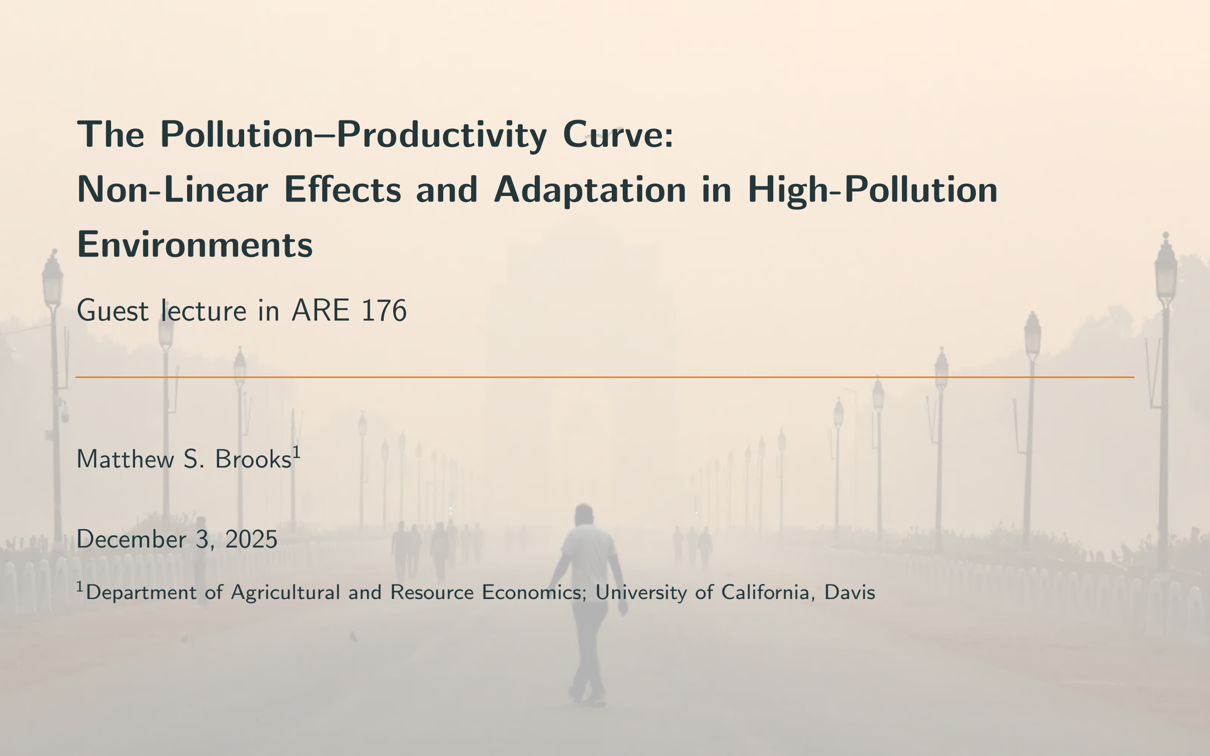

The Pollution–Productivity Curve: Non-Linear Effects and Adaptation in High-Pollution Environments

Guest lecture in ARE 176

Matthew S. Brooks[1]

December 3, 2025

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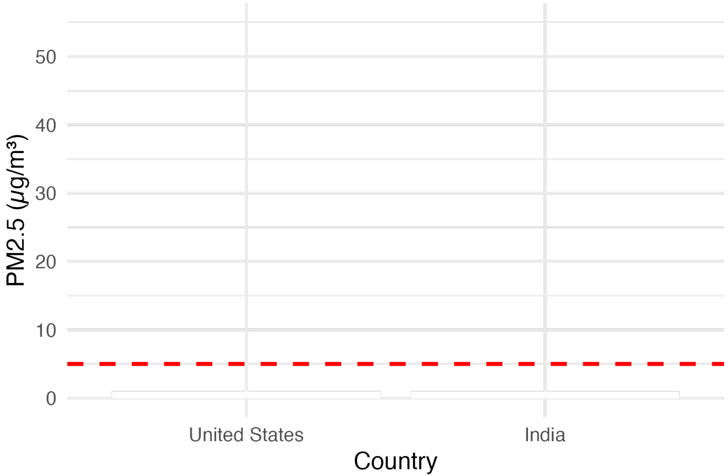
Fine particulate matter air pollution (PM2.5) is a problem.

Figure 1: Annual Average PM2.5 in U.S. and India in 2024



Source. `www.iqair.com`

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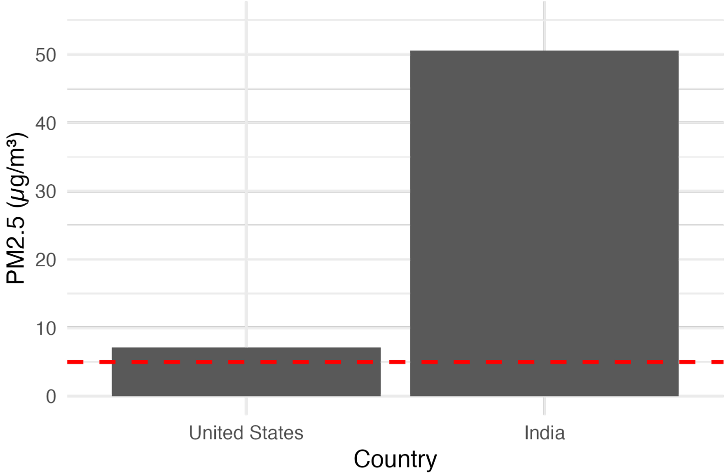
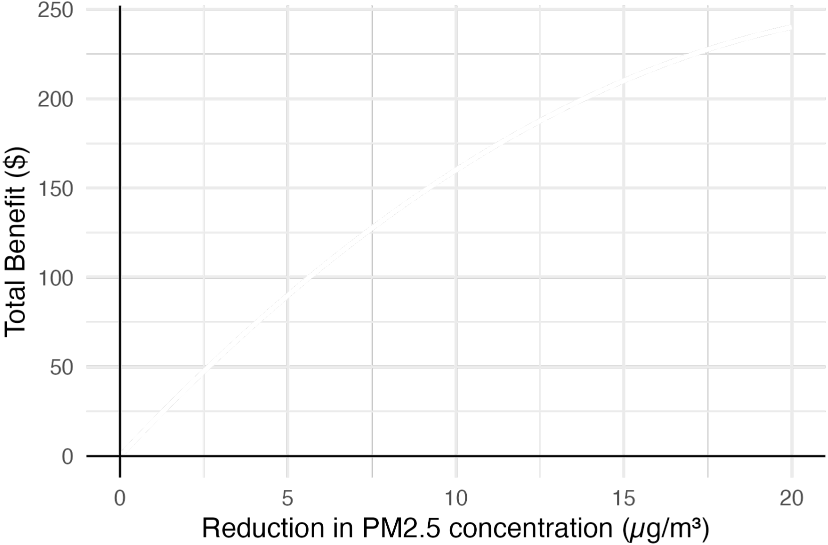


Source. www.iqair.com

How big are the benefits from cleaning the air?

Figure 2: Total Benefits from Air Quality Improvements



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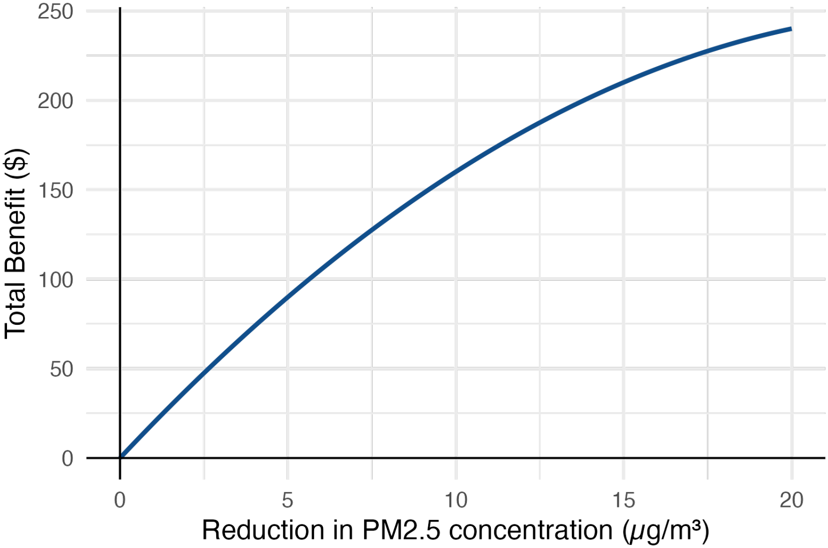
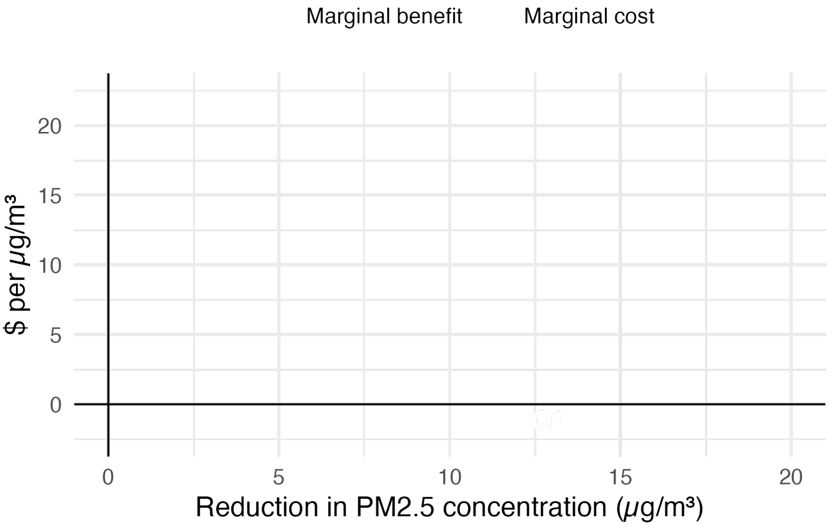


By how much should we clean the air?

Figure 3: Marginal Costs and Marginal Benefits of Clean Air Policy



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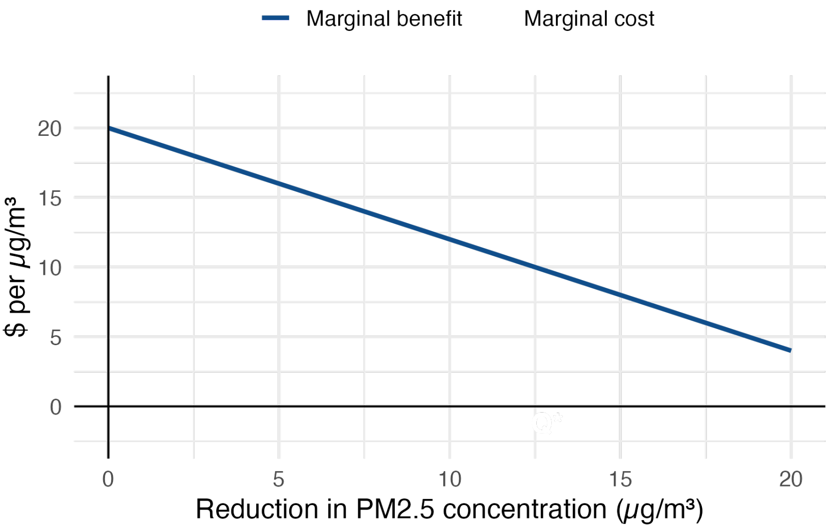

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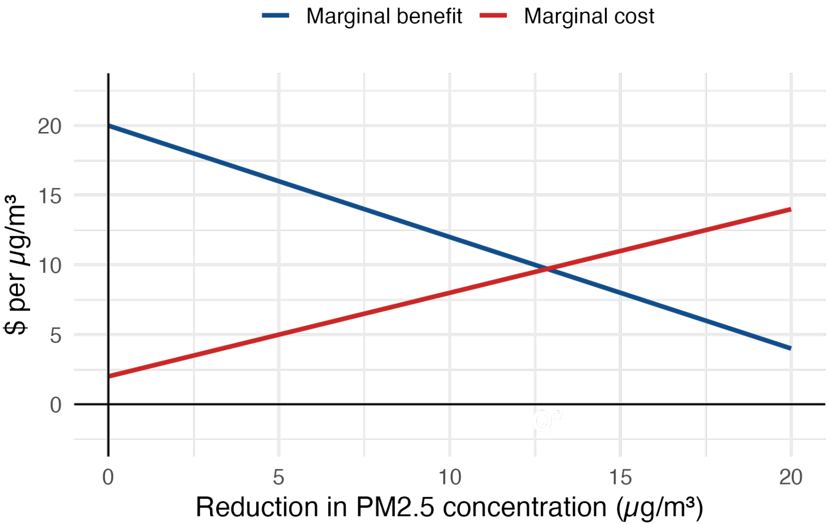

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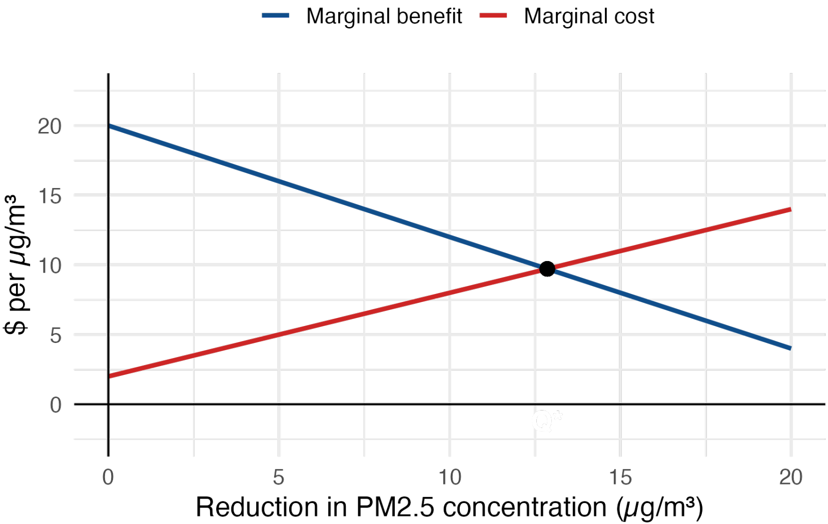

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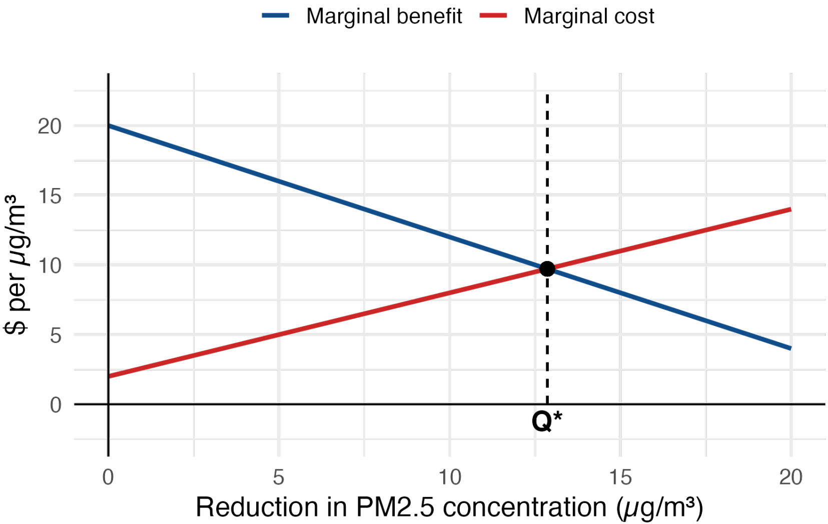

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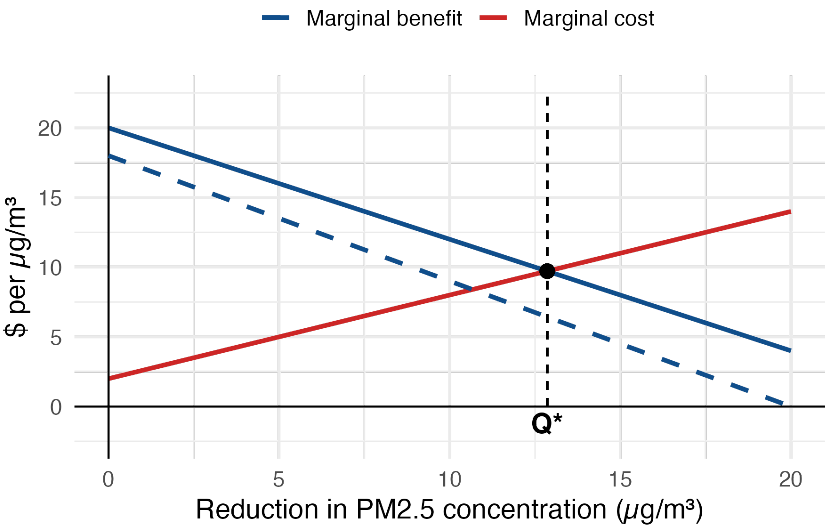

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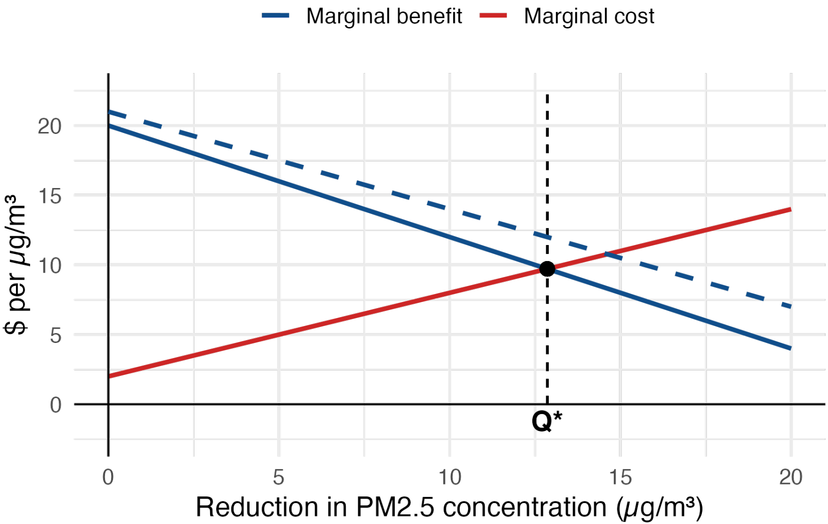
Figure 3: Marginal Costs and Marginal Benefits of Clean Air Policy



If the true benefits of cleaner air are greater than we currently assume, would the optimal amount of pollution reduction be higher or lower?

(A) Higher

(B) Lower

What are the benefits of cleaner air?

- Better health (Currie et al., 2009; Heft-Neal et al., 2023; Orellano et al., 2024)
- More productive workers (Archsmith et al., 2018; Adhvaryu et al., 2022; Hansen-Lewis, 2024)

Research question

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What is the effect of PM2.5 exposure on labor productivity?

- How does this vary by the level of PM2.5?
- How does this vary by long-term exposure?

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- How does this vary by the level of PM2.5?
- How does this vary by long-term exposure?

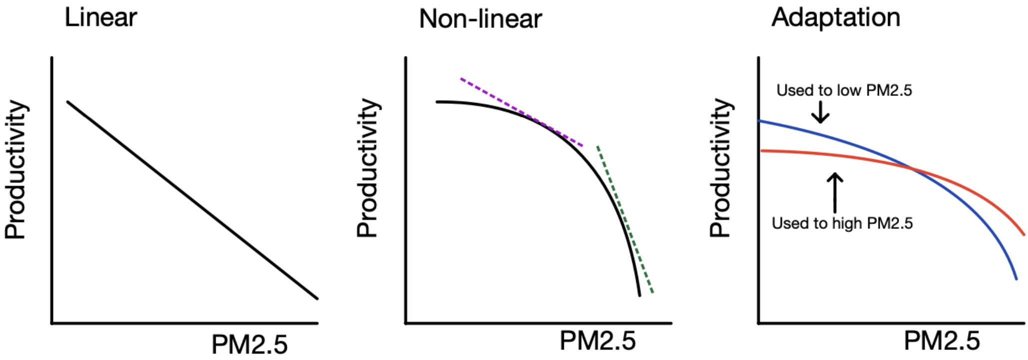
Why does this matter?

- Over one-third of the global population is exposed to hazardous annual average PM2.5 levels ($> 35\mu g/m^3$) (Rentschler and Leonova, 2023).
- Does a marginal increase in PM2.5 affect these people differently than people who are used to cleaner air?

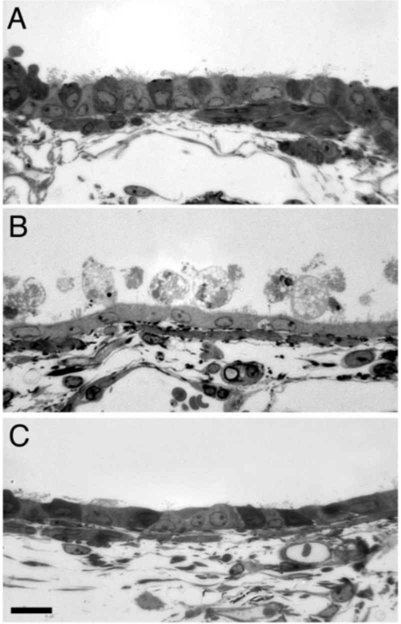
Outline

1. Introduction
2. Conceptual framework
3. Data
4. Empirical framework
5. Results
6. Conclusion

Figure 4: Dose-response of Productivity to PM2.5



What is the physiological evidence for adaptation to PM2.5 exposure?



This figure, reproduced from (West et al., 2003), displays three panels of microscopic images of cells in the lungs of mice.

- **Panel A** shows cells from mice that were in the control group and breathed clean air throughout the experiment
- **Panel B** shows cells from mice that were exposed to polluted air for one day
- **Panel C** shows cells from mice that were exposed to pollued air for 7 days
- Additional studies: (Kültz et al., 2015; Lee et al., 2018)

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Performance data

Figure 5: Outcome: run-scoring (binary)

Source: Wikipedia.

Why cricket?

- Granular data on performance
- Variation in match-day pollution exposure
- Variation in longer-term pollution exposure

Performance data

Figure 5: Outcome: run-scoring (binary)

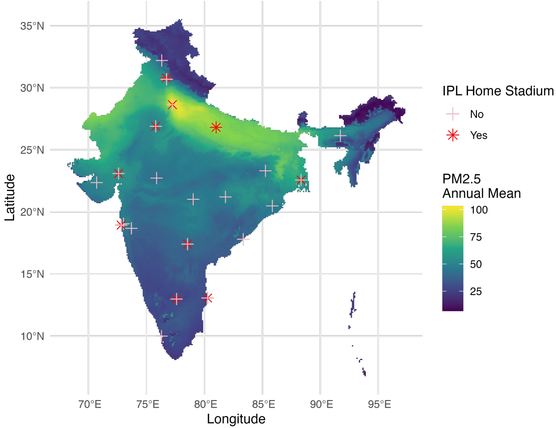
Source: Wikipedia.

Data characteristics:

- Granular data on performance: 183,572 deliveries (throws)
- 619 individuals
- 14 years (2008-2022)
- 773 matches
- 20 stadiums

PM2.5 air pollution in India varies across space and time

Figure 6: Annual average PM2.5

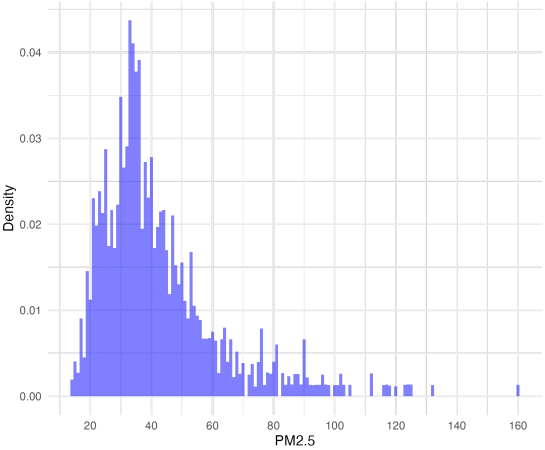


Notes. Annual mean PM2.5 in 2019 and IPL stadiums.

- Variation in typical pollution levels across the locations where teams train
- Day-to-day variation in pollution levels on the day on the match

PM2.5 air pollution in India varies across space and time

Figure 6: IPL Game PM2.5 Distribution



Notes. Distribution of PM2.5 at IPL games 2008-2022.

- Variation in typical pollution levels across the locations where teams train

- Day-to-day variation in pollution levels on the day on the match

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Main empirical approach

- Dependent variable: run-scoring
- Independent variable: PM2.5 on match-day
- Controls: who the bowler is, who the batter is, weather, home stadium, stage-of-game

Non-linear effects regression specification

- Dependent variable: run-scoring
- Independent variable: categories of PM2.5 on match-day (low, medium-low, medium, medium-high, high)
- Controls: who the bowler is, who the batter is, weather, home stadium, stage-of-game

Adaptation effects regression specification

- Dependent variable: run-scoring
- Independent variables: PM2.5 on match-day, bowler average PM2.5 level
- Controls: who the bowler is, who the batter is, weather, home stadium, stage-of-game

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iClicker #2

How do you think air pollution affects a batter's chance of scoring a run?

(A) It lowers the chance

(B) It raises the chance

(C) It has no effect

(D) Indeterminate

Result 1: PM increases run-scoring

A 10 $\mu g/m^3$ increase in PM2.5—equivalent to half a standard deviation—increases the probability that a bowler concedes a run by 0.41 percentage points (a 0.68% increase relative to a mean probability of 59.9%).

Table 1: PM2.5 exposure and run-scoring probability

Full table | Unforced errors | Hist. w/quintiles | Hist. w/residual PM2.5

	(1)	(2)
	$\mathbb{1}$ (At least one run scored)	
Match-day PM2.5	0.0041**	
	(0.0017)	
Q2 (Match-day PM2.5)		0.0074
		(0.0060)
Q3 (Match-day PM2.5)		0.010
		(0.0069)
Q4 (Match-day PM2.5)		0.014
		(0.0086)
Q5 (Match-day PM2.5)		0.028***
		(0.0099)
Weather controls	✓	✓
All FE	✓	✓
N	183,556	183,556

S.e.'s clustered two-way by match & bowler. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Interpretation

- 142.3 of 237.5 deliveries per game (60%) result in a run
- 0.41 ppt ↑ in run-scoring probability per delivery $\Longrightarrow$
  - 1.0% ↑ in run-scoring
  - ≈ 1 ↑ runs/game
  - ≈ 0.5 ↑ runs/team
  - ≈ 0.1 ↑ runs/bowler
- Average win-margin is 16.9 runs (median 8.0)

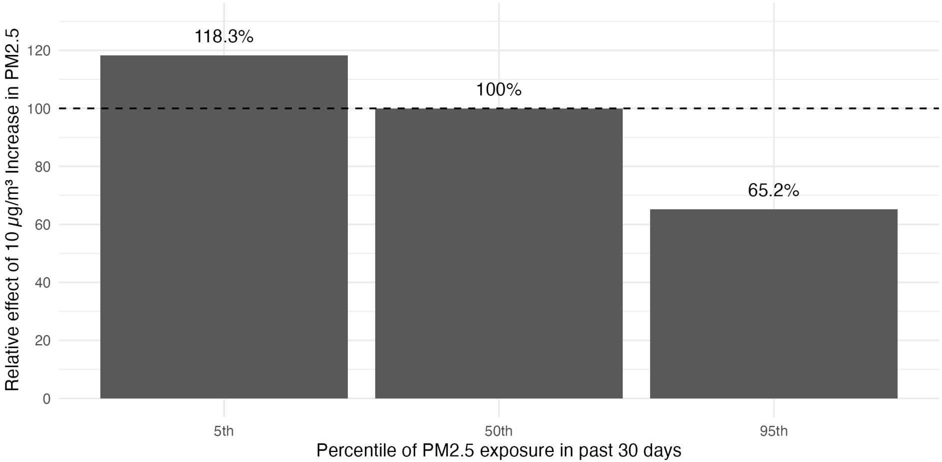
iClicker #3

If a player has been exposed to more air pollution over the past 30 days, do you think their performance will be more or less harmed by air pollution on match day?

(A) Less harmed
(B) More harmed
(C) No difference
(D) Indeterminate

Result 3: PM is less damaging for those used to it

Figure 7: Effect of 10 μg/m³ Increase in PM2.5 on Run-Scoring



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Summary

- Contemporaneous exposure to PM2.5 air pollution negatively impacts performance
- The effect is non-linear, with higher pollution impacting performance more
- Chronic exposure also damages performance
- Acclimation occurs, but cuts both ways:
    1. those with chronic exposure gain resilience
    2. those without it are more vulnerable

Feedback survey

Figure 8: QR code to survey

- **Survey URL:**
  `bit.ly/176matt`
- **Email:**
  `msbrooks@ucdavis.edu`
- **Website:**
  `mspitzerbrooks.github.io`

Adhvaryu, A., N. Kala, and A. Nyshadham (2022): "Management and Shocks to Worker Productivity," *Journal of Political Economy*, 130, 1–47, publisher: The University of Chicago Press.

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Kültz, D., J. Li, R. Sacchi, D. Morin, A. Buckpitt, and L. Van Winkle (2015): "Alterations in the proteome of the respiratory tract in response to single and multiple exposures to naphthalene," *PROTEOMICS*, 15, 2655–2668, _eprint: https://analyticalsciencejournals.onlinelibrary.wiley.com/doi/pdf/10.1002/pmic.201400445.

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Global Air Quality Guidelines Systematic Review and Meta-Analysis," *International Journal of Public Health*, 69, 1607683, publisher: SSPH+.

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Wang, S., M. Zhang, H. Zhao, P. Wang, S. H. Kota, Q. Fu, C. Liu, and H. Zhang (2024): "Reconstructing long-term (1980–2022) daily ground particulate matter concentrations in India (LongPMInd)," *Earth System Science Data*, 16, 3565–3577, publisher: Copernicus GmbH.

West, J. A. A., L. S. Van Winkle, D. Morin, C. A. Fleschner, H. J. Forman, and C. G. Plopper (2003): "Repeated inhalation exposures to the bioactivated cytotoxicant naphthalene (NA) produce airway-specific Clara cell tolerance in mice," *Toxicological Sciences: An Official Journal of the Society of Toxicology*, 75, 161–168.

Main regression specification

$$R_{ij\ell t} = \beta_1 \text{PM2.5}_{\ell d} + \mathbf{X}'_{\ell d}\phi + \psi_j + \phi_i + \delta_{\ell y} + \theta_n + \eta_o + \Lambda_i + \Delta_j + \varepsilon_{ij\ell t} \tag{1}$$

$R_{ij\ell t}$: run scored (binary) on delivery t

$\text{PM2.5}_{\ell d}$: PM2.5 on day d of match at location ℓ (units: 10 $\mu g/m^3$)

$\psi_j(\phi_i)$: bowler (batter) fixed effects

$\delta_{\ell y}$: stadium-by-year fixed effects

θ_n, η_o : innings, over fixed effects

$\mathbf{X}_{\ell d}$: weather controls: temp, temp^2, humidity, precipitation, air pressure, radiation, wind

$\Lambda_j(\Delta_i)$: dummy for whether stadium is home for bowler (batter)

Non-linear effects regression specification

$$R_{ij\ell t} = \sum_{k=2}^{5} \beta_k Q_k \left(\text{PM2.5}_{\ell d}\right) + \mathbf{X}'_{\ell d}\phi + \psi_j + \phi_i + \delta_{\ell y} + \theta_n + \eta_o + \Lambda_i + \Delta_j + \varepsilon_{ij\ell t} \tag{2}$$

$R_{ij\ell t}$: run scored (binary) on delivery t

$\text{PM2.5}_{\ell d}$: PM2.5 on day d of match at location ℓ (units: 10 $\mu g/m^3$)

$\psi_j(\phi_i)$: bowler (batter) fixed effects

$\delta_{\ell y}$: stadium-by-year fixed effects

θ_n, η_o : innings, over fixed effects

$\mathbf{X}_{\ell d}$: weather controls: temp, temp^2, humidity, precipitation, air pressure, radiation, wind

$\Lambda_j(\Delta_i)$: dummy for whether stadium is home for bowler (batter)

Acclimation regression specification

$$R_{ij\ell t} = \beta_1 \mathrm{PM2.5}_{\ell d} + \beta_2 \mathrm{PM2.5}_{\ell d} \times \mathrm{PM2.5}_{j0} + \beta_3 \mathrm{PM2.5}_{J(j)d} + \mathbf{X}'_{\ell d}\phi + \psi_j + \phi_i + \delta_{\ell y} + \theta_n + \eta_o + \Lambda_i + \Delta_j + \varepsilon_{ij\ell t} \tag{3}$$

$R_{ij\ell t}$: run scored (binary) on delivery t

$\mathrm{PM2.5}_{\ell d}$: PM2.5 on day d of match at location ℓ (units: 10 $\mu g/m^3$)

$\mathrm{PM2.5}_{j0}$: PM2.5 for bowler j across all games in IPL (units: 10 $\mu g/m^3$)

$\psi_j(\phi_i)$: bowler (batter) fixed effects

$\delta_{\ell y}$: stadium-by-year fixed effects

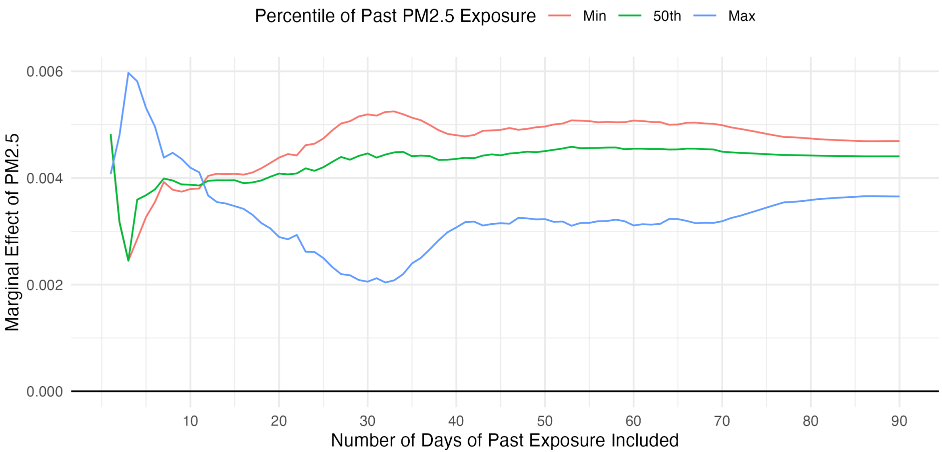
θ_n, η_o : innings, over fixed effects

$\mathbf{X}_{\ell d}$: weather controls: temp, temp^2, humidity, precipitation, air pressure, radiation, wind

$\Lambda_j(\Delta_i)$: dummy for whether stadium is home for bowler (batter)

Measure 2: Count of days above 50 μg/m³ Back

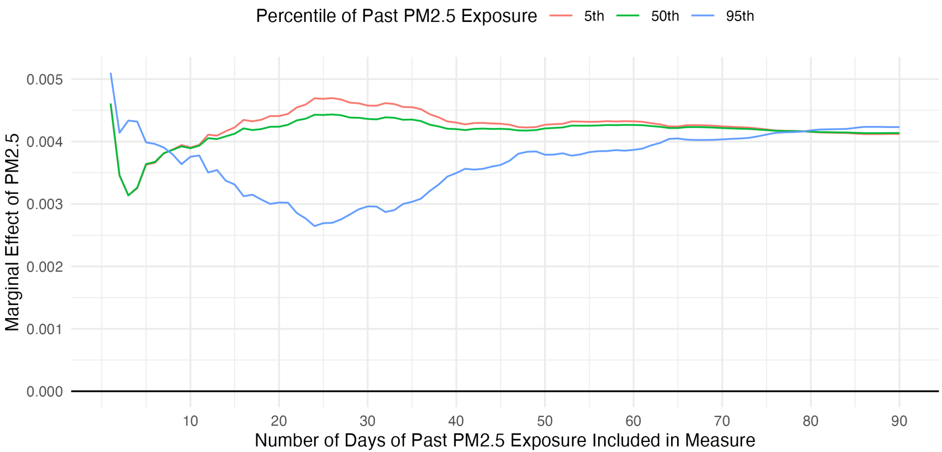
Figure 9: Effect of 10 μg/m³ Increase in PM2.5 on Run-Scoring



Notes. Estimates of β_2 from Equation 3 using $PM2.5_{j0} \equiv \sum_{d=1}^{X} \mathbf{1}(PM2.5_{dj} > Z)$.

Measure 3: Cooling degree-day analogue Back

Figure 10: Effect of 10 µg/m³ Increase in PM2.5 on Run-Scoring



Notes. Estimates of β_2 from Equation 3 using $PM2.5_{j0} \equiv \sum_{d=1}^{X} [\mathbf{1}(PM2.5_{dj} > Z)](PM2.5_{dj} - Z)$.

What can sports do for economics?

"Natural experiments, clean observability, precise measurement, high stakes, expert subjects, unimaginable detail, large datasets, exogenous rule changes, quasi-experimental variation, observable social effects, and no Hawthorne effects. These and other desirable attributes for empirical work are found in sports settings."
(Palacios-Huerta, 2025) Back

Three candidate datasets for air pollution Back

1. US Airnow ground monitors
   - Pro: high quality, available 2008-2024, hourly, rarely missing
   - Con: only in 5 cities (IPL in 20 stadiums)
2. MODIS AOD
   - Pro: available in all stadiums, across entire study time period
   - Con: low correlation with daily PM2.5 levels
3. Local reconstruction (Wang et al., 2024)
   - India-specific reconstruction dataset (Wang et al., 2024)
   - Resolution: 10km $\times$ 10km daily gridded Map
   - ML (gradient boosting decision tree) model incorporating ground monitors, remotely sensed products (MERRA-2, ERA5) Input table
   - Validated with US Airnow monitors—R^2 ranges from 0.71-0.91

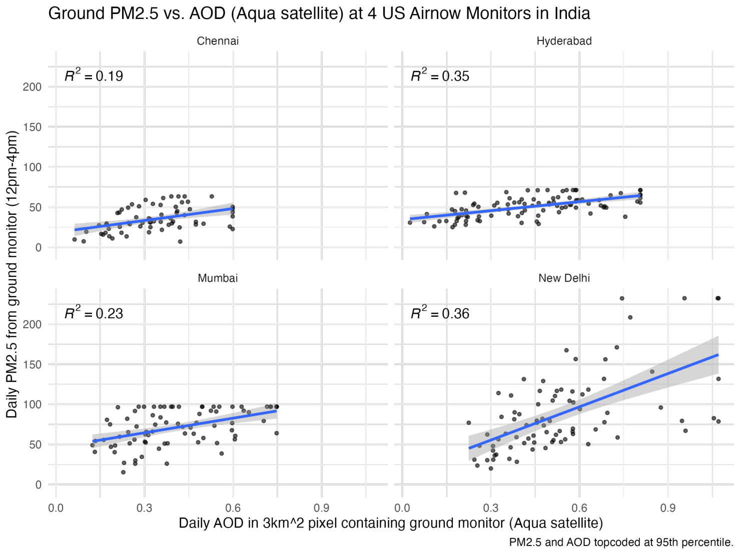
Figure 11: ERA5, MERRA-2, and ground observation data used in (Wang et al., 2024) Back

Type	Variable	Description	Spatial resolution	Temporal resolution
ERA5	SSRD	Surface solar radiation	$0.1^\circ \times 0.1^\circ$	Hourly
	BLH	Boundary layer height	$0.25^\circ \times 0.25^\circ$	Hourly
	EVAP	Evaporation	$0.1^\circ \times 0.1^\circ$	Hourly
	TEMP2	2 m air temperature	$0.1^\circ \times 0.1^\circ$	Hourly
	DEWP2	2 m dew point temperature	$0.1^\circ \times 0.1^\circ$	Hourly
	SP	Surface pressure	$0.1^\circ \times 0.1^\circ$	Hourly
	TPREC	Total precipitation	$0.1^\circ \times 0.1^\circ$	Hourly
	TCLOUD	Total cloud cover	$0.25^\circ \times 0.25^\circ$	Hourly
	UWIND10	10 m u component of wind	$0.1^\circ \times 0.1^\circ$	Hourly
	VWIND10	10 m v component of wind	$0.1^\circ \times 0.1^\circ$	Hourly
MERRA-2	BCSMASS	Black carbon surface mass concentration	$0.5^\circ \times 0.625^\circ$	Hourly
	OCSMASS	Organic carbon surface mass concentration	$0.5^\circ \times 0.625^\circ$	Hourly
	DUSMASS25	Dust $PM_{2.5}$ surface mass concentration	$0.5^\circ \times 0.625^\circ$	Hourly
	DUSMASS	Dust surface mass concentration	$0.5^\circ \times 0.625^\circ$	Hourly
	SO2SMASS	Sulfur dioxide surface mass concentration	$0.5^\circ \times 0.625^\circ$	Hourly
	SO4SMASS	Sulfate surface mass concentration	$0.5^\circ \times 0.625^\circ$	Hourly
	TOTEXTTAU	Total aerosol extinction [550 nm]	$0.5^\circ \times 0.625^\circ$	Hourly
Observation	$PM_{2.5}$, PM_{10}	Particulate matter	Point	Hourly

Notes. Source: (Wang et al., 2024)

Figure 12: U.S. Airnow vs. MODIS AOD

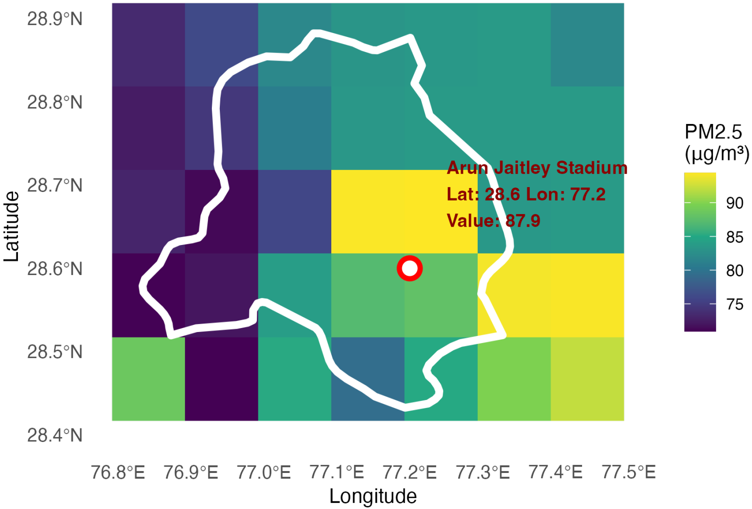
Back



Notes. This figure compares the reading of AOD from the MODIS Aqua satellite (passing over India at approximately 1:30pm) in a 3km radius around the location of USAirnow ground monitors in the 4 hour window centered at 1:30pm. Values are topcoded at the 95th percentile within a location.

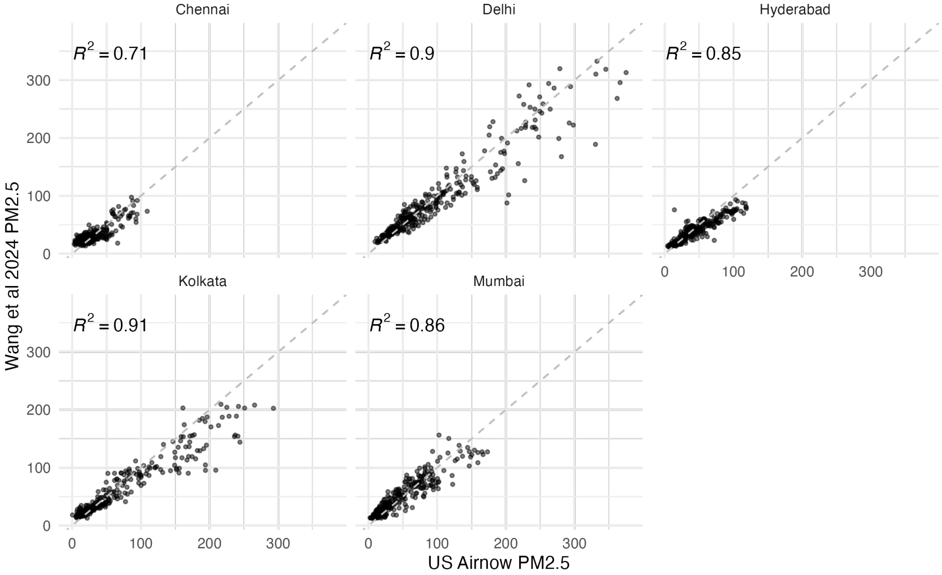
Figure 13: PM2.5 Raster Extraction Example - Arun Jaitley Stadium, Delhi on March 1, 2019

Back



Notes. This plot shows the raster of (Wang et al., 2024) on March 1, 2019 in the vicinity of Delhi. Delhi's city boundaries are indicated in white and the location of the cricket stadium is encircled in red.

Figure 14: (Wang et al., 2024) vs US Airnow PM2.5 in 2019 Back



Notes. This figure compares daily averages of PM2.5 concentrations from the LongPMInd model in (Wang et al., 2024) with ground monitor readings from the U.S. Airnow network at U.S. consulates and embassies in India in the year 2019.

PM2.5 and weather

- Weather data: ERA-5 (Muñoz Sabater, 2019), daily 11km × 11km gridded
- Variables: temperature, relative humidity, atmospheric pressure, precipitation, solar radiation, wind speed
- Positive correlation between run-scoring and temperature/wind; negative correlation with humidity/precipitation Correlation matrix

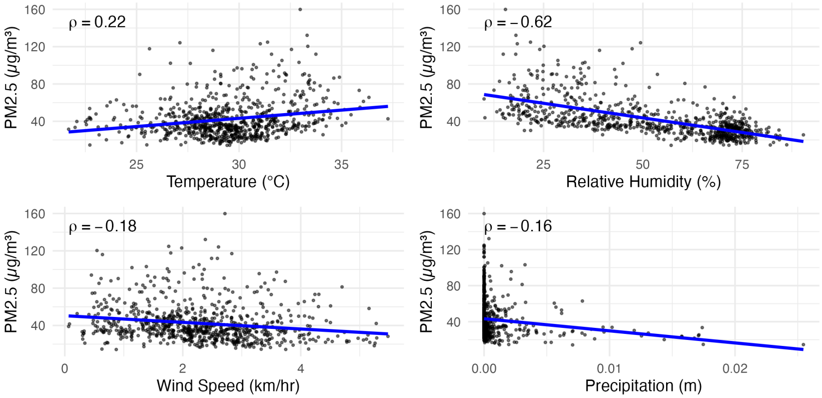


Table 2: PM2.5 and Weather Correlation Matrix Back

	Run	PM2.5	Temperature	Precipitation	Radiation	Wind	Humidity
Run	1	0.017	0.007	-0.002	0.003	0.001	-0.014
PM2.5	0.017	1	0.218	-0.153	0.230	-0.182	-0.619
Temperature	0.007	0.218	1	-0.254	0.232	0.234	-0.366
Precipitation	-0.002	-0.153	-0.254	1	-0.520	-0.070	0.253
Radiation	0.003	0.230	0.232	-0.520	1	0.108	-0.385
Wind	0.001	-0.182	0.234	-0.070	0.108	1	0.155
Humidity	-0.014	-0.619	-0.366	0.253	-0.385	0.155	1

PDS LASSO procedure (Belloni et al., 2014)

Back

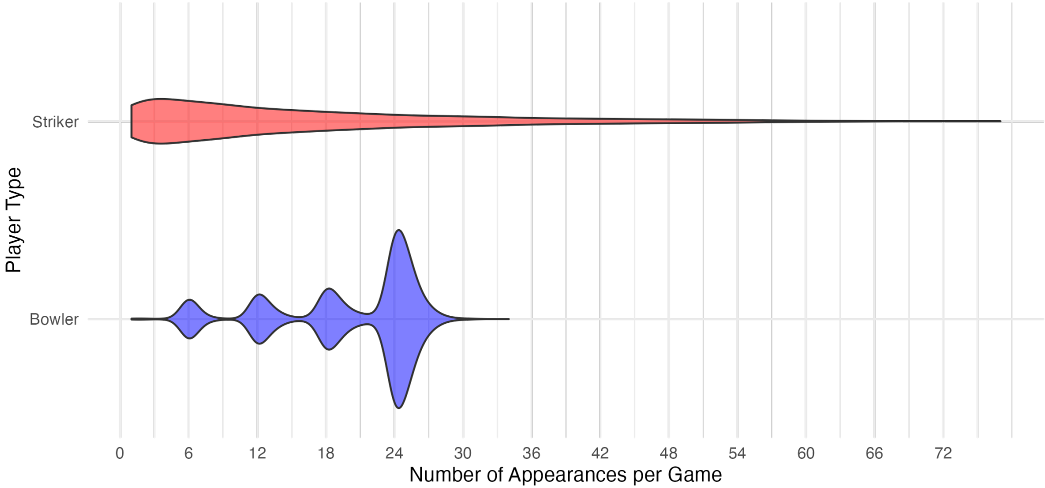
- Regress binary outcome (any runs scored from a delivery) on:
  - High-dimensional controls with **bowler fixed effects**
  - Heteroskedasticity-robust SEs, clustered at the **match** level
- Controls include:
  - Home stadium dummies for **bowler** and **batter** (2 vars)
  - Linear and quadratic terms for **6 weather variables** (12 vars)
  - Interactions:
    - Between linear weather terms (15 vars)
    - Each linear weather term $\times$ $PM_{2.5}$ (6 vars)
  - $\Rightarrow$ Total of **35 control variables**
- Apply **PDS Lasso** to select relevant controls before main regression.

PDS LASSO results

Back

- PDS Lasso selects only two interaction terms:
    1. Temperature $\times$ Relative Humidity
    2. Relative Humidity $\times$ Wind Speed
- Estimated $PM_{2.5}$ effect: **0.0035** ($p < 0.01$), close to baseline OLS (0.0041, $p < 0.05$)
- Robustness check: repeat PDS Lasso with **temperature** as regressor of interest
    - Coefficient on temperature: **0.0014** ($p = 0.10$)
    - About one-third the magnitude of $PM_{2.5}$; not statistically significant
- Matches played in generally **warm conditions** (71–99°F, mean 85°F)

Figure 15: Number of balls per game Back



Notes. This figure displays the count of number of balls per game for each type of player.

Back

Table 3: Summary Statistics of Long-run PM2.5 Variables

Definition	Distinct values	Mean	S.d.	Min	1^{st} perc.	99^{th} perc.	Max
Bowler PM2.5[a]	445	42.62	9.66	17.83	23.29	77.31	103.16
Bowler PM2.5[b]	107	40.35	7.58	22.76	25.20	63.17	69.13
Team stadium PM2.5[c]	13	46.94	18.33	25.11	25.11	83.59	83.59
Team stadium PM2.5[d]	13	51.66	20.71	28.27	28.27	96.23	96.23
Team stadium PM2.5[e]	13	47.54	15.85	26.66	26.66	77.70	77.70
Team stadium PM2.5[f]	13	43.40	15.21	22.28	22.28	70.49	70.49

[a] All IPL seasons. [b] IPL seasons 2008-2014. [c] 1998-2007. [d] 2008-2022.

[e] 2008-2022, IPL months. [f] 1998-2007, IPL months.

Notes. This table reports summary statistics for six alternative definitions of long-run PM2.5.

Alternative measures of long-run stadium PM2.5 exposure are highly correlated.

Figure 16: Correlation Matrix of Various Definitions of Long-term PM2.5

Back

	1998-2007	2008-2022	2008-2022 (Mar-May)	1998-2007 (Mar-May)
1998-2007	1.00	0.99	0.95	0.92
2008-2022		1.00	0.93	0.90
2008-2022 (Mar-May)			1.00	0.99
1998-2007 (Mar-May)				1.00

Notes. This plot is a correlation matrix of 4 measures of long-run stadium PM2.5 exposure.

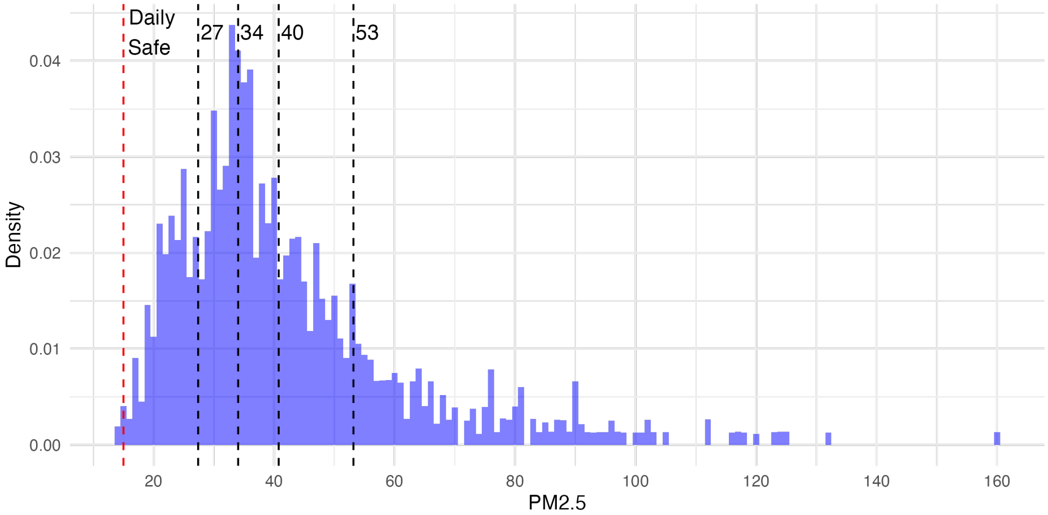
Table 4: Match PM2.5 exposure and run-scoring probability Back

	(1)	(2)	(3)	(4)	(5)	(6)
			$\mathbb{1}$ (At least one run scored)			
Match-day PM2.5	0.0041***	0.0027*	0.0041**			
	(0.0010)	(0.0014)	(0.0017)			
Q2 (Match-day PM2.5)				0.0027	0.0038	0.0074
				(0.0064)	(0.0069)	(0.0060)
Q3 (Match-day PM2.5)				0.00015	-0.00065	0.010
				(0.0065)	(0.0073)	(0.0069)
Q4 (Match-day PM2.5)				0.0086	0.0047	0.014
				(0.0076)	(0.0096)	(0.0086)
Q5 (Match-day PM2.5)				0.023***	0.017	0.028***
				(0.0069)	(0.010)	(0.0099)
Weather controls		✓	✓		✓	✓
All FE			✓			✓
N	183,572	183,572	183,556	183,572	183,572	183,556

Notes. Standard errors clustered two-way by match and bowler.

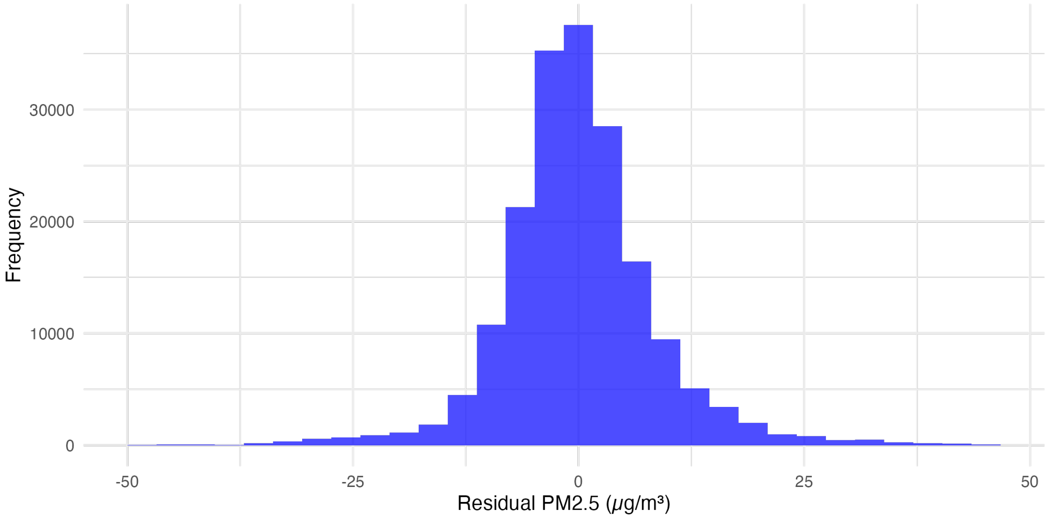
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 17: Histogram of Game PM2.5 with Quantiles Indicated Back



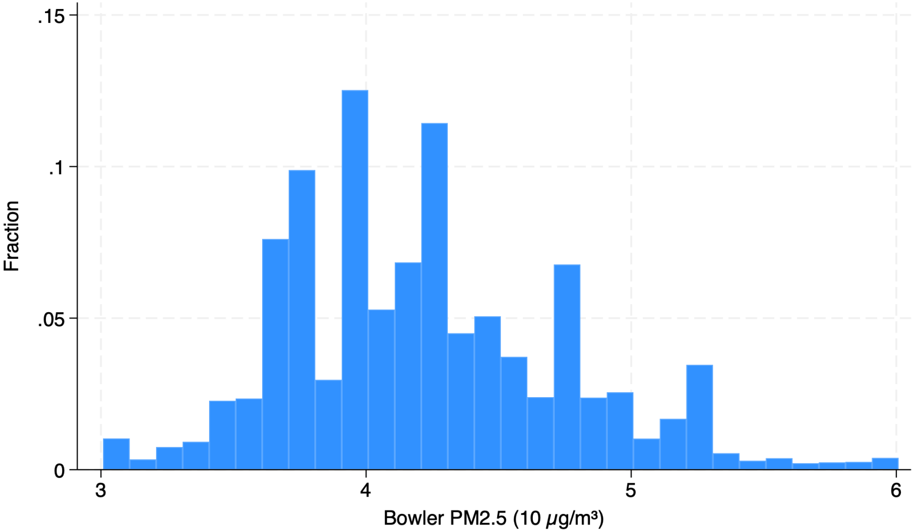
Notes. This figure displays the distribution of game PM2.5 with quantiles and WHO safe daily limit (15 mug/m^3) indicated.

Figure 18: Histogram of Residual PM2.5 Back



Notes. This figure displays a histogram of residual PM2.5 after controlling for all weather controls and fixed effects in Equation (1).

Figure 19: Histogram of Bowler PM2.5 Mean in IPL Games 2008-2022 Back



Notes. This figure displays the distribution of bowler mean PM2.5 (truncated to 1st through 99th percentiles) defined as the mean PM2.5 exposure across all games for a given bowler in the IPL 2008-2022.