

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

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Abstract

This paper studies whether workers adapt to air pollution using ball-by-ball data from Indian cricket, where match schedules and training locations generate variation in exposure. A $10 \mu\text{g m}^{-3}$ increase in match-day $\text{PM}_{2.5}$ reduces bowlers’ performance relative to batters’ by about 1 percent. This effect is statistically significant only in the top pollution quintile (over 5 times the U.S. annual average), although we cannot reject a linear dose–response. Higher exposure in the prior month attenuates this effect, consistent with adaptation, but lowers performance by more than attenuation offsets. Results suggest lowering baseline pollution, not merely averting extremes, yields productivity gains.

Keywords: Air pollution, labor productivity, adaptation

JEL codes: Q53, Q56, J24

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1 Introduction

The harmful effect of fine particulate matter (PM_{2.5}) air pollution on labor productivity is well documented ([Archsmith et al., 2018](#); [Adhvaryu et al., 2022](#); [Chang et al., 2019, 2016](#); [Graff Zivin and Neidell, 2012](#); [He et al., 2019](#); [Kahn and Li, 2020](#); [Mullins, 2018](#)). Yet this evidence comes overwhelmingly from settings where pollution is low by global standards. We know far less about its effects on the roughly 2.8 billion people—36% of the global population—for whom hazardous PM_{2.5} is not an occasional shock but a chronic condition of daily life ([Health Effects Institute, 2025](#)).¹ A central open question in such settings is whether workers adapt: whether accumulated past exposure moderates the productivity effect of an acute pollution shock. This is, at its core, a question about the difference between short- and long-run responses to a changing environment—a distinction fundamental to economics and central to a large literature on how output responds to temperature ([Burke and Emerick, 2016](#); [Dell et al., 2014](#); [Deschênes and Greenstone, 2007](#)), but one that remains largely unexplored for pollution. Answering it requires individual-level data of a kind that is scarce precisely where it matters most: high-frequency performance measures that separately identify acute and chronic exposure, and variation in workers’ pollution histories uncorrelated with their ability.

We study this question using ball-by-ball performance data from 773 matches in the Indian Premier League (IPL), India’s premier professional cricket competition, paired with a machine learning-based dataset providing daily PM_{2.5} estimates for each stadium ([Wang et al., 2024](#)).² This setting offers three features that together support credible identification. First, predetermined match schedules make contemporaneous PM_{2.5} exposure orthogonal to player ability and performance. Second, the league’s travel schedule, combined with an auction-based salary cap that distributes player quality roughly evenly across teams, generates variation in accumulated exposure that is plausibly unrelated to ability, which ball-by-ball data let us exploit through player-specific pollution

¹Following [Rentschler and Leonova \(2023\)](#), we classify annual average exposure to PM_{2.5} above 35 $\mu\text{g m}^{-3}$ —the least stringent [World Health Organization \(2021\)](#) interim target—as “hazardous.” For context, national annual average concentrations in the United States have generally remained below 10 $\mu\text{g m}^{-3}$ over the past decade.

²A “ball” is analogous to a pitch in baseball.

histories.³ Third, because each delivery is a direct contest between a bowler and a batter, we can identify how pollution's effect differs across tasks with distinct physical demands. This contest also defines our outcome: whether a delivery results in a run measures the bowler's performance relative to the batter's, so our estimates are net effects—pollution that harms both players registers only to the extent that it harms the bowler more—and understate the harm to either player alone.

We find that workers chronically exposed to high levels of air pollution partially adapt, becoming less sensitive to acute shocks. However, this adaptation comes at a cost: accumulated exposure itself degrades baseline performance, and the protective effect never outweighs cumulative harm relative to a low-exposure benchmark. We report four sets of results.

First, pollution significantly impairs worker performance: a $10 \mu\text{g m}^{-3}$ increase in $\text{PM}_{2.5}$ —half a standard deviation—raises the run-scoring probability by 0.42 percentage points (0.7% relative to the baseline mean), a deterioration in the bowler's performance relative to the batter's. To gauge this magnitude, reducing match-day exposure from the typical IPL level (sample median, $36.7 \mu\text{g m}^{-3}$) to the World Health Organization (WHO) daily safe limit ($15 \mu\text{g m}^{-3}$) would raise productive output by 2.3% for bowlers vis-à-vis batters. This asymmetry is consistent with the higher sustained physical exertion and respiration rates that bowling demands. Analyzing bowler-independent measures of performance, available only for a subset of matches, corroborates this interpretation, revealing a deterioration in bowler-specific performance as pollution rises.

Second, these effects are statistically detectable only in the highest pollution quintile—above $53 \mu\text{g m}^{-3}$, over 5 times higher than U.S. annual averages.⁴ Such high pollution levels are common in developing countries but rarely studied. We find no evidence of a threshold below which pollution is harmless, however: run-scoring probability rises steadily with pollution, and the dose-response is not distinguishable from linear.

³Our identifying assumption for the adaptation effect requires that long-term pollution exposure is not systematically correlated with player ability or other factors that may affect the response to contemporaneous pollution. The IPL's salary cap—which limits how much each team can spend on player compensation—provides support to the claim that player quality is roughly equal on average across teams. Empirically, we find no evidence that team or player performance is correlated with accumulated exposure (Figures H6 and H5).

⁴U.S. annual average $\text{PM}_{2.5}$ concentrations were consistently below $10 \mu\text{g m}^{-3}$ in the past decade (Health Effects Institute, 2025).

Third, workers chronically exposed to high pollution become less sensitive to acute shocks, consistent with adaptation over both short and long time horizons. Below $50 \mu\text{g m}^{-3}$, a $10 \mu\text{g m}^{-3}$ increase in match-day $\text{PM}_{2.5}$ raises the run-scoring probability by 0.8 percentage points for bowlers at the 10th percentile of past 30-day exposure but has no detectable effect for bowlers at the 90th percentile; the difference, 1.1 percentage points, is statistically significant ($p < 0.05$). Career-average exposure attenuates the acute response similarly: the marginal effect of match-day $\text{PM}_{2.5}$ is 62% smaller for bowlers at the 90th percentile of career exposure than for those at the 10th ($p < 0.10$). This attenuation is concentrated along the lower part of the dose–response curve: above $50 \mu\text{g m}^{-3}$, the acute effect is small and does not vary with exposure history.

Fourth, adaptation does not offset cumulative harm. Past exposure raises run-scoring probability directly, and although this cumulative harm declines as match-day pollution rises toward $50 \mu\text{g m}^{-3}$, the total effect of exposure relative to a low-exposure benchmark is harmful at every observed combination of match-day and past exposure. For virtually all policy-relevant scenarios, both acute and chronic pollution unambiguously impair productivity.

Adaptation is biologically plausible: the environmental toxicology literature has established that repeated exposure to air pollution triggers adaptive responses in lung cells within days to weeks ([Dimeo et al., 1981](#); [Hackney et al., 1977](#); [Hamade and Tankersley, 2009](#); [West et al., 2003](#)). Adaptation could also operate through behavioral channels (e.g., wearing masks or using inhalers) or psychological channels (e.g., coping strategies), though the IPL setting limits behavioral avoidance by requiring all players to attend every match in outdoor stadiums. We ground our empirical strategy in this toxicology literature, using it to inform the timescale over which we expect adaptation to emerge.

Our findings contribute to a literature on pollution and productivity that remains concentrated in low-pollution contexts ([Aguilar-Gomez et al., 2022](#)): key studies on pollution’s physical productivity effects overwhelmingly examine the United States, Europe, or China ([Archsmith et al., 2018](#); [Chang et al., 2016](#); [Graff Zivin and Neidell, 2012](#); [Mullins, 2018](#); [Chang et al., 2019](#); [He et al., 2019](#); [Guo and Fu, 2019](#); [Kahn and Li, 2020](#)), with only [Adhvaryu et al. \(2022\)](#) focusing on India. This

geographic concentration leaves the productivity effects of the high exposure levels typical of South Asia and Sub-Saharan Africa largely unmeasured. Moreover, prior work has largely left adaptation to chronic pollution unexplored: among these studies, only [He et al. \(2019\)](#) examine exposure beyond a week, and their distributed lag framework captures the level effect of past exposure rather than the interaction between past and contemporaneous exposure.

Two studies are closest in spirit to ours. [Archsmith et al. \(2018\)](#) study the effect of $\text{PM}_{2.5}$ on decision-making quality among baseball umpires in the United States, finding linear effects and testing for—but not detecting—non-linearities in a setting where mean $\text{PM}_{2.5}$ is approximately $10 \mu\text{g m}^{-3}$. While we cannot formally reject a linear dose–response, we find that marginal effects are only statistically detectable at concentrations above $53 \mu\text{g m}^{-3}$, well above their range. [Mullins \(2018\)](#) identifies adaptation to ozone among U.S. collegiate track and field athletes, finding that athletes accustomed to higher ozone concentrations in the seven days preceding the performance event experience smaller performance decrements when ozone is elevated.⁵ We extend this finding to $\text{PM}_{2.5}$, a solid particulate rather than a gas and the pollutant responsible for the largest share of the global burden of disease from air pollution ([Health Effects Institute, 2025](#)).⁶

We make three contributions. First, we extend the study of environmental adaptation to a new margin. The climate economics literature has shown that long-run temperature averages moderate the short-run response to temperature ([Burke and Emerick, 2016](#); [Dell et al., 2014](#); [Heutel et al., 2021](#)); we demonstrate a parallel dynamic for air pollution, showing that the effect of an acute $\text{PM}_{2.5}$ shock depends on a worker’s accumulated exposure. This implies that the productivity costs of short-run pollution shocks may differ substantially across populations with different long-run exposure, a heterogeneity that pooled estimates obscure.

Second, we develop a new person-based measure of pollution exposure to uncover this result. Unlike the climate economics literature which focuses almost exclusively on adaptation within

⁵In a related study, [Qin et al. \(2022\)](#) document that the performance of professional footballers in China is sensitive to the gap between match-day $\text{PM}_{2.5}$ and prior levels of exposure to $\text{PM}_{2.5}$, but leave open the question of how the magnitude of a same-day shock differs by past exposure levels.

⁶[Mullins \(2018\)](#) also tests for adaptation effects for $\text{PM}_{2.5}$ but does not find them. The divergent findings in our sample could be explained by the fact that levels of $\text{PM}_{2.5}$ in our sample are much higher than those in the U.S.

spatial units (such as agricultural fields, Census tracts, or nations), we shift the unit of analysis to the individual. We draw on the environmental toxicology literature to anchor the horizon over which adaptation should emerge in the physiological mechanisms identified in that field. Guided by this literature, we estimate the lag profile of recent exposure directly rather than imposing a window, and use it to fix the horizon over which recent exposure is measured for the adaptation specifications.

Third, we bring together two literatures that have studied the effects of air pollution largely in isolation. On one side, a quasi-experimental literature in environmental economics identifies the causal effect of contemporaneous exposure on health and economic outcomes (e.g., [Deryugina et al., 2019](#); [Graff Zivin and Neidell, 2012](#); [Schlenker and Walker, 2015](#)); on the other, a body of work in epidemiology relates long-run exposure to mortality and morbidity outcomes using prospective cohort designs that rely on selection-on-observables rather than quasi-experimental variation (e.g., [Dockery et al., 1993](#); [Lepeule et al., 2012](#); [Pope III et al., 2002](#)). Because these literatures study different outcomes with different research designs, the harm from contemporaneous exposure and that from accumulated exposure are rarely measured on a common scale. We develop a framework that places both effects—together with the protective effect of adaptation—on the same yardstick of performance, estimated within a single design. This allows us to compare their magnitudes directly: to ask not only whether contemporaneous and chronic exposure each impair performance, but how the per-unit harm of an acute shock compares to that of accumulated exposure, and whether adaptation is ever large enough to offset cumulative damage.

Our results have implications for environmental policy in emerging economies, where large swaths of the population work in outdoor, physical labor. Because we cannot reject a linear dose–response, the productivity gains from pollution control are not confined to extreme episodes: they accrue across the range of exposure that workers in this setting face, almost all of it above the WHO guideline. At the same time, while workers in chronically polluted environments develop partial resilience to acute shocks, cumulative performance losses from chronic exposure far outweigh this protective effect. Adaptation is not a solution to pollution—it is evidence of ongoing harm.

The remainder of this paper is organized as follows. Section [2](#) describes our setting and the

physiological basis for adaptation. Section 3 develops a conceptual framework. Sections 4 and 5 present our data and empirical strategy. Section 6 reports our results, and Section 7 concludes.

2 Background

2.1 Institutional details of cricket

Cricket is a bat-and-ball sport in which two teams alternate between batting and bowling, with the objective of scoring more runs than the opposition. The fundamental unit of play is the interaction between a bowler (analogous to a pitcher in baseball) and batter (analogous to a baseball batter), with each delivery of a ball representing a discrete episode of measurable performance. Bowlers are responsible for delivering the ball toward the batter’s wicket, employing various techniques to make run-scoring difficult, while batters attempt to score runs through offensive batting.⁷ Due to more intense physical activity (each delivery requires a running approach, for fast bowlers) resulting in an increased respiration rate, bowlers are more exposed to air pollution than batters.⁸ We therefore expect bowler performance to deteriorate more than batter performance when air pollution rises.

Our empirical setting is the Indian Premier League (IPL), the world’s premier Twenty20 cricket league.⁹ The IPL operates as a franchise system with ten teams based in different cities that span India’s diverse geography and differ substantially in average air quality owing to differences in vehicle traffic, industrial activity, and natural features (Figure 2). Each franchise is based at a home stadium in its host city, where it plays its home matches and conducts the majority of its training. The league fixes the full match schedule in advance of each season before air quality on any given match day is realized or can be reliably predicted. Players are allocated to teams through an annual auction conducted under a salary cap. Each franchise bids from the same fixed amount, so no team can outspend another in assembling its roster.

⁷Fielders, the third type of player, support the bowling side by catching batted balls and preventing runs.

⁸See Appendix A for details including physiological metrics.

⁹Twenty20, indicating two innings with 20 overs each, is one style of cricket that is designed to be played over an approximately three-hour period, in contrast to the traditional style in which matches can take days.

2.2 Physiological basis for adaptation

While the notion of adaptation to changing environmental conditions is not new to the economics literature ([Dell et al., 2014](#); [Burke and Emerick, 2016](#); [Moore, 2017](#); [Burke et al., 2024](#)), it is typically conceived as a behavioral response to long-run changes, consistent with an optimization framework. The adaptation under study here is similar in that it involves a response to a changing environment; however, the optimizing agent we focus on is not an individual person, but rather biochemical processes in cells.

The environmental toxicology literature has established that mice become resistant to the acute damages of air pollution with repeated exposure ([West et al., 2003](#); [Kültz et al., 2015](#); [Lee et al., 2018](#)). The key adaptation mechanism that the environmental toxicology literature has identified is that, when exposed to air pollution repeatedly, cells augment the rate at which they can produce glutathione in response to incoming air pollution.¹⁰ Studies have shown that this adaptation response occurs as quickly as after a week of repeated exposure to air pollution ([West et al., 2003](#)). However, little is known about how this response may amplify—or fade—over longer time horizons, motivating our empirical exploration of varying exposure windows (described in detail in [Section 4.3.1](#)).

3 Conceptual framework

Our primary outcome is worker performance. While productivity is a measure of output per input, we conceptualize performance as a measure of how well an outcome aligns with a desired goal. In our empirical setting, performance for a bowler is defined as the fraction of deliveries in which they do not concede a run. Generally, performance is a determinant of productivity: for a given level of input, worker performance determines the level of output.

Our conceptual framework ([Appendix C](#)) highlights three channels through which air pollution may affect worker performance: a non-linear dose–response relationship, adaptation to chronic exposure through behavioral and physiological pathways, and heterogeneous impacts across task

¹⁰See [Appendix B](#) for a detailed discussion of this mechanism.

types with different physical demands. We define a production function describing a cricket bowler's performance as $F(P, a)$ where P is pollution and a are adaptation measures that can occur in the long-run (either positive or negative). Equation 1 decomposes the total effect of pollution on performance into its constituent parts:

$$\underbrace{\frac{dF}{dp}}_{\text{Long-run effect}} = \underbrace{\frac{\partial F}{\partial p}}_{\text{Short-run effect}} + \underbrace{\frac{\partial F}{\partial a} \frac{da}{dp}}_{\text{Adaptation effect}} \quad (1)$$

Standard reduced-form estimates capture only the short-run effect $\frac{\partial F}{\partial p}$. By interacting current pollution with a longer-term average exposure in our empirical specifications, we can disentangle the short- and long-run effects.

4 Data

We combine three data sources: ball-by-ball performance data from 773 IPL matches in India (2008–2022), high-resolution daily PM_{2.5} estimates from both ground monitors and satellite-based sources, and weather controls.¹¹ This section describes each data source and discusses features relevant for our empirical analysis.

4.1 Cricket performance

We obtain ball-by-ball cricket performance data for the IPL from Cricsheet, an open-source repository of cricket match data (Cricsheet, 2024). Our analytic sample contains all matches in the IPL from 2008–2022 that took place in India, comprising over 180,000 deliveries (analogous to pitches in baseball) across 773 matches.¹² For each delivery, we observe detailed information including the

¹¹Several seasons (and parts of seasons) of the IPL were played outside India due to security and public health concerns. We exclude these matches from our analysis to focus on productivity impacts within the high-pollution setting of India.

¹²177 IPL matches took place outside India during these years due to security concerns; we exclude these from our sample.

identities of both the bowler and batter, the outcome of the delivery (such as the number of runs scored or wickets taken), and the precise match situation (such as the innings and over number). We combine these performance metrics with characteristics of each bowler and batter scraped from ESPN Cricinfo, which includes the national cricket team with which the player is associated, their age, and—for bowlers—their bowling style.¹³

Table 1 (panels B–E) describes summary statistics from these matches. We leverage the data’s ball-by-ball granularity by defining our main outcome as a binary indicator for whether any runs were conceded on a given delivery.¹⁴ The mean of the binary outcome—the run-scoring probability—is 59.9%.

4.2 PM_{2.5} exposure

Our primary source of air pollution data comes from Wang et al. (2024), who provide daily estimates of ground-level fine particulate matter (PM_{2.5}) concentrations at a 10 km × 10 km resolution across India for the period 1980–2022. These estimates are derived from a machine learning model that combines satellite data, meteorological information, and ground monitor readings. The high spatial resolution of this dataset allows us to precisely match daily air quality conditions to each of the 20 stadiums where IPL matches were played during our study period, including both the ten permanent home stadiums and ten additional stadiums that periodically hosted matches (Figure 2).¹⁵ We validate the Wang et al. (2024) data against the U.S. AirNow network and show that it better matches ground monitor PM_{2.5} readings than aerosol optical depth (AOD) from the Moderate Resolution

¹³Bowling styles can be categorized into “pace” (fast and medium) and “spin.” Pace bowlers optimize the speed of the delivery, requiring a long running approach, whereas spin bowlers focus on spinning the ball, requiring a substantially shorter running approach.

¹⁴This approach has three advantages over aggregate performance measures (such as total runs scored). First, it preserves the rich variation in the data, allowing us to control for both time-invariant characteristics of players and the evolving match situation. Second, it provides a player-level measure of performance based on specific bowler–batter interactions, rather than team-level outcomes that depend on many additional factors. Third, by focusing on the binary outcome of conceding any runs rather than the number of runs conceded, we avoid potential complications from cricket’s non-linear scoring system where certain outcomes (e.g., boundaries worth four or six runs) occur discretely based on specific field events rather than incremental performance differences. As a robustness test, we conduct analyses accounting for the full range of run outcomes (0, 1, 2, 3, 4, 5, or 6) using an ordered logit model.

¹⁵Specifically, we matched the latitude and longitude coordinates of each stadium to the corresponding 10 km × 10 km cell in the Wang et al. (2024) gridded data.

Table 1: Summary statistics: IPL matches in India 2008-2022

Variable	Unit	N	Mean	SD	Min	Median	Max
Panel A: Treatment variables							
Match-day PM _{2.5} ($\mu\text{g m}^{-3}$)	Match	773	42.29	20.05	14.23	36.65	159.91
Past 30-day PM _{2.5} ($\mu\text{g m}^{-3}$)	Match-team	1,544	45.82	12.21	22.56	44.01	94.36
Career PM _{2.5} ($\mu\text{g m}^{-3}$)	Bowler	445	42.62	9.66	17.83	41.67	103.16
Panel B: Cricket performance outcomes							
Runs scored	Delivery	183,572	1.255	1.630	0.000	1.000	6.000
1 (At least one run scored)	Delivery	183,572	0.599	0.490	0.000	1.000	1.000
Panel C: Bowler-independent outcomes							
No-ball (=1)	Delivery	183,572	0.004	0.063	0.000	0.000	1.000
Delivery length (m)	Delivery	116,414	6.36	2.70	-2.00	6.32	20.39
Delivery speed (km/h)	Delivery	113,975	116.44	21.28	79.87	124.45	154.40
Panel D: Bowler characteristics							
South Asian (=1)	Bowler	434	0.620	0.486	0.000	1.000	1.000
Pace bowler (=1)	Bowler	445	0.616	0.487	0.000	1.000	1.000
Age (years)	Bowler	434	25.74	4.51	16.43	25.45	41.58
Seasons in IPL	Bowler	445	3.2	2.7	1.0	2.0	12.0
Panel E: Cricket statistics							
Home bowler (=1)	Delivery	183,572	0.317	0.465	0.000	0.000	1.000
Home batter (=1)	Delivery	183,572	0.319	0.466	0.000	0.000	1.000
Innings	Delivery	183,572	1.5	0.5	1.0	1.0	4.0
Over	Delivery	183,572	10.2	5.7	1.0	10.0	20.0
Panel F: Weather controls							
Temperature ($^{\circ}\text{C}$)	Match	773	29.49	2.52	21.68	29.44	37.26
Humidity (%)	Match	773	52.17	19.90	10.02	54.25	90.41
Precipitation (m)	Match	773	0.0007	0.0024	0.0000	0.0000	0.0254
Pressure (1,000 Pa)	Match	773	97.41	3.52	84.60	98.07	101.23
Radiation (MJ/m^2)	Match	773	24.48	2.83	6.68	25.00	29.93
Wind speed (m/s)	Match	773	2.30	1.02	0.06	2.28	5.48

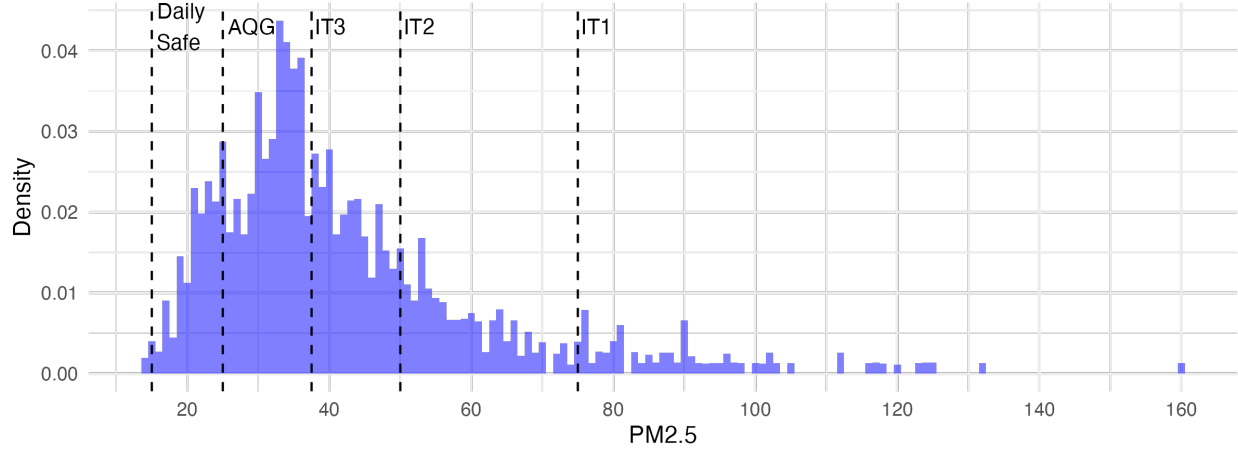
Notes: 183,572 deliveries in 773 IPL matches played in India, 2008-2022 (13 seasons, 20 stadiums, 445 bowlers, 575 batters). Delivery length and speed are observed only on the Hawk-Eye subset (512 matches). Past 30-day PM_{2.5} is the bowling team's mean over the 30 days before the match; career PM_{2.5} is the bowler's mean across all matches played. No-ball (=1) indicates a delivery ruled illegal on account of a bowler fault. Length is the distance in meters from the batter's stumps to the point where the delivery bounces, so a negative coefficient means fuller deliveries. Speed is the measured speed of the delivery in kilometers per hour, bottom-coded at the within-bowler-type (pace/spin) 5th percentile. Age is at IPL debut. Sources: cricsheet ([Cricsheet, 2024](#)); PM_{2.5} from [Wang et al. \(2024\)](#); weather from ERA5-Land ([Muñoz Sabater, 2019](#)).

Imaging Spectroradiometer (MODIS).¹⁶

These data provide complete coverage of all IPL matches during our study period. As shown in

¹⁶See Appendix D for details.

Figure 1: IPL match PM_{2.5} distribution with WHO thresholds indicated



Notes. This figure shows the distribution of PM_{2.5} at IPL matches in the period 2008–2022 with WHO thresholds for daily PM_{2.5} exposure indicated. WHO Interim Threshold 1 (IT1) is 75 $\mu\text{g m}^{-3}$, WHO Interim Threshold 2 (IT2) is 50 $\mu\text{g m}^{-3}$, WHO Interim Threshold 3 (IT3) is 37.5 $\mu\text{g m}^{-3}$, WHO Air Quality Guideline (AQG) is 25 $\mu\text{g m}^{-3}$, and The WHO Daily Safe exposure threshold (Daily Safe) is 15 $\mu\text{g m}^{-3}$. These thresholds are based on the levels of PM_{2.5} associated with higher short-term mortality risk (World Health Organization, 2021).

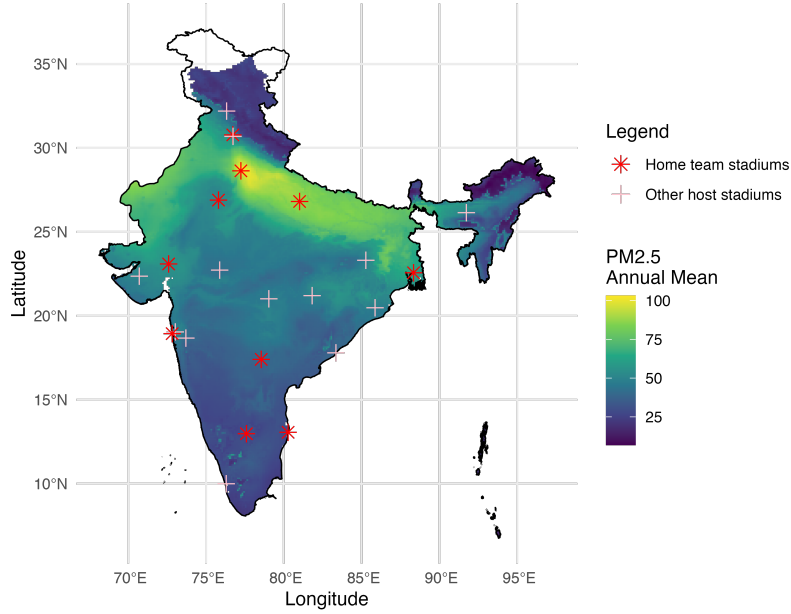
Figure 1, PM_{2.5} concentrations at IPL matches are far higher than in high-income country settings, with a mean of 42.3 $\mu\text{g m}^{-3}$ on match days (median 36.7), a maximum of 159.9 $\mu\text{g m}^{-3}$, and over 85% of matches exceeding the WHO daily safe limit of 15 $\mu\text{g m}^{-3}$ (World Health Organization, 2021). In addition, there is a wide dispersion of pollution across space, as shown in Figure 2.

4.3 Defining past exposure to PM_{2.5}

To identify how the effect of contemporaneous exposure varies by past exposure to PM_{2.5}, we need to develop a sound measure of past PM_{2.5}. The challenge with doing so is that players in the IPL move both within a season and across seasons. Therefore, choosing one location on which to base a player's exposure to pollution is problematic. Instead, we design our measure of past exposure to PM_{2.5} to track where a player is located based on their IPL travel schedule.¹⁷

¹⁷See Appendix E for an extended discussion of the justification for this approach.

Figure 2: Geographic distribution of cricket stadiums and PM_{2.5} in the IPL



Notes. This figure shows annual mean PM_{2.5} across India in 2019 as estimated by Wang et al. (2024) and the locations of cricket stadiums used in the Indian Premier League (IPL) from 2008–2022. Red asterisks indicate home stadiums of the ten IPL franchise teams: Chennai Super Kings (Chennai), Delhi Capitals (New Delhi), Gujarat Titans (Ahmedabad), Kolkata Knight Riders (Kolkata), Lucknow Super Giants (Lucknow), Mumbai Indians (Mumbai), Punjab Kings (Mullanpur), Rajasthan Royals (Jaipur), Royal Challengers Bengaluru (Bengaluru), and Sunrisers Hyderabad (Hyderabad). Pink crosses indicate other stadiums that have hosted IPL matches during this period but are not permanent home stadiums for any current IPL team. White space indicates no PM_{2.5} data available from Wang et al. (2024) for a given area.

4.3.1 Short-term past exposure

We ground our definition of short-term pollution exposure in the environmental toxicology literature which finds that mice exhibit tolerance to air pollution when exposed to it repeatedly for days to weeks (West et al., 2003). In Section 5.3 we estimate the horizon over which recent exposure affects performance in our context. We consider a maximum window of 30 days since players begin training at their home stadiums approximately 30 days before the IPL season starts.

Our primary measure of past exposure to PM_{2.5} is a bowler j 's mean PM_{2.5} over the past T days, where P indicates PM_{2.5}:¹⁸ $\bar{P}_{J(j)d} \equiv \frac{1}{T} \sum_{\tau=1}^T P_{J(j)\tau}$. Our main specifications use $T = 30$ days, a choice we motivate in Section 5.3.¹⁹ Since this measure extends into the past by at most one month

¹⁸Appendix F defines two alternative measures of past exposure (counts of days above a threshold and a degree-day analog) and explains why we rely on the mean.

¹⁹Results for T 1–30 are reported in Figure H12.

and there is a nine-month gap between seasons of the IPL, this past-exposure measure is assigned at the team-level, so that all bowlers on the same team receive the same level of exposure.²⁰ The measure of exposure is calculated over a rolling lookback window relative to a specific day, d .

Rules for assigning $PM_{2.5}$ exposure to teams To construct short-term past exposure, we assume the following. If they play a match on the next day: we assume they travel the day prior. So we assign them the value of $PM_{2.5}$ in the next match’s stadium. If they do not play a match on the next day, but did play a match on the previous day: we assume the team is still in the location of the previous match. So we assign them the value of $PM_{2.5}$ in the previous match’s stadium. If neither, we assign them the $PM_{2.5}$ for their home stadium.

In Figure 3, we compare the $PM_{2.5}$ estimates assigned to teams as opposed to the $PM_{2.5}$ at their home stadium for the 2018 season.²¹ The red line shows $PM_{2.5}$ exposure at the team’s home stadium; the blue line shows $PM_{2.5}$ exposure for each team given their assumed location. When the two lines overlap—as they do most of the time, since teams spend most of their time in their home stadium—the line is purple. Teams based in a high pollution location that travel to matches in lower pollution settings (e.g., Delhi Capitals), or vice versa (e.g., Chennai Super Kings) tend to have many days on which these two measures differ, reinforcing the need to more precisely estimate $PM_{2.5}$ exposure for each team.

4.3.2 Long-term past exposure

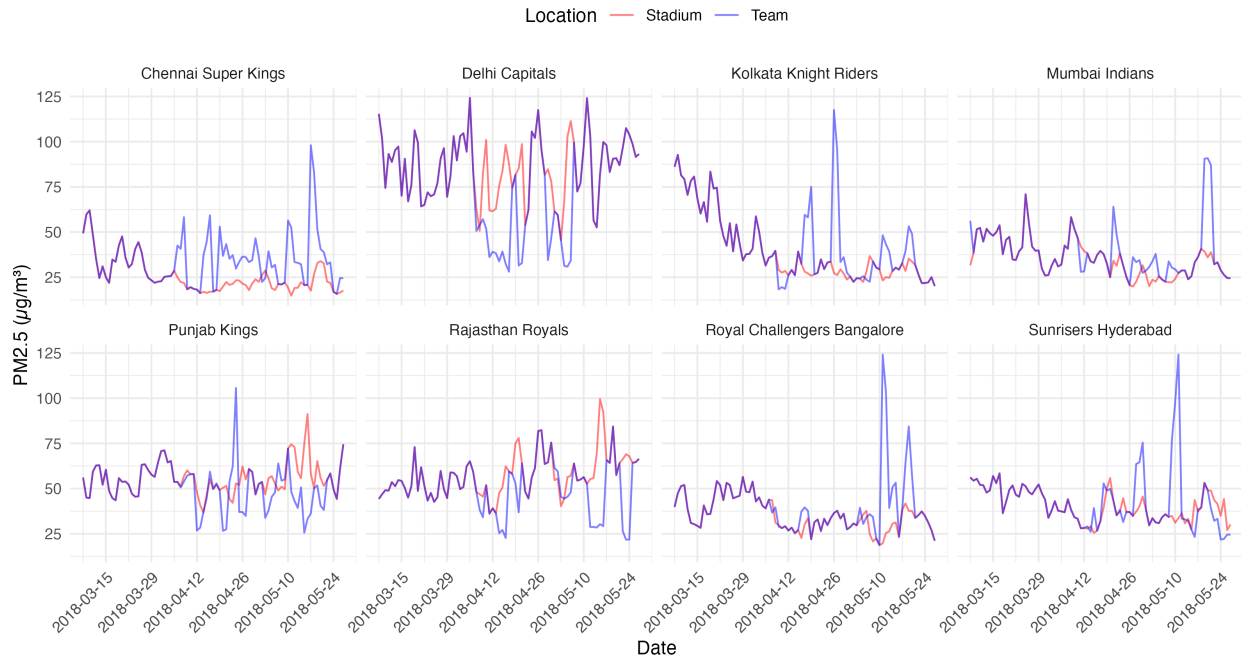
In addition to the measures of past exposure in Section 4.3.1 which vary for the same team (and individual) over time, we also test the robustness of our results for a measure that is fixed for each individual: the average of their exposure across all the matches they play in the IPL.²² For the average player in our sample, this is measured over a time span of 3.2 seasons (range: 1 to 12 seasons). The measure consists not only of a player’s home-stadium’s average, but also includes

²⁰The team-level of assignment is reflected in the subscript $J(j)$, where J is a function that maps bowler j to team J .

²¹Figure H3 shows the distribution of $PM_{2.5}$ exposure histories across all seasons for each of the eight teams with the highest numbers of matches in the IPL as of 2022. We combine the $PM_{2.5}$ exposure histories for teams that changed names across seasons but retained the same home city and stadium; the graph shows the most recent name of each team.

²²The distribution of this measure is displayed in Figure H9.

Figure 3: Team $PM_{2.5}$ exposure vs. home stadium $PM_{2.5}$ exposure in 2018



Notes. This figure compares the $PM_{2.5}$ estimates assigned to teams (based on their travel itinerary, as in Section 4.3.1) relative to the $PM_{2.5}$ at their home stadium. The red line shows the level of $PM_{2.5}$ exposure at the team’s home stadium whereas the blue line shows the $PM_{2.5}$ exposure for each team taking into account their away matches and travel schedule.

exposures from matches played in away-stadiums, though it is disproportionately weighted to the pollution levels at their home stadium (since teams play roughly half their matches at home). It only tracks their pollution exposure during IPL matches, not the rest of the year, and so is a measure of “on-the-job” exposure. If pollution exposure during cricket matches themselves contributes to a bowler’s ability to tolerate pollution while playing cricket, this measure appropriately captures that type of exposure.²³

4.4 Weather

$PM_{2.5}$ concentrations are influenced by many meteorological factors, which themselves may influence the performance of cricket players. We therefore include variables for temperature, humidity,²⁴

²³In Appendix G.3, we explore alternative definitions of long-term $PM_{2.5}$ exposure.

²⁴ERA5-Land contains dewpoint temperature rather than relative humidity. We calculate relative humidity from temperature and dewpoint temperature using the meteorological approximation outlined by Lawrence (2005).

and wind in our regression specifications. We obtain these weather variables from ERA5-Land, a state-of-the-art reanalysis dataset developed by the European Centre for Medium-Range Weather Forecasts, accessed through Google Earth Engine ([Muñoz Sabater, 2019](#)). The ERA5-Land data provide global coverage at approximately $11 \text{ km} \times 11 \text{ km}$ spatial resolution, enabling precise matching to stadium locations.

5 Empirical approach

We examine how air pollution affects cricket performance, with particular attention to how players' typical exposure levels moderate these effects. Our main analysis centers on ball-by-ball outcomes, using as our primary outcome variable a binary indicator for whether a bowler concedes a run on each delivery. The choice of a binary outcome is motivated by two considerations. First, conditional on scoring, the distribution of runs is heavily concentrated at one run (over 60% of scoring deliveries resulting in a single run, as shown in Figure [H2](#)), and higher run values (fours and sixes) are achieved through qualitatively different actions—hitting the ball to the boundary—rather than incremental performance differences, making a continuous measure potentially misleading.²⁵ Second, the binary outcome provides a clear interpretation: the marginal effect of pollution is the change in probability of a bowler conceding (or batter scoring) a run, where conceding a run indicates poor bowler performance.²⁶ We conceptualize run-concession as an error rate on the part of the bowler, analogous to the “correct-call” error rate for umpires used in [Archsmith et al. \(2018\)](#).

²⁵In Appendix [G.1](#) we specify and estimate ordered logit models that incorporate variation in the number of runs scored. We also test whether results are robust to an OLS model where the outcome is the number of runs scored per delivery.

²⁶There is a slight wrinkle for bowlers in that they also seek to get the batter out, which may justify allowing a run in rare cases. We consider this a minor consideration and abstract away from it in our analysis.

5.1 Effects of contemporaneous air pollution on performance

We examine the relationship between match-day $\text{PM}_{2.5}$ levels and the run-scoring probability with the following linear probability model:

$$R_{ij\ell t} = \beta P_{\ell d} + \mathbf{X}'_{\ell d} \gamma + \psi_j + \phi_i + \delta_{\ell y} + \mu_m + \theta_{n(t)} + \eta_{o(t)} + \Lambda_i + \Delta_j + \varepsilon_{ij\ell t} \quad (2)$$

where $R_{ij\ell t}$ is an indicator for whether at least one run is scored on the t^{th} delivery of the match, bowled by bowler j to batter i at location (stadium) ℓ . The unit of analysis is a single delivery (i.e., a single ball thrown from a bowler to a batter). The regressor of interest, P , is the daily mean value of $\text{PM}_{2.5}$ (measured in $10 \mu\text{g m}^{-3}$) estimated by Wang et al. (2024) in the 10 km grid cell containing the latitude and longitude of the stadium at which the match is played.²⁷ Our coefficient of interest, β , thus captures the effect of match-day $\text{PM}_{2.5}$ levels on the run-scoring probability. A positive β indicates that the run-scoring probability rises with daily mean $\text{PM}_{2.5}$, consistent with poorer performance of the bowler relative to the batter.

Our preferred specification includes bowler fixed effects (ψ_j), batter fixed effects (ϕ_i), stadium-by-year fixed effects ($\delta_{\ell y}$), month fixed effects (μ_m), innings fixed effects ($\theta_{n(t)}$) and over-phase fixed effects ($\eta_{o(t)}$).²⁸ It also includes dummy variables for whether the stadium is the home stadium for the batter (Λ_i) or bowler (Δ_j).²⁹ Bowler and batter fixed effects control for any time-invariant player-specific factors (such as innate ability), stadium-by-year fixed effects account for stadium-specific temporal trends that might correlate with both pollution levels and cricket performance as well as fixed characteristics of stadiums (e.g., elevation) that may influence performance, and innings

²⁷The standard measure of $\text{PM}_{2.5}$ is $1 \mu\text{g m}^{-3}$. When measured in these units, the effects we observe are very small in magnitude. Given the distribution of $\text{PM}_{2.5}$ in our sample (mean $42.3 \mu\text{g m}^{-3}$ and standard deviation $20.0 \mu\text{g m}^{-3}$; for full distribution see Figure 1), measuring $\text{PM}_{2.5}$ in $10 \mu\text{g m}^{-3}$ is appropriate. The effect sizes we observe are similar to those of other studies that measure effects in $10 \mu\text{g m}^{-3}$ (Adhvaryu et al., 2022).

²⁸The subscripts $n(t)$ and $o(t)$ indicate the innings, during which delivery t (synonymous to ball t) occurs. There are typically two innings per match. There are 20 overs per innings. The over-phase fixed effects coarsen the 20 overs into three phases: “powerplay overs” (1–6), where there are restrictions on fielders; middle overs (7–15); and “death overs” (16–20), the final overs in an innings.

²⁹Note that some matches are played at stadiums that are a home stadium for neither team, which prevents these two terms from being collinear. Bowlers and batters change teams across seasons which means these terms are not absorbed by the bowler and batter fixed effects.

and over-phase fixed effects control for stage-of-match effects that could influence playing styles and strategies. Month fixed effects absorb within-season variation in $\text{PM}_{2.5}$, along with changes in playing strategy over the course of a season that may be correlated with that variation. The dummy variables for the home stadium of the bowler and batter account for home field advantage. A vector of weather controls for the day d and location ℓ of the match ($\mathbf{X}_{\ell d}$) includes a linear and quadratic term for temperature, and linear terms for relative humidity, atmospheric pressure, precipitation, solar radiation, and wind speed.³⁰

Intuitively, Equation 2 exploits day-to-day variation in air pollution at the same stadium within a season, while controlling for differences in performance arising from bowler and batter average abilities and differing strategies throughout each match. We therefore interpret the coefficient of interest, β , as the marginal effect of a $10 \mu\text{g m}^{-3}$ rise in daily mean $\text{PM}_{2.5}$ on the run-scoring probability, independent of any other factors that may also affect it, $\text{PM}_{2.5}$, or both.

Identification in Equation 2 comes from the fact that cricket matches are scheduled well in advance (before reliable air pollution forecasts are available) and cannot be rescheduled due to pollution levels, making match-day $\text{PM}_{2.5}$ exposure orthogonal to player characteristics and performance potential.³¹

We acknowledge two potential threats to this identification approach. First, it is possible that higher profile matches—where playing strategies may systematically differ—may be disproportionately scheduled to occur on weekends so as to reach wider audiences. This would be a problem for identification if $\text{PM}_{2.5}$ is lower on weekends (due to, say, reduced vehicle traffic or industrial activity), or if crowd levels differed systematically and crowds could influence playing strategies. We address this concern by estimating Equation 2 with day-of-week fixed effects included so that identification comes from variation in pollution among matches on the same day of the week.³²

³⁰See Appendix G.2 for a more flexible approach to controlling for weather variables and interactions between weather variables.

³¹The Board of Control for Cricket in India (BCCI) lists its criteria for selecting the venues for matches and does not include air pollution considerations among them (BCCI, 2026). The full match schedule for the season is released weeks before the season starts, far before any reliable air pollution forecast might be available, making match-day $\text{PM}_{2.5}$ unrelated to the choice of when and where to hold a match.

³²We also note that the difference between average $\text{PM}_{2.5}$ levels during weekdays (457 matches with mean $\text{PM}_{2.5}$ of $42.83 \mu\text{g m}^{-3}$) and weekends (316 matches with mean $\text{PM}_{2.5}$ of $41.50 \mu\text{g m}^{-3}$) is negligible in magnitude and not

Second, players may adjust strategies once match-day $PM_{2.5}$ is realized. Even if $PM_{2.5}$ is orthogonal to player performance potential, it is plausible that players could adjust strategies once $PM_{2.5}$ is observed so that changes in performance cannot be interpreted as degradations per se. To address this concern, we empirically test whether there are systematic differences in strategies associated with $PM_{2.5}$. Specifically, we test whether $PM_{2.5}$ is associated with more experienced bowlers (defined as those with at least three prior IPL seasons) being chosen to bowl and whether $PM_{2.5}$ is associated with the order in which a bowler appears in the bowling sequence. We also estimate Equation 2 with bowler–batter pair fixed effects instead of individual bowler and individual batter fixed effects. Intuitively, this specification allows each bowler to have a different average ability depending on the batter they face, and vice versa. The specification only uses variation in $PM_{2.5}$ that occurs when the same bowler and batter face each other, alleviating the concern that certain bowler–batter pairs might be associated with $PM_{2.5}$ levels, perhaps as a result of playing strategies. In addition to these empirical tests, we emphasize that our outcome—run-scoring probability—captures a cricket metric that players are optimizing, regardless of strategies. If strategies were changing, we would view this as a mechanism by which this outcome of interest changes.

The validity of our estimates of the causal effect of air pollution on performance rests on the assumption that, conditional on our included fixed effects and controls, match-day pollution levels are uncorrelated with unobserved determinants of cricket performance.³³

All specifications cluster standard errors two-way by match and bowler to account for potential serial correlation in performance for bowlers and the fact that pollution exposure is measured for each match.

statistically significant.

³³One threat to this identifying assumption could arise if low (or high) quality players were chosen to play when pollution is high. Our individual batter and bowler fixed effects alleviate this concern by comparing performance within the same batter and bowler over matches with varying pollution concentrations. Another threat to identification could arise if coaches choose to field players who exhibit tolerance to pollution levels when pollution is high. While we cannot rule this out, such a pattern would make our estimates understate the effect of pollution on performance.

5.2 Non-linearity in the dose–response

To examine potential non-linearities in the pollution-performance relationship, we estimate the following specification replacing the continuous $\text{PM}_{2.5}$ measure with indicators for $\text{PM}_{2.5}$ quantiles:

$$R_{ij\ell t} = \sum_{k=2}^5 \beta_k Q_k(P_{\ell d}) + \mathbf{X}'_{\ell d} \gamma + \psi_j + \phi_i + \delta_{\ell y} + \mu_m + \theta_{n(t)} + \eta_{o(t)} + \Lambda_i + \Delta_j + \varepsilon_{ij\ell t} \quad (3)$$

where $Q_k(P_{\ell d})$ represents indicators for the second through fifth quintiles of match-day $\text{PM}_{2.5}$, with the lowest quintile serving as the reference category.

We implement spline regression with varying numbers and placements of knots to identify non-linearities in the response of performance to pollution. We estimate

$$R_{ij\ell t} = \sum_{m=0}^p \beta_m (P_{\ell d}^m) + \sum_{n=1}^N \beta_{p+n} (P_{\ell d} - \tau_n)^p \mathbf{1}\{P_{\ell d} \geq \tau_n\} + \mathbf{X}'_{\ell d} \gamma + \psi_j + \phi_i + \delta_{\ell y} + \mu_m + \theta_{n(t)} + \eta_{o(t)} + \Lambda_i + \Delta_j + \varepsilon_{ij\ell t} \quad (4)$$

where we vary the number of knots N , the locations of the knots along the distribution of $\text{PM}_{2.5}$, and the degree of the polynomial p . We focus on two linear spline specifications. The first places knots at the four WHO thresholds for air pollution: 25, 37.5, 50, and $75 \mu\text{g m}^{-3}$.³⁴ The second places a single knot at the $50 \mu\text{g m}^{-3}$ threshold.

5.3 Effects of short-run past exposure on performance

Following [Schwartz \(2000\)](#); [He et al. \(2019\)](#), we specify a polynomial distributed lag model to estimate the effect of recent days of past $\text{PM}_{2.5}$ exposure on match-day performance:

$$R_{ij\ell t} = \beta_0 P_{\ell d} + \sum_{s=1}^S \beta_s P_{J(j), d-s} + \mathbf{X}'_{\ell d} \gamma + \psi_j + \phi_i + \delta_{\ell y} + \mu_m + \theta_{n(t)} + \eta_{o(t)} + \Lambda_i + \Delta_j + \varepsilon_{ij\ell t} \quad (5)$$

where β_s is constrained to satisfy

³⁴See [Figure 1](#) for where these thresholds fall relative to the distribution of $\text{PM}_{2.5}$ in our sample.

$$\beta_s = \sum_{q=0}^Q \alpha_q g_q(s), \quad s = 1, \dots, S. \quad (6)$$

In Equation 6, Q is the degree of the polynomial (e.g., $Q = 2$ represents a polynomial of degree 2), and s indexes lags (i.e., $s = 1$ indicates $\text{PM}_{2.5}$ one day before the match, $s = 2$ indicates $\text{PM}_{2.5}$ two days before the match, and so on). S is the full window length (e.g., $S = 30$ when we consider the 30 days preceding the match). The parameter α_q is the coefficient on each orthonormal polynomial component, $g_q(s)$ of each β_s .

Our estimand of interest is the cumulative effect through a given lag window k (where $k \leq S$): $\sum_{s=1}^k \hat{\beta}_s$. This represents the effect of raising $\text{PM}_{2.5}$ by $10 \mu\text{g m}^{-3}$ on each of the k days preceding the match.

5.4 Heterogeneity in the effect of contemporaneous air pollution by past exposure

The specifications above estimate the average and non-linear effects of contemporaneous pollution on performance, treating all workers symmetrically regardless of their exposure histories. We now turn to our central question: does a worker’s accumulated past exposure to pollution moderate the contemporaneous effect? Our approach is to interact match-day $\text{PM}_{2.5}$ with measures of the player’s past exposure, using the two categories defined in Section 4.3: short-term measures (days to weeks, across matches for a given player on a given team) and a long-term measure (career-average exposure, fixed within player). Since short-term measures are assigned at the team level—all players on a team share the same travel itinerary—while the long-term measure is player-specific,³⁵ we tailor our specifications accordingly.

To claim that past exposure is causally affecting the response to contemporaneous exposure, we would have to assume that a player’s past exposure to pollution is uncorrelated with any characteristic that affects their response to contemporaneous pollution. While we cannot completely rule out the

³⁵Half of the bowlers in the sample play on two or more teams across the span of their career in the IPL.

existence of any such feature, we provide two arguments in support of this claim. The first is our knowledge of the assignment mechanism for long-term exposure. The IPL auction, with its salary cap for each team, supports the idea that player ability—the feature that most plausibly may modulate the response to pollution—is roughly evenly distributed across teams, and thus past exposure levels. The second is empirical. We provide a number of descriptive plots that fail to find differences along observable characteristics across both contemporaneous and past exposure levels.³⁶

5.4.1 Heterogeneity by short-term past exposure

To detect heterogeneity in the effect of contemporaneous air pollution by short-term past exposure, we estimate

$$R_{ij\ell t} = \beta_1 P_{\ell d} + \beta_2 P_{\ell d} \times \bar{P}_{J(j)d} + \beta_3 \bar{P}_{J(j)d} + \mathbf{X}'_{\ell d} \gamma + \psi_j + \phi_i + \delta_{\ell y} + \mu_m + \theta_{n(t)} + \eta_{o(t)} + \Lambda_i + \Delta_j + \varepsilon_{ij\ell t} \quad (7)$$

where $\bar{P}_{J(j)d}$ is the past T -day mean $\text{PM}_{2.5}$ exposure defined in Section 4.3.1 for bowler j on team J . Other variables are as defined in Equation 2. We include the full interaction of present $\text{PM}_{2.5}$ and past $\text{PM}_{2.5}$ to disambiguate the level-effect of past $\text{PM}_{2.5}$ itself from the modulating effect that past exposure may have on the harms of present exposure. Importantly, because this measure of past exposure changes over time for an individual, it is not collinear with bowler fixed effects.

Identification in Equation 7 comes from changes in $\text{PM}_{2.5}$ levels that a team is exposed to within a season as a result of their travel itinerary and realizations of $\text{PM}_{2.5}$ where they are located.

Non-linearity in the heterogeneous effect By specifying a linear interaction term between two continuous variables, the specification in Equation 7 imposes the restriction that the magnitude of the adaptation effect is constant across current (match-day) pollution levels. To explore whether past exposure moderates the effect of present exposure differently at different levels of present exposure,

³⁶Figure H6 shows that bowler performance (as indicated by the run-concession rate) is uncorrelated with career $\text{PM}_{2.5}$ exposure and Figure H5 which shows that team performance (as indicated by the win rate) is uncorrelated with home stadium $\text{PM}_{2.5}$.

we interact $\bar{P}_{J(j)d}$ with the linear spline specification in Equation 4.

5.4.2 Heterogeneity by long-term past exposure

The short-term measures above vary within player across matches, capturing adaptation that develops over days to weeks. We complement these with a measure of career-average exposure that captures adaptation accumulated over years. For the long-term measure defined in Section 4.3.2—a bowler’s mean $PM_{2.5}$ across all IPL matches—we estimate:

$$R_{ij\ell t} = \beta_1 P_{\ell d} + \beta_2 P_{\ell d} \times \bar{P}_{j0} + \mathbf{X}'_{\ell d} \gamma + \psi_j + \phi_i + \delta_{\ell y} + \mu_m + \theta_{n(t)} + \eta_{o(t)} + \Lambda_i + \Delta_j + \varepsilon_{ij\ell t} \quad (8)$$

where $\bar{P}_{j0}$ is long-term exposure to pollution for a given bowler, and other variables are as defined in Equation 2. Note that every bowler in the sample is assigned a measure of $\bar{P}_{j0}$; no bowlers are excluded from the estimation sample for these long-run adaptation effects. Identification in Equation 8 comes from the fact that average pollution levels at teams’ home stadiums are widely divergent, generating variation in players’ typical exposure levels that is uncorrelated with player ability.³⁷ Because career exposure is fixed within bowler, its level effect is absorbed by bowler fixed effects. We therefore omit the main effect of $\bar{P}_{j0}$ and identify the adaptation effect solely through the interaction term β_2 . As with the short-term past exposure measure, we interact $\bar{P}_{j0}$ with the linear spline specification in Equation 4 to allow for non-linearity in the heterogeneous effect.

It is important to emphasize that while the short- and long-term measures of past exposure capture a similar concept, they rely on fundamentally different sources of identifying variation. The short-term measure relies on idiosyncratic variation in $PM_{2.5}$ levels within a season, based on a team’s travel itinerary. We argue that this recent short-term $PM_{2.5}$ is not correlated with player performance. By contrast, the long-term measure of exposure uses variation in exposure across a career. A major concern in this approach is that there could be endogenous exit from the IPL:

³⁷This assumption is supported by the IPL’s auction and salary cap system, which ensures that each team has the same amount of money to buy players, resulting in teams having players of roughly equal ability on average.

specifically, the players who are most sensitive to $\text{PM}_{2.5}$ might leave. This could bias the estimate of β_2 in Equation 8 downward, overstating the adaptation effect.

We address this concern in two ways. First, we build a model to predict bowler exit. We then reweight the sample by an inverse-probability-weighting correction for attrition, so that those who exit early are upweighted. We then compare the estimate of the contemporaneous effect of $\text{PM}_{2.5}$ in the reweighted sample to the unweighted sample, to see if the effect of $\text{PM}_{2.5}$ is different. We also re-estimate the linear version of 8 and the spline version of 8 with one knot at $50 \mu\text{g m}^{-3}$ using these weights and compare these results to the same regressions without weights. If results are similar, this would suggest that attrition correlated with sensitivity to $\text{PM}_{2.5}$ is not artificially manufacturing an adaptation effect.

Second, we estimate Equation 8 for a series of subsamples. Ideally, we would estimate the equation on a balanced panel (i.e., only consisting of bowlers who appear in all 13 IPL seasons in our sample) but this is not possible—the maximum number of seasons a bowler appears in is 12 (Table 1). We therefore explore a series of short-career subsamples: bowlers whose entire IPL career spans at most 1 season, at most 2 (the median), at most 3 (the mean), at most 5, and at most 8 seasons. While we cannot completely rule out concerns of endogenous exit, if results are consistent across these subsamples, it would provide strong evidence that our main estimate is not driven by endogenous exit.

6 Results

Our empirical analysis proceeds in four steps. We first establish that air pollution significantly impairs productivity, then show that these effects are statistically detectable only at extreme pollution levels. We next present evidence of adaptation to chronic exposure at both short and long time horizons, before showing that this adaptation does not offset cumulative harm from sustained exposure.

6.1 Effects of contemporaneous air pollution on performance

Table 2 presents estimates of how match-day $\text{PM}_{2.5}$ exposure affects the run-scoring probability. Our preferred specification (column 3) includes fixed effects for bowlers, batters, stadium-by-year, month, innings, and over-phase, along with home stadium indicators and weather controls.³⁸ A $10 \mu\text{g m}^{-3}$ increase in $\text{PM}_{2.5}$ —half a standard deviation—raises the run-scoring probability by 0.42 percentage points ($p < 0.05$).³⁹ Given a mean run-scoring probability of 59.9%, this represents a 0.7% relative increase in the run-scoring probability.⁴⁰

To translate this estimate into policy-relevant terms, consider that median match-day $\text{PM}_{2.5}$ in our sample is $36.7 \mu\text{g m}^{-3}$ —more than twice the WHO daily safe limit of $15 \mu\text{g m}^{-3}$. Under the linear specification, moving from the median-level exposure in the IPL sample to the WHO safe limit would result in at least a 2.3% increase in productive output.⁴¹ Section 6.2 examines whether this per-unit effect varies with the level of pollution.

Several robustness checks support our main result. First, restricting the sample to the 27.4% of observations with a ground-monitor $\text{PM}_{2.5}$ reading from the U.S. AirNow network yields a positive but statistically insignificant linear estimate and imprecise quintile estimates (Table I9), reflecting the smaller sample. Second, applying the multiple imputation correction for measurement error in remotely sensed data proposed by Proctor et al. (2026) reduces the coefficient by 49% but leaves it statistically significant at the 5% level. Third, including day-of-week fixed effects yields similar results (Table I2), indicating that these patterns are not driven by scheduling high profile matches on

³⁸Table I6 reports an alternate specification using bowler–batter pair fixed effects, with qualitatively similar results: the run-scoring probability increases by 0.40 percentage points per $10 \mu\text{g m}^{-3}$. We use individual bowler and batter fixed effects in our main specification to align with the heterogeneity analyses in Section 5.4, which rely on bowler fixed effects.

³⁹Sample mean $\text{PM}_{2.5}$ is $42.3 \mu\text{g m}^{-3}$ (SD 20.0; range 14.2 to 159.9).

⁴⁰We view this estimate as a lower bound on the total performance losses from pollution exposure. Pollution likely impairs both bowlers and batters; our estimates capture only the net disadvantage for the bowler, not the absolute effect on each.

⁴¹Productive output is defined, from the perspective of the bowler, as the probability that a delivery concedes no run, i.e., one minus the run-scoring probability. We obtain the 2.3% figure as follows. Our preferred linear specification implies that a $10 \mu\text{g m}^{-3}$ increase in $\text{PM}_{2.5}$ raises the run-scoring probability by 0.42 percentage points. Median match-day $\text{PM}_{2.5}$ in the analytic sample is $36.7 \mu\text{g m}^{-3}$, so moving to the WHO 24-hour air-quality guideline of $15 \mu\text{g m}^{-3}$ represents a reduction of $21.7 \mu\text{g m}^{-3}$. Applying the estimated effect to this gap yields a 0.91 percentage-point decline in the run-scoring probability, equivalently a 0.91 percentage-point gain in productive output. Expressed relative to mean productive output in the sample (0.40), this corresponds to a 2.3% increase.

Table 2: PM_{2.5} exposure and run-scoring probability

	(1)	(2) Linear	(3)	(4) Quintiles	(5) Spline
	1 (At least one run scored)				
Match-day PM _{2.5}	0.0041*** (0.0010)	0.0027* (0.0014)	0.0042** (0.0018)		
Q2 (Match-day PM _{2.5})				0.0076 (0.0060)	
Q3 (Match-day PM _{2.5})				0.010 (0.0070)	
Q4 (Match-day PM _{2.5})				0.014 (0.0090)	
Q5 (Match-day PM _{2.5})				0.028*** (0.011)	
Match-day PM _{2.5} between 0 and 50 µg m ⁻³					0.0044 (0.0037)
Match-day PM _{2.5} between 50 and 160 µg m ⁻³					0.0041** (0.0020)
Weather controls		✓	✓	✓	✓
Bowler FE			✓	✓	✓
Batter FE			✓	✓	✓
Stadium-by-year FE			✓	✓	✓
Month FE			✓	✓	✓
Home stadium FE			✓	✓	✓
Innings FE			✓	✓	✓
Over phase FE			✓	✓	✓
N	183,572	183,572	183,556	183,556	183,556
R ²	0.00028	0.00039	0.047	0.047	0.047
p: quintiles jointly zero				0.08	
p: equal slopes across segments					0.95

Notes. The outcome variable is a binary indicator equal to 1 if at least one run is scored on a delivery and 0 otherwise (mean 0.599). All PM_{2.5} variables are measured in 10 µg m⁻³. Quintile 1 of match-day PM_{2.5} is 14-27; Quintile 2 is 27-34, Quintile 3 is 34-41, Quintile 4 is 41-53, and Quintile 5 is 53-160 µg m⁻³. Columns (1)–(3) enter match-day PM_{2.5} linearly, adding weather controls in column (2) and fixed effects in column (3). Column (4) replaces the linear term with PM_{2.5} quintile indicators, where the lowest quintile (Q1) is the omitted category. Column (5) instead enters match-day PM_{2.5} as a continuous piecewise-linear spline with a single knot at 50 µg m⁻³. Columns (2)–(5) include controls for weather conditions including temperature, temperature squared, relative humidity, wind speed, precipitation, atmospheric pressure, and solar radiation. Columns (3)–(5) additionally include fixed effects for individual bowlers, batters, stadium-by-year, month, innings, and over phase. Following [Correia \(2015\)](#), 16 singleton observations are dropped in columns (3)–(5). Standard errors (in parentheses) are two-way clustered at the match and bowler levels.

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

days of the week when $PM_{2.5}$ tends to be lower. Fourth, we do not detect an association between strategies and $PM_{2.5}$ along the margins we test: bowler–batter pair arrangements (Table 16), more experienced bowlers playing in a match (Table 17), or the order in which bowlers bowl, conditional on bowling (Table 18). These tests support the idea that the change in run-scoring probability we observe is a degradation in performance, not a deliberate change in strategy.

The identification of this effect depends critically on controlling for weather conditions that correlate with pollution. A naive regression (column 1 of Table 2) yields a coefficient of 0.41 percentage points ($p < 0.01$), but adding weather controls in column 2 reduces this to 0.27 percentage points, reflecting omitted variable bias: $PM_{2.5}$ and humidity are negatively correlated ($\rho = -0.62$) while run-scoring decreases with humidity, and $PM_{2.5}$ and temperature are positively correlated ($\rho = 0.22$) while run-scoring increases with temperature.⁴² The fixed effects in our preferred specification restore the coefficient magnitude, indicating that pollution’s effect operates largely independently once we properly account for confounding weather factors.⁴³

Importantly, the consistently positive relationship between pollution and run-scoring reveals an asymmetry: pollution disproportionately impairs bowlers relative to batters. Since each delivery represents direct competition, increased scoring probability necessarily implies bowlers’ performance deteriorates more. This finding reflects differential physical demands—bowlers maintain a running approach requiring higher respiration rates while batters engage in intermittent activity—and aligns with the physiological evidence that establishes respiration as the primary channel through which people are exposed to particulate matter (Hamanaka and Mutlu, 2025).⁴⁴

In Table 3, we test the hypothesis that bowlers are harmed by pollution by examining outcomes

⁴²See Table 11 for raw correlations between run-scoring, $PM_{2.5}$, and all weather variables.

⁴³This result is also confirmed using the post-double-selection (PDS) LASSO method (Belloni et al., 2014); see Appendix G.2 for details.

⁴⁴An important distinction related to the length of the running approach (and thus respiration rates) among cricket bowlers is the bowling style, i.e., “pace” or “spin.” Pace bowlers optimize the speed of the delivery, requiring a long running approach, whereas spin bowlers focus on spinning the ball, requiring a substantially shorter running approach. Our hypothesis that the higher respiration rates of bowlers relative to batters (as a result of their running approach) is responsible for the differential effect of $PM_{2.5}$ on bowlers vis-à-vis batters implies that pace bowlers should be more affected by $PM_{2.5}$ than spin bowlers. Table 15 presents results using the specification in column 3 of Table 2 with the addition of an interaction of $PM_{2.5}$ with a dummy for whether the bowler is a pace bowler. While we cannot reject the null hypothesis that the effect of $PM_{2.5}$ is the same across the two types of bowlers, the positive sign on the interaction points toward a larger harmful effect for pace bowlers, consistent with our hypothesized mechanism.

that are independently produced by the bowler and find evidence of bowler-specific impairment. We use data from the Hawk-Eye computer vision system that tracks the speed and location of the delivery and link these data at the delivery-level to 66% of matches in our analytic sample (Hawk-Eye, 2022).⁴⁵ We replicate the analyses in Table 2 for three bowler-independent outcomes: whether a delivery is ruled a “no-ball” (an illegal delivery attributable to a bowler fault), length (the distance between where the ball bounces and the batter, m), and speed (how fast the ball is bowled, km h^{-1}) separately for pace and spin bowlers. For pace bowlers, pollution raises the probability of a no-ball by 0.045 percentage points per $10 \mu\text{g m}^{-3}$ ($p < 0.05$), relative to a base rate of 0.53% (column 1). Pace bowlers also systematically bowl the ball so that it bounces closer to the batter (“fuller” deliveries) as pollution levels rise: the linear estimate is negative but imprecise (column 3), while the quintile estimates are statistically significant from the third quintile onward (column 4). We cannot reject the null hypothesis that pollution does not affect the speed at which pace bowlers deliver the ball (column 5). In addition, neither the no-ball nor the length response is confined to the top quintile (columns 2 and 4): both are statistically significant by the third quintile and rise with match-day $\text{PM}_{2.5}$, and the fifth-quintile estimate is no larger than the fourth-quintile one for no-balls (0.29 versus 0.30 percentage points) and only modestly larger for length (0.29 versus 0.23 m).⁴⁶

6.2 Non-linearity in the dose–response

We next ask whether the per-unit effect varies with the level of pollution. Column 4 of Table 2 replaces the continuous $\text{PM}_{2.5}$ measure in our preferred specification with quintile indicators (Equation 3). In this specification, only the fifth quintile shows a statistically significant effect: exposure to $\text{PM}_{2.5}$ above $53 \mu\text{g m}^{-3}$ increases run-scoring probability by 2.8 percentage points ($p < 0.01$) relative to the lowest quintile. The second through fourth quintiles show smaller, imprecisely estimated effects that rise steadily with exposure (0.8, 1.0, and 1.4 percentage points).

⁴⁵Table I4 reports a within-spell test of speed fatigue.

⁴⁶Table I3 replicates Table 3 with individual over fixed effects instead of over phase fixed effects. We find similar results overall, and stronger results for delivery length: the coefficient on match-day $\text{PM}_{2.5}$ in the linear specification (Column 3) is statistically significant at the 10% level.

Table 3: PM_{2.5} and bowler-specific outcomes, pace and spin bowlers

	(1) No-ball (=1)	(2)	(3) Length (m)	(4)	(5) Speed (km/h)	(6)
	Linear	Quintile	Linear	Quintile	Linear	Quintile
<i>Panel A. Pace bowlers only</i>						
Match-day PM _{2.5}	0.00045** (0.00020)		-0.02001 (0.01544)		0.08726 (0.06763)	
Q2 (Match-day PM _{2.5})		0.00089 (0.00089)		-0.10681 (0.06504)		0.03020 (0.23543)
Q3 (Match-day PM _{2.5})		0.00166* (0.00096)		-0.19424*** (0.07224)		-0.07670 (0.25313)
Q4 (Match-day PM _{2.5})		0.00304*** (0.00107)		-0.22727*** (0.08335)		0.11211 (0.29253)
Q5 (Match-day PM _{2.5})		0.00286*** (0.00110)		-0.28836*** (0.09389)		0.33550 (0.32634)
Outcome mean	0.0053	0.0053	6.8770	6.8770	127.7380	127.7380
N	118,508	118,508	80,913	80,913	79,346	79,346
R ²	0.0132	0.0132	0.1369	0.1370	0.7007	0.7007
<i>Panel B. Spin bowlers only</i>						
Match-day PM _{2.5}	-0.00011 (0.00016)		-0.00130 (0.01371)		-0.00511 (0.05780)	
Q2 (Match-day PM _{2.5})		0.00106* (0.00054)		-0.07144 (0.04312)		-0.31828 (0.29196)
Q3 (Match-day PM _{2.5})		0.00087* (0.00051)		-0.01871 (0.04858)		-0.58126** (0.28258)
Q4 (Match-day PM _{2.5})		0.00119 (0.00100)		-0.04784 (0.06962)		-0.47603 (0.35483)
Q5 (Match-day PM _{2.5})		0.00024 (0.00119)		-0.01466 (0.10183)		-0.74393** (0.36976)
Outcome mean	0.0014	0.0014	5.1843	5.1843	90.5525	90.5525
N	59,926	59,926	35,477	35,477	34,605	34,605
R ²	0.0140	0.0141	0.0810	0.0811	0.3334	0.3337
Weather controls	✓	✓	✓	✓	✓	✓
Bowler, batter, stadium-by-year, month, home stadium, innings, and over phase FE	✓	✓	✓	✓	✓	✓

Notes. Each pair of columns shares a dependent variable: no-ball (=1) in columns (1)-(2), delivery length in columns (3)-(4), and delivery speed in columns (5)-(6). The two panels share both the specification and the outcomes and differ only in which deliveries enter the sample. All three outcomes are produced by the bowler alone, independently of what the batter does, and so isolate bowler impairment. No-ball (=1) indicates a delivery ruled illegal on account of a bowler fault. Length is the distance in meters from the batter's stumps to the point where the delivery bounces, so a negative coefficient means fuller deliveries. Speed is the measured speed of the delivery in kilometers per hour, bottom-coded at the within-bowler-type (pace/spin) 5th percentile. In the first column of each pair, match-day PM_{2.5} enters linearly and is measured in 10 µg m⁻³; the second column instead enters indicators for the quintile of match-day PM_{2.5}, with the lowest quintile (Q1) omitted, so the reported coefficients are level shifts against Q1 in the outcome's own units. Quintiles are cut separately on each outcome's own estimation sample. Every regression includes controls for weather conditions including temperature, temperature squared, relative humidity, wind speed, precipitation, pressure, and solar radiation and fixed effects for individual bowlers, batters, stadium-by-year, month, innings, and over phase (powerplay/middle/death), as well as indicators for whether the bowling and batting teams are at their home stadium. Panel A restricts the sample to the 118,524 deliveries bowled by pace bowlers and Panel B to the 59,945 bowled by spin bowlers. (An additional 5,103 deliveries whose bowler could not be matched to bowling-style metadata enter neither panel, so the two panels do not sum to the 183,572 deliveries in the full sample.) Length and speed are ball-tracking measures observed only on the subset of 512 matches matched to Hawk-Eye data, so columns (3)-(6) are estimated on smaller samples than columns (1)-(2); for those columns bowler type is taken from the Hawk-Eye delivery-level bowling style rather than from the player metadata. Following [Correia \(2015\)](#), singleton observations are dropped, and sample sizes are reported for every column and panel. Standard errors (in parentheses) are two-way clustered at the match and bowler levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

This pattern is notable given that even our lowest quintile ($14\text{--}27\ \mu\text{g m}^{-3}$) substantially exceeds the WHO’s $15\ \mu\text{g m}^{-3}$ daily limit, and the second quintile ($27\text{--}34\ \mu\text{g m}^{-3}$) is roughly double it.⁴⁷ The absence of significant effects in quintiles 2–4 relative to quintile 1, despite exposure levels considered hazardous by international standards, suggests that the differential impacts on bowlers vis-à-vis batters are detectable in our data only at the extreme pollution levels common in developing countries but rarely observed in settings typically studied.⁴⁸

The $53\ \mu\text{g m}^{-3}$ threshold above which we detect significant effects lies well above the empirical support of the closest prior productivity studies: Archsmith et al. (2018) report a mean $\text{PM}_{2.5}$ of approximately $10\ \mu\text{g m}^{-3}$ and a maximum of approximately $40\ \mu\text{g m}^{-3}$ in their U.S. baseball umpire sample; Chang et al. (2016) report $\text{PM}_{2.5}$ ranging from 2 to $60\ \mu\text{g m}^{-3}$ in their U.S. pear-packing sample; and Adhvaryu et al. (2022) report a mean of $26\ \mu\text{g m}^{-3}$ in their Indian garment factory sample. Our quintile 5 thus lies outside the empirical range of these comparison settings, so prior work could not have observed the effects we detect at these levels.

Figure 4 plots the spline specification in Equation 4 with knots at the four WHO thresholds. The point estimates are relatively flat through moderate pollution levels, rise more steeply between 50 and $75\ \mu\text{g m}^{-3}$, and flatten thereafter. That said, the confidence band admits a straight line throughout, consistent with the equal slopes in column 5 of Table 2. Studies confined to low-pollution settings cannot observe this part of the dose–response, where billions of workers operate daily.

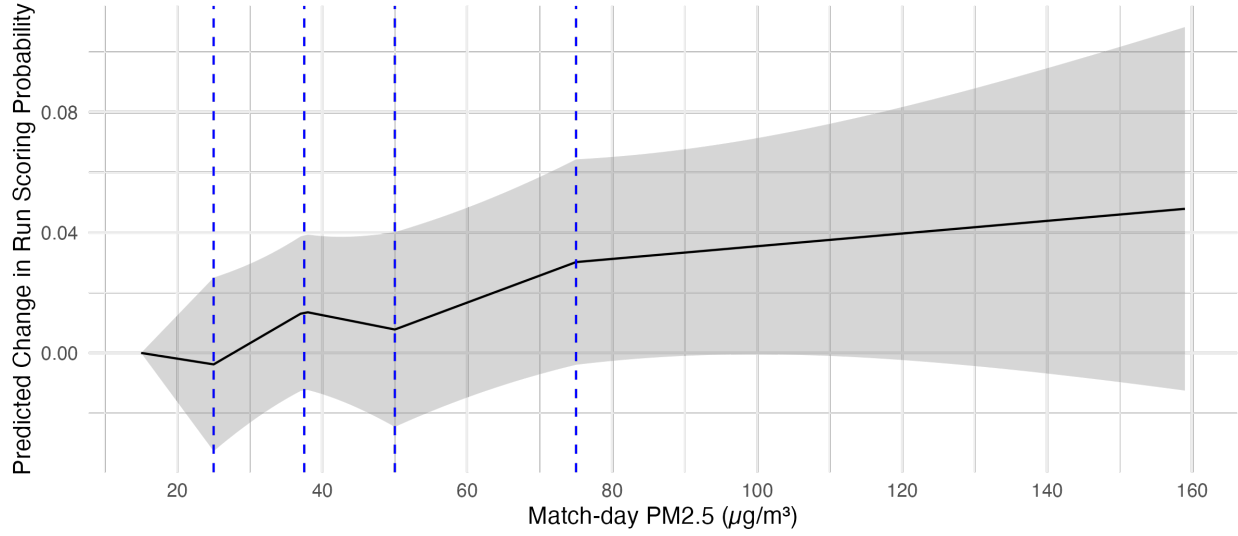
6.3 Evidence of adaptation to chronic exposure

We next examine whether workers adapt to chronic pollution exposure, potentially mitigating acute productivity losses. This analysis leverages variation in exposure histories that arise from how players are assigned to teams in cities with different baseline pollution through the IPL’s salary cap

⁴⁷Only 5 of 773 matches (0.60% of delivery observations) fall below WHO’s $15\ \mu\text{g m}^{-3}$ daily limit, making comparing effects relative to that category unfeasible in this context.

⁴⁸It is worth emphasizing that these results do not indicate that lower levels are harmless: the quintile estimates rise steadily across the distribution, and column 5, which enters match-day $\text{PM}_{2.5}$ as a piecewise-linear spline with a single knot at $50\ \mu\text{g m}^{-3}$, yields nearly identical slopes below and above the knot (0.44 and 0.41 percentage points per $10\ \mu\text{g m}^{-3}$), so we cannot reject a linear dose–response.

Figure 4: Effect of PM_{2.5} on run-scoring probability (linear spline, WHO thresholds)



Notes. Figure displays predicted changes in run-scoring probability as a function of match-day PM_{2.5} estimated using Equation 4 with $p = 1$ and knots at WHO targets: 25, 37.5, 50, and 75 $\mu\text{g m}^{-3}$. Dashed lines indicate knot locations. The shaded area represents 95% confidence intervals.

and auction system.⁴⁹

6.3.1 Temporal dynamics: Short-term adaptation

We begin by examining how recent pollution exposure affects sensitivity to match-day pollution.

Our primary measure is the bowler's mean PM_{2.5} over the preceding T days ($\bar{P}_{J(j)d}$).

Table 4 reports the distributed-lag estimates from Equation 5 using a polynomial of degree 2.⁵⁰ Conditional on the preceding 30 days of exposure, the match-day effect is unchanged from

⁴⁹The team assignment mechanism creates variation in short- and long-term exposure histories that appears to be unrelated to factors that affect player performance or the response to pollution shocks. While we cannot definitively rule out that exposure histories are correlated with other factors that may affect player performance or the marginal effect of contemporaneous pollution, we find no evidence in support of this claim. Variation in home stadium average PM_{2.5} exposure is not correlated with team quality as indicated by the proportion of matches that teams win (Figure H5), nor is career PM_{2.5} exposure correlated with the average career performance of bowlers as indicated by their career run-concession rate (Figure H6). This lack of systematic correlation is expected given that each cricket team is provided with an equal amount of funding with which to buy players in each season's auction for players. This rule in the tournament prevents teams from purchasing systematically better players on average due to wealth.

⁵⁰We choose a polynomial of degree 2 since it is the lowest degree that allows the cumulative effect of PM_{2.5} exposure to be non-monotone over the 30-day window. Allowing for additional flexibility by using polynomials of degree 3 and above does not improve the fit of the model while increasing standard errors at the 30-day lag. Despite this, the estimate of the effect of cumulative exposure over the 30 days preceding the match is quite similar using polynomials of degrees 0, 1, 2, 3, 4, remaining within the 0.34–0.36 percentage point range. Table I10 shows results for polynomials of degrees 0, 1, 2, 3, 4, as well as an unrestricted lag profile.

Table 4: Almon (polynomial) distributed lag over 30 days

Almon polynomial, $Q = 2$ 1 (At least one run scored)						
Match-day PM _{2.5}	0.00418** (0.00176)					
<i>Cumulative effect of past exposure, lags 1 through k days (k = 30 is the whole window):</i>						
k =	10	20	21	22	23	24
	0.00088 (0.00152)	0.00266 (0.00187)	0.00282 (0.00188)	0.00296 (0.00187)	0.00309* (0.00184)	0.00320* (0.00180)
k =	25	26	27	28	29	30
	0.00329* (0.00175)	0.00337** (0.00169)	0.00342** (0.00163)	0.00345** (0.00159)	0.00346** (0.00158)	0.00343** (0.00163)
N	183,556					
R ²	0.0472					
Weather controls			✓			
Bowler, batter, stadium-by-year, month, home stadium, innings, and over phase FE			✓			

Notes. The outcome variable is a binary indicator equal to 1 if at least one run is scored on a delivery and 0 otherwise (mean 0.599). All PM_{2.5} variables are measured in 10 $\mu\text{g m}^{-3}$. The specification is the same as that in Table 2, column 3, plus the bowling team's PM_{2.5} on each of the 30 days before the match. The profile is restricted to a polynomial of degree $Q = 2$ in the lag index s as described in Equation 6. The cumulative entries report $\sum_{s=1}^k \beta_s$, the effect of raising PM_{2.5} by 10 $\mu\text{g m}^{-3}$ on each of the s days before the match. (This effect is calculated for each of days 1 through 30; we display it for a subset of these days for brevity.) Following Correia (2015), 16 singleton observations are dropped. Standard errors (in parentheses) are two-way clustered at the match and bowler levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2 (0.42 percentage points per 10 $\mu\text{g m}^{-3}$, $p < 0.05$). The cumulative effect of raising PM_{2.5} by 10 $\mu\text{g m}^{-3}$ on each of the preceding k days is small and imprecise over the first 10 days (0.09 percentage points) and 20 days (0.27 percentage points), becomes statistically significant at 23 days (0.31 percentage points, $p < 0.10$) and at the 5% level from 26 days (0.34 percentage points), and is largest at 29 days (0.35 percentage points) before flattening; over the full 30-day window it is 0.34 percentage points ($p < 0.05$). Recent exposure therefore has a level effect on current performance that accumulates over roughly three to four weeks in this context.⁵¹

Because the cumulative effect of past exposure becomes detectable at three to four weeks and

⁵¹We note that the horizon at which the cumulative effect becomes statistically significantly different from zero is not a definitive measure of “over what range past exposure matters.” This is because cumulative dose rises mechanically with the window length while precision improves mechanically as well since there is more variation for identification over longer exposure windows. We therefore supplement this conclusion with Table I11. This table shows that point estimates suggest most of the effect is in the 6–25 day range (Panel B), with days 21–30 contributing approximately 22% of the total cumulative effect (0.08 of 0.34 percentage points, Panel A). We choose 30 days because it is approximately one month and therefore a convenient benchmark. Our main adaptation results are robust to alternate choices of a 20-day (Table I26) or 24-day (Table I27) window.

stabilizes over the 26–30-day range (Table 4), we use a 30-day window for our main specifications. Columns 1 and 2 of Table 5 present our main short-term adaptation results. Column 1 estimates the baseline continuous specification, with both match-day $\text{PM}_{2.5}$ and past 30-day mean entering linearly alongside their interaction. The main effects are nearly identical: 0.67 percentage points for match-day $\text{PM}_{2.5}$ and 0.60 percentage points for the 30-day mean—statistically indistinguishable from each other ($p = 0.74$, Table 5). However, a $10 \mu\text{g m}^{-3}$ increase in the 30-day mean implies 30 times the cumulative dose of a single day’s exposure. That past and present exposure have similar coefficients despite this vast difference indicates contemporaneous exposure is far more harmful per unit exposure.

The marginal effect of match-day pollution varies substantially with bowlers’ recent exposure. Figure 5 plots the marginal effect of match-day $\text{PM}_{2.5}$ within each segment of the spline in column 2 of Table 5.⁵² Below $50 \mu\text{g m}^{-3}$, at low recent exposure (10th percentile, $32 \mu\text{g m}^{-3}$), a $10 \mu\text{g m}^{-3}$ increase in match-day pollution increases run-scoring by approximately 0.8 percentage points ($p = 0.06$), while at high recent exposure (90th percentile, $64 \mu\text{g m}^{-3}$), the same match-day increase has no positive effect (approximately -0.3 percentage points, not statistically different from zero). The difference between the two, -1.1 percentage points, is statistically significant at the 5% level. Above $50 \mu\text{g m}^{-3}$, the marginal effects at both exposure levels are small (approximately 0.3 and 0.5 percentage points) and not statistically different from one another. The below-50 differential indicates that bowlers with higher recent pollution exposure are substantially less sensitive to acute pollution shocks. The continuous interaction term in column 1 of Table 5 is consistent with this heterogeneity: it is negative but not statistically significant ($p = 0.42$), reflecting that the adaptation effect is concentrated below $50 \mu\text{g m}^{-3}$. This finding is not an artifact of the 30-day window: the interaction term is negative and statistically significant at the 5% level for every window from 20 to 30 days (Figure H12).⁵³

⁵²Figure H10 shows the same estimation results presented in levels.

⁵³Column 2 of Table I14 shows the same pattern with quintiles of match-day $\text{PM}_{2.5}$ in place of the spline, while keeping past 30-day mean $\text{PM}_{2.5}$ continuous, as in column 4 of Table 2. Every quintile’s interaction with past exposure is negative, but only the fifth quintile’s is statistically significant (-0.010 , $p < 0.05$). This implies that moving from the first to the fifth quintile of match-day $\text{PM}_{2.5}$ raises the run-scoring probability by 4.0 percentage points for bowlers at the 10th percentile of past exposure but by only 0.8 percentage points at the 90th ($p < 0.05$ for the difference), results that

Table 5: Short-term adaptation to PM_{2.5}

	(1) Linear	(2) Spline, knot at 50 $\mu\text{g m}^{-3}$
	$\mathbb{1}$ (At least one run scored)	
Match-day PM _{2.5}	0.00674* (0.00357)	
Past 30-day PM _{2.5}	0.00595* (0.00344)	0.01651** (0.00644)
Match-day PM _{2.5} $\times$ Past 30-day PM _{2.5}	-0.00053 (0.00065)	
Match-day PM _{2.5} between 0 and 50 $\mu\text{g m}^{-3}$		0.01901** (0.00823)
Match-day PM _{2.5} between 50 and 160 $\mu\text{g m}^{-3}$		0.00071 (0.00516)
0–50 $\mu\text{g m}^{-3} \times$ Past 30-day PM _{2.5}		-0.00342** (0.00168)
50–160 $\mu\text{g m}^{-3} \times$ Past 30-day PM _{2.5}		0.00072 (0.00107)
Weather controls	✓	✓
Bowler, batter, stadium-by-year, month, home stadium, innings, and over phase FE	✓	✓
<i>N</i>	183,556	183,556
<i>R</i> ²	0.05	0.05
<i>p</i> : match-day = past 30-day	0.74	
<i>p</i> : dose–response linear		0.11
<i>p</i> : no moderation	0.42	0.12
<i>p</i> : moderation constant across segments		0.09

Notes. The dependent variable is an indicator equal to 1 if at least one run is scored on the delivery and 0 otherwise (mean 0.599). All PM_{2.5} variables are measured in 10 $\mu\text{g m}^{-3}$. Past 30-day PM_{2.5} is the bowling team’s mean PM_{2.5} over the 30 days before the match. In column (1), match-day PM_{2.5} and past 30-day are in levels and are interacted. Column (2) replaces the linear match-day dose with a continuous piecewise-linear spline with one knot at 50 $\mu\text{g m}^{-3}$ and interacts each segment slope with past 30-day PM_{2.5}. The reported *p*-values are for tests that: the two segment slopes are equal, so the dose–response is linear; there is no moderation, which in column (1) is the single interaction and in column (2) is both segment $\times$ past 30-day interactions jointly; and the two interactions of column (2) are equal to one another, which is the restriction that reduces its moderation to the single linear-by-linear parameter of column (1). Both columns include controls for temperature, temperature squared, relative humidity, wind speed, precipitation, atmospheric pressure, and solar radiation, and indicators for whether the bowling and batting teams are at their home stadium, together with fixed effects for individual bowlers, batters, stadium-by-year, month, innings, and over phase. Following [Correia \(2015\)](#), 16 singleton observations are dropped. Standard errors (in parentheses) are two-way clustered at the match and bowler levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

6.3.2 Long-term adaptation across career exposure

We now examine whether the adaptation patterns observed over 30-day windows extend to career-average exposure. Columns 1 and 2 of Table 6 present results using each bowler’s mean PM_{2.5}

are consistent with the spline. Specifically, each quintile coefficient is the effect of moving from the lowest quintile to that one, and its interaction measures how much adaptation shrinks that effect as past exposure rises. In the spline, adaptation operates only below 50 $\mu\text{g m}^{-3}$. Because the top quintile begins at 53 $\mu\text{g m}^{-3}$, the move from the first quintile to the fifth spans that entire below-50 range and so picks up the adaptation effect in full; the moves to the second, third, and fourth quintiles span progressively less of it and carry progressively smaller interactions (−0.002, −0.007, and −0.008).

Table 6: Long-term adaptation to PM_{2.5}

	(1) Linear	(2) Spline, knot at 50 $\mu\text{g m}^{-3}$
	$\mathbb{1}$ (At least one run scored)	
Match-day PM _{2.5}	0.01289** (0.00537)	
Match-day PM _{2.5} $\times$ Career PM _{2.5}	-0.00193* (0.00116)	
Match-day PM _{2.5} between 0 and 50 $\mu\text{g m}^{-3}$		0.03170** (0.01395)
Match-day PM _{2.5} between 50 and 160 $\mu\text{g m}^{-3}$		0.00272 (0.00775)
0–50 $\mu\text{g m}^{-3}$ $\times$ Career PM _{2.5}		-0.00657** (0.00320)
50–160 $\mu\text{g m}^{-3}$ $\times$ Career PM _{2.5}		0.00039 (0.00180)
Weather controls	✓	✓
Bowler, batter, stadium-by-year, month, home stadium, innings, and over phase FE	✓	✓
<i>N</i>	183,556	183,556
<i>R</i> ²	0.05	0.05
<i>p</i> : dose–response linear		0.12
<i>p</i> : no moderation	0.10	0.08
<i>p</i> : moderation constant across segments		0.11

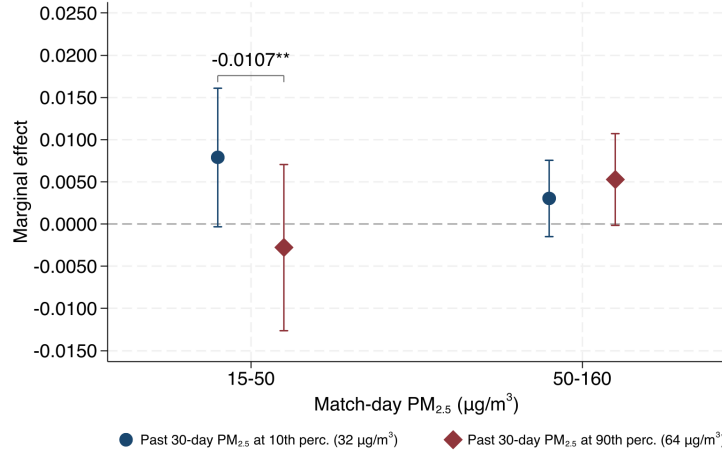
Notes. The dependent variable is an indicator equal to 1 if at least one run is scored on the delivery and 0 otherwise (mean 0.599). All PM_{2.5} variables are measured in 10 $\mu\text{g m}^{-3}$. Career PM_{2.5} is the bowler’s mean PM_{2.5} exposure across all matches played in the cricket league. In column (1), match-day PM_{2.5} and career PM_{2.5} are in levels and are interacted. Column (2) replaces the linear match-day dose with a continuous piecewise-linear spline with one knot at 50 $\mu\text{g m}^{-3}$ and interacts each segment slope with career PM_{2.5}. The reported *p*-values are for tests that: the two segment slopes are equal, so the dose–response is linear; there is no moderation, which in column (1) is the single interaction and in column (2) is both segment $\times$ career interactions jointly; and the two interactions of column (2) are equal to one another, which is the restriction that reduces its moderation to the single linear-by-linear parameter of column (1). Both columns include controls for temperature, temperature squared, relative humidity, wind speed, precipitation, atmospheric pressure, and solar radiation, and indicators for whether the bowling and batting teams are at their home stadium, together with fixed effects for individual bowlers, batters, stadium-by-year, month, innings, and over phase. Following [Correia \(2015\)](#), 16 singleton observations are dropped. Standard errors (in parentheses) are two-way clustered at the match and bowler levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

across all IPL matches as the measure of long-term exposure. Column 1 of Table 6 estimates the linear interaction specification parallel to our short-term analysis.⁵⁴ The interaction coefficient is -0.0019 , negative and statistically significant ($p < 0.10$), pointing toward smaller responses to match-day pollution among bowlers with higher career-average exposure.⁵⁵ The economic

⁵⁴We also estimate a mirrored response for batters as a robustness check in Table I16. In this specification, the interaction for bowlers is negative and statistically significant while the interaction term for batters is not statistically different from zero. This robustness check strengthens our main finding that bowlers adapt over their careers, while finding no evidence of batter adaptation. We do not estimate this mirrored specification for batters in for short-term (past 30-day exposure) due to correlation between recent bowler and batter PM_{2.5} exposure ($\rho = 0.16$).

⁵⁵These results are robust to using place-based measures rather than person-specific career averages. When we replace individual career exposure with team home stadium pollution, interaction coefficients remain consistently negative but become smaller and statistically insignificant, indicating that measurement precision matters: person-specific measures

Figure 5: Match-day $\text{PM}_{2.5}$ marginal effects by spline segment and past 30-day $\text{PM}_{2.5}$



Notes. This figure shows how the marginal effects of match-day $\text{PM}_{2.5}$ differ along two dimensions: (i) the level of match-day $\text{PM}_{2.5}$ exposure and (ii) the level of past 30-day $\text{PM}_{2.5}$ exposure. Coefficient estimates and 95% confidence intervals come from column (2) of Table 5. Each coefficient is the implied marginal effect of a $10 \mu\text{g m}^{-3}$ increase in match-day $\text{PM}_{2.5}$ on the run-scoring probability within one segment of the spline. The horizontal axis is the match-day $\text{PM}_{2.5}$ range each segment covers, and within each range the two markers set past 30-day $\text{PM}_{2.5}$ to the 10th percentile of past 30-day $\text{PM}_{2.5}$ ($32 \mu\text{g m}^{-3}$) and to the 90th ($64 \mu\text{g m}^{-3}$). (They are dodged left and right so their intervals do not overlap.) * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

magnitude is substantial: at zero career exposure, the marginal effect is 1.3 percentage points; at mean career exposure ($42.6 \mu\text{g m}^{-3}$), it falls to 0.47 percentage points; at high career exposure ($60 \mu\text{g m}^{-3}$), it attenuates close to zero, though remaining weakly positive.⁵⁶

The marginal effects implied by column 1 of Table 6 at the 10th and 90th percentiles of career exposure (32.7 and $53.8 \mu\text{g m}^{-3}$; reported in Table I15) are 0.66 and 0.25 percentage points, respectively—a 62% reduction in the acute sensitivity ($p < 0.10$ for the difference). To benchmark this against prior work, the reduction is larger than the ozone-adaptation effect of approximately capturing actual cumulative exposure based on players' movements over time yield larger adaptation effects than cruder place-based proxies (Table I18).

⁵⁶An alternative—and coarser—way to conceptualize long-term exposure to air pollution is simply to assign players exposure based on their country. We observe the national cricket team for which each bowler in the IPL plays, which we use as a proxy for their primary country of residence. We categorize bowlers into those from South Asian countries and those not. We assume those from South Asian countries are used to higher pollution levels. In Table I19 we present the same specification as column 1 of Table 6, replacing the Career $\text{PM}_{2.5}$ measure with a dummy for whether a bowler is from a South Asian country. We see qualitatively similar results: while we cannot reject the null hypothesis that the effect of $\text{PM}_{2.5}$ is the same across the two types of bowlers, the negative sign on the interaction points toward bowlers from South Asia experiencing smaller marginal effects of $\text{PM}_{2.5}$, consistent with our hypothesis that people who experience chronically high levels of $\text{PM}_{2.5}$ partially adapt to it.

43% documented by Mullins (2018)⁵⁷ for U.S. collegiate track and field athletes, extending the finding that workers chronically exposed to higher pollution levels develop reduced sensitivity to acute shocks.

Column 2 of Table 6 interacts career exposure with the linear spline in match-day PM_{2.5}.⁵⁸ As with recent exposure, adaptation operates below 50 $\mu\text{g m}^{-3}$: the below-50 slope falls by 0.66 percentage points for each 10 $\mu\text{g m}^{-3}$ of career PM_{2.5} ($p < 0.05$), whereas the above-50 interaction is small, positive, and not statistically significant (0.04 percentage points). The two interactions are jointly significant ($p = 0.08$), although the test that they equal one another does not reject at conventional levels ($p = 0.11$).⁵⁹

We thoroughly investigate the concern of endogenous exit and find that it is not responsible for these results. Exit from the IPL is common: the average number of exiting bowlers per season is 27 (against an average of 34 new bowlers per season, Table I23). Bowlers who play more often, have been in the IPL for longer, and are from a South Asian country and are younger are more likely to appear in the next IPL season; those who perform worse (as measured by runs conceded per delivery) are less likely to appear in the next IPL season (Table I24).⁶⁰ When we weight the sample by inverse probability of attrition, we find that the sensitivity to match-day PM_{2.5} is higher in the weighted sample than the unweighted one (1.0 vs. 0.41 percentage points, $p < 0.05$, Table I25). That the weighted estimate is larger is consistent with the theory that bowlers who are more sensitive to PM_{2.5} may be more likely to exit, all else equal. However, this dynamic does not explain away the adaptation results we observe across the unweighted sample. When we estimate Column 2 of Table 6 with the weighted sample, we can still reject the null hypothesis of no moderation at the 10% level.

⁵⁷This is the percent decrease in the marginal effect of ozone for those in the top bin of prior exposure to the middle bin using the estimates in Table 2 of Mullins (2018).

⁵⁸Figure H11 presents these estimation results in predicted levels (analogous to Figure H10 for recent exposure).

⁵⁹Column 2 of Table I15 examines heterogeneity across the match-day pollution distribution using quintile indicators. Consistent with both our baseline findings and the short-term adaptation results, only the fifth quintile of match-day PM_{2.5} exhibits a statistically significant negative interaction with career exposure (-0.016 , $p < 0.10$); the fourth-quintile interaction is similar in size but imprecise (-0.015). As in the short-term analysis, results line up with the spline: each interaction measures how much adaptation shrinks the effect of moving from the lowest quintile to a higher one, and the interactions are largest for the fourth and fifth quintiles (-0.015 and -0.016), whose moves span most or all of the below-50 range in which the spline in column 2 of Table 6 finds the adaptation effect.

⁶⁰Notably, we do not find evidence that sensitivity to PM_{2.5} is correlated with age, though we interpret these results with caution given the limited age range available in this sample.

As an additional robustness check, we estimate Equation 8 on short-career subsamples in Table I20. In every subsample, the estimate on the interaction of match-day $\text{PM}_{2.5}$ with career $\text{PM}_{2.5}$ is negative. While it is not statistically significant in all samples, this is plausibly due to a much smaller sample size of deliveries and bowlers in the more restrictive samples.⁶¹ We also estimate the spline specification in Column 2 of Table 5 for the sample of bowlers who appear in at least three seasons (the mean), restricting to their first three seasons. Here, we find that the negative interaction term on the below $50 \mu\text{g m}^{-3}$ portion of the spline is even larger in magnitude and more statistically precise than when estimated in the full sample (-0.91 percentage points, $p < 0.01$, Table I22). In summary, we find no evidence that this estimate of adaptation over a career spanning horizon is driven by players who are sensitive to $\text{PM}_{2.5}$ exiting the IPL.

6.4 The tradeoff between adaptation and cumulative harm

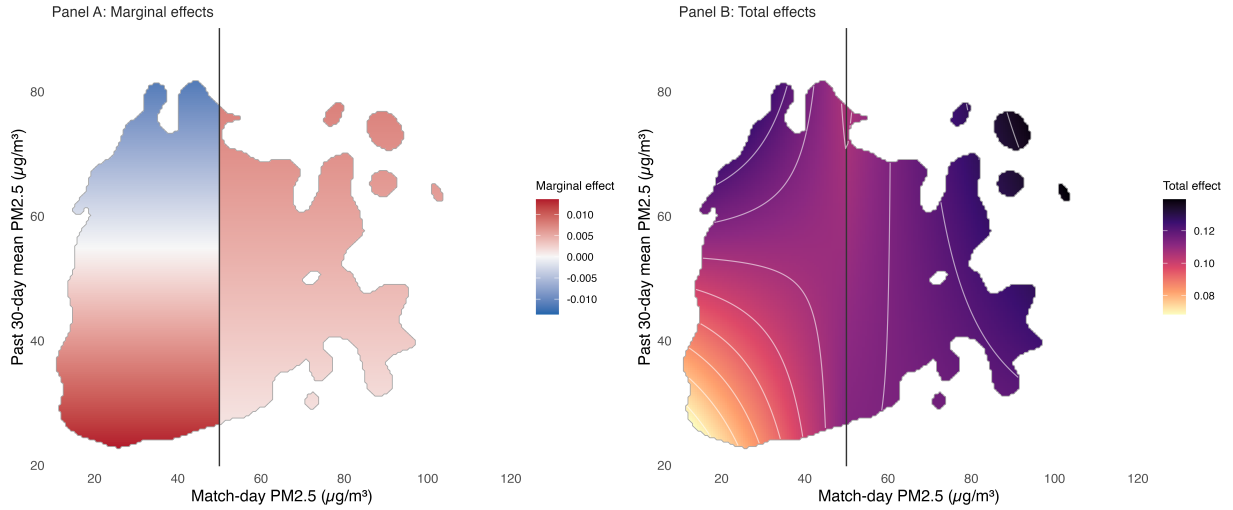
Our findings establish that past exposure generates two opposing effects: it reduces sensitivity to acute pollution shocks (adaptation) while simultaneously degrading baseline performance (cumulative harm). This raises a critical question: under what conditions, if any, does the protective adaptation effect of raising past exposure outweigh the cumulative damage?

We address this question by examining both marginal effects and total effects of match-day and past 30-day $\text{PM}_{2.5}$ exposure. Column 2 of Table 5 also identifies the marginal effect of past 30-day exposure on current performance as a function of match-day pollution. This reverses the perspective from our previous analyses: rather than examining how past exposure moderates the effect of present pollution, we examine how present pollution moderates the effect of past exposure.

As shown in column 2 of Table 5, the level effect of past exposure is positive and substantial (1.7 percentage points per $10 \mu\text{g m}^{-3}$, $p < 0.05$), indicating that higher past exposure harms current performance through cumulative physiological damage. This marginal effect declines as match-day

⁶¹We also estimate an analogous version of this table with long-career subsamples (i.e., keeping bowlers who appear in at least X seasons, using only their first X seasons of data) in Table I21. Results are consistent: every estimate of the interaction term is negative, and across the samples we choose (1, 2, 3, 5, and 8 seasons), 3 of the 5 interaction estimates are statistically significant.

Figure 6: Marginal and total effects



Notes. This figure compares the marginal and total effects of contemporaneous and short-run past PM_{2.5} on run-scoring. Effects are calculated using the estimated coefficients in column (2) of Table 5, a linear spline in match-day PM_{2.5} with one knot at 50 µg m⁻³ and each segment slope interacted with the bowling team's past 30-day mean PM_{2.5}. The vertical line at 50 µg m⁻³ in each panel indicates the location of the spline's knot. The plane is the set of (match-day PM_{2.5}, past 30-day PM_{2.5}) pairs, and color indicates the marginal effects (Panel A) and total effects relative to PM_{2.5}=0 for both measures (Panel B). White color indicates regions outside the joint support of the two exposure measures.

pollution rises toward 50 µg m⁻³ (by 0.34 percentage points for every 10 µg m⁻³ of match-day PM_{2.5}, $p < 0.05$); above 50 µg m⁻³ it no longer declines (the corresponding interaction is 0.07 percentage points and not statistically significant). Panel A of Figure 6 shows the complementary perspective: below 50 µg m⁻³, the marginal effect of match-day PM_{2.5} is positive at low past exposure and turns negative at high past exposure, while above 50 µg m⁻³ it is small and positive at all levels of past exposure.

Two caveats apply to this observation. First, the estimates above 50 µg m⁻³ are imprecise: the slope of the above-50 segment and its interaction with past exposure are both statistically indistinguishable from zero (Table 5, column 2). Over the observed range of exposures, raising both acute and chronic exposure impairs productivity, even as adaptation moderates the acute response.

Second, this is a statement about the marginal effect, not the total effect: raising past exposure can reduce harm at the margin without making any exposure level beneficial relative to a low-exposure benchmark. Considering the total effect of PM_{2.5} exposure makes it clear that there is no level of

exposure—either on the day of the match or over the previous 30 days—that is beneficial relative to a scenario with low pollution. Figure 6 plots the total effect of PM_{2.5} exposure on the run-scoring probability, calculated as the predicted run-scoring probability at given levels of match-day and past 30-day PM_{2.5} minus the predicted run-scoring probability in a benchmark scenario where both match-day and 30-day PM_{2.5} are zero. When viewed in this way, the effect on run-scoring probability is above zero—indicating harm for bowlers—at any level of match-day or past 30-day exposure.⁶²

The visualization of the total effect in Figure 6 reveals two additional patterns. First, increasing match-day exposure by one unit results in a steeper gradient of harm (i.e., larger marginal effects) than increasing past 30-day exposure by one unit. This is indicated by the fact that moving from left to right results in crossing more contour lines than moving from bottom to top and is a visual presentation of the result in column 1 of Table 5 which shows that match-day PM_{2.5} is more harmful per unit than past 30-day PM_{2.5}. Second, the effect of increasing match-day PM_{2.5} is dependent on the level of exposure to PM_{2.5} in the past 30-days. This is evident by comparing the result of moving along the match-day PM_{2.5} axis while holding past 30-day PM_{2.5} constant at a high-level (say, 80 $\mu\text{g m}^{-3}$) versus moving along the same axis while holding past 30-day PM_{2.5} constant at a low-level (say, 20 $\mu\text{g m}^{-3}$). When past 30-day PM_{2.5} is low, the effect of raising match-day PM_{2.5} is larger than when it is high. This is the visual analog of the negative coefficient on the interaction between the below-50 segment and past 30-day PM_{2.5} in column 2 of Table 5 and is consistent with adaptation.

⁶²Intuitively, the joint relationship between present exposure, past exposure, and harm can be pictured as the elevation surface in Figure 6, with the two exposure measures defining the horizontal plane and harm corresponding to height. The protective (marginal) result says that, holding present exposure fixed, raising past exposure moves downhill to a lower elevation. That point nonetheless remains well above the base of the surface—the benchmark of low exposure on both margins—so the total effect is still harmful.

7 Discussion and conclusion

This paper documents how air pollution affects worker productivity in a high-pollution developing-country context, yielding three key insights. First, this effect is statistically detectable only at the extreme levels above $53 \mu\text{g m}^{-3}$ that billions of workers experience daily but that are rarely studied. Second, workers partially adapt to chronic exposure over both short-term (30-day) and long-term (career-spanning) horizons. However, this adaptation comes at a substantial cost: our third insight is that the cumulative harm from sustained exposure far outweighs any protective benefit of adaptation.

The asymmetric effects across worker roles provide insight into the mechanisms through which pollution impairs productivity. Bowlers, who maintain high respiration rates during their running approach, experience greater performance degradation than batters, who engage in more intermittent physical activity. This pattern aligns with physiological evidence establishing respiration as the primary channel for particulate matter exposure. For workplace policy, this suggests that pollution control measures should prioritize protection for workers in physically intensive roles, and that task assignments might strategically account for pollution exposure during high-pollution episodes.

Our evidence indicates that workers accustomed to higher pollution levels are substantially less sensitive to acute pollution shocks over both 30-day and career-spanning horizons. Below $50 \mu\text{g m}^{-3}$, a match-day increase that raises the run-scoring probability by 0.8 percentage points for a bowler with low recent exposure has no detectable effect for a bowler with high recent exposure, and the acute response is 62% smaller for bowlers with high career exposure than for those with low career exposure. In both cases the attenuation operates along the lower part of the dose–response curve; above $50 \mu\text{g m}^{-3}$ the acute effect is small and does not vary with exposure history. Adaptation thus blunts the response to moderate pollution rather than to extreme episodes, consistent with physiological and behavioral adjustments that develop through sustained exposure.

However, adaptation does not resolve the productivity costs of pollution. The protective effect never outweighs cumulative harm relative to a low-exposure benchmark: the total effect of exposure is harmful at every observed combination of match-day and past exposure. For virtually all policy-relevant exposure scenarios, both acute and chronic pollution unambiguously impair

productivity.

These findings carry three important policy implications. First, because the effects we detect lie at levels far above those typically studied, interventions targeting high-pollution episodes—such as temporary factory closures, construction bans, or vehicle restrictions during pollution spikes—may generate substantial productivity benefits in heavily polluted regions.

Second, populations typically exposed to clean air are especially vulnerable to pollution spikes. Wildfire smoke in the United States and Canada provides a salient contemporary example: populations accustomed to clean air experience intermittent exposure to hazardous pollution without the physiological adaptation that might partially buffer impacts. Our findings suggest such episodic exposures may be particularly harmful precisely because affected populations lack adaptive capacity developed through sustained exposure.

Third, and most importantly, our results therefore reinforce rather than undermine the case for aggressive pollution control in chronically polluted settings. Adaptation is not a solution to pollution; it is evidence of ongoing harm—the continuing costs that workers bear in persistently polluted environments. For the billions of workers operating in such environments across the developing world, reducing pollution exposure remains the main path to protecting both productivity and long-term health.

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