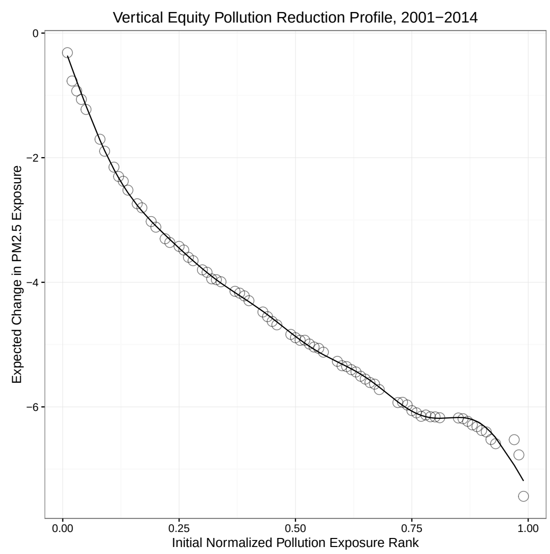
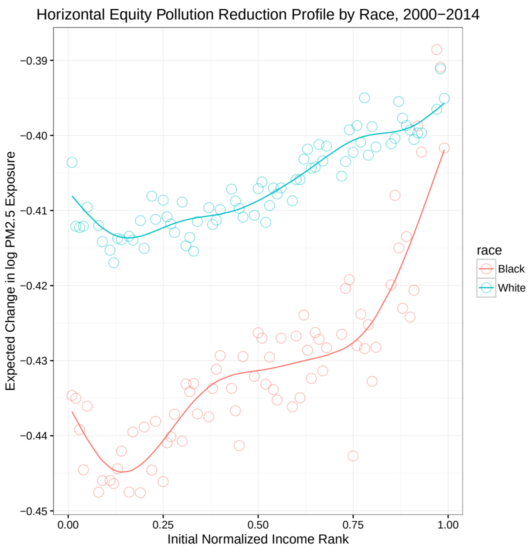


(d) Absolute, Vertical Equity, 2001-2014

Source: Author's Calculations from IRS 1040, 2000 & 2010 Decennial Census and ACAG Satellite data

Figure 10: Pollution-Reduction Profiles, 2000-2014, by Race



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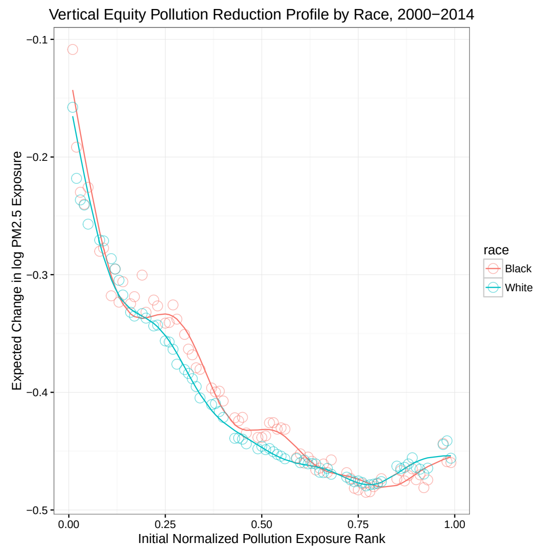

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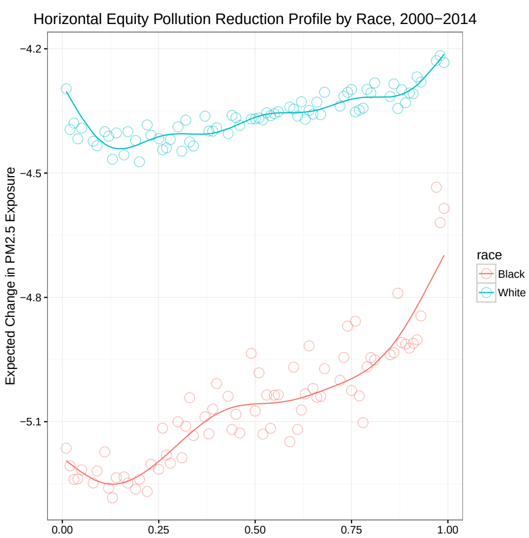

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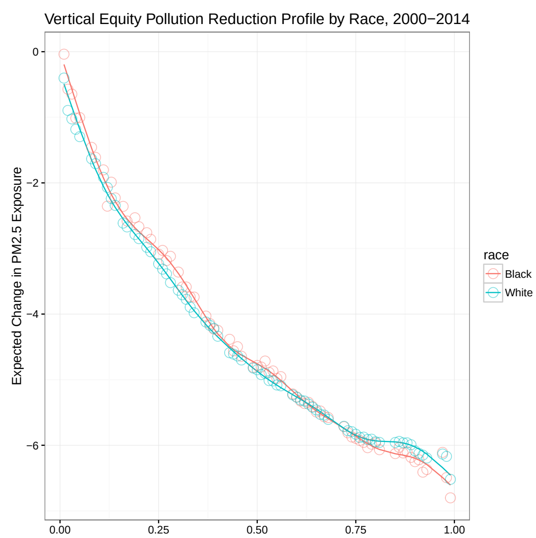
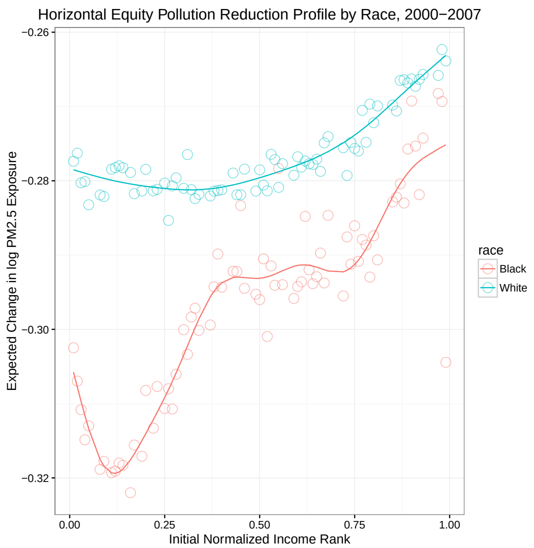


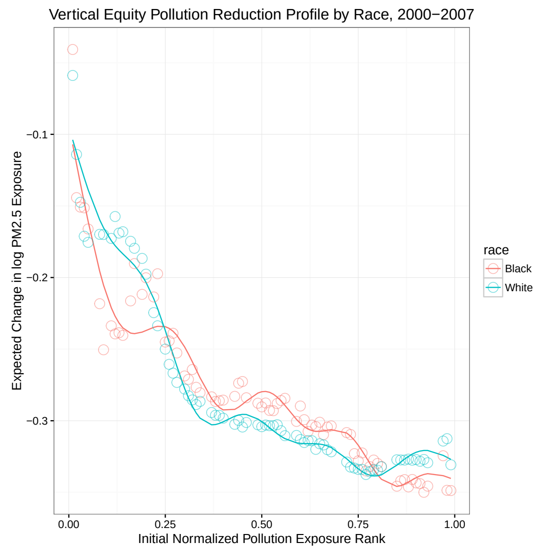
(d) Absolute, Vertical Equity

Source: Author's Calculations from IRS 1040, 2000 & 2010 Decennial Census and ACAG Satellite data

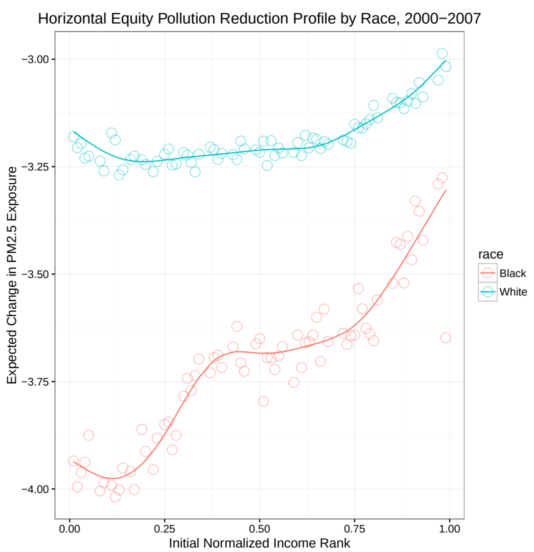
Figure 11: Pollution-Reduction Profiles, 2000-2007, by Race



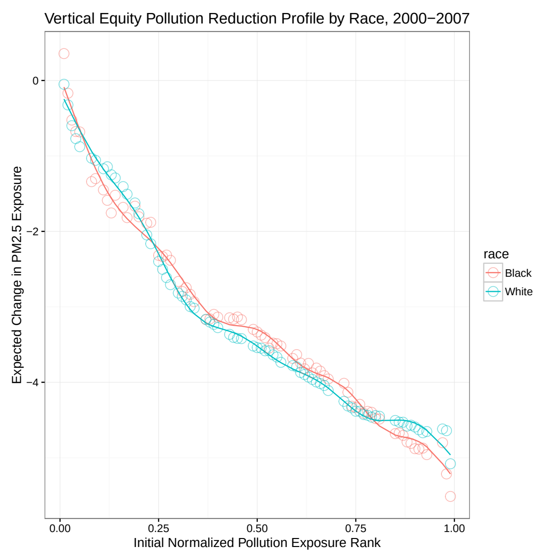
(a) Relative, Horizontal Equity



(b) Relative, Vertical Equity



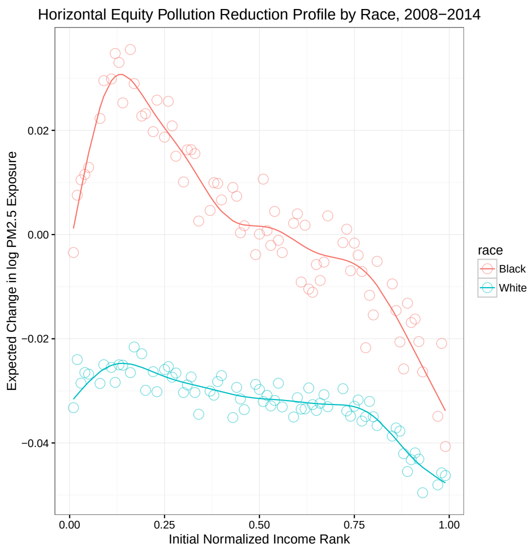
(c) Absolute, Horizontal Equity



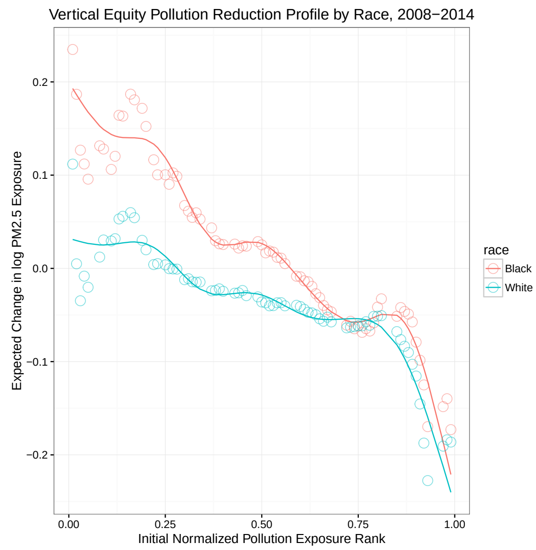
(d) Absolute, Vertical Equity

Source: Author's Calculations from IRS 1040, 2000 & 2010 Decennial Census and ACAG Satellite data

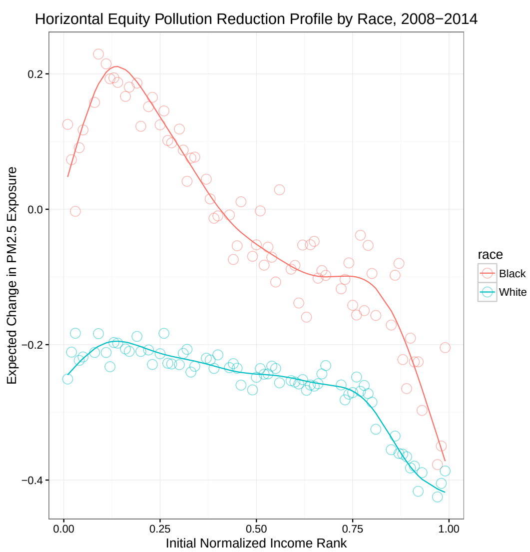
Figure 12: Pollution-Reduction Profiles, 2008-2014, by Race



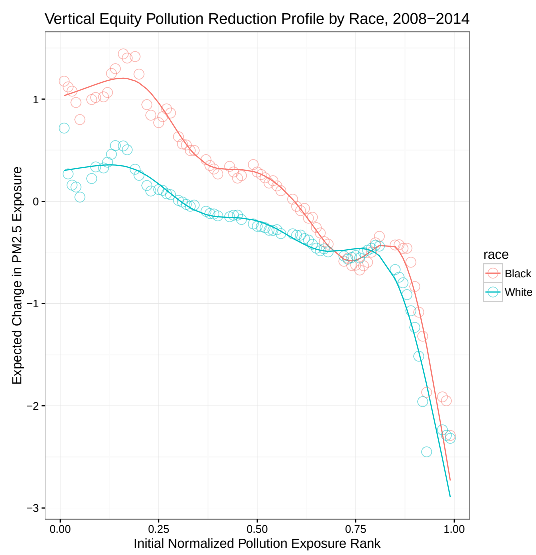
(a) Relative, Horizontal Equity



(b) Relative, Vertical Equity



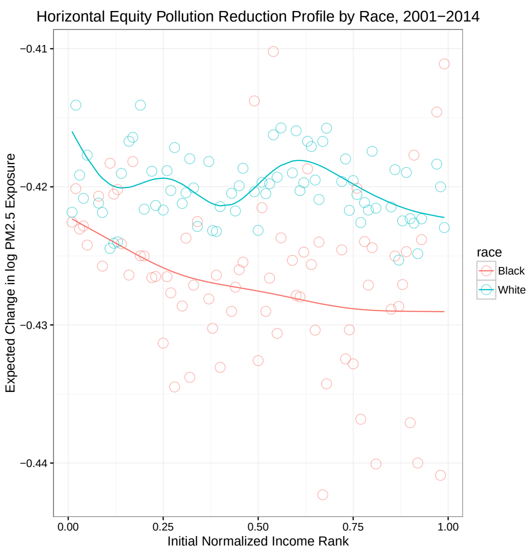
(c) Absolute, Horizontal Equity



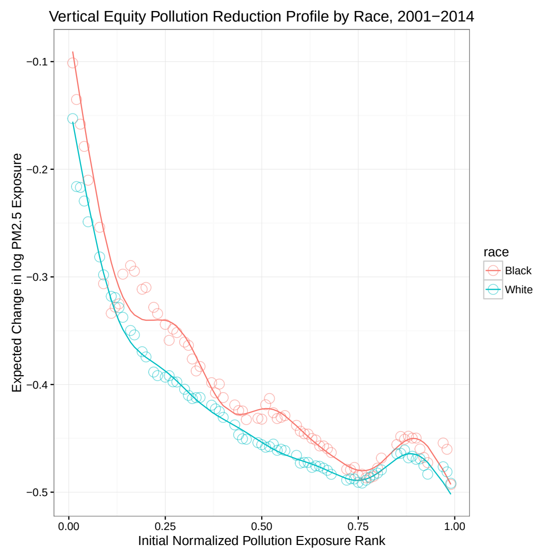
(d) Absolute, Vertical Equity

Source: Author's Calculations from IRS 1040, 2000 & 2010 Decennial Census and ACAG Satellite data

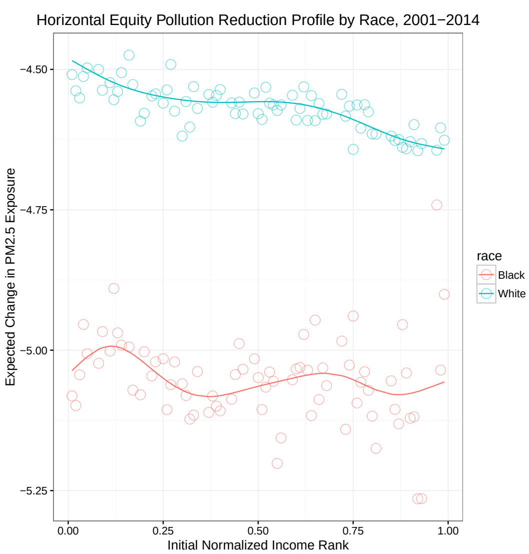
Figure 13: Pollution-Reduction Profiles, 2001-2014, by Race



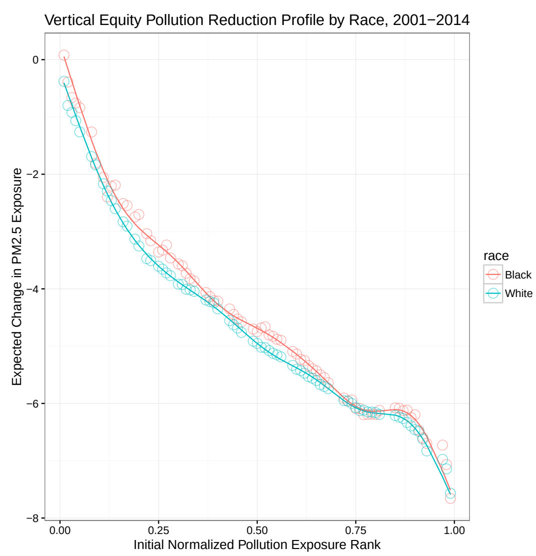
(a) Relative, Horizontal Equity



(b) Relative, Vertical Equity



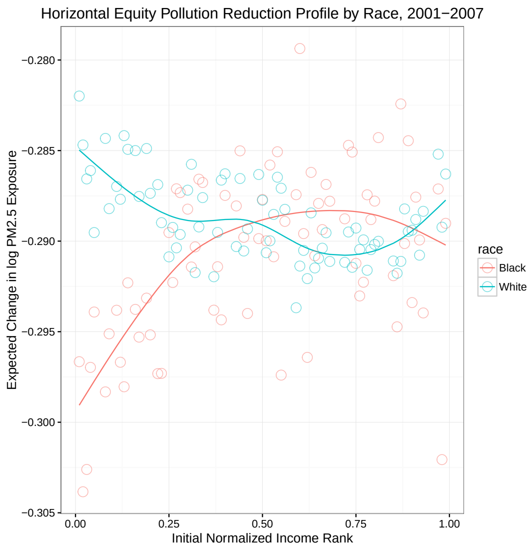
(c) Absolute, Horizontal Equity



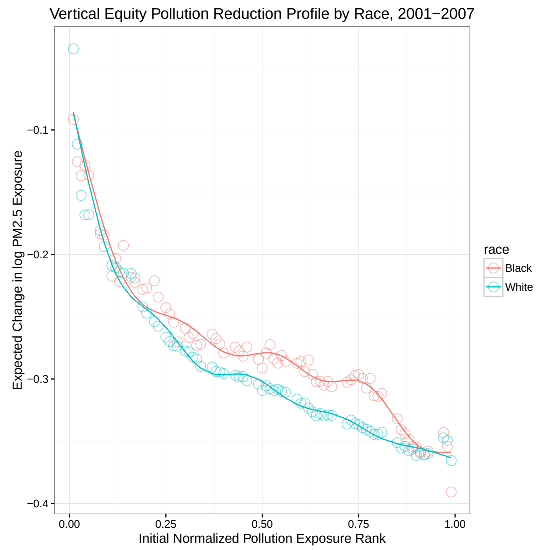
(d) Absolute, Vertical Equity

Source: Author's Calculations from IRS 1040, 2000 & 2010 Decennial Census and ACAG Satellite data

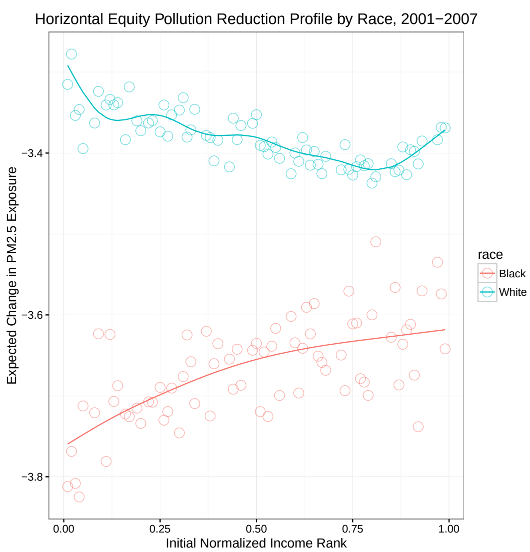
Figure 14: Pollution-Reduction Profiles, 2001-2007, by Race



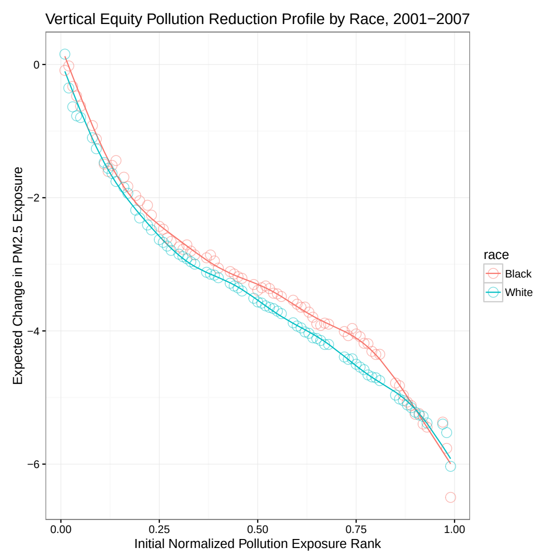
(a) Relative, Horizontal Equity



(b) Relative, Vertical Equity



(c) Absolute, Horizontal Equity



(d) Absolute, Vertical Equity

Source: Author's Calculations from IRS 1040, 2000 & 2010 Decennial Census and ACAG Satellite data

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A Trends in Cross-Sectional Environmental Inequality

This appendix replicates and extends analyses of trends in cross-sectional environmental inequality described in Voorheis (2016). This previous paper used aggregate demographic information at the Census tract level to estimate environmental inequality measures. In the following analysis, on the other hand, I use the individual-level exposure for individuals in the linked IRS 1040-Census data.

To calculate the level of environmental inequality in each year, and the cumulative level of environmental inequality over the period 2000–2014, I use the dashboard approach introduced in Voorheis (2016). This approach acknowledges the multiple dimensions of environmental inequality, and proposes the use of several measures, each of which captures a specific aspect of environmental inequality. Examining environmental inequality from multiple angles (using different measures) can provide a fuller picture of how distributions of environmental hazards have evolved over time, and allows for more nuanced analysis of the distributional impacts of environmental policy.

The first dimension on which measures of environmental inequality can be placed concerns whether they respect vertical or horizontal equity. Vertical equity measures treat individuals anonymously, and solely make social evaluations on the overall distribution of environmental hazards. Vertical equity measures rank individuals by exposure, and hence consider more exposed individuals to be disadvantaged. Horizontal equity measures, on the other hand, do not treat individuals anonymously. Horizontal equity measures are concerned with disparities between subgroups of the population, and hence rank individuals by group membership (this ranking implies a ranking of advantage). Horizontal equity measures may use a discrete ranking (if the subgroups are racial or ethnic groups) or a continuous ranking (as in income).

The second dimension along which environmental inequality measures can be placed concerns whether they capture relative or absolute disparities. Formally, this amounts to a statement about the invariance properties of an environmental inequality measure. Consider a generic environmental inequality measure $I(x, h)$, which takes as inputs a vector of individual exposures x, and, if it respects horizontal equity, a vector of group identities h. An environmental inequality index is translation invariant if:

$$\forall t : I(x + t, h) = I(x, h)$$

where t is a vector with identical entries. Alternately, an environmental inequality index is scale invariant if:

$$\forall s : I(sx, h) = I(x, h)$$

where s is a vector with identical entries. Environmental inequality measures which satisfy translation invariance are absolute environmental inequality indexes, and will aggregate gaps in exposure between individuals. Environmental inequality measures which satisfy scale invariance are relative environmental inequality indexes, and will aggregate ratios of individuals' exposure.

The use of relative vs. absolute environmental inequality measures for social evaluation will depend in large part on understanding the dose-response function that links exposure to environmental hazards to negative health outcomes (morbidity and mortality). The use of relative environmental inequality measures is ethically sensible in the case where this dose-response function is approximately linear. If the dose response function is non-linear, on the other hand, using absolute environmental inequality measures is ethically sensible.

In this study, I use several measures of cross-sectional environmental inequality, covering all four "quadrants" of the dashboard. To capture relative environmental inequality that respects vertical equity concerns, I will estimate the transformation of the Atkinson index introduced in Sheriff and Maguire (2014):

$$A\left(x\right) = \left(\frac{1}{N}\sum_{i=1}^{N}\left(\frac{x_i}{\mu_x}\right)^{1-\alpha}\right)^{\frac{1}{1-\alpha}} - 1,\ \alpha \leq 0$$

To capture absolute inequality that respects vertical equity, I will use a Kolm-Pollak type index:

$$K\left(x\right) = -\frac{1}{\kappa}\ln\frac{1}{N}\sum_{i=1}^{N}e^{-\kappa(x_i-\mu_x)}, \kappa < 0$$

For further discussion of the properties of the measures, see Voorheis (2016) and Sheriff and Maguire (2014). Both indexes require the specification of an environmental inequality aversion parameter (α, κ). These parameters imply utilitarian judgment as $(\alpha, \kappa) \to 0$, and Rawlsian judgments as $(\alpha, \kappa) \to \infty$. I calculate the Atkinson and Kolm-Pollak indexes for a range of environmental inequality measures in a range $\alpha, \kappa \in [0.5, 2.5]$.

To capture horizontal equity, I calculate a series of gaps (for absolute environmental inequality) and ratios (for relative inequality). I calculate these gaps across three different groupings: first, I compare pollution exposure between racial and ethnic groups, between income groups, and between race-by-income groups. Since I am using demographic data from both the the 2000 and 2010 decennial Census I include 7 groups: Hispanic (of any race), White non-Hispanic, Black non-Hispanic, Asian/Pacific Islander non-Hispanic, Native American non-Hispanic and Other non-Hispanic. I calculate the gaps and ratios for each non-white group relative to non Hispanic Whites (the "advantaged" group). For income, I divide the distribution into three groups: "poor" (bottom quartile), "middle" (middle two quartiles) and "rich" (top quartile). Finally, I compute race-by-income ratios and gaps by comparing each non-white-rich group to rich non-Hispanics whites. For each pair of groups to be compared I compute group specific means and vigintiles (quantiles in 0.05,....,0.95). Thus the gap in these means/vigintiles serves as a measure of absolute environmental inequality that respects horizontal equity, while the ratio of these means/vigintiles serves as a measure of relative environmental inequality that respects horizontal equity.

A.1 Cross-sectional Environmental Inequality

Quantile function plots are important suggestive evidence, but are difficult to summarize for the use of policy evaluation. Thus, I now begin to formally measure environmental inequality using the measures in defined in the dashboard. I begin with the vertical equity measures. Trends in the the Kolm-Pollak index (which is an absolute environmental inequality measure) and the Atkinson index are summarized in Figure 15. These plots are shown for environmental inequality aversion parameters of $\alpha, \kappa = 0.5$, but qualitatively similar results obtain using more Rawlsian inequality aversion parameters up to $\alpha, \kappa = 2.5$. Absolute environmental inequality has largely declined over the period 2000-2014; consistent with the overall trends in exposure, the largest declines in absolute environmental inequality occur between 2002-2014. On the other hand, relative environmental inequality measured by the Atkinson index does not exhibit any clear pattern, with wide year-over-year swings around a mean of about 0.017.

I next turn to measures of environmental inequality that respect horizontal equity. I will consider two stratifications of individuals into subgroups—first, by race and ethnicity, and second, by income bins ("poor", "middle" and "rich"). As a first step to analyzing horizontal equity, I first plot the trends in race specific average PM2.5 exposure in Figure 16. All racial and ethnic groups have seen broad declines in exposure over this period. Given these relatively coarse racial and ethnic categories I use, it appears that Native Americans actually have the lowest average exposure, and, in general, blacks have the highest exposure (although Asian-Americans have higher average exposure in 2007-8 and 2013).

It is difficult, however, to visualize how to judge these trends through a horizontal equity lens: the dashboard measures all refer to gaps or ratios in exposure between these groups rather than absolute trends in exposure for subgroups. Thus, I turn to how these subgroup differences have evolved over time. To simplify exposition, I will focus on the subgroup differences that have taken up a central position in the Environmental Justice literature: the difference in exposure between blacks and whites, and the difference in exposure between poor and rich individuals.

Figure 17 summarizes how the average black-white gap and black-white ratio of PM2.5 exposure have evolved over the period 2000-2014. On average, this gap is smaller at the end of the sample than at the beginning, decreasing by around twofold from 1.6 $\mu g/m^3$ in 2000 to $0.8 \mu g/m^3$ in 2014. There has been less change in the black-white ratio over timem which is consistent with the trends in vertical equity measures above, and provides confirmatory evidence for scale-invariant changes in pollution exposure. In contrast, there has been very little change in the gap in exposure between the top quatile of the income distribution and the bottom quintile of the income distribution, as shown in Figure 18.

To investigate further how horizontal equity varies across the pollution exposure distribution, I move beyond the mean, and consider how black-white gaps vary across both quantiles of the race-specific exposure distribution, and time. Figure 19 summarizes how the black-white gaps and ratios have evolved over time at each quantile $q \in 0.05, ..., 0.95$. Mirroring the trends in the average black-white gap, there have been declines in the gap in exposure for most quantiles. However, it is notable that the least exposed tail of the exposure distribution actually sees larger declines in the gap in exposure than does the most-exposed.

The above evidence suggests that exposure has been declining, and, viewed cross-sectionally, this reduction in exposure has coincided with a decrease in environmental inequality. Analysis of these trends across repeated cross-sections, however, cannot necessarily yield any inference about how the exposure of any given individual has evolved over time. To this end, I consider two ways of summarizing this individual experience. First, I present analysis of the cumulative exposure across individuals, and second, I present evidence on how individual exposure has evolved, summarized by the pollution-reduction profiles defined above.

A.2 Cumulative Pollution Exposure

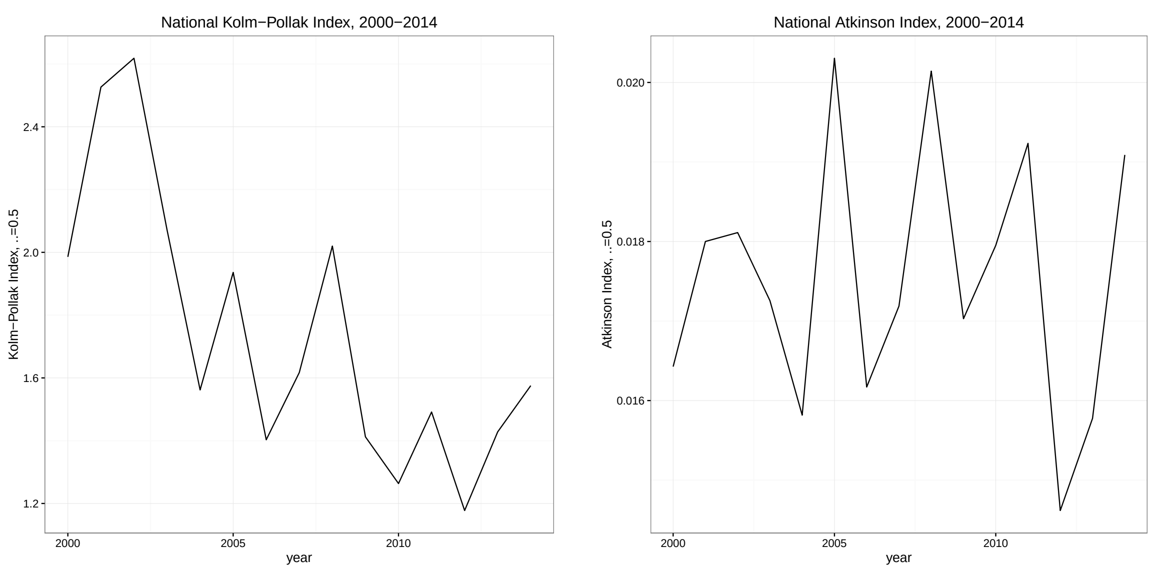
The cross-sectional analysis above used information from all individuals who appeared on a 1040 tax return and who could be linked to Decennial Census records (either 2000 or 2010). However, not all individuals appear on a tax return in each year, and thus it is not possible to measure cumulative exposure using tax return address information for all individuals who appear in any cross section. Even so, there remain a large number of individuals who appear on a tax return in each year over the period 2000-2014. As shown in table 1, the average cross-section contains about 250 million records, while just over 100 million individuals can be tracked over time.

Table 2 summarizes the average cumulative exposure by race and ethnicity from 2000–2014, as well as the cumulative exposure at the 10th and 90th percentiles of the cumulative exposure distribution. The average black individual's cumulative exposure is 171.9 $\mu g/m^3$, compared to an average cumulative exposure for whites of 158.2 $\mu g/m^3$. This corresponds to a black-white cumulative gap of 13.726 $\mu g/m^3$, or a black-white cumulative exposure ratio of 1.086. The cumulative exposure gap is mechanically larger than any year's exposure gap, and is thus hard to compare. However, the black-white cumulative ratio, which captures relative environmental inequality, is comparable to the individual annual black-white ratios, and is in fact smaller than most individual annual ratios. Consistent with this, the absolute vertical equity environmental inequality measure, the Kolm-Pollak index is 118.05 for cumulative exposure (larger than any year's annual Kolm-Pollak index), while the relative vertical equity environmental inequality measure, the Atkinson index is 0.014 (smaller than most annual Atkinson indexes in the period).

There is interesting heterogeneity across the pollution exposure distribution for cumulative exposure, paralleling the repeated cross section approach above. Figure 20 graphs the black-white gap in cumulative exposure across percentiles of the cumulative exposure distribution. Black-white gaps in cumulative exposure are again larger at the bottom of the exposure distribution than at the top. This may be at least in part a product of the relative distribution of black and white populations across urban and rural areas.

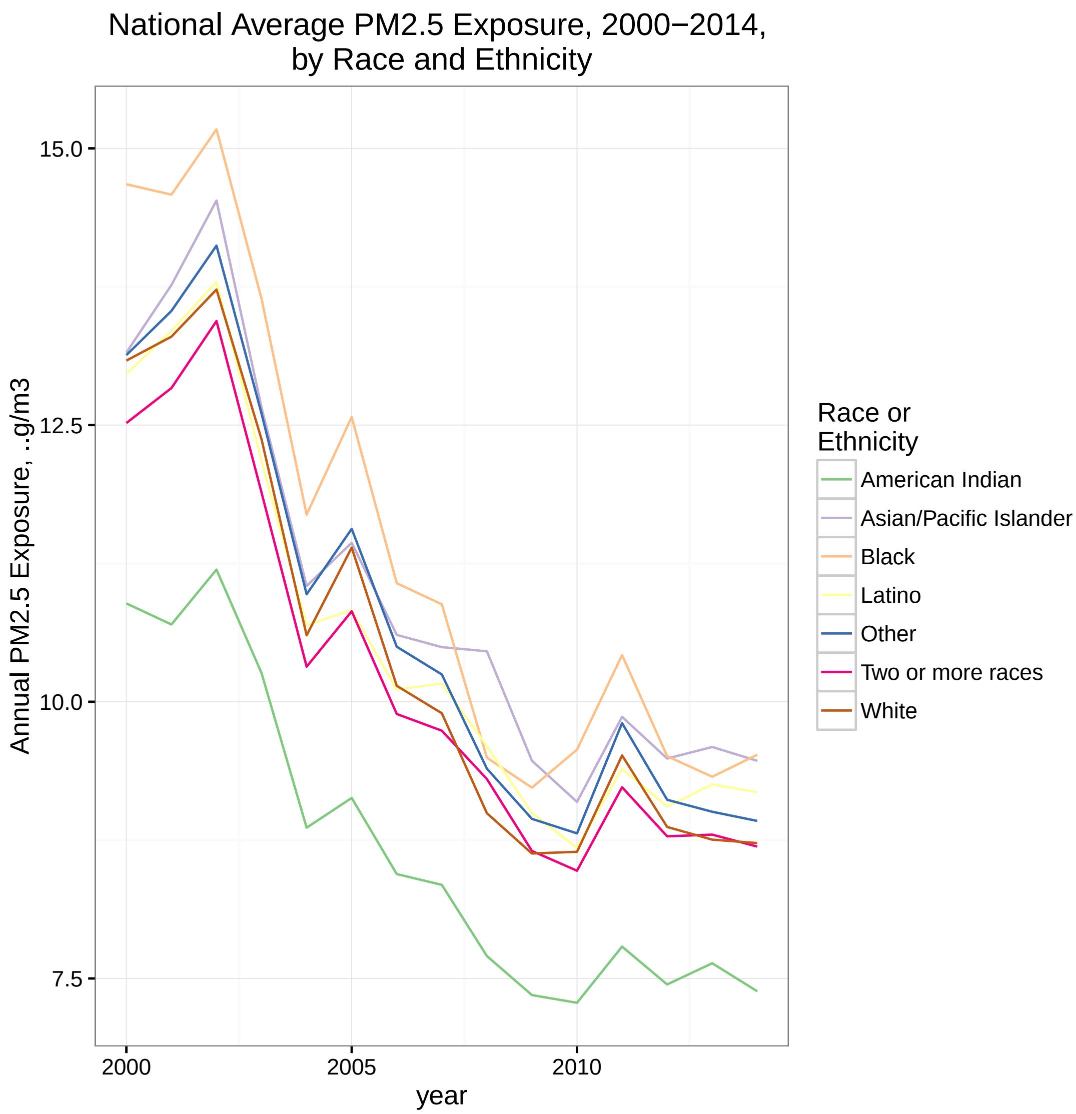
B Additional Tables and Figures

Figure 15: National Environmental Inequality, 2000-2014 (Kolm-Pollak and Atkinson Indices)



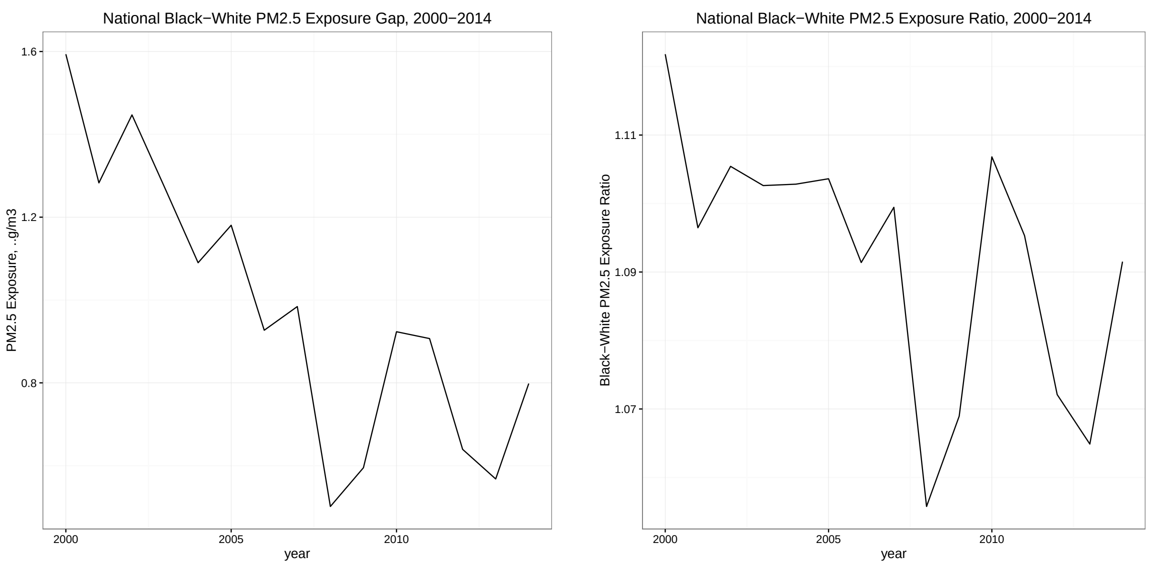
Source: Author's Calculations from IRS 1040, 2000 & 2010 Decennial Census and ACAG Satellite data

Figure 16: National Average PM2.5 Exposure, 2000-2014, by Race



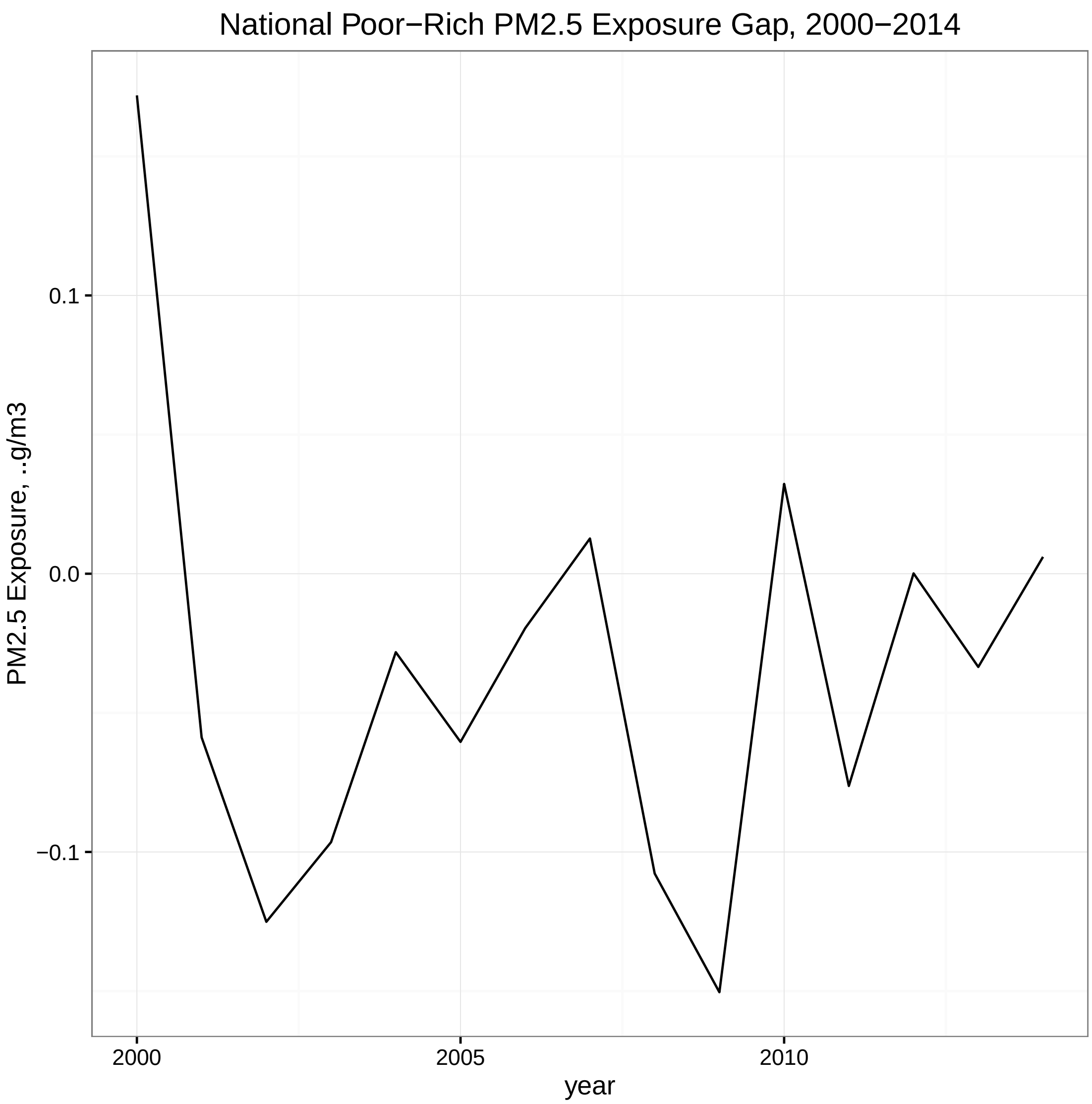
Source: Author's Calculations from IRS 1040, 2000 & 2010 Decennial Census and ACAG Satellite data

Figure 17: Black-White Gaps and Ratios, 2000-2014



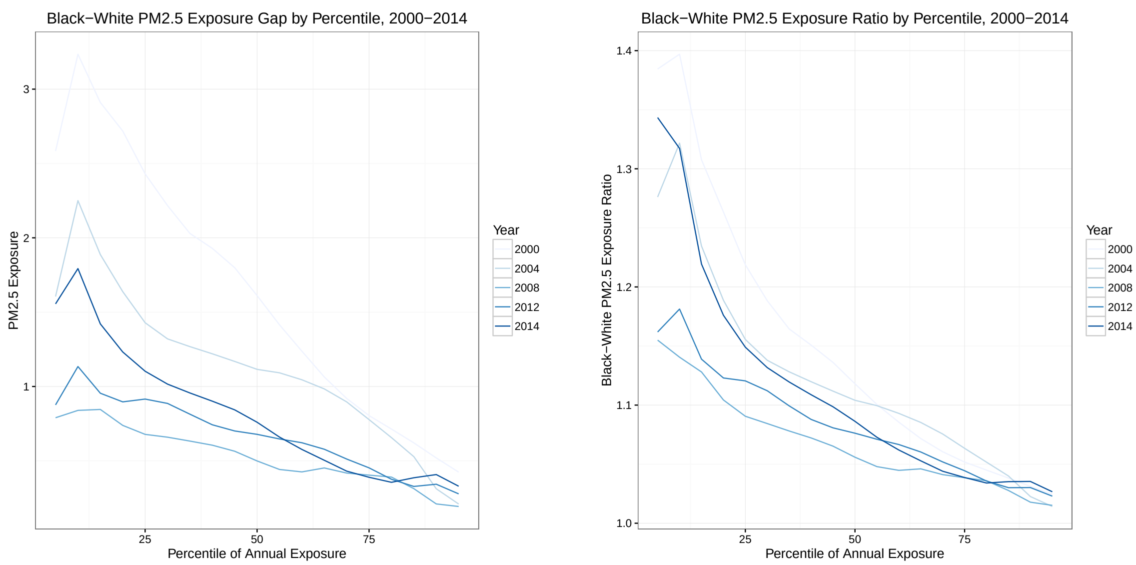
Source: Author's Calculations from IRS 1040, 2000 & 2010 Decennial Census and ACAG Satellite data

Figure 18: Poor-Rich Gaps, 2000-2014



Source: Author's Calculations from IRS 1040, 2000 & 2010 Decennial Census and ACAG Satellite data

Figure 19: Black-White Gaps and Ratios, 2000-2014, by Percentile

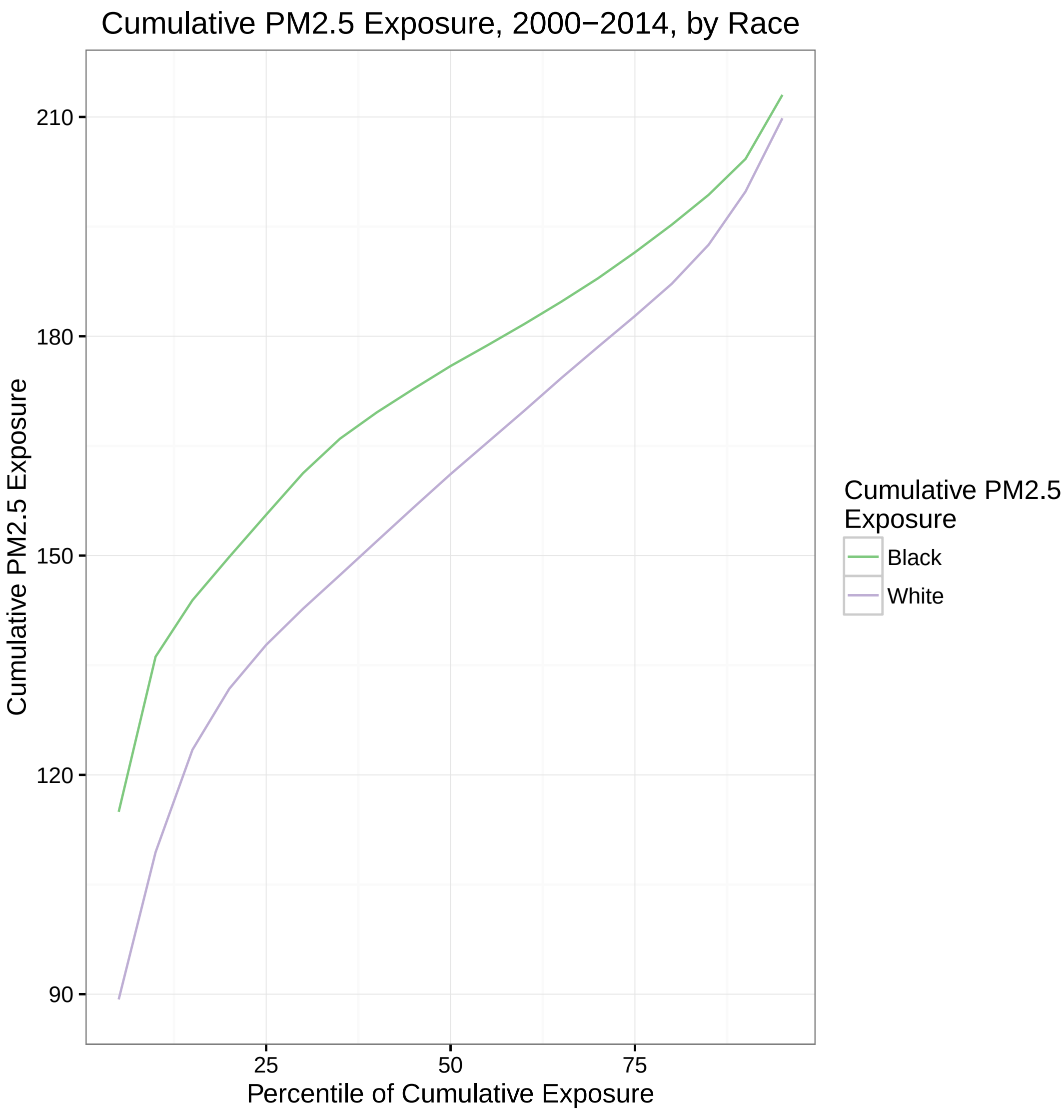


Source: Author's Calculations from IRS 1040, 2000 & 2010 Decennial Census and ACAG Satellite data

Table 2: Cumulative PM2.5 Exposure, by Race & Ethnicity

	Race/Ethnicity	Mean	10th Percentile	90th Percentile
1	White	158.193	109.427	199.799
2	Latino	161.765	95.116	229.262
3	Asian/Pacific Islander	166.655	108.361	229.052
4	Other	160.544	108.118	203.003
5	Black	171.919	136.172	204.263
6	Two or more races	158.125	90.206	206.353
7	American Indian	137.801	73.275	187.448

Figure 20: Cumulative Black-White Gap, 2000-2014, by Percentile



Source: Author's Calculations from IRS 1040, 2000 & 2010 Decennial Census and ACAG Satellite data