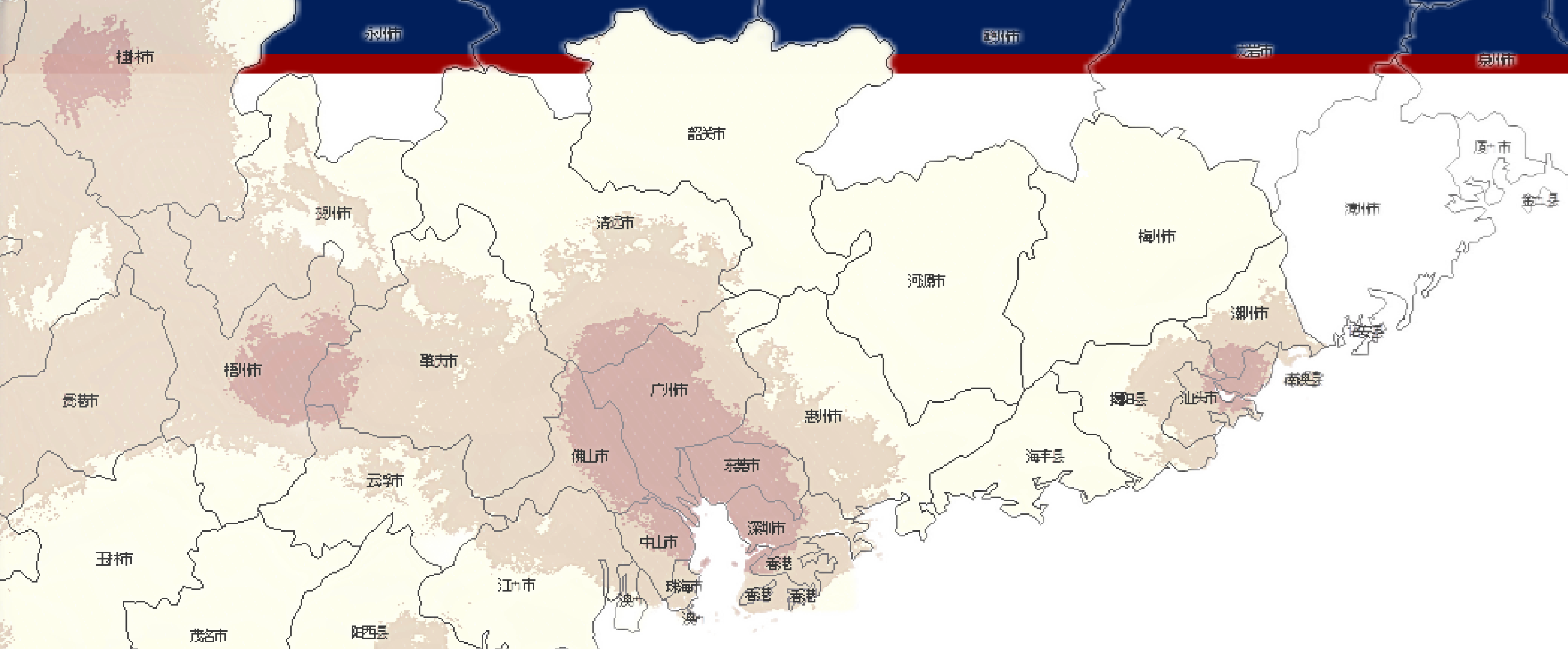


Breathing inequality:

Inequalities in air-pollution exposure among sociodemographic groups -- an application for South China

Sukie Xiuqi Yang[1], Fan Wang[2], Emily Hannum[1], and Jere R. Behrman[1]

[1]University of Pennsylvania; [2]University of Houston

Question: How to quantify inequalities in air pollution exposure between socio-demographic groups such as education?

Many discussions focus
differential vulnerability
(β)

Little discussion on
differential exposure
(x)

Penn Demography

Motivation and Significance

Existing literature…

focuses on the individual mean (within a certain time frame such as a year) (e.g., Jbaily et al. 2022)

- **Exposure matters not only in the sum /average level but also in terms of the extremes that one is exposed to (WHO 2021).**

focuses on between-group mean differences, despite the fact that much of the heterogeneities remain within-group.

- **This obscures heterogeneity within groups, making it difficult to target the truly over-burdened subgroup(s) and resulting in overgeneralized policy suggestions.**

has not fully investigated the intersection of different sociodemographic characteristics.

- **Inequalities do not act independently of one another and often "intersect" in various ways to produce disparate vulnerabilities (Pellow, 2018: 37).**

Penn Demography

Data and methods

Existing literature…

Our approach…

focuses on individual mean (within a certain time frame such as a year) (e.g., Jbaily et al. 2022)

Indicator trans-formed individual exposure levels: $$\underbrace{\widehat{Z}_{l,y}(\widehat{z})}_{\substack{\text{Aggregate exposure} \\ \text{above } \widehat{z} \\ \text{at location } l \\ \text{in period/year } y}} = \sum_{t=1}^{T_y} \left(Z_{l,y,t} \cdot \underbrace{\mathbf{1}\left(Z_{l,y,t} > \widehat{z}\right)}_{\substack{\text{Subperiod/month } t \\ \text{exposure above} \\ \text{critical threshold } \widehat{z}}} \right)$$

focuses on between-group mean differences, despite the fact that much of heteroge-neities remain within-group.

Within group inequality and across group inequality, measured with P80 to P20 ratio or COV

has not fully investigated intersection of different socio-demographic characteristics.

Intersectional cross-group P80/P20 or COV with different thresholds

Low data input requirements:

Historical, predicted ground-level PM2.5 concentrations based on satellite remote sensing

Census Statistics from China, 2010 (County-level)

Penn Demography

Overview of the results

Table 1

- Within-group (e.g., among less-educated) exposure inequality substantially larger than across-group (e.g., between less and more educated) inequality.

Table 2

- Group-specific mean of means is below critical pollution threshold, but large share of group are exposed to high pollution during parts of the year.

Figure 1

- Better-educated urban population is exposed to substantially more pollution, gradient sharper among urban non-migrants.

Table 3

- Zero education-exposure-inequality among rural migrants; sharp inequality among urban non-migrants as critical pollution threshold rises.

Penn Demography

Key takeaways

Methodologically

- To better understand the environmental inequality across socio-demographic groups, we need to examine the full distribution of air pollution in time and space.
- This study offers an intuitive approach to measuring population exposure disparities that illuminates inequalities without intensive data requirements and can inform the development of targeted policies that reduce health risks for the overexposed groups.
- In quantifying environmental inequalities, P80/P20 ratio is more robust to outliers while COV is more sensitive to the tails, but these measures are complementary.

Substantively

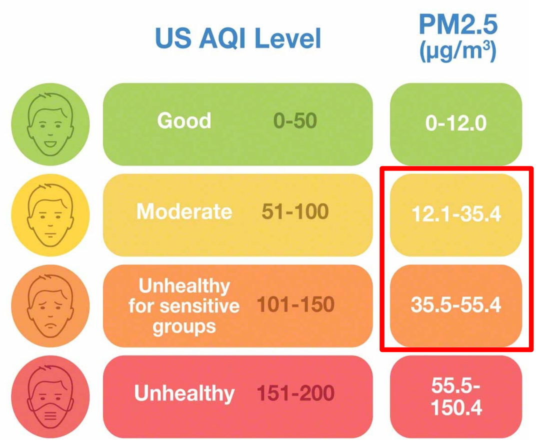
- In contrast to conventional wisdom that socially vulnerable groups are exposed to more pollution, we find that highly educated migrant populations were overburdened with air pollution compared to less-educated migrants, with regard to their population share.
- In the discussion of environmental inequality, more attention should be paid to differential exposure, in addition to differential vulnerability.
- The education-migration intersection is important in the Chinese context.

Breathing inequality: Inequalities in air pollution exposure among sociodemographic groups – an application for South China

Sukie Xiuqi Yang[1], Fan Wang[2], Emily Hannum[1], and Jere R. Behrman[1]
[1]University of Pennsylvania; [2]University of Houston

Introduction

Mounting evidence over the past several decades has demonstrated the inequitable distribution of air pollution among sociodemographic groups. We develop novel group-based environmental measures to investigate the distributional patterns of PM2.5 air pollution across sociodemographic groups. We demonstrate the approach using sociodemographic groups defined by age, education, area of residence and migration status, but the approach can be used for any groupings for which tabulated, geo-linked population data are available.



Air pollution is closely related to public health, and the threshold 35 $\mu g/m^3$ demarcates the healthy and unhealthy level of air quality. Such a threshold is also the first interim target recommended by the recent AQG guidelines proposed by medical, public health, and scientific societies (WHO 2021). It is noticeable that different thresholds are given with different averaging time, and the the 24-hour threshold is defined by the 99th percentile of the year. This suggests that percentile-based measures are commonly used in policy literature and that exposure does not only matter in terms of the sum or average level but also in terms of the extremes that one is exposed to.

WHO Recommended Air Quality Guideline and Interim Targets (WHO, 2021)

Pollutant	Averaging time	Interim target 1	Interim target 2	Interim target 3	Interim target 4	AQG level
$PM_{2.5}$, μg/m³	Annual	35	25	15	10	5
	24-hour[a]	75	50	37.5	25	15

[a] 99th percentile (i.e. 3–4 exceedance days per year).

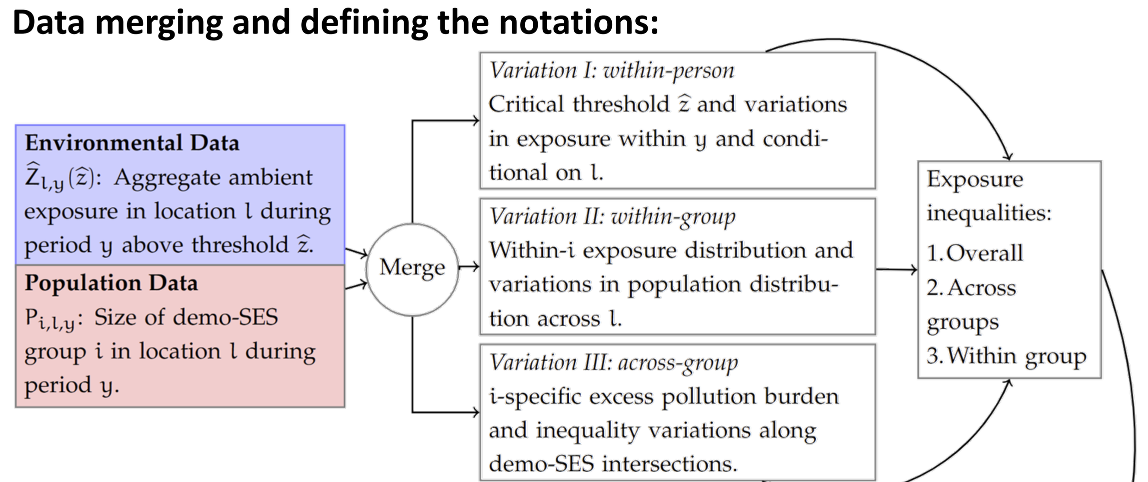
Literature and Limitation

Existing literature…

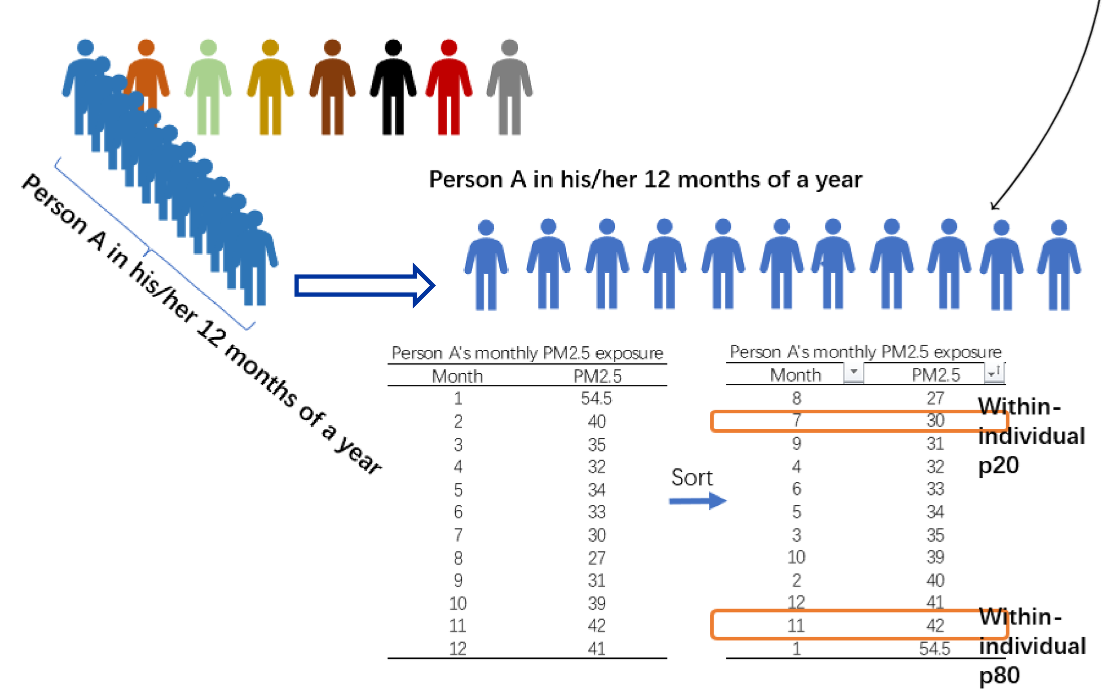
- focuses on the individual mean (within a certain time frame such as a year) (e.g., Jbaily et al. 2022)
  - Exposure matters not only in the sum /average level but also in terms of the extremes that one is exposed to (WHO 2021).
- focuses on between-group mean differences, despite the fact that much of the heterogeneities remain within-group.
  - This obscures heterogeneity within groups, making it difficult to target the truly over-burdened subgroup(s) and resulting in over-generalized policy suggestions.
- has not fully investigated the intersection of different sociodemographic characteristics.
  - Inequalities do not act independently of one another and often "intersect" in various ways to produce disparate vulnerabilities (Pellow, 2018: 37).

Methodology

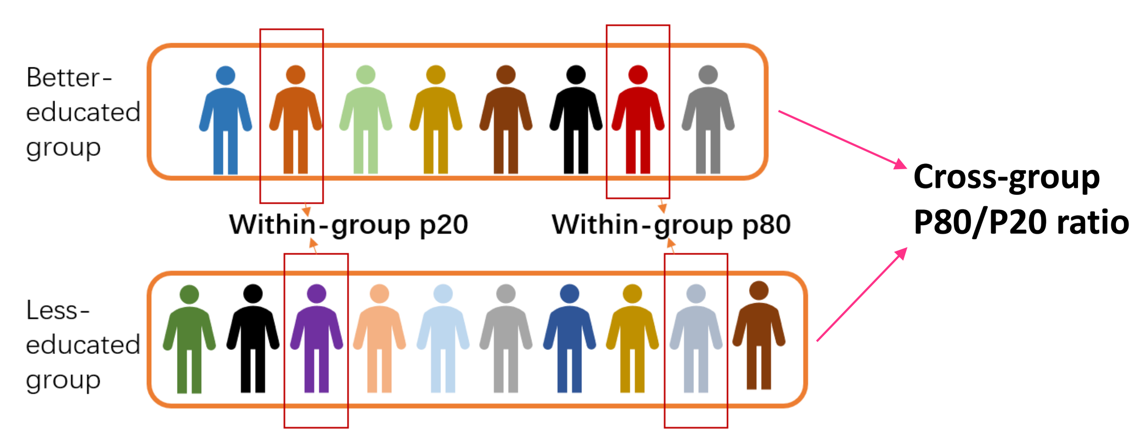
Data merging and defining the notations:



Within-individual distribution:



Within-group and across-group distribution:



We define $\mathcal{E}_{i,y}$ as the share of pollution burden for population group *i* that is in excess of its population share as:

$$\mathcal{E}_{i,y} = \left(\left(\frac{\mathcal{P}_{i,y} \times \mathcal{Z}_{i,y}}{\sum_{\widehat{i}}^{N} \left(\mathcal{P}_{\widehat{i},y} \times \mathcal{Z}_{\widehat{i},y} \right)} \right) \times \frac{1}{\mathcal{P}_{i,y}} \right) - 1 = \frac{\mathcal{Z}_{i,y}}{Z_y} - 1$$

We propose a indicator transformation function with a exposure threshold parameter:

$$\underbrace{\widehat{Z}_{l,y}(\widehat{z})}_{\substack{\text{Aggregate}\\ \text{exposure}\\ \text{above } \widehat{z}\\ \text{at location } l\\ \text{in period/year } y}} = \sum_{t=1}^{T_y} \left(Z_{l,y,t} \cdot \underbrace{\mathbf{1}\left(Z_{l,y,t} > \widehat{z}\right)}_{\substack{\text{Subperiod/month } t\\ \text{exposure above}\\ \text{critical threshold } \widehat{z}}} \right)$$

Results and Conclusions

Takeaway 1: None of the binary sociodemographic factors account for a substantial amount of variation, and greater heterogeneities remain within group, suggesting that additional grouping may need to be considered. After accounting for the exposure threshold, the inequality between groups is considerably greater.

Table 1: $PM_{2.5}$ exposures across demographic groups, cross-group and within-group inequality, and indicator-transformed group exposures.

	Gender		Age		Education		Migration		Area	
	Male	Female	Prime-age[†]	O/W	⩽ 9 years	O/W	Migrant	O/W	Urban	Rural
Panel A. Conventional group mean approach[‡]										
Average level of exposure	34.02	33.92	34.41	33.57	33.59	35.21	36.01	32.92	34.98	30.51
Coefficient of variation	0.00		0.01		0.02		0.04		0.05	
Panel B. Excess exposure, within group inequality, and percentiles										
Excess exposure relative to pop.[§]	0.00	-0.00	0.01	-0.01	-0.01	0.03	0.06	-0.03	0.03	-0.10
Within-group P80 to P20 ratio	1.27		1.24		1.25		1.22		1.20	
Cross-group P80 to P20 ratio	1.00		1.02		1.05		1.09		1.14	
Panel C. Indicator transformed exposure[¶] with threshold = 35										
Excess exposure relative to pop.	0.00	-0.01	0.04	-0.03	-0.04	0.10	0.18	-0.09	0.09	-0.31
Within-group P80 to P20 ratio	1.97		1.92		1.81		1.76		2.45	
Cross-group P80 to P20 ratio	1.01		1.07		1.14		1.30		1.58	

Note: First, within each year, given ambient pollution ($PM_{2.5}$) exposure variations across locations and calendar months, we compute the overall 80th to 20th percentile ambient exposure ratios (Shown in Panel A). Second, for the dichotomous groups in Panels B C, D, E, and F, we compute group-specific relative ambient exposures, which is the ratio of the share of ambient pollution each group is exposed to divided by the share of population that the group accounts for in the overall population. Third, conditional on each one of the two dichotomous groups, we compute the within-group 80th to 20th percentile ambient exposure ratios. Fourth, we compute the across-group 80th to 20th percentile ratios—in this setting, given that there are only two groups and the smaller group in each dichotomous set has more than 20 percent of population, the across-group ratios reflect the ratio of ambient exposures of the two groups.

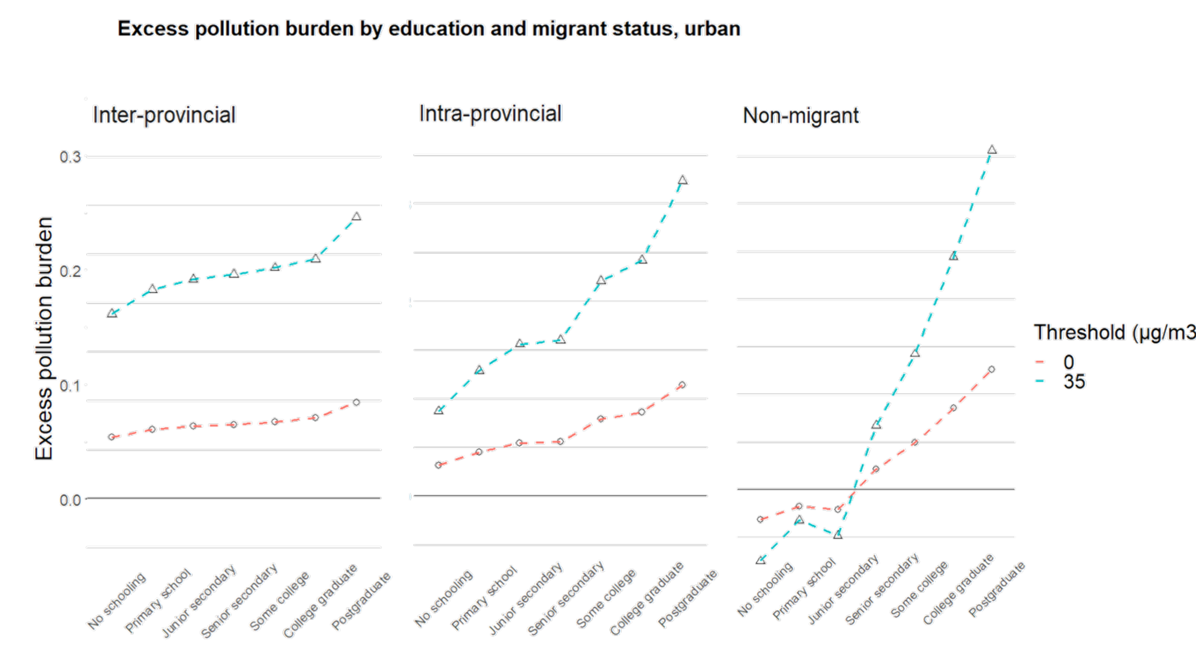
Takeaway 2: To better understand the environmental inequality across socio-demographic groups, we need to examine the full distribution of air pollution in time and space.

Table 2: Within-individual and within-group distributions of $PM_{2.5}$ exposures, computed as deviation from the 35 $\mu g/m^3$ $PM_{2.5}$ threshold.

	Within-individual[†] exposure		
	20^{th} percentile (2nd lowest months)	50^{th} percentile	80^{th} percentile (2nd highest months)
Group A. Less or equal to junior-secondary (9 years)			
Within-group[‡] 20th percentile	-12.59	-5.25	3.49
Within-group 50th percentile	-9.42	-1.41	8.48
Within-group 80th percentile	-6.87	2.65	13.48
Group B. Greater than junior-secondary (9 years)			
Within-group 20th percentile	-11.38	-3.93	5.52
Within-group 50th percentile	-8.14	0.21	10.59
Within-group 80th percentile	-5.44	4.17	14.56

Note: We compute the within-individual and within-group ambient $PM_{2.5}$ exposure levels, subtract these by 35, and present the values in the table here. For illustration, we focus on inequality across education groups. [†] Within-individual distribution refers to the distribution of $PM_{2.5}$ exposures during the span of a particular timeframe for an individual, assumed to be living at the same location. Given monthly data over a calendar year, using the closest-neighbor method for computing quantiles, the 20th percentile corresponds to the month with the second lowest level of $PM_{2.5}$ exposure for an individual. [‡] Within-group distribution refers to the distribution over a particular moment or percentile of the individual-specific $PM_{2.5}$ distribution across all individuals within a socio-demographic group. The within-group 20^{th} percentile of the within-individual 80^{th} percentile corresponds to the 20^{th} percentile of $PM_{2.5}$ exposure across all individual-specific second highest month of $PM_{2.5}$ exposure for individuals from a particular socio-demograhpic group.

Takeaway 3: Better-educated urban population is exposed to substantially more pollution, gradient sharper among urban non-migrants.



Takeaway 4: Zero education-exposure-inequality among rural migrants; sharp inequality among urban non-migrants as pollution critical threshold rises.

	Area and migration status conditioning		# of education group	Threshold 0	Threshold 25	Threshold 35	Threshold 40
Panel A. **p80/p20 Ratio**	-	-	2	1.047	1.081	1.137	1.184
	-	-	7	1.048	1.087	1.141	1.185
	rural	inter-provincial	7	1.001	1.000	1.007	1.037
	rural	intra-provincial	7	1.005	1.011	1.044	1.035
	rural	nonmigrant	7	1.008	1.013	1.047	1.099
	urban	inter-provincial	7	1.001	1.002	1.004	1.007
	urban	intra-provincial	7	1.001	1.004	1.004	1.011
	urban	nonmigrant	7	1.043	1.082	1.122	1.150
Panel B. **Coefficient of variation (COV)**	-	-	2	0.021	0.035	0.059	0.078
	-	-	7	0.026	0.044	0.073	0.095
	rural	inter-provincial	7	0.001	0.002	0.006	0.009
	rural	intra-provincial	7	0.002	0.006	0.016	0.019
	rural	nonmigrant	7	0.005	0.008	0.030	0.038
	urban	inter-provincial	7	0.002	0.002	0.009	0.025
	urban	intra-provincial	7	0.012	0.018	0.026	0.054
	urban	nonmigrant	7	0.030	0.054	0.080	0.098

Notes: From green to red, the level of inequality increases from low to high. Different inequality quantities under the "Threshold" columns are generated based on the indicator transformation function shown in the Methodology section.

Reference

For the full working paper with reference, please scan the QR code.

Acknowledgement and Contact

This paper is part of the project "Prenatal Air Pollution Exposures and Early Childhood Outcomes," which is supported by a grant from the Penn China Research and Engagement Fund (PIs: Behrman and Hannum) and by National Science Foundation Grant 1756738 (PI: Hannum).

Contact yangxq@sas.upenn.edu if you have any comments.

References

Clark, Lara P., Dylan B. Millet, and Julian D. Marshall. 2014. "National Patterns in Environmental Injustice and Inequality: Outdoor NO2 Air Pollution in the United States." Edited by Yinping Zhang. *PLoS ONE* 9, no. 4 (April 15, 2014): e94431. https://doi.org/10.1371/journal.pone.0094431.

Jbaily, Abdulrahman, Xiaodan Zhou, Jie Liu, Ting-Hwan Lee, Leila Kamareddine, Stéphane Verguet, and Francesca Dominici. 2022. "Air Pollution Exposure Disparities Across US Population and Income Groups." *Nature* 601, no. 7892 (7892): 228–233. https://doi.org/10.1038/s41586-021-04190-y.

Pirlea, Florina, and Wendy Ven-dee Huang. 2019. "The Global Distribution of Air Pollution," September 12, 2019. https://datatopics.worldbank.org/world-development-indicators/stories/the-global-distribution-of-air-pollution.html.

Rosofsky, Anna, Jonathan I. Levy, Antonella Zanobetti, Patricia Janulewicz, and M. Patricia Fabian. 2018. "Temporal Trends in Air Pollution Exposure Inequality in Massachusetts." *Environmental Research* 161 (February): 76–86. https://doi.org/10.1016/j.envres.2017.10.028.

Tessum, Christopher W., Joshua S. Apte, Andrew L. Goodkind, Nicholas Z. Muller, Kimberley A. Mullins, David A. Paolella, Stephen Polasky, et al. 2019. "Inequity in Consumption of Goods and Services Adds to Racial–ethnic Disparities in Air Pollution Exposure." *Proceedings of the National Academy of Sciences* 116, no. 13 (March 26, 2019): 6001–6006. https://doi.org/10.1073/pnas.1818859116.

Thomas, Kimberley, R. Dean Hardy, Heather Lazrus, Michael Mendez, Ben Orlove, Isabel Rivera-Collazo, J. Timmons Roberts, et al. 2019. "Explaining Differential Vulnerability to Climate Change: A Social Science Review." *WIREs Climate Change* 10, no. 2 (March). https://doi.org/10.1002/wcc.565.

Wang, Yuzhou, Joshua S. Apte, Jason D. Hill, Cesunica E. Ivey, Regan F. Patterson, Allen L. Robinson, Christopher W. Tessum, et al. 2022. "Location-Specific Strategies for Eliminating US National Racial-Ethnic PM2.5 Exposure Inequality." *Proceedings of the National Academy of Sciences* 119, no. 44 (November): e2205548119. https://doi.org/10.1073/pnas.2205548119.

Wu, Shanshan, and Matthew T. Heberling. 2013. "The Distribution of Pollution and Environmental Justice in Puerto Rico: A Quantitative Analysis." *Population and Environment* 35, no. 2 (December): 113–132. https://doi.org/10.1007/s11111-013-0188-6.

Zhang, Ruohao, Huan Li, and Neha Khanna. 2021. "Environmental Justice and the COVID-19 Pandemic: Evidence from New York State." *Journal of Environmental Economics and Management* 110 (October 1, 2021): 102554. https://doi.org/10.1016/j.jeem.2021.102554.

Zhao, Hongyan, Guannan Geng, Qiang Zhang, Steven J. Davis, Xin Li, Yang Liu, Liqun Peng, et al. 2019. "Inequality of Household Consumption and Air Pollution-Related Deaths in China." *Nature Communications* 10, no. 1 (December): 4337. https://doi.org/10.1038/s41467-019-12254-x.