BREAD-IGC Virtual PhD Lecture on Inequality of Environmental Damages

Reed Walker
UC Berkeley

November 2023

General Framework for Exploring Environmental Inequality

What do we mean when we use the phrase "environmental inequality"?

- Inequality in exposure to environmental harms?
- Inequality in the effects of environmental harms?
- Inequality in the effects of policy addressing environmental harms?

Answer: all of the above

This Talk

1. Measurement
2. Valuation
3. Estimation / Impacts

Part 1: Measurement

Issues of environmental inequality have risen to prominence in recent political and policy forums

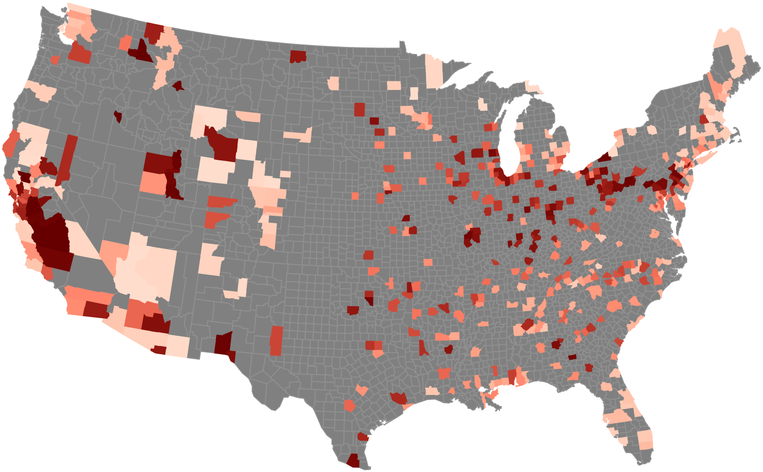
- Modern day "Environmental Justice" movement has catalyzed these efforts

Very Active Area of Research:

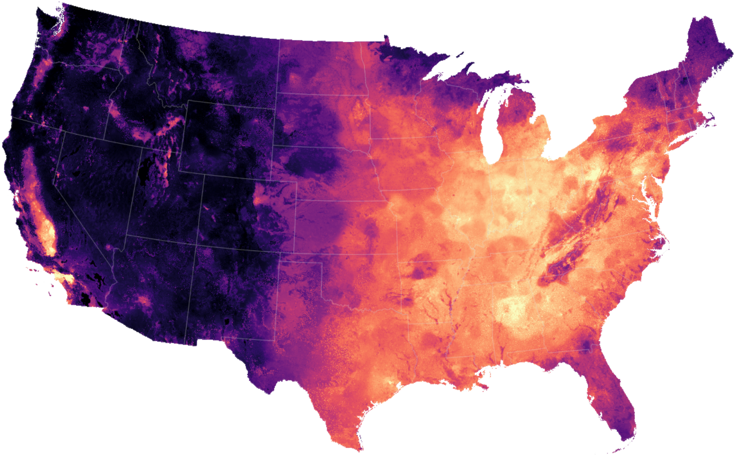
- Increasing recognition of disparate burdens / policy experimentation / etc...
- Data and measurement has improved <u>dramatically</u> in past 10 years

Measurement Improvement: Example #1 Air Quality

PM2.5 Levels as Measured By Environmental Protection Agency (EPA) Monitoring Network



PM2.5 Satellite / Remote Sensing Pollution Measurements



Di et al. (2018), 1km resolution, 2000-2015

Measurement Improvement: Example #2 Wealth/Income

Remote sensing + Social Media Data + Cell Phones + Machine Learning = comprehensive wealth measures at high resolution

Microestimates of wealth for all low- and middle-income countries

Guanghua Chi[a,1,2], Han Fang[b], Sourav Chatterjee[b], and Joshua E. Blumenstock[a,1,3]

[a]School of Information, University of California, Berkeley, CA 94720; and [b]Meta, Inc., Menlo Park, CA 94025

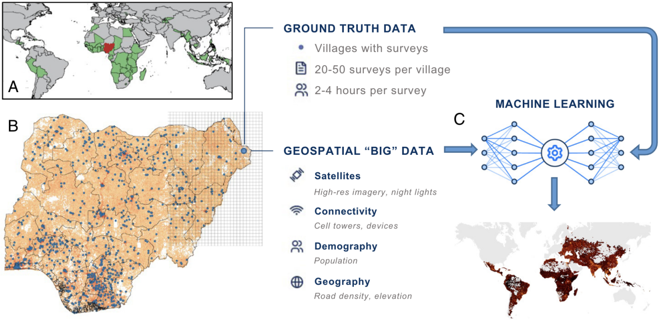
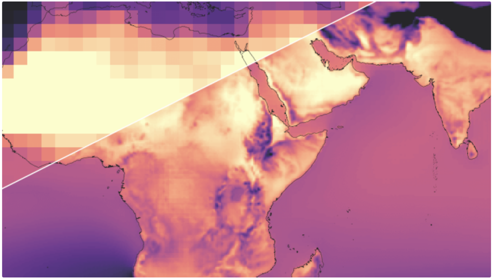


Fig. 2. Overview of approach. (*A*) Nationally representative household survey data are obtained from 56 different countries around the world. (*B*) In Nigeria, for example, there are 40,680 households surveyed in 899 unique survey locations (“villages”). Geospatial “big” data from satellites and other existing sensors are also sourced from each location. (*C*) These data are used to train a machine-learning algorithm that predicts microregional poverty from nontraditional data, even in regions where no ground-truth data exists.

Measurement Improvement: Example #3 Climate

Downscaled and bias-corrected climate model projections allowing for localized climate change impact analysis



CIL Global Downscaled Projections for Climate Impacts Research (CC-BY-4.0)

Climate Impact Lab Global Downscaled Projections for Climate Impacts Research (CC-BY-4.0)

Overview

The World Climate Research Programme's 6th Coupled Model Intercomparison Project (CMIP6) represents an enormous advance in the quality, detail, and scope of climate modeling.

The Global Downscaled Projections for Climate Impacts Research dataset makes this modeling more applicable to understanding the impacts of changes in the climate on humans and society with two key developments: trend-preserving bias correction and downscaling. In this dataset, the Climate Impact Lab provides global, daily minimum and maximum air temperature at the surface (`tasmin` and `tasmax`) and daily cumulative surface precipitation (`pr`) corresponding to the CMIP6 historical, ssp1-2.6, ssp2-4.5, ssp3-7.0, and ssp5-8.5 scenarios for 25 global climate models on a 1/4-degree regular global grid.

Measurement Improvement: Many Other Examples!

Recent examples of huge advances in measurement/monitoring

- Surface temperatures useful heat for urban heat island and other applications
- Soil moisture for agriculture
- High resolution rainfall data for Africa
- Comprehensive measures of deforestation
- Land use using satellite imagery

Note: much of this new data is based on predictive models and forecasts, and one needs to be careful + aware of prediction error / model uncertainty when doing inference (see e.g., Proctor, Carleton, and Sum 2023)

Measurement of exposure / inequality as an end goal

Lot's of compelling "descriptive papers" to be written with new data on measurement

- Often these exercises lead to lots of questions / hypotheses about why such patterns exist
- Descriptive work often spurs new research ideas / topics / papers

Part 2: From Measurement to Quantifying Damages (i.e. Valuation)

Economists spend lots of time thinking about how differences in exposure translate into differences in well-being or economic welfare.

The key tool for translating exposure of any type of non-market good into dollar or welfare measure is a damage function

- Damage function related to carbon emissions
- Damage function associated with fine-small particulate exposure
- etc...

Setting the Stage: Damage Functions and Their Components

Environmental Externality (e.g., air pollution): imposes a social cost that may be written as a general function of two components:

1. Level of exposure to environmental conditions, e
2. Attributes that may influence how exposure affects well-being (i.e., vulnerability), x

$$Damage = f(e, x)$$

Vulnerability may be related to:

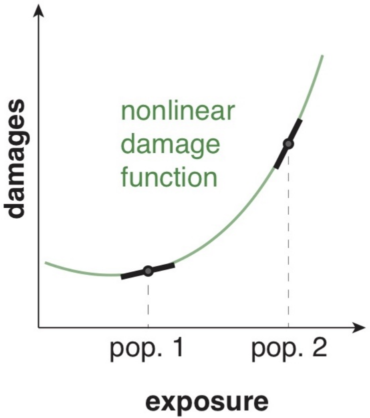
- Differences in preferences (e.g. I really dislike dirty air)
- Adaptive investments (e.g., air conditioning)
- Overall health (e.g., older people more sensitive)

Damage Function: translates exposure and individual attributes into damages in welfare terms, such as willingness to pay (WTP)

Damage Function:

Damage Function: a way of converting exposure e into economic cost, taking into account that vulnerability and the underlying drivers of vulnerability x are important inputs into cost calculation.

$$Damage = f(e, x)$$



Sources of Vulnerability Important for Damage Calculations

To mitigate harms of air pollution (i.e. reduce vulnerability), individuals could wear masks all the time, stay inside, purchase air conditioning, etc...

- These actions are costly and displace consumption of utility generating goods.
- i.e. these costs should factor into a damage function

Hence, WTP for wellbeing or, conversely, avoiding damages is a function of:

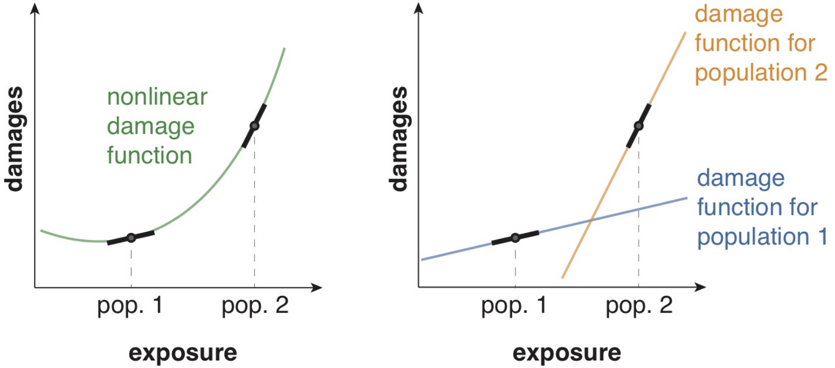
1. Factors that enter utility directly (e.g., the probability of dying)
2. Costly investments that help influence these factors (Grossman 1972)

Understanding the Sources of Heterogeneity

How do we identify the sources of heterogeneity in marginal damages?

- Do marginal damages differ because baseline exposure differs or because vulnerability differs?

Heterogeneity in marginal damages result from nonlinear damage functions or differing vulnerability.



Understanding the Sources of Heterogeneity

How do we identify the <u>sources</u> of heterogeneity in marginal damages?

- Do marginal damages differ because baseline exposure differs or because vulnerability differs?

These are **causal** questions, and we need a strategy to address various forms of confounding or omitted variable bias.

- Ideally have exogenous variation in environmental exposure AND exogenous variation in modifier (i.e. level of exposure or adaptive technologies)
- Not always possible and thus need to be cautious in attributing observed differences in damages to a single causal factor...

Part 3: Estimation / Impact of a Change in Environmental Quality

Policy change: Policy may change exposure, producing a benefit equal to change in damages.

For individual i with prepolicy exposure e_i and post policy exposure $e_i + \Delta e_i$, a policy generates benefits equal to the change in damages

$$f(e_i + \Delta e_i, x_i) - f(e_i, x_i)$$

Distributional Effects: Policy may have distributional effects for two reasons:

1. Policies can generate different changes in exposure for different groups
2. Damages (i.e., vulnerability) may differ across groups (even with equal exposure change)

Estimation / Impact: Two Primary Approaches

Exploring policy effects on exposure:

1. Simulation, forecasting, or estimating the response of physical systems (e.g., climate, pollution, forest density) to policy scenarios
   - EU introduces a carbon tax $\rightarrow$ lower GHG emissions $\rightarrow$ global climate model (GCM) to simulate/forecast future environmental outcomes
2. Retrospective analyses: historical data used to explore effects of past policies
   - Effects of Clean Air Act on distribution of air quality

Which tool you use depends on setting / question / data availability

Application: Currie, Voorheis, and Walker (2021) / Measurement and Estimation/Impact

Salient narrative that low income minorities disproportionately live in areas that are characterized by environmental degradation/ elevated pollution levels etc

Given rise to the modern day "Environmental Justice" movement

Existing evidence is somewhat piecemeal and indirect

- Proxies for environmental exposure (i.e. proximity to toxic plant)
- Data is scarce (i.e. 775 counties in US with EPA pollution monitors)

Very little evidence on population-wide patterns in racial pollution disparities and/or underlying drivers of these patterns

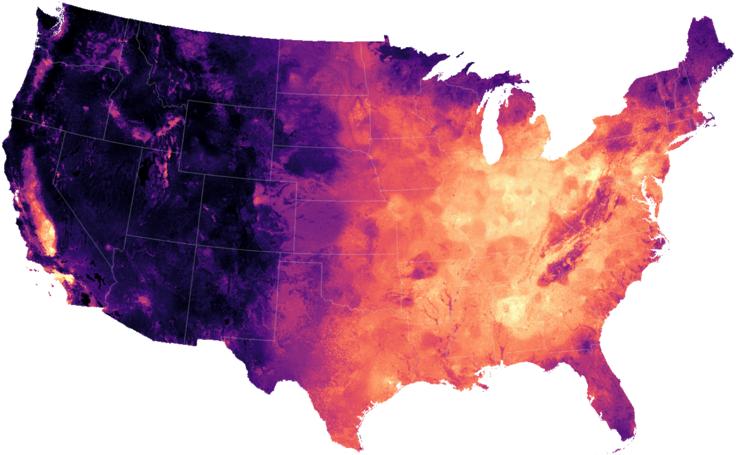
Currie, Voorheis, and Walker (2021): Environmental Inequality

Newly available data and associated findings raise a number of interesting and important questions:

- To what extent does spatial granularity of exposure alter our understanding of questions pertaining to environmental inequality?

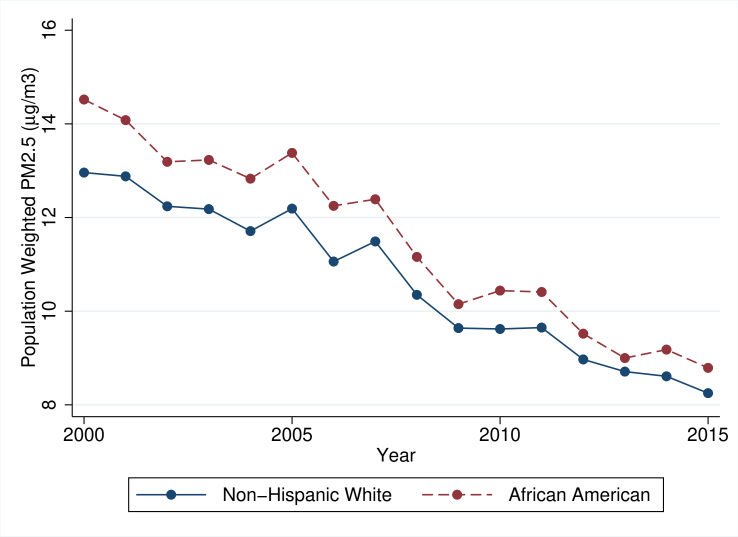
1. **Measurement**: Combine spatially continuous pollution data with large-scale demographic data $\Rightarrow$ provide new facts on environmental disparities in US
2. **Impact/Estimation**: Explore how the US Clean Air Act has contributed to observed findings on environmental disparities

PM2.5 Satellite / Remote Sensing Pollution Measurements



Di et al. (2018), 1km resolution, 2000-2015... linked to administrative survey data from 32 million individuals

Black White Pollution Trends: PM2.5



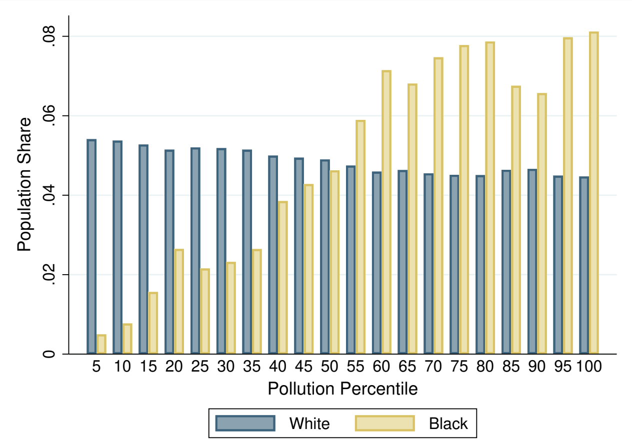
Source: Di et al. (2018)

Why are Black Neighborhoods Getting (Relatively) Cleaner?

One Possibility: Environmental policy disproportionately improves air quality in areas where African Americans are overrepresented

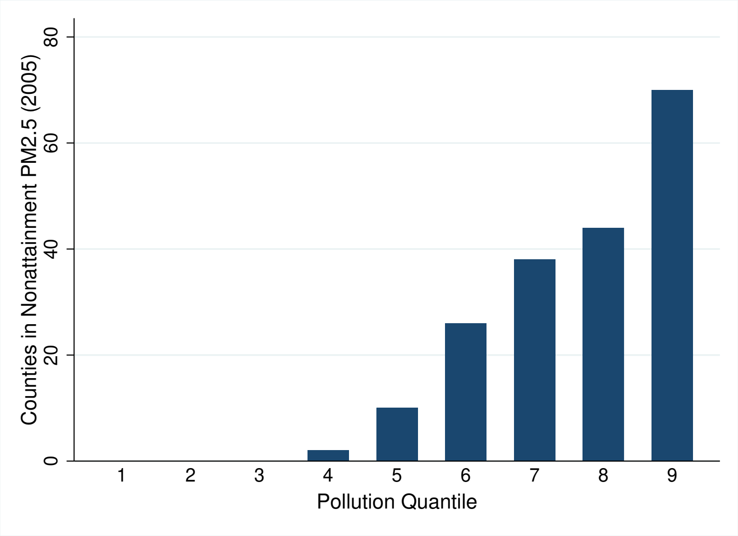
The Clean Air Act targets / cleans up only the most polluted areas

- Explore how this spatial targeting has affected the black/white pollution gap.

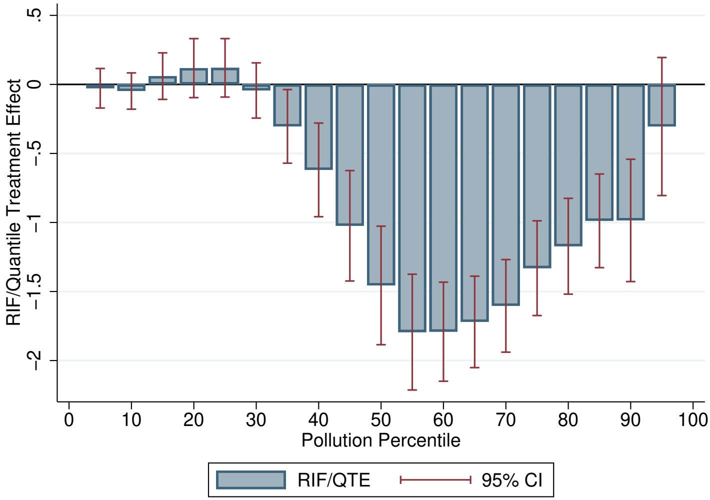


County PM2.5 Nonattainment Designations by Pollution Quantile

CAA Only Affects Part of the Pollution Distribution



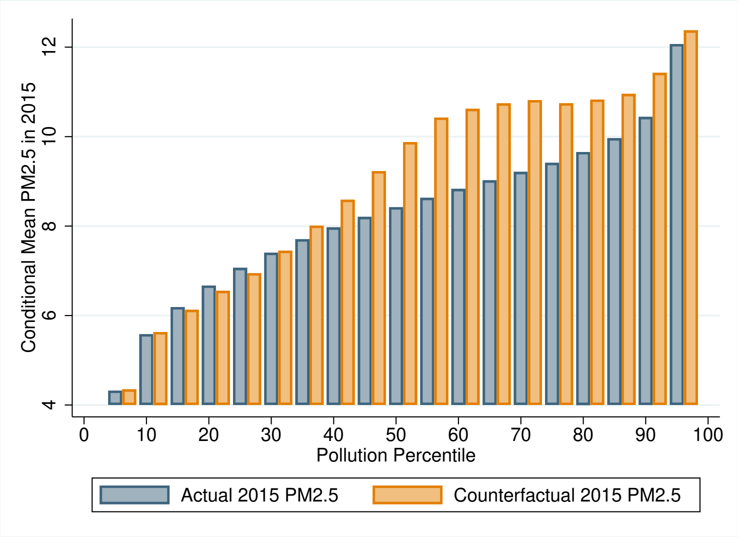
Quantile Treatment Effects of CAA on PM2.5 Distribution



Estimates include county and State-Year fixed effects. Standard errors clustered by CZ

No State-Year FE

Counterfactual 2015 PM2.5 Pollution Implied by RIF Treatment Effects



Calculating the Effect of CAA Regulations on the Black-White PM2.5 Gap

Main Counterfactual	
2015 Counterfactual Black-White Gap:	0.97
Counterfactual *Change* in Black-White Gap:	-0.23
Actual *Change* in Black-White Gap:	-0.59
% of Actual Gap Attributable to CAA:	**61.2%**

Wrapping Up

A 60% improvement in the Black-White PM2.5 gap from 2000-2015

- Existing differences in exposure and reductions in disparities *not* explained by individual characteristics or differential mobility
- Minority communities are seeing greater improvements in air quality in large part due to the targeted nature of the CAA
- The CAA has compressed the pollution distribution from the top, disproportionately benefitting African Americans