Income, Wealth, and Environmental Inequality in the United States

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Abstract

This paper explores the relationship between pollution exposure, income, wealth, and race by combining administrative data from U.S. tax returns between 1979-2016, various measures of pollution exposure, and sociodemographic information from linked survey and administrative data. In the first year of our data, the relationship between household income and ambient pollution levels nationally is approximately zero for both non-Hispanic White and Black households. However, at every single percentile of household income, African Americans are exposed to, on average, higher levels of particulates than non-Hispanic White households. By 2016, the relationship between income and ambient pollution exposure has steepened, primarily for African Americans, reflecting changes in where rich and poor households 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 largely mimic the relationships seen in observational data. Black-White differences in household income explain about 10 percent of the observed gap in pollution exposure by 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 being 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 exposures 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 data on environmental exposures, as air pollution 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 exposure on a spatially continuous basis. Second, data availability on income and wealth, especially disaggregated by race or other demographic characteristics is not typically available at the spatial resolution at which exposure differences are increasingly found. Third, existing evidence on the relationships between income, wealth, and environmental exposures stem from observational correlations. We know very little about the causal effect of increases in household income and/or wealth on pollution exposure. Accordingly, we know very little about whether relative improvements in income or wealth are likely to lead to relative improvements in environmental 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, IRS 1040 tax returns between 1979-2016 (containing information on residential location and income) with high-resolution, remote sensing measurements of ambient air pollution, and sociodemographic information from linked survey (Decennial Census and American Community Survey) and administrative data to provide systematic evidence on the relationship between pollution exposure, economic well-being, and race. Our primary measure of economic well-being is derived from 5 year averages of annual income meant to approximate "permanent income," although we explore alternative income and wealth definitions throughout. Our primary measure of environmental exposures comes from satellite-derived measures

of fine-scale particulate exposure ($PM_{2.5}$), although we explore other environmental outcomes as well.

We begin by documenting new facts about the observational relationships between income, wealth, and ambient pollution exposure at the individual level, showing how these relationships differ by race, and how these income-exposure 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 pollution exposure for a subset of our data. Lastly, we explore some of the potential mechanisms linking pollution exposure to income and wealth and, in particular, how these mechanisms have contributed to race-specific changes in the income-exposure gradient over time.

We find that the relationship between income, wealth, and environmental exposures is relatively weak nationally. In the first year of our data, 1984, the relationship between our measure of permanent income and exposure to $PM_{2.5}$ is approximately zero for both non-Hispanic Black and non-Hispanic White populations.[2] However, at *every single income percentile*, Black households were exposed to significantly higher levels of particulate pollution than non-Hispanic White households. By 2016, there continues to be almost no relationship between permanent income and $PM_{2.5}$ exposure for White households, whereas Black households and other racial minorities now have steeper income-exposure gradients. While small in magnitude, these relative changes in income-exposure gradients portend a narrowing of the $PM_{2.5}$ exposure gap between Black and White households at the upper end of the income distribution.

We see that income is much more negatively correlated with $PM_{2.5}$ exposure for all racial groups when we limit our analysis to within-metro area income-exposure relationships. Richer households are exposed to lower levels of $PM_{2.5}$ than lower income households in a metro area, and this is true for all race groups. However, the racial gaps in pollution exposure remain throughout the income distribution. For example, in 1984, the average Black household in the 99th percentile of the

[1] Details of this process are described below. We exclude individuals 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.

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

permanent income distribution is exposed to higher levels of $PM_{2.5}$ than the average White household in the 1st percentile of the same income distribution. By 2016, however, the Black household income-exposure gradient has steepened significantly relative to the White income-exposure gradient. The average Black household in the 99th percentile of the permanent income distribution is now exposed to levels of $PM_{2.5}$ equivalent to White households in the 75th percentile of the income distribution.

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 households over the past 40 years rather than relative improvements to air quality in historically Black communities. We show that the set of neighborhoods or Census Tracts that Black households live in 2016 are both more numerous and span a wider range of environmental outcomes than in the 1980's where Black households were more likely to be living in a narrower set of predominantly urban, Census Tracts with relatively high pollution levels. This same expansion to the set of neighborhoods households reside in also holds for Hispanic and Asian households, and is also associated with a corresponding steepening of the income-exposure gradient over time.

These descriptive facts, however, do not tell us whether relative improvements in income or wealth are likely to lead to relative improvements in environmental quality for an individual household. We leverage the set of individuals in our data who experienced large, one-time windfalls in 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, on average, associated with a persistent 0.04 μgm^3 reduction in $PM_{2.5}$ 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 $PM_{2.5}$ for White households and a 0.012% reduction in $PM_{2.5}$ for Black households.

What do these estimates imply for the existing racial exposure gaps in $PM_{2.5}$ exposure? Back of the envelope calculations suggest that harmonizing median income between Black and White

households would lead to a 10 percent reduction in the overall Black-White gap in $PM_{2.5}$ exposure in 2016. Thus, while extremely wealthy Black and White households are increasingly living in similar communities as measured by air quality, the Black-White pollution exposure gap at the lower parts of the income distribution are large enough that income or wealth harmonization alone is unlikely to lead to an eradication of the racial gap in pollution exposure. These conclusions, of course, do not reflect the fact that aggregate changes to income or wealth of a specific group may affect environmental exposures, not simply through mobility but also through other channels such as political and/or collective action. Understanding these broader social processes 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 Cain et al. (2023) for a recent overview of the economics literature exploring with these issues. While there exists an extensive literature documenting that low-income and racial minorities are disproportionately exposed to higher levels of pollution concentrations or higher numbers of facilities that release fugitive air emissions (Hsiang et al., 2019; Currie et al., 2023), we know of no paper that explores the causal effect of income on pollution exposure nor discusses how these relationships differ across the income distribution, by race, and over time. While there have been papers exploring patterns of racial disparities by race and/or income (Liu et al., 2021), these papers use aggregated data from the American Community Survey and/or Decennial Census which precludes investigations of pollution exposure by income, separately by race, which is the primary focus of this paper.[3]

Second, there is a large literature seeking to explore the determinants of location choice, and specifically how location choices may differ by race and/or income. Some of this work explores individual preferences for public goods such as air quality or school quality in shaping location choice

[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 from the Decennial Census or American Community Survey is available at the census tract level, which has an average geographic resolution of 93 km^2. Additionally, public-use data reports median household income by race at the census tract level which precludes the analysis of exposure differences across the income distribution within a census tract.

(see e.g., Bayer et al. (2007)). Other work seeks to understand how shocks to household income affect outcomes, such as housing and/or neighborhood choice (Golosov et al., 2021; Bulman et al., 2022). Lastly, there is a literature attempting to understand racial differences in neighborhood choice, and how those 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). However, we are not aware of any paper which relates the broad underlying trends in location decisions by different racial groups to differences in pollution exposure, particularly how these relationships differ across 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 environmental exposures by race and over time. Section **??** explores how the descriptive relationships compare to causal relationships between income and pollution exposure. Section 6 concludes.

2 Data

2.1 Longitudinal Data on Income, Race, Ethnicity, and Wealth

We leverage confidential microdata held at the US Census Bureau to study the distribution of air pollution by race and income. The data linkage infrastructure at the Census Bureau allows us to link administrative records on income with demographic information (age, race and ethnicity) from Decennial Census and American Community Survey data. 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 resolved to the Census block group level. We link these taxpayers using Protected Identification Keys (see Layne et al. (2014)) to their responses in 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 Hispanic origin of any race, Non-hispanic White, Black and Asian (we define

non-Hispanic AIAN, NHPI, some other race and two or more races categories, although due to small samples we do not include these groups in our analyses). For each year of the administrative tax data, we restrict observations to positive AGI tax units and prime aged (age 25-54) taxpayers. 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. Our 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 EITC, non-taxable pension contributions (e.g., to 401(k)'s), and any earned income not reported to the IRS. Income is always 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, with only those who file taxes included. This captures the vast majority of the US population, but there are 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 cash welfare programs have been largely replaced by transfers working through the tax system (such as the Earned Income Tax Credit). 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, it is notable that these increases have been roughly similar across the age distribution and across race and ethnicity. Our findings are robust to using raking weights that reweight our observed tax data to match the desired marginal totals. We also explore 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, both of which provide information on income 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 permanent income and/or wealth. Our primary measure of permanent income follows Cesarini et al. (2023). 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.[4]

We also construct a measure of wealth using the capitalization approach proposed by Saez and Zucman (2016). The US tax system primarily taxes income as a base, not wealth (with the exception of local property taxes), and thus the tax system does not create administrative records on wealth. Some flows related to wealth, however, are captured in the administrative tax data. As such, 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.[5] 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 capitalization factors from (Saez and Zucman, 2020) for each year 1979-2016 to our tax data, which allows us to calculate a measure of financial wealth at the micro level. This measure of wealth accounts for around half of aggregate wealth, but it is unequally distributed: many (sometimes most, depending on the year) tax units have zero wealth under this measure.

Our linked microdata approach provides several key advantages over other ways to study income-pollution relationships. First, because we are able to leverage a longer time series of administrative tax data, we can cover substantially longer time periods than would be possible using, for instance,

[4]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.

[5]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."

American Community Survey microdata. Second, we are able to capture an estimate of individual level permanent income and/or wealth for the entire tax filing population; the only other source of wealth-by-race information is from small surveys such as the Survey of Consumer Finances. Third, we are able to consistently measure race and ethnicity at the individual level using composite, harmonized demographic data from the Census Bureau, which allows us to avoid issues with changing race and ethnicity measurement across Decennial Census and ACS collections. Fourth, we can leverage much greater geographic granularity. Finally, using administrative tax data allows us to better measure the whole income distribution, particularly in the tails, where survey measurement error is most acute.

2.2 Pollution Exposure Data

We combine our demographic data on households with high-resolution, remote sensing measurements of particulate exposure ($PM_{2.5}$) from Meng et al. (2019) at the Census Block Group level using 2010 Census Block Group boundary definitions. 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 satellite remote sensing with chemical transport modeling and in-situ ground-based measurements of $PM_{2.5}$ to construct a gridded data product of the contiguous United States from 1981-2016 on a 0.01 degree by 0.01 degree (0.9 km by 1.1 km) grid.

We supplement data on $PM_{2.5}$ with data on NO_2, another criteria air pollutant, regulated under the Clean Air Act's National Ambient Air Quality Standards. NO_2 is a combustion byproduct that has been associated with multiple adverse health outcomes. We use data from Di et al. (2019), which uses an ensemble model to integrate multiple machine learning algorithms with a variety of inputs, including chemical transport models. 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 intersect this gridded raster data with 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 estimated exposure 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 with 2010 Census Block Group boundaries and assign the average Block Group level RSEI score to each individual in our linked IRS-Census microdata.

2.3 Identifying shocks to income designed to approximate lottery winnings

We use the longitudinal income information from the tax data to identify households that experienced a large, transitory income shock in a single year. We design this process 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". The algorithm is meant to approximate lottery winnings by identifying tax units that experience one-time, large income shocks. To do this, we follow 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 household 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. To additionally hone in on shocks that are more likely to be "lottery wins", we exclude individuals 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 (which are less likely to reflect exogenous windfalls).

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. 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 nonetheless identify a set of individuals who appear to experience lottery-like shocks. We validate this approach using information on state-level lottery winners from Maine that we link to our core sample. Appendix Figure A1 compares the income trajectories of true lottery winners from Maine to the income trajectories 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. 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.

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 when exploring mechanisms underlying income-exposure relationships. For a subset of our individuals who were in sample in the 2000 Census long form or the 2001-2016 American Community Surveys, we merge in housing characteristics, including home ownership, property values, rent paid, and housing structure characteristics such as year built and number of bedrooms.

At the aggregate/neighborhood level, we merge in information on school quality, crime, and demographic context. 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 reports crime counts by month for each reporting agency.[6] After aggregating up to the reporting agency level, the data is matched to county FIPS codes using the 2012 LEAIC crosswalk

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

and aggregated at the county level for merging with our core sample. Finally, we construct Block Group-level demographic characteristics (population shares) using the ACS microdata corresponding to a given year: college educated share, non-Hispanic Black population share, Hispanic population share, fraction employed, and fraction in poverty.[7] We then merge the demographic characteristics to our core sample at the Block Group level using 2010 Census Block Group boundaries.

3 Income, Wealth, and Pollution Exposure

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

Figure 1a shows the average exposure to the pollutant $PM_{2.5}$ in 1984 by percentile of the 1984 income distribution. The relationship between household income and pollution exposure nationally is approximately zero. Households in the first percentile of the income distribution are exposed, on average, to similar $PM_{2.5}$ levels as those households at the median or upper end of the income distribution. This relationship corresponds to a $PM_{2.5}$–permanent income elasticity of -0.0042, which is not statistically significant.[8]

- **RW: this elasticity needs to be disclosed and numbers updated to reflect permanent income measure**

Figure 1b shows the same income-exposure relationship but in 2016. There are two primary differences relative to 1984. First, air quality has improved dramatically in this 30+ year time span — average $PM_{2.5}$ exposure in the United States has fallen by more than 60%, from 21 $\mu g/m^3$

[7] Any individual who is not non-Hispanic White was classified as belonging to a minority race.
[8] This elasticity is estimated from the microdata, regressing log $PM_{2.5}$ exposure on log permanent income.

to 7.3 μg/m^3. Second, the $PM_{2.5}$-income relationship has rotated slightly, now showing a downward trending relationship between $PM_{2.5}$ exposure and income, corresponding to a $PM_{2.5}$–income elasticity of -0.0155%.

- **RW: this elasticity needs to be disclosed and numbers updated above and below to reflect permanent income measure**

What does this relationship imply for overall environmental inequality? There are significant differences in household income between Black and White households. Median income for Black households was about 60 percent of median income for White households in 2016. A simple back-of-the-envelope calculation, using the 2016 income elasticity of -0.0155, suggests that harmonizing median income would lead to a 0.62 percent reduction in Black $PM_{2.5}$ exposure. This corresponds to a 0.07μg/m^3 reduction in 2016 $PM_{2.5}$ levels, which would amount to a 9 percent reduction in the overall Black-White gap $PM_{2.5}$ exposure in 2016.[9]

3.1 The Income-Exposure Gradients by Race

It is possible that these income-exposure 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 households. Black households are presented in red, whereas White households are presented in blue. Figure 2a shows that, in 1984, the income-exposure gradients for Black Households look somewhat similar to that of White households; they are both relatively flat. However, at every single income percentile, Black households are exposed to, on average more $PM_{2.5}$ than White households. Figure 2b shows that these same qualitative patterns exist in 2016 - Black households are exposed to higher levels of pollution than White households at every single percentile of the income distribution. However, Figure 2b also highlights where some of the rotation in the income gradient seen in Figure 1b comes from. While White households in 2016 continue to have a relatively flat national income-exposure gradient, the Black gradient has rotated slightly by 2016. Appendix

[9] Average $PM_{2.5}$ exposure for Black households in 2016 was 7.9μg/m^3, and the Black-White mean exposure gap in 2016 was 0.8μg/m^3.

Figure A2 plots these same income-exposure gradients for Hispanic and Asian households, in both 1984 and 2016. The patterns for racial minorities are largely similar; racial minorities in the United States are exposed to higher levels of ambient $PM_{2.5}$ at every single income percentile, on average, in both 1984 and 2016.

While average exposures of have been falling for all race groups, the relative positions within the pollution distribution have remained largely constant. Appendix Figure A3 plots the average rank in the $PM_{2.5}$ distribution for each permanent income percentile, separately by race. The average White household throughout the income distribution is also at the median of the $PM_{2.5}$ distribution in both 1984 and 2016. Black households, in 1984, are about 15 percentile ranks higher in the pollution distribution than White households. By 2016, these gaps are narrowing at the upper end of the income distribution, but even the richest Black households are living in neighborhoods that are, on average, 10 percentile ranks more polluted than similarly wealthy White households.

Table 1 presents the corresponding $PM_{2.5}$-income elasticities by race, separately for 1984 and 2016. Panel A presents regression results where we regress log(permanent income) on log($PM_{2.5}$) using a 1984 cross-section, separately for four different race categories: White, Black, Hispanic, and Asian. These elasticities are statistically insignificant and small in absolute value. Income profiles for all race groups, i.e., on average, low-income and high-income households within the same racial group are exposed to the similar pollution levels. Panel B of Table 1 presents rank-rank elasticities where we regress $PM_{2.5}$ percentile rank on the percentile rank of households in the overall 1984 income distribution. This rank-rank specification tells us, how a percentile increase in household income is associated with the average rank of a given household in the overall pollution distribution. Like Panel A, these relationships are relatively weak and not statistically significant.

Panels C and D of Table 1 present the corresponding elasticity and rank-rank relationships for 2016, respectively. In contrast to 1984, we now observe negative and statistically significant income gradients for all racial minorities. For example, a 10 percent increase in Black household income is associated with a 0.16 percent reduction in $PM_{2.5}$ exposure. Panel D shows that Black and White households at the very bottom of the income distribution experience, on average a 20 percentile rank

difference in the $PM_{2.5}$ distribution, despite having very similar incomes. While Black, Hispanic, and Asian households have a steeper income-exposure gradient than White households, these differences are not strong enough to fully offset this rank gap, even at higher income percentiles. The predicted rank of Black households in the 100th percentile of the income distribution is still 12 percentile ranks higher in the pollution distribution than a corresponding White household at the 100th percentile of the income distribution.[10]

Our permanent income concept is only available for the 1040 filing population. Appendix Figure A4 explores the sensitivity of our results by using reported W-2 income for employed non-filers (available from 2005 onwards). The income gradients for Black and White households look similar when using AGI based on 1040 filings versus an imputed AGI measure using W-2 income for non-filers.

Results thus far combine differences in pollution exposure that stem from differences in location choices across many types of locations, ranging from rural to urban to suburban. Appendix Figure A5 shows that these qualitative patterns remain similar when focusing on central cities, rural areas, smaller metro areas, or suburban areas. We classify households into location type using the urban-rural classification scheme of Ingram and Franco (2014). In every single location type (central city, rural, suburban), racial minority households are exposed to, on average, higher levels of $PM_{2.5}$ at every income percentile.

Appendix Figure A6 plots wealth-exposure gradients using an alternative measure of wealth derived by capitalizing capital income flows reported on 1040's in a given year. It's important to note that a significant fraction of households in our data have zero wealth using this measure. There are meaningful level differences in exposure for those with and without household wealth; however, within the distribution of non-zero wealth exposure patterns largely resemble the patterns we see for household income. In both 1984 and 2016 the relationship between $PM_{2.5}$ and wealth is very small and statistically insignificant.

The Appendix presents income-exposure relationships using alternative pollution measures. Ap-

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

pendix Figure A7a presents income-exposure gradients by race for ambient NO_2 concentrations in 2016. The patterns for NO_2 look broadly similar to the patterns for PM2.5 – namely, racial minority households are exposed to higher levels of ambient NO_2 at every single income percentile, on average. Nationally, these elasticities are close to zero or weakly positive for White and Black households. Asian and Hispanic households have somewhat more negative income-exposure gradients for NO_2 than Black or White households.

Appendix Figure A7b presents income-exposure gradients using 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 PM2.5 figures from before. In this case, Black households are exposed to higher RSEI scores at every single income percentile, on average. However, the income-exposure gradient for Black households is far steeper than for White households. Thus, at the very upper end of the income distribution, there is nearly convergence in environmental outcomes for this exposure measure.

Across different measures of environmental exposures, different measures of income or wealth, and different years a simple fact endures – racial minority households 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 exposure gaps by income. For example, perhaps minority households, either by choice or necessity, live in areas with cheaper rents or housing, and it's these differences in neighborhood attributes that offset some of these exposure differences by income. Or, perhaps there are other amenities, such as schooling or crime, for which minority households of a given income may have stronger preferences for than air quality. To explore these questions further, we compute the conditional Black-White gap in pollution exposure by income percentile, before and after controlling for other observable characteristics of households and neighborhoods. We combine the 2016 data with other demographic data to better understand the role of observable differences in neighborhood and/or household characteristics in explaining these 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 earnings records using a unique, individual identifier.[11] 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 household pollution exposure on a series of indicator variables for income vigintile, fully interacted with indicator variables for race (where White is the omitted category). We include controls for housing and rental values, school proficiency, and crime. The coefficients on the race×income percentile indicator interaction terms provide a measure of the conditional gap (relative to White households) 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 for the year 2016. For Black households, the conditional and unconditional gaps in PM2.5 exposure at each income vigintile are similar, suggesting that differences in income, housing, rent, schooling, and crime are unable to explain the pollution gaps that exist between Black and White households. The results for other racial groups are similar.

3.2 Within-City Relationships

In practice, a significant share of mobility occurs within metro areas, and we explore how these income-pollution gradients may 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 plus adjacent counties that are socioeconomically tied to the urban center by commuting.

Figure 4 plots these within-CBSA income gradients, separately for Black and White households in both 1984 and 2016. We create these binned scatter plots by first computing within-CBSA permanent income percentiles for each year. We then calculate the average $PM_{2.5}$ exposure in each CBSA×year and subtract this value from each of the household exposures within each CBSA in our data. Lastly,

[11] If individuals move between when we observe their household income in 2016 and the housing information they provided in a previous year survey, there will be measurement error in this regressor.

we compute the average, de-meaned value of $PM_{2.5}$ for each race and income bin.[12] The top figure plots these income gradients in 1984, and the bottom figure corresponds to 2016. As before, we see significant racial gaps in pollution exposure at every single income percentile. Somewhat different than before, however, we see a negative relationship between income and exposure in both 1984 and 2016 for both Black and White households. These income gradients suggest that in 1984, a Black household in the 95th percentile of the income distribution is exposed to, on average, a level of pollution exposure that is higher than a White household at the 5th percentile of the CBSA specific income distribution. By 2016, there has been a relative steepening of the Black income gradient compared to the White, such that the richest Black households in the 95th percentile of the income distribution are exposed to $PM_{2.5}$ levels equivalent to White households at the 75th percentile of the income distribution. Appendix Figure A8 plots these same relationships for all race groups, and the patterns look broadly similar.

Table 2 reports within-CBSA pollution–income elasticities and within-CBSA rank-rank relationships for 1984 and 2016. These results come from regressing log or rank of household $PM_{2.5}$ exposure on log or rank of household income, controlling for CBSA-specific fixed effects. As suggested by Figure 4, there are several differences compared to the national pollution-income relationships. First, the pollution-income elasticity's 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 households and a 0.010% reduction in $PM_{2.5}$ for Black households. Second, the White and Black pollution-income elasticities are converging over time. In 1984, the within-CBSA pollution–income relationship was less elastic for Black households than White households (-0.010 vs. -0.014). In 2016, the within-CBSA pollution-income elasticity for Black households had converged and even steepened relative to that of White households (-0.017 vs. -0.016).

Appendix Figure A9 plots within-CBSA, permanent income-exposure gradients in 2016 for two other measures of pollution exposure, NO_2 and the RSEI score. These pollutants show similar patterns to those for PM2.5. First, racial minorities continue to be exposed to higher levels of

[12] We group all households that do not reside within a CBSA boundary into their own artificial CBSA.

ambient exposure throughout the income distribution. Second, the income-elasticities are also steeper for racial minorities relative to non-Hispanic White households; there is nearly complete convergence in exposure outcomes at the very upper end of the within-CBSA income distribution.

What changed between 1984 to 2016 that led to a steepening of the Black-income gradient relative to White? Figure 5 plots the fraction of households that live in central cities and suburbs by income percentile and race. Figure 5a shows that, in 1984, around 50 percent of Black households 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 households lived in suburbs. At upper ends of the income distribution, this rate rises to 34 percent of Black households. Figure 5b shows that, by 2016, the fraction of Black households that live in city centers has fallen by about 10 percentage points throughout the income distribution. Where did these households 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 households shares similar patterns of movements out of city centers towards suburbs, but the magnitudes are quite a bit 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 households moved in greater numbers to suburbs, this movement pulled down the Black PM2.5 income gradient relative to the comparatively stable White PM2.5 income gradient. This can partially be seen in Figure 6, which overlays the fraction of households that live in city centers with the average $PM_{2.5}$ exposure, separately by race and income percentile. For example, Figure 6b shows that as wealthier, non-Hispanic White households move to city centers, non-Hispanic White $PM_{2.5}$ exposure gradually increases. Conversely, as richer Black households increasingly move out of city centers, the average $PM_{2.5}$ exposure for Black households 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-specific income gradients in 2016 would look like in a counterfactual

world where households were living in 1984 locations (i.e. shutting down mobility as a channel). The basic idea is to merge 2016 $PM_{2.5}$ exposure data to 1984 household locations and estimate income elasticities by race. 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 households fixed in their 1984 locations. As you 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 looks from Column (3) looks almost identical to Column (1). This suggests that almost all of the steepening of the income elasticity for Black households comes through changes in household locations since the 1980's.

4 Causal Effects 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.

We leverage transitory income shocks, meant to approximate lottery winnings (hereafter "lottery winners"), to estimate the causal effect of increases in income and/or lifetime wealth on a household's pollution exposure. As described above, we follow Cesarini et al. (2023) by annuitizing the windfall income over a 20 year horizon. 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 generalized 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:

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

where y_{iet} is either the $PM_{2.5}$ concentration in the Census Block Group where household i lives in year t and event time k or the income or wealth level of household i in year t and event time k, $\mathbf{1}(t - W_{it} = e)$ is an indicator for household i being e periods away from winning the lottery at time t. γ_{st} are CBSA-year fixed effects, and ϵ_{ist} is the unobservable component of pollution exposures. 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. $\beta_{-1} = 0$.[13] Standard errors are clustered at the CBSA level to account for correlation in air pollution, both across time and space.

Figure 7 plots the main set of estimates for both income 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 income corresponds to about a $7500 or 10 percentile ranks. Figure 7d shows an immediate reduction in $PM_{2.5}$ exposure of -0.04$\mu g/m^3$ that persists for all post-win time periods. As such, a one-time increase of $7,500 in permanent income is associated with a 0.04 $\mu g/m^3$ reduction in $PM_{2.5}$ exposure. This corresponds to an average elasticity of around 0.009.

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

[13] We also implement a variant of this specification using the estimator proposed in Sun and Abraham (2021) to address potential concerns with dynamic timing of treatment as discussed in **?**. The results are nearly identical, but have not yet been disclosed.

To translate these results into a pollution-income elasticity, we use the post-lottery win period as an instrument for permanent income. More specifically, we estimate the following first stage and IV specifications using the same notation as equation (1), dropping the event time notation from the previous equation:

$$\begin{aligned} \log(income_{it}) &= \alpha_1 + \beta \mathbf{1}(t \geq W_{it}) \times \mathbf{1}(winner)_i + \delta \mathbf{1}(winner)_i + \gamma_{st} + \nu_{ist} \\ \log(PM2.5_{it}) &= \alpha 2 + \beta \log(\widehat{income}_{it}) + \mathbf{1}(winner)_i + \gamma_{st} + \epsilon_{ist} \end{aligned} \tag{2}$$

where $\log(income_{it})$ is the log of household i's income in year t, $\log(PM2.5_{it})$ is log $PM_{2.5}$ concentration in the Census Block Group where household i lives in year t, $\mathbf{1}(t \geq W_{it})$ is an indicator for whether year t is after the lottery win-year for household i (i.e. whether it is the post-lottery win period), $\mathbf{1}(winner)_i$ is an indicator for household i being a lottery winner, γ_{st} correspond to CBSA×year fixed effects, ϵ_{ist} is the unobservable component of pollution exposures, 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 households. In Panel C shows there is a strong first stage relationship for all race groups. In Panel D, we present the IV elasticities by race. We see that a 1% increase in real AGI is associated with a 0.015% reduction in $PM_{2.5}$ for White households and a 0.012% reduction in $PM_{2.5}$ for Black households. 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 households are not statistically significant at conventional significance levels.

What do these estimates imply for the existing racial exposure gaps in $PM_{2.5}$ exposure? Median income for Black households was about 60 percent of median income for White households in 2016. Using these estimates, harmonizing median incomes between Black and White households would lead to a 0.744 percent reduction in Black $PM_{2.5}$ levels in 2016 (about 0.06 $\mu g/m^3$). Thus, while there is a statistically significant effect of income on environmental outcomes, the overall magnitudes are

economically small.

Appendix Figure A10 shows that the entirety of the observed effects on air pollution come from lottery winners moving to new locations after the lottery win. Households who move after their lottery win-year see a decline in $PM_{2.5}$ exposure of 0.1 $\mu g/m^3$ on average, while those who do not move see no reduction in pollution exposure.

Appendix Figure A11 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.[14] Figure A11a shows that larger win sizes are associated with a higher likelihood of moving, whereas Figure A11b 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 $PM_{2.5}$ exposure decline of -0.13 $\mu g/m^3$, an estimate that is over three times as large as the baseline result of -0.04 $\mu g/m^3$.

5 Trading Off Environmental and Housing Services

To understand how households might be trading off different amenities, other than environmental amenities, in their location decision after winning the lottery, we estimate a separate set of regression models exploring how lottery winnings affect other location attributes. We estimate Equation (2) but replace log $PM_{2.5}$ with the log of different amenities, such as property values, rent, homeownership rate, school proficiency rate, and crime rates, as described in Section 2.4. The results in Appendix Table A4 suggest that, on average, a large income shock induces households 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.

- Need to update Table A1 with new set of results
- Placeholder for amenity tables by race

[14] Note that these amounts correspond to the overall size of the windfall gain, not the annuitized amount of permanent income received.

While higher income is associated with "better" neighborhood amenities, we know less about the ways in which minority choices over location may differ from non-minority choices. For example, do minorities 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 trades in the market place differ, or do minorities simply spend less money for housing by moving into neighborhoods with more $PM_{2.5}$ pollution? To answer this question, we leverage the longitudinal nature of our data with insights developed in earlier work by Depro and Timmins (2012).

Consider a function where total housing expenditure is a function of two independent variables: pollution and housing services....

5.1 Benchmarking to the literature

A number of researchers have recently used lottery winnings to understand the causal effects of new-found resources or wealth on a vector of individual and household choices (Bulman et al., 2021, 2022; Golosov et al., 2021). 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 households with large wins are more likely to move to neighborhoods that are, on average, wealthier. Similarly, Golosov et al. (2021) estimate that winning the lottery leads to an immediate, one-off 3.5 percentage point (25 percent) increase in the annual moving rate. They find that lower-income household are the most responsive to a change in wealth. Their mobility estimates for households in the lowest income quartile are most similar to ours (5 percentage points). Past work suggests that households do not seem to systematically move to higher quality neighborhoods, as measured by a range of characteristics (local-area opportunity indices, poverty rates, and educational attainment).

6 Conclusion

The relationship between income, wealth, and environmental inequality in the United States reveals significant disparities in pollution exposure, particularly across racial lines. By examining administrative data from U.S. tax returns and pollution exposure metrics from 1979 to 2016, this study uncovers persistent and evolving environmental inequalities.

Initially, in 1984, the study found that the national relationship between household income and ambient pollution levels was nearly zero. However, African American households were consistently exposed to higher levels of particulates compared to non-Hispanic White households at every income percentile. Over the subsequent decades, from 1984 to 2016, while overall air quality improved, the income-exposure gradient became more pronounced, especially for African Americans. By 2016, wealthier Black households experienced steeper declines in pollution exposure compared to their White counterparts, though the gap remained significant. This change is attributed to the mobility of Black households into more diverse and suburban neighborhoods, indicating shifts in residential patterns rather than improvements in traditionally Black urban areas.

The study's causal analysis, utilizing quasi-random income shocks such as lottery winnings, supports the observational data. It confirms that increases in income can lead to reductions in pollution exposure, though these effects are modest. Specifically, a 1 percent increase in income results in a 0.015 percent reduction in PM2.5 exposure for White households and a 0.012 percent reduction for Black households. Despite these gains, the existing racial gap in pollution exposure would only marginally decrease with income harmonization, suggesting that other structural factors play a significant role.

- massive improvements in environmental quality are beginning to decouple the income/environmental gradient - so much so, that over some range of income in more recent years, environmental quality looks to be an inferior good for richer households. Whether and to what extent environmental quality is a

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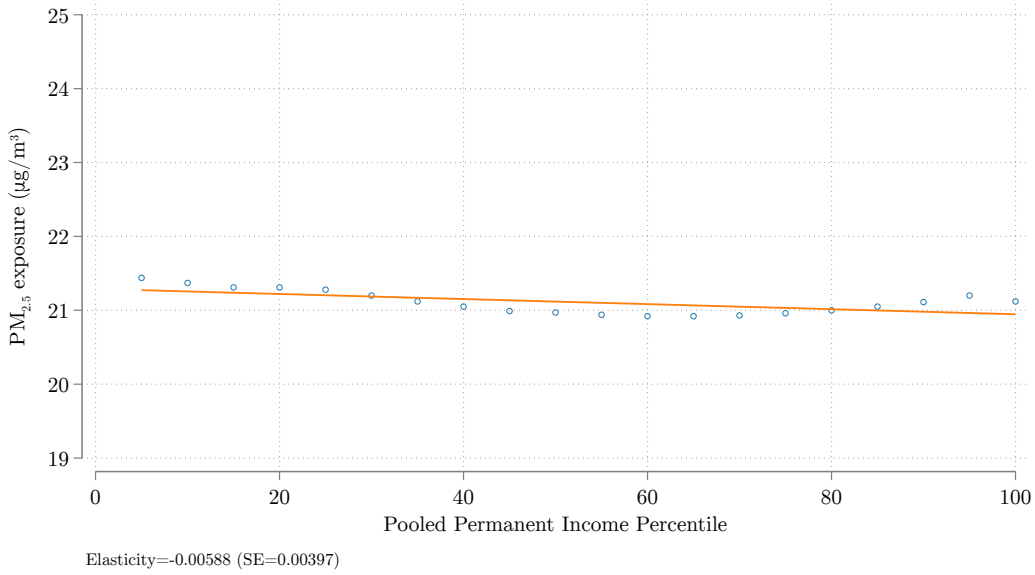
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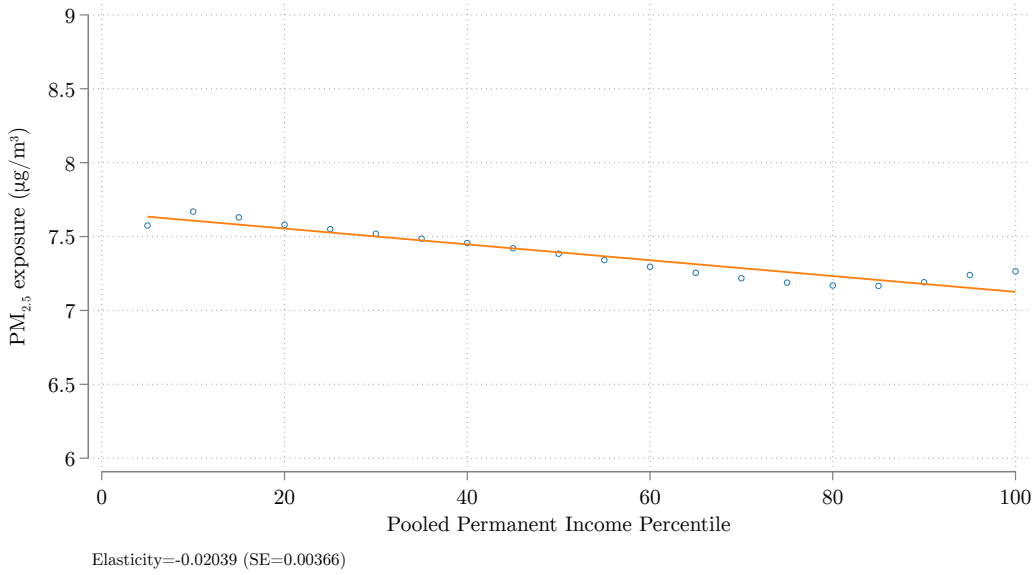
7 Tables and Figures

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

(a) 1984



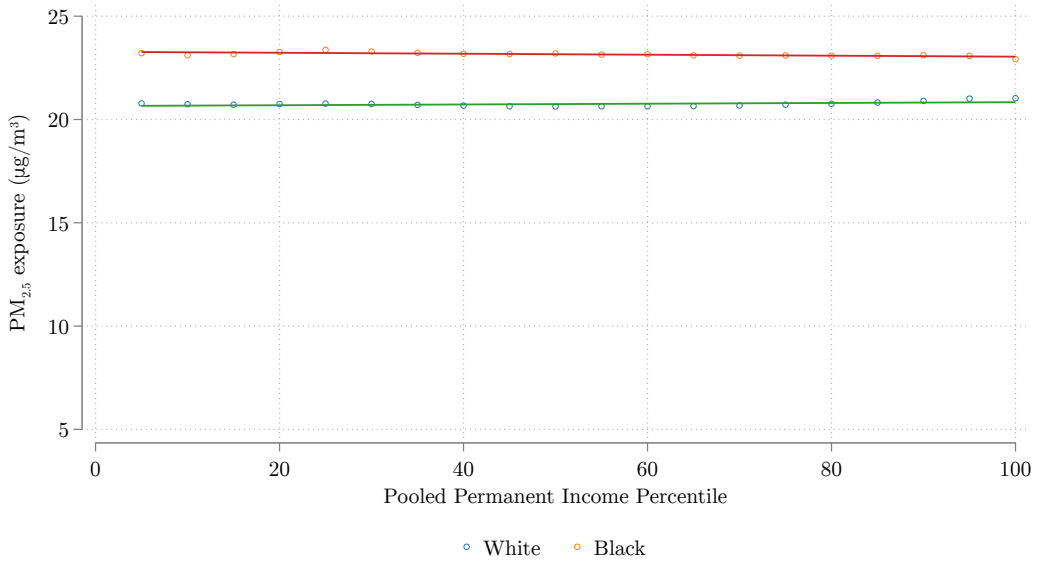
(b) 2016



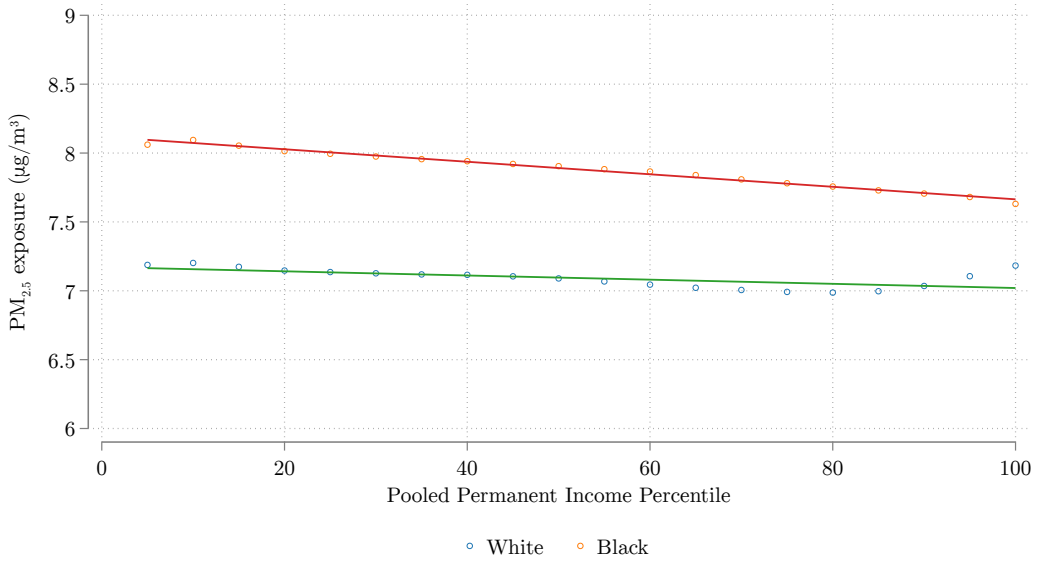
NOTES: These figures plot the average $PM_{2.5}$ exposure level by permanent income percentile for a given year. The income percentiles are constructed from all prime-aged U.S. tax filers in a given year who report positive adjusted gross income. The plotted line represents the best linear fit to these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

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

(a) 1984

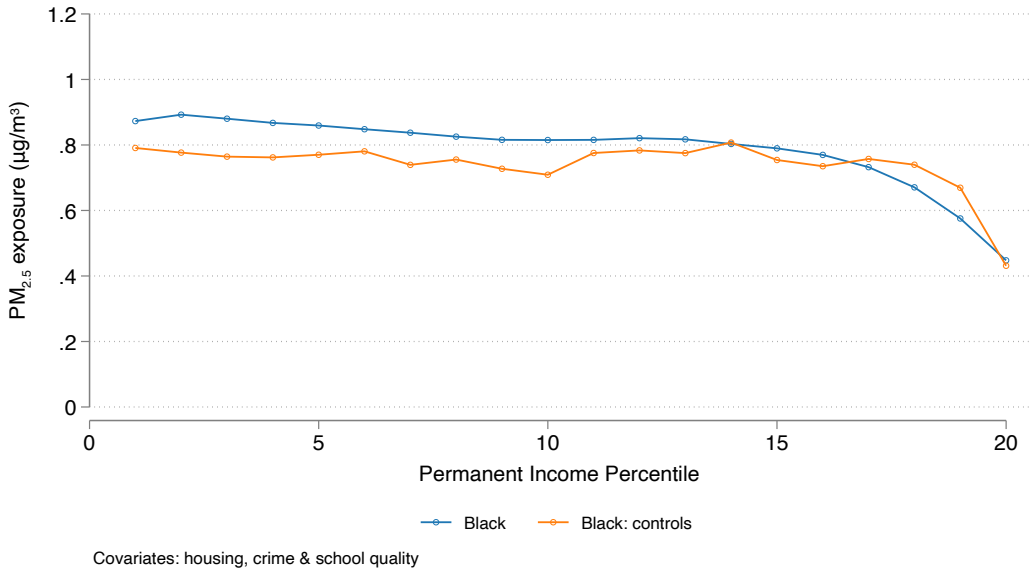


(b) 2016



NOTES: These figures plot the average $PM_{2.5}$ exposure level 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.

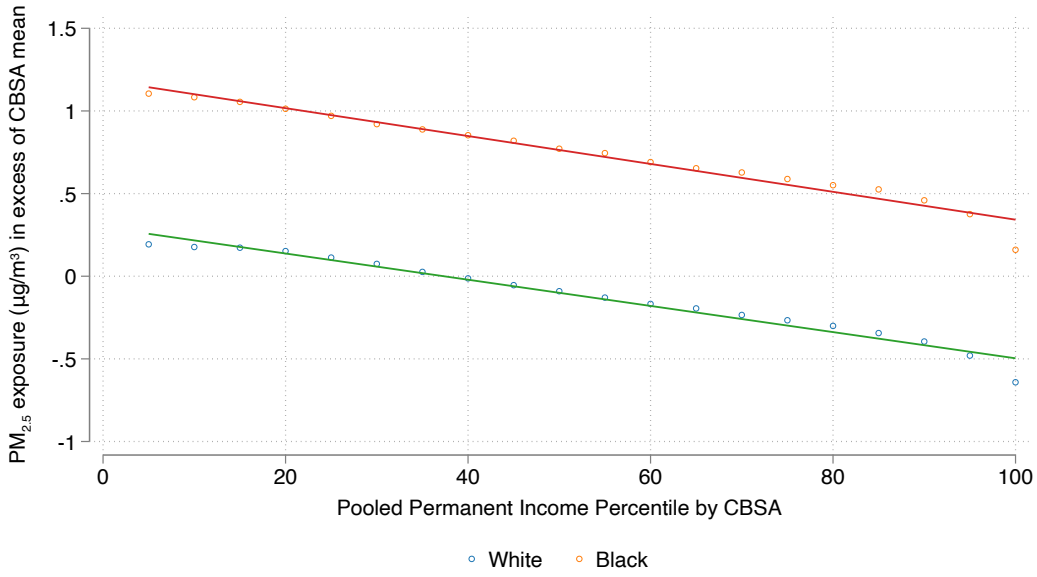
Figure 3: Conditional versus Unconditional Black-White Gap in $PM_{2.5}$ Exposure by Income



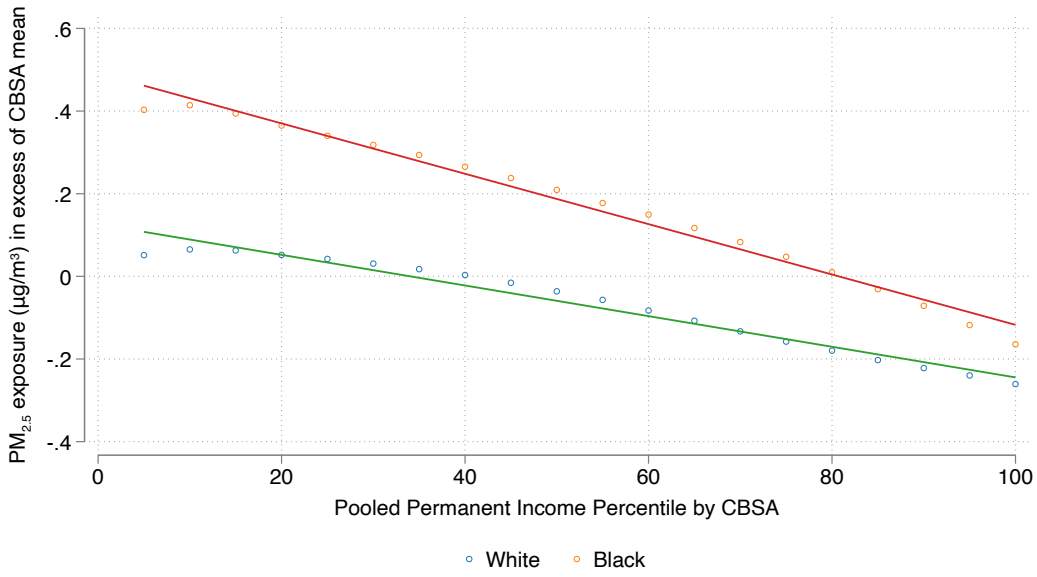
NOTES: This figure plots the average difference in Black versus White household $PM_{2.5}$ exposure level by permanent income percentile in 2016. The blue line represents the Black-White gap in conditional mean $PM_{2.5}$ exposure at a given income percentile. The orange line represents the Black-White gap in conditional mean $PM_{2.5}$ exposure 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



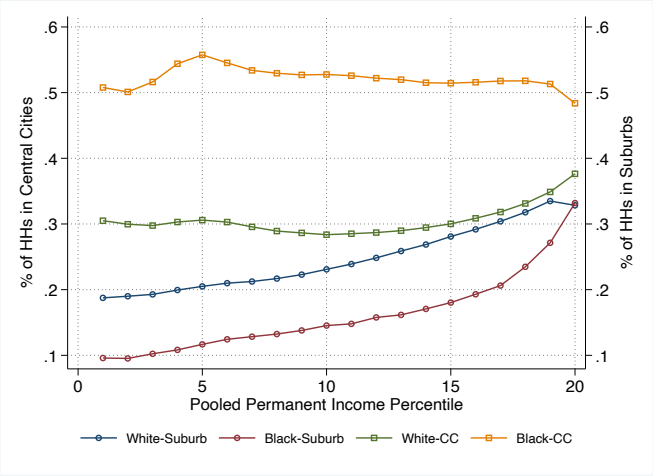
(b) 2016



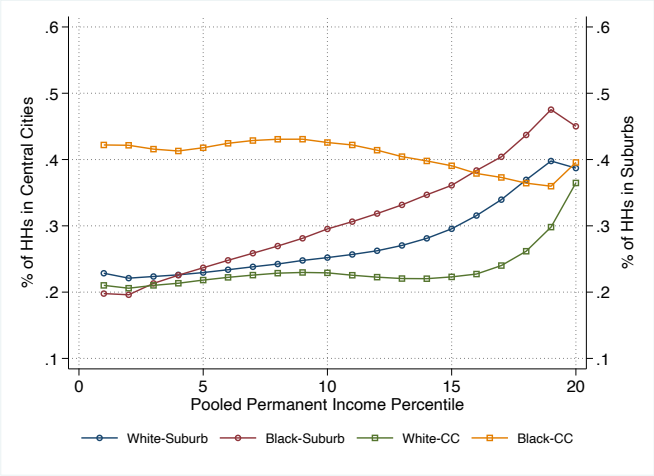
NOTES: These figures plot the average $PM_{2.5}$ exposure level in excess of the CBSA mean by CBSA-specific permanent income percentile, separately by race. The pollution exposure averages are calculated as the household exposure in excess of the overall CBSA mean, averaged across each percentile rank 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



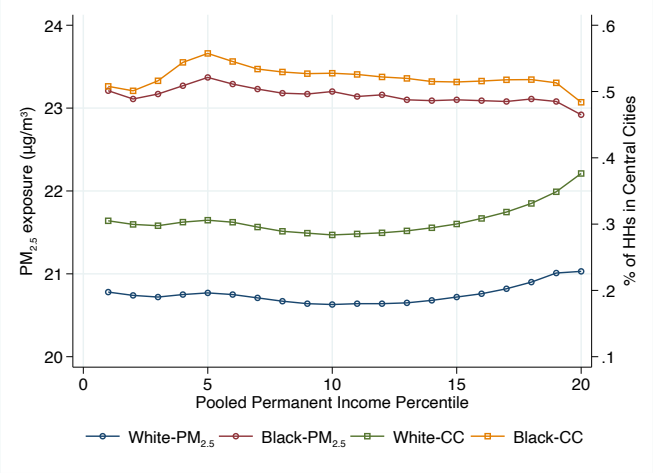
(b) 2016



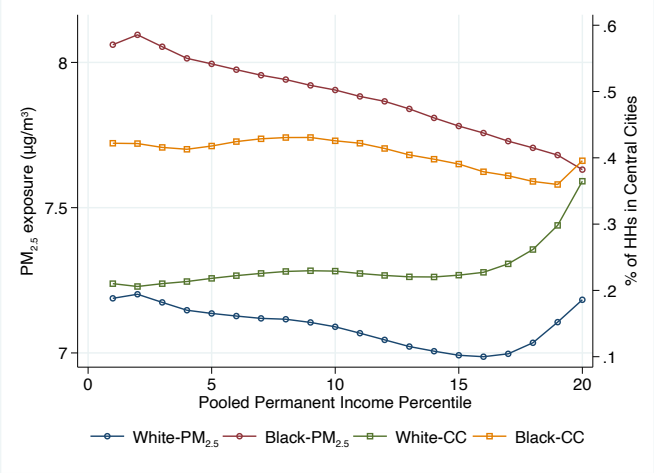
Notes: These figures plot the percentage of households that reside in central cities and suburban locations, separately by race and income percentile. Figure 5a plots these patterns for 1984 while Figure 5b plots these patterns for 2016. The income percentiles are constructed from all prime-aged U.S.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



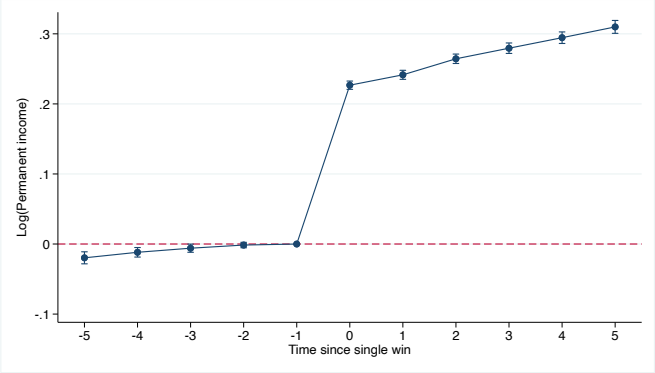
(b) 2016



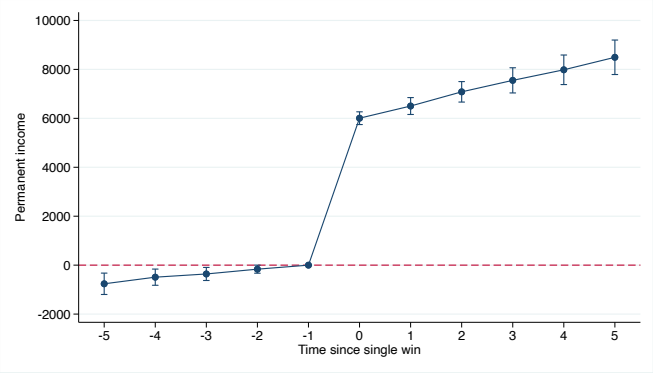
Notes: These figures plot the average $PM_{2.5}$ exposure level by permanent income percentile overlaid with the percentage of households that reside in central cities, separately by race. Figure 6a plots these patterns for 1984 while Figure 6b plots these patterns for 2016. The income percentiles are 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

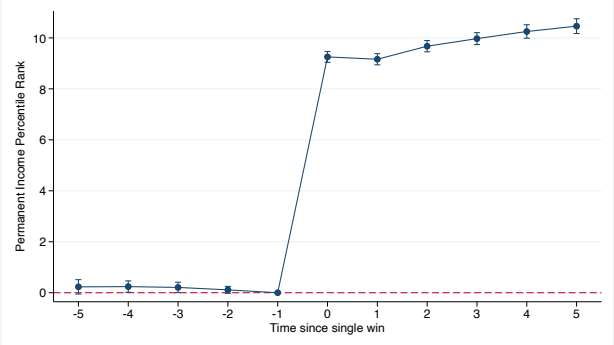
(a) Log(Permanent Income)



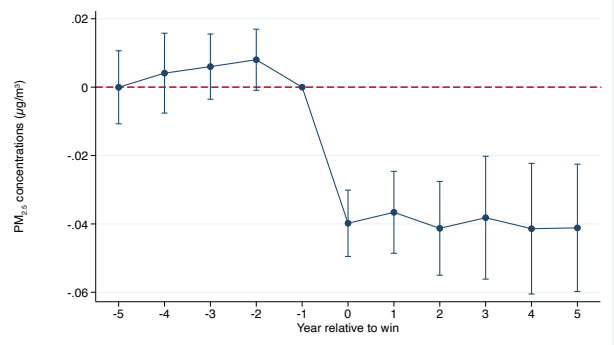
(b) Permanent Income



(c) Permanent Income Percentile Rank



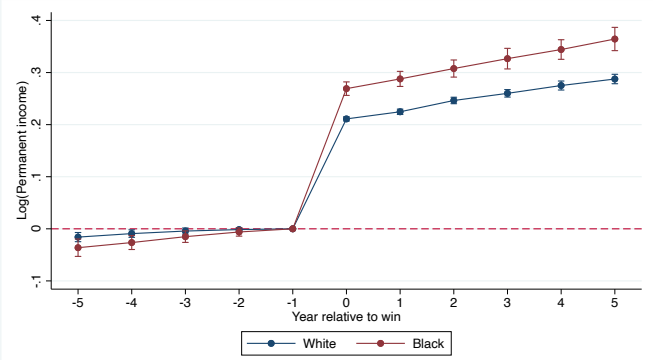
(d) $PM_{2.5}$ Concentrations



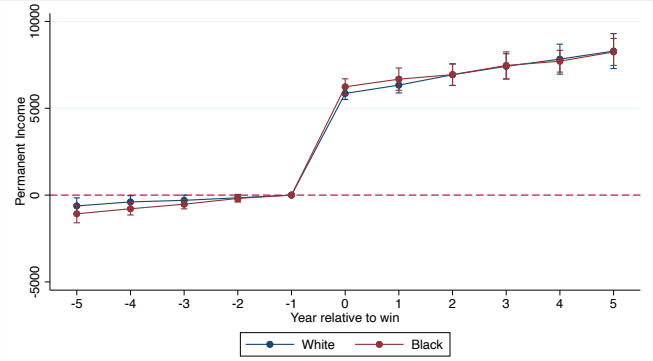
NOTES: These event study figures plot the $\hat{\beta}_e$ coefficients from Equation (1) estimated with various outcomes, as labeled. All specifications are estimated with CBSA×year fixed effects. Standard errors are clustered at the CBSA level.

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

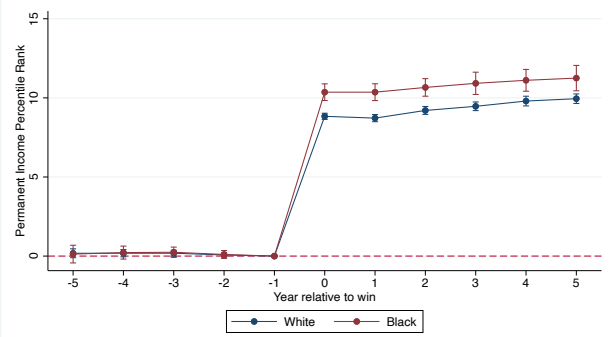
(a) Log(Permanent Income)



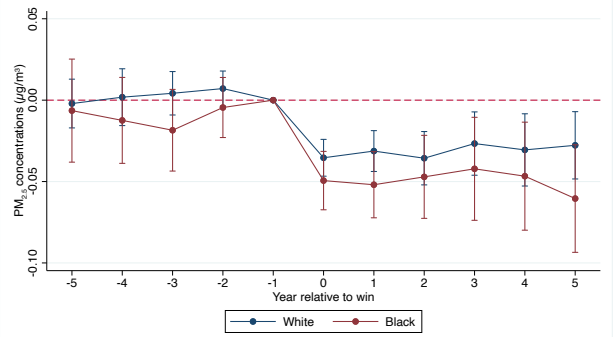
(b) Permanent Income



(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: PM2.5-Permanent Income Estimates by Race and Year

	Panel A: PM2.5 elasticity in 1984			
Dep. variable: Log PM2.5 exposure	White	Black	Hispanic	Asian
Log Permanent Income	0.0043	-0.0021	0.0106	-0.0140
	(0.0051)	(0.0041)	(0.0085)	(0.0038)
N	39810000	4519000	3003000	1104000
	Panel B: PM2.5 rank elasticity in 1984			
Dep. variable: PM2.5 exposure 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	39810000	4519000	3003000	1104000
	Panel C: PM2.5 elasticity in 2016			
Dep. variable: Log PM2.5 exposure	White	Black	Hispanic	Asian
Log Permanent Income	-0.0045	-0.0160	-0.0156	-0.0225
	(0.0046)	(0.0028)	(0.0028)	(0.0050)
N	59630000	10380000	13000000	4996000
	Panel B: PM2.5 rank elasticity in 2016			
Dep. variable: PM2.5 exposure 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	59630000	10380000	13000000	4996000

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 household rank in the 1984 $PM_{2.5}$ distribution on the household 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 PM2.5-Permanent Income Estimates by Race and Year

	Panel A: PM2.5 elasticity in 1984			
Dep. variable: Log PM2.5 exposure	White	Black	Hispanic	Asian
Log Permanent Income	-0.0142	-0.0099	-0.0093	-0.0176
	(0.0011)	(0.0010)	(0.0017)	(0.0015)
N	39810000	4519000	3003000	1104000
	Panel B: PM2.5 rank elasticity in 1984			
Dep. variable: PM2.5 exposure 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	39810000	4519000	3003000	1104000
	Panel C: PM2.5 elasticity in 2016			
Dep. variable: Log PM2.5 exposure	White	Black	Hispanic	Asian
Log Permanent Income	-0.0157	-0.0167	-0.0195	-0.0198
	(0.0012)	(0.0013)	(0.0020)	(0.0021)
N	59630000	10380000	13000000	4996000
	Panel B: PM2.5 rank elasticity in 2016			
Dep. variable: PM2.5 exposure 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	59630000	10380000	13000000	4996000

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 household rank in the 1984 $PM_{2.5}$ distribution on the household 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 PM2.5-Permanent Income Estimates: 1984 Locations with 2016 PM2.5

	(1) Black 1984 OLS Elasticity	(2) Black 2016 Actual	(3) Black 2016 Counterfactual
Log Permanent Income	**TO BE DISCLOSED**		
Model	CBSA FE	CBSA FE	CBSA FE

NOTES:

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

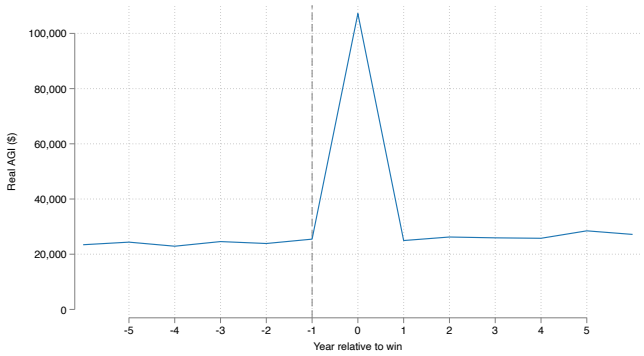
	Panel A: OLS elasticity			
	White	Black	Hispanic	Asian
Log Permanent Income	-0.0172	-0.0152	-0.0153	-0.0125
	(0.0025)	(0.0021)	(0.0037)	(0.0039)
	Panel B: Reduced form			
	White	Black	Hispanic	Asian
Winner × Post	-0.0040	-0.0042	-0.0035	-0.0066
	(0.0013)	(0.0015)	(0.0021)	(0.0056)
	Panel C: First stage			
	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	420000	68000	52000	23000

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.

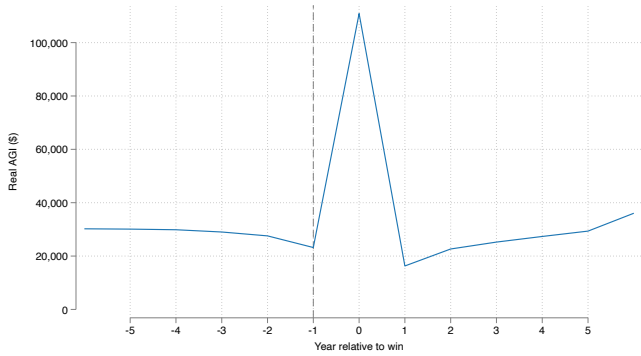
Appendix Figures and Tables

Figure A1: Comparison of Income Trajectories of Maine Lottery Winners to Synthetic "Lottery Winners"

(a) Maine



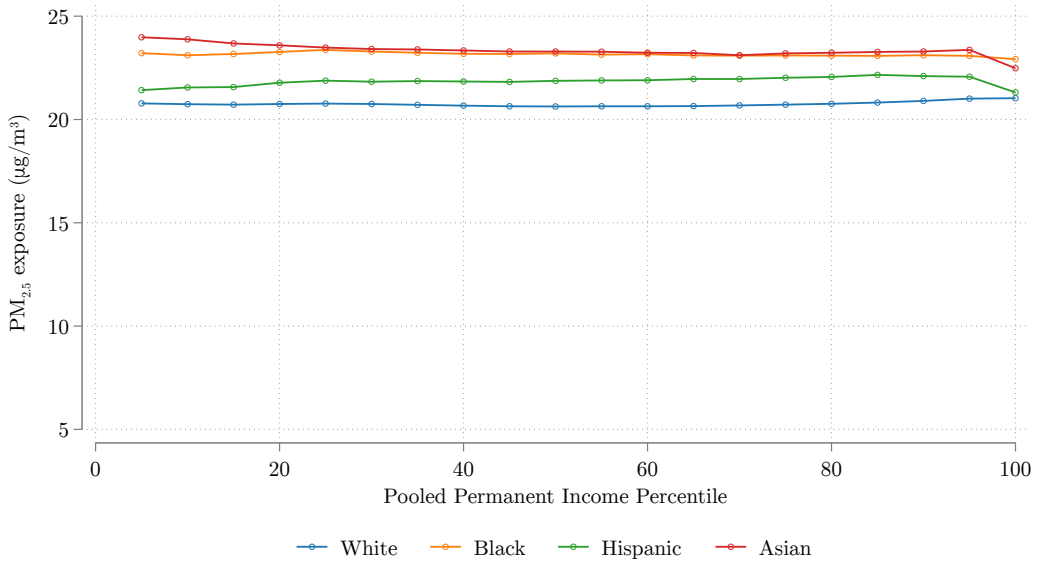
(b) Synthetic



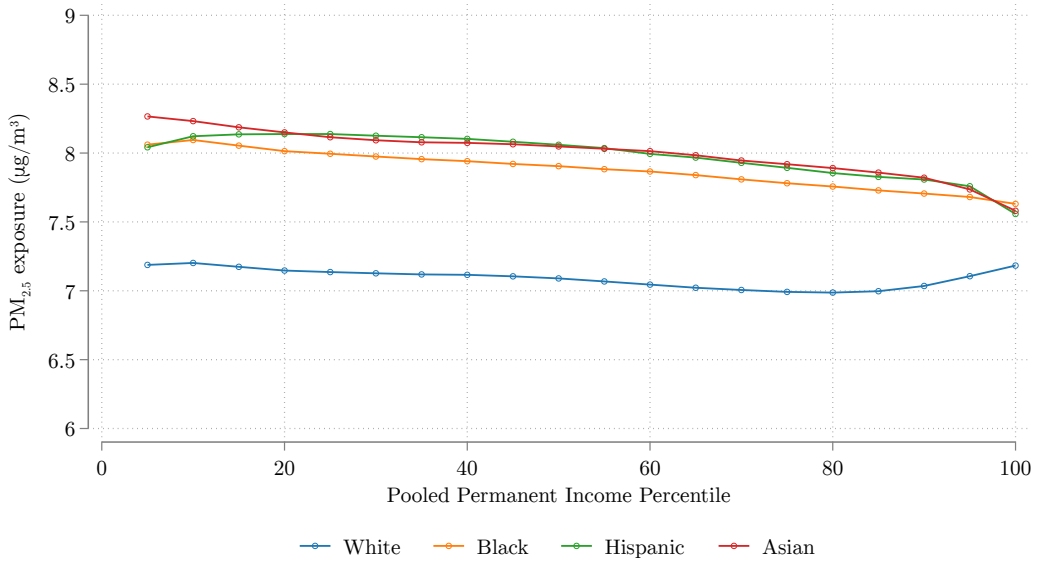
Notes: Panel A plots the income trajectories of lottery winners in Maine in the years before and after winning the lottery. Panel B plots the income trajectories of synthetic lottery winners from the national sample in the years before and after winning the lottery.

Figure A2: Relationship Between Permanent Income and $PM_{2.5}$ Exposure, Separately by Race

(a) 1984



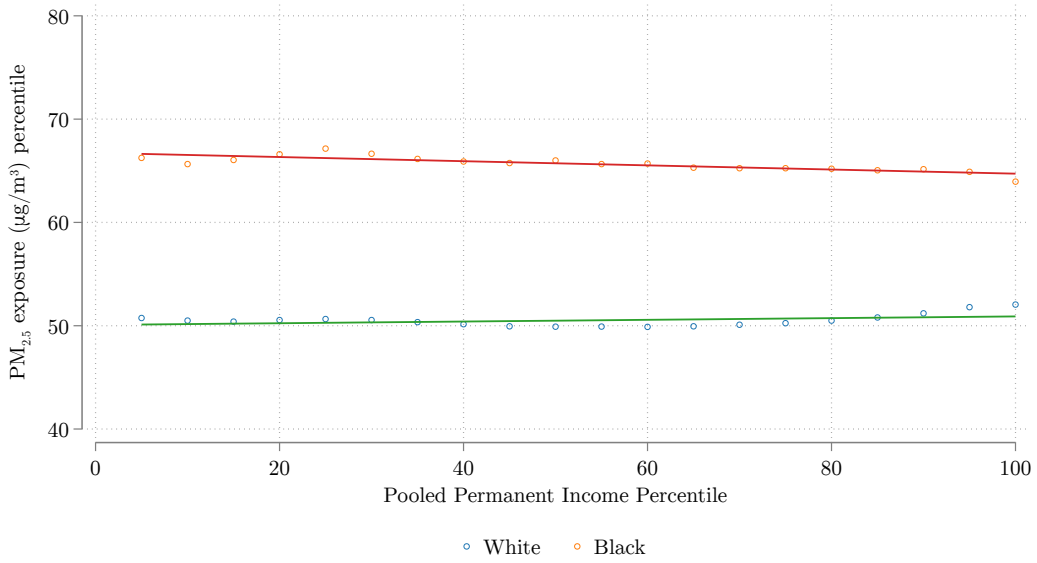
(b) 2016



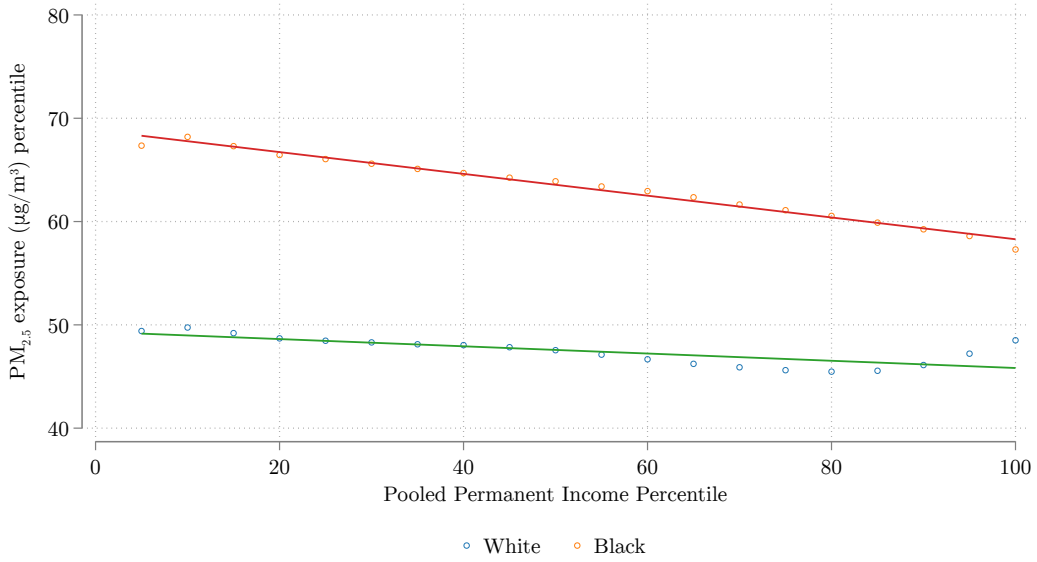
NOTES: These figures plot the average $PM_{2.5}$ exposure level by permanent income percentile for a given year, separately by race. The income percentiles are constructed from all prime-aged U.S. tax filers in a given year who report positive adjusted gross income.

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

(a) 1984

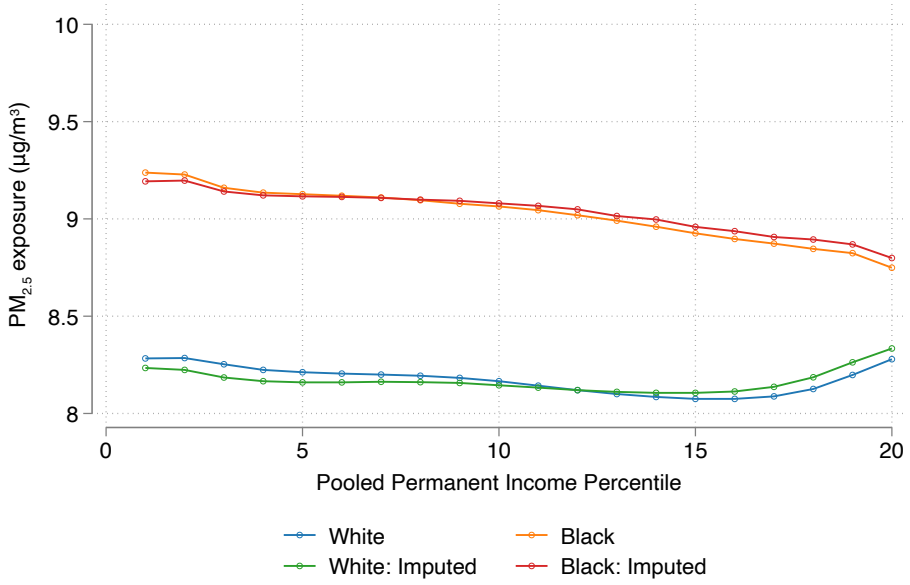


(b) 2016



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.

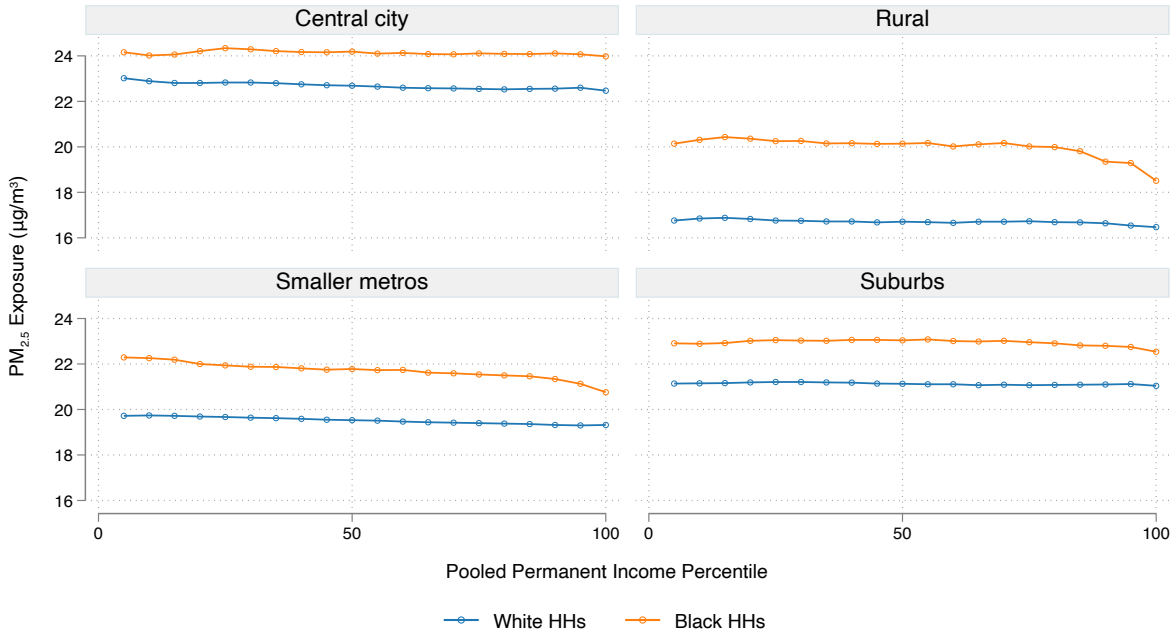
Figure A4: Relationship Between Permanent Income and PM2.5 Exposure using W-2 Imputed Income for Non-filers, 2016



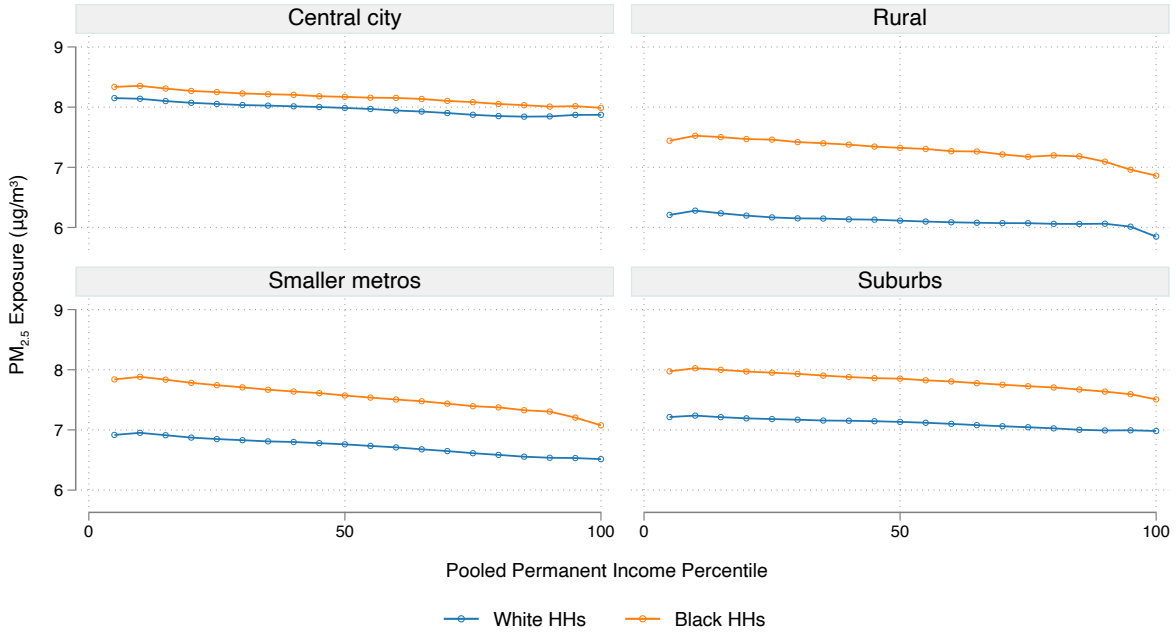
Notes: These figures plot the average $PM_{2.5}$ exposure level by permanent income percentile in 2016, separately by race. The income percentiles are constructed from all prime-aged U.S. tax filers in a given year who report positive adjusted gross income. The imputed AGI percentile ranks are constructed 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 A5: Relationship Between Permanent Income and PM2.5 Exposure, by Urban Area Type

(a) 1984



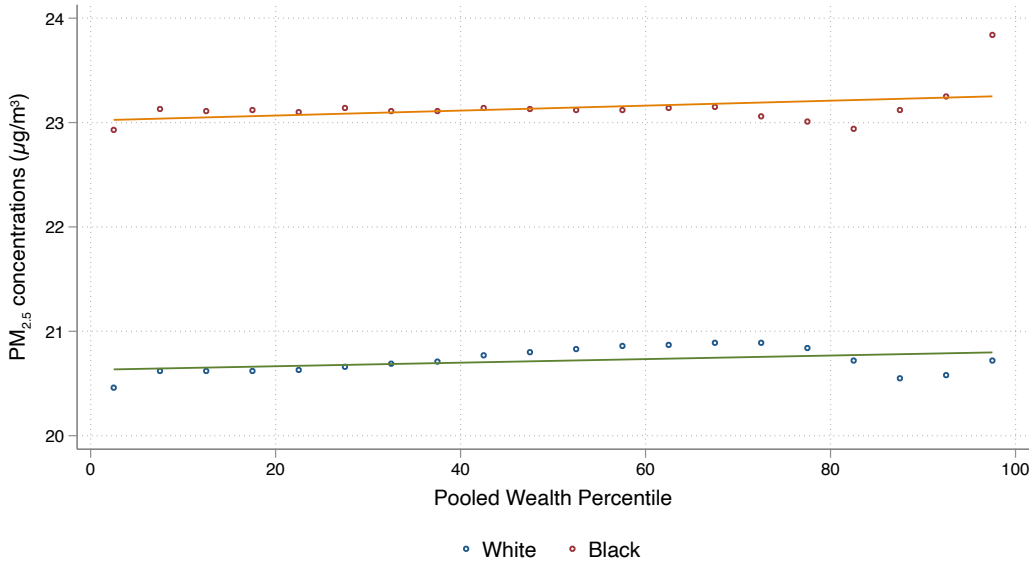
(b) 2016



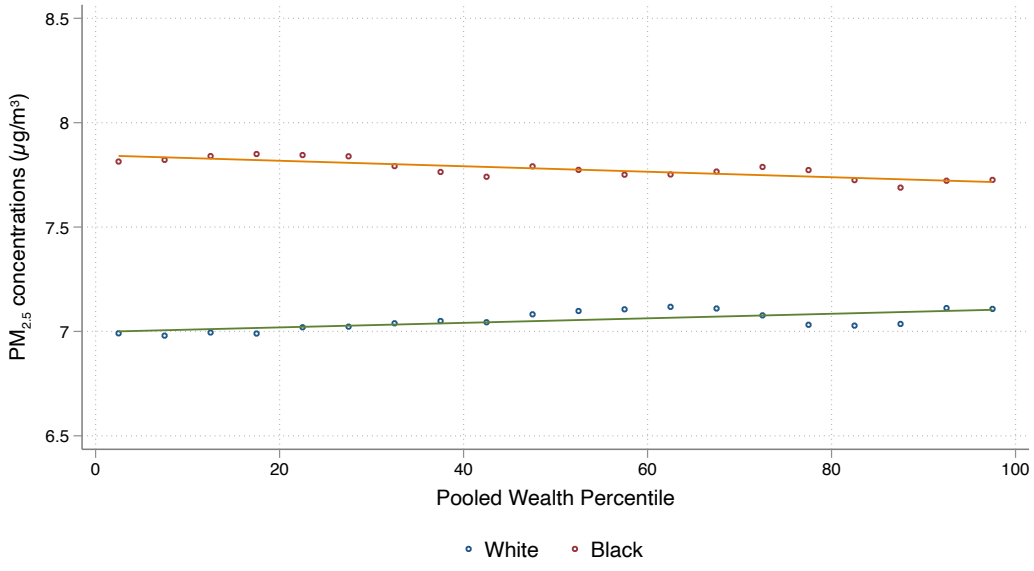
Notes: These figures plot the average $PM_{2.5}$ exposure level by permanent income percentile in 2016, separately by race. The income percentiles are constructed from all prime-aged U.S. tax filers in a given year who report positive adjusted gross income. We classify households into locations using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

Figure A6: Relationship Between Wealth and $PM_{2.5}$ Exposure, Separately by Race

(a) 1984



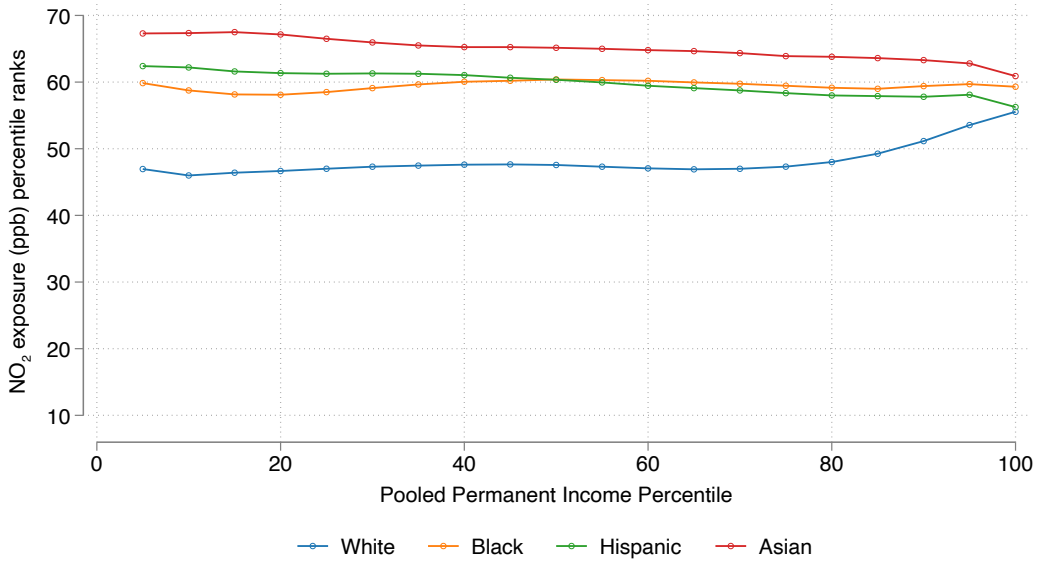
(b) 2016



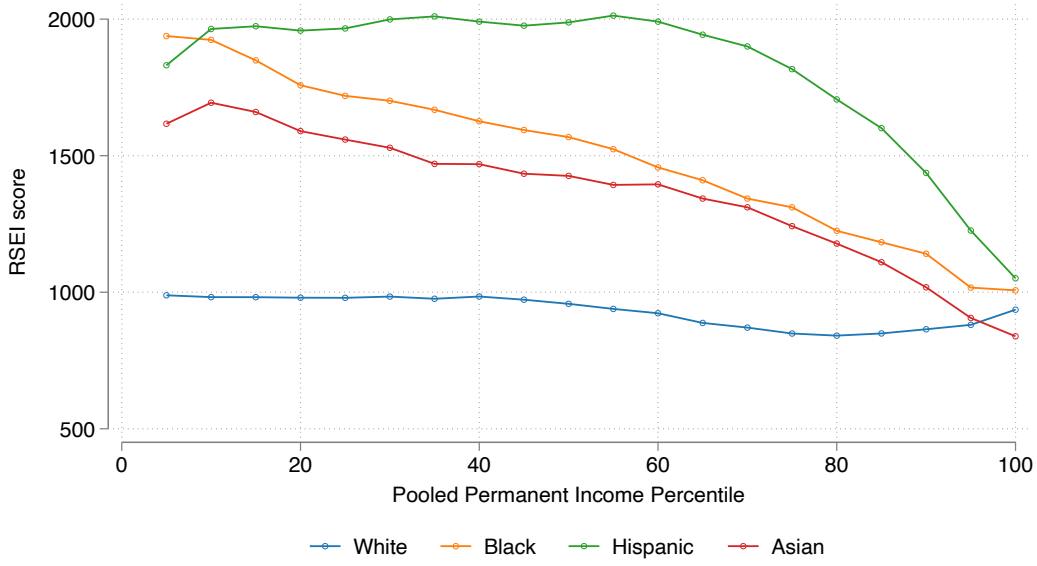
NOTES: These figures plot the average $PM_{2.5}$ exposure level by wealth percentile for a given year, separately by race. The wealth percentiles are constructed from all prime-aged U.S. tax filers in a given year who have non-zero capital income. The plotted line represents the best linear fit to these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

Figure A7: Relationship Between Permanent Income and Other Pollutants in 2016, Separately by Race

(a) NO_2



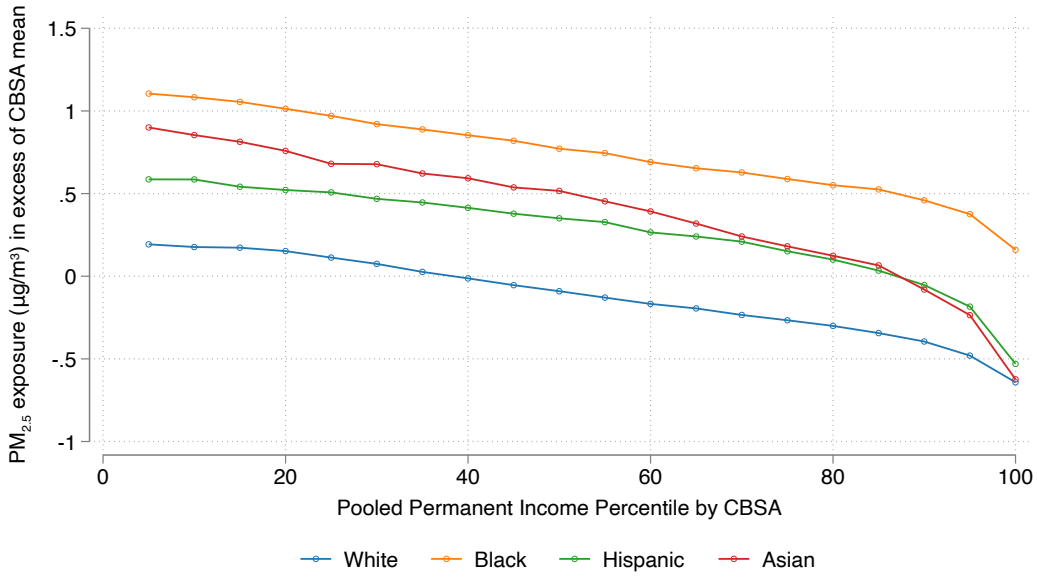
(b) RSEI



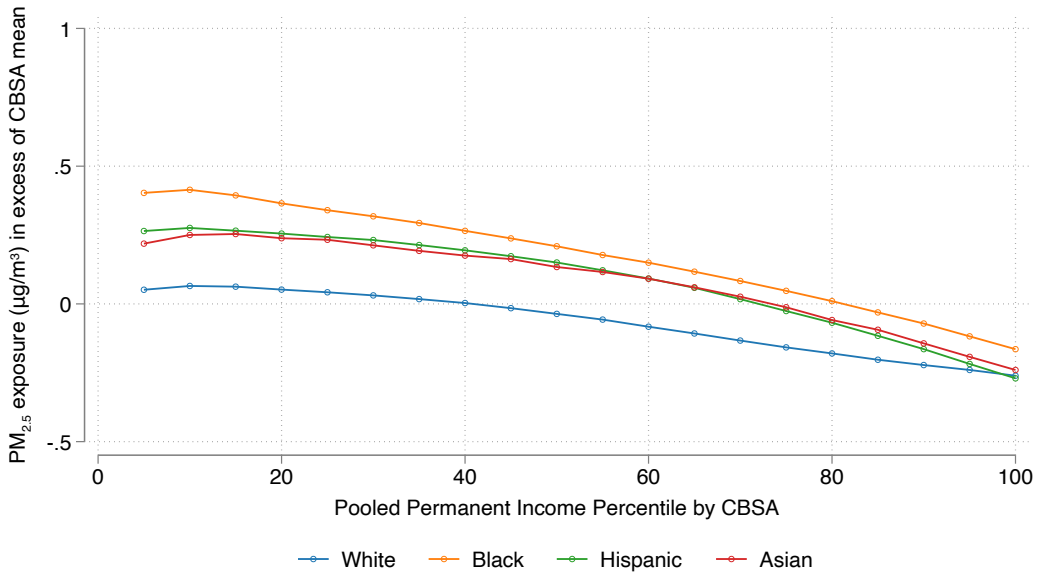
NOTES: These figures plot the average concentrations of NO_2 and the average RSEI score by permanent income percentile in 2016, separately by race. The income percentiles are constructed from all prime-aged U.S. tax filers in a given year who report positive adjusted gross income.

Figure A8: Relationship Between Income and $PM_{2.5}$ Exposure, Within CBSA

(a) 1984



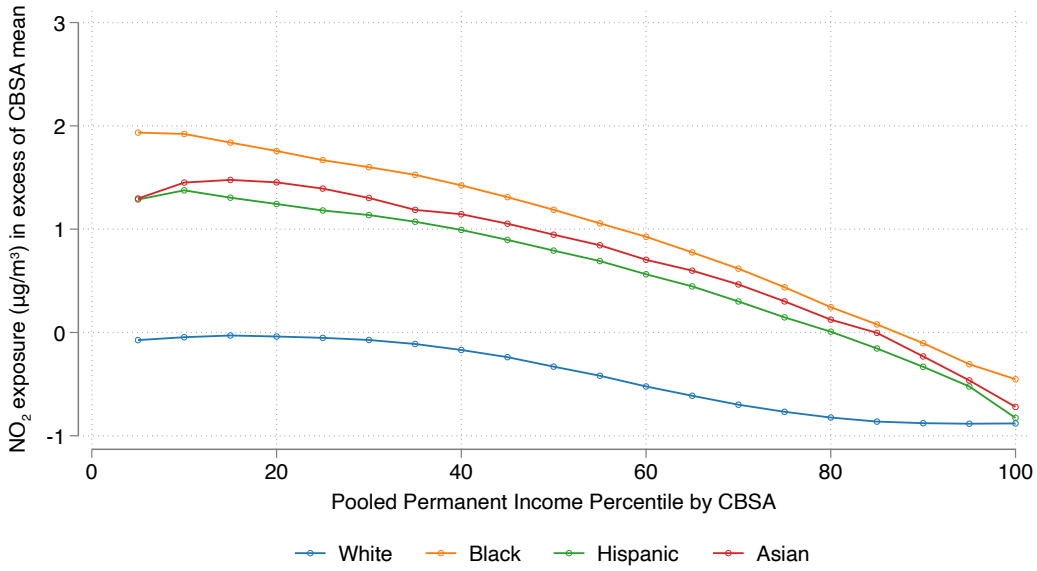
(b) 2016



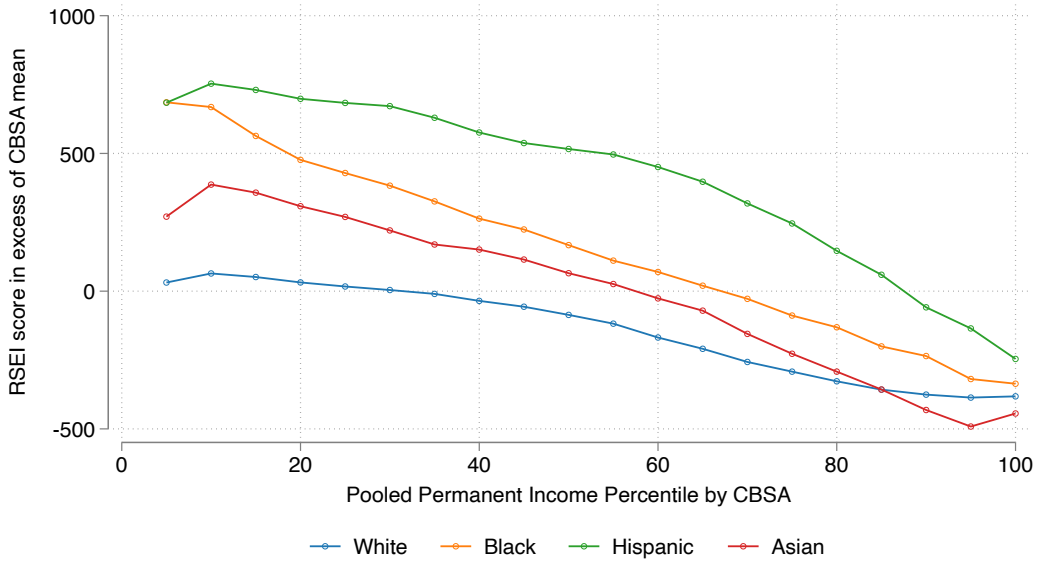
NOTES: These figures plot the average $PM_{2.5}$ exposure level in excess of the CBSA mean by CBSA-specific permanent income percentile, separately by race. The pollution exposure averages are calculated as the household exposure in excess of the overall CBSA mean, averaged across each percentile rank 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 A9: Relationship Between Permanent Income and Other Pollutants in 2016, Within CBSA, Separately by Race

(a) NO_2

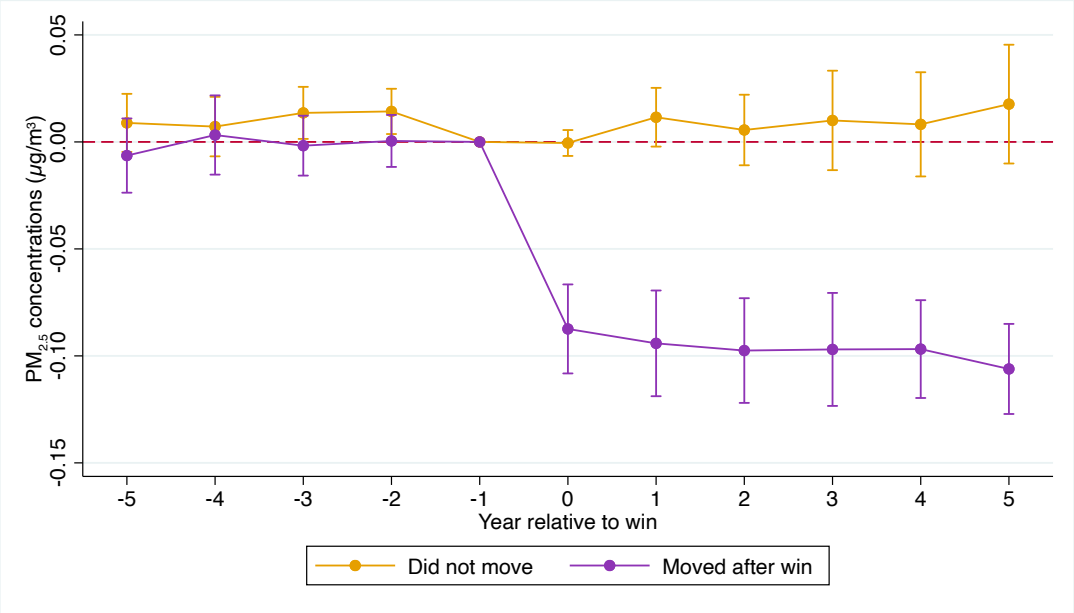


(b) RSEI



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 exposure averages are calculated as the household exposure 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.

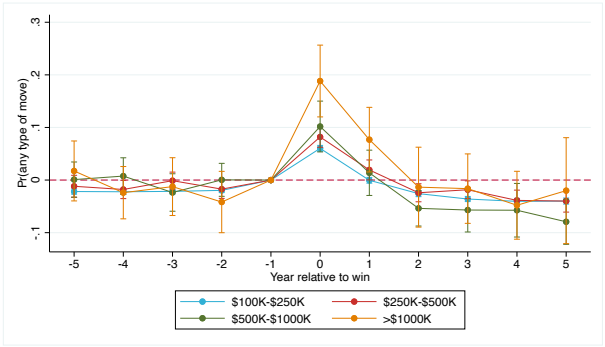
Figure A10: Event Study Estimates Using Lottery Winners, by Mobility Status



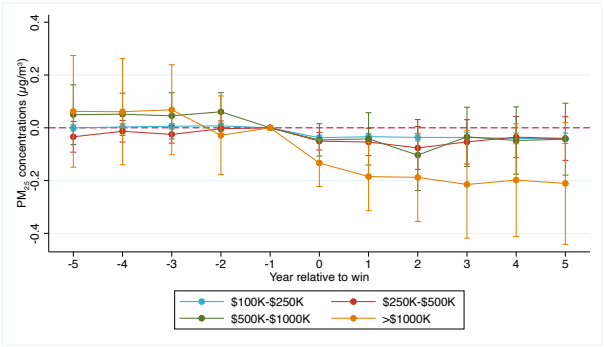
NOTES: This figure plots the $\hat{\beta}_e$ coefficients from Equation (1) for households that move after a lottery win and for households that do not move after a lottery win. All specifications are estimated with CBSA×year fixed effects. Standard errors are clustered at the CBSA level.

Figure A11: 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 A11a is a binary indicator for whether a move was observed in a given period. The dependent variable in Figure A11b corresponds to household $PM_{2.5}$ exposure. All specifications are estimated with CBSA×year fixed effects. Standard errors are clustered at the CBSA level.

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

	Panel A: White Subsample						
	Log(PM2.5)	Log Property Value	Log(Rent)	Log Homeownership	Log School Proficiency	Log Crime Rate PC	Log Violent Crime Rate PC
Log Real AGI	-0.01142	0.06028	0.03802	0.06682	0.01971	-0.01762	-0.02207
	(0.0005500)	(0.002520)	(0.001670)	(0.002340)	(0.001310)	(0.001760)	(0.002500)
Constant	2.359	8.09500	5.363	3.313	3.906	8.514	7.337
	(0.005350)	(0.02437)	(0.01644)	(0.02286)	(0.01285)	(0.01724)	(0.02452)
N	1840000	1840000	1840000	1840000	1840000	1840000	1840000
	Panel B: IV elasticity						
	Log(PM2.5)	Log Property Value	Log(Rent)	Log Homeownership	Log School Proficiency	Log Crime Rate PC	Log Violent Crime Rate PC
Log Real AGI	-0.03727	0.5640	0.1776	0.4454	0.1280	-0.06963	-0.08147
	(0.02358)	(0.06238)	(0.02923)	(0.06176)	(0.02467)	(0.03271)	(0.04311)
Constant	2.608	3.243	4.019	-0.3340	2.863	9.015	7.909
N	1840000	1840000	1840000	1840000	1840000	1840000	1840000

Notes: The table displays OLS estimates from regressing various log amenity attributes on log AGI in Panel A using the matched control sample. Panel B and C display the first stage and IV elasticity estimates from Equation (2) 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.

Table A2: Matched-controls Lottery OLS, 1st stage, & IV results with CBSA×year FEs: all amenities, 2001-2016 consistent sample

	Panel A: OLS elasticity						
	log(crimepc)	log(homeownership)	log(pctprof)	log(propertyval)	log(rent)	log(violcrimepc)	l(pmCE)
Log Real AGI	-0.0342	0.1079	0.0363	0.1190	0.0633	-0.0405	-0.0207
	(0.0046)	(0.0047)	(0.0030)	(0.0056)	(0.0033)	(0.0063)	(0.0015)
	Panel B: IV elasticity						
	log(crimepc)	log(homeownership)	log(pctprof)	log(propertyval)	log(rent)	log(violcrimepc)	l(pmCE)
Log Real AGI	-0.0208	0.1149	0.0169	0.0939	0.0538	-0.0282	-0.0092
	(0.0097)	(0.0146)	(0.0051)	(0.0138)	(0.0104)	(0.0153)	(0.0064)
N	261000	261000	261000	261000	261000	261000	261000

Notes: The table displays OLS estimates from regressing various log amenity attributes on log AGI in Panel A using the matched control sample. Panel B and C display the first stage and IV elasticity estimates from Equation (2) 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.

Table A3: Matched-controls Lottery OLS, 1st stage, & IV results with CBSA×year FEs: all amenities, 2001-2016 consistent sample

	Panel A: OLS elasticity						
	log(crimepc)	log(homeownership)	log(pctprof)	log(propertyval)	log(rent)	log(violcrimepc)	l(pmCE)
Log Real AGI	-0.0427	0.1249	0.0256	0.0956	0.0783	-0.0499	-0.0169
	(0.0093)	(0.0115)	(0.0057)	(0.0133)	(0.0079)	(0.0119)	(0.0024)
	Panel B: IV elasticity						
	log(crimepc)	log(homeownership)	log(pctprof)	log(propertyval)	log(rent)	log(violcrimepc)	l(pmCE)
Log Real AGI	-0.0331	0.1527	0.0062	0.0677	0.0553	-0.0495	-0.0085
	(0.0126)	(0.0282)	(0.0100)	(0.0218)	(0.0185)	(0.0161)	(0.0038)
N	30000	30000	30000	30000	30000	30000	30000

Notes: The table displays OLS estimates from regressing various log amenity attributes on log AGI in Panel A using the matched control sample. Panel B and C display the first stage and IV elasticity estimates from Equation (2) 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.

Table A4: Matched-controls 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 Real AGI	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 Real AGI	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 in Panel A using the matched control sample. Panel B and C display the first stage and IV elasticity estimates from Equation (2) 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.