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INCOME, WEALTH, AND ENVIRONMENTAL INEQUALITY IN THE UNITED STATES

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ABSTRACT

This paper explores the relationships between air pollution, income, and wealth by combining administrative data from U.S. tax returns between 1979–2016, various measures of air pollution, and sociodemographic information from linked survey and administrative data. Historically, the relationship between income and ambient pollution levels nationally is approximately zero for both non-Hispanic White and Black individuals. However, at every single percentile of the national income distribution, Black individuals are exposed to, on average, higher levels of air pollution than White individuals. By 2016, the relationship between income and air pollution had steepened, primarily for Black individuals, driven by changes in where rich and poor Black individuals live. We utilize quasi-random shocks to income to examine the causal effect of changes in income and wealth on pollution exposure over a five year horizon, finding that these income–pollution elasticities map closely to the values implied by our descriptive patterns. We calculate that Black-White differences in income can explain 10 percent of the observed gap in air pollution levels in 2016.

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1 Introduction

Social scientists have long posited that environmental inequality may be rooted in various forms of economic inequality. One implication of this supposition is that if society could address some of the underlying inequality in economic opportunity, we might expect to see much less environmental inequality (Banzhaf et al., 2019).

However, we have a relatively cursory understanding of the relationship between environmental hazards such as air pollution and correlates of economic well-being such as income or wealth. There are three main reasons for this: first, until very recently, there has been a relative paucity of high-resolution, representative data on air pollution, as in situ monitors are few and far between (Fowlie et al., 2019). The recent advent of low-cost sensors and remote sensing technology has significantly improved our ability to measure and monitor air pollution on a spatially continuous basis. Second, data on income and wealth, especially disaggregated by race, ethnicity or other demographic characteristics are not typically available at the spatial resolution at which differences in air pollution are increasingly found. Third, existing evidence on the relationships between income, wealth, and air pollution stems from observational correlations. We know very little about the causal effect of increases in income and/or wealth on air pollution exposure. Accordingly, we know very little about whether relative improvements in income or wealth are likely to lead to relative improvements in air quality, whether income–pollution relationships differ across racial or demographic groups, or whether these relationships have been stable over time.

This paper combines administrative data from the universe of de-identified, Internal Revenue Service (IRS) form 1040 tax returns between 1979–2016 (containing information on residential location and income) with high-resolution, satellite-derived estimates of ambient air pollution, and sociodemographic information from linked Decennial Census and American Community Survey (ACS) data to provide systematic evidence on the relationship between pollution exposure and economic well-being. Our primary measure of economic well-being is derived from 5 year averages of annual income which are meant to approximate "permanent income", although we explore alternative income and wealth definitions throughout. Our primary measure of air pollution comes from satellite-derived measures of particulate matter smaller than 2.5 microns ($PM_{2.5}$), although we also explore other measures of air pollution.

We begin by documenting new descriptive facts about the relationships between income, wealth, and ambient air pollution exposure at the individual level, showing how these relationships differ by race and ethnicity, and how these income–pollution gradients have changed over time. We then use longitudinal tax data to identify a set of individuals who experience one-time, plausibly exogenous windfalls to income, most likely from lottery winnings.[1] These income shocks allow us to examine, in an event-study framework, the causal effect of changes in income and wealth on air pollution exposure for a subset of individuals in our data. Lastly, we explore some of the potential mechanisms underlying the relationship between pollution exposure, income and wealth and, in particular, how these mechanisms have contributed to race-specific changes in income–pollution gradients over time.

We find that the relationship between income, wealth, and pollution exposures is relatively weak nationally. In 1984, the first year that we have both income and pollution information, the correlation between our measure of permanent income and $PM_{2.5}$ is approximately zero. However, at *every single income percentile* of the national income distribution, non-Hispanic Black individuals were exposed to significantly higher levels of fine particulate pollution than non-Hispanic White individuals.[2] In 2016, there remained almost no relationship between permanent income and $PM_{2.5}$ exposure for White individuals. However, income–pollution gradients steepened for Black individuals and other racial minorities. While small in magnitude, these relative changes in income–pollution gradients portend a narrowing of $PM_{2.5}$ exposure gaps between Black and White individuals at the upper end of the income distribution. Similar patterns exist when we restrict our attention to within-metro area relationships between income and pollution.

Why have these income-exposure gradients changed over time, especially for racial minorities? We use a simple decomposition to show that almost all of the steepening of the income-exposure gradient reflects changes in the locations of Black individuals over the past 40 years rather than

[1] Details of this process are described below. We exclude tax filers who filed schedules C, D, or E and individuals who received other investment income to avoid misclassifying lumpy realizations of capital gains or taxable profits from business, leaving only one-time transitory income shocks such as lottery wins.

[2] Hereafter we refer to these groups simply as Black and White respectively.

relative improvements to air quality in historically Black communities. Relatedly, we show that the set of neighborhoods or Census Tracts that Black individuals live in 2016 are both more numerous and span a wider range of environmental outcomes than in the 1980's. This reflects the broader demographic trend of wealthier minorities moving to suburbs, where suburban locations tend to have lower levels of air pollution than urban centers.

These descriptive facts, however, do not tell us whether relative improvements in income or wealth lead to relative improvements in air quality, as there are many potential confounding factors. For example, existing research points to possible reverse causality in the pollution-income relationship; pollution exposure may directly affect incomes, human capital accumulation, and/or labor productivity (Graff Zivin and Neidell, 2013; Isen et al., 2017; Colmer and Voorheis, 2021; Borgschulte et al., 2024).We leverage the set of individuals in our data who experienced large, one-time positive shocks to income to better understand the causal effect of income or wealth on ambient pollution exposure. We convert these income windfalls into a permanent income measure following the methods proposed in Cesarini et al. (2023). We estimate that a one-time, average windfall of \$90,000 is associated with a persistent 0.04 $\mu g/\mathrm{m}^3$ reduction in $\mathrm{PM}_{2.5}$ concentrations. Using these windfalls as an instrument for permanent income, we estimate that between 1999–2016 a 1% increase in income is associated with a 0.015% reduction in $\mathrm{PM}_{2.5}$ for White individuals and a 0.012% reduction in $\mathrm{PM}_{2.5}$ for Black individuals.

What do these estimates imply for the existing racial gaps in $\mathrm{PM}_{2.5}$ air pollution? Back of the envelope calculations suggest that harmonizing median income between Black and White individuals would be associated with a 10 percent reduction in the overall Black-White $\mathrm{PM}_{2.5}$ gap in 2016. Thus, while high-income Black and White individuals are increasingly living in similar communities as measured by air quality, the Black-White pollution gap in lower parts of the income distribution is large enough that income or wealth harmonization alone is unlikely to close the racial gap in pollution exposure. These conclusions, of course, do not reflect the fact that aggregate changes to the income or wealth of a specific group may affect environmental exposures, not simply through mobility but also through other channels such as political engagement and/or collective action (Banzhaf, 2012;

Banzhaf et al., 2019). Understanding these broader social processes and the ways in which they affect relative environmental exposure should be a high priority for future research.

This paper builds upon a number of distinct literatures. First, there is a large body of research which highlights the broad patterns of environmental inequality in the United States and seeks to uncover the historical, economic, and social determinants of these outcomes (see e.g., Cain et al. (2023) for a recent overview of the economics literature exploring these issues). While there exists an extensive literature documenting that places with lower median income and/or a greater share of racial minorities have disproportionately higher concentrations of air pollution or are closer to facilities that release fugitive air emissions (U.S. GAO, 1983; Chavis and Lee, 1987; Mohai et al., 2009; Banzhaf et al., 2019; Hsiang et al., 2019; Colmer et al., 2020; Currie et al., 2023), we know of no other paper that explores the causal effect of individual income on pollution exposure nor discusses how these relationships differ across the income distribution, by race, ethnicity, and over time. Moreover, existing research documenting patterns of exposure by race, ethnicity and/or income typically use publicly available aggregate data from the American Community Survey and/or Decennial Census which preclude investigations of pollution exposure by income within narrow race and ethnicity groups, at spatial resolutions in which pollution disparities are increasingly found.[3] Additionally, public-use data reports median household income by race or ethnicity at the census tract level which precludes the analysis of pollution differences across the income distribution within a census tract.[4]

Second, there is a large literature seeking to understand the determinants of location choice, and specifically how location choices may differ by race, ethnicity and/or income. Some of this work explores individual preferences for public goods such as air quality or school quality in shaping location choice (see e.g., Bayer et al. (2007)). Other work seeks to understand how shocks to income affect

[3]Recent evidence suggests that environmental exposures may be extremely localized, even within distances of 1km (Apte et al., 2017). Existing, public-use data on economic well-being by race or ethnicity from the Decennial Census or American Community Survey are available at the census tract level, which has an average geographic resolution of 93 km^2.

[4]In fact, using public-use data to estimate the pollution-income elasticity (both nationally and by race) leads to meaningfully different elasticity estimates. For example, using median income reported at the census tract level to estimate the national pollution-income elasticity yields an estimate that is almost 3 times larger than our estimate using microdata.

housing decisions and neighborhood choice (Golosov et al., 2024; Bulman et al., 2022). Lastly, there is a literature attempting to understand racial differences in neighborhood locations, and how those location choices may be affected by income, preferences, and constraints (Bayer et al., 2021; Aliprantis et al., 2022; Bartik and Mast, 2022; Christensen and Timmins, 2022; Monarrez and Schönholzer, 2023). We are not aware, however, of any paper which relates the broad underlying trends in location decisions by different racial groups to differences in pollution exposure, or how these relationships differ throughout the entire income distribution.

The paper proceeds as follows. Section 2 provides a more detailed overview of the data used in the analysis. Section 3 provides new descriptive facts about the relationships between income and air pollution by race, ethnicity and over time. Section 4 contrasts these descriptive relationships with causal relationships between income and pollution exposures estimated using a quasi-lottery design. Section 5 concludes.

2 Data

2.1 Longitudinal Microdata on Income, Wealth, Race and Ethnicity

We leverage confidential microdata held at the US Census Bureau to study the distribution of air pollution by race, ethnicity and income. The data linkage infrastructure at the Census Bureau allows us to link administrative records on income from federal income tax returns with individual-level demographic information (race and ethnicity, sex, age) from Decennial Census and American Community Survey data.[5] We start from the universe of 1040 tax returns in tax years 1979, 1984, 1989, 1994, 1995 and 1998-2016, and select all primary and secondary tax filers. The tax records give us information on tax unit adjusted gross income (AGI) and location, which we geocode to the Census Block Group level using information from the Census Master Address File. We link these taxpayers using Protected Identification Keys (PIKs, see Layne et al. (2014)) to their responses in

[5]The linked microdata used in this paper are very similar to the data used in Chetty et al. (2019) and Voorheis et al. (2024); it is comparable to restricting the Environmental Impacts Frame (Voorheis et al., 2024) to primary and secondary tax filers.

the Decennial Census in 2000, 2010, and the 2005-2019 American Community Surveys. We assign race and ethnicity based on the most recent and non-imputed response across these datasets. We construct mutually exclusive race and ethnicity definitions, focusing on four groups: Hispanic origin of any race, non-Hispanic White, non-Hispanic Black, and non-Hispanic Asian. For each year in the tax data, we restrict to tax units with positive adjusted gross income (AGI) and to taxpayers who are prime aged (age 25-54). Note that since we retain both primary and secondary tax payers in subsequent analysis, we are implicitly assigning a per-adult equivalence scale to each tax unit's AGI.

Our primary measure of income is AGI, which is drawn directly from IRS 1040s. This pre-tax income measure is inclusive of labor market earnings, earnings from self-employment and pass-through entities, capital income and capital gains, taxable transfers such as unemployment insurance, social security, and disability benefits. This income measure excludes non-taxable cash transfers such as TANF and SSI, in-kind benefits such as SNAP, all refundable tax credits such as the Earned Income Tax Credit (EITC), any earned income not reported to the IRS, and is net of pre-tax pension contributions (e.g., to 401(k)'s). Income is measured prior to the deduction of individual income taxes and employee-level payroll taxes.

While using administrative tax data provides a number of advantages, it remains a selected sample of the US population because only those who file taxes are included. This captures the vast majority of the US population, especially when restricting to prime aged adults, but there remain differences in filing rates by geography, income and demographic characteristics (Mazur and Plumley, 2007). In our setting, the most important concern is that changes in the US social safety net between the 1980s and the present have changed filing incentives for low income populations, as non-taxable cash welfare programs have been largely replaced by refundable tax credits such as the EITC. Other changes in the tax system have incentivized filing for a broader set of the population, particularly for families with children and a larger fraction of retirees. Although filing rates have increased markedly, we observe that these increases have been broadly similar across the age distribution and across race and ethnicity. Our findings are robust to a reweighting strategy that weights our observed tax data to match the desired marginal totals. We also explore the sensitivity of our main estimates to using other income measures from demographic surveys like the American Community Survey and/or information from employer W-2 forms, data sources which provide income information for both filers and non-filers.

Since AGI is potentially a noisy and incomplete measure of financial wealth and well-being (Poterba, 1989, 1991), we focus on two additional measures of resources available to individuals in our sample: permanent income and financial wealth. We calculate a measure of permanent income, following Cesarini et al. (2023), which is our preferred measure of resources for the key results in our analysis. In its simplest form, this amounts to average income over a five year horizon (e.g., 1979-1984 or 2011-2016). In specifications where we explore the causal effects of income windfalls on environmental outcomes, described in more detail below, we annuitize the windfall income over a 20 year horizon.[6] This measure mitigates the contribution of year-to-year transitory variation in income that might bias our understanding of income–pollution relationships when using AGI in a given year and is not possible using existing public-use data.

We also construct a measure of financial wealth using a capitalization approach in the spirit of Saez and Zucman (2016). The US tax system primarily taxes income as a base, not wealth (with the exception of local property taxes). Consequently, the tax system does not create administrative records on wealth directly. Some income flows related to wealth, however, are captured in the administrative tax data. It is possible to estimate the stock of wealth from these flows via a capitalization approach. We use various capitalization factors (the ratio of the stock of wealth to the flow of income from this wealth in the Federal Reserve's Flow of Funds data) to estimate the size of the stock of wealth which would produce the flow of capital income we observe on a given tax return.[7] The tax data held by the Census Bureau contains information on four key flows from capital income: dividends from equities, taxable income from bonds and fixed income accounts, nontaxable interest income (from municipal bonds and other special securities), and rental income. We apply

[6]We first calculate the annual payout these windfalls would sustain if they were annuitized over a 20-year period with an annual real return of 2%. We then add the annuitized income windfall to our measure of average income to derive a measure of total permanent income.

[7]As described in Saez and Zucman (2020), "if the ratio between the stock of interest-bearing assets in the Financial Accounts and the total flow of interest income reported in tax returns is 50, then someone with $1,000 in interest is assigned $50,000 in bonds, saving accounts, and other interest generating assets."

capitalization factors from Saez and Zucman (2020) for each year 1979-2016 to our tax data, which allows us to calculate a measure of wealth held in taxable accounts or assets at the individual level. This measure of wealth accounts for around half of aggregate wealth (Saez and Zucman, 2020), but it is unequally distributed: many (in some years, most) tax units have zero wealth under this measure. In addition, it does not account for measures of wealth that may vary importantly along margins of race and ethnicity, such as housing wealth or wealth in the form of tax advantaged retirement accounts.

Our linked microdata approach provides several key advantages that allow us to contribute to this literature. First, we have a large panel of individuals that allows us to construct, for the first time, estimates of permanent income and wealth for the entire tax filing population and relate these measures to pollution exposure at high spatial resolution. Second, this longitudinal data allows us to explore, in a causal framework, how a change in wealth for a single individual affects their pollution exposure over time, holding fixed other determinants of exposure and location choice, such as prices, preferences, information sets, or local economic conditions. Finally, using administrative tax data allows us to better measure the entire income distribution, particularly in the tails, where survey measurement error is most acute (Bollinger et al., 2019).

2.2 Pollution Data

We combine our individual-level data with high-resolution, satellite-derived estimates of fine particulate matter ($PM_{2.5}$) air pollution provided by Meng et al. (2019). We focus on $PM_{2.5}$ because of its high morbidity and mortality risk, because of its disproportionate impact on the monetized benefits of federal regulation, and because newly available data provide fine-scale estimates spanning nearly four decades. Meng et al. (2019) combine remotely sensed measures of Aerosol Optical Depth with a chemical transport model, combined with in-situ ground-based measurements to estimate annual average $PM_{2.5}$ concentrations for $\sim$8.6 million grid cells each measuring 0.01° by 0.01° ($\sim$0.9 km by $\sim$1.1 km) for the contiguous United States for each year between 1981–2016. As these gridcells are approximately the size of the typical urban Census Block Group, we resolve the gridded data to the

Block Group level, by constructing annual average concentrations for each Census Block Group using 2010 Census Block Group boundary definitions.

We supplement data on $PM_{2.5}$ with ancillary satellite-derived data on NO_2, another criteria air pollutant regulated under the Clean Air Act's National Ambient Air Quality Standards. We use data from Di et al. (2019), which uses an ensemble model to integrate multiple machine learning algorithms used to predict NO_2 based on in-situ monitors, chemical transport models, and land use patterns. This NO_2 model covers the entire contiguous U.S. with daily predictions on 1-km-level grid cells from 2000 to 2016 (Di et al., 2022). Similar to above, we calculate annual average concentrations for each Census Block Group using 2010 Census Block Group boundary definitions.

Lastly, we use data from the Environmental Protection Agency's (EPA) Risk-Screening Environmental Indicators (RSEI) model. RSEI incorporates information from EPA's Toxics Release Inventory (TRI), which tracks certain toxic chemical environmental releases and other waste management activities at federal facilities and larger industrial facilities across the United States. RSEI calculates ambient concentrations near each emitting facility using an EPA dispersion model called AERMOD for each reported release in the TRI. Risk-related result values (RSEI Scores) are then calculated for each modeled chemical release by multiplying the toxicity weight of the chemical by the size of the estimated release and the number of potentially exposed people. These RSEI scores are then aggregated across all chemical releases and resolved to a regular 810 meter grid. We intersect these gridded RSEI aggregate scores for the year 2016 with 2010 Census Block Group boundaries and assign the average Block Group level RSEI score to each individual in our data.

Throughout the paper we use the term exposure to mean outdoor ambient pollution concentrations at an individual's location. We acknowledge that experienced air pollution may differ due to differences in housing quality and/or individual behaviors, such as commuting.

2.3 Identifying lottery-like income shocks

We use the longitudinal income information from the tax data to identify tax units that experienced a one-time, large, positive income shock in a single year. We design this algorithm to identify individuals who are observationally similar to individuals who win the lottery. For ease of exposition we refer to these identified individuals as "lottery winners." We begin by following all tax units over the period 2001 through 2016, and for each overlapping three year period within this range, we identify all tax filers that have the following income process: 1) they have real AGI less than $75,000 (approximately the median filer income in 2023 dollars) in t=1 and t=3; 2) they experience a large income shock in t=2 such that the income in t=2 is at least $100,000 more than incomes in either t=1 or t=3.[8] To increase the likelihood of identifying "lottery wins," we exclude individuals who filed 1040s with schedules C, D, or E and individuals who received any other investment income. This avoids misclassifying lumpy realizations of capital gains or taxable profits from business.

Once we have identified all individuals who experience exactly one such "lottery win" event, we merge indicators for being a lottery winner onto the individual panel of linked tax and demographic data described above. We convert these windfall income gains into a measure of permanent income by calculating the annual payout these windfalls would sustain if they were annuitized over a 20-year period with an annual real return of 2% and then adding the annuitized income windfall to our measure of average income, following Cesarini et al. (2023).

Although our approach could be improved with additional data not currently available at the Census Bureau (e.g., W-2G filings for gambling winnings), it does identify a set of individuals who appear to experience plausibly exogenous "lottery-like" shocks. We validate this approach using information on observed state-level lottery winners from Maine that we link to our core sample.[9]

2.4 Additional data on individuals and locations

In addition to our core panel of microdata on income, wealth, race and ethnicity, we use additional data on individuals or neighborhoods to explore potential mechanisms underlying our income–

[8] These sample restrictions imply that our "lottery winners" have below median income relative to the entire population. However, winners are similar to below median income individuals along other observable dimensions (pre-win pollution, income, financial wealth, etc.). In subsequent sections, we also explore sensitivity to these definitions, in particular as they relate to win amounts.

[9] Appendix Figure A2 compares the average income trajectory of true lottery winners from Maine to the average income trajectory for our classified lottery winners in the national sample. The average income process is qualitatively very similar for the Maine lottery winners compared to our constructed lottery winners.

pollution relationships. For the subset of individuals who were respondents in the 2000 Census long form or the 2005-2016 American Community Surveys, we merge in housing characteristics at the address level, including home ownership, property values, rent paid, and housing structure characteristics such as year built and number of bedrooms.

At the neighborhood level, we merge in information on school quality, crime, and demographics. We use school district-level data on reading and math student proficiency from EdFacts by the U.S. Department of Education. For tax year 2016, we use proficiency data from the 2016-2017 school year. We use the 2016 National Center for Education Statistics (NCES) crosswalk files to match each census tract to a school district. We construct property and violent crime rates using the Return A files from the Uniform Crime Reporting Program (UCR) from the FBI. The raw data report crime counts by month for each reporting agency.[10] After aggregating up to the reporting agency level, the data are matched to county FIPS codes using the 2012 LEAIC crosswalk and aggregated at the county level for merging with our core sample.

3 Income, Wealth, and Air Pollution

We begin our analysis by presenting a series of figures showing how pollution levels differ along the entire permanent income distribution and how these relationships differ by race and ethnicity. We begin by grouping individuals into permanent income percentiles corresponding to the year-specific vigintile of the national permanent income distribution and calculating average $PM_{2.5}$ concentrations by income vigintile. We do this first for the year 1984 (the first year we observe both tax returns and $PM_{2.5}$ data) and again for 2016 (the last year of the $PM_{2.5}$ data).

Figure 1a shows average $PM_{2.5}$ concentrations in 1984 by percentile of the 1984 income distribution. The relationship between individual income and $PM_{2.5}$ exposure nationally is approximately zero. Individuals in the first vigintile of the income distribution are exposed, on average, to similar $PM_{2.5}$ levels as individuals at the median or upper end of the income distribution. This relationship corresponds to a $PM_{2.5}$–permanent income elasticity of -0.0059, which is not statistically significant

[10] A reporting agency is a law enforcement agency or a law enforcement reporting entity.

at conventional significance levels.[11]

Figure 1b shows the same income–pollution relationship in 2016. There are two primary differences relative to 1984. First, air quality has improved dramatically in the intervening decades — average $PM_{2.5}$ concentrations in the United States declined by more than 60%, from 21 μg/m^3 to 7.3 μg/m^3. Second, the income–pollution relationship has rotated slightly, resulting in a downward trending relationship. This corresponds to a $PM_{2.5}$–permanent income elasticity of -0.0204%.[12]

What does this relationship imply for overall environmental inequality? There are significant differences in income between Black and White individuals. Median income for Black individuals was about 60 percent of median income for White individuals in 2016. A simple back-of-the-envelope calculation, using the 2016 income elasticity of -0.0204, suggests that harmonizing median income would lead to a 1.35 percent reduction in Black $PM_{2.5}$ concentrations. This corresponds to a 0.11 μg/m^3 reduction in 2016 $PM_{2.5}$ levels, which is about 14 percent of the overall Black-White gap in $PM_{2.5}$ concentrations.[13]

It is possible, however, that these income-pollution relationships differ for different demographic groups. To explore this possibility further, Figure 2 plots $PM_{2.5}$-income gradients, separately by race for Black and White individuals. Black individuals are presented in light blue, whereas White individuals are presented in red. Figure 2a shows that, in 1984, the income–pollution gradient for Black individuals was similar to that of White individuals; they are both relatively flat. However, at every single percentile of the national income distribution, Black individuals were exposed to higher $PM_{2.5}$ concentrations than White individuals, on average. Figure 2b shows that these same qualitative patterns exist in 2016 — Black individuals were exposed to higher $PM_{2.5}$ concentrations than White individuals at every single percentile of the income distribution. However, Figure 2b also highlights

[11] This elasticity is estimated from the microdata, regressing log $PM_{2.5}$ concentrations on log permanent income.

[12] Our measure of permanent income in 1984 is constructed as the average of AGI in 1979 and 1984, while permanent income for 2016 is constructed as the average of AGI from 2011 to 2016. We do not have annual income data in the early part of the sample. This raises the possibility that permanent income for 1984 is measured with greater error, and this could matter because greater measurement error in 1984 could lead to an attenuated slope in that year. We estimated a modified version of 2016 permanent income using only 2011 and 2016 data, excluding the intervening years, to mirror what is possible in the earlier period. The 2016 slope is nearly identical when using either 6 or 2 years of data to construct this income measure.

[13] In 2016, mean $PM_{2.5}$ concentrations for Black individuals were 7.9 μg/m^3. The mean Black-White $PM_{2.5}$ gap was 0.8 μg/m^3.

where some of the rotation in the income gradient seen in Figure 1b comes from. While White individuals in 2016 continued to have a relatively flat national income–pollution gradient, the Black gradient had rotated slightly.[14] Appendix Figure A3 plots these same income–pollution gradients for Hispanic and Asian individuals, in both 1984 and 2016. The patterns for racial minorities are largely similar; racial minorities in the United States were, on average, exposed to higher levels of ambient $PM_{2.5}$ at every single income percentile in both 1984 and 2016.[15]

While in absolute terms, average $PM_{2.5}$ concentrations have been falling for all race and ethnic groups, relative positions within the pollution distribution have remained largely constant. Appendix Figure A4 plots the average rank in the $PM_{2.5}$ distribution for each permanent income percentile, separately by race and ethnicity. The average White individual throughout the income distribution is at or below the median of the $PM_{2.5}$ distribution in both 1984 and 2016. Black individuals, in 1984, are about 15 percentile ranks higher in the pollution distribution than White individuals. By 2016, these gaps are narrowing at the upper end of the income distribution, but even the richest Black individuals are living in areas that are, on average, 10 percentile ranks more polluted than similarly wealthy White individuals.

Table 1 presents the corresponding income–pollution elasticities by race and ethnicity for 1984 and 2016. Panel A presents results from regressions of $\log(PM_{2.5})$ on log(permanent income) using a 1984 cross-section, separately for four different race and ethnicity categories: White, Black, Hispanic, and Asian. These elasticities are statistically insignificant and small in absolute value, with the exception of the Asian sub-group. On average, low-income and high-income individuals of the same race or ethnicity are exposed to similar $PM_{2.5}$ concentrations. Panel B of Table 1 presents rank-rank elasticities generated from a regression of an individual's percentile rank in the $PM_{2.5}$ distribution on their percentile rank in the overall 1984 income distribution, by race/ethnicity. This rank-rank

[14] Notably, if these gradients are estimated with public neighborhood-level data, as shown in Appendix Figure A1, the income-pollution relationship for White individuals in 2016 would appear to be negative and U-shaped. Moreover, the lowest-income White individuals would appear to be exposed to similar $PM_{2.5}$ concentrations as low-income Black individuals—which is not what we find using microdata.

[15] These patterns persist when using income percentiles, as opposed to the 20 vigintiles presented here. Throughout, we are presenting visual patterns using 20 income vigintiles (as opposed to percentiles) to mitigate Census Bureau concerns about data disclosure.

specification tells us how a percentile increase in individual income is associated with the average rank of a given individual in the overall pollution distribution. For White, Black, and Hispanic individuals, these estimates are also statistically insignificant and small in absolute value.

Panels C and D of Table 1 present the corresponding elasticities and rank-rank relationships for 2016. In contrast to 1984, we now observe negative and statistically significant elasticities for all racial minority groups. For example, the Black column in Panel C shows that a 10 percent increase in Black income is associated with a 0.16 percent reduction in $PM_{2.5}$ concentrations. The intercept in Panel D shows that Black and White individuals at the very bottom of the income distribution experience, on average a 20 percentile rank difference in the $PM_{2.5}$ distribution, despite having similar incomes. While Black, Hispanic, and Asian individuals have a steeper income–pollution gradient than White individuals, these differences are not strong enough to fully offset this rank gap, even at higher income percentiles. For example, the predicted pollution rank of Black individuals in the top percentile of the income distribution remains 12 percentile ranks higher in the pollution distribution than a corresponding White individual in the top percentile of the income distribution.[16]

Our permanent income concept is only calculated for the tax filing population. Appendix Figure A5 explores the sensitivity of our results by using reported W-2 income for employed non-filers (available starting in tax year 2005). Estimated income gradients for Black and White individuals are qualitatively similar when using AGI for tax filers only versus an expanded AGI measure imputing W-2 income for non-filers.

Results thus far combine differences in pollution concentrations that stem from differences in location choices across the entire country, with locations ranging from rural to urban to suburban. We explore heterogeneity in income-exposure relationships by location, classifying individuals into location type using the urban-rural classification scheme of Ingram and Franco (2014). Appendix Figure A6 shows that the overall patterns remain similar when focusing on central cities, rural areas, smaller metro areas, or suburban areas. In every single location type (central city, rural, suburban), racial minority individuals are exposed to, on average, higher levels of $PM_{2.5}$ at every

[16] Average White $PM_{2.5}$ rank in the top percentile of income = 47.11 - 0.0325*100 = 44. Average Black $PM_{2.5}$ rank in the top percentile of income = 66.48-0.1007*100 = 56.

income percentile.

Appendix Figure A7 plots wealth-pollution gradients using our measure of financial wealth derived by capitalizing capital income flows reported on a tax filer's 1040 form. There are meaningful level differences in pollution for those with and without wealth; however, within the distribution of non-zero wealth, the wealth-pollution relationship largely resembles the pattern we see for income. In both 1984 and 2016, the relationship between $PM_{2.5}$ and wealth is very small and statistically insignificant.

Figures A8a and A8b report income–pollution relationships using alternative measures of pollution. Appendix Figure A8a presents income–pollution gradients by race and ethnicity for ambient NO_2 concentrations in 2016. The patterns for NO_2 look broadly similar to the patterns for $PM_{2.5}$. Black, Hispanic, and Asian individuals are exposed to higher levels of ambient NO_2 than White individuals at every single percentile of the national income distribution. The implied income–pollution elasticities are close to zero and weakly positive for White and Black individuals.

Appendix Figure A8b presents income–pollution gradients using toxicity data from the EPA's Risk-Screening Environmental Indicators (RSEI) model in 2016. Again, these patterns largely mimic the patterns we see in the 2016 $PM_{2.5}$ figures from before. On average, Black individuals are exposed to higher RSEI scores at every single income percentile. However, the income–pollution gradient for Black individuals is much steeper than for White individuals. At the very top of the income distribution, environmental outcomes nearly converge for this pollution measure.

Across different measures of pollution, different measures of income or wealth, and different years, a simple fact endures – racial minorities are exposed to higher levels of ambient pollution on average at every single income percentile. This naturally raises the question as to why these differences exist and whether there are other observable or unobservable factors that might help explain these pollution gaps by income. For example, perhaps minorities, either by choice or necessity, live in areas with cheaper rent or housing, and it's these differences in neighborhood attributes that offset some of these pollution differences by income (i.e. compensating differentials). Or, perhaps there are other amenities or housing services, such as schooling or crime, for which racial minorities choose to consume more of in place of environmental quality. We begin exploring these questions by combining the 2016 income data with other survey responses and neighborhood data to better understand the role of observable differences in neighborhood and/or individual characteristics in explaining these race-and-ethnicity by income pollution gaps. For example, individuals who responded to the 2000 Census long form or the 2001-2016 American Community Surveys provide survey information on housing values and/or rental prices, which we are able to merge with our income measures using a unique, individual identifier. We also merge in information on school quality and crime using EdFacts proficiency data from the 2016-2017 school year at the Census Tract level. Lastly, we include county-level measures of property and violent crime rates the FBI's Uniform Crime Reporting Program. We then run a regression of individual pollution exposure on a series of indicator variables for income vigintile, fully interacted with an indicator variable for Black (where White is the omitted category), controlling for housing and rental values, school proficiency, and crime.[17]

The coefficients on the Black×income vigintile interaction terms provide a measure of the conditional gap (relative to White individuals) in pollution exposure that remains after controlling for differences in these observable characteristics at a given income vigintile. Figure 3 plots the conditional and unconditional gaps by race and ethnicity for the year 2016. For Black individuals, the conditional and unconditional gaps in $PM_{2.5}$ concentrations at each income vigintile are similar, suggesting that differences in housing prices, rent, schooling, and crime are unable to explain the pollution gaps that exist between Black and White individuals at each level of income. The results for other racial groups are similar.[18]

[17]In this exercise, we limit the sample to the set of individuals who identify as White or Black in our data, although we have replicated this exercise of other race and ethnic groups. To allow for potentially non-linear effects of housing prices and rents, we construct property value quartiles of the monthly rent and property value variables within each year, nationally. For the ACS years when property values were reported in binned values (2000-2007), the quartile cutoff points are determined based off of the binned values.

[18]There is a case to be made that housing prices themselves should capture variation in other amenities, as these amenities would typically be capitalized into the housing value. We have explored similar exercises to those described above where we only control for housing prices or only control for amenities (and not prices). In both cases, the results are similar to those presented here. Observable differences in rents, housing prices, and/or other amenities cannot explain the gaps in air pollution exposure we observe throughout the income distribution.

3.1 Within-City Income-Pollution Relationships

In practice, a significant share of mobility occurs within metro areas, and thus the tradeoffs that individuals face in location choices often occur on a much more local scale. We explore how income–pollution gradients differ when looking within a city or metro area. We focus on Core-Based Statistical Area's (CBSA) which consist of one or more counties (or equivalents) anchored by an urban center of at least 10,000 people. For each CBSA, we calculate the average pollution exposure in that CBSA-year, and we subtract that value from each individual's exposure.[19] We then calculate the average residual exposure by permanent income percentile, where income percentiles are computed according to the national income distribution in a given year.[20]

Figure 4 plots these income gradients in both 1984 and 2016. As before, we see significant racial gaps in pollution exposure across the income distribution. Somewhat differently than before, however, we see a negative relationship between income and pollution in both 1984 and 2016 for both Black and White individuals. These income gradients suggest that in 1984, a Black individual in the 95th percentile of the income distribution is exposed to pollution concentrations that are, on average, higher than a White individual's pollution exposure at the 5th percentile of the income distribution. By 2016, there has been a relative steepening of the Black income gradient compared to the White, such that the richest Black individuals in the top vigintile of the income distribution are exposed to $PM_{2.5}$ levels equivalent to White individuals at the 75th percentile of the income distribution. Appendix Figure A9 plots these same relationships for all race and ethnic groups, and the patterns look broadly similar.

Table 2 reports within-CBSA income–pollution elasticities and within-CBSA rank-rank relationships for 1984 and 2016. These results come from regressing log or rank of individual $PM_{2.5}$ concentrations on log or rank of individual income, controlling for CBSA-specific fixed effects. As suggested by Figure 4, there are several differences compared to the national income–pollution relationships,

[19] We group all individuals who live outside a CBSA boundary into a single, composite CBSA. Results are not sensitive to excluding these individuals altogether or removing these individuals from the previous, nationwide exercise.

[20] We have explored sensitivity to using the within-CBSA income distribution as opposed to the national distribution, and the results remain visually and economically similar.

although the magnitude of the differences remains small. First, the income–pollution elasticities and rank-rank relationships in 1984 are negative and statistically significant. On average, a 1% increase in income is associated with a 0.014% reduction in $PM_{2.5}$ for White individuals and a 0.010% reduction in $PM_{2.5}$ for Black individuals. Second, the White and Black income–pollution elasticities converge over time. In 1984, the within-CBSA income–pollution relationship was less elastic for Black individuals than White individuals (-0.010 vs. -0.014). In 2016, the within-CBSA income–pollution elasticity for Black individuals was slightly steeper than the elasticity for White individuals (-0.017 vs. -0.016).

Why are the within-CBSA elasticity estimates more negative than the national estimates? When looking at within-CBSA, income-exposure gradients we are implicitly shutting down between-CBSA variation in pollution levels across locations by subtracting the CBSA-specific mean pollution from the data prior to averaging. Thus, the primary reason for why national and CBSA-specific slopes differ is this within-CBSA variation — richer cities that are more densely populated are also relatively polluted when compared to poorer, less economically vibrant metro areas. Thus, while it's true that within both of these city types, richer individuals on average live in cleaner neighborhoods, the "between" variation in pollution is contributing to a flatter line in the national estimates.

Appendix Figure A10 plots within-CBSA, permanent income-pollution gradients in 2016 for two other measures of pollution, NO_2 and the RSEI score. These pollutants show similar patterns to those for $PM_{2.5}$. First, racial minorities continue to be exposed to higher levels of ambient pollution throughout the income distribution. Second, the income-elasticities are also steeper for racial minorities relative to non-Hispanic White individuals; there is nearly complete convergence in pollution outcomes at the very upper end of the income distribution.

What changed between 1984 and 2016 that led to a steepening of the Black-income gradient relative to the White gradient? Figure 5 plots the fraction of individuals that live in central cities and suburbs by income percentile, race and ethnicity. Figure 5a shows that, in 1984, around 50 percent of Black individuals in each income percentile lived in city centers, and this rate was fairly constant throughout the income distribution. At lower income percentiles, about 10 percent of Black individuals lived in suburbs. At upper ends of the income distribution, this rate rises to 34 percent of Black individuals. Figure 5b shows that, by 2016, the fraction of Black individuals that live in city centers has fallen by about 10 percentage points throughout the income distribution. Where did these individuals end up? The vast majority of them ended up in the suburbs, as the corresponding suburban shares rose by a similar 10 percentage points throughout the income distribution. The distribution of White individuals displays similar patterns of movements out of city centers towards suburbs, but the magnitudes are substantially smaller.

Why do these trends in population shares matter for the steepening of the Black-income gradient relative to White? Suburban areas tend to have lower $PM_{2.5}$ levels than city centers. As richer Black individuals moved in greater numbers to suburbs, this movement pulled down the Black $PM_{2.5}$ income gradient relative to the comparatively stable White $PM_{2.5}$ income gradient. This can partially be seen in Figure 6, which overlays the fraction of individuals that live in city centers with the average $PM_{2.5}$ exposure, separately by race, ethnicity and income percentile. For example, Figure 6b shows that as wealthier, non-Hispanic White individuals move to city centers, non-Hispanic White $PM_{2.5}$ exposure gradually increases. Conversely, as richer Black individuals increasingly move out of city centers, the average $PM_{2.5}$ exposure for Black individuals falls.

Another way to see how changes in relative mobility have affected the income-exposure relationships is to use a statistical decomposition. We follow the decomposition exercise proposed in Currie et al. (2023) to see what the race and ethnicity-specific income gradients in 2016 would look like in a counterfactual world where individuals were living in 1984 locations (i.e. shutting down mobility as a channel). To do this we assign 2016 block group level $PM_{2.5}$ concentrations to 1984 tax data to estimate income-exposure elasticities by race and ethnicity. In other words, these regressions are using 1984 income (and locations) and 2016 pollution levels. Table 3 presents results. Columns (1) and (2) show the original Black elasticity estimate in 1984 and 2016 from Table 2. Column (3) presents the counterfactual 2016 elasticity, holding individuals fixed in their 1984 locations. As one can see by comparing across the columns, even though 2016 pollution levels have declined significantly since 1984, the counterfactual Black $PM_{2.5}$-Income elasticity from Column (3) looks almost identical to Column (1). This suggests that almost all of the steepening of the income elasticity for Black individuals comes through changes in where minorities live in 2016 relative to the 1980's.

What happened between 1984 and 2016 such that high-income Black individuals are moving to environmentally cleaner, more suburban locations? Is it because this group now demands more environmental quality with increased income, or that there are other changes in labor market opportunities or housing market constraints for this group? As is typical in the literature on location choice, it is difficult with data on observed choices alone to distinguish between changes in preferences and/or changes in the constraints faced by certain groups. Bayer et al. (2021) make a compelling case that any sort of "racial sorting" or homophily preferences among Black households dramatically limits the choice of neighborhoods to choose from, especially 30-40 years ago. Since 1984, the set of communities (i.e. Census Block Groups) that Black households live in today is much larger and more suburban than the set of communities in 1984, and it is this broader set of neighborhood choices available today that may explain some of this pattern. Relatedly, Bartik and Mast (2022) suggest the relative movements of Black households to suburban locations over the past 40 years have been driven primarily by changes in relative suburban amenities and housing prices. However, Christensen and Timmins (2022) present compelling evidence that Black individuals are discriminatorily steered towards neighborhoods with worse amenities.

4 The Causal Effect of Permanent Income on Pollution Exposure

The broad patterns described above are descriptive in nature and reflect observational correlations. We know much less about the causal effect of increases in income or wealth on the locational choices of households, and in particular, how that interacts with pollution exposure. It is possible, for example, that some of the observed relationships between pollution and income may arise vis-a-vis reverse causality. For example, research has shown how pollution exposure may affect both labor productivity and/or human capital accumulation, and thus some of the observed relationship between low-income individuals living in polluted areas may reflect such channels.

To circumvent these possible issues, we leverage transitory income shocks, designed to approximate lottery winnings (we refer to individuals who receive these shocks hereafter as "lottery winners"), to estimate the causal effect of increases in income and/or lifetime wealth on an individual's pollution exposure. We first calculate the annual payout these windfalls would sustain if they were annuitized over a 20-year period with an annual real return of 2%. We then add the annuitized income windfall to our measure of average income to derive a measure of total permanent income.

We employ an event-study design that exploits variation in the timing of "lottery wins". The event study specification flexibly lets us estimate the transitional dynamics associated with income gains on short, medium, and long run outcomes while also implicitly testing the identifying assumption of our difference-in-difference style estimator. Lottery participants and/or recipients of transitory income shocks are not a random subset of the population. We restrict our attention to the set of individuals in our data who experience these one time shocks to income. Thus, we are implicitly comparing lottery winners to not-yet lottery winners, relying on the plausibly random timing in these lottery wins for identification.

Denote W_{it} as the year in which an individual i first wins the lottery. We estimate the following specification:

$$y_{ist} = \sum_{e=-5}^{E=5} \beta_e \mathbf{1}(t - W_{it} = e) + \gamma_{st} + \epsilon_{ist} \tag{1}$$

where y_{ist} is either the $PM_{2.5}$ concentration in the Census Block Group where individual i lives in year t and event time k or the permanent income or wealth level of individual i in year t and event time k, $\mathbf{1}(t - W_{it} = e)$ is an indicator for individual i being e periods away from winning the lottery at time t. γ_{st} are CBSA-year fixed effects, and ϵ_{ist} is the error term. We consider event-time $e = \{-5, -4, -3, -2, 0, 1, 2, 3, 4, 5\}$ and normalize the coefficients relative to the period prior to the lottery win, i.e. $\beta_{-1} = 0$.

Figure 7 plots the main results for income-related outcomes and $PM_{2.5}$ exposure. Figure 7a shows that "winning the lottery" is associated with an approximately 25 percent increase in permanent income. Figures 7b and 7c show that this 25 percent increase in permanent income corresponds to about \$7500 or 10 percentile ranks. Figure 7d shows an immediate reduction in $PM_{2.5}$ of -0.04 $\mu g/m^3$ that persists for all post-win time periods. Thus, a one-time increase of \$7,500 in permanent income is associated with a 0.04 $\mu g/m^3$ reduction in $PM_{2.5}$.

To further understand whether income gains affect pollution exposures differentially by race and ethnicity, we separately estimate Equation (1) for White and Black individuals. Figure 8 presents results. While both Black and White individuals experience similar gains in permanent income levels, Black individuals experience larger percentage increases in income. These larger relative increases in income translate into a slightly larger, though statistically indistinguishable, decrease in $PM_{2.5}$ exposure relative to White individuals.

We translate these estimates into income–pollution elasticities by using the post-lottery win period as an instrument for permanent income. We use a two-stage least squares instrumental variable estimator. The following first stage and second-stage specifications use the same notation as equation (1) but drop the event time notation:

$$\log(income_{it}) = \beta \mathbf{1}(t \geq W_{it}) + \gamma_{st} + \nu_{ist} \tag{2}$$

$$\log(\mathrm{PM}_{2.5it}) = \delta \log(\widehat{income}_{it}) + \rho_{st} + \varepsilon_{ist} \tag{3}$$

where $\log(income_{it})$ is the log of individual i's permanent income in year t, $\log(\mathrm{PM}_{2.5it})$ is log $PM_{2.5}$ concentration in the Census Block Group where individual i lives in year t, $\mathbf{1}(t \geq W_{it})$ is an indicator equal to one for whether year t is after the lottery win-year for individual i (i.e. whether it is the post-lottery win period), γ_{st} and ρ_{st} correspond to CBSA×year fixed effects in each model, ε_{ist} is the unobservable component of pollution concentrations, and ν_{ist} is the unobservable component of the income process. We cluster standard errors at the CBSA level.

Table 4 presents the corresponding set of results. Panel A presents the corresponding OLS elasticity for this sample and time period (1991–2016). We see that, much like 2016 estimates in Table 2, the corresponding elasticity is around -0.016 for both White and Black individuals. Panel B replicates the reduced form specification embodied in Figure 8 in table form, where a lottery win is associated with a reduction in $PM_{2.5}$ concentrations of around 0.04 μg/m^3 for Black and White individuals. Panel C shows there is a strong first stage relationship between "winning the lottery" and permanent income for all race and ethnic groups. Panel D presents the IV elasticities by race and ethnicity. We see that a 1% increase in permanent income is associated with a 0.015% reduction in $PM_{2.5}$ for White individuals and a 0.012% reduction in $PM_{2.5}$ for Black individuals. The magnitude of the IV elasticity is very similar to the OLS estimates during this sample period, though the point estimates for Hispanic and Asian individuals are not statistically significant at conventional significance levels.

What do these estimates imply for the existing racial exposure gaps in $PM_{2.5}$ exposure? Equalizing median income between Black and White individuals would be associated with a a 0.79 percent reduction in Black $PM_{2.5}$ exposure. This corresponds to a 0.062 $\mu g/m^3$ reduction in 2016 $PM_{2.5}$ levels, which would amount to an ∼8 percent reduction in the overall Black-White exposure gap in $PM_{2.5}$. Thus, while there is a statistically significant effect of income on air pollution exposure, the overall magnitudes, in terms of their ability to explain racial gaps in pollution exposure, are small.

Appendix Figure A11 shows that the entirety of the observed effects on air pollution come from lottery winners moving to new locations after the lottery win. Individuals who move after their lottery win-year see a decline in $PM_{2.5}$ concentrations of 0.1 $\mu g/m^3$ on average, while those who do not move see no reduction in pollution.

Appendix Figure A12 shows that the size of the lottery winnings has a somewhat heterogenous effect on outcomes. We estimate the same event study specification for four separate win-size bins: \$100K-\$250K, \$250K-\$500K, \$500K-\$1000K, >\$1000K.[21] Figure A12a shows that larger win sizes are associated with a higher likelihood of moving, whereas Figure A12b shows this leads to a correspondingly larger decrease in pollution exposure. For example, lottery winners who see a windfall gain in income over one million dollars see an initial decline in $PM_{2.5}$ concentrations of -0.13 $\mu g/m^3$, an estimate that is over three times as large as the baseline result of -0.04 $\mu g/m^3$.

Lastly, Appendix Table A1 explores how lottery winnings affect other aspects of location choice, such as home prices, rental values, or other local amenities such as schooling or crime. Panel A

[21]Note that these amounts correspond to the overall size of the windfall gain, not the annuitized amount of permanent income received. We have also explored the effects of smaller win amounts. "Lottery wins" that are smaller than \$25k are not associated with statistically significant improvements in environmental quality.

presents IV estimates of the effect of permanent income on housing and location outcomes for White individuals, whereas Panel B presents the same IV estimates for Black individuals. In addition to moving to less polluted areas, the results suggest that, on average, a large income shock induces individuals to move to areas with higher property values, higher rent, higher homeownership rates, higher school proficiency rates, lower crime rates, and lower violent crime rates.

A number of researchers have recently used lottery winnings to understand the causal effects of newfound resources or wealth on a number of individual and household choices (Bulman et al., 2021, 2022; Golosov et al., 2024). Bulman et al. (2021) explore the effects of lottery wins on college attendance, finding modest effects that imply that financial constraints alone do not inhibit attendance. Consistent with our mobility results, they estimate that individuals with large wins are more likely to move to neighborhoods that are, on average, wealthier. Similarly, Golosov et al. (2024) estimate that winning the lottery leads to an immediate, one-off 3.5 percentage point (25 percent) increase in the annual moving rate. This effect is somewhat smaller than what we estimate here, though these differences likely stem from differences in the sample of lottery winners and how each study measures mobility.[22] Golosov et al. (2024) also explore whether mobility is associated with moves to better Census Tracts, as proxied by a range of outcomes. Like Golosov et al. (2024) (Figures IX and X), we see lottery winners moving to, on average, somewhat better neighborhoods (as measured by school proficiency or crime rates), though in the present study and the Golosov et al. (2024) study, the overall effect sizes are small in magnitude.

Appendix Table A1 also highlights some differences in income elasticities by race and ethnicity. While these differences are not large enough to be statistically significant, they do highlight some

[22] Golosov et al. (2024) find that a lottery winner, as measured by winnings above $30,000 in the W2-G, sees a sharp uptick in the likelihood of moving in the annual moving rate within the first 2 years (approximately 3.5 percentage points or 25% relative to the mean mobility rate). We observe a similar although slightly larger move probability in the 1-2 years after a windfall income gain, equal to approximately 7 percentage points. The effect dissipates rapidly after year 2, as in Golosov et al. (2024). The differences in effect sizes between this study and Golosov et al. (2024) likely emerge from underlying differences in the sample of lottery winners and/or the data on mobility. First, our algorithm for selecting "lottery winners" restricts winners to have had average income less than $75,000 in the year prior to the windfall income gain. Golosov et al. (2024) find that the increase in the probability of moving for winners in the lowest quartile of the income distribution is about 5 times as large as that of the winners in the highest quartile of the income distribution. Second, our definition of moving is based on differences in Census Block Groups, whereas Golosov et al. (2024) explore movements between Tracts which will miss any within-Tract mobility.

key questions for future research. While higher income is associated with "better" neighborhood amenities, we know less about the ways in which minority group choices over location may differ from locationchoices made by White people. For example, do non-White people take on more $PM_{2.5}$ for similar housing stock? If so, why? Is it because the rates at which $PM_{2.5}$ and housing are traded in the market place differ, or do non-White people simply spend less money on housing by moving into neighborhoods with more $PM_{2.5}$ pollution? Do these patterns reflect differences in preferences or willingness to pay, or do they reflect different sets of constraints for certain groups? This remains an active and ongoing research area, for which clear answers have yet to emerge.

5 Conclusion

We combine administrative tax data with spatially resolved estimates of pollution exposure and other household demographic surveys to provide new facts about the relationships between income, wealth, and environmental inequality by race and ethnicity.

We find that in the first year of our data, 1984, the relationship between income and air pollution exposure, nationally, is approximately zero. However, at every single income percentile, in rural, suburban, and urban locations, racial minorities were exposed to higher concentrations of $PM_{2.5}$.

By 2016, however, the income elasticity of pollution exposure has steepened, especially for racial minorities. Racial minorities at the top of the income distribution are increasingly living in neighborhoods that resemble White individuals, as measured by air quality. This steepening of the income-pollution gradient for racial minorities is primarily driven by the relatively recent movements of wealthier racial minorities to suburban areas. These suburban neighborhoods tend to have lower pollution concentrations than the urban areas where racial minorities disproportionately lived. At the bottom of the income distribution, significant racial gaps in pollution exposure persist.

We leverage the longitudinal nature of our data to explore the causal effect of income on individual pollution exposure. We focus on a subgroup of individuals in our data who experienced large, one-time windfall gains in income, and we follow these individuals over time to better understand how these income gains translate into environmental services. These causal estimates of the income-pollution elasticity mimic the descriptive elasticities in the data. While there are statistically significant relationships between income and air pollution exposure, these relationships are relatively weak even today. Our estimates imply that harmonizing median income between Black and White individuals would lead to a 7-8 percent decrease in the Black-White $PM_{2.5}$ exposure gap in 2016.

It is certainly possible, and even likely, that income can affect environmental quality in ways not captured in this study. For example, the estimates from this study examine the average effect of personal income on pollution exposure for a subset of individuals. These estimates, therefore, do not reflect the fact that aggregate changes to income or wealth of larger groups or communities may affect environmental quality, not simply through mobility but also through other channels such as political organizing and/or collective action. Understanding these broader social processes should be a high priority for future research.

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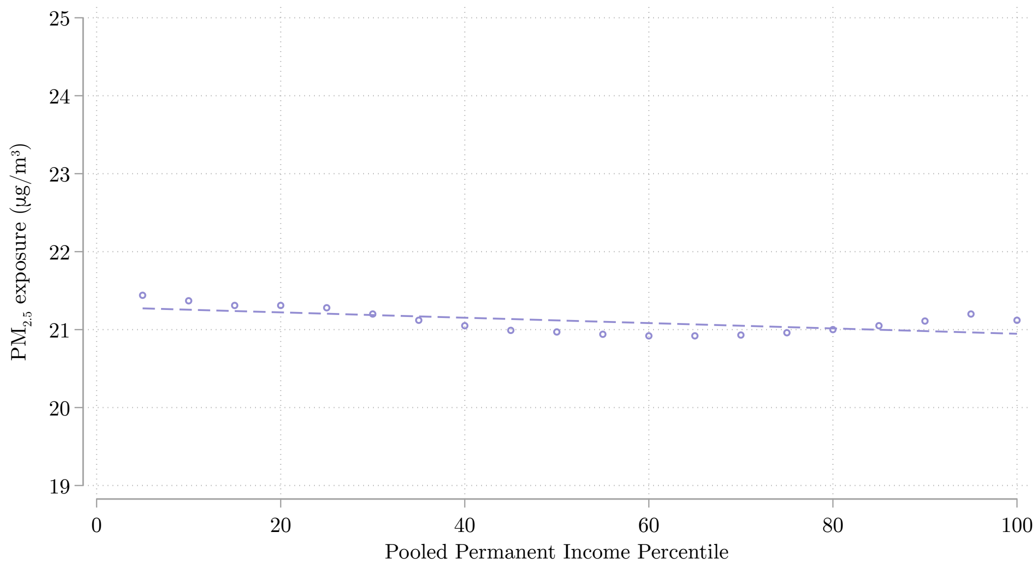
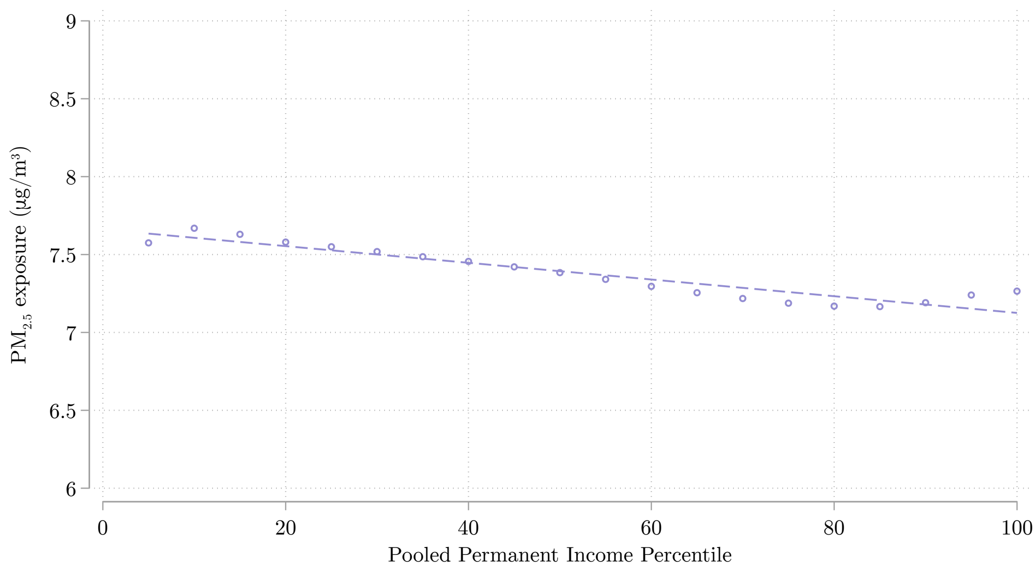
Tables and Figures

Figure 1: Relationship Between Permanent Income and $PM_{2.5}$ Exposure

(a) 1984



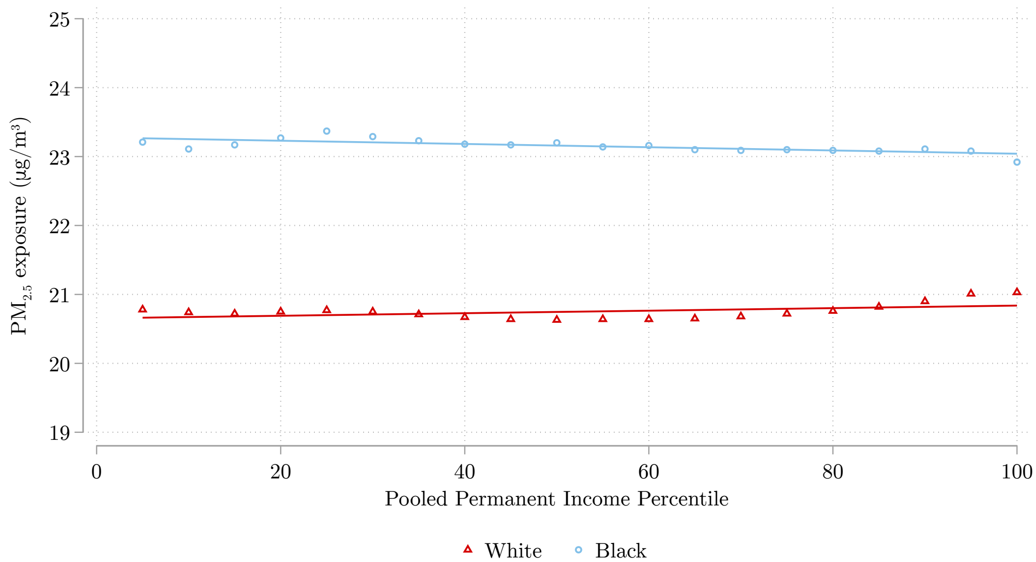
(b) 2016



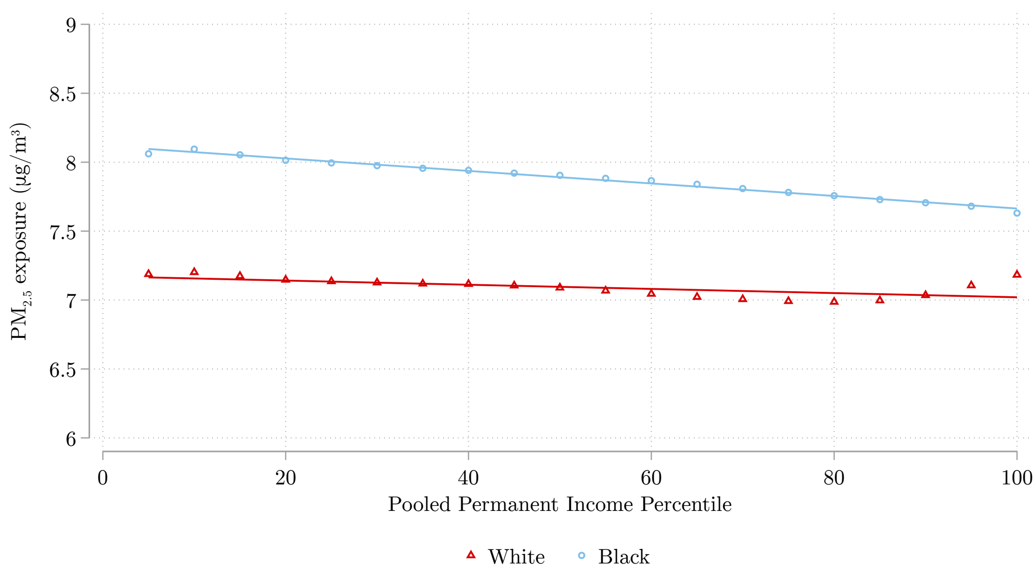
NOTES: These figures plot the average $PM_{2.5}$ concentration by permanent income percentile for a given year. The income percentiles are constructed from all prime-aged U.S. tax filers in a given year who report positive adjusted gross income. The plotted line represents the best linear fit to these conditional means.

Figure 2: Relationship Between Permanent Income and PM$_{2.5}$ Exposure, Separately by Race

(a) 1984

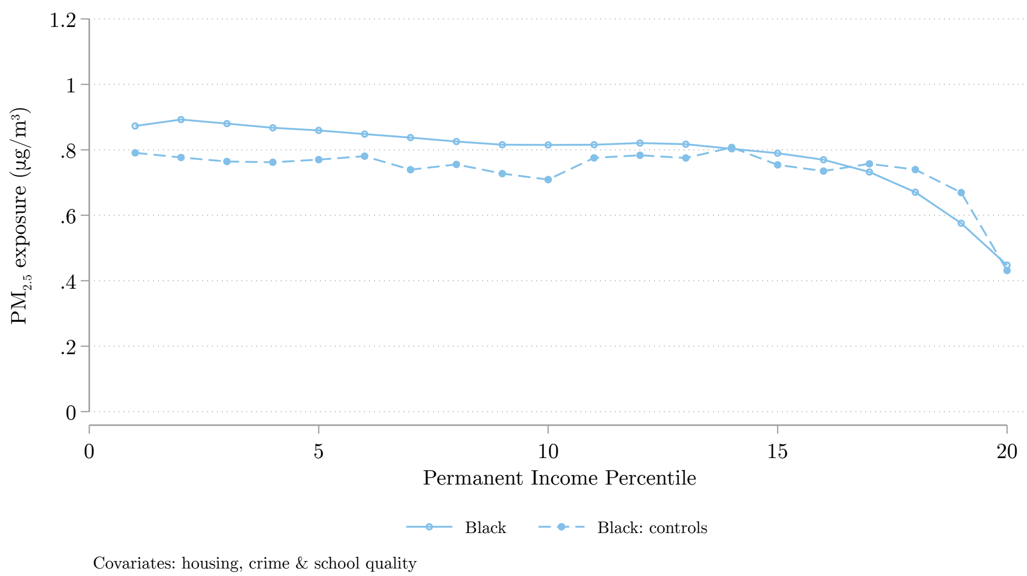


(b) 2016



NOTES: These figures plot the average PM$_{2.5}$ concentration by permanent income percentile for a given year, separately by race. The income percentiles are constructed from all prime-aged U.S. tax filers in a given year who report positive adjusted gross income. The plotted line represents the best linear fit to these conditional means.

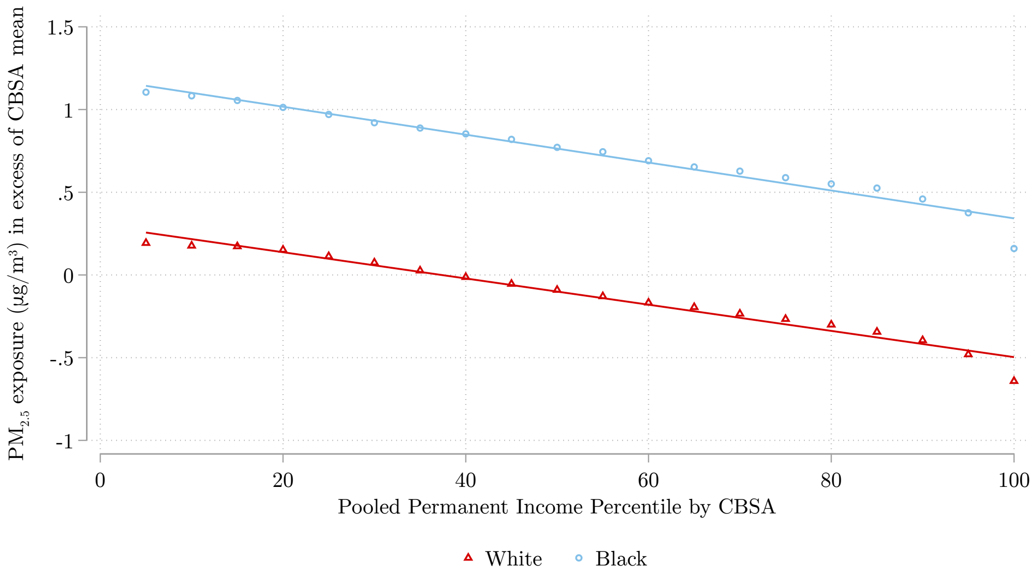
Figure 3: Conditional versus Unconditional Black-White Gap in $PM_{2.5}$ Exposure by Income



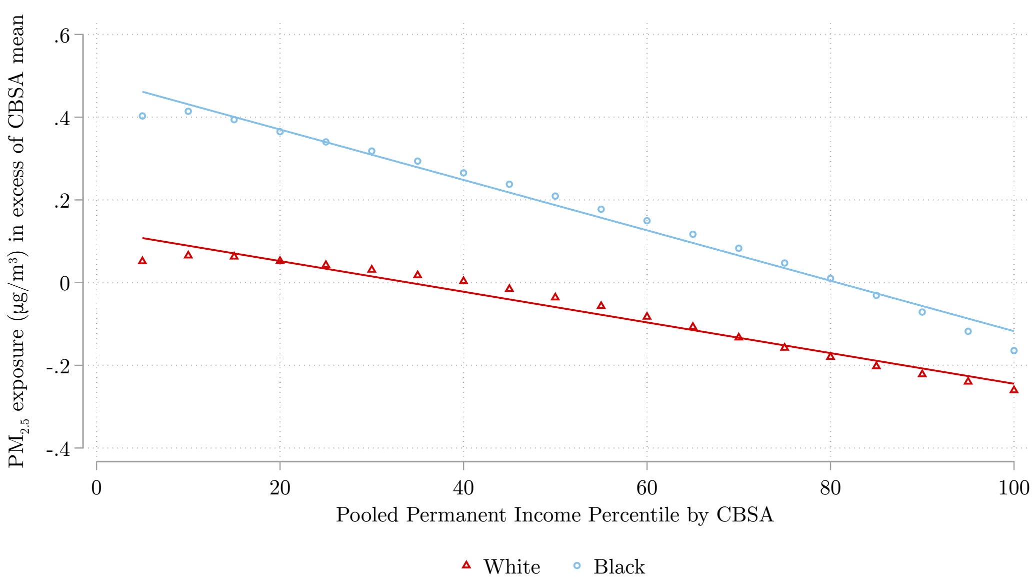
Notes: This figure plots the average difference in Black versus White individual $PM_{2.5}$ concentrations by permanent income percentile in 2016. The blue line represents the Black-White gap in conditional mean $PM_{2.5}$ concentrations at a given income percentile. The orange line represents the Black-White gap in conditional mean $PM_{2.5}$ concentrations at a given income percentile after including linear controls for housing characteristics from the American Community Survey (occupancy type, building year built, bedrooms, rent quartiles, and property value quartiles), math and reading school proficiency rates from EdFacts, and crime rates per capita from the FBI UCR program. The income percentiles are constructed from all prime-aged U.S. tax filers in a given year who report positive adjusted gross income.

Figure 4: Relationship Between Income and $PM_{2.5}$ Exposure, Within CBSA

(a) 1984



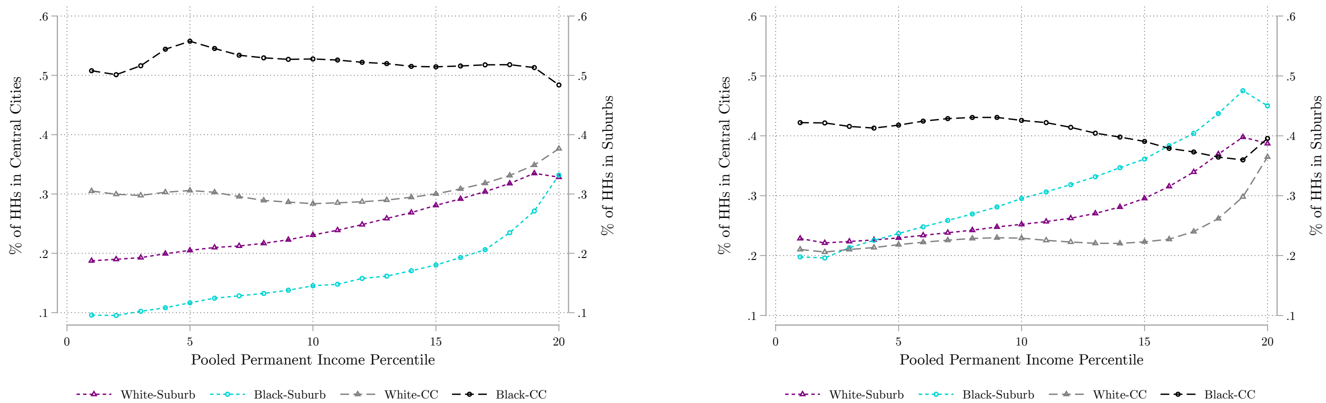
(b) 2016



NOTES: figures plot the average $PM_{2.5}$ concentration in excess of the CBSA mean by CBSA-specific permanent income percentile, separately by race. The pollution concentration averages are calculated as the individual concentration in excess of the overall CBSA mean, averaged across each percentile rank and race. The permanent income percentile ranks are constructed to be specific to each CBSA. All non-CBSA individuals are classified as belonging to one CBSA. The plotted line represents the best linear fit to these conditional means.

Figure 5: Urbanization and Suburbanization Rates by Income Percentile

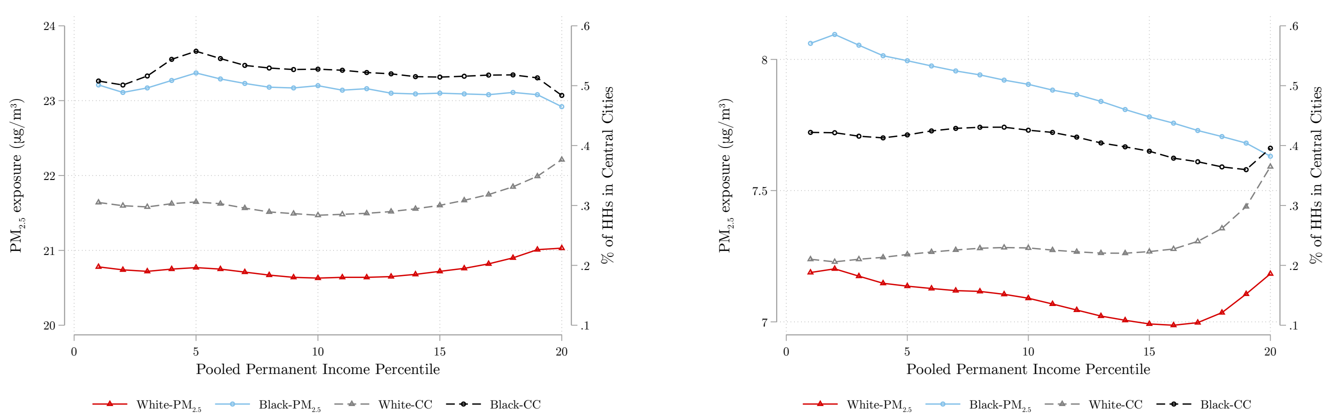
(a) 1984 (b) 2016



Notes: These figures plot the percentage of individuals that reside in central cities and suburban locations, separately by race and income percentile. Figure 5a plots these patterns for 1984 while Figure 5b plots these patterns for 2016. The income percentiles are constructed from all prime-aged U.S. tax filers in a given year who report positive adjusted gross income.

Figure 6: Urbanization Rates and $PM_{2.5}$ Exposure by Income Percentile

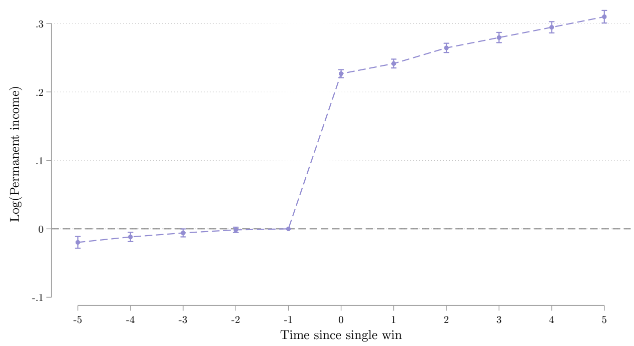
(a) 1984 (b) 2016



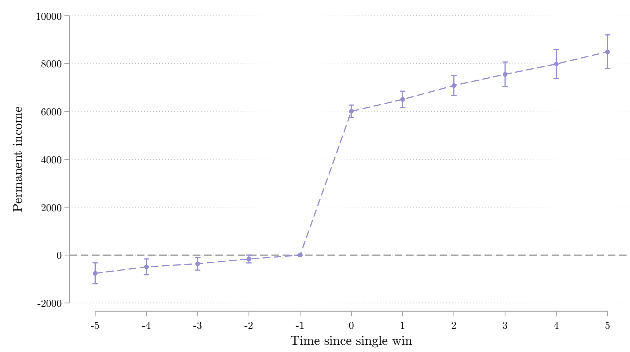
Notes: figures plot the average $PM_{2.5}$ concentration by permanent income percentile overlaid with the percentage of individuals that reside in central cities, separately by race. Figure 6a plots these patterns for 1984 while Figure 6b plots these patterns for 2016. The income percentiles are constructed from all prime-aged U.S. tax filers in a given year who report positive adjusted gross income.

Figure 7: Event Study Estimates Using Lottery Winners

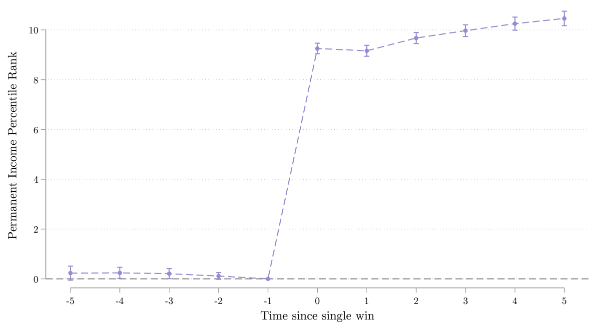
(a) Log(Permanent Income)



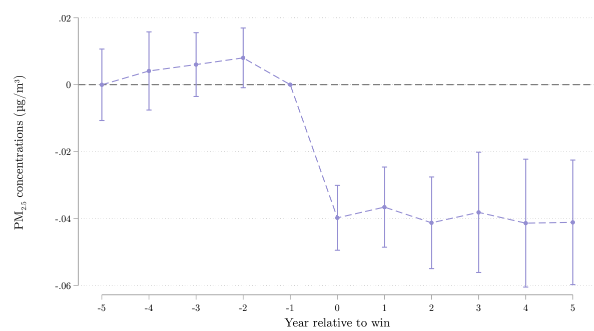
(b) Permanent Income



(c) Permanent Income Percentile Rank



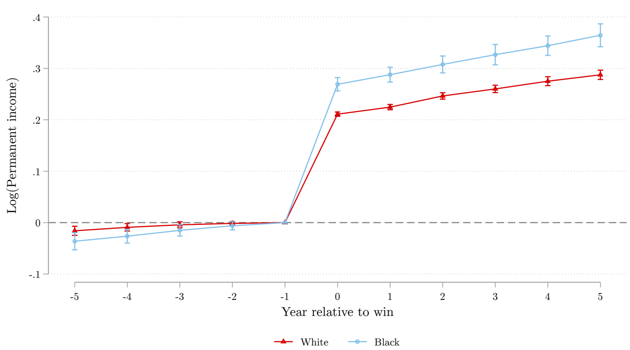
(d) $PM_{2.5}$ Concentrations



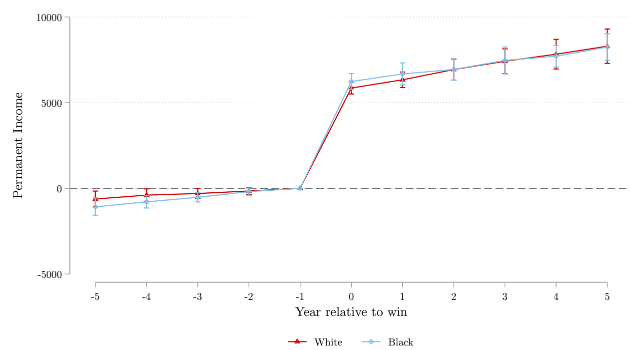
NOTES: These event study figures plot the $\hat{\beta}_e$ coefficients from Equation (1) estimated with various outcomes, as labeled. All specifications are estimated with CBSA×year fixed effects. Standard errors are clustered at the CBSA level.

Figure 8: Event Study Estimates Using Lottery Winners, by Race

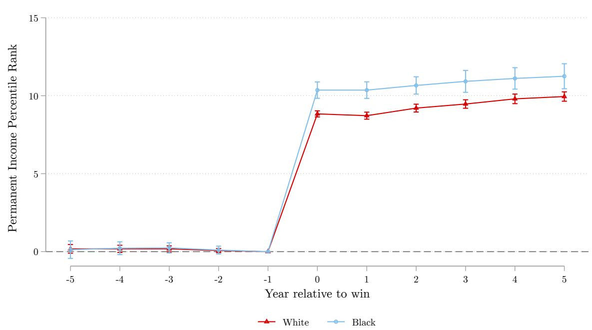
(a) Log(Permanent Income)



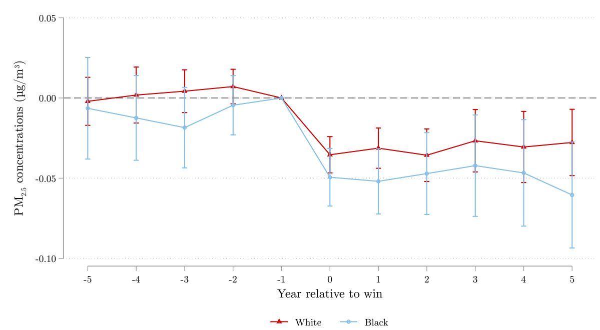
(b) Permanent Income



(c) Permanent Income Percentile Rank



(d) $PM_{2.5}$ Concentrations



NOTES: These event study figures plot the $\hat{\beta}_e$ coefficients from Equation (1) estimated with various outcomes, as labeled. All specifications are estimated with CBSA×year fixed effects. Standard errors are clustered at the CBSA level.

Table 1: $PM_{2.5}$–Permanent Income Estimates by Race and Year

	Panel A: $PM_{2.5}$ elasticity in 1984			
Dep. variable: Log $PM_{2.5}$ concentration	White	Black	Hispanic	Asian
Log Permanent Income	0.0043	-0.0021	0.0106	-0.0140
	(0.0051)	(0.0041)	(0.0085)	(0.0038)
N	39,810,000	4,519,000	3,003,000	1,104,000
	Panel B: $PM_{2.5}$ rank elasticity in 1984			
Dep. variable: $PM_{2.5}$ rank	White	Black	Hispanic	Asian
Permanent Income Rank	0.0098	-0.0152	0.0307	-0.0397
	(0.0169)	(0.0190)	(0.0344)	(0.0132)
Constant	47.99	64.48	50.74	62.94
	(2.75)	(3.04)	(8.64)	(7.59)
N	39,810,000	4,519,000	3,003,000	1,104,000
	Panel C: $PM_{2.5}$ elasticity in 2016			
Dep. variable: Log $PM_{2.5}$ concentration	White	Black	Hispanic	Asian
Log Permanent Income	-0.0045	-0.0160	-0.0156	-0.0225
	(0.0046)	(0.0028)	(0.0028)	(0.0050)
N	59,630,000	10,380,000	13,000,000	4,996,000
	Panel D: $PM_{2.5}$ rank elasticity in 2016			
Dep. variable: $PM_{2.5}$ rank	White	Black	Hispanic	Asian
Permanent Income Rank	-0.0325	-0.1007	-0.0723	-0.0952
	(0.0188)	(0.0169)	(0.0129)	(0.0166)
Constant	47.11	66.48	63.04	64.36
	(2.16)	(1.96)	(4.33)	(5.55)
N	59,630,000	10,380,000	13,000,000	4,996,000

NOTES: This table presents 16 separate regression estimates. Each panel reflects a model×year, where each column represents estimates from a different race group. For example, Panel A presents elasticity estimates for 1984, separately by race. Panel B presents similar estimates except where we regress individual rank in the 1984 $PM_{2.5}$ distribution on the individual rank in the 1984 income distribution, separately by race. Panels C and D present corresponding estimates for the year 2016. Standard errors are clustered at the CBSA level.

Table 2: Within-CBSA $PM_{2.5}$–Permanent Income Estimates by Race and Year

	Panel A: $PM_{2.5}$ elasticity in 1984			
Dep. variable: Log $PM_{2.5}$ concentration	White	Black	Hispanic	Asian
Log Permanent Income	-0.0142	-0.0099	-0.0093	-0.0176
	(0.0011)	(0.0010)	(0.0017)	(0.0015)
N	39,810,000	4,519,000	3,003,000	1,104,000
	Panel B: $PM_{2.5}$ rank elasticity in 1984			
Dep. variable: $PM_{2.5}$ rank	White	Black	Hispanic	Asian
Permanent Income Rank	-0.0481	-0.0509	-0.0360	-0.0632
	(0.0033)	(0.0053)	(0.0055)	(0.0082)
Constant	51.08	65.78	53.25	64.07
	(0.18)	(0.19)	(0.21)	(0.40)
N	39,810,000	4,519,000	3,003,000	1,104,000
	Panel C: $PM_{2.5}$ elasticity in 2016			
Dep. variable: Log $PM_{2.5}$ concentration	White	Black	Hispanic	Asian
Log Permanent Income	-0.0157	-0.0167	-0.0195	-0.0198
	(0.0012)	(0.0013)	(0.0020)	(0.0021)
N	59,630,000	10,380,000	13,000,000	4,996,000
	Panel D: $PM_{2.5}$ rank elasticity in 2016			
Dep. variable: $PM_{2.5}$ rank	White	Black	Hispanic	Asian
Permanent Income Rank	-0.0731	-0.1067	-0.0904	-0.0985
	(0.0052)	(0.0091)	(0.0102)	(0.0103)
Constant	49.35	66.68	63.78	64.56
	(0.29)	(0.30)	(0.42)	(0.61)
N	59,630,000	10,380,000	13,000,000	4,996,000

NOTES: This table presents 16 separate regression estimates. Each panel reflects a model×year, where each column represents estimates from a different race group. For example, Panel A presents elasticity estimates for 1984, separately by race. Panel B presents similar estimates except where we regress individual rank in the 1984 $PM_{2.5}$ distribution on the individual rank in the 1984 income distribution, separately by race. Panels C and D present corresponding estimates for the year 2016. All regressions include CBSA fixed effects. Standard errors are clustered at the CBSA level.

Table 3: Counterfactual $PM_{2.5}$-Permanent Income Estimates: 1984 Locations with 2016 $PM_{2.5}$

	(1) Black 1984 Observed Elasticity	(2) Black 2016 Observed Elasticity	(3) Black 2016 Counterfactual Elasticity
Log Permanent Income	-0.0099	-0.0167	-0.0085
	(0.0010)	(0.0013)	(0.0008)
Model	CBSA FE	CBSA FE	CBSA FE

NOTES: This table presents 3 separate regressions, one per column. Columns (1) and (2) present estimates of the within-CBSA, income-pollution gradient for Black individuals in 1984 and 2016, respectively. These estimates come from Table 2. Column (3) presents a counterfactual, where Black individuals live in the same Census Block Groups as Black individuals in 1984, but pollution in those Block Groups has been updated to the 2016 levels. This counterfactual is designed to understand how shutting migration patterns for Black individuals between 1984 and 2016 would affect estimates of the 2016 pollution-income gradient.

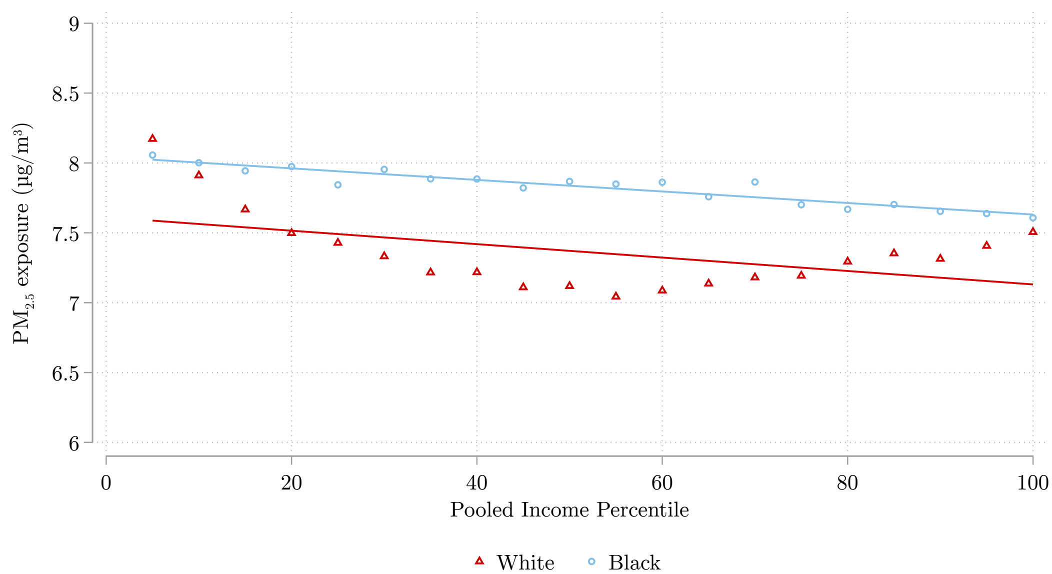
Table 4: Lottery estimates: Income-$PM_{2.5}$ Elasticities by Race (1999-2016)

	White	Black	Hispanic	Asian
	Panel A: OLS elasticity			
	White	Black	Hispanic	Asian
Log Permanent Income	-0.0172	-0.0152	-0.0153	-0.0125
	(0.0025)	(0.0021)	(0.0037)	(0.0039)
	Panel B: Reduced form			
	White	Black	Hispanic	Asian
Winner × Post	-0.0040	-0.0042	-0.0035	-0.0066
	(0.0013)	(0.0015)	(0.0021)	(0.0056)
	Panel C: First stage			
	White	Black	Hispanic	Asian
Winner × Post	0.2626	0.3361	0.3200	0.2969
	(0.0046)	(0.0108)	(0.0160)	(0.0190)
1st stage F stat	3200.0	969.3	399.2	243.2
	Panel D: IV elasticity			
	White	Black	Hispanic	Asian
Log Permanent Income	-0.0152	-0.0124	-0.0110	-0.0221
	(0.0049)	(0.0043)	(0.0064)	(0.0190)
N	420,000	68,000	52,000	23,000

NOTES: This table presents 16 separate regression estimates based on Equation (2) in the text. Each panel reflects a different model, where each column represents estimates from a different race group. For example, Panel A presents OLS elasticity estimates using the sample of lottery winners from 1999-2016, separately by race. Panel B presents the "reduced form" relationship between winning a lottery and $PM_{2.5}$ exposure. Panel C presents the corresponding "first stage" relationship between winning the lottery and log(permanent income). Lastly, Panel D presents the corresponding IV estimate of the income-$PM_{2.5}$ exposure elasticity. All regressions include CBSA×year fixed effects. Standard errors are clustered at the CBSA level.

Appendix Figures and Tables

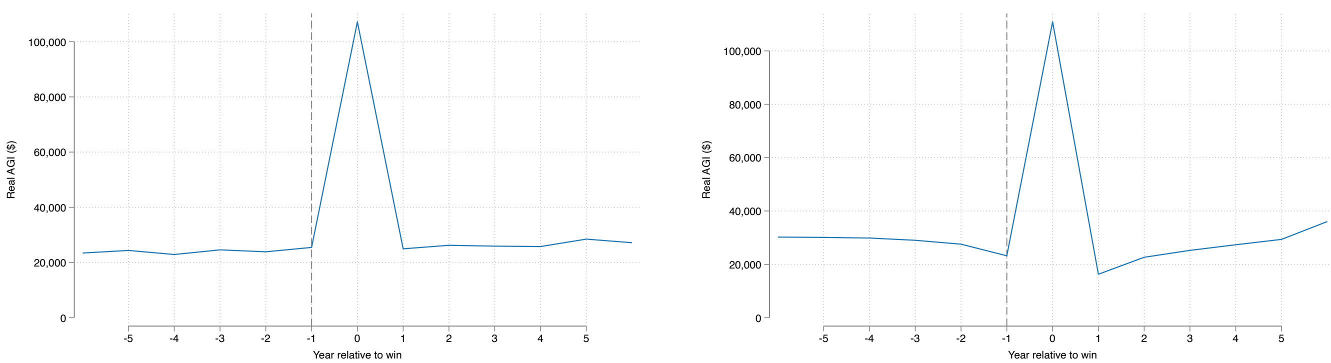
Figure A1: Relationship Between Income and $PM_{2.5}$ Exposure in 2016, Separately by Race: Public-Data Estimates



Notes: This figure plots the average $PM_{2.5}$ concentration by income percentile for 2016, separately by race, when using public data. The income percentiles are constructed from public-use census-tract level estimates of median income as reported by the 5-year 2012-2016 ACS. Pollution levels are aggregated up to the census tract level from the census block group level.

Figure A2: Comparison of Income Trajectories of Maine Lottery Winners to Synthetic "Lottery Winners"

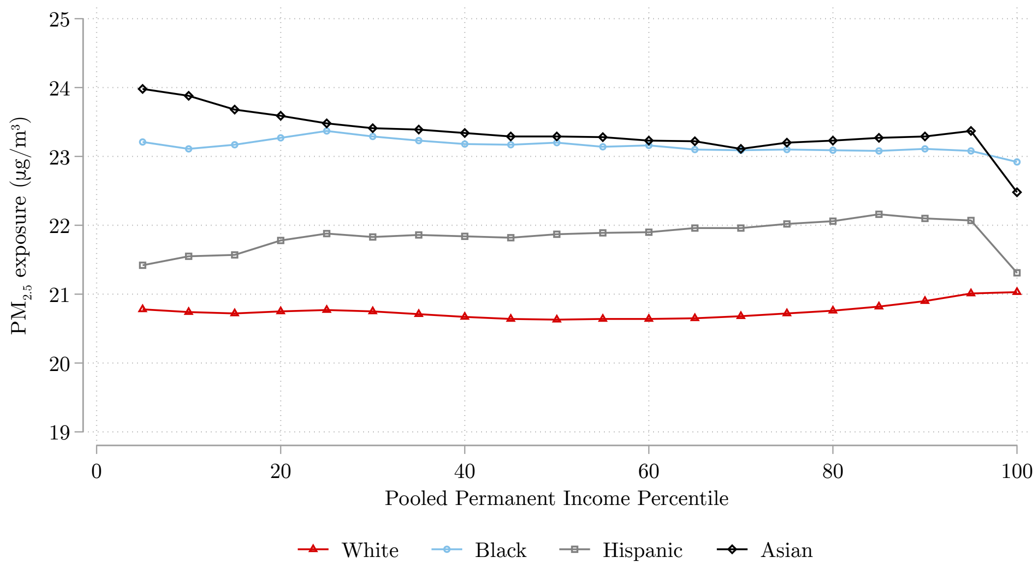
(a) Maine (b) Synthetic



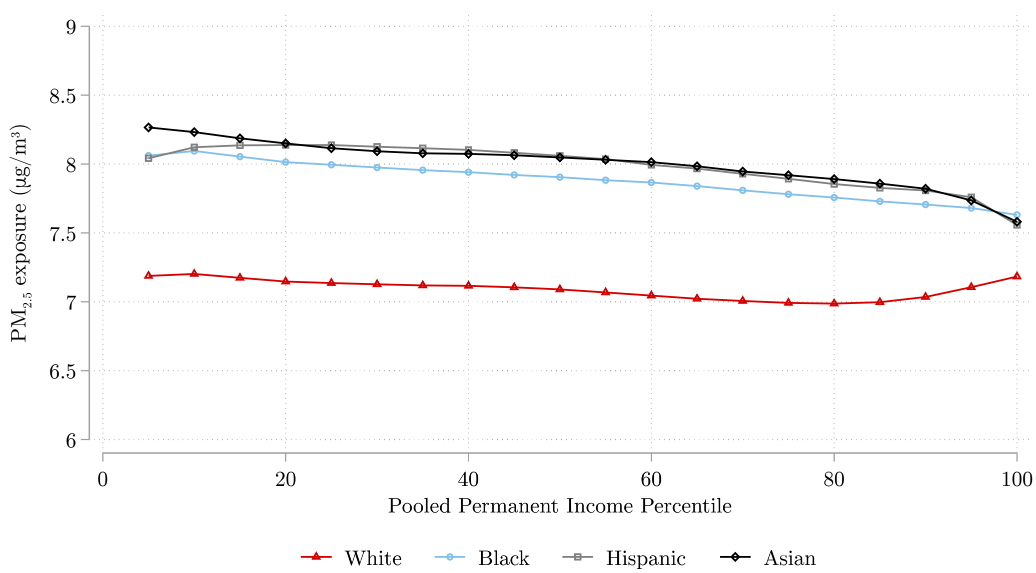
Notes: Panel A plots the income trajectories of lottery winners in Maine in the years before and after winning the lottery. Panel B plots the income trajectories of synthetic lottery winners from the national sample in the years before and after winning the lottery.

Figure A3: Relationship Between Permanent Income and $PM_{2.5}$ Exposure, Separately by Race

(a) 1984



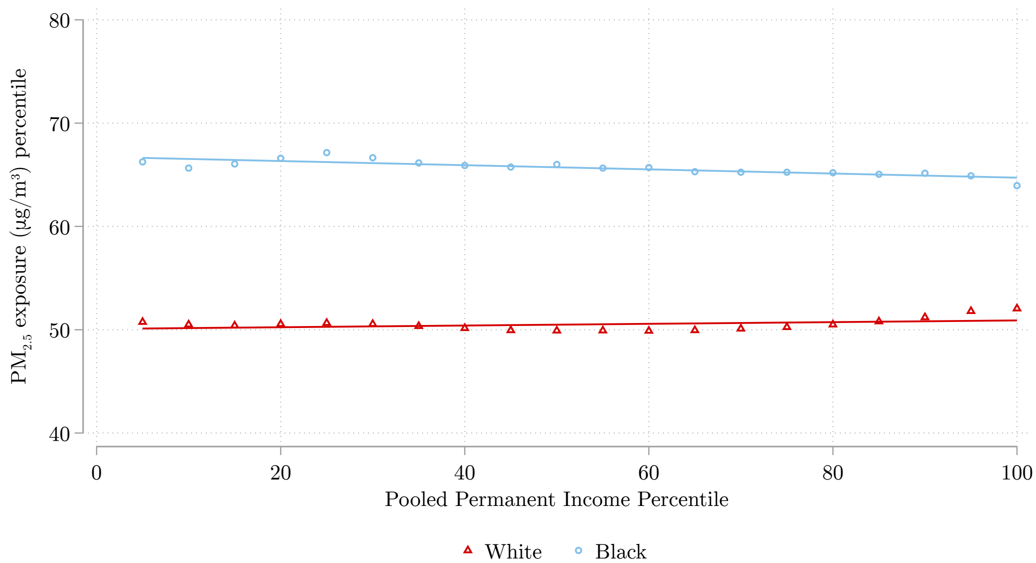
(b) 2016



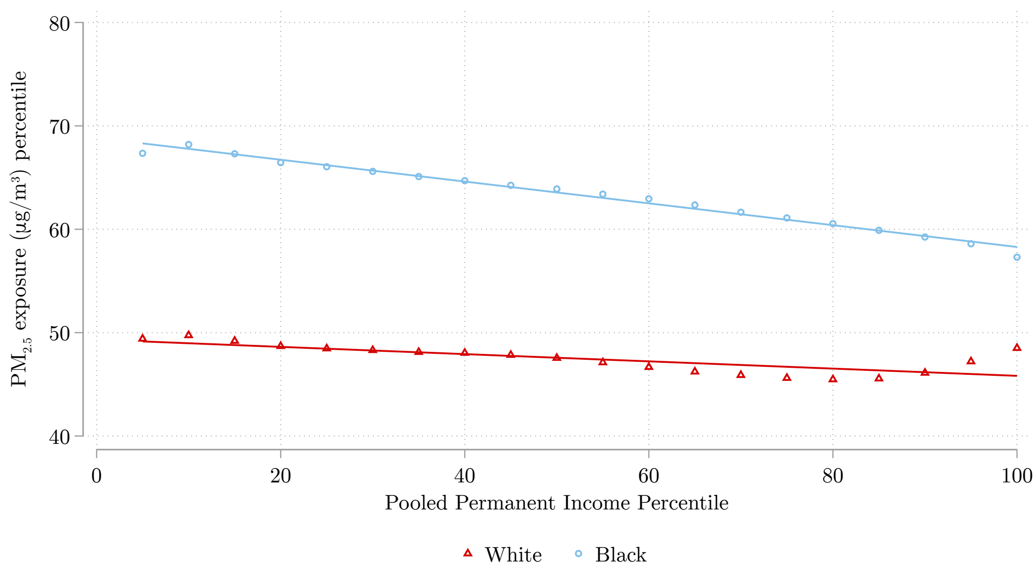
Notes: These figures plot the average $PM_{2.5}$ concentration by permanent income percentile for a given year, separately by race. The income percentiles are constructed from all prime-aged U.S. tax filers in a given year who report positive adjusted gross income.

Figure A4: Relationship Between Permanent Income and $PM_{2.5}$ Rank, Separately by Race

(a) 1984

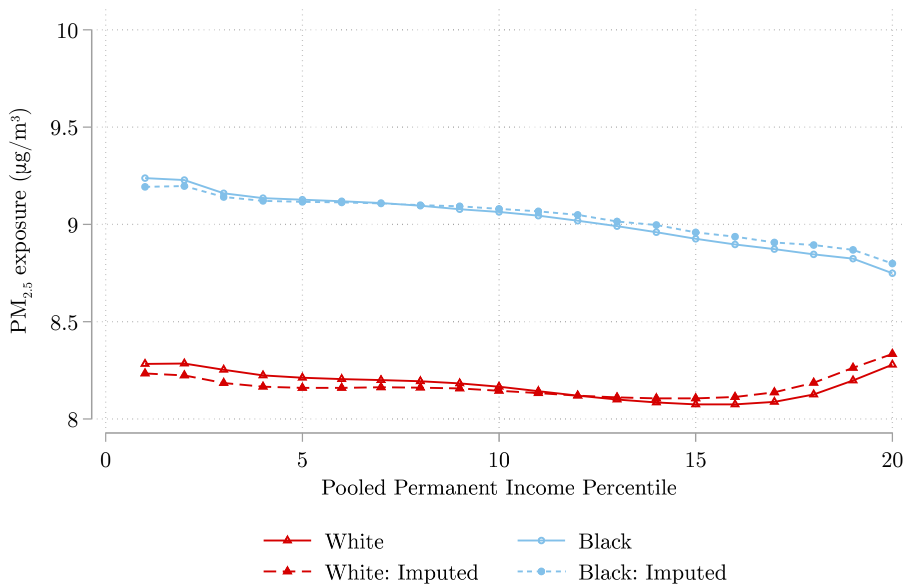


(b) 2016



NOTES: These figures plot the average $PM_{2.5}$ percentile rank in the national pollution distribution by permanent income percentile for a given year, separately by race. The income percentiles are constructed from all prime-aged U.S. tax filers in a given year who report positive adjusted gross income. The plotted line represents the best linear fit to these conditional means.

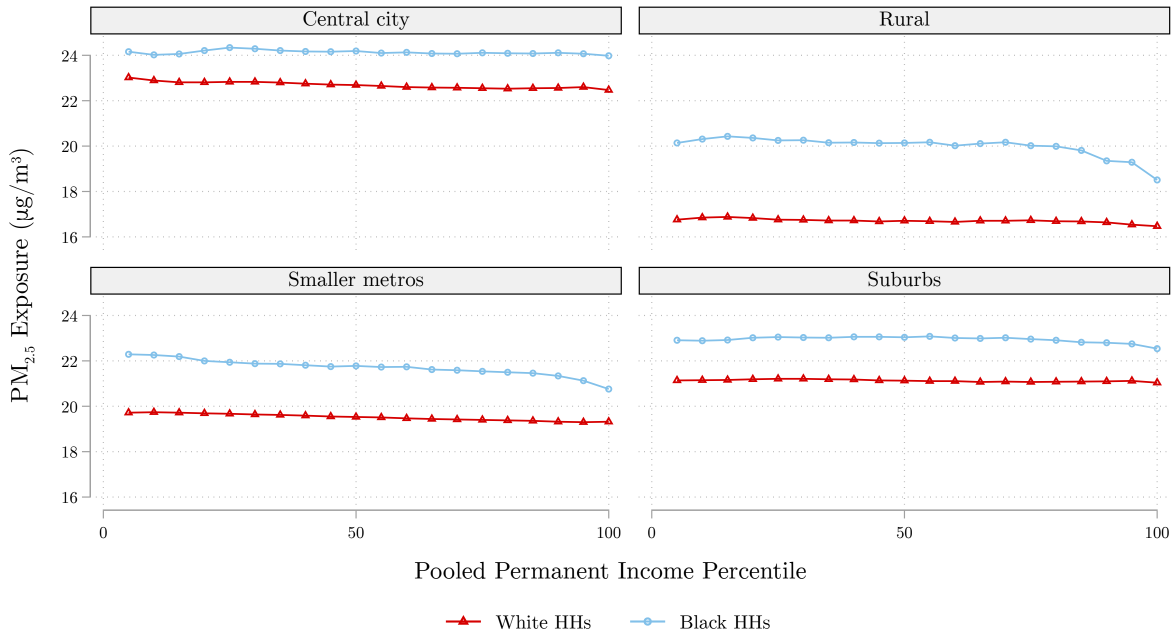
Figure A5: Relationship Between Permanent Income and $PM_{2.5}$ Exposure using W-2 Imputed Income for Non-filers, 2016



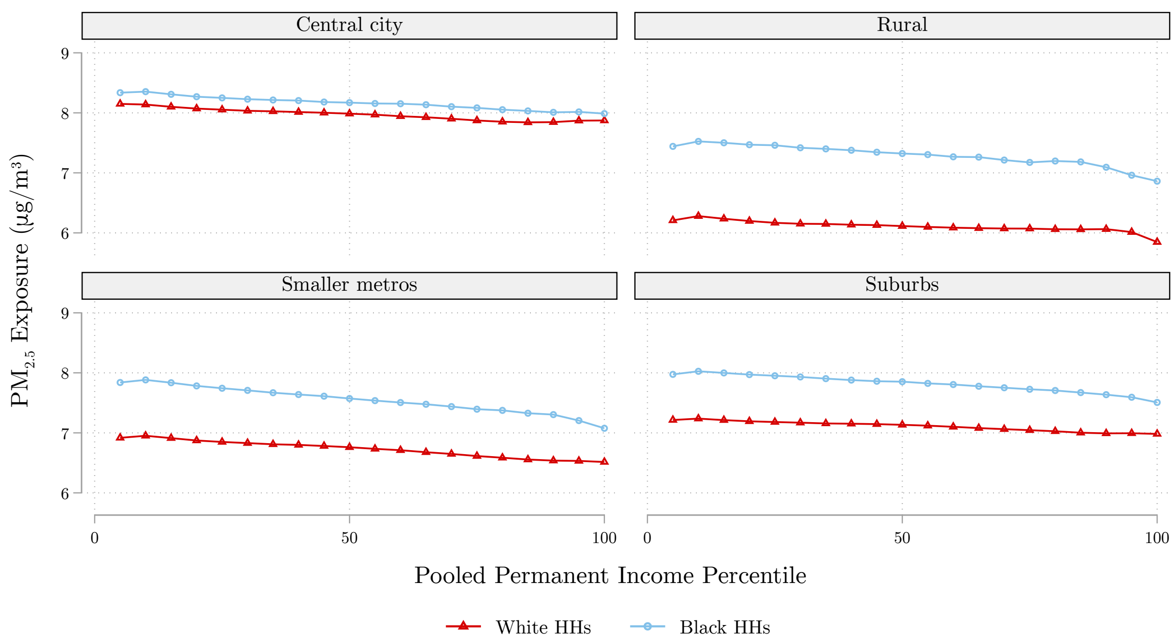
Notes: These figures plot the average $PM_{2.5}$ concentration by permanent income percentile in 2016, separately by race. The income percentiles are constructed from all prime-aged U.S. tax filers in a given year who report positive adjusted gross income. The imputed AGI percentile ranks are constructed using W-2 reported wages as the AGI for non-filers, i.e. individuals who do not file a Form 1040 and thus have no reported AGI.

Figure A6: Relationship Between Permanent Income and $PM_{2.5}$ Exposure, by Urban Area Type

(a) 1984



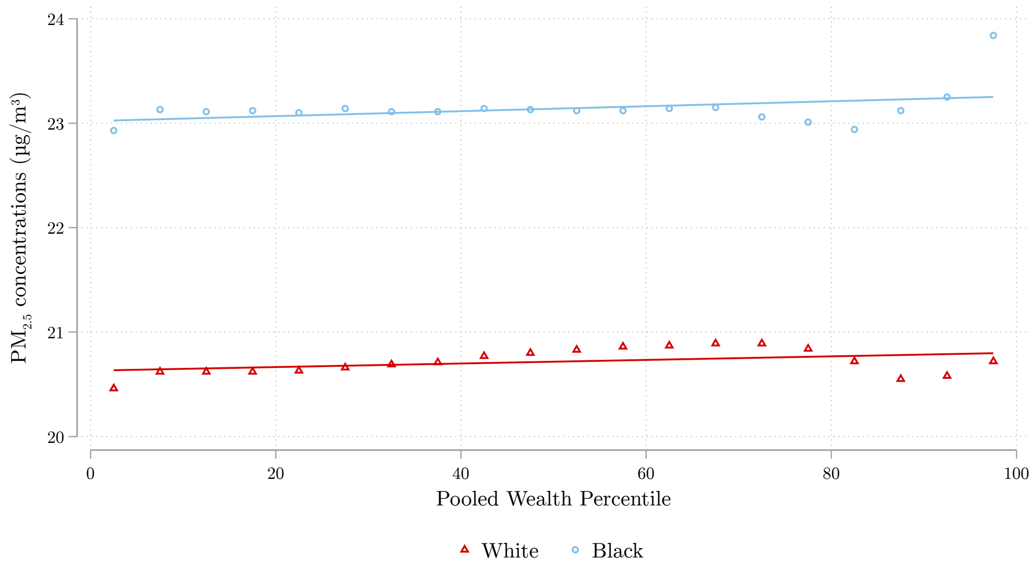
(b) 2016



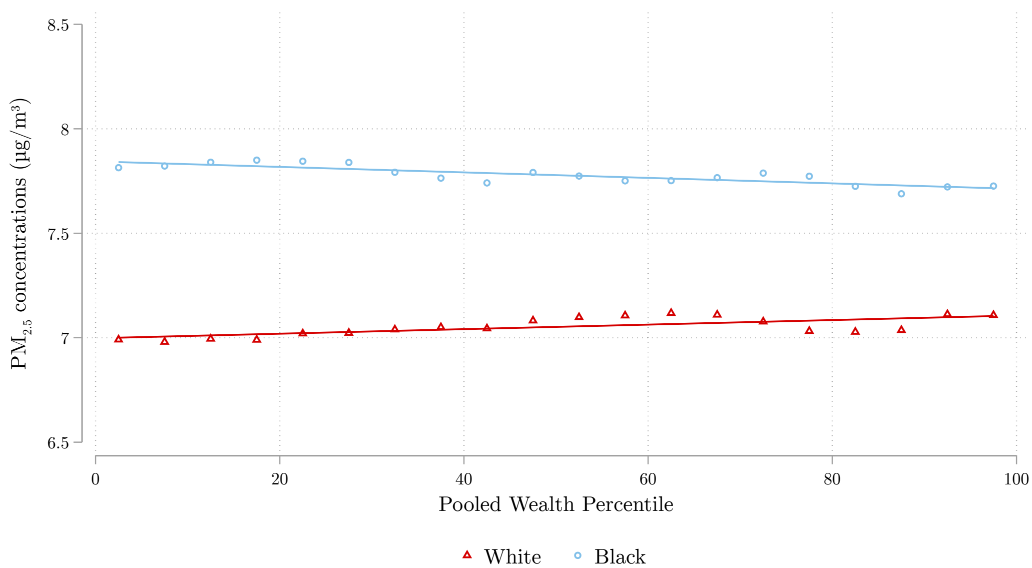
Notes: These figures plot the average $PM_{2.5}$ concentration by permanent income percentile in 2016, separately by race. The income percentiles are constructed from all prime-aged U.S. tax filers in a given year who report positive adjusted gross income. We classify individuals into locations using the urban-rural classification scheme of Ingram and Franco (2014).

Figure A7: Relationship Between Wealth and $PM_{2.5}$ Exposure, Separately by Race

(a) 1984



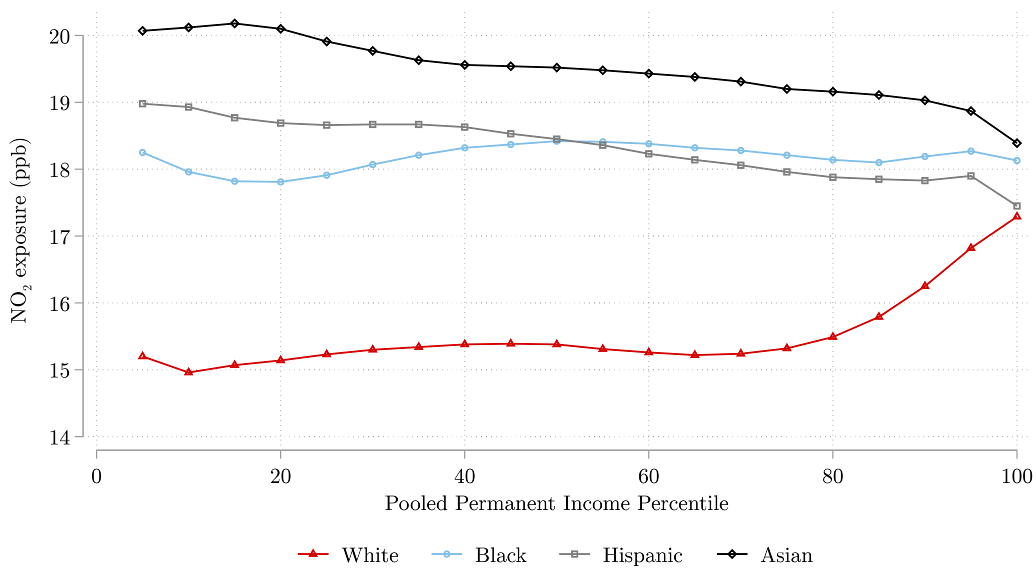
(b) 2016



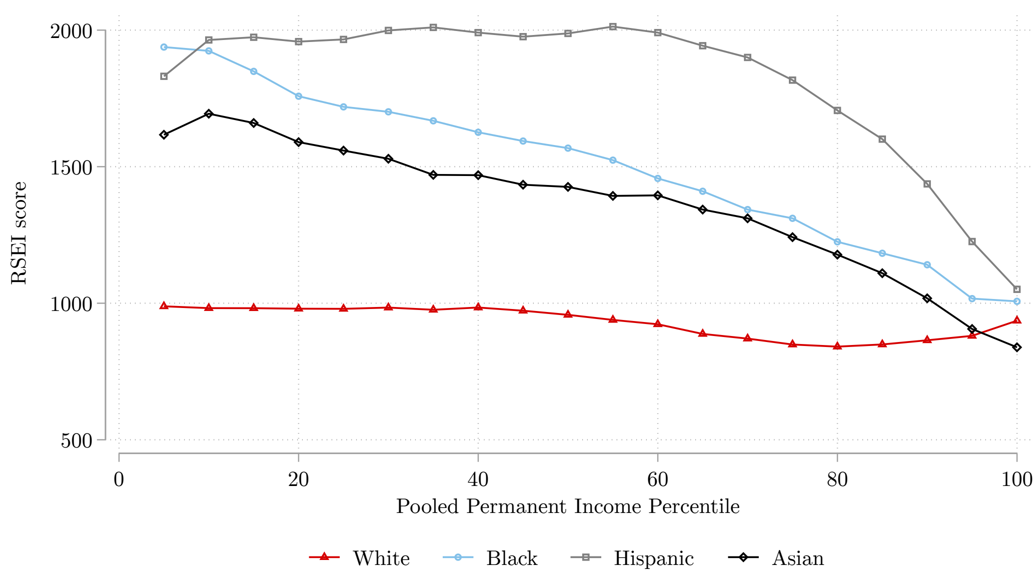
NOTES: These figures plot the average $PM_{2.5}$ concentration by wealth percentile for a given year, separately by race. The wealth percentiles are constructed from all prime-aged U.S. tax filers in a given year who have non-zero capital income. The plotted line represents the best linear fit to these conditional means.

Figure A8: Relationship Between Permanent Income and Other Pollutants in 2016, Separately by Race

(a) NO_2



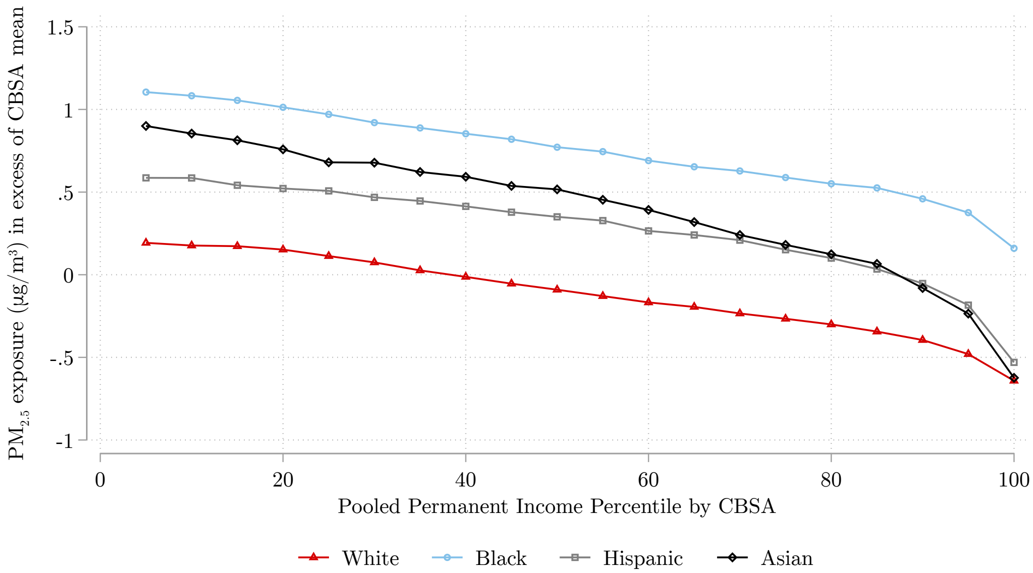
(b) RSEI



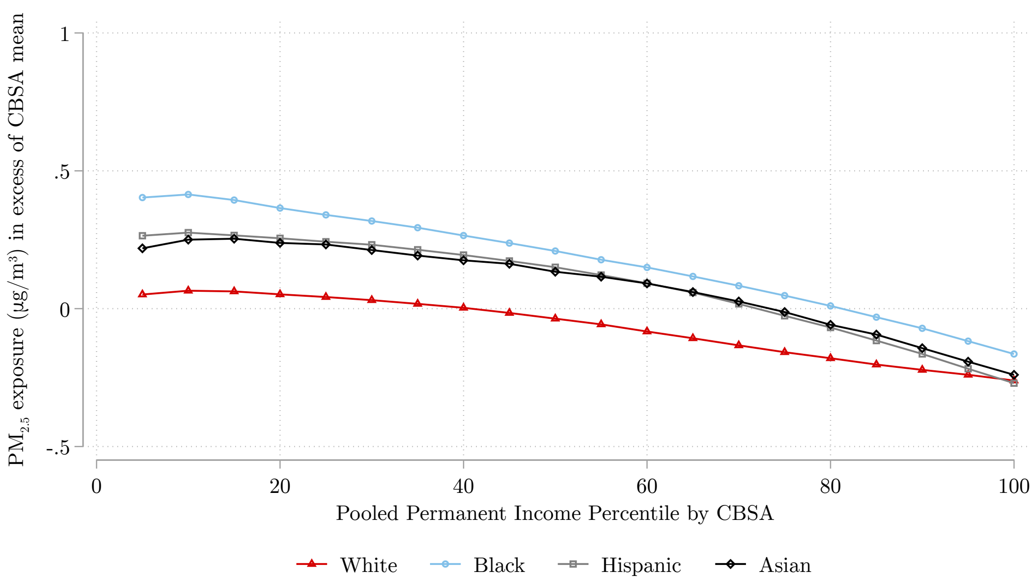
NOTES: These figures plot the average concentrations of NO_2 and the average RSEI score by permanent income percentile in 2016, separately by race. The income percentiles are constructed from all prime-aged U.S. tax filers in a given year who report positive adjusted gross income.

Figure A9: Relationship Between Income and $PM_{2.5}$ Exposure, Within CBSA

(a) 1984



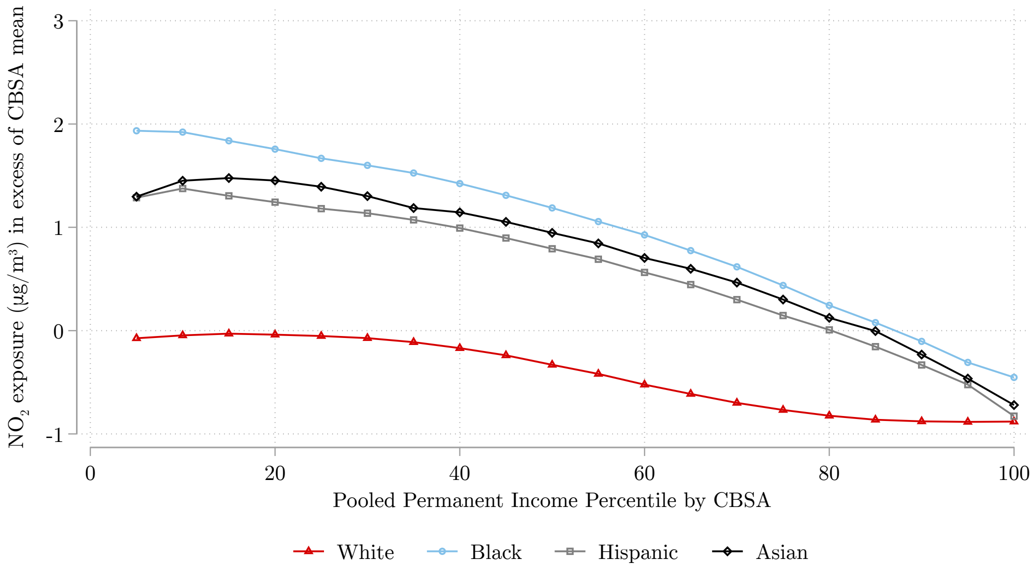
(b) 2016



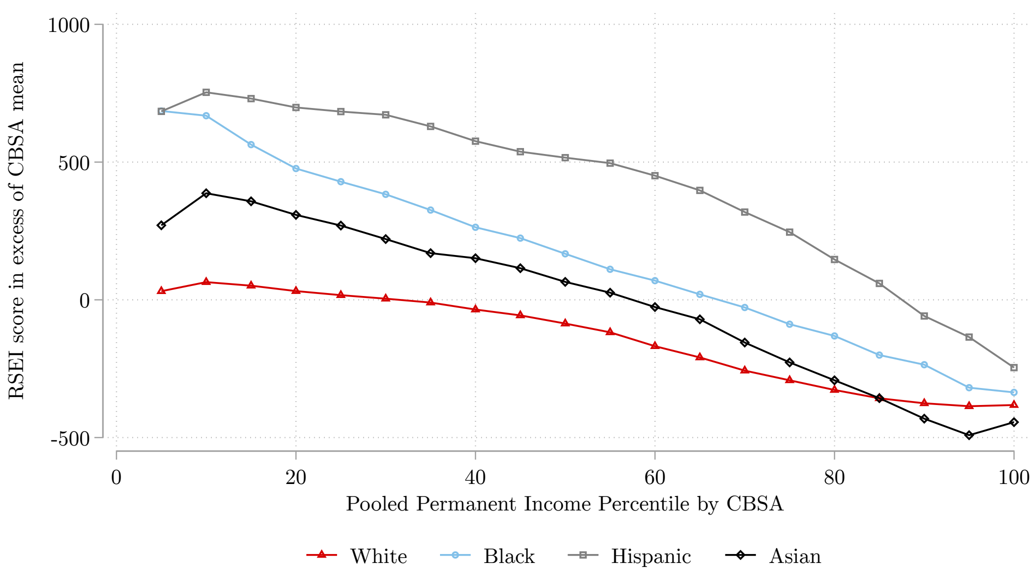
NOTES: These figures plot the average $PM_{2.5}$ concentration in excess of the CBSA mean by CBSA-specific permanent income percentile, separately by race. The pollution concentration averages are calculated as the individual concentration in excess of the overall CBSA mean, averaged across each percentile rank and race. The permanent income percentile ranks are constructed to be specific to each CBSA. All non-CBSA individuals are classified as belonging to one CBSA. The plotted line represents the best linear fit to these conditional means.

Figure A10: Relationship Between Permanent Income and Other Pollutants in 2016, Within CBSA, Separately by Race

(a) NO_2

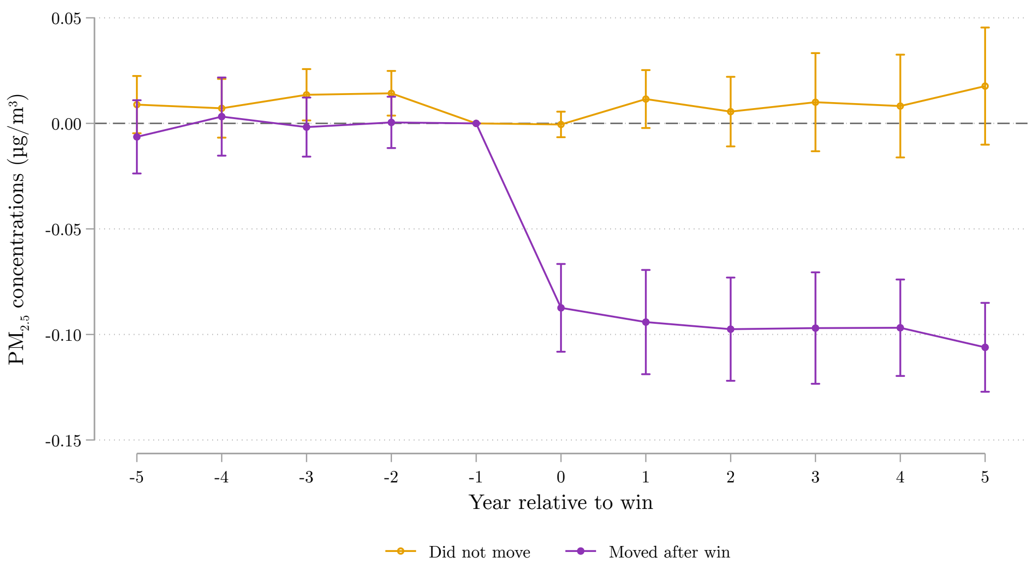


(b) RSEI



Notes: These figures plot the average concentrations of NO_2 and the average RSEI score by permanent income percentile in 2016, separately by race. The pollution concentration averages are calculated as the individual concentration in excess of the overall CBSA mean, averaged across each percentile rank and race. The permanent income percentile ranks are constructed to be specific to each CBSA. All non-CBSA individuals are classified as belonging to one CBSA. The plotted line represents the best linear fit to these conditional means.

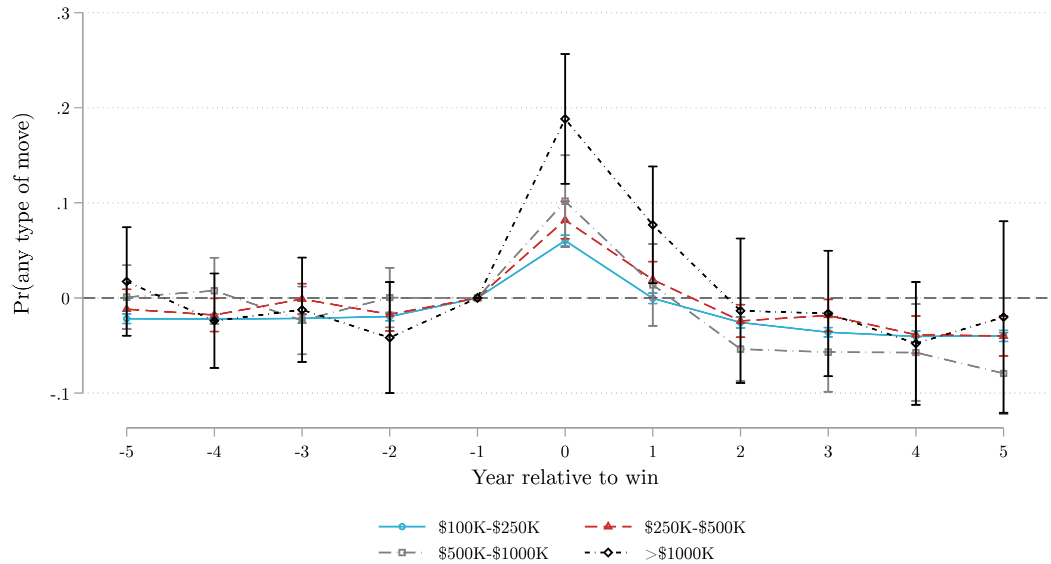
Figure A11: Event Study Estimates Using Lottery Winners, by Mobility Status



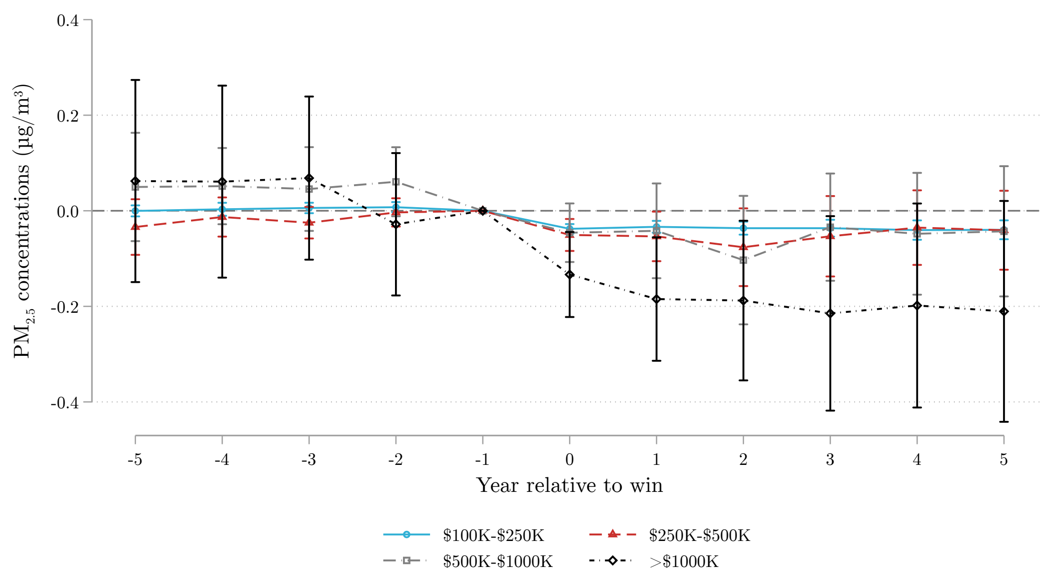
NOTES: This figure plots the $\hat{\beta}_e$ coefficients from Equation (1) for individuals that move after a lottery win and for individuals that do not move after a lottery win. All specifications are estimated with CBSA×year fixed effects. Standard errors are clustered at the CBSA level.

Figure A12: Lottery Heterogeneity By Size of Lottery Winnings

(a) Mobility by Lottery Win Amount



(b) $PM_{2.5}$ by Lottery Win Amount



Notes: These event study figures plot the $\hat{\beta}_e$ coefficients from Equation (1) estimated for each win size bin separately. All specifications are estimated with CBSA×year fixed effects. The dependent variable in Figure A12a is a binary indicator for whether a move was observed in a given period. The dependent variable in Figure A12b corresponds to individual $PM_{2.5}$ exposure. All specifications are estimated with CBSA×year fixed effects. Standard errors are clustered at the CBSA level.

Table A1: Winners-only Lottery OLS, 1st stage, & IV results with CBSA×year FEs: all amenities, 2001-2016 consistent sample

	Panel A: White Sample					
	Log Property Value	Log(Rent)	Log Homeownership	Log School Proficiency	Log Crime Rate PC	Log Violent Crime Rate PC
Log Permanent Income	0.0921	0.0367	0.0980	0.0151	-0.0174	-0.0256
	(0.0091)	(0.0085)	(0.0100)	(0.0039)	(0.0065)	(0.0090)
N	188000	188000	188000	188000	188000	188000

	Panel B: Black Sample					
	Log Property Value	Log(Rent)	Log Homeownership	Log School Proficiency	Log Crime Rate PC	Log Violent Crime Rate PC
Log Permanent Income	0.0677	0.0553	0.1527	0.0062	-0.0331	-0.0495
	(0.0219)	(0.0185)	(0.0282)	(0.0100)	(0.0126)	(0.0161)
N	30000	30000	30000	30000	30000	30000

Notes: The table displays OLS estimates from regressing various log amenity attributes on log AGI using a sample of lottery winners that was merged to various amenity datasets, yielding a smaller sample size compared to Table (4). Panel A and B display the IV elasticity estimates from Equation (2) estimated separately for White and Black non-Hispanic individuals but replacing log $PM_{2.5}$ with other amenity attributes as labeled. All specifications include CBSA×year fixed effects. Standard errors are clustered by CBSA.