The Pollution–Productivity Curve

Non-Linear Effects and Adaptation in High-Pollution Environments

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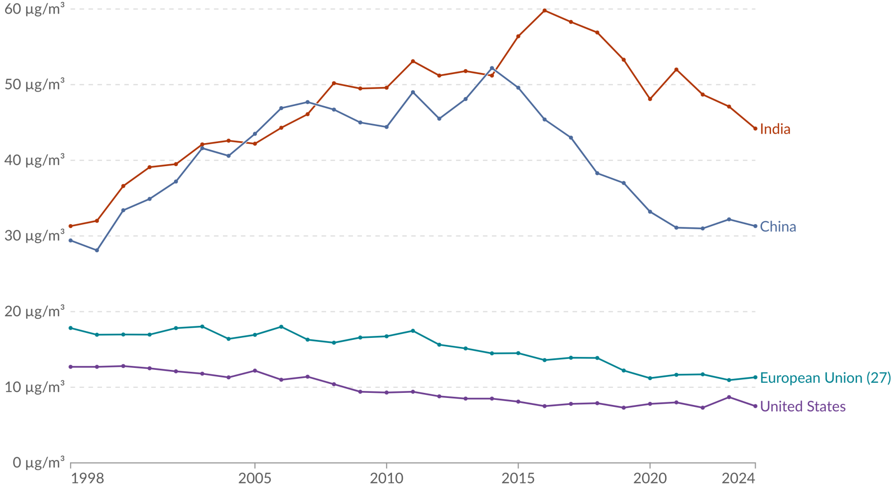
Exposure to outdoor air pollution, 1998 to 2024

Our World in Data

Annual population-weighted average concentration of fine particulate matter (PM2.5)[1] in the air, measured in micrograms per cubic meter (µg/m³). Exposure to fine particulate matter can pose significant health risks. This data includes pollution from human and natural sources.



Data source: SatPM, Atmospheric Composition Analysis Group, Washington University in St. Louis (2026)

Research question

Does the marginal effect of contemporaneous $PM_{2.5}$ exposure on labor productivity vary by accumulated exposure to $PM_{2.5}$?

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Why does this matter?

- 2.8 billion people are exposed to hazardous annual average $PM_{2.5}$ ($> 35\,\mu g/m^3$) (Rentschler and Leonova, 2023) Map
- Does chronic exposure change the harm from acute pollution shocks?
  1. Non-linearities in the dose-response
  2. Physiological adaptation

Related literature Contributions

This paper

What we do:

- Estimate effect of $PM_{2.5}$ on individual-level labor productivity
- Use performance data from 14 years of professional cricket in India

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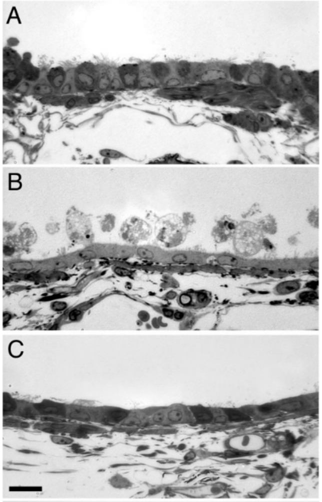
Why cricket:

- High-frequency, individual-level performance measures
- High pollution setting (mean $PM_{2.5}$=42 $\mu g\, m^{-3}$)
- Variation in workers' contemporaneous *and* accumulated exposure that is uncorrelated with their ability

Why could adaptation be possible?



West et al. (2003) Fig. 2

Three panels of microscopic images of cells in the lungs of mice

- **Panel A** control: clean air
- **Panel B** treatment 1: exposed to polluted air for 1 day
- **Panel C** treatment 2: exposed to polluted air for 7 days

Mechanism: augmented production of glutathione, an antioxidant that shields lung cells from air pollution (Kültz et al., 2015; Lee et al., 2018)

Roadmap

Setting: Cricket in India as a natural experiment

IPL, 2008–2022: 773 matches · 183,572 deliveries · 619 players · 24 stadiums in 10 cities Summary stats Data sources

Outcome: run-scoring (mean 0.60)

Figure 2. Delivery: bowler vs. batter

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Identification strategy:

1. Contemporaneous exposure: matches scheduled before pollution forecasts $\implies$ match-day pollution orthogonal to player ability
2. Past exposure: equal salary budget across teams $\implies$ player talent distributed evenly Teams Bowlers

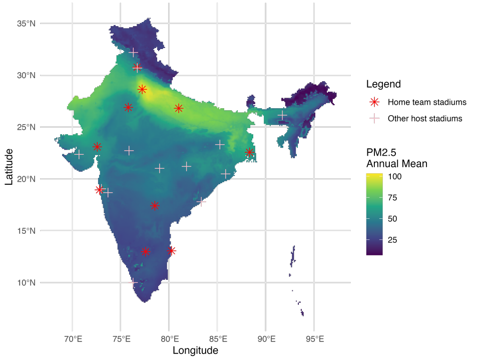

Figure 2. Annual $PM_{2.5}$ and IPL stadiums (2019) PM Data

Outline

Econometric specifications

$$R_{ij\ell t} = \beta\, \mathrm{PM2.5}_{\ell d} + \varepsilon_{ij\ell t}$$

- $R_{ij\ell t}$: binary for run scored in delivery t
- $\mathrm{PM2.5}_{\ell d}$: match-day $PM_{2.5}$ at stadium ℓ on day d (units: $10\,\mu g\,m^{-3}$)

Econometric specifications

$$R_{ij\ell t} = \beta \, \mathrm{PM2.5}_{\ell d} + \mathbf{X}'_{\ell d}\gamma + \psi_j + \phi_i + \delta_{\ell y} + \theta_{n(t)} + \eta_{o(t)} + \Lambda_{iy} + \Delta_{jy} + \varepsilon_{ij\ell t} \quad (1)$$

- $R_{ij\ell t}$: binary for run scored in delivery t
- $\mathrm{PM2.5}_{\ell d}$: match-day $\mathrm{PM}_{2.5}$ at stadium ℓ on day d (units: $10\,\mu\mathrm{g\,m^{-3}}$)
- $\mathbf{X}_{\ell d}$: temperature, relative humidity, precipitation, solar radiation, wind speed
- ψ_j: bowler FE; ϕ_i: batter FE; $\delta_{\ell y}$: stadium $\times$ year FE, $\theta_{n(t)}$: innings FE; $\eta_{o(t)}$: over FE Λ_{iy}, Δ_{jy}: home stadium FE
- SEs two-way clustered at the match and bowler levels

Econometric specifications

$$R_{ij\ell t} = \sum_{k=2}^{5} \beta_k Q_k \left(\mathrm{PM2.5}_{\ell d}\right) + \mathbf{X}'_{\ell d}\gamma + \psi_j + \phi_i + \delta_{\ell y} + \theta_{n(t)} + \eta_{o(t)} + \Lambda_{iy} + \Delta_{jy} + \varepsilon_{ij\ell t} \qquad (2)$$

- $R_{ij\ell t}$: binary for run scored in delivery t
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Econometric specifications

$$R_{ij\ell t} = \beta_1 \, \text{PM2.5}_{\ell d} + \beta_2 \, \text{PM2.5}_{\ell d} \times \overline{\text{PM2.5}}_{J(j)d} + \beta_3 \, \overline{\text{PM2.5}}_{J(j)d} + \mathbf{X}'_{\ell d}\gamma + \psi_j + \phi_i + \delta_{\ell y} + \theta_{n(t)} + \eta_{o(t)} + \Lambda_{iy} + \Delta_{jy} + \varepsilon_{ij\ell t} \quad (3)$$

- $R_{ij\ell t}$: binary for run scored in delivery t
- $\text{PM2.5}_{\ell d}$: match-day $\text{PM}_{2.5}$ at stadium ℓ on day d (units: $10\,\mu\text{g}\,\text{m}^{-3}$)
- $\overline{\text{PM2.5}}_{J(j)d}$: past 30-day mean $\text{PM}_{2.5}$ exposure for bowler j on team J Alt. def.
- $\mathbf{X}_{\ell d}$: temperature, relative humidity, precipitation, solar radiation, wind speed
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$$R_{ij\ell t} = \beta_1\,\mathrm{PM2.5}_{\ell d} + \beta_2\,\mathrm{PM2.5}_{\ell d} \times \overline{\mathrm{PM2.5}}_{j0} + \mathbf{X}'_{\ell d}\gamma + \psi_j + \phi_i + \delta_{\ell y} + \theta_{n(t)} + \eta_{o(t)} + \Lambda_{iy} + \Delta_{jy} + \varepsilon_{ij\ell t} \tag{4}$$

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- $\overline{\mathrm{PM2.5}}_{j0}$: career mean $PM_{2.5}$ for bowler j
- $\mathbf{X}_{\ell d}$: temperature, relative humidity, precipitation, solar radiation, wind speed
- ψ_j: bowler FE; ϕ_i: batter FE; $\delta_{\ell y}$: stadium $\times$ year FE, $\theta_{n(t)}$: innings FE; $\eta_{o(t)}$: over FE Λ_{iy}, Δ_{jy}: home stadium FE

Outline

Result 1: $PM_{2.5}$ raises run-scoring probability

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

	(1)	(2)
	$\mathbb{1}$ (At least one run scored)	
Match-day PM2.5	0.0041**	
	(0.0017)	
Q2 (Match-day PM2.5)		
Q3 (Match-day PM2.5)		
Q4 (Match-day PM2.5)		
Q5 (Match-day PM2.5)		
Weather controls	✓	
All FE	✓	
N	183,556	
R^2	0.052	

Notes. SEs two-way clustered at match and bowler levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

How big is this effect?

- Match-day $PM_{2.5}$: median **36.7** vs. WHO limit **15** $\mu g\, m^{-3}$
- $+10\ \mu g\, m^{-3}$ $PM_{2.5} \Rightarrow +0.41$ pp run-concession probability
- Reducing to the WHO limit ($-21.7\ \mu g\, m^{-3}$):

  $\Rightarrow$ +2.2% productive output

Productive output = P(bowler concedes no run); sample mean 0.401.
Calc: $21.7 \times 0.041 = 0.89$ pp $\div\ 0.401 = 2.2\%$.

Result 2: Effects most pronounced at high $PM_{2.5}$ levels

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Q3 (Match-day PM2.5)		0.0099
		(0.0069)
Q4 (Match-day PM2.5)		0.013
		(0.0086)
Q5 (Match-day PM2.5)		0.027***
		(0.0099)
Weather controls	✓	✓
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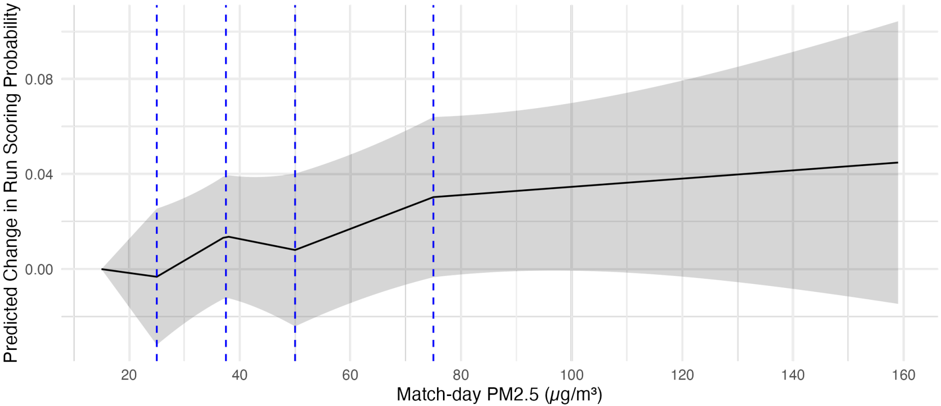

Figure 3. Linear spline estimation of effect of $PM_{2.5}$ on run-scoring probability (knots at WHO thresholds of 25, 37.5, 50, 75 $\mu g\, m^{-3}$).

Table 2. Short-term adaptation to $PM_{2.5}$ exposure (key coefficients) Full table ME ME diff

	(1)	(2)
	$\mathbb{1}$ (At least one run scored)	
Match PM2.5	0.0066*	
	(0.0034)	
Past 30-day PM2.5	0.0061*	
	(0.0034)	
Match PM2.5 $\times$ Past 30-day PM2.5	-0.00055	
	(0.00063)	
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Match PM2.5 × Past 30-day PM2.5	$\boxed{-0.00055}$	
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Match PM2.5 × Past 30-day PM2.5	$\boxed{-0.00055}$	
	$\boxed{(0.00063)}$	
Q5 (Match PM2.5)		0.069***
		(0.025)
Q5 (Match PM2.5) × Past 30-day PM2.5		−0.0095*
		(0.0051)
Weather controls	✓	✓
All FE	✓	✓
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Result 3a: Short-term adaptation: ∼41% reduction in marginal effect

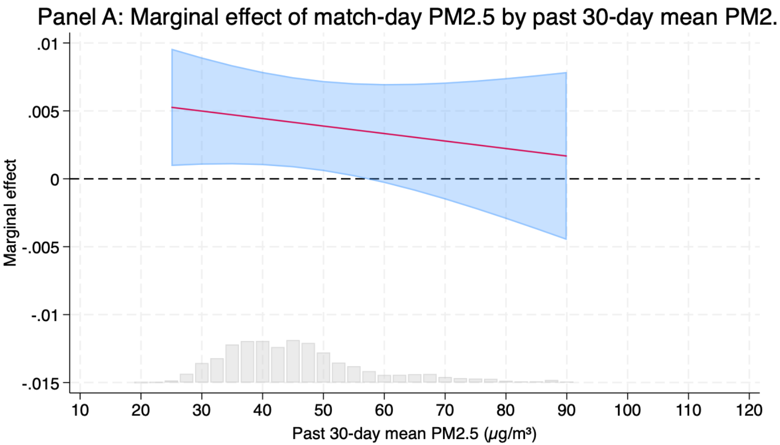

Figure 4. Marginal effect of match-day $PM_{2.5}$ on run-scoring probability by bowler's past 30-day mean $PM_{2.5}$. Median past: 45 $\mu g\,m^{-3}$; 95th percentile: 92 $\mu g\,m^{-3}$.

Table 3. Long-term adaptation to $PM_{2.5}$ exposure (key coefficients) Full table

	(3)	(4)
	$\mathbb{1}$ (At least one run scored)	
Match PM2.5	0.013**	
	(0.0052)	
Match PM2.5 × Career PM2.5	−0.0020*	
	(0.0011)	
Q5 (Match PM2.5)		0.097**
		(0.037)
Q5 × Career PM2.5		−0.016*
		(0.0086)
Weather controls	✓	✓
All FE	✓	✓
N	183,556	183,556
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Result 3b: Long-term adaptation: ∼36% reduction in marginal effect

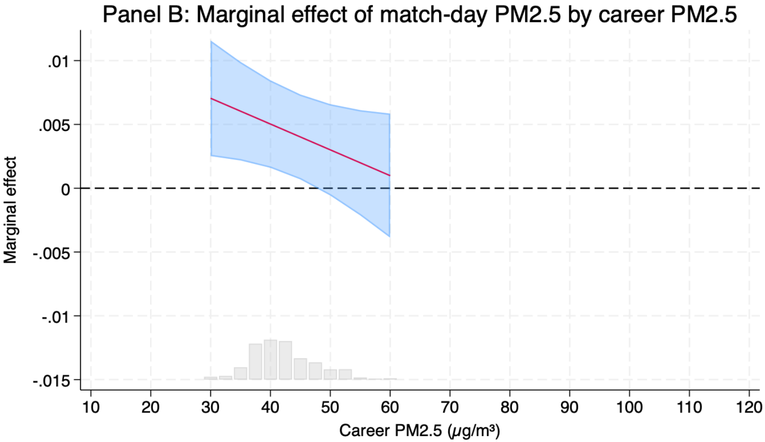

Figure 5. Marginal effect of match-day $PM_{2.5}$ by bowler's career mean ($PM2.5_{j0}$). Median career exposure: 42 $\mu g\, m^{-3}$; 95th percentile: 52 $\mu g\, m^{-3}$.

Result 4a: Adaptation does not offset cumulative harm

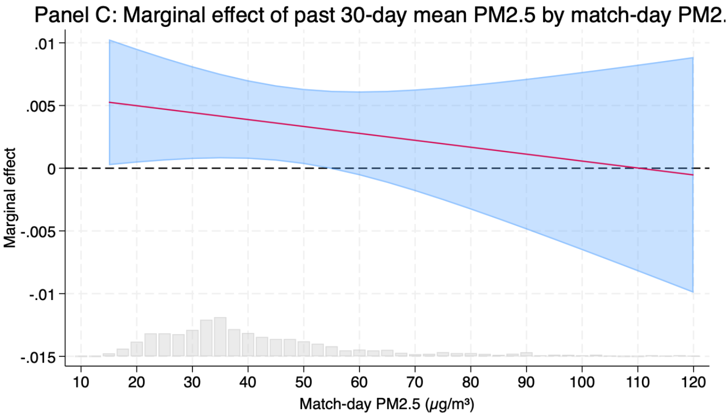

Figure 6. Marginal effect of past 30-day mean $PM_{2.5}$ on run-scoring probability, by match-day $PM_{2.5}$ level.

Result 4b: Total effect indicates harm at all levels

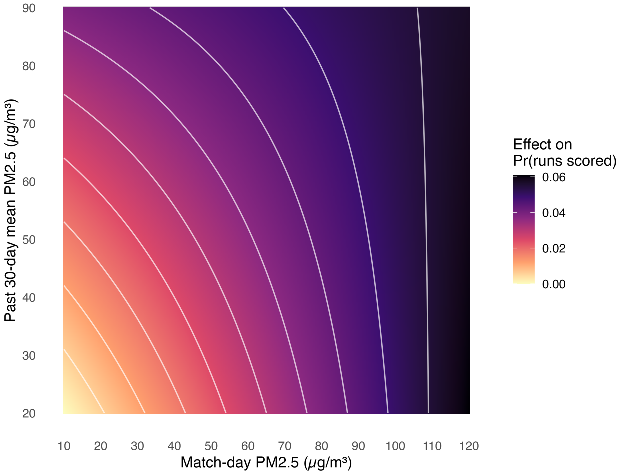

Figure 7. Total effects relative to when match-day and past 30-day $PM_{2.5}$ are 10 $\mu g\, m^{-3}$.

Outline

1. Introduction
2. Empirical setting and data
3. Econometric specifications
4. Results
5. Conclusion

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Thanks! `msbrooks@ucdavis.edu` `mspitzerbrooks.github.io`

Why should we care about particulate matter air pollution?

- $PM_{2.5}$ is the largest environmental risk factor (Brauer, 2024)

Leading risks 2021	95% UI for Ranking
1 Particulate matter pollution	(1 to 2)
2 High systolic blood pressure	(1 to 2)
3 Smoking	(3 to 6)
4 Low birthweight and short gestation	(3 to 6)
5 High fasting plasma glucose	(3 to 6)
6 High body-mass index	(3 to 10)
7 High LDL cholesterol	(7 to 10)
8 Kidney dysfunction	(6 to 10)
9 Child growth failure	(6 to 14)
10 High alcohol use	(7 to 11)
11 Unsafe sex	(11 to 17)
12 Diet low in fruits	(11 to 22)
13 Unsafe water source	(11 to 24)
14 Diet high in sodium	(8 to 36)
15 Diet low in whole grains	(12 to 23)
16 Secondhand smoke	(11 to 26)
17 Iron deficiency	(12 to 23)
18 Lead exposure	(10 to 52)
19 Unsafe sanitation	(14 to 23)
20 Occupational injuries	(15 to 21)
21 Drug use	(17 to 24)
22 Low temperature	(19 to 26)
23 No access to handwashing facility	(11 to 53)
24 Diet low in vegetables	(20 to 29)
25 Diet low in omega-6 polyunsaturated fatty acids	(11 to 53)

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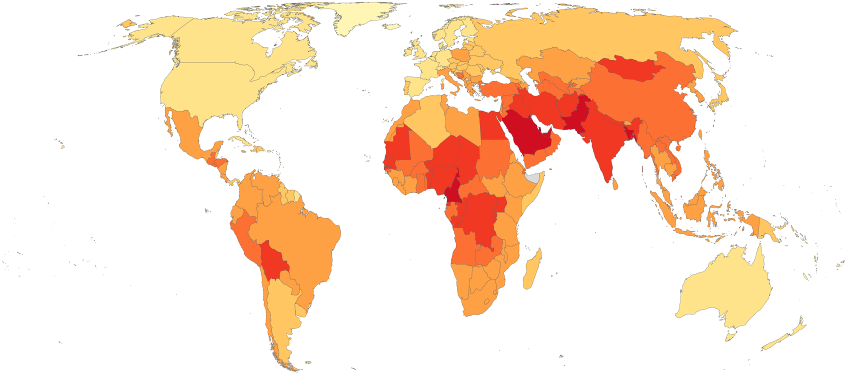
This paper: effect of air pollution on the performance of cricket players in India

Back

Outdoor Air Pollution Exposure

Population-weighted annual mean PM2.5, 2024 • Source: Our World in Data

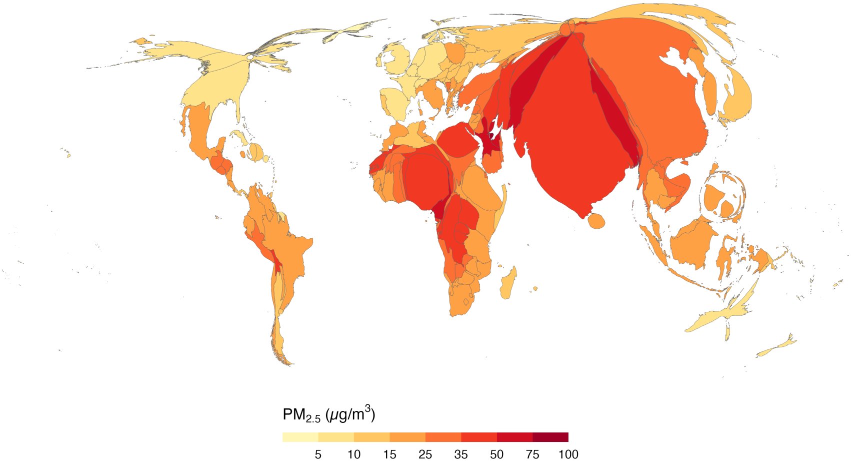


$PM_{2.5}$ ($\mu g/m^3$)

5 10 15 25 35 50 75 100

Air Pollution Exposure, Scaled by Population

Country area ∝ population (2022, World Bank) • shading = PM2.5, 2024



Results preview

1. Workers in a high pollution setting partially adapt to chronic exposure
   - Marginal effects of contemporaneous exposure fall with chronic exposure
2. Adaptation does not offset cumulative harm
   - Reduction in marginal effect outweighed by harm from chronic exposure

Related literature

Back

$PM_{2.5}$ and labor productivity

- **Solid evidence but almost exclusive focus on contemporaneous exposure in low-pollution settings**
  - US & Europe (Graff Zivin and Neidell, 2012; Chang et al., 2016; Archsmith et al., 2018; Borgschulte et al., 2022); China (He et al., 2019; Chang et al., 2019); India (Adhvaryu et al., 2022)
- **Non-linearities: mixed evidence, depends on the levels**
  - Lichter et al. (2017); Hoffmann and Rud (2024)

Climate economics

- **Adaptation (how shocks vary with baseline levels)**
  - Dell et al. (2014); Mérel and Gammans (2021); Mérel et al. (2024)

Contributions

Back

1. **New evidence:** individual-level adaptation to $PM_{2.5}$ in a chronically high-pollution setting
   - Wide range of pollution enables detection of non-linearities
2. **New method:** develop a person-based measure of pollution exposure
   - Time window for adaptation aligned with physiological mechanisms in environmental toxicological literature
   - Pair these insights with a data-driven approach
3. **New setting:** empirical setting overcomes identification challenge in climate economics literature stemming from correlations between baseline levels and place-based characteristics

Data sources

Back

- **Cricket performance metrics.** Publicly accessible delivery-level data, including identify of bowler and batter and whether run was scored (Cricsheet, 2024).
- **$PM_{2.5}$ exposure.** Machine learning algorithm (learns relationship between satellite imagery and ground monitors) provides 10km x 10km gridded daily mean estimates (Wang et al., 2024).
- **Weather variables.** ERA5-Land daily 11km $\times$ 11km gridded reanalysis data (Muñoz Sabater, 2019).

Team quality is uncorrelated with long-term $PM_{2.5}$ Back

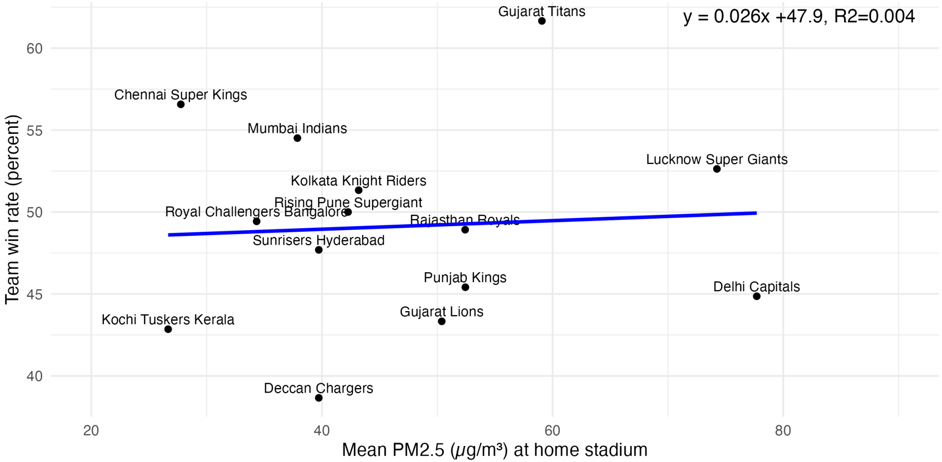


Figure 8. Team win rates vs. home-city mean $PM_{2.5}$.

Bowler quality is uncorrelated with long-term $PM_{2.5}$ Back

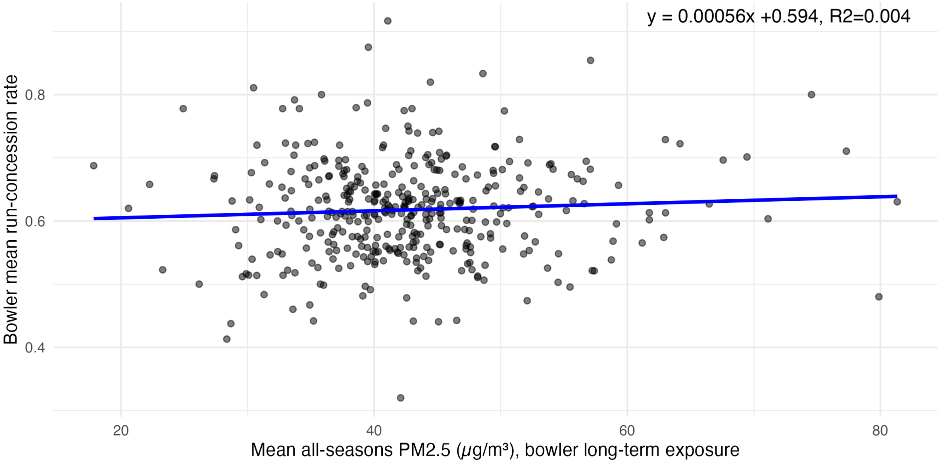


Figure 9. Bowler run-concession rates vs. career mean $PM_{2.5}$.

Table 4. Summary Statistics: IPL Matches in India 2008-2022 ▸ Back ▸ Full table

Variable	Mean	SD	Min	Median	Max
Panel A: Treatment variable					
$PM_{2.5}$ (μg/m^3)	42.32	20.01	14.23	36.67	159.91
Panel B: Bowler performance outcome					
Run conceded (=1)	0.599	0.490	0.000	1.000	1.000
Panel C: Weather controls					
Temperature (°C)	29.49	2.51	21.68	29.44	37.26
Humidity (%)	52.14	19.91	10.02	54.14	90.41
Precipitation (m)	0.0007	0.0023	0.0000	0.0000	0.0254
Wind speed (m/s)	2.29	1.01	0.06	2.28	5.48

Notes: Unit of observation is a delivery. Sample includes 183,572 deliveries across 773 IPL matches, across 13 seasons, 20 stadiums, 15 teams, 445 bowlers, and 575 batters.

Table 5. Summary Statistics: IPL Matches in India 2008-2022 ▸ Back

Variable	Mean	SD	Min	Median	Max
Panel A: Treatment variable					
$PM_{2.5}$ (μg/m^3)	42.32	20.01	14.23	36.67	159.91
Panel B: Bowler performance outcomes					
Runs conceded	1.255	1.630	0.000	1.000	6.000
Run conceded (=1)	0.599	0.490	0.000	1.000	1.000
Panel C: Cricket statistics					
Home bowler (=1)	0.317	0.465	0.000	0.000	1.000
Home batter (=1)	0.319	0.466	0.000	0.000	1.000
Innings per match	2.0	0.2	1.0	2.0	4.0
Overs per match	38.5	3.5	9.0	40.0	42.0
Panel D: Weather controls					
Temperature (°C)	29.49	2.51	21.68	29.44	37.26
Humidity (%)	52.14	19.91	10.02	54.14	90.41
Precipitation (m)	0.0007	0.0023	0.0000	0.0000	0.0254
Pressure (1,000 Pa)	97.44	3.51	84.60	98.11	101.23
Radiation (MJ/m^2)	24.49	2.82	6.68	25.03	29.93
Wind speed (m/s)	2.29	1.01	0.06	2.28	5.48

Notes: Unit of observation is a delivery (i.e., a single ball thrown by a bowler to a batter). The sample includes 183,572 deliveries across 773 IPL matches held in India during 2008-2022. These matches took place across 13 seasons, 20 stadiums, 15 teams, 445 bowlers, and 575 batters. The sample excludes 177 IPL matches which took place during this period outside India. Innings per match and overs per match are computed at the match level. All other cricket statistics are computed at the delivery level. "Runs conceded" is the number of runs a bowler concedes in a delivery. "Run conceded (=1)" is a binary variable for whether at least one is conceded. Cricket data are from Cricsheet (2024). $PM_{2.5}$ is from the Wang et al. (2024) daily gridded dataset. Weather controls are from ERA5-Land daily reanalysis data (Muñoz Sabater, 2019).

Data: $PM_{2.5}$ exposure across IPL matches

▸ Back

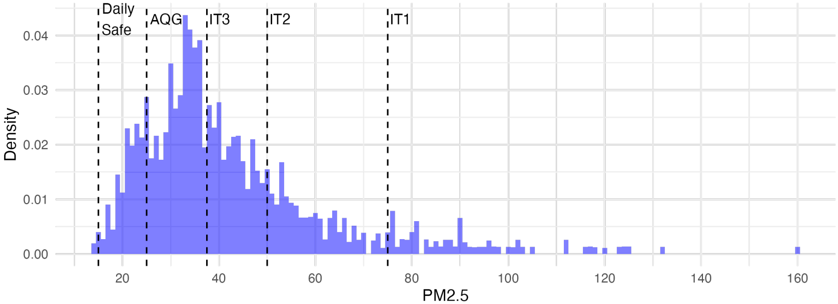


Figure 10. Match-day $PM_{2.5}$ distribution, IPL 2008–2022

- ML product, 10 km × 10 km daily (Wang et al., 2024)
- Fuses satellite, ground monitors, meteorological data
- Validated vs. U.S. AirNow (R^2: 0.71–0.91) Validation

$PM_{2.5}$ data validation: Wang et al. vs. U.S. AirNow

▸ Back

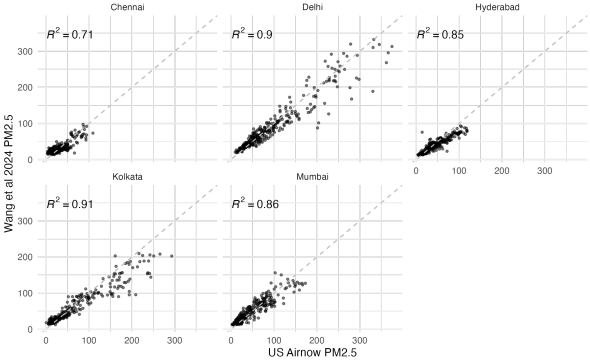


Figure 11. Daily $PM_{2.5}$ from Wang et al. (2024) ML product vs. U.S. AirNow ground monitors at five Indian cities. $R^2 = 0.71$–0.91 across cities.

Alternative measures of short-term past exposure

Back to spec. Back to ME

Three measures of $\overline{\text{PM2.5}}_{J(j)d}$ (windows $X = 1, \ldots, 90$ days):

1. **Mean PM$_{2.5}$:** $\overline{\text{PM2.5}}_{J(j)d} = \dfrac{1}{X} \displaystyle\sum_{d=1}^{X} \overline{\overline{\text{PM2.5}}_{J(j)d}}$
2. **Days above threshold Z:** $\overline{\text{PM2.5}}_{J(j)d} = \displaystyle\sum_{d=1}^{X} \mathbf{1}(\overline{\text{PM2.5}}_{J(j)d} > Z)$
3. **Degree-day analogue:** $\overline{\text{PM2.5}}_{J(j)d} = \displaystyle\sum_{d=1}^{X} \mathbf{1}(\overline{\text{PM2.5}}_{J(j)d} > Z) \cdot (\overline{\text{PM2.5}}_{J(j)d} - Z)$

Measure	Window	Attenuation
(1) Mean PM$_{2.5}$	24 days	$\sim$41%
(2) Days above 50 μg m^{-3}	32 days	$\sim$54%
(3) Degree-days above 50 μg m^{-3}	24 days	$\sim$40%

Identifying the relevant exposure window: ∼30 days

Back

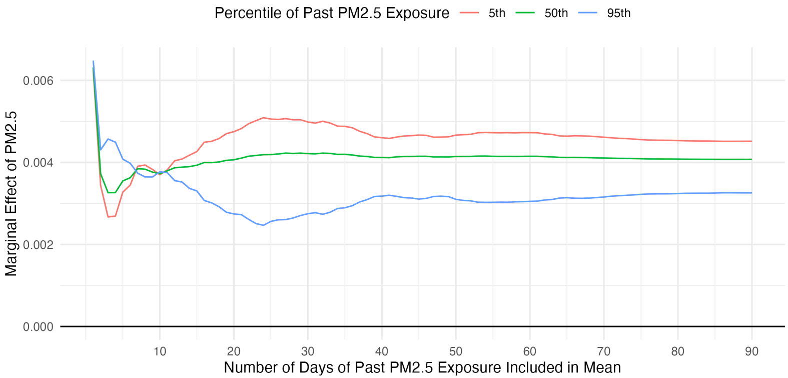


Figure 12. Marginal effect of match-day $PM_{2.5}$ on run-scoring probability, interacted with mean past $PM_{2.5}$ at each lookback window (1–90 days).

Average marginal effect of match-day $PM_{2.5}$ is constant

Back

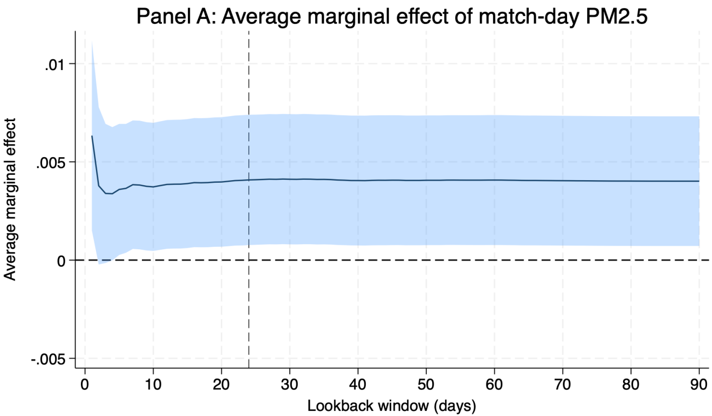


Figure 13. Marginal effect of a 10 µg m^{-3} increase in match-day $PM_{2.5}$ (Equation 3).

Difference for high- and low- exposed max at ∼30 days

Back Alt. def. Alt. vis.

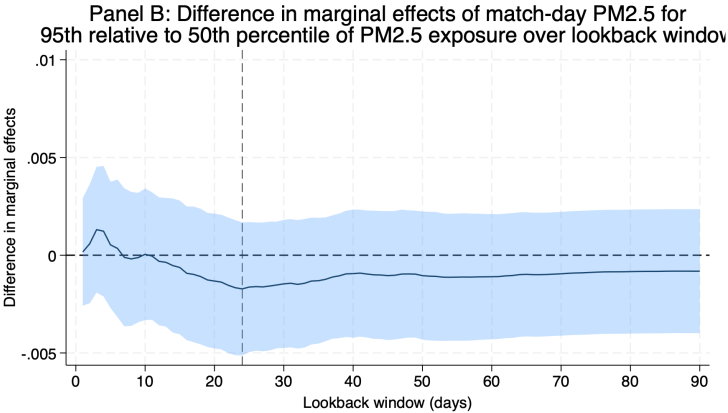


Figure 14. Difference in two marginal effects: (i) the marginal effect for bowlers at the 95th percentile of exposure over the lookback window and (ii) same 50th percentile (Equation 3).

Table 6. Short-term adaptation to $PM_{2.5}$ exposure

▸ Back

	(1)	(2)
	𝟙 (At least one run scored)	
	Short-term adaptation	
Match PM2.5	0.0066*	
	(0.0034)	
Past 30-day PM2.5	0.0061*	0.0089**
	(0.0034)	(0.0043)
Match PM2.5 × Past 30-day PM2.5	-0.00055	
	(0.00063)	
Q2 (Match PM2.5)		0.0097
		(0.019)
Q3 (Match PM2.5)		0.034*
		(0.021)
Q4 (Match PM2.5)		0.041*
		(0.023)
Q5 (Match PM2.5)		0.069***
		(0.025)
Q2 (Match PM2.5) × Past 30-day		-0.00099
		(0.0046)
Q3 (Match PM2.5) × Past 30-day		-0.0060
		(0.0048)
Q4 (Match PM2.5) × Past 30-day		-0.0068
		(0.0051)
Q5 (Match PM2.5) × Past 30-day		-0.0095*
		(0.0051)
Weather controls	✓	✓
All FE	✓	✓
N	183,556	183,556
R^2	0.052	0.052

Notes. Outcome mean 0.599. PM2.5 in 10 $\mu g/m^3$. Col. (1): continuous interaction with past 30-day mean PM2.5; col. (2): PM2.5 quintile indicators interacted with past 30-day mean (Q1 omitted). All columns include full FE and weather controls. SEs two-way clustered at match and bowler levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7. Long-term adaptation to $PM_{2.5}$ exposure

▸ Back to Long-term Regression

	(3)	(4)
	$\mathbb{1}$ (At least one run scored)	
	Long-term adaptation	
Match PM2.5	0.013**	
	(0.0052)	
Match PM2.5 × Career PM2.5	-0.0020*	
	(0.0011)	
Q2 (Match PM2.5)		-0.011
		(0.034)
Q3 (Match PM2.5)		0.031
		(0.034)
Q4 (Match PM2.5)		0.076*
		(0.039)
Q5 (Match PM2.5)		0.097**
		(0.037)
Q2 (Match PM2.5) × Career PM2.5		0.0042
		(0.0082)
Q3 (Match PM2.5) × Career PM2.5		-0.0053
		(0.0081)
Q4 (Match PM2.5) × Career PM2.5		-0.015*
		(0.0090)
Q5 (Match PM2.5) × Career PM2.5		-0.016*
		(0.0086)
Weather controls	✓	✓
All FE	✓	✓
N	183,556	183,556
R^2	0.052	0.052

Notes. Outcome mean 0.599. PM2.5 in 10 $\mu g/m^3$. Col. (3): continuous interaction with career mean PM2.5; col. (4): PM2.5 quintile indicators interacted with career mean (Q1 omitted). Career mean absorbed by bowler FE at level; identified via interaction. All columns include full FE and weather controls. SEs two-way clustered at match and bowler levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

References i

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.

Archsmith, J., A. Heyes, and S. Saberian (2018): "Air Quality and Error Quantity: Pollution and Performance in a High-Skilled, Quality-Focused Occupation," *Journal of the Association of Environmental and Resource Economists*, 5, 827–863.

Borgschulte, M., D. Molitor, and E. Y. Zou (2022): "Air Pollution and the Labor Market: Evidence from Wildfire Smoke," *The Review of Economics and Statistics*, 1–46.

Brauer, M. e. a. (2024): "Global burden and strength of evidence for 88 risk factors in 204 countries and 811 subnational locations, 1990–2021: a systematic analysis for the Global Burden of Disease Study 2021," *The Lancet*, 403, 2162–2203.

Chang, T., J. Graff Zivin, T. Gross, and M. Neidell (2016): "Particulate Pollution and the Productivity of Pear Packers," *American Economic Journal: Economic Policy*, 8, 141–169.

Chang, T. Y., J. Graff Zivin, T. Gross, and M. Neidell (2019): "The Effect of Pollution on Worker Productivity: Evidence from Call Center Workers in China," *American Economic Journal: Applied Economics*, 11, 151–172.

Cricsheet (2024): "Cricsheet," `https://cricsheet.org/`.

Dell, M., B. F. Jones, and B. A. Olken (2014): "What Do We Learn from the Weather? The New Climate-Economy Literature," *Journal of Economic Literature*, 52, 740–798.

Graff Zivin, J. and M. Neidell (2012): "The Impact of Pollution on Worker Productivity," *American Economic Review*, 102, 3652–3673.

He, J., H. Liu, and A. Salvo (2019): "Severe Air Pollution and Labor Productivity: Evidence from Industrial Towns in China," *American Economic Journal: Applied Economics*, 11, 173–201.

Hoffmann, B. and J. P. Rud (2024): "The Unequal Effects of Pollution on Labor Supply," *Econometrica*, 92, 1063–1096, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.3982/ECTA20484.

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.

Lee, S.-H., S.-H. Hong, C.-H. Tang, Y. S. Ling, K.-H. Chen, H.-J. Liang, and C.-Y. Lin (2018): "Mass spectrometry-based lipidomics to explore the biochemical effects of naphthalene toxicity or tolerance in a mouse model," *PLOS ONE*, 13, e0204829, publisher: Public Library of Science.

Lichter, A., N. Pestel, and E. Sommer (2017): "Productivity effects of air pollution: Evidence from professional soccer," *Labour Economics*, 48, 54–66.

Muñoz Sabater, J. (2019): "ERA5-Land monthly averaged data from 1950 to present," Copernicus Climate Change Service (C3S) Climate Data Store (CDS). Available at `www.doi.org/10.24381/CDS.68D2BB30` (accessed on November 16, 2024).

Mérel, P. and M. Gammans (2021): "Climate Econometrics: Can the Panel Approach Account for Long-Run Adaptation?" *American Journal of Agricultural Economics*, 103, 1207–1238, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/ajae.12200.

Mérel, P., E. Paroissien, and M. Gammans (2024): "Sufficient statistics for climate change counterfactuals," *Journal of Environmental Economics and Management*, 124, 102940.

Rentschler, J. and N. Leonova (2023): "Global air pollution exposure and poverty," *Nature Communications*, 14, 4432, publisher: Nature Publishing Group.

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.

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.