The Pollution–Productivity Curve

Non-Linear Effects and Adaptation in High-Pollution Environments

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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?

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

This paper: Antecedents in lit.

- **Empirical setting:** cricket players in India, high-pollution (mean $PM_{2.5}$=$42.3\,\mu g/m^3$)
- **Results preview:** players partially adapt to $PM_{2.5}$, but adaptation does not offset harm from cumulative exposure

Setting: Cricket in India as a natural experiment

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

Outcome: run-scoring (mean $= 0.60$)

Figure 1. Delivery: bowler vs. batter

Setting: Cricket in India as a natural experiment

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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
   Team quality vs. PM
   - Short-term: travel schedules within an IPL season
   - Long-term: career average over all matches in IPL

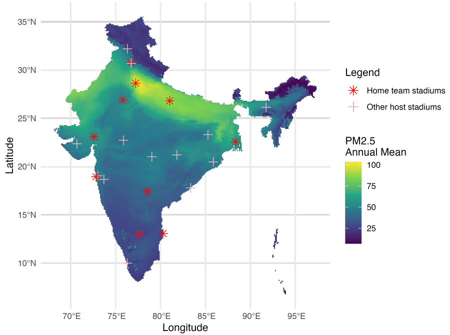
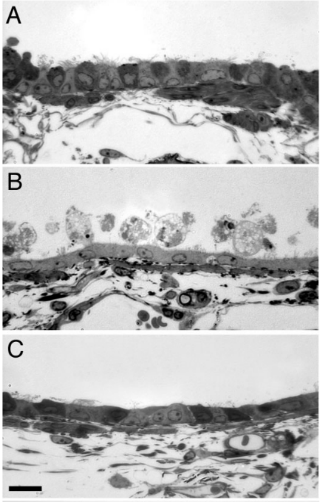


Figure 1. Annual $PM_{2.5}$ and IPL stadiums (2019)
▸ PM Data

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)

Econometric specifications

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

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

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

- $R_{ij\ell t}$: binary for run scored in delivery t
- $\text{PM2.5}_{\ell d}$: match-day $PM_{2.5}$ at stadium ℓ on day d (units: $10\,\mu g/m^3$)
- $\mathbf{X}_{\ell d}$: 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_{iy}: home stadium dummies for batter and bowler
- SEs two-way clustered at the match and bowler levels

Econometric specifications

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

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Econometric specifications

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

- $R_{ij\ell t}$: binary for run scored in delivery t
- $\text{PM2.5}_{\ell d}$: match-day $PM_{2.5}$ at stadium ℓ on day d (units: $10\,\mu g/m^3$)
- $\text{PM2.5}_{J(j)d}$: past d-day mean $PM_{2.5}$ exposure for bowler j on team J Alt. def.
- $\mathbf{X}_{\ell d}$: 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
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Econometric specifications

$$R_{ij\ell t} = \beta_1 \, \text{PM2.5}_{\ell d} + \beta_2 \, \text{PM2.5}_{\ell d} \times \text{PM2.5}_{j0}$$
$$+ \mathbf{X}'_{\ell d}\gamma + \psi_j + \phi_i + \delta_{\ell y} + \theta_{n(t)} + \eta_{o(t)} + \Lambda_{iy} + \Delta_{jy} + \varepsilon_{ij\ell t}$$

- $R_{ij\ell t}$: binary for run scored in delivery t
- $\text{PM2.5}_{\ell d}$: match-day $PM_{2.5}$ at stadium ℓ on day d (units: $10\,\mu g/m^3$)
- 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_{iy}: home stadium dummies for batter and bowler
- SEs two-way clustered at the match and bowler levels

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	183,556
R^2	0.052	0.052

Notes. Outcome mean is 0.599. PM2.5 in 10 $\mu g/m^3$. PM2.5 quintile cut-points: 27, 34, 41, 53 $\mu g/m^3$. SEs two-way clustered at match and bowler levels.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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

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)		0.0072
		(0.0060)
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	✓	✓
All FE	✓	✓
N	183,556	183,556
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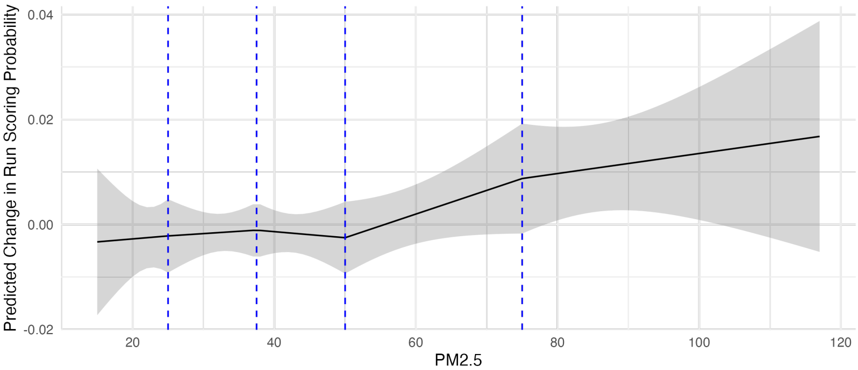

Figure 2. Linear spline estimation of effect of $PM_{2.5}$ on run-scoring probability (knots at WHO thresholds of 25, 37.5, 50, 75 $\mu g/m^3$).

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

	(1)	(2)
	$\mathbb{1}$ (At least one run scored)	
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)	
Q5 (Match PM2.5)		0.069***
		(0.025)
Q5 × Past 30-day PM2.5		−0.0095*
		(0.0051)
Weather controls	✓	✓
All FE	✓	✓
N	183,556	183,556
R^2	0.052	0.052

Notes. Col. (1): continuous interaction; col. (2): quintile indicators interacted with past 30-day mean (Q1 omitted; Q2–Q4 omitted here for space). SEs two-way clustered at match and bowler levels.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Short-term adaptation: ∼41% reduction in marginal effect

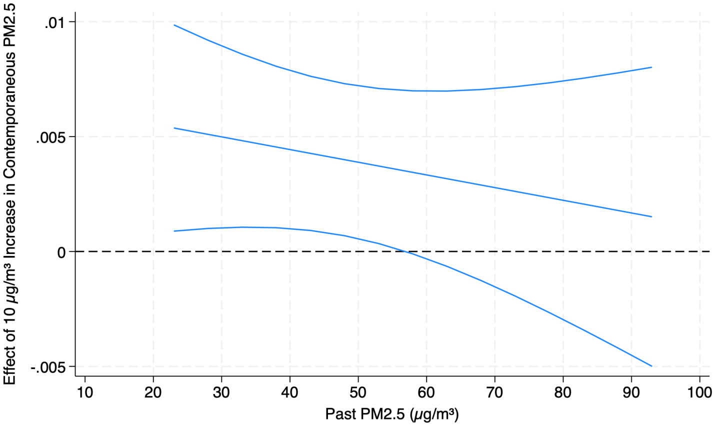

Figure 3. Marginal effect, with 95% CI indicated, of match-day $PM_{2.5}$ on run-scoring probability by bowler's past 30-day mean $PM_{2.5}$. Median past exposure: 45 $\mu g/m^3$; 95th percentile: 92 $\mu g/m^3$

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
R^2	0.052	0.052

Notes. Col. (3): continuous interaction with career mean PM2.5; col. (4): quintile indicators interacted with career mean (Q1 omitted; Q2–Q4 omitted here for space). Career mean absorbed by bowler FE at level; identified via interaction. SEs two-way clustered at match and bowler levels.

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Long-term adaptation: ∼36% reduction in marginal effect

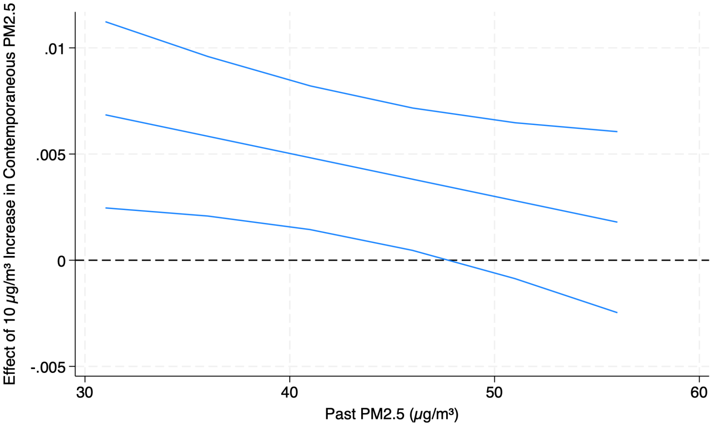

Figure 4. Marginal effect, with 95% CI indicated, of match-day $PM_{2.5}$ by bowler's career mean ($PM2.5_{j0}$). Median career exposure: 42 $\mu g/m^3$; 95th percentile: 52 $\mu g/m^3$

Adaptation does not offset cumulative harm

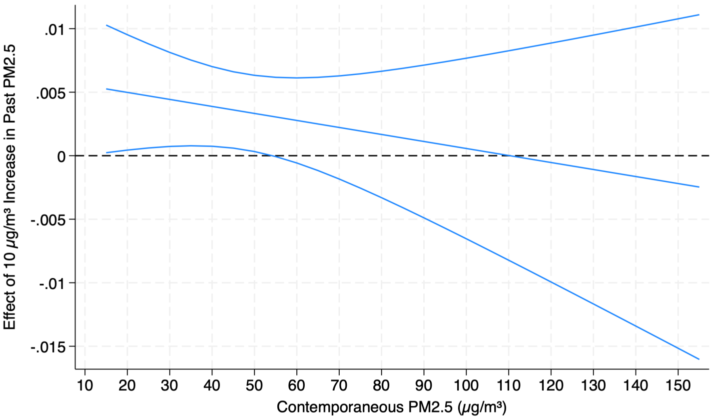

Figure 5. Marginal effect, with 95% CI indicated, of past 30-day mean $PM_{2.5}$ on run-scoring probability, by match-day $PM_{2.5}$ level. Adaptation's protective effect dominates only above $\sim 110\,\mu g/m^3$ — just 1.4% of matches.

Conclusion

1. **Non-linear dose-response.** Productivity effects are most pronounced at high $PM_{2.5}$ levels. Linear extrapolations from low-pollution settings understate damages at the levels faced by billions of workers in the developing world.
2. **Workers partially adapt.** Past 30-day mean exposure attenuates the acute $PM_{2.5}$ effect by $\sim$41% (short-term); career exposure attenuates it by $\sim$36% (long-term).
3. **Adaptation $\neq$ solution.** The cumulative harm from sustained exposure far outweighs any protective benefit of adaptation except under extraordinarily rare conditions.
4. **Relevance to billions of workers.** Findings may apply to the large number of workers involved in physical labor outdoors in developing countries (agriculture, street vending, etc.)

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3. **Adaptation $\neq$ solution.** The cumulative harm from sustained exposure far outweighs any protective benefit of adaptation except under extraordinarily rare conditions.

4. **Relevance to billions of workers.** Findings may apply to the large number of workers involved in physical labor outdoors in developing countries (agriculture, street vending, etc.)

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

Prior literature: $PM_{2.5}$ and labor productivity ▸ Back

- **Solid evidence but disproportionate focus on low-pollution settings**
  - US & Europe: Graff Zivin and Neidell (2012), Archsmith et al. (2018), Chang et al. (2016), Borgschulte et al. (2022)
  - China: He et al. (2019), Kahn and Li (2020), Guo and Fu (2019)
  - India: Adhvaryu et al. (2022); review: Aguilar-Gomez et al. (2022)
  - Most studies use instruments (wind, inversions) that preclude cumulative exposure histories: Chung et al. (2025), Hansen-Lewis (2026), Hill et al. (2024), Merfeld (2023)
- **Non-linearities: beginning to be documented**
  - Arceo et al. (2016), Hoffmann and Rud (2024) — but adaptation largely unexplored
- **Two closest papers study adaptation**
  - Mullins (2018): collegiate track & field, US — ozone not $PM_{2.5}$; low pollution levels
  - Qin et al. (2022): soccer, China — outcomes confounded by team dynamics; acclimation window limited to 1 day

This paper: Individual-level identification of adaptation in a high-pollution setting, across short- and long-run exposure windows.

Identification: team quality is uncorrelated with long-term $PM_{2.5}$

Back

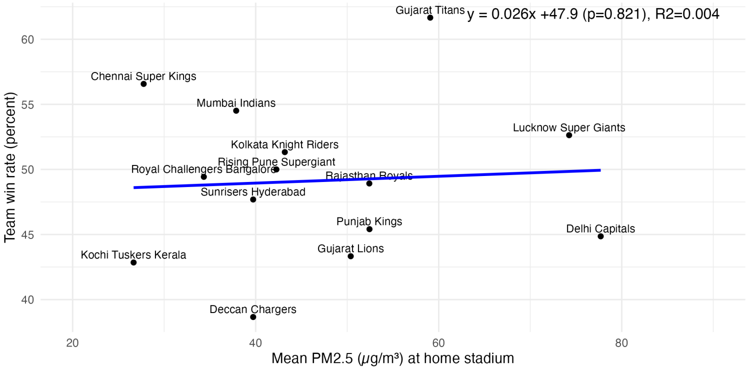

Figure 6. Team win rates vs. home-city mean $PM_{2.5}$. No meaningful correlation consistent with the IPL salary cap preventing ability sorting by pollution environment.

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

▸ Back

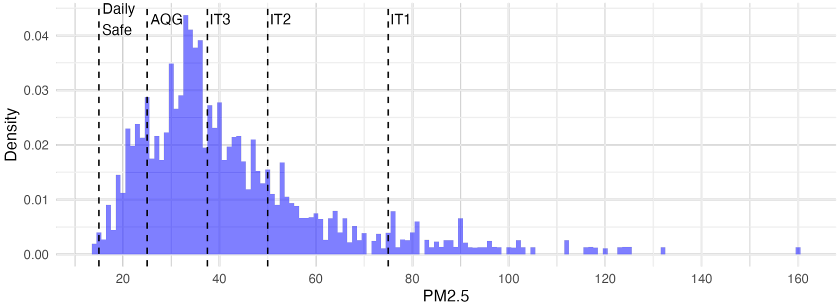

Figure 7. Match-day $PM_{2.5}$ distribution, IPL 2008–2022

$PM_{2.5}$ source: Wang et al. (2024)

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

Summary statistics:

- Mean: 42.3 $\mu g/m^3$ (SD: 20.0)
- Range: 14.2 – 159.9 $\mu g/m^3$
- 85% exceed WHO daily limit (15 $\mu g/m^3$)

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

▸ Back

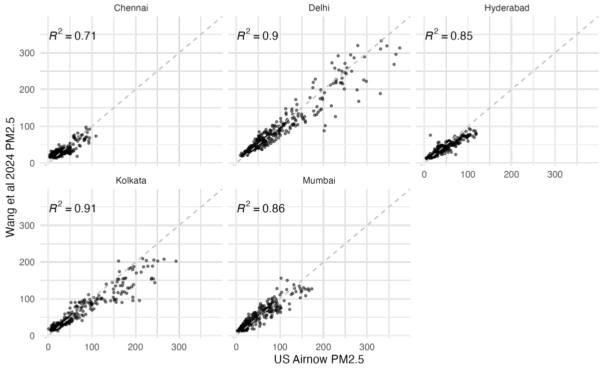

Figure 8. Daily $PM_{2.5}$ from Wang et al. (2024) ML product vs. U.S. AirNow ground monitors at five Indian cities. $R^2 = 0.71$–0.91 across cities.

Alternative measures of short-term past exposure

Back

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

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

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

Attenuation $\equiv \frac{ME_{p50} - ME_{p95}}{ME_{p50}}$, where ME_{pY} is the marginal effect of PM$_{2.5}$ on run-scoring at the Y^{th} percentile of past exposure.

Identifying the relevant exposure window: ∼30 days

Back

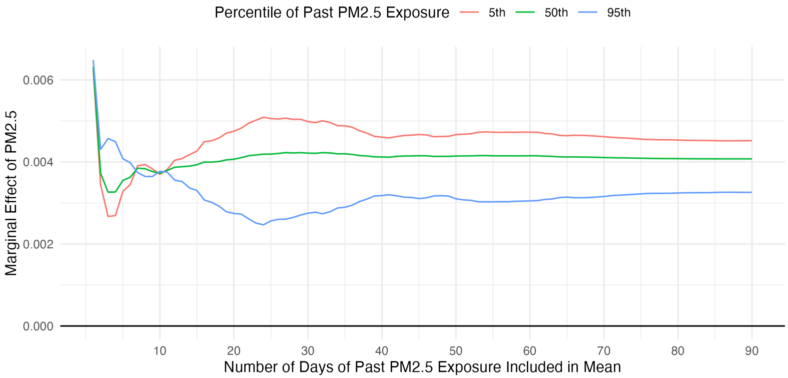

Figure 9. Marginal effect of match-day $PM_{2.5}$ on run-scoring probability, interacted with mean past $PM_{2.5}$ at each lookback window (1–90 days).

Alternative exposure measures

Table 4. 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 5. 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

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