Air Pollution and Economic Opportunity in the United States[*]

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Abstract

Neighborhoods are an important determinant of economic opportunity in the United States. Less clear is *how* neighborhoods affect economic opportunity. Here we provide early evidence on the importance of environmental quality in shaping economic opportunity. Combining 36 years of satellite derived $PM_{2.5}$ concentrations measured over roughly 8.6 million grid cells with individual-level administrative data provided by the U.S. Census Bureau and Internal Revenue Service (IRS), we first document a new fact: early-life exposure to particulate matter is one of the top five predictors of upward mobility in the United States. Next, using regulation-induced reductions in prenatal pollution exposure following the 1990 Clean Air Act Amendments, we estimate significant increases in adult earnings and upward mobility. Combining our estimates with new individual-level measures of pollution disparities at birth our estimates can account for up to 20 percent of Black-White earnings gaps, and 25 percent of the Black-White gap in upward mobility estimated in Chetty et al. (2018b). Combining our estimates with experiment-induced reductions in pollution exposure from the Moving to Opportunity (MTO) experiment, we can account for 15 percent of the total neighborhood earnings effect estimated in Chetty et al. (2016). Collectively, these findings suggest that disparities in environmental quality may play a meaningful role in explaining observed patterns of income inequality and economic opportunity in the United States.

[*]Any opinions and conclusions expressed herein are those of the authors and do not necessarily reflect the views of the U.S. Census Bureau. The Census Bureau's Disclosure Review Board and Disclosure Avoidance Officers have reviewed this data product for unauthorized disclosure of confidential information and have approved the disclosure avoidance practices applied to this release, authorization numbers CBDRB-FY21-CES014-007, CBDRB-FY21-CES014-036, CBDRB-FY21-CES014-044 and CBDRB-FY22-CES014-001.

1 Introduction

Neighborhoods shape economic opportunity (Chetty et al., 2014; Sharkey and Faber, 2014; Chetty et al., 2016; Galster and Sharkey, 2017; Chetty et al., 2018b; Chetty and Hendren, 2018a,b; Chyn and Katz, 2021). But what it is about neighborhoods that matters for economic opportunity is less clear.

One margin that has received little attention is the role of environmental quality. In the past decade our understanding of the economic consequences of environmental quality has grown dramatically. It is now well established that even acute exposure to pollution has both immediate and persistent long-run effects on health, educational attainment, learning, decision-making, productivity, criminal activity, labor force participation, and earnings (Chay and Greenstone, 2003b; Currie and Neidell, 2005; Graff Zivin, J. and Neidell, M., 2012; Schlenker and Walker, 2015; Chang et al., 2016; Ebenstein et al., 2016; Isen et al., 2017; Chang et al., 2018). Higher exposure to particulate matter in early childhood has even been shown to have persistent effects across generations affecting later-life economic outcomes for the children of those that were in-utero exposed (Colmer and Voorheis, 2019). Alongside these causal estimates, it is widely documented that economic and environmental inequality walk hand-in-hand. Disadvantaged communities are disproportionately exposed to higher levels of pollution (Commission for Racial Justice, United Church of Christ, 1987; Mohai et al., 2009; Banzhaf et al., 2019; Colmer et al., 2020; Currie et al., 2020). Taken together, it is natural to consider how much of a role environmental quality could contribute to systemic disparities in economic opportunity and inequality.

To date, understanding the role of environmental quality in shaping economic opportunity has been constrained by data availability. While access to administrative data has driven research on inequality and opportunity into new frontiers, comprehensive historical data on environmental quality has lagged behind. We take advantage of recent advances in the availability of both environmental and administrative data, combining 36 years of satellite-derived, high-resolution data on particulate matter smaller than 2.5 microns ($PM_{2.5}$) concentrations, with U.S. Census Bureau linked survey data and administrative records on individuals' residences, earnings and economic mobility.

We begin by presenting a new set of stylized facts. Replicating the analysis conducted by Chetty et al. (2014), we show that the spatial distribution of early childhood exposure to particulate matter and the spatial distribution of economic opportunity are strongly correlated. We document that $PM_{2.5}$ exposure is one of the top five predictors of upward mobility in the United States. We further show that at the individual level, pollution exposure in utero is correlated with individual level upward mobility, measured by the difference between a child's income rank and their parent's rank.

To explore the contribution of environmental quality to economic opportunity we engage in two empirical exercises. Our first analysis provides new estimates of the effect of prenatal particulate matter exposure on later-life earnings and upward mobility. Exploiting the introduction of the 1990 Clean Air Act Amendments, we estimate that a 1 $\mu g/m^3$ reduction in prenatal $PM_{2.5}$ exposure is associated with a $1,105 increase in later-life W-2 earnings. This estimate is substantially larger than existing estimates. We argue this difference is driven by both differences in identifying variation, which plausibly result in larger effects, and improvements in data quality, which reduce measurement error. We also estimate that a 1 $\mu g/m^3$ reduction in prenatal $PM_{2.5}$ exposure is associated with a 1.29 percentile rank point increase in upward mobility. For context, the raw correlation between exposure to $PM_{2.5}$ at birth and upward mobility for the 1981 cohort is 0.17 rank points per $\mu g/m^3$ of $PM_{2.5}$.

Combining this estimate with observed prenatal $PM_{2.5}$ gaps we calculate the share of later-life income disparities that can be accounted by our estimate. We calculate that about 20 percent of the contemporary black-white gap in earnings and 25 percent of the black-white gap in upward intergenerational income mobility can be accounted for by racial gaps in prenatal pollution exposure.

Our second exercise, more directly examines the role that environmental quality may play in contributing to the overall "neighborhood effect" on earnings. We revisit the Moving to Opportunity experiment, run by the U.S. Department of Housing and Urban Development, which offered a randomly selected subset of families living in high-poverty housing projects subsidized housing vouchers to move to lower-poverty neighborhoods in the mid-1990s. This intervention generated plausibly exogenous variation in neighborhood environments for otherwise comparable families, providing an opportunity to evaluate the effects of improving neighborhood environments on low-income families (Ludwig et al., 2013; Chetty et al., 2016). Chetty et al. (2016) estimate that the MTO delivered significant increases in later-life earnings for children who moved prior to the age of 13. We present new results showing that treated families experienced persistently lower levels of $PM_{2.5}$ compared to families that did not receive the program. Combining the causal effect of MTO on particulate matter exposure with our estimate of early childhood exposure on later life earnings, we quantify how much of the overall MTO–earnings effect can be accounted for by early-life pollution exposure. Our calculations suggest that the MTO-induced improvements in early life $PM_{2.5}$ exposure can account for 10-30 percent of the earnings effects for children who moved before the age of 13, estimated in Chetty et al. (2016).

Collectively, our findings suggest that environmental quality may play a non-trivial role in explaining systemic patterns of economic opportunity and inequality in the United States.

Our findings contribute to several literatures. First, we contribute to the literature on economic inequality and opportunity. Within this literature, the importance of neighborhoods has been established for the economic opportunities of children (Chetty et al., 2016, 2018a; Chyn, 2018; Deutscher, 2019). However, the particular bundle of characteristics that makes a neighborhood an "opportunity bargain" (Chetty et al., 2018a) has largely remained a black box. We provide evidence to suggest that environmental quality may be an important factor underlying the "neighborhood effect."

Second, we contribute to the literature on the economic importance of environmental quality. To date, much of the focus has been on the short and long-term effects of gestational exposure on health and later life labor market outcomes (Chay and Greenstone, 2003b; Isen et al., 2017; Currie et al., 2013). Although this literature has consistently found that "pollution matters", the degree to which pollution effects contribute to aggregate patterns of economic opportunity has not been discussed. We are the first to directly connect pollution exposure with aggregate patterns of economic opportunity and inequality, as well as providing direct evidence of the effect of prenatal pollution exposure on intergenerational income mobility. This evidence connects with recent work showing multigenerational effects of pollution exposure Colmer and Voorheis (2019), deepening our understanding of how environmental quality can have persistent effects on economic circumstances.

Third, we contribute to the literature on measuring environmental inequality and its causes and consequences. Although a large literature has documented the existence of disparities in exposure across demographic groups (Commission for Racial Justice, United Church of Christ, 1987; Mohai et al., 2009; Banzhaf et al., 2019; Colmer et al., 2020; Currie et al., 2020), less is known about how these disparities have evolved over time, and what the downstream implications of these disparities are. Following Colmer et al. (2020) and Currie et al. (2020) who use satellite data to explore the trends in environmental inequality, we show that pre-existing racial disparities in pollution exposure in 1981 account for a non-trivial share of contemporary racial economic disparities.

2 The Correlation Between Environmental Quality and Economic Opportunity

Despite decades of research on racial and economic disparities in pollution exposure, a systematic evaluation of the relationship between environmental quality and economic opportunity has been hindered by data availability. The main issue is that environmental monitoring networks are sparse. Fowlie et al. (2019) document that fewer than 20 percent of counties contain a monitor that is capable of recording fine particulate matter. Hsiang et al. (2018) calculate that only 40 percent have a monitor capable of recording any of the criteria air pollutants regulated under the Clean Air Act.

Only recently has systematic data on air pollution over time and space become available (Di et al., 2016; Van Donkelaar et al., 2016; Meng et al., 2019). These data products combine spatially continuous satellite measurements of pollution correlates (e.g., aerosol optical depth) with other observable pollution correlates—such as emissions inventories, chemical transport models, weather patterns—to provide a high-resolution and consistent understanding of particulate matter concentrations over time and space. We utilize 36 years of annual and monthly $\mathrm{PM}_{2.5}$ estimates between 1981 and 2016 for $\sim$8.6 million U.S. grid cells that measure 0.01° by 0.01° (0.9 km by 1.1 km). We spatially intersect this data with Census tract boundary files and link it to individual-level administrative records.

On average, these estimates match up well with the "ground truth" as measured by EPA monitors (Colmer et al., 2020). In-sample measures of fit are very high. However, evidence suggests that satellite-derived measures may deviate from the ground truth in the tails of the pollution distribution (Fowlie et al., 2019). Specifically, estimates tend to be downward biased for high concentrations of $PM_{2.5}$ (Di et al., 2016; Van Donkelaar et al., 2016; Meng et al., 2019). Given existing evidence on the incidence of high pollution, this suggests that prediction errors will attenuate measured disparities, providing a lower bound on true gaps in exposure.

2.1 County-Level Facts

Using this data we explore the correlation between early life pollution exposure and upward mobility at the county-level. In Figure 1 we plot three maps of the United States. Panel (a) plots county-level measures of upward mobility for the individuals born between 1978–1982, first presented by Chetty et al. (2014). Panel (b) plots county-level average daily $\mathrm{PM}_{2.5}$ concentrations for the year 1981, aggregated by the authors from new data provided by Meng et al. (2019). Panel (c) plots a heatmap representation of the two measures, presenting a continuous representation of the pollution-mobility relationship. We see that there is substantial spatial heterogeneity in both upward mobility and $\mathrm{PM}_{2.5}$ levels. The most striking observation, however, is the strong visual relationship between the two. In Figure 2 we formalize this relationship, presenting the bivariate relationship between the two variables. We estimate a strong negative correlation between early life $\mathrm{PM}_{2.5}$ levels and upward mobility. A 1 $\mu g/m^3$ reduction in $\mathrm{PM}_{2.5}$ is associated with a 1.28 rank point increase in upward mobility. For context, a 1 $\mu g/m^3$ increase in $\mathrm{PM}_{2.5}$ would be equivalent to moving from the 50th to the 75th percentile of the $PM_{2.5}$ distribution in 2016, and a 1.28 point increase in upward mobility is approximately one tenth the size of the black-white gap in upward mobility from Chetty et al. (2018b).

Second, we document that environmental quality is an important correlate of upward mobility. In Figure 3 we juxtapose the relationship between $PM_{2.5}$ and upward mobility with the bivariate relationships between upward mobility and other neighborhood characteristics, first presented in Chetty et al. (2014). All correlates are standardized for comparability. We observe that $PM_{2.5}$ is one of the top five strongest predictors of upward mobility in the United States. The association between upward mobility and a one standard deviation increase in $PM_{2.5}$ is comparable in magnitude to the association between upward mobility and a one standard deviation increase in the share of residents that are black, a one standard deviation decrease in the share of workers that live within 15 minutes of work, a one standard deviation increase in the Gini coefficient, a one standard deviation decrease in income-adjusted test scores, a one standard deviation increase in the share of high school dropouts, a one standard deviation decrease in the social capital index, a one standard deviation decrease in the share of households that are married, a one standard deviation increase in the share of single moms, and a one standard deviation decrease in the teenage labor force participation rate. We do not claim causality here. Rather, we highlight the empirical relevance of early-life $PM_{2.5}$ concentrations as a predictor of upward mobility.

2.2 Individual-Level Facts

We also explore the correlation between prenatal $PM_{2.5}$ exposure and individual measures of economic disparities using the Census Bureau's data linkage infrastructure. The Census Bureau's data linkage infrastructure allows us to link data at the address, individual and firm level. The address-based linkages capitalize on the Census Bureau's Master Address File, while the person-based linkages capitalize on a reference file of all individuals who either have a Social Security Number or have filed taxes with an Individual Taxpayer Identification Number (ITIN). The unique anonymized keys that are crucial to this data linkage process – Master Address File Identifiers (MAFIDs) and Protected Identification Keys (PIKs) – are assigned to administrative records, surveys, decennial census and third-party datasets by Census staff using the enterprise Personal Validation System (Wagner and Layne, 2014). Once these keys have been attached to a file, it is possible to link that file with any of the other files in the data linkage infrastructure.

For our individual level analyses, we construct a dataset which takes advantage of the Census Bureau's linkage infrastructure to follow individuals over time and identify parent-child relationships. Our individual-level dataset starts from survey responses to the 2001-2019 American Community Surveys (ACS).[1] These surveys provide detailed sociodemographic information – including age, race, sex, education, occupation and family structure – for a very large sample of the U.S. population. We then restrict these individual responses to those born between 1976-1998. From this sample frame we link each birth to their parents based on filing status in the IRS 1040 universe from 1994-1999.[2] We assign the primary tax filer on this tax form as the child's parent.

With these parent-child links in hand, we identify the place of birth for each child and the economic circumstances of each parent at the time of birth. To do this, we link each parent to their 1040 tax returns in the years 1969, 1974, 1979, 1984 and 1989. We then assign place of birth (resolved at the census tract, zip code and county) and parental income information from the form filed in the year closest to the child's birth. Due to the incomplete coverage of tax data held by Census before 1989 we can't rule out measurement error in birth location; however, our results are robust to using place of birth at the county level from the Census Numident and to restricting the sample to those born in the exact filing years.[3]

Finally, we identify later-life economic outcomes for each child. We link all individuals to form W-2s and 1040s between 2010–2018. We then calculate total annual earnings by summing all earnings and deferred compensation across all W-2s received by an individual in a given year. Labor earnings only captures employee compensation. Earnings from independent contractors or self-employed individuals do not appear in this measure. To address this, we also measure Adjusted Gross Income from the form 1040 in which an individual appears as a primary or secondary tax filer. This measure includes all income sources.

Using this data we construct an individual level measure of economic mobility which is similar in spirit to the Chetty et al. (2014) measure used in our county-level analysis. Specifically, we calculate the difference between a child's income rank and their parent's rank in the parental income distribution.[4] This measure is similar in spirit to the upward mobility measure used in Chetty et al. (2014), which we use in our county-level analysis. This measure captures a relative mobility concept, which we argue is the relevant concept for this time period, as it abstracts from changes in the cross-sectional income distribution and the distribution of income growth which arose during our sample period. In subsequent analysis we will also consider the relationship between environmental quality and absolute

[1] $\approx$ 93 percent of individuals in the ACS can be assigned a PIK, the unique linkage key needed to link individuals across datasets.

[2] While the IRS required the reporting of SSNs and other personally identifiable information for dependents after the 1986 tax reforms, this information was not digitally captured until the 1990s.

[3] The Census Numident is an administrative records file derived from Social Security Administration SS-5 forms that is the universe of all individuals who have applied for a Social Security Number.

[4] We use Adjusted Gross Income as our measure of income.

measures of economic well-being such as labor market earnings.

We show the correlation between individual level upward mobility—the difference between an individual's rank at age 30 and their parent's rank around the child's birth—and an individual's prenatal exposure to $PM_{2.5}$ for a single cohort of individuals born in 1981. Panel B of figure 2 presents the bivariate relationship between these individual-level variables. As with our county-level analysis, we estimate a negative relationship, however there is substantially more heterogeneity. In particular, the non-parametric relationship between individual mobility and $PM_{2.5}$ exposure exhibits more of a U-shaped pattern, with higher levels of upward mobility at high levels of $PM_{2.5}$ exposure. The previous aggregate analysis may have obscured this, as many of the largest counties (e.g. Los Angeles County, CA) are also highly polluted. However, given that this is the unconditional association we are not able to give any clear interpretation to why this pattern arises. Note that the best linear approximation of this non-linear relationship (the line of best fit shown in Figure 2) between early-life air pollution exposure and upward mobility remains negative with a slope of 0.19 in rank points. In the following section, we set out to identify the causal effect of prenatal $PM_{2.5}$ exposure on earnings and our measures of economic opportunity. We then combine these estimates with individual-level measures of environmental and economic disparities to quantify the contribution that air pollution may play in accounting for observed economic disparities in the United States.

3 The Causal Effect of Prenatal $PM_{2.5}$ Exposure on Earnings and Economic Mobility: Evidence from the 1990 Clean Air Act Amendments

To identify the causal effect of particulate matter on earnings we exploit plausibly exogenous variation in prenatal air pollution exposure that arises from the introduction of the 1990s Clean Air Act Amendments (CAAA). By leveraging improvements in the measurement of $PM_{2.5}$ exposure and a more detailed set of administrative records, we are able to refine the approach taken by a number of previous studies (Chay and Greenstone, 2003a; Isen et al., 2017; Voorheis, 2017; Colmer and Voorheis, 2019).

3.1 Data

Our sample frame for this analysis comes from the 2001-2019 American Community Survey (ACS), which we link to longitudinal information from administrative records.

To analyze the effects of the 1990 CAAA, we refine this analysis dataset to a subsample of U.S.-born ACS respondents who were born between 1989-1996, a time period that spans the enactment of the nonattainment designations we leverage in our research design, while ensuring that the youngest cohort will have meaningful labor market activity in our contemporary IRS data (individuals born in 1996 were 23 in tax year 2019).

To measure prenatal exposure to ambient air pollution, we utilize the most detailed geographic information available. The pre-1989 Form 1040 data housed at the Census Bureau contains information on the exact address of parents when they filed their tax returns (street address, city, state and zip code). We first attempt to geocode these addresses to the Census tract level using the Master Address File IDs (MAFIDs) assigned to the 1040s. However, not all cases can be assigned a MAFID, so we additionally use the zip code information in the Form 1040 data to locate individuals (either to assign them to a zipcode tabulation area (ZCTA), or a county). This provides three potential levels of geography to assign pollution exposure: Census tract, zipcode, or county. We focus on the county level results to be consistent with the descriptive evidence, and present results using alternative exposure definitions in sensitivity analysis.

We measure economic outcomes primarily through income information available in IRS data. We focus on two measures of income: total annual earnings (including deferred compensation) from Form W-2, and adjusted gross income from Form 1040. As we have multiple endpoint observations for individuals (annually from 2016-2019), we create a stacked dataset, with each row corresponding to a year in which income is earned. This will allow us to control for year-of-birth by year of income earned unobservables, accounting for lifecycle earnings patterns (since individuals affected born after the nonattainment designations will always be younger than those born before). We adjust all income amounts to 2012 dollars, which allows for easy direct comparisons with Chetty et al. (2018a) and Isen et al. (2017).

3.2 Research Design

Exposure to air pollution is correlated with many observable and unobservable characteristics that are also correlated with long-run economic and social outcomes. To identify the causal effect of prenatal pollution exposure we need to identify exogenous variation. We do this by exploiting plausibly exogenous, regulation-induced variation in prenatal $PM_{2.5}$ exposure. Specifically, we exploit the introduction of new regulatory particulate matter standards that affected some counties, but not others, following the introduction of the 1990 Clean Air Act Amendments. This style of research design build on a well-established literature (Chay and Greenstone, 2003a; Isen et al., 2017; Voorheis, 2017; Colmer and Voorheis, 2019; Currie et al., 2020).

The Clean Air Act was first implemented in 1963, but limited federal oversight of state efforts led to disappointing results. It wasn't until Congress enacted the Clean Air Act Amendments of 1970 and established the EPA, dramatically increasing federal powers to address air pollution, that the regulation started to have an effect. The 1970 Amendments relied on "command and control" regulations, using criteria that focused on the health benefits of cleaner air without consideration of the economic costs. The legislation was instigated through the national ambient air quality standards (NAAQS), which set the maximum allowable levels of "criteria air pollutants" – sulfur dioxide, carbon monoxide, nitrogen dixoide, lead, particulates, and ozone. Based on these standards the EPA determines the set of counties that are in "nonattainment". The consequences of nonattainment are severe. State governments have to implement a pollutant-specific plan describing how nonattainment counties will be brought into compliance. If a state does not act or develops an inadequate plan, then federal funding for the state air pollution control program, highway construction, and sewage treatment plants can be withheld. The EPA can also ban permits required for new or modified constructions that could source pollution, or impose its own federal plan on nonattainment counties. These powers are sufficiently broad that even the threat of regulatory action has been associated with reductions in pollution Keohane et al. (2009).

Since the 1970 amendments, there have been several other major amendments, alongside hundreds of additional policy designations as scientific consensus about the harms of pollution and feasible compliance technologies have evolved. Our focus is on the 1990 Clean Air Act Amendments, which updated the national ambient air quality standards, broadened the enforcement powers of the EPA, and created new market-based mechanisms, such as the sulfur dioxide allowance-trading program to address acid rain. The 1990 amendments also resulted in the regulation of "toxic" air pollutants. 189 hazardous air pollutants were identified and emission standards were implemented that provided "an ample margin of safety to protect publish health," by minimizing the amount of toxic pollution that was released into the air.

Our identifying variation comes from the updating of the NAAQS standards, which affects some counties but not others through nonattainment designations.[5] New standards were introduced for particulates smaller than 10 microns (PM_{10}) and for nitrogen oxides (NO_x). Note that these standards did not directly target the fine particulates measured in our data ($PM_{2.5}$). Rather, these regulations affected all particles smaller than 10 microns and NO_x an important precursor to the formation of fine particles (NO_x reacts with other atmospheric chemicals to create fine particulates). The introduction of these new standards

[5]The other changes that arose from the 1990 CAAA were common across all counties.

resulted in new counties falling into nonattainment, providing regulation-induced variation in particulate matter exposure.

We estimate the effect of these new nonattainment designations on prenatal $PM_{2.5}$ exposure using a difference-in-differences research design. We define an indicator variable to be equal to one if an individual's county of birth becomes subject to the new nonattainment designations (zero otherwise) and interact this with an indicator variable each cohort.[6] Treated individual's are those that were conceived in nonattainment counties following the introduction of the 1990 CAA.

We estimate the following specification,

$$\begin{aligned} PM2.5_{i,c,s,m,t} &= \alpha_1(Nonattainment_{c,1990} \times \mathbb{1}[t > 1991]) \\ &\quad + \alpha_c + \alpha_{s,t} + \alpha_m + \gamma X_i' + \delta X_c' t + \nu_{i,c,s,t} \end{aligned} \tag{1}$$

where i indexes each individual, c indexes the county of birth, s indexes the state of birth, m indexes the month of birth, and t indexes the year of birth, i.e., the cohort.

Prenatal exposure to $PM_{2.5}$ is measured for each individual i, where $PM2.5_{i,c,s,m,t}$ is the average particulate matter concentration that individual i was exposed to in county of birth c in month m and year t. $PM_{2.5}$ is measured in $\mu g/m^3$. We regress this measure of exposure on a time-invariant county indicator equal to 1 if a county is designated in nonattainment of the updated 1990 PM_{10} and NO_x standards, $Nonattainment_{c,1990}$, and interact this term with an indicator equal to 1 for the years after the 1990 CAA amendments went into affect, $1[t > 1991]$. The interaction term is therefore equal to 1 for individuals born in nonattainment counties following the implementation of the 1990 CAAA. The parameter of interest is α_1, which under the assumption of parallel trends and non-interference, provides an estimate of the average treatment effect on the treated for nonattainment designation on prenatal TSP exposure in the years after CAAA regulations went into effect. We include county-of-birth fixed effects to control for time-invariant unobserved determinants of prenatal pollution exposure and state-of-birth $\times$ year fixed effects to control for time-varying determinants of prenatal pollution exposure that are common across all individuals born in state s in year t. We also include month-of-year fixed effects to control for seasonality in exposure. Following the existing nonattainment designation literature we also include additional controls: X_j' is a vector of individual characteristics, including age, race, and sex, as well as prenatal exposure to temperature and rainfall. $X_c't$ is a vector of county-level characteristics, measured in

[6]We observe that nonattainment counties are either in nonattainment of the PM_{10} standard or both the PM_{10} and NO_x standard.

1980, interacted with linear and quadratic time trends. Across all specifications we cluster our standard errors by the an individual's county of birth—the level at which we measure exposure.

Consistent with previous research exploring the 1970 and 2005 Clean Air Act Amendments we show that prenatal exposure to the new nonattainment designations is associated with substantial and persistent reductions in prenatal $PM_{2.5}$ exposure. Following the introduction of the 1990 CAA we estimate that prenatal exposure to $PM_{2.5}$ concentrations in nonattainment counties fell by 1.32 $\mu g/m^3$ (Table 1). This reduction is similar in magnitude to the declines in prenatal TSP exposure following the 1970 Clean Air Act Amendments.[7]

Figure 4 presents cohort-specific estimates from a distributed-lag model. We see that before the new regulations, individuals in nonattainment counties were not differentially exposed to $PM_{2.5}$, providing support for the parallel trends assumption. Following the implementation of the 1990 CAA, we estimate a sharp and persistent drop in prenatal $PM_{2.5}$ exposure. The reductions are driven by counties that are in non-attainment of both the PM_{10} and NO_x standard. This does not mean that the PM_{10} nonattainment by itself wasn't effective, just that it wasn't sufficient to reduce levels of $PM_{2.5}$, a more granular measure of particulates.

We use this plausibly exogenous variation as an instrument to identify the effects of prenatal $PM_{2.5}$ exposure on later-life economic outcomes. We estimate the following specification,

$$\begin{aligned} Y_{i,c,s,m,t,y} &= \beta \widehat{PM2.5}_{i,c,s,m,t} \\ &\quad + \alpha_c + \alpha_{s,t} + \alpha_m + \alpha_{t,y} + \gamma X_i' + \delta X_c' t + \epsilon_{i,c,s,m,t,y} \end{aligned} \tag{2}$$

To account for lifecycle earnings effects in our stacked dataset, we control for year of birth by tax year fixed effects, in addition to the standard state-of-birth by birth-year, county-of-birth, and month-of-birth fixed effects.

We consider three main outcomes: 1) individual labor market earnings as measured on form W-2; 2) tax unit adjusted dross income (AGI, which we will abuse notation and refer to as family income) as measured by form 1040; and 3) a measure of upward economic mobility – the difference in AGI ranks between an individual around age 30 and their parent (at the time of the individual's birth).

We have shown that the first-stage is relevant and that the relationship between nonat-

[7]TSP concentrations fell in nonattainment counties by $\approx$10 $\mu g/m^3$. The crude ratio between $PM_{2.5}$ and TSP is 0.22.

tainment and $PM_{2.5}$ exposure is plausibly identified, assuming parallel trends. If we assume that the exclusion restriction holds, the coefficient of interest, β, identifies the effect of a one-unit increase in CAAA-driven prenatal $PM_{2.5}$ exposure on later-life earnings.

The exclusion restriction assumption – that the 1990 CAAA only affected later-life outcomes through reductions in prenatal $PM_{2.5}$ exposure may not hold. It is possible that nonattainment designations affected outcomes in ways other than the estimated reductions in pollution. Isen et al. (2017) and Colmer and Voorheis (2019) make the point that nonattainment designations could affect economic competitiveness (Greenstone, 2002; Greenstone et al., 2012; Walker, 2011, 2013). However, existing evidence suggests that the effects on the broader local economy are small, affecting less than 0.7 percent of the total workforce (Walker, 2013). By contrast, the reduction in pollution benefited everyone in non-attainment counties. We can't rule out that the 1990 CAAA contributed to a decline in economic conditions in nonattainment counties. However, since effects on competitiveness would be expected to have the opposite effect on health to reductions in pollution exposure, it is plausible that the 2SLS estimates will at worst, understate the effects of prenatal $PM_{2.5}$ exposure. The reduced form effect of nonattainment remains valid and is interpreted as the net effect of the nonattainment designations on later-life outcomes. Our reduced form and corresponding 2SLS estimates produce conceptually identical results, suggesting that violations of the exclusion restriction are unlikely to be a first-order concern.

3.3 Results

Table 2 summarises our estimates of the effect of regulation-induced decreases in $PM_{2.5}$ on later-life economic outcomes. In column 1 we see that a 1 $\mu g/m^3$ reduction in prenatal $PM_{2.5}$ exposure is associated with a \$1,105 increase in later life W-2 earnings; the reduced form effect of prenatal exposure to nonattainment is associated with a \$1,553 increase in later life W-2 earnings.[8] In column 2 we observe similar estimates for the relationship between prenatal $PM_{2.5}$ exposure and later-life AGI, however, they are less precisely estimated – a 1 $\mu g/m^3$ reduction in prenatal $PM_{2.5}$ exposure is associated with a \$1,313 reduction in annual AGI. Column 3, presents the relationship between prenatal $PM_{2.5}$ exposure and our measure of upward mobility. We estimate that a 1 $\mu g/m^3$ reduction in prenatal $PM_{2.5}$ exposure is associated with a 1.28 rank point increase in upward mobility, about a tenth of the size of the black-white mobility gap in Chetty et al. (2018b).

These effects are substantially larger than previous estimates of the long-term effect of

[8]The first-stage estimate predicts a 1.383 $\mu g/m^3$ reduction in $PM_{2.5}$, which combined with our second-stage estimate would predict a \$1,528 effect of pollution reductions from nonattainment. This suggests that any effects on competitiveness are unlikely to be a first-order concern.

prenatal pollution exposure. Isen et al. (2017) estimate that a 10 $\mu g/m^3$ reduction in Total Suspended Particulates, induced by the 1970 Clean Air Act Amendments was associated with a $352 increase in earnings. Total Suspended Particulates – defined as the total mass of particles smaller than 100 microns – are much coarser than $PM_{2.5}$. Consequently, we need to re-scale existing estimates to make a proper comparison. Using all EPA monitor observations from monitor sites that had co-located active $PM_{2.5}$ and TSP monitors, we calculate a crude scaling factor between TSP concentrations and $PM_{2.5}$ concentrations as 4.35. A 10 $\mu g/m^3$ reduction in TSP corresponds to a 2.29 $\mu g/m^3$ decrease in $PM_{2.5}$. As such, the Isen et al. (2017) estimate is consistent with a $153.60 increase in earnings per $\mu g/m^3$ of $PM_{2.5}$.[9] Our baseline estimate on W-2 earnings is 7 times larger.

There are a number of plausible origins for increase in magnitude. First, our results rely on different policy variation—the EPA's regulations after the 1990 Clean Air Act focus on finer particulates than the regulations after the 1970 Clean Air Act. Since finer particles are more damaging to health, the 1990s nonattainment designations may have had a much larger effect on prenatal health than the 1970s. While the crude reduction in particles is similar across the two policies, the actual reduction in $PM_{2.5}$ from the 1990 CAAA is likely much larger than the reductions in 1970 as it would have been easier and lower cost to reduce coarser particulates. Second, our assignment of place of birth differs from Isen et al. (2017) and Colmer and Voorheis (2019)—we use information on the location an individual's parent filed taxes rather than the place of birth reported to the Social Security Administration. We believe that using tax data locations may more accurately capture exposure, since SSA locations may correspond to the hospital a child was born in rather than their residence. Any classical measurement error in exposure will have attenuated previous estimates. Third, our data on exposure is different from the previous literature. As noted earlier, the satellite-derived data product performs similarly to the ground-based monitors in areas where the monitor network has coverage. Importantly, however, the satellite derived data product allows us to observe exposure for all counties, including those not monitored. This in turn means that our sample is closer to being nationally representative (since it includes individuals born in all counties, not a selected sample born in monitored counties).

Our results are quantitatively and qualitatively robust to a large array of sensitivity tests, including transformations of the outcome variables, imputing zeroes for individuals who cannot be linked to a W-2 or 1040, and changing the geographic level of exposure. Finally, our results are also robust to the level of geographic granularity used in assigning pollution exposure to individuals.

We also present cohort-specific estimates of the reduced form. As with the first stage

[9] $\$351.74/2.29 = \$153.60$.

distributed-lag estimates, there are no statistically significant or economically meaningful differences between individuals born in treatment and control counties before the nonattainment designations went into effect, providing additional support for the parallel trends assumption. Consistent with the overall post-treatment estimates presented in Table 2, we see that all cohorts born in nonattainment counties following the introduction of the 1990 CAAA have higher later-life earnings, relative to those born in attainment counties. We observe a similar pattern for our cohort-specific estimates of nonattainment on AGI (Panel c of Figure 4) and upward mobility (Panel d of Figure 4). The cohort-specific estimates are less precisely estimated.

4 Exploring the Contribution of Environmental Quality to Economic Opportunity

To better understand how much broader patterns of economic opportunity are explained by variation in air quality, we engage in two quantitative thought experiments. First, we combine our causal estimates of the effect of early life $PM_{2.5}$ exposure on earnings and economic mobility with observed patterns of individual-level pollution and economic disparities. The objective of this exercise is to calculate how much early-life pollution exposure can account for Black-White earnings and economic opportunity gaps. Second, we leverage exogenous variation in early life pollution exposure, arising from the Moving to Opportunity experiment, to explore how much of the overall "neighborhood earnings effect" can be accounted for by air quality in early childhood.

4.1 How Much Does Prenatal Pollution Exposure Contribute to Black-White Earnings and Opportunity Gaps?

Our first analysis combines our estimates of the long-run economic effects of prenatal pollution exposure with cohort-specific disparities in $PM_{2.5}$ exposure. With these measures, we provide an estimate of the role that disparities in air quality at birth play in contributing to later-life economic disparities. Specifically, we consider how much racial gaps in pollution exposure at birth contribute to contemporary gaps in both the level of income and upward mobility.

We use our linked dataset to estimate the cohort-specific Black-White gap in $PM_{2.5}$ exposure at birth – for the 1981 cohort, we find that this gap is 2.43 $\mu g/m^3$ using county-level pollution data, and 2.53 $\mu g/m^3$ using Census tract level pollution data. We then use our linked dataset to calculate the cohort-specific racial earnings gaps at age 30 using Form W-2 data.[10] We calculate that the Black-white gap in earnings for the 1981 cohort is $13,600. Using our central estimate of the effect of $PM_{2.5}$ exposure on earnings, we calculate that $2685 of the $13,600 racial income gap can be accounted for by environmental inequality at birth – 19.7 percent of the total gap.[11]

We conduct a similar analysis for understanding the contribution of environmental inequality at birth in shaping the Black-White economic mobility gap. Chetty et al. (2018b) estimate that there is a 13 rank point difference in upward mobility between white and black individuals born around 1978–1982. Taking our 1981 cohort racial $PM_{2.5}$ gaps and the effect of pollution exposure on upward mobility from table 2, we calculate that 3.11 points out of 13 can be accounted for by $PM_{2.5}$ disparities at birth – 23.9 percent of the overall mobility gap.

We note caveats. This thought experiment combines non-marginal changes in pollution exposure with a marginal local average treatment effect estimate of pollution damages. Our analysis implicitly assumes a linear dose response function. If the dose response function is convex, marginal damages will decrease as the pollution gap shrinks. In this case, our calculations will overstate the contribution of early life pollution exposure. If the dose response function is concave, marginal damages will increase as the pollution gap shrinks. In this case, our calculations will understate the contribution of early life pollution exposure. Given the size of the pollution gaps, we don't think that assuming linearity in the dose response function over this range is totally unreasonable. In the following section we exploit the Moving to Opportunity Experiment to induce a marginal change in pollution exposure. In doing so, we also explore the degree to which reduced $PM_{2.5}$ exposure in early childhood might contribute to the "total neighborhood" effect on earnings estimated by Chetty et al. (2016) for the children that moved in response to the intervention before the age of 13.

4.2 Environmental Quality and "The Neighborhood Effect": Evidence from the Moving to Opportunity Experiment.

In the mid 1990s, the U.S. Department of Housing and Urban Development (HUD) conducted the Moving to Opportunity (MTO) experiment. The objective was to examine whether moving public housing recipients to lower poverty neighborhoods improved the economic and social outcomes of adults. Families were tracked over time, and HUD collected outcomes for both children and adults at the end of the experiment.

[10]We average all non-missing annual W-2 observations for an individual for the years in which they are between 28-32.

[11]If we use the upper and lower bounds of the 95 percent confidence interval for our earnings estimate, we account for between $366 (2.7 percent) and $5,032 (37 percent) of the Black-white earnings gap.

The MTO experiment randomized recipients into three groups: the treatment group received a voucher that could only be used in a low poverty neighborhood; the Section 8 group received a voucher that could be used anywhere; the control group did not receive a voucher.

Evaluations during and after the experiment found little evidence of improvements in the economic circumstances for the treatment groups (Kling et al., 2007; Sanbonmatsu L et al., 2011). However, more recent work documents that children in the treatment group who were younger than 13 when they moved experienced higher incomes as adults (Chetty et al., 2016).

We set out to explore the degree to which improvements in environmental quality may have contributed to this earnings effect. We do this by estimating whether voucher-induced movements resulted in lower exposure to $PM_{2.5}$ and combine estimates of the change in pollution with our estimates of the $PM_{2.5}$–earnings relationship. The premise of our analysis, based on the literature documenting the importance of early childhood for human capital formation, is that children who moved earlier in life may have disproportionately benefited more from improvements in air quality relative to children who moved later.

4.2.1 Data

We use data from HUD on the individuals that participated in the Moving to Opportunity experiment. We focus on those that were younger than 13 years old at time of randomization. Following Chetty et al. (2016), we restrict the sample to those older than 23 in tax years 2008 - 2012.

We identify demographic information, survey responses, and survey weights from the MTO Final Analysis dataset provided by HUD. We construct quarterly address history over the duration of the MTO experiment (1994 - 2010) for all participants using the MTO Final Evaluation Residential Address History dataset. This dataset provides the census tract that every MTO participant lived in during the experiment.

We merge the MTO participants' residential histories to the Census tract level measures of $PM_{2.5}$ concentrations discussed above. We define an individual's pollution exposure as the duration weighted average of each quarter's $PM_{2.5}$ exposure up to the age of 18, or calculate annual average pollution exposure for each year through age 18.

We also merge the MTO participants to income information from IRS tax data to measure their economic outcomes. We follow Chetty et al. (2016) and focus on two outcomes: individual earnings, which we measure using annual average wage income from Form W-2s, and tax unit level total income, which we measure as the adjusted gross income reported on form 1040. For comparability with previous literature, we measure this income information from the years 2008–2012.

4.2.2 Research Design

We estimate the intent-to-treat (ITT) effect of the MTO treatments on children's exposure to $PM_{2.5}$. We estimate OLS regressions of the form:

$$Y_{i,s} = \alpha + \beta_1 Exp_{i,s} + \beta_2 S8_{i,s} + \delta_s + \epsilon_{i,s} \tag{3}$$

where $Y_{i,s}$ denotes outcomes for individual i in randomization site s. The outcomes we focus on are time-weighted $PM_{2.5}$ pollution exposure, wage income, and adjusted gross income. Exp_i and $S8_i$ are whether the individual was assigned to the experimental or Section 8 groups and δ_s is a set of randomization site fixed effects. We weight regressions using the standard MTO final analysis weights, which adjust for differences in sampling probabilities across sites and over time. We cluster standard errors by family, the level at which randomization occured.

Randomization site fixed effects account for inherent differences between the five randomization sites (Baltimore, Boston, Chicago, New York, and Los Angeles), which is particularly important in this context because of differing baseline pollution levels between cities.

β_1 and β_2, respectively, provide estimates of the association between being offered the experimental voucher or the Section 8 voucher and our outcomes of interest, relative to the control group. Because some families do not use the vouchers, the estimates capture the intent to treat effect.

4.2.3 Results

Table 3 presents estimates of the relationship between being offered vouchers and income, for individuals whose families received the voucher before the age of 13. In column 1, we estimate that children assigned to the experimental group have annual W-2 earnings that are $1,300 higher than the control group. We estimate no statistically significant effects of assignment to the Section 8 group. These findings very closely match the estimates in Chetty et al. (2016).

In column 2, we turn to the effects of MTO randomization group assignment on adjusted gross income (AGI). Wage earnings are a component of AGI, though they come from different IRS datasets. The AGI results match the W-2 results: children assigned to the experimental group have annual AGI earnings that are $2,000 higher than the control group. Likewise, we estimate no significant effect of Section 8 vouchers on annual AGI earnings.

In column 3, we estimate the relationship between treatment assignment and post-treatment $PM_{2.5}$ exposure. We estimate that being offered the experimental voucher is associated with a 0.170 $\mu g/m^3$ reduction in $PM_{2.5}$ exposure, relative to the control group. This is a 1 percent reduction in exposure relative to the mean. Section 8 voucher recipients do not appear to experience significant reductions in exposure relative to the control group.

4.2.4 How Much of the MTO-Earnings Effect can be explained by MTO-induced reductions $PM_{2.5}$ Exposure?

We have shown that receiving MTO low poverty vouchers reduced children's lifetime pollution exposure and increased earnings. In Section 3, we estimated that plauisbly exogenous variation in prenatal $PM_{2.5}$ exposure was associated with meaningful increases in later-life earnings and upward mobility, and that non-marginal changes in pollution (based on the Black-white $PM_{2.5}$ gap at birth) can account for a non-trivial share of the contemporary Black-white income gap. Now, we explore the degree to which the marginal reduction in pollution induced by the MTO experiment can account for the overall "neighborhood effect" on earnings.

As shown, the MTO experiment increased earnings by about $1,300 for children whose family were offered the voucher before the age of 13; and decreased exposure to $PM_{2.5}$ by about 0.17 $\mu g/m3$. Combining our estimate of the reduction in pollution with our baseline estimate of the effect of $PM_{2.5}$ on earnings from Section 3, we calculate that $187 (14.7 percent) of the $1,300 effect can be accounted for by reductions in childhood $PM_{2.5}$ exposure.[12] This is slightly lower than the accounting exercise for black-white earnings gaps. However, together these exercises paint a remarkably similar picture – childhood $PM_{2.5}$ exposure is an important driver of economic mobility in the United States.

5 Conclusion

We have shown, using a variety of datasets and research designs, that exposure to ambient air pollution is closely related to economic opportunity in the United States. We document that early life exposure to fine particulate matter is one of the top five predictors of intergenerational income mobility in the United States. We argue that this strong correlation may, at least in part, reflect a causal relationship between air quality and economic opportunity. We provide evidence for this claim in two parts: first, we present new evidence that plausibly exogenous shocks to pollution exposure have large effects on later life economic

[12] Using alternate assumptions about the effect of $PM_{2.5}$ on earnings and the effect of MTO on earnings and $PM_{2.5}$ yields a plausible range from 10-31 percent.

outcomes, sizeable enough to account for meaningful shares of racial economic disparities in the United States; second, we show that random variation in exposure to pollution from the Moving to Opportunity experiment, combined with our estimates of the $PM_{2.5}$–earnings relationship, can account for 15 percent of the overall "neighborhood effect" on earnings. Collectively, we our results suggest that exposure to environmental hazards might be an important determinant of economic opportunity.

These results underline the importance of understanding disparities in pollution exposure: environmental inequality exacerbates economic inequality. However, these results also provide hope: in the period since the cohort studied by Chetty et al. (2014) were born, there have been dramatic improvements in average air quality as well as significant reductions in Black-white $PM_{2.5}$ exposure gaps (Currie et al., 2020; Colmer et al., 2020). To the extent that our findings are stable over time, this suggests that pollution-driven economic opportunity may substantially improve going forwards, as less-exposed cohorts grow up and enter the labor force. Whether overall economic opportunity improves or worsens over time will ultimately depend on the other drivers. Future work should continue to better understand these effects and how amenable they are to policy intervention. Our findings suggest that place is not immutable. We can improve economic opportunity within neighborhoods: reducing exposure to environmental hazards is an easier problem to solve than making neighborhoods high opportunity.

References

Banzhaf, S., L. Ma, and C. Timmins, "Environmental justice: The economics of race, place, and pollution," *Journal of Economic Perspectives*, 2019, *33* (1), 185–208.

Chang, T.Y., J. Graff Zivin, T. Gross, and M. Neidell, "Particulate Pollution and the Productivity of Pear Packers," *American Economic Journal: Economic Policy*, 2016, *8* (3), 141–69.

_ , W. Huang, and Y. Wang, "Something in the Air: Pollution and the Demand for Health Insurance," *The Review of Economic Studies*, 2018, *85* (3), 1609–1634.

Chay, K. and M. Greenstone, "Air Quality, Infant Mortality, and the Clean Air Act of 1970," Working Paper 10053, National Bureau of Economic Research October 2003.

_ and _ , "The Impact of Air Pollution on Infant Mortality: Evidence from Geographic Variation in Pollution Shocks Induced by a Recession," *The Quarterly Journal of Economics*, 2003, *118* (3), 1121–1167.

Chetty, R. and N. Hendren, "The Effects of Neighborhoods on Intergenerational Mobility I: Childhood Exposure Effects," *Quarterly Journal of Economics*, 2018.

_ and _ , "The Effects of Neighborhoods on Intergenerational Mobility II: County Level Estimates," *Quarterly Journal of Economics*, 2018.

_ , J. Friedman, N. Hendren, M. Jones, and S. Porter, "The Opportunity Atlas: Mapping the Childhood Roots of Social Mobility," *NBER Working Paper 25147*, 2018.

_ , J.N. Friedman, N. Hendren, M.R. Jones, and S.R. Porter, "The Opportunity Atlas: Mapping the Childhood Roots of Social Mobility," *NBER Working Paper 25147*, 2018.

_ , N. Hendren, and L. Katz, "The Effects of Exposure to Better Neighborhoods on Children: New Evidence from the Moving to Opportunity Experiment," *American Economic Review*, 2016, *106* (4), 855–902.

_ , _ , P. Kline, and E. Saez, "Where is the land of Opportunity? The Geography of Intergenerational Mobility in the United States *," *The Quarterly Journal of Economics*, 2014, *129* (4), 1553–1623.

Chyn, E., "Moved to Opportunity: The Long-Run Effect of Public Housing Demolition on the Labor Market Outcomes of Children," *American Economic Review*, 2018, *108* (10), 3028–56.

_ **and L. Katz**, "Neighborhoods Matter: Assessing the Evidence for Place Effects," *NBER Working Paper 28953*, 2021.

Colmer, J. and J. Voorheis, "The Grandkids Aren't Alright: The Intergenerational Effects of Prenatal Pollution Exposure," *Mimeo*, 2019.

_ **, I. Hardman, J. Shimshack, and J. Voorheis**, "Disparities in PM2.5 air pollution in the United States," *Science*, 2020, *369* (6503), 575–578.

Commission for Racial Justice, United Church of Christ, "Toxic Wastes and Race in the United States: A National Report on the Racial and Socio-Economic Characteristics of Communities with Hazardous Waste Sites," 1987.

Currie, J. and M. Neidell, "Air pollution and infant health: what can we learn from California's recent experience?," *Quarterly Journal of Economics*, 2005, *120* (3), 1003–1030.

_ **, J. Voorheis, and R. Walker**, "What Caused Racial Disparities in Particulate Exposure to Fall? New Evidence from the Clean Air Act and Satellite-Based Measures of Air Quality," *NBER Working Paper 26659*, 2020.

Currie, Janet, Joshua S. Graff Zivin, Jamie Mullins, and Matthew J. Neidell, "What Do We Know About Short and Long Term Effects of Early Life Exposure to Pollution?," Working Paper 19571, National Bureau of Economic Research October 2013.

Deutscher, N., "Place, Peers, and the Teenage Years: Long-Run Neighborhood Effects in Australia," *American Economic Journal: Applied Economics*, 2019.

Di, Q., I. Kloog, P. Koutrakis, A. Lyapustin, Y. Wang, and J. Schwartz, "Assessing PM2.5 exposures with high spatiotemporal resolution across the continental United States," *Environmental Science & Technology*, 2016, *50* (9), 4712–4721.

Donkelaar, A. Van, R.V. Martin, M. Brauer, N.C. Hsu, R.A. Kahn, C. Levy, A. Lyapustin, A.M. Sayer, and D.M. Winker, "Global estimates of fine particulate matter using a combined geophysical-statistical method with information from satellites, models, and monitors," *Environmental Science & Technology*, 2016, *50* (7), 3762–3772.

Ebenstein, A., V. Lavy, and S. Roth, "The Long-Run Economic Consequences of High-Stakes Examinations: Evidence from Transitory Variation in Pollution," *American Economic Journal: Applied Economics*, 2016, *8* (4), 36–65.

Fowlie, M., E. Rubin, and R. Walker, "Bringing Satellite-Based Air Quality Estimates Down to Earth," *AEA Papers and Proceedings*, 2019, *109*, 283–88.

Galster, G. and P. Sharkey, "Spatial Foundations of Inequality: A Conceptual Model and Empirical Overview," *RSF: The Russell Sage Foundation Journal of the Social Sciences*, 2017, *3* (2), 1–33.

Graff Zivin, J. and Neidell, M., "The Impact of Pollution on Worker Productivity," *American Economic Review*, 2012, *102* (7), 3652–73.

Greenstone, M., "The Impacts of Environmental Regulations on Industrial Activity: Evidence from the 1970 and 1977 Clean Air Act Amendments and the Census of Manufactures," *Journal of Political Economy*, 2002.

_ , J. List, and C. Syverson, "The Effects of Environmental Regulation on the Competitiveness of US Manufacturing," *Mimeo*, 2012.

Hsiang, S., P. Oliva, and R. Walker, "The Distribution of Environmental Damages," *Review of Environmental Economics and Policy*, 2018.

Isen, A., M. Rossin-Slater, and R. Walker, "Every Breath You Take — Every Dollar You'll Make: The Long-Term Consequences of the Clean Air Act of 1970," *Journal of Political Economy*, 2017.

Keohane, Nathaniel O., Erin T. Mansur, and Andrey Voynov, "Averting Regulatory Enforcement: Evidence from New Source Review," *Journal of Economics & Management Strategy*, 2009, *18* (1), 75–104.

Kling, Jeffrey R, Jeffrey B Liebman, and Lawrence F Katz, "Experimental Analysis of Neighborhood Effects," *Econometrica*, 2007, *75* (1), 83–119.

L, . Sanbonmatsu, J. Ludwig, L. Katz, L.A. Gennetian, G.J. Duncan, R.C. Kessler, E. Adam, T.W. McDade, and S.T. Lindau, "Moving to Opportunity for Fair Housing Demonstration Program – Final Impacts Evaluation.," Technical Report, US Department of Housing& Urban Development, PD&R 2011.

Ludwig, J., G. Duncan, L. Gennetian, L. Katz, R. Kessler, J. Kling, and L. Sanbonmatsu, "Long-Term Neighborhood Effects on Low-Income Families: Evidence from Moving to Opportunity," *American Economic Review*, 2013, *103* (3), 226–31.

Meng, J., C. Li, R. V. Martin, A. van Donkelaar, P. Hystad, and M. Brauer, "Estimated Long-term (1981-2016) Concentrations of Ambient Fine Particulate Matter across North America from Chemical Transport Modeling, Satellite Remote Sensing and Ground-based Measurements.," *Environmental Science & Technology*, 2019, *53* (9), 5071–5079.

Mohai, P., D. Pellow, and J.T. Roberts, "Environmental Justice," *Annual Review of Environment and Resources*, 2009, *34*, 405–430.

Schlenker, W. and W.R. Walker, "Airports, Air pollution, and Contemporaneous Health," *The Review of Economic Studies*, 2015, *83* (2), 768–809.

Sharkey, P. and J.W. Faber, "Where, When, Why, and For Whom Do Residential Contexts Matter? Moving Away from the Dichotomous Understanding of Neighborhood Effects," *Annual Review of Sociology*, 2014, *40* (1), 559–579.

Voorheis, J., "Air Quality, Human Capital Formation and the Long-term Effects of Environmental Inequality at Birth," Working Paper 2017-05, US Census Bureau 2017.

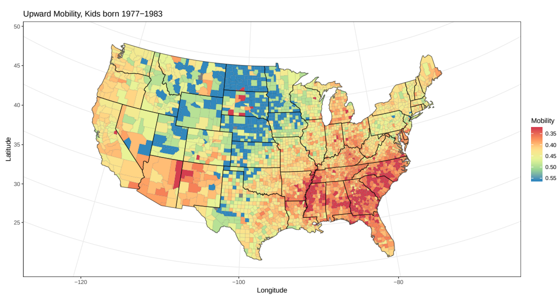
Wagner, D. and M. Layne, "The Person Identification Validation System (PVS): Applying the Center for Administrative Records Research and Applications (CARRA) Record Linkage Software," *Mimeo*, 2014.

Walker, R., "Environmental Regulation and Labor Reallocation," *American Economic Review: Papers and Proceedings*, 2011.

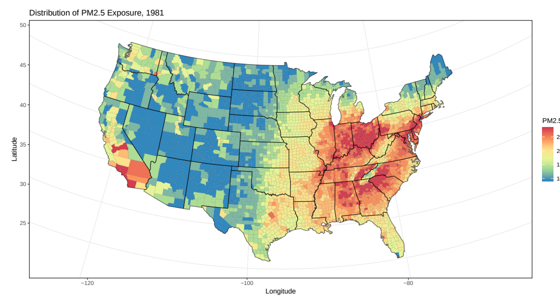
_ , "The Transitional Costs of Sectoral Reallocation: Evidence from the Clean Air Act and the Workforce," *Quarterly Journal of Economics*, 2013.

Tables and Figures

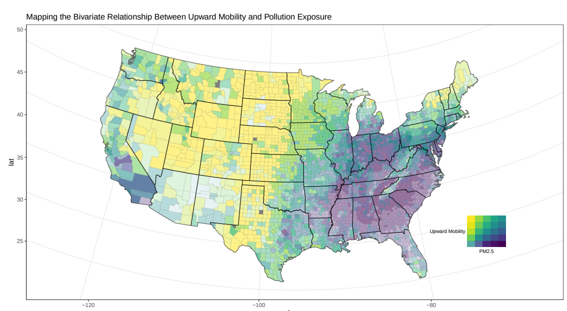
Figure 1: Spatial Variation in Upward Mobility and Environmental Quality



(a) Upward Mobility



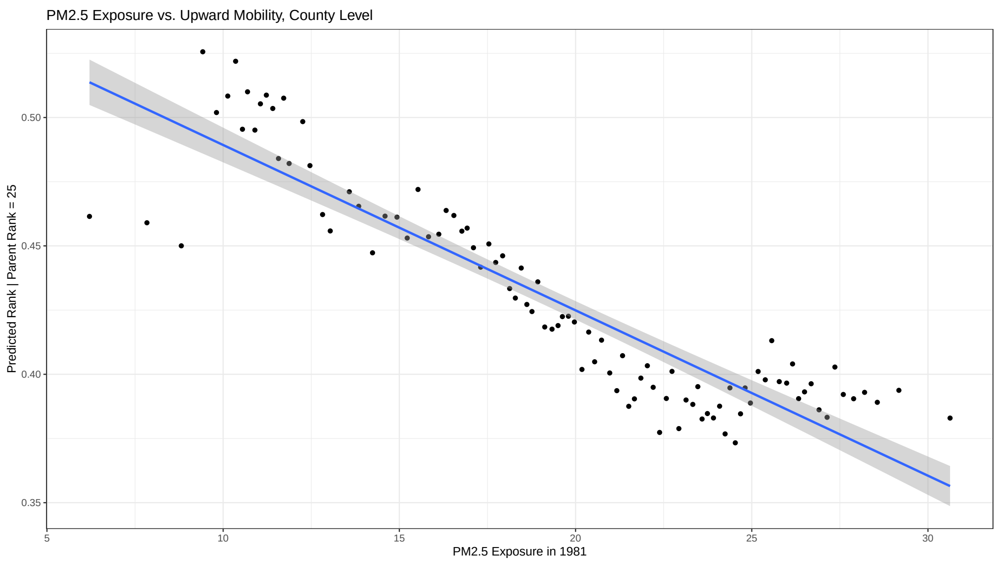
(b) $PM_{2.5}$



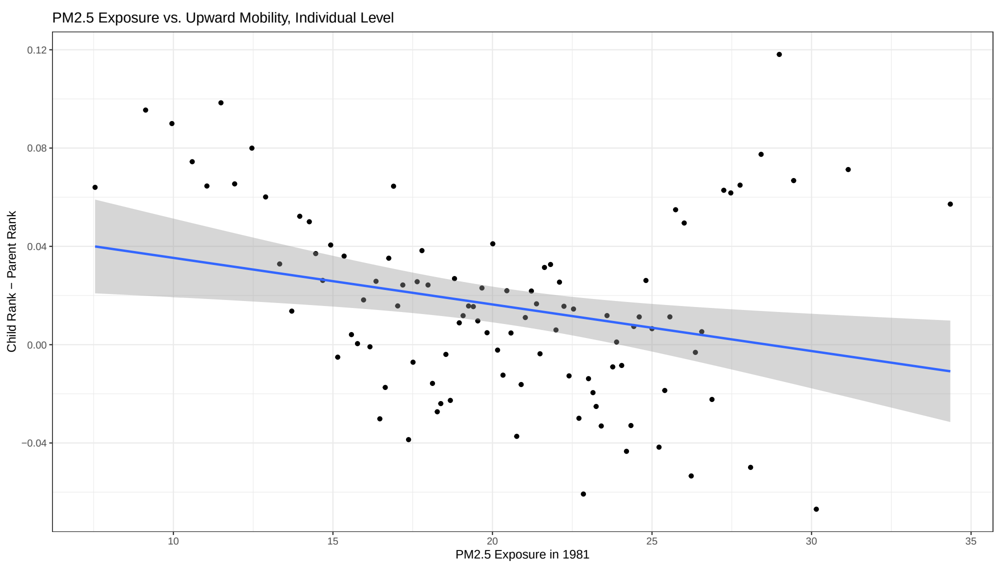
(c) Pollution-Mobility Matrix

Source: Author's calculations using data from Meng et al. (2019) and Chetty et al. (2014). The maps summarize the county-level distribution of upward mobility and pollution exposure. The top panel maps the county-level measures of upward mobility (the predicted rank for a child born to parents at the 25th percentile) from Chetty et al. (2014). The middle panel maps county-level annual average PM2.5 concentrations in 1981. County-level averages are calculated by intersecting the gridded data from Meng et al. (2019) with Census tracts and then calculating a tract population weighted average for each county. The bottom panel maps the two county-level variables together using a bivariate color palette.

Figure 2: The Bivariate Relationship between early life $PM_{2.5}$ Exposure and Upward Mobility



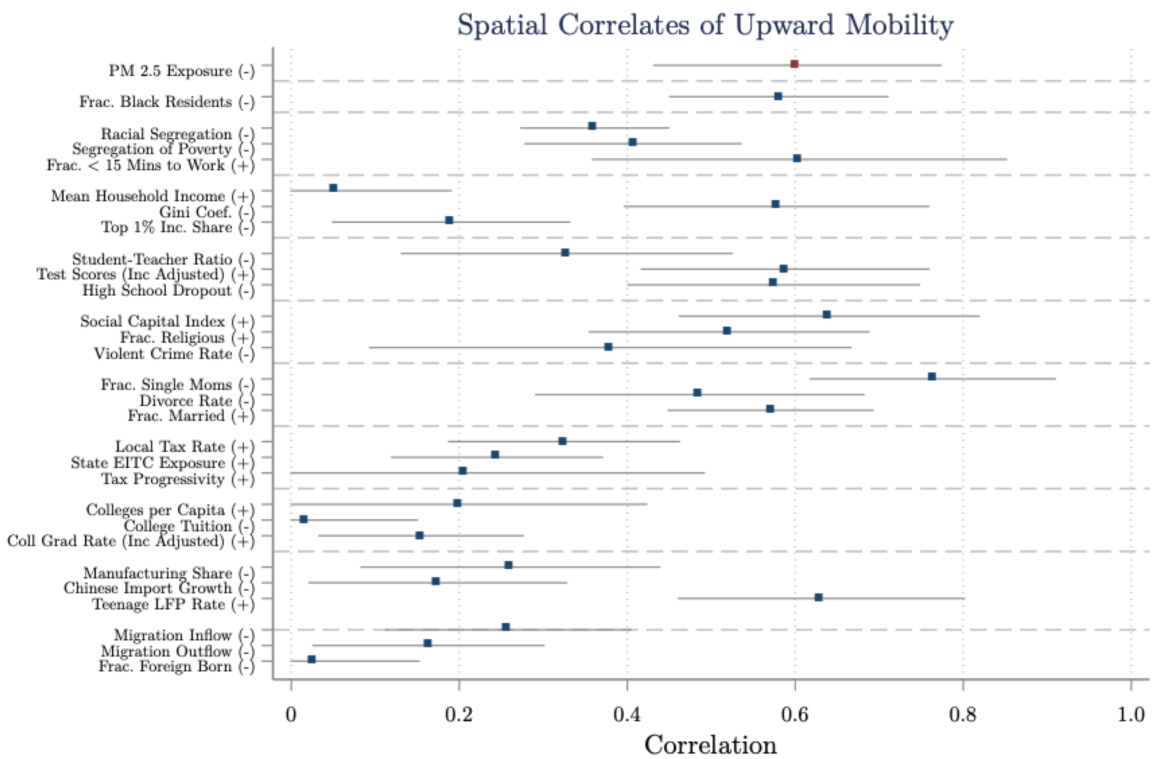
(a) County-level



(b) Individual-level

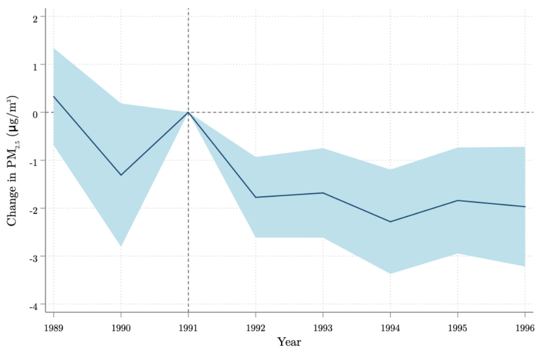
Source: Author's calculations using data from Meng et al. (2019), Chetty et al. (2014), IRS 1040s, ACS 2001-2019. Panel a) summarizes the bivariate relationship between county-level $PM_{2.5}$ and county-level predicted upward mobility (child rank - parent rank). Panel b) summarizes the bivariate relationship between individual-level PM2.5 exposure compared to individual level upward mobility (child rank - parent rank). Each point reflects the average upward mobility and PM2.5 within each percentile bin of the $PM_{2.5}$ distribution. Error bars reflect the 95 percent confidence intervals calculated with robust standard errors clustered at the county of birth level.

Figure 3: The Relative Importance of $PM_{2.5}$ as a Correlate of Upward Mobility

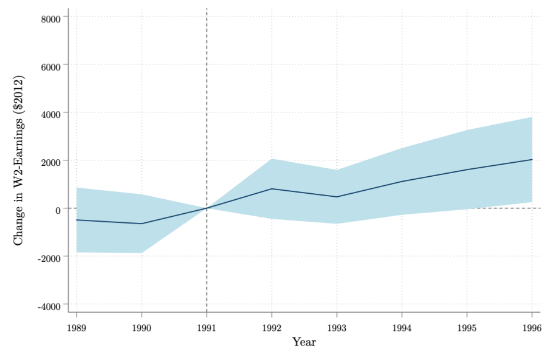


Source: Author's calculations using data from Meng et al. (2019) and Chetty et al. (2014). See figure 1 for more details. This figure shows bivariate correlations between county-level upward mobility and county-level PM2.5, as well as correlations between upward mobility and other county-level characteristics from Chetty et al. (2014).

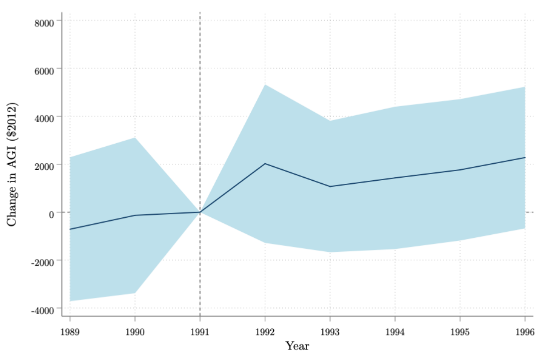
Figure 4: Cohort-Specific Estimates of the Relationship between Prenatal Nonattainment Exposure and Our Main Outcomes.



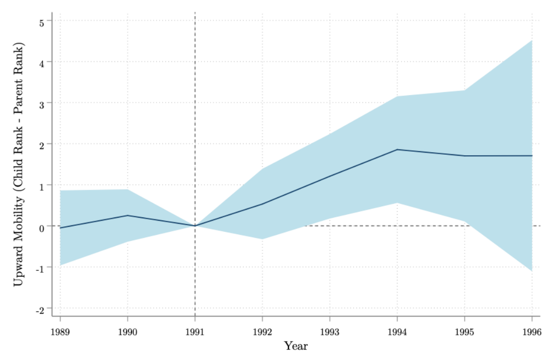
(a) Prenatal $PM_{2.5}$ Exposure



(b) W2 Earnings ($2012)



(c) AGI ($2012)



(d) Upward Mobility

Source: IRS 1040s, IRS W-2s, ACS 2001-2019, Census Numident and author's calculations using data from Meng et al. (2019). These figures present cohort-specific estimates of the association between prenatal exposure to nonattainment designations and our main outcomes of interest. Panel a) presents estimates of the association between prenatal exposure to nonattainment and prenatal $PM_{2.5}$ exposure. This is the first-stage of our analysis. Panel b) presents estimates of the association between prenatal exposure to nonattainment and later-life W2 earnings. Panel c) presents estimates of the association between prenatal exposure to nonattainment and later-life AGI. Panel d) presents estimates of the association between prenatal exposure to nonattainment and later-life upward mobility, measured as the difference in AGI income rank between children and their parents. Error bars reflect the 95 percent confidence intervals calculated with robust standard errors clustered at the county of birth level.

Table 1: First Stage Effect of Nonattainment on $PM_{2.5}$

	(1) $PM_{2.5}$
PM10 Nonattainment	-0.1563 (0.1203)
PM10 and NOx Nonattainment	-1.383*** (0.3368)
Fixed Effects	Birth County, Birth-State × Year, Birth Month
Individual Controls	Yes
County-level Controls	Yes
Observations	3,428,000
First Stage F-Stat	9.74

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Source: Source: IRS 1040s, IRS W-2s, ACS 2001-2019, Census Numident and author's calculations using data from Meng et al. (2019). This table shows the first stage effect of nonattainment PM_{10} and NO_x designations on $PM_{2.5}$ exposure at birth.

Table 2: Effect of $PM_{2.5}$ On Adult Economic Outcomes

	(1) W-2 Earnings	(2) AGI	(3) Upward Mobility
Panel A: IV			
$PM_{2.5}$ ($\mu g/m^3$)	-1105**	-1313*	-0.0128**
	(493.2)	(693.4)	(0.005855)
Panel B: Reduced Form			
Nonattainment × Post	1553***	1922**	0.01103**
	(531.9)	(868.8)	(0.005443)
Fixed Effects	Birth County, Birth Year × Tax Year, Birth State × Birth Year, Birth Month		
Individual Controls	Yes	Yes	Yes
County-level Controls	Yes	Yes	Yes
Observations	10,610,000	13,710,000	13,710,000
Control Mean	$25,490	$35,340	0.66
First Stage F-Stat	9.69	9.74	9.74

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Source: Source: IRS 1040s, IRS W-2s, ACS 2001-2019, Census Numident and author's calculations using data from Meng et al. (2019). This table shows the second stage effect of PM2.5 on earnings, AGI and upward mobility in panel A, and the reduced form effecto fof nonattainment PM_{10} and NO_x designations on on earnings, AGI and upward mobility in panel B. Column 1 uses a sample consisting of individuals born between 1989-1996 who have W-2 earnings between 2016-2019. Columns 2 and 3 use a sample consisting of individuals born between 1989-1996 who are a primary or secondary 1040 filer between 2016-2019. Upward mobility in column 3 is defined as the child's AGI rank in 2016-2019 subtracted from their parent's AGI rank in their year of birth.

Table 3: MTO Intent-to-Treat Effect on Earnings and Pollution Exposure

	(1) W-2 Earnings	(2) 1040 AGI	(3) $PM_{2.5}$
Exp Group	1300.0**	2001***	-0.170**
	(626.5)	(730.7)	(0.0692)
S8 Group	582.2	1078	0.0271
	(666.3)	(710.7)	(0.0718)
Site FE	Yes	Yes	Yes
Observations	9,500	9,500	9500
Control Mean	-	-	16.14

NOTES: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Source: HUD MTO, IRS 1040s, IRS W-2s and Meng et al. (2019). This table shows the Intent to Treat effect of random assignment into the MTO experimental group and into the Section 8 group on pollution exposure. Column 1 show effects on earnings as measured as the annual earnings across all Form W-2s, while column 2 shows the effects on AGI income on form 1040s. Column 3 shows the effects on $PM_{2.5}$ exposure.

Online Appendices – Not for Publication

A Additional Results and Robustness Tests

Table A1: Robustness Check: Alternate Geographic Granularity (Earnings)

	(1) W-2 Earnings	(2) W-2 Earnings	(3) W-2 Earnings
Panel A: IV			
$PM_{2.5}$ ($\mu g/m^3$)	-961.2***	-989.1**	-1105**
	(330)	(403.1)	(493.2)
Panel B: Reduced Form			
Nonattainment × Post	1553***	1553***	1553***
	(531.9)	(531.9)	(531.9)
Exposure Level	Tract	Zip Code	County
Fixed Effects	Birth County, Birth Year × Tax Year, Birth State × Birth Year, Birth Month		
Individual Controls	Yes	Yes	Yes
County-level Controls	Yes	Yes	Yes
Observations	8,945,000	10,610,000	10,610,000
First Stage F-Stat	19.47	14.36	9.69

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Source: Source: IRS 1040s, IRS W-2s, ACS 2001-2019, Census Numident and author's calculations using data from Meng et al. (2019). See table 2 for more information. This table shows the effect of PM2.5 and nonattainment on earnings, using different definitions of pollution exposure. Column 1 uses $PM_{2.5}$ exposure resolved to the Census tract level, while columns 2 and 3 use zip code and county level resolution respectively.

Table A2: Robustness Check: Alternate Geographic Granularity (AGI)

	(1) 1040 AGI	(2) 1040 AGI	(3) 1040 AGI
Panel A: IV			
$\text{PM}_{2.5}$ ($\mu g/m^3$)	-1274*** (487)	-1162** (564.9)	-1313* (693.4)
Panel B: Reduced Form			
Nonattainment × Post	1922** (868.8)	1922** (868.8)	1922** (868.8)
Exposure Level	Tract	Zip Code	County
Fixed Effects	Birth County, Birth Year × Tax Year, Birth State × Birth Year, Birth Month		
Individual Controls	Yes	Yes	Yes
County-level Controls	Yes	Yes	Yes
Observations	11,520,000	13,710,000	13,710,000
First Stage F-Stat	19.26	14.44	9.74

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Source: Source: IRS 1040s, IRS W-2s, ACS 2001-2019, Census Numident and author's calculations using data from Meng et al. (2019). See table 2 for more information. This table shows the effect of PM2.5 and nonattainment on AGI, using different definitions of pollution exposure. Column 1 uses $\text{PM}_{2.5}$ exposure resolved to the Census tract level, while columns 2 and 3 use zip code and county level resolution respectively.

Table A3: Robustness Check: Effect of $PM_{2.5}$ On Adult Economic Outcomes, Log/IHS

	(1) W-2 Earnings	(2) AGI	(3) Earnings	(4) AGI
Panel A: IV				
$PM_{2.5}$ ($\mu g/m^3$)	-0.03004**	-0.0207**	-0.02827**	-0.01375**
	(0.01225)	(0.01037)	(0.01156)	(0.01147)
Transformation	Log	Log	IHS	IHS
Fixed Effects	Birth County, Birth Year × Tax Year, Birth State × Birth Year, Birth Month			
Individual Controls	Yes	Yes	Yes	Yes
County-level Controls	Yes	Yes	Yes	Yes
Observations	10,610,000	13,710,000	10,610,000	13,710,000
Control Mean	$25,490	$35,340	$25,490	$35,340
First Stage F-Stat	9.69	9.74	9.69	9.74

Notes:Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Source: Source: IRS 1040s, IRS W-2s, ACS 2001-2019, Census Numident and author's calculations using data from Meng et al. (2019). See table 2 for more information. This table shows the effect of PM2.5 on earnings and AGI using different transformations of the dependent variable. Columns 1 and 2 use a logarithmic transformation (which implicitly excludes zero and negative values), while columns 3 and 4 use an inverse hyperbolic sine, which allow for zero and negative valued income.