

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

Matthew S. Brooks[†] Faraz Usmani[‡]

June 26, 2026

PLEASE [CLICK HERE](#) FOR THE LATEST VERSION OF THIS PAPER.

Abstract

This paper provides novel evidence that workers in a high particulate matter air pollution setting partially adapt to chronic exposure, but that adaptation does not offset cumulative harm. Using ball-by-ball data from professional cricket in India, we find that a $10 \mu\text{g m}^{-3}$ increase in same-day $\text{PM}_{2.5}$ reduces performance by about 1 percent. Effects are non-linear, with the largest marginal damages above approximately $50 \mu\text{g m}^{-3}$. Workers with the highest past exposure are roughly 40 percent less sensitive to acute shocks than those with median exposure histories, consistent with adaptation. Nevertheless, chronic exposure degrades performance by more than this adaptation offsets.

Keywords: Air pollution, labor productivity, adaptation

JEL codes: Q53, Q56, J24

*We are grateful for feedback from colleagues at the 22nd Occasional Workshop in Environmental and Resource Economics at UC Santa Barbara, the Indian Statistical Institute in New Delhi, University of Massachusetts Amherst, Middlebury College, the 2025 Association of Environmental and Resource Economists Summer Conference, the 25th Annual University of Colorado Boulder Environmental and Resource Economics Workshop, and the Natural Resource Economics and Policy Lab at UC Davis. We thank Katrina Jessoe, Travis Lybbert, and Jamie Hansen-Lewis for invaluable advice and Jamie Mullins, James Archsmith, E. Somanathan, Teevrat Garg, Nick Sanders, and Piyush Gandhi for helpful conversations. Any remaining errors are our own.

[†]Department of Agricultural and Resource Economics; University of California, Davis; One Shields Avenue, Davis, CA 95616; msbrooks@ucdavis.edu.

[‡]Global Energy Alliance for People and Planet, 2445 M Street NW, Suite 700, Washington DC 20037; faraz.usmani@energyalliance.org.

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 mediates 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 ([Samuelson, 1947](#)) 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 histories.³ Third, because each delivery is a direct contest between a bowler and a batter, we can identify how pollution’s effect differs

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.

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 [G3](#) and [G2](#)).

across tasks with distinct physical demands.

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 only dominates cumulative harm under rare pollution conditions. 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—increases the probability that a bowler concedes a run by 0.41 percentage points (0.68% relative to the baseline mean). To gauge this magnitude, reducing match-day exposure from the typical IPL level (sample median, $37 \mu\text{g m}^{-3}$) to the WHO daily safe limit ($15 \mu\text{g m}^{-3}$) would raise productive output by 2.2% for bowlers vis-à-vis batters. Because run-scoring reflects the outcome of bowler-batter interactions, this asymmetry indicates that pollution disproportionately impairs bowlers relative to batters, consistent with the higher sustained physical exertion and respiration rates that bowling demands. Tracking player-level performance data for a subset of matches corroborates this interpretation, revealing a non-linear deterioration in bowler-specific performance as pollution rises.

Second, these effects are non-linear, with the most pronounced effects in the highest pollution quintile (above $53 \mu\text{g m}^{-3}$)—levels common in developing countries but rarely studied. At lower concentrations, marginal effects are smaller.

Third, workers chronically exposed to high pollution become less sensitive to acute shocks, consistent with adaptation over both short and long time horizons. Bowlers with higher career-average $\text{PM}_{2.5}$ exposure exhibit marginal responses to acute shocks approximately 36% smaller than those with median career exposure. Over shorter windows, the attenuation peaks at approximately 30 days, where highly exposed bowlers experience marginal effects about 41% smaller than those at the median. This attenuation is most pronounced when contemporaneous pollution is high yet remains below workers’ typical exposure levels.

Fourth, adaptation does not offset cumulative harm. At the margin, the protective effect of adaptation dominates cumulative damage only at pollution levels above $110 \mu\text{g m}^{-3}$ —a threshold exceeded in just 1.8% of observations. But this small marginal benefit of adaptation—conditional on extreme acute pollution episodes—does not result in a net benefit relative to a counterfactual with low acute and chronic 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, which motivates both our exploration of varying exposure windows and the timescales 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 may obscure important non-linearities that emerge only at the high exposure levels typical of South Asia and Sub-Saharan Africa. 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 $10 \mu\text{g m}^{-3}$. Our results suggest that non-linearities emerge only 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.⁴ 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).⁵

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 mediate the short-run response to temperature (Burke and Emerick, 2016; Dell et al., 2014; Heutel et al., 2021; Mérel and Gammans, 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

⁴In 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.

⁵Mullins (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.

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 literature which focuses almost exclusively on adaptation within 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 focus our search for the time window over which adaptation occurs that is aligned with the physiological mechanisms identified in that field. Guided by this literature, we execute a data-driven approach in our empirical setting to identify the window of past exposure that is associated with adaptation.

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. The non-linearities we document imply that curbing extreme pollution episodes may generate disproportionately large productivity gains. 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 except under extremely rare conditions. 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. Cricket is distinctive among team sports in that it features players in highly specialized roles who engage in a series of repeated individual contests within a team framework (Bartlett, 2003). Specifically, 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.⁶

Our empirical setting is the Indian Premier League (IPL), the world’s premier Twenty20 cricket league.⁷ The IPL operates as a franchise system with ten teams based in different cities: Chennai, Delhi, Ahmedabad, Kolkata, Lucknow, Mumbai, Mullanpur, Jaipur, Bengaluru, and Hyderabad (Figure 3). These cities span India’s diverse geography, from coastal regions to inland valleys, and differ substantially in average air quality owing to differences in vehicle traffic, industrial activity, and natural features. 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. Teams do not choose the dates or venues of their fixtures, and the calendar is set 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.

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.

⁶Fielders, the third type of player, support the bowling side by catching batted balls and preventing runs.

⁷Twenty20, indicating two innings with 20 overs each, is one style of cricket that is designed to be played over an approximately 3 hour period, in contrast to the traditional style in which matches can take days.

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).⁸ 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.⁹

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.

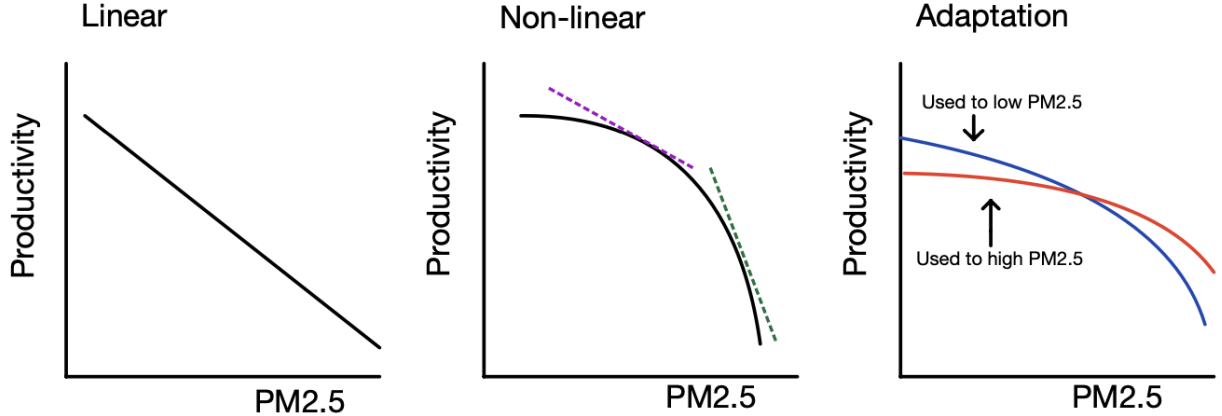
Our conceptual framework highlights three channels through which air pollution may affect worker performance: a non-linear dose–response relationship, adaptation to chronic exposure through behavioral and physiological pathways, and heterogeneous impacts across task types with different physical demands.

First, the marginal effect of pollution on performance may vary with the level of pollution. As depicted in the left panel of Figure 1, a linear damage function implies constant marginal effects across all pollution levels. However, the relationship could be concave (middle panel), where the drop in productivity from an increase in pollution is larger at higher pollution

⁸In randomized controlled trials exposing mice to varying levels of air pollution over time, Cells in the respiratory tract and lungs—i.e., the cells hit hardest by air pollution—can mitigate the damage from air pollution using an antioxidant called glutathione. Glutathione is present in both humans and mice and is understood to perform a similar function in humans as in mice (Ketterer et al., 1983), an insight that serves as the basis for an extensive literature investigating the effects of air pollution on mice to learn about implications for humans.

⁹While the body does not become completely immune to air pollution at all levels, this physiological adaptation allows it to endure higher levels of air pollution than it would otherwise while suffering minimal damage from an acute episode of exposure.¹⁰ Consistent with this adaptation mechanism, West et al. (2003) shows that mice who were exposed over seven days to air pollution have an intact cellular structure that is more similar to mice who were never exposed to air pollution than to mice that experienced only a single episode of exposure. (To visualize the effects of this adaptation response, Figure G1 shows magnified images of cells from the lungs of mice after a single day of air pollution exposure (panel B) and seven days of exposure (panel C), relative to a control group of mice who were exposed to clean air during the same period (panel A).)

Figure 1: Dose response of performance to pollution



levels.¹¹

Second, the effect of pollution may vary systematically across individuals based on their typical exposure levels, consistent with adaptation.¹² The right panel of Figure 1 illustrates how performance might differ between individuals accustomed to high versus low pollution levels.¹³ The figure suggests a potential crossing of damage functions: individuals adapted to high pollution might perform better than their low-pollution counterparts when pollution is high, but worse when pollution is low.

Third, the impact of pollution on performance may vary by the type of task performed, with tasks that require certain types of effort or prolonged exposure being more vulnerable to pollution's effects. In addition, as discussed in Section 2.2, accumulated exposure may generate both negative effects (cumulative physiological damage) and positive effects (behavioral and physiological acclimatization), with the net impact depending on their relative magnitudes.

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).¹⁴ Equation 1 decomposes the total effect of pollution on performance

¹¹Alternatively, the relationship could be convex, though the key insight remains: there is little theoretical justification for assuming constant marginal effects across all pollution levels.

¹²Conceptually, adaptation can be viewed as another form of non-linearity. Whereas a non-linear dose response means that marginal effects vary across the level of contemporaneous exposure, adaptation means that marginal effects vary across the level of typical exposure.

¹³Similarly, we could categorize damage functions into different tasks, with different damage functions for each type of task.

¹⁴This builds on the conceptual framework in Hagerty (2022) which is applied to long-term changes in agricultural practices.

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. By estimating $F(P, a)$ flexibly so that the slope can vary across the domain of exposure, we can detect non-linear effects of pollution on performance.

4 Data

We combine three data sources: ball-by-ball performance data from 773 IPL matches in India (2008–2022), high-resolution daily $\text{PM}_{2.5}$ estimates from both ground monitors and satellite-based sources, and weather controls.¹⁵ 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.¹⁶ For each delivery, we observe detailed information including the 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.¹⁷

Table 1 Panels B and C describes summary statistics from these matches. We leverage

¹⁵Several 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.

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

¹⁷Bowling styles can be categorized into “fast” and “spin.” Fast 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.

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.¹⁸ The mean of the binary outcome of run-concession 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 10km × 10km 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 venues and ten additional stadiums that periodically hosted matches (Figure 3).¹⁹ We validate the Wang et al. (2024) data against the U.S. AirNow network. We choose the U.S. AirNow network to perform validation since it is a high quality ground monitor network that was not included in the training data for the calibration of the model in Wang et al. (2024).²⁰ Figure G5 demonstrates a strong correlation between the Wang et al. (2024) dataset and ground readings. By contrast, Figure G6 reports the results of an analogous exercise with MODIS AOD, and shows a much weaker correlation. We therefore choose Wang et al. (2024) as our source of data for PM_{2.5} concentrations.²¹

These data provide complete coverage of all IPL matches during our study period. As shown in Figure 2, PM_{2.5} concentrations at IPL matches are far higher than in high-income country settings, with a mean of 42 $\mu\text{g m}^{-3}$ on match days (median 37), a maximum of 160 $\mu\text{g m}^{-3}$, 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,

¹⁸This 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.

¹⁹Specifically, we matched the latitude and longitude coordinates of each stadium to the corresponding 10km × 10km cell in the Wang et al. (2024) gridded data.

²⁰Wang et al. (2024) use ground monitor readings from India’s Central Pollution Control Board to train their model.

²¹In both validation exercises, we compare estimates from the data product in the cell containing the US Airnow ground monitor. For Wang et al. (2024), these are 10km x 10 km grid cells. For MODIS AOD, these are 3km x 3km grid cells.

Table 1: Summary Statistics: IPL Matches in India 2008-2022

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

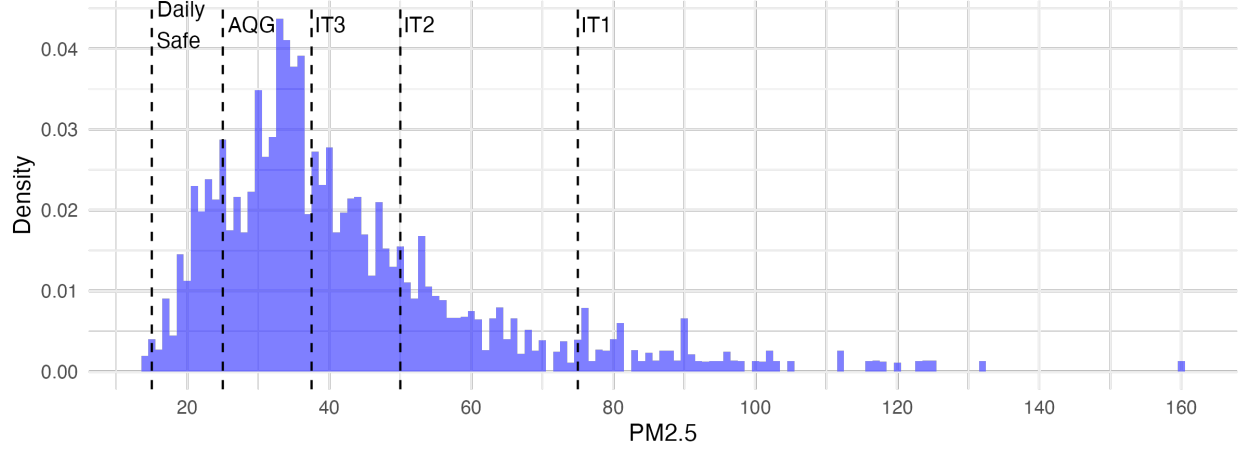
Notes: Unit of observation is a delivery (i.e., a single ball thrown by a bowler to a batter). The sample includes 183,572 deliveries across 773 IPL matches held in India during 2008-2022. These matches took place across 13 seasons, 20 stadiums, 15 teams, 445 bowlers, and 575 batters. The sample excludes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

as shown in Figure 3.

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

Figure 2: 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](#)).

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.²²

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 seven days ([West et al., 2003](#)). Although the study found tolerance effects after seven days, this does not mean that this is the only time window in which these effects may occur—we therefore flexibly adjust our time window from 1 to 90 days prior to the match.²³

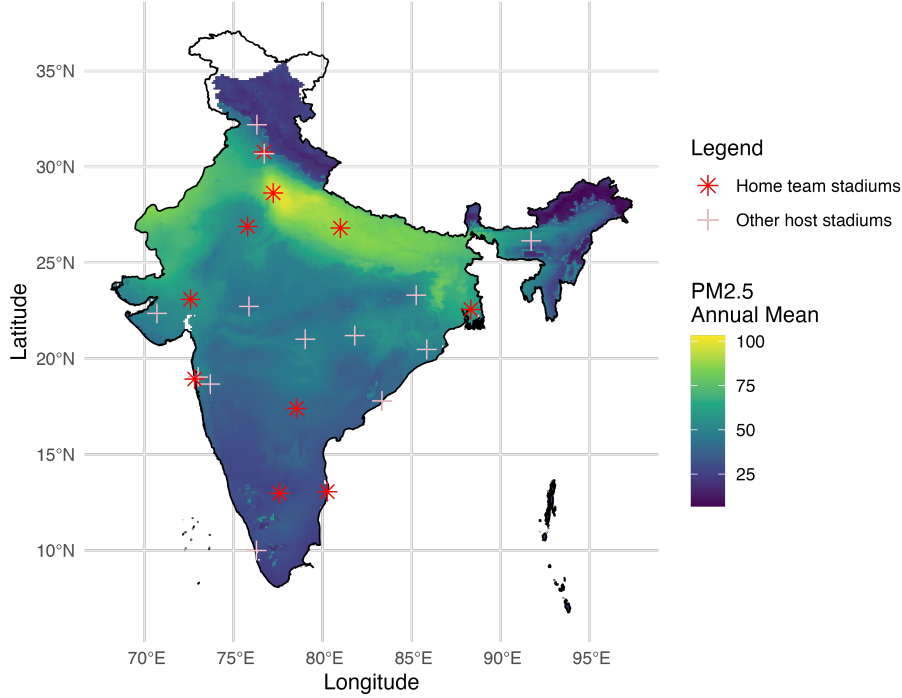
Our primary measure of past exposure to PM_{2.5} is a bowler j ’s mean PM_{2.5} over the past T days, where P indicates PM_{2.5}.²⁴

²²See Appendix B for an extended discussion of the justification for this approach.

²³For example, related empirical work has found that tolerance develops during an exposure period of 21 days ([West et al., 2002](#)). In personal communication with Laura Van Winkle, one of the authors of [West et al. \(2003\)](#), she suggested that tolerance effects may be even more pronounced after a longer period of exposure, but that the logistics of running a study with mice over a prolonged period are complicated, which pushes empirical studies towards shorter exposure time frames. This limitation of prior empirical studies motivates our search for adaptation over a longer time horizon.

²⁴We also explore robustness to alternative measures (including counts of days above various thresholds and a degree day analog) as described in Appendix C

Figure 3: 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 venues for any current IPL team. White space indicates no PM_{2.5} data available from Wang et al. (2024) for a given area.

$$\bar{P}_{J(j)d} \equiv \frac{1}{T} \sum_{\tau=1}^T P_{J(j)\tau} \quad (2)$$

We consider lookback window lengths, T , ranging from 1 to 90 days. Since this measure extends into the past by at most three months 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.²⁵ 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 past exposure levels for our measure of short-term past exposure, we adopt a set of assumptions for assigning a team's

²⁵The team-level of assignment is reflected in the subscript $J(j)$, where J is a function that maps bowler j to team J .

exposure to pollution within a season for days on which a team does not play a match.

1. If the team plays a match on a given day, we assign the $\text{PM}_{2.5}$ for the $10 \times 10\text{km}$ grid in Wang et al. (2024) containing the stadium for the match to the team.
2. If the team does not play a match on a given day, we implement the following set rules:
 - (a) If the team plays a match on the next day, we assume the team travels to the new match location on that day, so we assign it the $\text{PM}_{2.5}$ for the location of the next match’s stadium.
 - (b) If the team does 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 $\text{PM}_{2.5}$ for the location of the previous match’s stadium.
 - (c) If neither of these are the case, we assign them the $\text{PM}_{2.5}$ for their home stadium.

Figure 4 shows the distribution of $\text{PM}_{2.5}$ exposure histories for each of the eight teams with the highest numbers of matches in the IPL as of 2022.²⁶ In Figure 5, we compare the $\text{PM}_{2.5}$ estimates assigned to teams (based on their travel itinerary, as described above) as opposed to the $\text{PM}_{2.5}$ at their home stadium for the 2018 season. The red line shows the level of $\text{PM}_{2.5}$ exposure at the team’s home stadium where the team spends a disproportionate amount, though not all, of their time. The blue line shows the $\text{PM}_{2.5}$ exposure for each team taking into account their away matches and travel schedule. 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. However, there are some teams that have extended periods of exposure that differ from the exposure levels at their home stadium. This tends to be the case for a team based in a high pollution location that travels to matches in lower pollution settings (e.g., Delhi Capitals), or a team with low pollution at its home stadium that then travels to higher pollution areas (e.g., Chennai Super Kings). That the red and blue lines are not consistently overlapping underscores the importance of carefully accounting for the actual levels of exposure each individual team faces.

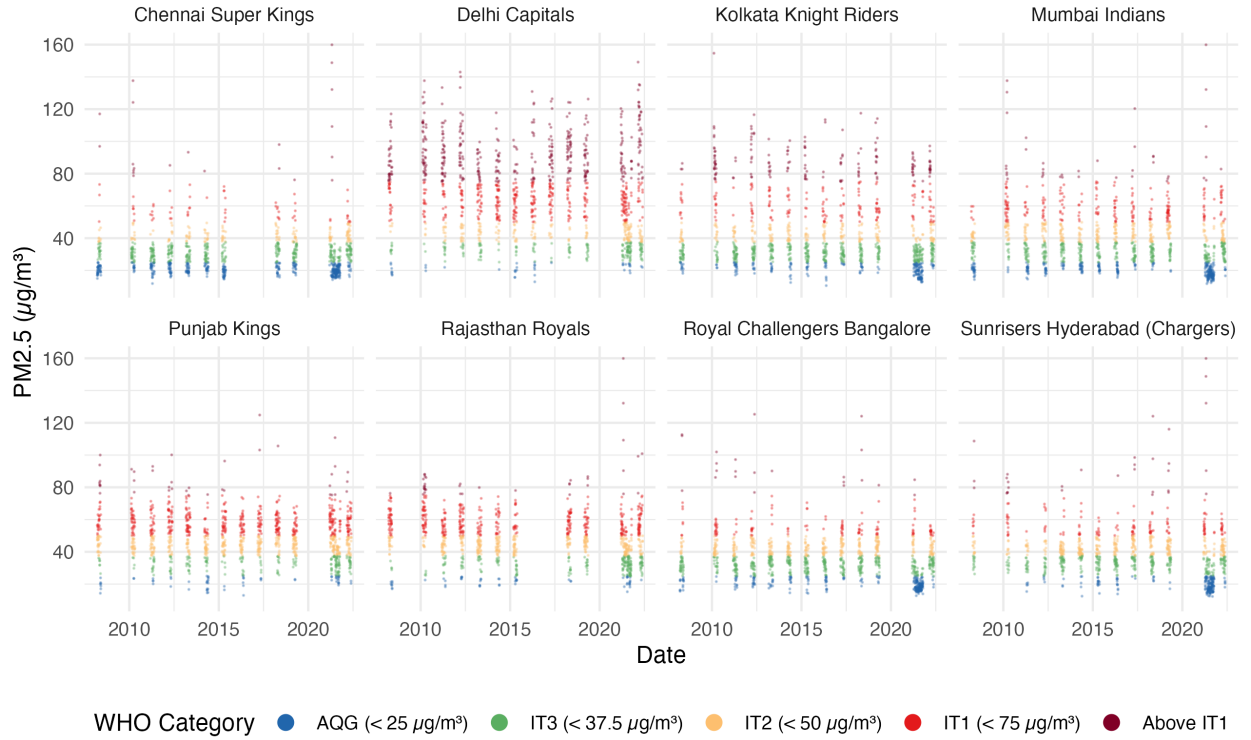
4.3.2 Long-term past exposure

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.²⁷

²⁶We combine the $\text{PM}_{2.5}$ 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.

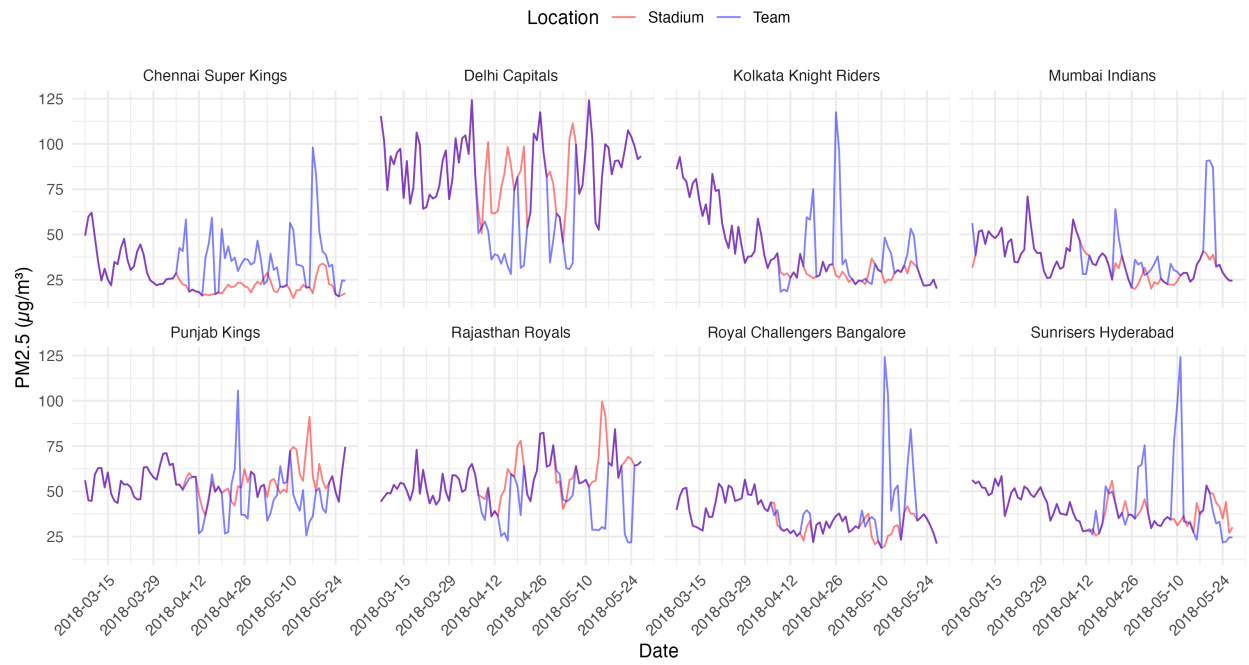
²⁷The distribution of this measure is displayed in Figure G7.

Figure 4: Team PM_{2.5} Exposure Histories in IPL, 2008-2022



Notes. This figure displays the PM_{2.5} exposure history of each IPL team in the years 2008-2022. Teams are assumed to be exposed to the level of PM_{2.5} in their home stadium, unless they are playing a match at an away stadium, in which case they are exposed to the PM_{2.5} at that location. The IPL takes place in three months each year and we assume teams are present and training in their home stadiums 30 days before the start date of each season. We do not interpolate PM_{2.5} exposure between seasons, leading to blank spaces between the clusters of dots for each season.

Figure 5: 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.

For the average player in our sample, this is measured over a time span of 3.2 years (range: 1 to 12 years). The measure consists not only of a player’s home-stadium’s average, but also includes exposures from matches played in away-stadiums, though 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. In Appendix F.3, we explore alternative definitions of long-term $PM_{2.5}$ exposure.

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,²⁸ 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 mediate 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 percent of scoring deliveries resulting in a single run, as shown in Figure G4), 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.²⁹ Second, the binary outcome provides a clear interpretation: the marginal effect of pollution is the change in probability of a

²⁸ERA5-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).

²⁹In Appendix F.1 we specify and estimate ordered logit models that incorporate variation in the number of runs scored.

bowler conceding (or batter scoring) a run, where conceding a run indicates poor bowler performance.³⁰ 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).

5.1 Effects of contemporaneous air pollution on performance

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

$$R_{ij\ell t} = \beta P_{\ell d} + \mathbf{X}'_{\ell d} \gamma + \psi_j + \phi_i + \delta_{\ell y} + \theta_{n(t)} + \eta_{o(t)} + \Lambda_i + \Delta_j + \varepsilon_{ij\ell t} \quad (3)$$

where $R_{ij\ell t}$ is an indicator for whether a bowler concedes a run on a delivery from bowler j to batter i from ball-of-match t 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 10km grid cell containing the latitude and longitude of the stadium at which the match is played.³¹ Our coefficient of interest, β , thus captures the effect of match-day $\text{PM}_{2.5}$ levels on run-concession probability. A positive β indicates that run-concession 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 ($\delta_{\ell y}$), innings fixed effects ($\theta_{n(t)}$), and over fixed effects ($\eta_{o(t)}$).³² It also includes dummy variables for whether the stadium is the home stadium for the batter (Λ_i) or bowler (Δ_j).³³ Bowler and batter fixed effects control for any time-invariant player-specific factors (such as innate ability), stadium-by-year fixed effects account for venue-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 and over fixed effects control for stage-of-match effects that could influence playing styles and strategies. The dummy variables for the home stadium of the

³⁰There 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.

³¹The 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 2), 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).

³²The subscripts $n(t)$ and $o(t)$ indicate the innings and over, respectively, during which delivery t (synonymous to ball t) occurs. There are typically two innings per match and 20 overs per inning.

³³Note 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.

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.³⁴

Intuitively, Equation 3 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 probability that a bowler concedes a run, independent of any other factors that may also affect run-concession, $\text{PM}_{2.5}$, or both.

Identification in Equation 3 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.³⁵ 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.³⁶

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.

5.2 Non-linear effects at extreme pollution levels

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 $\text{PM}_{2.5}$

³⁴See Appendix F.2 for a more flexible approach to controlling for weather variables and interactions between weather variables.

³⁵The 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, 2025). The full match schedule for the season is released weeks before the season starts (ESPNcricinfo, 2026), 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.

³⁶One 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.

quantiles:

$$R_{ij\ell t} = \sum_{k=2}^5 \beta_k Q_k(P_{\ell d}) + \mathbf{X}'_{\ell d} \gamma + \psi_j + \phi_i + \delta_{\ell y} + \theta_{n(t)} + \eta_{o(t)} + \Lambda_i + \Delta_j + \varepsilon_{ij\ell t} \quad (4)$$

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. The spline allows us to construct the dose-response function of performance to pollution as a series of piece-wise functions across varying levels of pollution, while allowing the slope (and in polynomials of degree $p > 1$, the curvature) of the function to vary. This estimation procedure allows us to directly answer whether the dose-response function exhibits non-linearities. To do this, we estimate

$$R_{ij\ell t} = \sum_{m=0}^p \beta_m (P_{\ell d}^m) + \sum_{n=1}^N \beta_{p+n} (P_{\ell d} - \tau_n)^p \mathbf{1}\{P_{\ell d} \geq \tau_n\} + \mathbf{X}'_{\ell d} \gamma + \psi_j + \phi_i + \delta_{\ell y} + \theta_{n(t)} + \eta_{o(t)} + \Lambda_i + \Delta_j + \varepsilon_{ij\ell t} \quad (5)$$

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 . Our main spline specification places knots at the four WHO thresholds for air pollution: 25, 37.5, 50, and 75 $\mu\text{g m}^{-3}$.³⁷

5.3 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 mediate 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,³⁸ 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

³⁷See Figure 2 for where these thresholds fall relative to the distribution of $\text{PM}_{2.5}$ in our sample.

³⁸Half of the bowlers in the sample play on two or more teams across the span of their career in the IPL.

characteristic that affects their response to contemporaneous pollution. While we cannot completely rule out the 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.³⁹

5.3.1 Heterogeneity by short-term past exposure

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

$$R_{ij\ell t} = \beta_1 P_{\ell d} + \beta_2 P_{\ell d} \times \bar{P}_{J(j)d} + \beta_3 \bar{P}_{J(j)d} + \mathbf{X}'_{\ell d} \gamma + \psi_j + \phi_i + \delta_{\ell y} + \theta_{n(t)} + \eta_{o(t)} + \Lambda_i + \Delta_j + \varepsilon_{ij\ell t} \quad (6)$$

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 3. 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.

Data-driven process for determining relevant lookback window Because the toxicology literature establishes that cellular adaptation can emerge within seven days but provides little guidance on the precise timescale over which it peaks or fades (West et al., 2003), we adopt a data-driven approach to select the relevant lookback window. We estimate Equation 6 separately for each lookback window length T from 1 to 90 days.⁴⁰ For each regression, we compute the marginal effect of match-day $\text{PM}_{2.5}$ at the 95th and 50th percentiles of $\bar{P}_{J(j)d}$ and calculate the percent differential:

$$(ME_{p50} - ME_{p95}) / ME_{p50}$$

³⁹Figure G3 shows that bowler performance (as indicated by the run-concession rate) is uncorrelated with career $\text{PM}_{2.5}$ exposure and Figure G2 which shows that team performance (as indicated by the win rate) is uncorrelated with home stadium $\text{PM}_{2.5}$.

⁴⁰See Section 4.3.1 for the definition of this term, defined relative to lookback window length T days.

where ME_{pY} denotes the marginal effect of match-day $PM_{2.5}$ evaluated at the Y^{th} percentile of past exposure. We select the lookback window that maximizes this differential, i.e., the window over which high past exposure most attenuates the acute response.

Non-linearity in the heterogeneous effect By specifying a linear interaction term between two continuous variables, the specification in Equation 6 imposes the restriction that the magnitude of the adaptation effect is constant across current (match-day) pollution levels. In the estimating equations in this section, we relax this assumption. Our approach is to put current $PM_{2.5}$ exposure into bins, while treating past exposure continuously.⁴¹

To explore whether past exposure mediates the effect of present exposure differently at different levels of present exposure, we interact the past exposure measure with quintile indicators of present exposure in Equation 7:

$$R_{ij\ell t} = \sum_{k=2}^5 \beta_{1k} Q_k(P_{\ell d}) + \sum_{k=2}^5 \beta_{2k} Q_k(P_{\ell d}) \times \bar{P}_{J(j)d} + \beta_3 \bar{P}_{J(j)d} + \mathbf{X}'_{\ell d} \gamma + \psi_j + \phi_i + \delta_{\ell y} + \theta_{n(t)} + \eta_{o(t)} + \Lambda_i + \Delta_j + \varepsilon_{ij\ell t}. \quad (7)$$

This approach builds on the strategy to estimate non-linear effects of contemporaneous exposure in Equation 4, and the quintile notation is the same as in that equation.

5.3.2 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:

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

where $\bar{P}_{j0}$ is long-term exposure to pollution for a given bowler, and other variables are as defined in Equation 3. 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.⁴² Because career exposure is fixed

⁴¹An alternative approach, discussed in Appendix F.4, instead relaxes the assumption that the magnitude of the adaptation effect is constant across *past* pollution levels. In sum, these specifications put past exposure into bins while treating present exposure continuously.

⁴²This 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

within bowler, its level effect is absorbed by bowler fixed effects. We therefore omit the main effect of $\overline{P_{j0}}$ and identify the adaptation effect solely through the interaction term β_2 . We also estimate the non-linear variant that interacts quintile indicators of match-day $\text{PM}_{2.5}$ with career exposure (Equation 7).

6 Results

Our empirical analysis proceeds in four steps. We first establish that air pollution significantly impairs productivity, then demonstrate that these effects are concentrated 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 probability of run-scoring. Our preferred specification (column 3) includes fixed effects for bowlers, batters, stadium-by-year, innings, and overs, along with weather controls.⁴³ A $10 \mu\text{g m}^{-3}$ increase in $\text{PM}_{2.5}$ —half a standard deviation—raises the probability that a bowler concedes a run by 0.41 percentage points ($p < 0.05$).⁴⁴ Given a mean run-concession probability of 59.9%, this represents a 0.7% relative increase in the probability of a bowler conceding a run.⁴⁵

To translate this estimate into policy-relevant terms, consider that median match-day $\text{PM}_{2.5}$ in our sample is $37 \mu\text{g m}^{-3}$ —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 2.2% increase in productive output.⁴⁶ As

average.

⁴³Table H4 reports an alternate specification using bowler-batter pair fixed effects, with qualitatively similar results: run-scoring increases by 0.42 percentage points per $10 \mu\text{g m}^{-3}$, and the marginal effect is larger at higher exposure levels. We use individual bowler and batter fixed effects in our main specification to align with the heterogeneity analyses in Section 5.3, which rely on bowler fixed effects.

⁴⁴Sample mean $\text{PM}_{2.5}$ is $42.3 \mu\text{g m}^{-3}$ (SD 20.0; range 14.2 to 159.9).

⁴⁵We 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.

⁴⁶Productive output is defined, from the perspective of the bowler, as the probability that a delivery concedes no run, i.e. one minus the run-concession probability. We obtain the 2.2% 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-concession probability by 0.41 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 0.89 percentage-point decline in the run-concession probability, equivalently a 0.89 percentage-point gain in productive output. Expressed relative to mean productive output

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

	(1)	(2)	(3)	(4)	(5)	(6)
	$\mathbb{1}$ (At least one run scored)					
Match-day PM _{2.5}	0.0041*** (0.0010)	0.0027* (0.0014)	0.0041** (0.0017)			
Q2 (Match-day PM _{2.5})				0.0027 (0.0064)	0.0038 (0.0069)	0.0072 (0.0060)
Q3 (Match-day PM _{2.5})				0.00015 (0.0065)	-0.00065 (0.0073)	0.0099 (0.0069)
Q4 (Match-day PM _{2.5})				0.0086 (0.0076)	0.0047 (0.0096)	0.013 (0.0086)
Q5 (Match-day PM _{2.5})				0.023*** (0.0069)	0.017 (0.010)	0.027*** (0.0099)
Weather controls		✓	✓		✓	✓
Bowler FE			✓			✓
Batter FE			✓			✓
Stadium-by-year FE			✓			✓
Home stadium FE			✓			✓
Innings FE			✓			✓
Over FE			✓			✓
N	183,572	183,572	183,556	183,572	183,572	183,556
R^2	0.00028	0.00039	0.052	0.00032	0.00043	0.052

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). PM_{2.5} is measured in 10 $\mu\text{g}/\text{m}^3$. Quantiles 1 through 5 of PM_{2.5} are separated at 27, 34, 41, and 53 $\mu\text{g}/\text{m}^3$, respectively. Columns (1–3) present results from regressions of this run indicator on match-day PM_{2.5} levels (measured in 10 $\mu\text{g}/\text{m}^3$). Columns (4–6) present results from regressions using PM_{2.5} quintile indicators, where the lowest quintile (Q1) is the omitted category. Columns (3) and (6) include fixed effects for individual batters, bowlers, stadium-by-year, home stadium, innings, and over. Columns (2), (3), (5) and (6) include controls for weather conditions including temperature, temperature squared, relative humidity, precipitation, solar radiation, and wind speed. Following [Correia \(2015\)](#), 16 singleton observations are dropped in columns (3) and (6). Standard errors (in parentheses) are two-way clustered at the match and bowler levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

we show in Section 6.2, this linear estimate understates per-unit damage at the very high pollution levels where most of the productivity loss is concentrated.

Two robustness checks support our main result. First, restricting the sample to the 27.4% of observations with a ground-monitor PM_{2.5} reading from the US AirNow network yields qualitatively similar but less precise estimates (Table H5), 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.

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 ($p < 0.001$), 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.⁴⁷ 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.⁴⁸

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).⁴⁹

In Appendix E, we test the hypothesis that bowlers are harmed by pollution by examining in the sample (0.40), this corresponds to a $0.89/40.1 = 2.2\%$ increase.

⁴⁷See Table H1 for raw correlations between run-scoring, PM_{2.5}, and all weather variables.

⁴⁸This result is also confirmed using the PDS LASSO method (Belloni et al., 2014); see Appendix F.2 for details.

⁴⁹An important distinction related to the length of the running approach (and thus respiration rates) among cricket bowlers is the bowling style, i.e. “fast” or “spin.” Fast 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 fast bowlers should be more affected by PM_{2.5} than spin bowlers. Table H9 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 fast 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 fast bowlers, consistent with our hypothesized mechanism.

outcomes 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). We replicate the analyses in Table 2 for two bowler-independent outcomes: speed (how fast the ball is bowled, km/h) and length (the distance between where the ball bounces and the batter, m). We cannot reject the null hypothesis that pollution does not affect speed. However, we find convincing evidence that bowlers systematically bowl the ball so that it bounces closer to the batter (“fuller” deliveries) as pollution levels rise. Anecdotal evidence suggests that while a ball that bounces extremely close to the batter (a “yorker”) is one of the most difficult deliveries for the batter to hit, a ball that just misses this target becomes fairly easy to hit (Jamil et al., 2023; Weston, 2024). A yorker is thus a high-risk, high-reward strategy whose payoff is contingent on precise execution. The evidence we find is consistent with the idea that bowlers are more likely to make an error when attempting to bowl yorker-like deliveries as pollution rises, leading to higher rates of run-concession. As in Table 2, these effects are non-linear with larger marginal effects at higher pollution levels.

6.2 Non-linear effects at extreme pollution levels

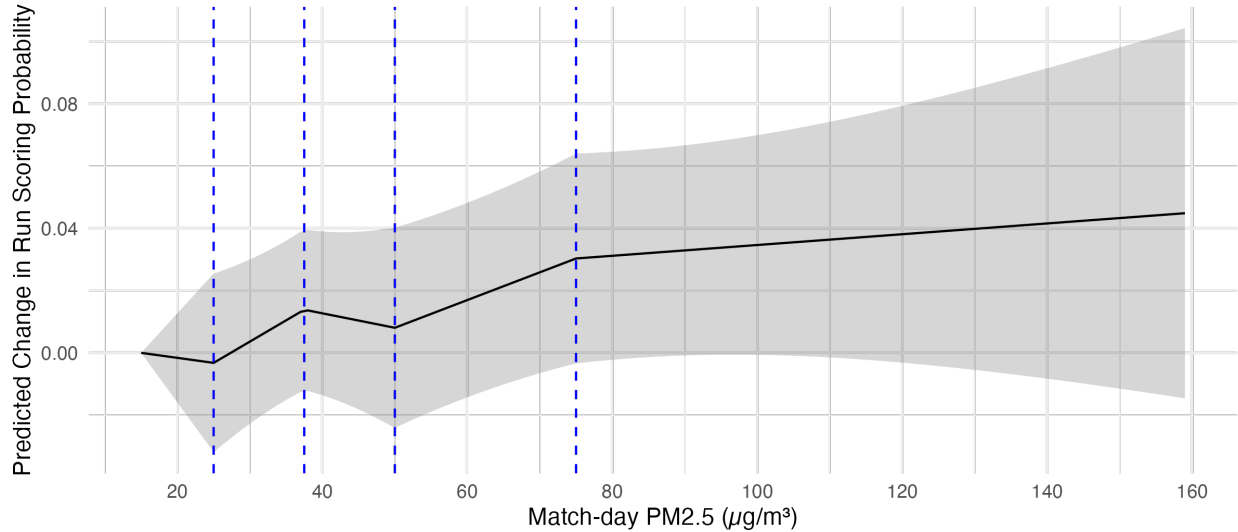
The average effect masks important non-linearities in the pollution–productivity relationship. Columns 4–6 of Table 2 replace the continuous $\text{PM}_{2.5}$ measure with quintile indicators, revealing that productivity impacts are most pronounced at the highest exposure levels. In our preferred specification (column 6), only the fifth quintile shows a statistically significant effect: exposure to $\text{PM}_{2.5}$ above $53 \mu\text{g m}^{-3}$ increases run-concession probability by 2.7 percentage points ($p < 0.01$) relative to the lowest quintile. The second through fourth quintiles show small, insignificant effects.

This non-linearity is notable given that even our lowest quintile ($0\text{--}27 \mu\text{g m}^{-3}$) 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 more than double WHO guidelines. The absence of significant effects in quintiles 2–4 relative to quintile 1, despite exposure levels considered hazardous by international standards, suggests that differential impacts for bowlers vis-à-vis batters materialize only at extreme pollution levels common in developing countries but rarely observed in settings typically studied.

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, plausibly explaining why prior work has not detected the non-linearities we document.

Figure 6: Effect of $\text{PM}_{2.5}$ on Run Probability (Linear Spline, WHO Thresholds)



Notes. Figure displays predicted changes in run-scoring probability as a function of match-day $\text{PM}_{2.5}$ estimated using Equation 5 with $p = 1$ and knots at WHO targets: $25, 37.5, 50,$ and $75 \mu\text{g m}^{-3}$. Dashed lines indicate knot locations.

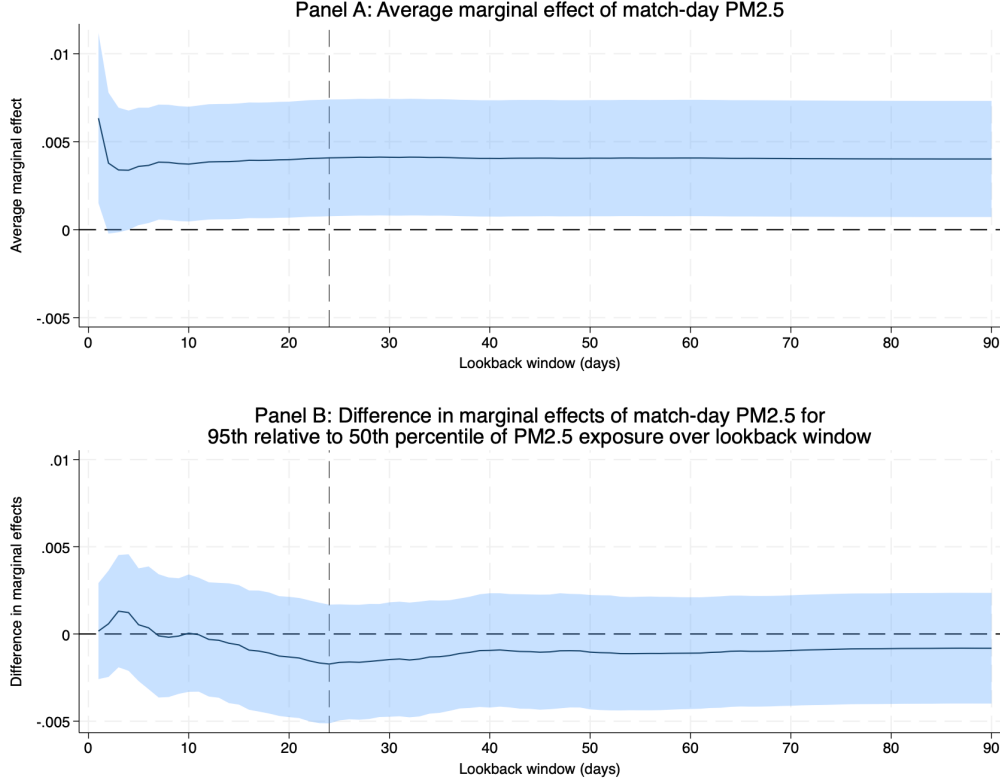
Figure 6 confirms this pattern using the spline specification in Equation 5. The dose-response function remains relatively flat through moderate pollution levels before steepening markedly above $50 \mu\text{g m}^{-3}$. This threshold effect has important implications: linear extrapolations from low-pollution studies would substantially understate productivity losses in high-pollution settings 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 and auction system.⁵⁰

⁵⁰The 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

Figure 7: Marginal Effect of $\text{PM}_{2.5}$ on Probability of Run-Scoring



Notes. Marginal effects are estimated from Equation 6. Panel A shows the marginal effect (with 95% confidence intervals) of a $10 \mu\text{g m}^{-3}$ increase in match-day $\text{PM}_{2.5}$. Panel B shows the difference (with 95% confidence intervals) in two marginal effects: (i) the marginal effect for bowlers at the 95th percentile of exposure of the lookback window and (ii) the marginal effect for bowlers at the 50th percentile of exposure of the lookback window. A negative difference indicates a smaller marginal effect for bowlers at the 95th percentile. The vertical line at 24 days indicates the length of the lookback window over which the absolute value of this differential achieves its maximum.

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 $\text{PM}_{2.5}$ over the preceding T days ($\bar{P}_{J(j)d}$, defined in Equation 2).

Figure 7 illustrates this search by plotting marginal effects estimated from Equation 6.⁵¹

claim. Variation in home stadium average $\text{PM}_{2.5}$ exposure is not correlated with team quality as indicated by the proportion of matches that teams win (Figure G2), nor is career $\text{PM}_{2.5}$ exposure correlated with the average career performance of bowlers as indicated by their career run-concession rate (Figure G3). 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.

⁵¹See Figure G8 for an alternate visualization of this search and Appendix C for results with alternative

Panel A shows that the average marginal effect of match-day $\text{PM}_{2.5}$ remains roughly constant, regardless of the lookback window T used to construct $\bar{P}_{J(j)d}$. By contrast, Panel B shows that this average masks substantial heterogeneity: for bowlers at the 95th percentile of past exposure, the marginal effect is attenuated relative to bowlers at the 50th percentile, with the differential largest at lookback windows of 20–30 days. This attenuation peaks at 24 days, where the marginal effect for highly exposed bowlers is 41% smaller than for those at the median.⁵² Taken together, the two panels reveal the central pattern: averaging across bowlers obscures meaningful adaptation among the chronically exposed.

The differential peaks at 24 days and remains large across the 20–30-day range (Figure 7); we use a 30-day window for our main specifications as a round number within this range.⁵³ Columns 1 and 2 of Table 3 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: 0.66 percentage points for match-day $\text{PM}_{2.5}$ and 0.61 percentage points for the 30-day mean—statistically indistinguishable from each other ($p = 0.81$). 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. As shown in Panel A of Figure 8, at low recent exposure ($20 \mu\text{g m}^{-3}$), a $10 \mu\text{g m}^{-3}$ increase in match-day pollution increases run-scoring by approximately 1.0 percentage point, while at high recent exposure ($80 \mu\text{g m}^{-3}$), the same match-day increase raises run-scoring by only 0.5 percentage points—a 50% reduction. These two marginal effects are statistically different from one another, indicating that bowlers with higher recent pollution exposure are substantially less sensitive to acute pollution shocks.⁵⁴ The continuous interaction term in column 1 of Table 3 is consistent with this heterogeneity: it is negative but not statistically significant ($p = 0.38$), reflecting that the differential is most pronounced at the tails of the past-exposure distribution rather than on average.

Column 2 of Table 3 examines whether this adaptation varies across the pollution definitions of past exposure; findings are similar.

⁵²Figure G9 presents an alternative visualization of how of the magnitude of this differential varies with the length of the lookback window.

⁵³Results are not sensitive to this choice; using 24-day or 20-day windows yields qualitatively identical findings.

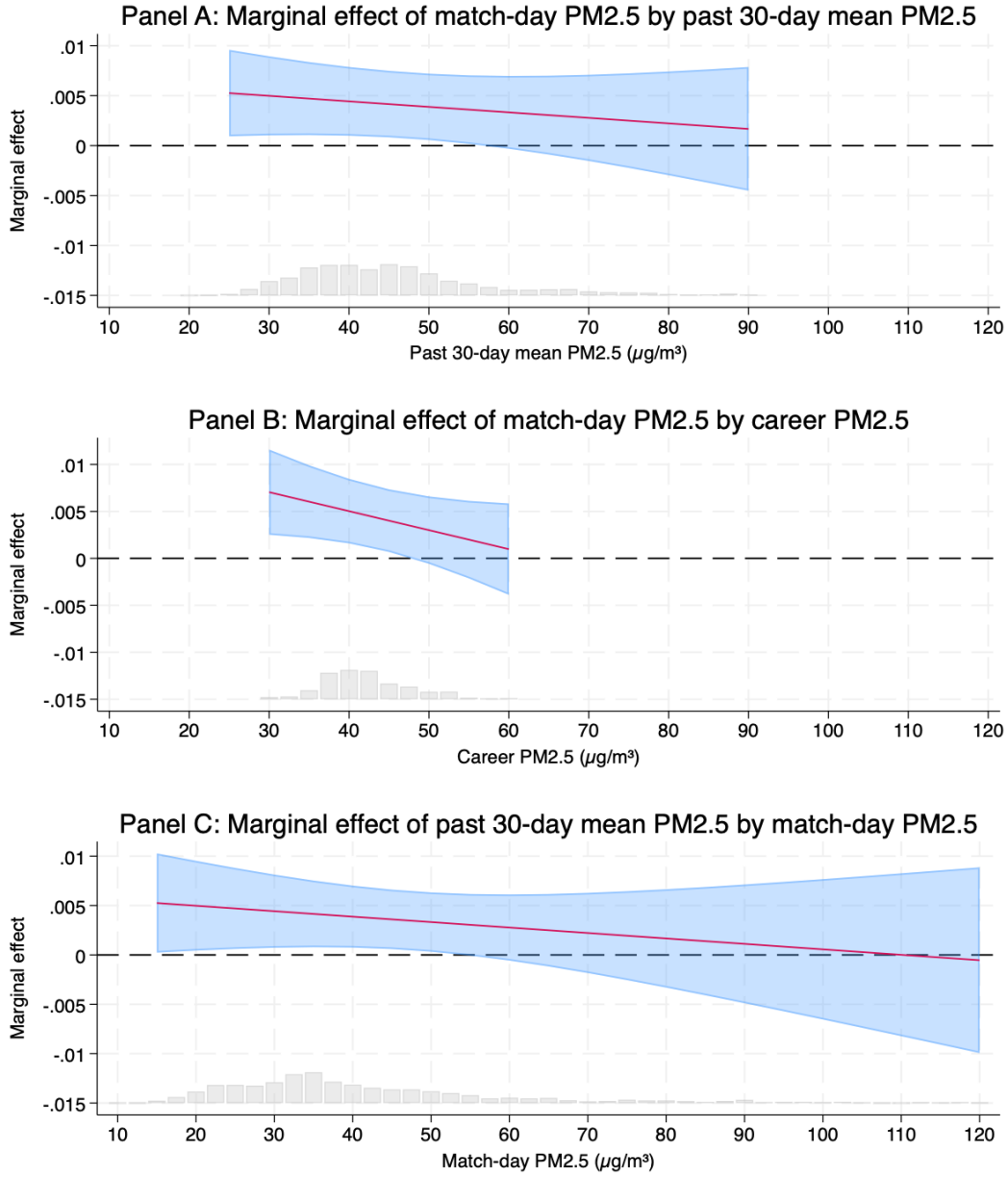
⁵⁴A natural extension of this line of reasoning is to ask whether batters exhibit a similar adaptation response. Since bowlers tend to run more than batters and therefore have higher respiration rates and exposure to $\text{PM}_{2.5}$, our main specifications focuses on the adaptation response of bowlers. As a robustness check, we also estimate a mirrored response for batters in Table H14. This analysis is inconclusive given the lack of statistical significance on the interaction term—Match $\text{PM}_{2.5} \times$ Past 30-day $\text{PM}_{2.5}$ (batter)—for batters.

Table 3: Adaptation to PM_{2.5} exposure: short-term and long-term

	(1)	(2)	(3)	(4)
	Short-term		Long-term	
	$\mathbb{1}$ (At least one run scored)			
Match PM _{2.5}	0.0066* (0.0034)		0.013** (0.0052)	
Past 30-day PM _{2.5}	0.0061* (0.0034)	0.0089** (0.0043)		
Match PM _{2.5} X Past 30-day PM _{2.5}	-0.00055 (0.00063)			
Q2 (Match PM _{2.5})		0.0097 (0.019)		-0.011 (0.034)
Q3 (Match PM _{2.5})		0.034* (0.021)		0.031 (0.034)
Q4 (Match PM _{2.5})		0.041* (0.023)		0.076* (0.039)
Q5 (Match PM _{2.5})		0.069*** (0.025)		0.097** (0.037)
Q2 (Match PM _{2.5}) X Past 30-day PM _{2.5}		-0.00099 (0.0046)		
Q3 (Match PM _{2.5}) X Past 30-day PM _{2.5}		-0.0060 (0.0048)		
Q4 (Match PM _{2.5}) X Past 30-day PM _{2.5}		-0.0068 (0.0051)		
Q5 (Match PM _{2.5}) X Past 30-day PM _{2.5}		-0.0095* (0.0051)		
Match PM _{2.5} X Career PM _{2.5}			-0.0020* (0.0011)	
Q2 (Match PM _{2.5}) X Career PM _{2.5}				0.0042 (0.0082)
Q3 (Match PM _{2.5}) X Career PM _{2.5}				-0.0053 (0.0081)
Q4 (Match PM _{2.5}) X Career PM _{2.5}				-0.015* (0.0090)
Q5 (Match PM _{2.5}) X Career PM _{2.5}				-0.016* (0.0086)
Weather controls	✓	✓	✓	✓
Stadium-by-year FE	✓	✓	✓	✓
Home stadium FE	✓	✓	✓	✓
Over FE	✓	✓	✓	✓
Innings FE	✓	✓	✓	✓
Bowler FE	✓	✓	✓	✓
Batter FE	✓	✓	✓	✓
<i>N</i>	183,556	183,556	183,556	183,556
<i>R</i> ²	0.052	0.052	0.052	0.052

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). Match PM_{2.5} is the PM_{2.5} concentration on the match day. Past 30-day PM_{2.5} is the bowler's mean PM_{2.5} exposure over the preceding 30 days. Column (1) includes both measures in levels and their interaction. Column (2) replaces match-day PM_{2.5} with quintile indicators (the lowest quintile omitted) and interacts them with past 30-day PM_{2.5}. Column (3) and (4) replace past 30-day PM_{2.5} with career PM_{2.5} (excluding the level term for career PM_{2.5} which is absorbed by bowler fixed effects). Standard errors are two-way clustered by match and bowler. Following [Correia \(2015\)](#), 16 singleton observations are dropped. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 8: Marginal Effects



Notes. Plots show marginal effects (with 95% confidence intervals) plotted against the moderator variable, with a rug plot of the moderator's distribution shown at the bottom of each panel. Panel A plots the marginal effect (with 95% confidence intervals) of a $10 \mu\text{g m}^{-3}$ increase in match-day PM_{2.5} as a function of mean PM_{2.5} exposure over the preceding 30 days. Marginal effects are computed from Equation 6 using the estimated coefficients in column 1 of Table 3. Panel B plots the marginal effect (with 95% confidence intervals) of a $10 \mu\text{g m}^{-3}$ increase in match-day PM_{2.5} as a function of career-average PM_{2.5} exposure. Marginal effects are computed from Equation 8 using the estimated coefficients in column 3 of Table 3. Panel C plots the marginal effect (with 95% confidence intervals) of past PM_{2.5}, defined as the 30-day mean as in Equation 2, on the probability of run-scoring for varying levels of match-day PM_{2.5}. Marginal effects are computed from Equation 6 using the estimated coefficients in column 1 of Table 3.

distribution by replacing continuous match-day $\text{PM}_{2.5}$ with quintile indicators while keeping past 30-day mean $\text{PM}_{2.5}$ continuous. This asymmetric discretization is motivated by the non-linearity in match-day effects documented in Table 2, columns 4–6; we present the mirrored specification (continuous match-day, discretized past 30-day mean) in Appendix F.4 and find consistent evidence of adaptation concentrated at high contemporaneous pollution levels. The pattern aligns with our baseline non-linearity findings in Table 2: only the top quintile of match-day $\text{PM}_{2.5}$ shows a statistically significant interaction with past 30-day mean (-0.0095 , $p < 0.10$). This indicates that recent exposure primarily buffers performance when contemporaneous pollution is extremely high—above $53 \mu\text{g m}^{-3}$.

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 3 and 4 of Table 3 present results using each bowler’s mean $\text{PM}_{2.5}$ across all IPL matches as the measure of long-term exposure. Column 3 estimates the linear interaction specification parallel to our short-term analysis. The interaction coefficient is -0.0020 ($p < 0.10$), indicating bowlers with higher career-average exposure exhibit smaller responses to match-day pollution.⁵⁵ The economic magnitude is substantial: at zero career exposure, the marginal effect is 1.3 percentage points; at the sample mean ($42.3 \mu\text{g m}^{-3}$), it falls to 0.49 percentage points; at high career exposure ($60 \mu\text{g m}^{-3}$), it attenuates close to zero, though remaining weakly positive.⁵⁶

Panel B of Figure 8 visualizes this gradient across the observed distribution of career exposures. For bowlers at the 95th percentile of long-term exposure ($70.6 \mu\text{g m}^{-3}$ average), the marginal effect of match-day $\text{PM}_{2.5}$ is 0.27 percentage points, compared to 0.42 percentage points for bowlers with median exposure ($44.0 \mu\text{g m}^{-3}$)—a 36% reduction in the acute sensitivity. To benchmark this against prior work, the 36% adaptation premium is comparable

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 capturing actual cumulative exposure based on players’ movements over time yield larger adaptation effects than cruder place-based proxies (Table H3).

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 H10 we present the same specification as column 3 of Table 3, 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.

in magnitude to the ozone-adaptation effect of approximately 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 4 of Table 3 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 fourth and fifth quintiles of match-day PM_{2.5} exhibit statistically significant negative interactions with career exposure (-0.015 , $p < 0.10$ and -0.016 , $p < 0.10$, respectively). Adaptation effects remain concentrated at elevated pollution levels.⁵⁸

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 PM_{2.5} exposure. Panel C of Figure 8 plots 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.

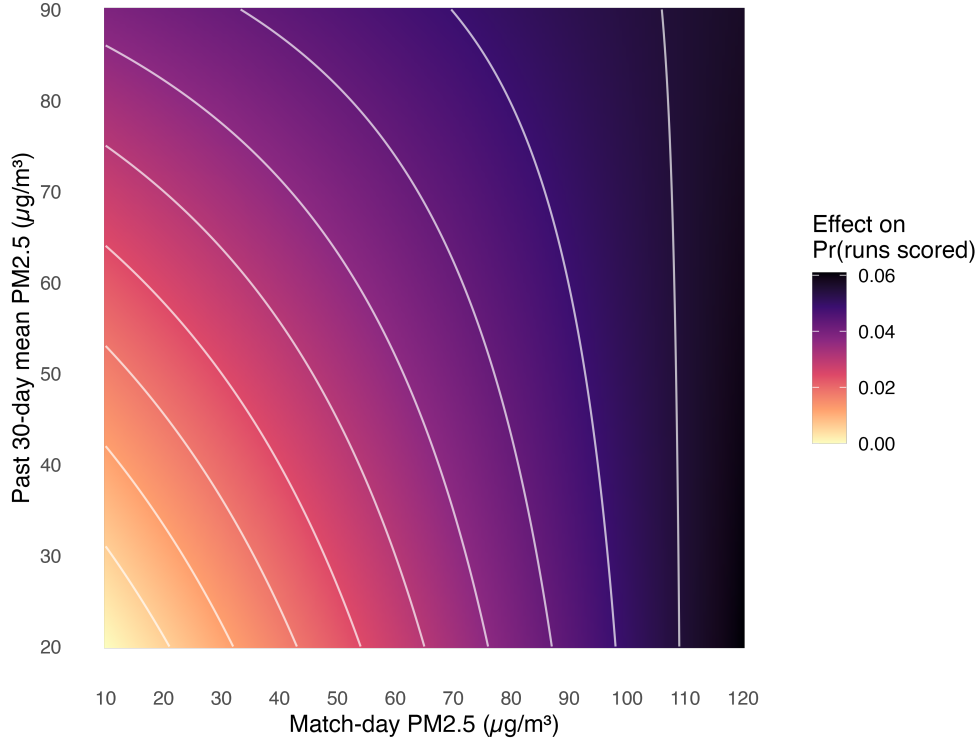
At low match-day pollution (20–40 $\mu\text{g m}^{-3}$), the marginal effect of past exposure is positive and substantial: higher past exposure unambiguously harms current performance through cumulative physiological damage. As match-day pollution rises above 60–70 $\mu\text{g m}^{-3}$, this marginal effect declines, crossing zero around 110 $\mu\text{g m}^{-3}$. Beyond this threshold, the marginal effect becomes negative indicating that increasing past exposure is protective, providing resilience that dominates the cumulative harm when facing extremely high acute exposure.

However, there are two major caveats to this observation. First, this crossover occurs at extraordinarily rare pollution levels. Only 1.4% of matches (comprising 1.8% of deliveries) in our sample exceed 110 $\mu\text{g m}^{-3}$ —more than seven times WHO daily guidelines. The widening confidence intervals at these extreme levels reflect data sparsity and underscore the uncertainty

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).

⁵⁸Table H13 employs the triple-interaction specification introduced in the short-term analysis, interacting top-quintile match-day PM_{2.5}, an indicator for career exposure exceeding match-day levels, and continuous match-day PM_{2.5}. The triple interaction coefficient is -0.15 ($p < 0.05$), an order of magnitude larger than the corresponding short-term estimate of -0.029 . This suggests that career-long adaptation provides substantially stronger protection against extreme acute exposures than recent 30-day adaptation alone.

Figure 9: Total Effects



Notes. Total effects, estimated from Equation 6, are calculated relative to a scenario where match-day and past 30-day $\text{PM}_{2.5}$ are both set to $10 \mu\text{g m}^{-3}$.

surrounding estimates in this range. For the vast majority of observed pollution levels, 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 $\text{PM}_{2.5}$ 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 9 plots the total effect of $\text{PM}_{2.5}$ exposure on the probability of run-scoring, calculated as predicted probability of run-scoring at given levels of match-day and past 30-day $\text{PM}_{2.5}$ minus the predicted probability of run-scoring in a benchmark scenario where both match-day and 30-day $\text{PM}_{2.5}$ are $10 \mu\text{g m}^{-3}$. When viewed in this way, the effect on run-concession probability is above zero—indicating harm for bowlers—at any level of match-day or past 30-day exposure.⁵⁹

⁵⁹Intuitively, the joint relationship between present exposure, past exposure, and harm can be pictured as the elevation surface in Figure 9, 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

The visualization of the total effect in Figure 9 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 3 which shows that match-day $\text{PM}_{2.5}$ is more harmful per unit than past 30-day $\text{PM}_{2.5}$. Second, the effect of increasing match-day $\text{PM}_{2.5}$ is dependent on the level of exposure to $\text{PM}_{2.5}$ in the past 30-days. This is evident by comparing the result of moving along the match-day $\text{PM}_{2.5}$ axis while holding past 30-day $\text{PM}_{2.5}$ constant at a high-level (say, $80 \mu\text{g m}^{-3}$) versus moving along the same axis while holding past 30-day $\text{PM}_{2.5}$ constant at a low-level (say, $20 \mu\text{g m}^{-3}$). When past 30-day $\text{PM}_{2.5}$ is low, the effect of raising match-day $\text{PM}_{2.5}$ is larger than when it is high. This is the visual analog of the negative coefficient on the interaction term in Column 1 of Table 3 and is consistent with adaptation.

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 highly non-linear—marginal effects are substantially higher at extreme levels above $53 \mu\text{g m}^{-3}$, ranges 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 except under extraordinarily rare conditions.

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 reveals that workers accustomed to higher pollution levels are substantially less sensitive to acute pollution shocks, with this protective effect strengthening over longer

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.

exposure horizons—career-long adaptation provides significantly stronger buffering than recent 30-day adaptation alone. Crucially, adaptation is most pronounced when workers face extremely high contemporaneous pollution that nonetheless remains below their typical exposure levels, suggesting that physiological and behavioral adjustments develop gradually through sustained exposure.

However, adaptation does not resolve the productivity costs of pollution. The protective effect only dominates cumulative harm at rare pollution levels above $110 \mu\text{g m}^{-3}$ —a threshold exceeded in just 1.8% of our observations. For virtually all policy-relevant exposure scenarios, both acute and chronic pollution unambiguously impair productivity.

These findings carry three important policy implications. First, the concentration of effects at extreme pollution levels suggests that 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. Reducing exposure from, say, 70 to $50 \mu\text{g m}^{-3}$ produces larger marginal benefits than reducing exposure from 40 to $20 \mu\text{g m}^{-3}$.

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.

References

- ADHVARYU, A., N. KALA, AND A. NYSHADHAM (2022): “Management and Shocks to Worker Productivity,” *Journal of Political Economy*, 130, 1–47, publisher: The University of Chicago Press.
- AGUILAR-GOMEZ, S., H. DWYER, J. G. ZIVIN, AND M. NEIDELL (2022): “This Is Air: The “Nonhealth” Effects of Air Pollution,” *Annual Review of Resource Economics*, 14, 403–425, publisher: Annual Reviews.
- ARCHSMITH, J., A. HEYES, AND S. SABERIAN (2018): “Air Quality and Error Quantity: Pollution and Performance in a High-Skilled, Quality-Focused Occupation,” *Journal of the Association of Environmental and Resource Economists*, 5, 827–863.
- BARTLETT, R. M. (2003): “The science and medicine of cricket: an overview and update,” *Journal of Sports Sciences*, 21, 733–752, publisher: Routledge.
- BCCI (2025): “BCCI extends cut-off time for IPL 2025 matches to avoid called off ties,” .
- BELLONI, A., V. CHERNOZHUKOV, AND C. HANSEN (2014): “Inference on Treatment Effects after Selection among High-Dimensional Controls,” *The Review of Economic Studies*, 81, 608–650.
- BURKE, M. AND K. EMERICK (2016): “Adaptation to Climate Change: Evidence from US Agriculture,” *American Economic Journal: Economic Policy*, 8, 106–140.
- BURKE, M., M. ZAHID, M. C. M. MARTINS, C. W. CALLAHAN, R. LEE, T. AVIRMED, S. HEFT-NEAL, M. KIANG, S. M. HSIANG, AND D. LOBELL (2024): “Are We Adapting to Climate Change?” *NBER Working Paper*.
- CHANG, T., J. GRAFF ZIVIN, T. GROSS, AND M. NEIDELL (2016): “Particulate Pollution and the Productivity of Pear Packers,” *American Economic Journal: Economic Policy*, 8, 141–169.
- CHANG, T. Y., J. GRAFF ZIVIN, T. GROSS, AND M. NEIDELL (2019): “The Effect of Pollution on Worker Productivity: Evidence from Call Center Workers in China,” *American Economic Journal: Applied Economics*, 11, 151–172.
- CORREIA, S. (2015): “Singletons, Cluster-Robust Standard Errors and Fixed Effects: A Bad Mix,” Working Paper.
- CRICSHEET (2024): “Cricsheet,” <https://cricsheet.org/>.
- DELL, M., B. F. JONES, AND B. A. OLKEN (2014): “What Do We Learn from the Weather? The New Climate-Economy Literature,” *Journal of Economic Literature*, 52, 740–798.
- DERYUGINA, T., G. HEUTEL, N. H. MILLER, D. MOLITOR, AND J. REIF (2019): “The Mortality and Medical Costs of Air Pollution: Evidence from Changes in Wind Direction,” *American Economic Review*, 109, 4178–4219.

- DESCHÊNES, O. AND M. GREENSTONE (2007): “The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather,” *American Economic Review*, 97, 354–385.
- DIMEO, M. J., M. G. GLENN, M. J. HOLTZMAN, J. R. SELLER, J. A. NADEL, AND H. A. BOUSHEY (1981): “Threshold Concentration of Ozone Causing an Increase in Bronchial Reactivity in Humans and Adaptation with Repeated Exposures,” *American Review of Respiratory Disease*, 124, 245–248, publisher: American Thoracic Society - AJRCCM.
- DOCKERY, D. W., C. A. POPE, X. XU, J. D. SPENGLER, J. H. WARE, M. E. FAY, B. G. FERRIS, AND F. E. SPEIZER (1993): “An Association between Air Pollution and Mortality in Six U.S. Cities,” *New England Journal of Medicine*, 329, 1753–1759.
- ESPNCRICINFO, N. G. G. I. N. E. A. (2026): “IPL 2026 to begin on March 28, final scheduled for May 31,” .
- GRAFF ZIVIN, J. AND M. NEIDELL (2012): “The Impact of Pollution on Worker Productivity,” *American Economic Review*, 102, 3652–3673.
- GUO, M. AND S. FU (2019): “Running With a Mask? The Effect of Air Pollution on Marathon Runners’ Performance,” *Journal of Sports Economics*, 20, 903–928, publisher: SAGE Publications.
- HACKNEY, J. D., W. S. LINN, J. G. MOHLER, AND C. R. COLLIER (1977): “Adaptation to short-term respiratory effects of ozone in men exposed repeatedly,” *Journal of Applied Physiology*, 43, 82–85, publisher: American Physiological Society.
- HAGERTY, N. (2022): “Adaptation to Surface Water Scarcity in Irrigated Agriculture,” *Unpublished Manuscript*.
- HAMADE, A. K. AND C. G. TANKERSLEY (2009): “Interstrain variation in cardiac and respiratory adaptation to repeated ozone and particulate matter exposures,” *American Journal of Physiology-Regulatory, Integrative and Comparative Physiology*, 296, R1202–R1215, publisher: American Physiological Society.
- HAMANAKA, R. B. AND G. M. MUTLU (2025): “Particulate matter air pollution: effects on the respiratory system,” *The Journal of Clinical Investigation*, 135, publisher: American Society for Clinical Investigation.
- HAWK-EYE (2022): “HawkeyeStats,” Available at: <https://github.com/alittlefitness/HawkeyeStats>. Accessed June 22, 2026.
- HE, J., H. LIU, AND A. SALVO (2019): “Severe Air Pollution and Labor Productivity: Evidence from Industrial Towns in China,” *American Economic Journal: Applied Economics*, 11, 173–201.

- HEALTH EFFECTS INSTITUTE (2025): “State of Global Air 2025: A Report on Air Pollution and Its Role in the World’s Leading Causes of Death,” Report, Health Effects Institute, Boston, MA, produced in partnership with IHME and NCD Alliance.
- HEUTEL, G., N. H. MILLER, AND D. MOLITOR (2021): “Adaptation and the Mortality Effects of Temperature across U.S. Climate Regions,” *The Review of Economics and Statistics*, 103, 740–753.
- JAMIL, M., S. KERRUISH, S. MEHTA, A. PHATAK, D. MEMMERT, AND A. MCROBERT (2023): “Identifying which factors impact bowling and batting performances during the “death” phase of an innings in international men’s 50-over cricket,” *International Journal of Performance Analysis in Sport*, 23, 111–124.
- KAHN, M. E. AND P. LI (2020): “Air pollution lowers high skill public sector worker productivity in China,” *Environmental Research Letters*, 15, 084003, publisher: IOP Publishing.
- KETTERER, B., B. COLES, AND D. J. MEYER (1983): “The role of glutathione in detoxication,” *Environmental Health Perspectives*, 49, 59–69, publisher: Environmental Health Perspectives.
- KÜLTZ, D., J. LI, R. SACCHI, D. MORIN, A. BUCKPITT, AND L. VAN WINKLE (2015): “Alterations in the proteome of the respiratory tract in response to single and multiple exposures to naphthalene,” *PROTEOMICS*, 15, 2655–2668, eprint: <https://analyticalsciencejournals.onlinelibrary.wiley.com/doi/pdf/10.1002/pmic.201400445>.
- LAWRENCE, M. G. (2005): “The Relationship between Relative Humidity and the Dewpoint Temperature in Moist Air: A Simple Conversion and Applications,” *Bulletin of the American Meteorological Society*, 86, 225–234.
- LEE, S.-H., S.-H. HONG, C.-H. TANG, Y. S. LING, K.-H. CHEN, H.-J. LIANG, AND C.-Y. LIN (2018): “Mass spectrometry-based lipidomics to explore the biochemical effects of naphthalene toxicity or tolerance in a mouse model,” *PLOS ONE*, 13, e0204829, publisher: Public Library of Science.
- LEPEULE, J., F. LADEN, D. DOCKERY, AND J. SCHWARTZ (2012): “Chronic Exposure to Fine Particles and Mortality: An Extended Follow-up of the Harvard Six Cities Study from 1974 to 2009,” *Environmental Health Perspectives*, 120, 965–970.
- MOORE, F. C. (2017): “Learning, adaptation, and weather in a changing climate,” *Climate Change Economics*, 08, 1750010, publisher: World Scientific Publishing Co.
- MULLINS, J. T. (2018): “Ambient air pollution and human performance: Contemporaneous and acclimatization effects of ozone exposure on athletic performance,” *Health Economics*, 27, 1189–1200, eprint: <https://onlinelibrary.wiley.com/doi/pdf/10.1002/hec.3667>.
- MUÑOZ SABATER, J. (2019): “ERA5-Land monthly averaged data from 1950 to present,” Copernicus Climate Change Service (C3S) Climate Data Store (CDS). Available at www.doi.org/10.24381/CDS.68D2BB30 (accessed on November 16, 2024).

- MÉREL, P. AND M. GAMMANS (2021): “Climate Econometrics: Can the Panel Approach Account for Long-Run Adaptation?” *American Journal of Agricultural Economics*, 103, 1207–1238.
- POPE III, C. A., R. T. BURNETT, M. J. THUN, E. E. CALLE, D. KREWSKI, K. ITO, AND G. D. THURSTON (2002): “Lung Cancer, Cardiopulmonary Mortality, and Long-term Exposure to Fine Particulate Air Pollution,” *JAMA*, 287, 1132–1141.
- PROCTOR, J., T. CARLETON, AND S. SUM (2026): “Parameter recovery using remotely sensed variables,” *Journal of the Association of Environmental and Resource Economists*, Forthcoming.
- QIN, Y., J. WU, AND R. ZHANG (2022): “Can Professional Football Players Adapt to Air Pollution? Evidence From China,” *Journal of Sports Economics*, 23, 277–300, publisher: SAGE Publications.
- RENTSCHLER, J. AND N. LEONOVA (2023): “Global air pollution exposure and poverty,” *Nature Communications*, 14, 4432, publisher: Nature Publishing Group.
- SAMUELSON, P. A. (1947): *Foundations of Economic Analysis*, Cambridge, MA: Harvard University Press.
- SCHLENKER, W. AND W. R. WALKER (2015): “Airports, Air Pollution, and Contemporaneous Health,” *The Review of Economic Studies*, 83, 768–809.
- WANG, S., M. ZHANG, H. ZHAO, P. WANG, S. H. KOTA, Q. FU, C. LIU, AND H. ZHANG (2024): “Reconstructing long-term (1980–2022) daily ground particulate matter concentrations in India (LongPMInd),” *Earth System Science Data*, 16, 3565–3577.
- WEST, J. A. A., L. S. VAN WINKLE, D. MORIN, C. A. FLECHNER, H. J. FORMAN, AND C. G. PLOPPER (2003): “Repeated inhalation exposures to the bioactivated cytotoxicant naphthalene (NA) produce airway-specific Clara cell tolerance in mice,” *Toxicological Sciences: An Official Journal of the Society of Toxicology*, 75, 161–168.
- WEST, J. A. A., K. J. WILLIAMS, E. TOSKALA, S. J. NISHIO, C. A. FLECHNER, H. J. FORMAN, A. R. BUCKPITT, AND C. G. PLOPPER (2002): “Induction of Tolerance to Naphthalene in Clara Cells Is Dependent on a Stable Phenotypic Adaptation Favoring Maintenance of the Glutathione Pool,” *The American Journal of Pathology*, 160, 1115–1127.
- WESTON, D. (2024): “IPL 2024 - The Trouble With Yorkers & Short Balls,” *Dan’s Newsletter*, Substack newsletter, available at <https://danweston.substack.com/p/ipl-2024-the-trouble-with-yorkers> (accessed June 25, 2026).
- WORLD HEALTH ORGANIZATION (2021): “WHO global air quality guidelines: particulate matter (PM_{2.5} and PM₁₀), ozone, nitrogen dioxide, sulfur dioxide and carbon monoxide,” Tech. rep.

Supplemental Appendix to
“The Pollution–Productivity Curve: Non-Linear Effects
and Adaptation in High-Pollution Environments”

MATTHEW S. BROOKS[†]
University of California,
Davis

FARAZ USMANI[‡]
Global Energy Alliance for
People and Planet

[†]University of California, Davis. msbrooks@ucdavis.edu.

[‡]Global Energy Alliance for People and Planet. faraz.usmani@energyalliance.org.

Appendix A Glutathione’s role in cellular adaptation to repeated pollution exposure

When air pollution enters the body through respiration, it brings with it a variety of harmful chemicals that the body must process in order to expel. The first step of this process, known as Phase I metabolism, involves converting the molecule into a more polar version of itself—often a reactive electrophile—which can result in it becoming more toxic. This is a preliminary step which is necessary for Phase II, in which the body makes the molecule more water soluble, and thus easier to excrete. Glutathione in the lungs (in both its substrate and enzyme form), performs this second step by attaching itself to the molecules produced from Phase I (a process known as conjugation), neutralizing the reactive electrophiles, thereby completing Phase II metabolism.

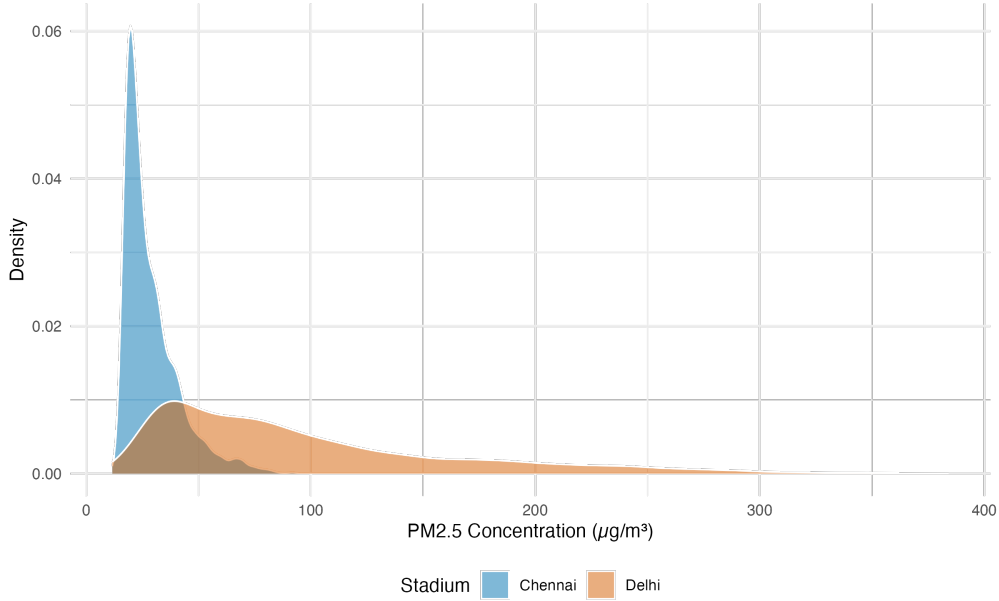
At low levels of pollution, there is enough glutathione present at baseline to neutralize the harmful effects of air pollution. As air pollution increases, however, the body becomes unable to produce glutathione at a sufficient rate to conjugate incoming electrophiles from air pollution. The rate limiting step in the chemical reaction for the body to produce glutathione is the enzyme γ -glutamylcysteine synthetase (γ -GCS), which itself must be produced by cells in the lungs. The key adaptation that the environmental toxicology literature has identified is that, when exposed to air pollution repeatedly, cells augment their ability to produce γ -GCS, enabling them to produce glutathione more quickly in response to incoming air pollution.

While the body does not become completely immune to air pollution at all levels, augmenting the ability to produce γ -GCS enables it to endure higher levels of air pollution than it would otherwise while suffering minimal damage from an acute episode of exposure. To visualize the effects of this adaptation response, Figure G1 shows magnified images of cells from the lungs of mice after a single day of air pollution exposure (panel B) and 7 days of exposure (panel C), relative to a control group of mice who were exposed to clean air during the same period (panel A). The key insight is that the mice who were exposed over 7 days have an intact cellular structure that is more similar to the control cells than to the ones that experienced only a single episode of exposure.

Appendix B Measuring past exposure to PM_{2.5}

Our approach to exploring heterogeneity in the short-run effect of pollution by exposure to pollution in the long-run builds on the person-based approach to measuring pollution exposure histories in environmental toxicology (Dodson et al., 2007; Garcia et al., 2013). In this approach, we assign a measure of accumulated pollution exposure to each person, taking into account their travel itinerary over a fixed window of time. Following the climate econometrics literature (Dell et al., 2014), we conceptualize each team’s home stadium as having its own pollution “climate,” where daily pollution levels are realizations from this distribution. When teams play a match at a stadium in a rival’s city, they experience a new pollution climate—daily pollution levels there are realizations from a different distribution rather than from the same one. This framework is consistent with the observed data indicating diverging average pollution levels across stadiums (Figure 3). For example, in Figure B1 we see that although there is a common support of the probability mass at low pollution levels,

Figure B1: Probability Density Functions of PM_{2.5} in Two Example Stadiums



Notes. This figure displays the probability density function (PDF) of PM_{2.5} concentration in two example stadiums with divergent distributions of PM_{2.5}.

the Delhi stadium regularly experiences pollution levels that the stadium in Chennai never experiences.

This approach, to our knowledge, is new to the economics literature and offers several advantages, along with a few challenges. The advantage of measuring person-specific adaptation is that we can track exposure to pollution for the same individual over time. This is a more precise way to measure pollution exposure than assuming, for example, that all individuals with an address in a district live and work in that district and therefore are exposed continuously to the pollution levels there. People move fairly regularly, especially lower-income migratory workers, who may work in one place during one season of the year and reside in another during other parts of the year. This movement may also occur within a day: for example, sleeping in a high-pollution exposed area but working in a low-exposure area, or vice versa.

The challenges of the person-based approach is developing a conceptually sound measure of long-term exposure to pollution. Typically, the long-term exposure level for a unit is considered to be fixed. However, in the IPL context, players may switch teams across seasons. Among players who played in more than one season in our sample, the mean number of times each player switched teams is 0.97,⁶⁰ with a maximum of 7. The traditional space-based approach to long-term exposure measures would suggest assigning a long-term PM_{2.5} level to a player based on the location of their home-stadium, but this is problematic when their home stadium changes across years. We therefore explore alternative definitions of long-term

⁶⁰The average number of team switches is over twice as high—2.04—when weighting players according to the number of deliveries in which they appear in our sample.

exposure, discuss the advantages and drawbacks of each, and make a recommendation for how to measure this consistently in similar settings.

Appendix C Alternative definitions of short-term past exposure to PM_{2.5}

We explore the following additional two types of measures:

1. Number of days in past T days where PM_{2.5} was above Z threshold
E.g. WHO thresholds i.e. $Z \in \{25, 37.5, 50, 75\}$

$$P_{J(j)d} = \sum_{\tau=1}^T \mathbf{1}(P_{J(j)\tau} > Z) \quad (\text{C.1})$$

2. Degree day analogous measure (number of units above Z threshold for each day above Z threshold in past T days)

$$P_{J(j)d} = \sum_{d=1}^T [\mathbf{1}(P_{J(j)\tau} > Z)](P_{j\tau} - Z) \quad (\text{C.2})$$

We note that the measures in Equations C.1, C.2 are piece-wise linear functions of the measure in Equation 2. We therefore expect them to yield somewhat similar results. However, each measure presumes a conceptually distinct hypothesis as to how past exposure to PM_{2.5} may affect the body. Use of the measure in Equation 2 would suggest that the mean level of exposure in the past, say, 30 days is meaningful. Measuring the mean, however, may obscure substantial variation in intensity of exposure over time. For example, in the hypothetical extreme case of someone who is exposed alternately to a day with perfectly clean air (i.e., 0 $\mu\text{g m}^{-3}$) and then a day with some of the most polluted air, say, 80 $\mu\text{g m}^{-3}$, the measure in Equation 2 would be 40 $\mu\text{g m}^{-3}$. This would be the same as that measure for someone who is exposed to days of exactly 40 $\mu\text{g m}^{-3}$ each day, even though the experience of being exposed to extreme pollution and then clean air alternately may be quite different than being exposed to moderate pollution consistently.

The measure in Equation C.1 corrects for this coarseness to some extent by counting how many “bad” days of pollution there were for a team in a given time window, where “bad” is a threshold that can be adjusted. The underlying idea is that there is a certain threshold beyond which exposure to PM_{2.5} is harmful and below which it is not. We use the thresholds that WHO sets ([World Health Organization, 2021](#)) for the Air Quality Guideline (25 $\mu\text{g m}^{-3}$, Interim Target 3 (37.5 $\mu\text{g m}^{-3}$), Interim Target 2 (50 $\mu\text{g m}^{-3}$) and Interim Target 1 (75 $\mu\text{g m}^{-3}$), and explore robustness of the measure to each threshold. Returning to the example above, using the threshold of 50 $\mu\text{g m}^{-3}$ would mean that the measure in Equation C.1 would be 15 in the alternating case and 0 in the consistent case.

The measure in Equation C.2 is a further refinement of that in Equation C.1—it quantifies not only whether a day has “bad” pollution, but also “how bad” it is; in other words, by how

much it exceeds a given threshold. This method is analogous to a cooling degree day in the climate literature. The underlying idea is that it matters not only whether $\text{PM}_{2.5}$ exceeds a threshold, but by how much it exceeds it. Several studies in the epidemiological literature have adopted a similar approach (Lin et al., 2018; Chen et al., 2020; Xiao et al., 2022) but, to our knowledge, such an approach to measurement has not yet been explored in the economics literature. Returning to the first example and using a threshold of $50 \mu\text{g m}^{-3}$, the team exposed to alternate 0 and $80 \mu\text{g m}^{-3}$ days for 30 days would be assigned $30 \times 15 = 450$ for this measure, while the team exposed to $40 \mu\text{g m}^{-3}$ consistently would be assigned 0. The advantage of Equation C.2 relative to Equation C.1 is that Equation C.2 makes it possible to distinguish between a scenario where on the “high” days in the alternating scenario the high is, say, $55 \mu\text{g m}^{-3}$ versus $80 \mu\text{g m}^{-3}$. The former measure would be the same in both cases (since the “high” day is above 50 in both cases) while the latter would reflect this variation.

In addition to these three measures (and the varying thresholds of Z), we also vary the time window in which we look at past exposure from 1 day prior to the match to 90 days prior to it. For the pollution exposure history for matches early in each season, we extend back only 30 days prior to the season start.⁶¹ This decision reflects the fact that teams tend to only start to train in their home stadiums several weeks before the season starts.

Table C1 demonstrates this pattern is robust across all three measurement approaches. The window yielding the largest differential between high- and low-past-exposure bowlers is 24 days for mean exposure (41% reduction in marginal effect), 32 days for days above $50 \mu\text{g m}^{-3}$ (54%), and 24 days for cumulative above $50 \mu\text{g m}^{-3}$ (40%). This convergence on a 24–32-day window—approximately one month—provides confidence we are capturing a real phenomenon rather than statistical artifact. Notably, the differential is twice as large (82%) when counting days above $75 \mu\text{g m}^{-3}$, suggesting these patterns are particularly pronounced at extreme pollution levels, consistent with medical evidence on antioxidant upregulation following severe exposures (Ketterer et al., 1983; Plopper et al., 2001; West et al., 2003).

⁶¹This means that any measure with a lookback window greater than 30 days uses a maximum of a 30 day lookback window for the matches that take place within 30 calendar days of the season start date. This causes some mechanical lowering of the count variables (in Equations C.1 and C.2) for matches early in the season, though we view this as a minor issue.

Table C1: Adaptation differentials across exposure measures and lookback windows

		Optimal window (days)	Differential at optimal window (%)
Panel A	Mean exposure (Eq. 2)		
	Mean over window	24	41.1
Panel B	Days above threshold (Eq. C.1)		
	Days above $37.5 \mu\text{g m}^{-3}$	81	68.6
	Days above $50 \mu\text{g m}^{-3}$	32	54.0
	Days above $75 \mu\text{g m}^{-3}$	24	81.5
Panel C	Degree-day analogue (Eq. C.2)		
	Cumulative above $25 \mu\text{g m}^{-3}$	24	40.5
	Cumulative above $37.5 \mu\text{g m}^{-3}$	24	42.7
	Cumulative above $50 \mu\text{g m}^{-3}$	24	40.3
	Cumulative above $75 \mu\text{g m}^{-3}$	24	44.3

Notes. This table reports the percent differential in the marginal effect of match-day $\text{PM}_{2.5}$ between bowlers at the 50th and 95th percentiles of past exposure, for three measures of recent $\text{PM}_{2.5}$ exposure. The differential is defined as $(ME_{p50} - ME_{p95})/ME_{p50}$, where ME_{pY} denotes the marginal effect of match-day $\text{PM}_{2.5}$ evaluated at the Y^{th} percentile of past exposure. Marginal effects are estimated from Equation 6. The three measures are (A) the mean over the lookback window, (B) the number of days above selected WHO thresholds, and (C) degree-day analogues defined relative to the same thresholds. For each measure, we vary the lookback window from 1 to 90 days. Column 1 reports the number of days in the lookback window that maximizes the differential; column 2 reports the percent differential using that window.

Appendix D Additional institutional details of cricket

The IPL was valued at over \$10 billion USD in 2022 (Times, 2022). Cricket players in the IPL are high-salaried workers, with the top performing players regularly earning in the range of \$1 to \$2 million USD in the span of a two-month season (MoneyBall, 2025). The productivity effects of air pollution on cricket players are thus economically important in their own right. In addition, studying the IPL offers an opportunity to learn about the effects of pollution on labor productivity in a high-wage setting, a departure from the empirical settings where many prior effects were estimated (e.g. factory work, agricultural labor).

In addition, the distinct physical demands across playing positions in Twenty20 cricket create variation in how air quality might affect different types of players. Fast bowlers face the most intense physiological requirements (Noakes and Durandt, 2000). During delivery, a bowler accelerates through their run-up reaching speeds of approximately 22 kilometers per hour, plants their front foot with ground reaction forces between 2.4 and 5.8 times their body weight, and decelerates rapidly after ball release (Bartlett, 2003). In Twenty20 cricket, fast bowlers perform approximately 23 sprints per hour of play, with significantly less recovery time between high-intensity efforts compared to other positions (Petersen et al., 2010). During

bowling spells, heart rates can reach 180–190 beats per minute, and in hot conditions, bowlers have recorded sweat rates up to 1.5 liters per hour, comparable to marathon runners (Noakes and Durandt, 2000).

For batters, the physical requirements combine intermittent high-intensity running with periods of technical performance (Noakes and Durandt, 2000), surrounded by periods of rest. In Twenty20 cricket, batters perform approximately 15 sprints per hour (Petersen et al., 2010). The activity pattern, however, is highly intermittent: mean heart rates during a day’s cricket rarely exceed 128 beats per minute for batters. Over a complete Twenty20 innings, batters cover approximately 3.5 kilometers in total distance—a relatively small amount considering that innings last about 1.5 hours. Only about 20 percent of this distance is covered in high-intensity running (Petersen et al., 2010). Unlike fast bowlers who run before delivering each ball, a batter’s main strenuous task is not running, but the technical demands of facing deliveries from bowlers that can exceed 140 kilometers per hour (Bartlett, 2003). These factors indicate that batters’ requirements are less physically demanding than bowlers’ requirements, suggesting that bowlers may be more affected by air pollution than are batters. The discrete nature of cricket’s bowler–batter interactions generates rich data on individual performance, enabling precise measurement of productivity effects.

Appendix E Mechanism: detecting bowler-specific impairment

Although we observe that run-concession increases with higher $PM_{2.5}$ concentrations and interpret this relationship as indicating harm for bowlers vs. batters, the run-concession outcome is jointly produced by bowlers and batters so we cannot completely attribute all harm to bowlers. To investigate this further, we look at bowler-specific outcomes that are realized before the batter is involved. These are two: (a) speed of the delivery and (b) location where the ball bounces on its delivery to the batter.⁶² We obtain these outcomes by linking our ball-by-ball sample to Hawk-Eye delivery tracking, available for 513 of the 773 matches in our sample (66% coverage) (Hawk-Eye, 2022). Tracking data are taken from the men’s IPL Hawk-Eye release, which records the release speed and the three-dimensional pitch and arrival coordinates of each delivery.

We re-estimate our main specifications in Table 2 with these outcomes in Tables H6 and H7 (Table H8 reports the same results as Table H7 but for the subset of fast/pace bowlers).

Surprisingly, delivery speed shows no response to pollution in our preferred specification (column 3).⁶³ Speed therefore does not appear to be the margin along which bowlers adjust their performance. Pitch length, by contrast, does respond (Tables H7–H8). In interpreting these results it is important to note that the negative coefficient indicates that deliveries land *closer* to the batter. While this does not indicate unambiguously negative performance for the bowler, it does indicate a systematically different type of delivery that is associated with higher $PM_{2.5}$ concentrations. It could be part of the mechanism explaining why run-concession

⁶²In cricket, unlike baseball, the ball bounces once before arriving at the batter.

⁶³We also estimate this specification for the subset of pace/fast bowlers but the results are similar (no statistically significant effect). Results available upon request.

increases as $\text{PM}_{2.5}$ rises.

Appendix F Additional robustness checks

F.1 Robustness: incorporating variation in number of runs scored

In our main specifications, we define the outcome as a binary indicator for whether a bowler conceded a run. This definition abstracts away from variation in the number of runs scored, conditional on scoring any run. As a robustness check, we also estimate an ordered logit model which treats each number of runs scored as a discrete category with a higher number indicating poor performance for the bowler and bowling team:

$$\log \left(\frac{P(R_{ij\ell t} \leq r)}{P(R_{ij\ell t} > r)} \right) = \beta P_{\ell d} + \mathbf{X}'_{\ell d} \gamma + \psi_j + \phi_i + \delta_{\ell y} + \theta_{n(t)} + \eta_{o(t)} + \Lambda_i + \Delta_j + \varepsilon_{ij\ell t} \quad (\text{F.1})$$

where $R_{ij\ell t}$ is the number of runs scored ($R_{ij\ell t} \in \{0, 1, 2, 3, 4, 5, 6\}$). The results estimating Equation F.1 are reported in Table H11 and are qualitatively similar to those estimating analogous regressions in Tables 2 and 3.

F.2 Robustness: weather interactions

Our identification relies on match-day pollution being as-good-as-randomly assigned with respect to performance potential. The IPL’s scheduling rules—matches scheduled months in advance based on stadium availability and broadcast considerations—strongly support this assumption. However, we address potential confounding from weather conditions that both influence $\text{PM}_{2.5}$ and directly affect performance.

We implement Post-Double Selection (PDS) Lasso (Belloni et al., 2014) with $\text{PM}_{2.5}$ as the treatment variable, regressing run-scoring on 29 potential controls: home stadium dummies, linear and quadratic weather terms, and pairwise weather interactions. The procedure selects no controls as outcome predictors but identifies three $\text{PM}_{2.5}$ predictors: atmospheric pressure and temperature-humidity and humidity-wind interactions. The final regression yields a coefficient of 0.31 percentage points ($p < 0.05$), similar in magnitude to our baseline result of 0.41 percentage points, confirming our results are not driven by complex weather patterns.

As a benchmark, we repeat this procedure with temperature as the treatment variable. We cannot reject the null hypothesis that temperature’s coefficient (-0.06 percentage points, $p = 0.595$) is zero, even though matches occur in warm conditions (71–99 °F, mean 85 °F) where heat stress might substantially impair performance.

F.3 Robustness: alternative measures of long-term past exposure to $\text{PM}_{2.5}$

Table H2 presents six additional alternative definitions of long-term $\text{PM}_{2.5}$. Our preferred definition for long-term exposure to $\text{PM}_{2.5}$ is the mean exposure to $\text{PM}_{2.5}$ across all IPL matches (in all seasons) for a given bowler. This is reported in the first row and has as many

distinct values as there are bowlers. The advantage of this measure is that it is bowler-specific, reflecting the fact that the bowler is the unit of observation that could potentially adapt over time. The downside of this measure is that it incorporates future data on $\text{PM}_{2.5}$ exposure into past matches. We find that pollution levels are serially correlated within bowler, which supports the use of this metric.

In the second row, we calculate a similar measure, but instead of taking the mean across all matches in the IPL (2008-2022) we split the panel in two (2008-2014 and 2015-2022) and take the mean exposure to $\text{PM}_{2.5}$ across matches in the first half of the panel. Since there are fewer distinct players in the first half of the IPL, the number of distinct values is substantially smaller. This measure addresses the temporal problem of the first measure since we can restrict estimating to the second half of the panel, using the first half as a baseline. A major drawback in doing so, however, is loss of statistical power from loss of sample size.

The remaining four rows of the table report means of $\text{PM}_{2.5}$ in the location of the home-stadium for a given IPL team. There are 13 teams that have been in the IPL, so there are 13 distinct values.⁶⁴ In row 3, we calculate this mean over the 10 years prior to the IPL (1998-2007) to get a baseline exposure level. In row 4, we calculate the mean over the period of the IPL (2008-2022). In the next two alternative definitions, we account for the fact that IPL matches occur only in three months of the year—March, April, and May—and construct measures analogous to those in rows 3 and 4. These measures all assign long-term pollution to a bowler on the basis of the team they play on, but since they can switch teams between seasons, these measures are not bowler-specific, but bowler-team specific. We include all alternative definitions of long-term exposure as robustness checks.

We report estimates of Equation 8 in Table H3 for the long-term definitions of $\text{PM}_{2.5}$ in rows 1 and 2 of Table H2. For the definitions in rows 3-6, we alter the specification to include bowling team-by-year fixed effects instead of bowler fixed effects, since the assignment of long-term $\text{PM}_{2.5}$ to each bowler changes depending on what team they are on in each year.⁶⁵ We estimate the slightly modified specification:

$$R_{ij\ell t} = \beta_1 P_{\ell d} + \beta_2 P_{\ell d} \times \bar{P}_{J(j,y)} + \mathbf{X}'_{\ell d} \gamma + \psi_{yJ(j,y)} + \phi_i + \delta_{\ell y} + \theta_{n(t)} + \eta_{o(t)} + \varepsilon_{ij\ell t} \quad (\text{F.2})$$

where $\psi_{J(j,y)}$ represent bowling team-by-year fixed effects. Note that $J(j,y)$ is a function that maps bowler j in year y to team J .

⁶⁴There are 10 teams in the IPL currently, but some have come and gone, leading to 13 distinct teams over the 2008-2022 period.

⁶⁵Note that we include both bowling team-by-year fixed effects and stadium-by-year fixed effects since these represent two different things: the stadium is the stadium at which the match is played (which may or may not be a home stadium for either team), while the bowling team-by-year fixed effects control for the team's home stadium.

F.4 Robustness: alternative specification for non-linearity in the heterogeneous effect of contemporaneous PM_{2.5} by past PM_{2.5} exposure

While Equation 7 treats past exposure to PM_{2.5} as continuous and bins current PM_{2.5} exposure, Equation F.3 takes the opposite approach. In Equation F.3, we dichotomize past exposure based on whether it exceeds match-day exposure and treat present exposure as continuous.

$$\begin{aligned} R_{ij\ell t} = & \beta_0 + \beta_1 P_{\ell d} + \beta_2 \mathbf{1}(\bar{P}_{J(j)d} > P_{\ell d}) \\ & + \beta_3 (P_{\ell d} \times \mathbf{1}(\bar{P}_{J(j)d} > P_{\ell d})) \\ & + \mathbf{X}'_{\ell d} \gamma + \psi_j + \phi_i + \delta_{\ell y} + \theta_{n(t)} + \eta_{o(t)} + \Lambda_i + \Delta_j + \varepsilon_{ij\ell t} \end{aligned} \quad (\text{F.3})$$

In Equation F.4, we include a dummy for highest-quintile current exposure ($Q5_{\ell d}$) and estimate the triple interaction of this dummy with the dummy for high past exposure and the continuous measure of current exposure. This approach allows us to isolate how having higher prior exposure than on match-day mediates the effect of current exposure *when pollution is especially high*. The triple interaction—top quintile $\times$ past-exceeds-present $\times$ match-day PM_{2.5}—is negative and highly significant (-0.029 , $p < 0.01$). This result isolates the conditions under which adaptation is most pronounced: when contemporaneous PM_{2.5} is in the top quintile and the bowler’s recent exposure history exceeds current conditions. In other words, adaptation manifests most clearly when bowlers face extreme pollution that is nonetheless lower than what they have recently experienced.

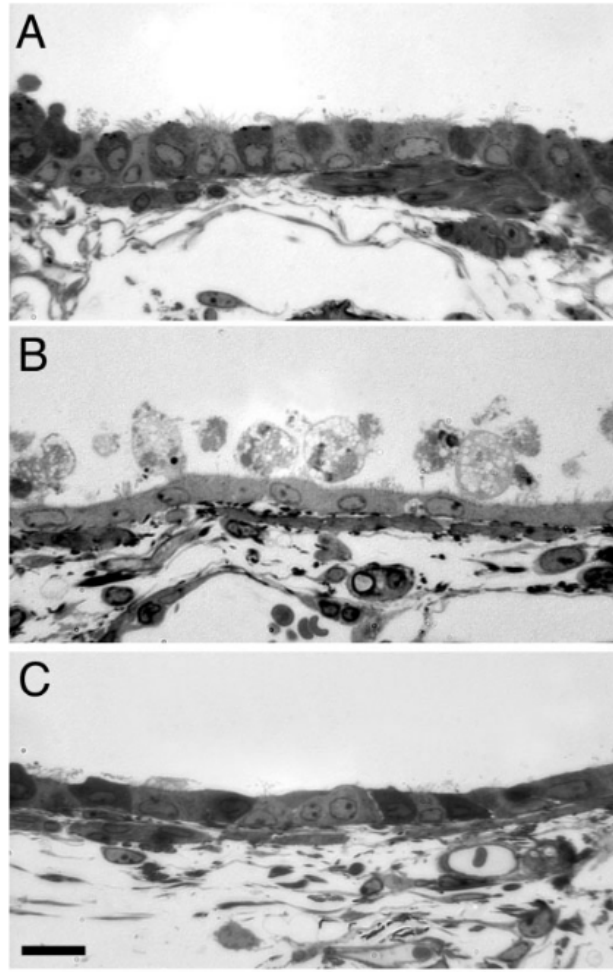
$$\begin{aligned} R_{ij\ell t} = & \beta_0 + \beta_1 P_{\ell d} + \beta_2 Q5_{\ell d} + \beta_3 \mathbf{1}(\bar{P}_{J(j)d} > P_{\ell d}) \\ & + \beta_4 (P_{\ell d} \times Q5_{\ell d}) + \beta_5 (P_{\ell d} \times \mathbf{1}(\bar{P}_{J(j)d} > P_{\ell d})) \\ & + \beta_6 (Q5_{\ell d} \times \mathbf{1}(\bar{P}_{J(j)d} > P_{\ell d})) \\ & + \beta_7 (P_{\ell d} \times Q5_{\ell d} \times \mathbf{1}(\bar{P}_{J(j)d} > P_{\ell d})) \\ & + \mathbf{X}'_{\ell d} \gamma + \psi_j + \phi_i + \delta_{\ell y} + \theta_{n(t)} + \eta_{o(t)} + \Lambda_i + \Delta_j + \varepsilon_{ij\ell t} \end{aligned} \quad (\text{F.4})$$

The basic intuition behind this approach is that it allows us to characterize the dose-response between a continuous measure of contemporaneous pollution exposure and performance, while leaving open the possibility the dose-response may be different along two dimensions: (i) when past exposure is high and (ii) when contemporaneous exposure is high, or both. We estimate these equations for both the short-term (past 30-day) and long-term (career average) measures of past pollution exposure defined in Sections 4.3.1 and 4.3.2.

Results from the specifications in Equations F.3 and F.4 are reported in columns 1 and 2, respectively, of Table H12 (H13) for short-term (long-term) adaptation to PM_{2.5} exposure.

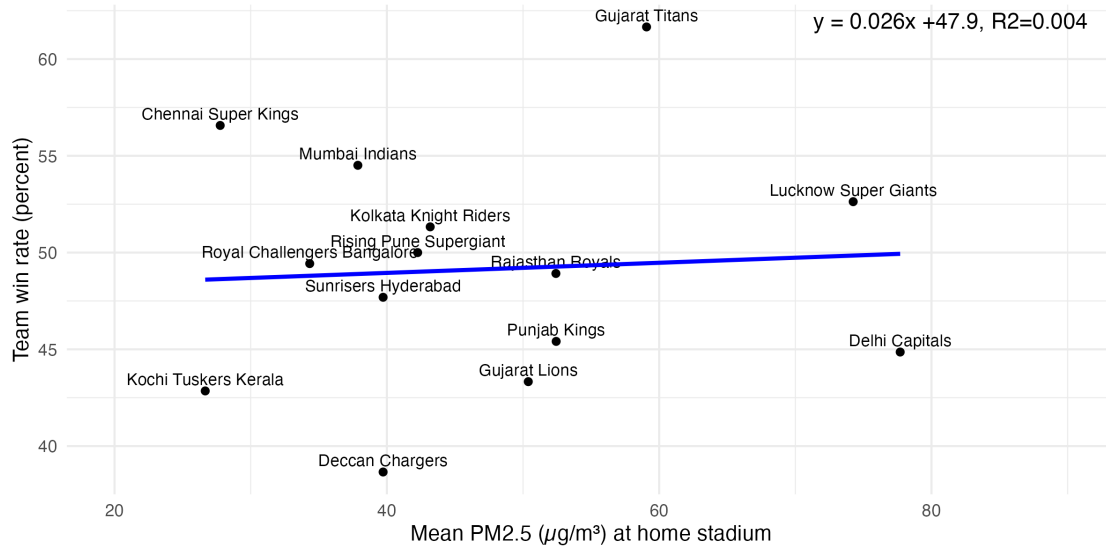
Appendix G Additional figures

Figure G1: Cellular adaptation to repeated exposure to air pollution



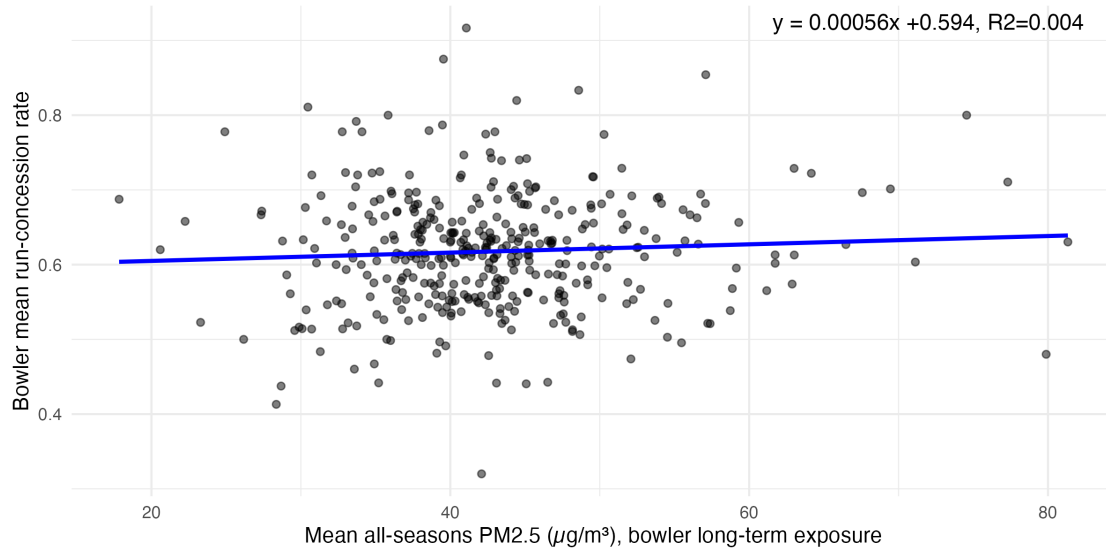
Notes. This figure, reproduced from [West et al. \(2003\)](#), displays three panels of microscopic images of cells in the lungs of mice. Panel A shows cells from mice that were in the control group and breathed clean air throughout the experiment. Panel B shows cells from mice from the treatment group that was exposed to polluted air for one day, and had their cells imaged 24 hours after. Panel C shows cells from mice that were exposed to the same level of air pollution as those in Panel B, except they were exposed for 7 days instead of 1. As for the cells in Panel B, their cells are imaged 24 hours after their last exposure.

Figure G2: Team quality is not correlated with long-term PM_{2.5} exposure



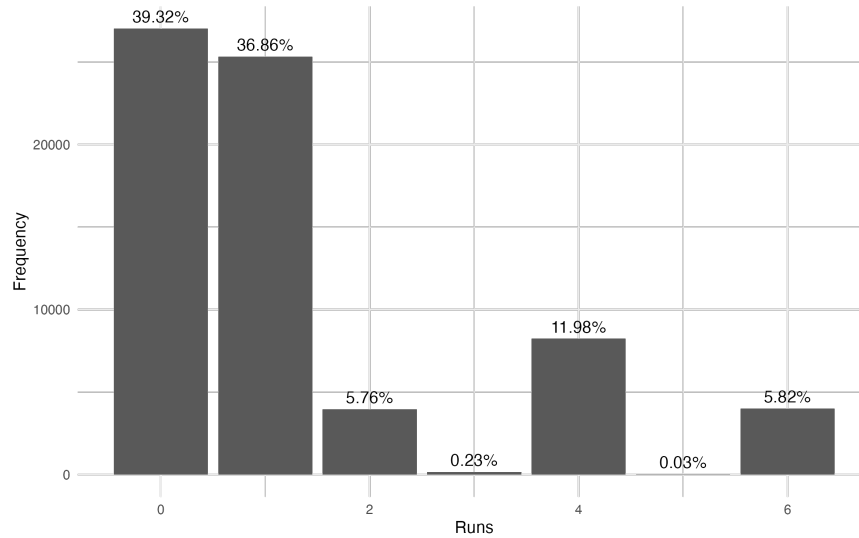
Notes. This figure shows the win rate (number of matches won out of all matches played) for IPL teams as plotted against the average PM_{2.5} at the team's home stadium. Average PM_{2.5} is defined as the mean level of PM_{2.5} at the team's home stadium during March, April, and May (the months when IPL matches typically occur) for the study period, 2008-2022. The lack of significant relationship between win rate and PM_{2.5} is robust to alternative definitions of long-term PM_{2.5}, such as including non-IPL months, or including PM_{2.5} levels before the IPL franchise began. Note that the Pune Warriors, who played only 2011-2013 and had the lowest win-rate (26.7%, more than 2 standard deviations below the mean) are excluded from this graph. The lack of significant relationship also holds when including them.

Figure G3: Bowler quality is not correlated with long-term PM_{2.5} exposure



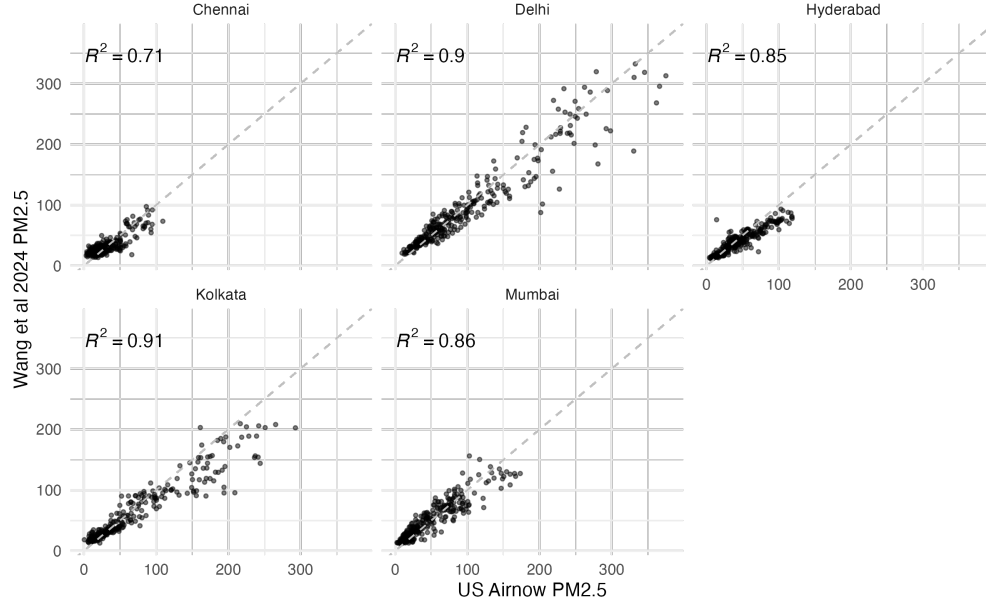
Notes. This figure shows the run-concession rate (number of deliveries that result in a run divided by the total number deliveries) for bowlers as plotted against the average PM_{2.5} the bowler is exposed to across all matches in the IPL (i.e., career PM_{2.5} in Equation 8). Bowlers who deliver fewer than 24 deliveries (the theoretical maximum for one match) are excluded from this plot; this results in excluding 56 bowlers. The non-significant relationship holds when including these bowlers.

Figure G4: Histogram of Runs



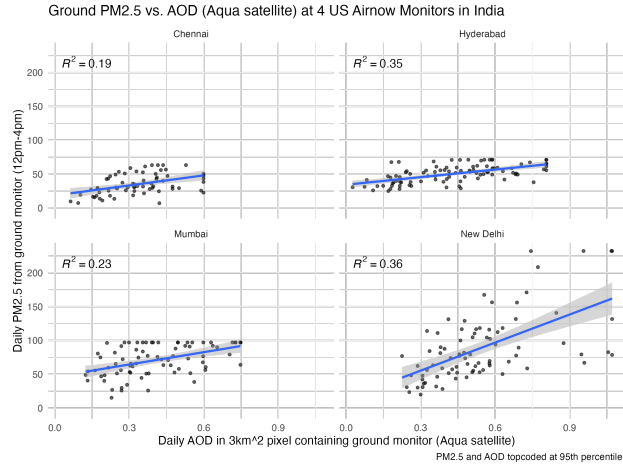
Notes. This figure shows the distribution of the outcome variable (runs scored) in our analysis.

Figure G5: U.S. Airnow vs. Wang et al. (2024) Daily PM_{2.5}



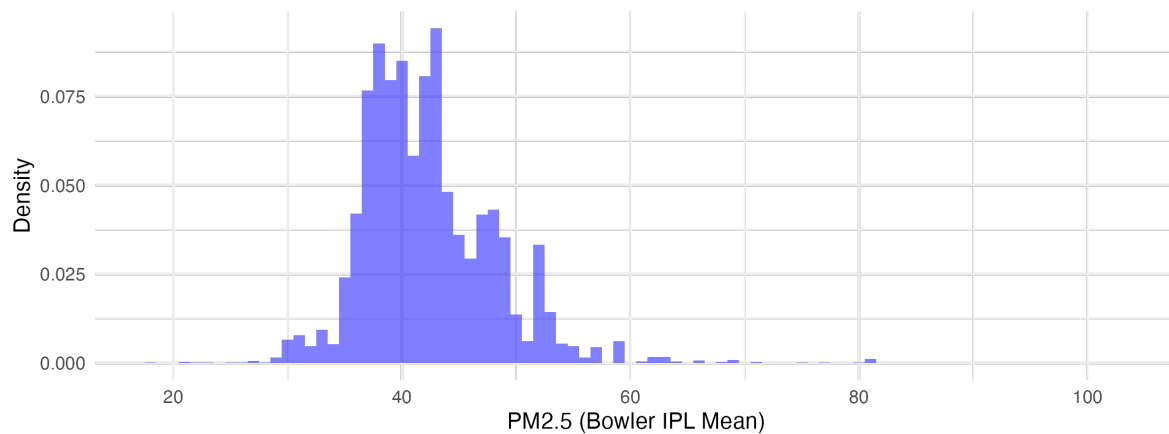
Notes. This figure displays the correlation between Wang et al. (2024) estimates of PM_{2.5} and ground observations of PM_{2.5} at five cities with a U.S. AirNow ground monitor, a network of high-quality monitors that are calibrated to EPA standards. Each dot represents a daily mean value of PM_{2.5}. The 45 degree line is shown for reference. Values of Wang et al. (2024) PM_{2.5} are taken from the 10km × 10km grid cell containing the latitude and longitude coordinates of the U.S. AirNow ground monitor. Importantly, the U.S. AirNow network is not included as training data for the Wang et al. (2024) model.

Figure G6: U.S. Airnow vs. MODIS AOD



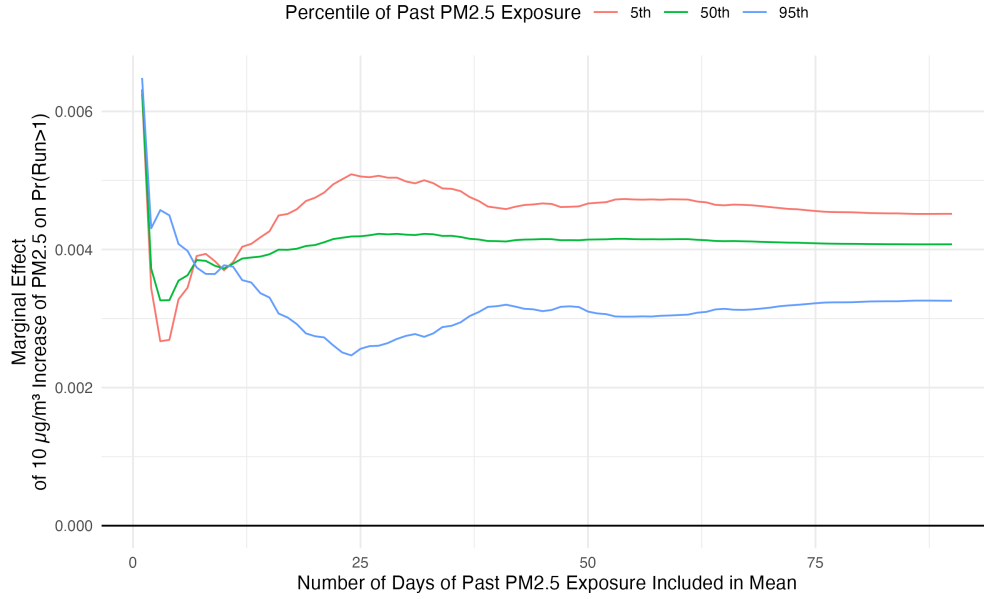
Notes. This figure displays the correlation between Aerosol Optical Depth from the MODIS Aqua satellite (which passes over India approximately once per day in the afternoon) with ground observations of PM_{2.5} at five cities with a U.S. AirNow ground monitor. Each dot represents a daily mean value of PM_{2.5}. AOD is calculated as the mean AOD in the 3km x 3km pixel containing the ground monitor. Both PM_{2.5} and AOD are topcoded at the 95th percentile.

Figure G7: Histogram of Bowler Career $PM_{2.5}$ Mean in IPL matches 2008-2022



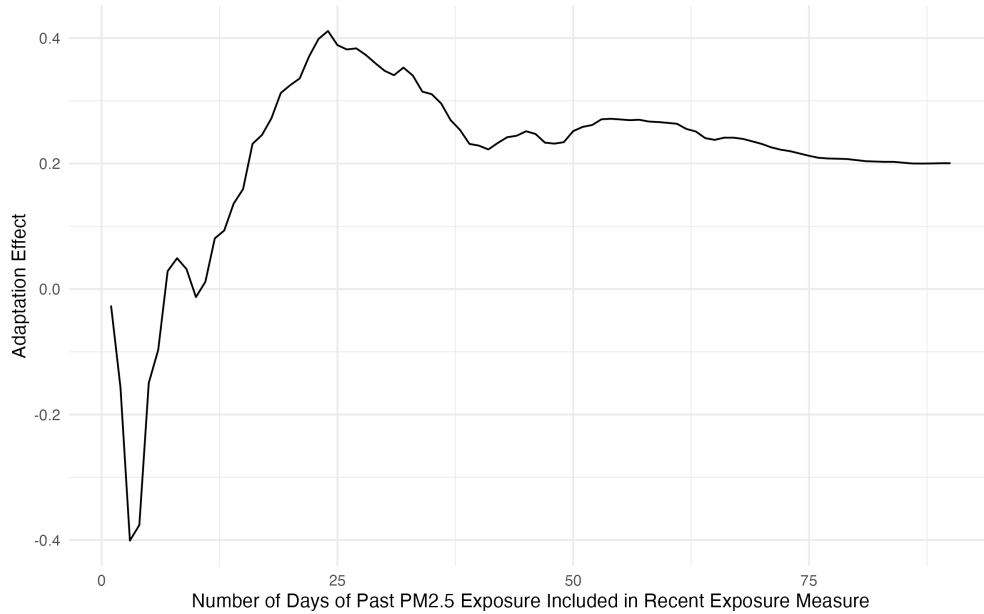
Notes. This figure displays the distribution of bowler mean $PM_{2.5}$ defined as the mean $PM_{2.5}$ exposure across all matches for a given bowler in the IPL 2008-2022 (i.e. $PM_{2.5j0}$ in Equation 8).

Figure G8: Marginal Effect of PM_{2.5} on Run Probability for Varying Exposure Windows



Notes. Figure shows the marginal effect (with 95% confidence intervals) of a 10 $\mu\text{g m}^{-3}$ increase in match-day PM_{2.5} for bowlers at the 5th, 50th, and 95th percentiles of past exposure. Marginal effects are estimated from Equation 6.

Figure G9: Magnitude of Adaptation Effect for Varying Exposure Windows



Notes. Figure displays the adaptation effect, defined as $\frac{ME_{p50} - ME_{p95}}{ME_{p50}}$ where ME_{pY} are marginal effects of PM_{2.5} on run-scoring for the Y^{th} percentiles of mean past exposure to PM_{2.5}. Marginal effects are estimated from Equation 6.

Appendix H Additional tables

Table H1: PM2.5 and Weather Correlation Matrix

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

Notes: Run is a binary indicator equal to 1 if at least one run is scored on a delivery and 0 otherwise. Correlations computed from delivery-level data. PM2.5 and weather variables are measured at the match-level.

Table H2: Summary Statistics of Long-run PM2.5 Variables

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

^a All IPL. ^b IPL 2008-2014. ^c 1998-2007. ^d 2008-2022. ^e 2008-2022, IPL months. ^f 1998-2007, IPL months.

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

Table H3: Robustness of Long-term PM2.5 Measures

	(1)	(2)	(3)	(4)	(5)	(6)
		1 (At least one run scored)				
Match PM2.5	0.0052 (0.0060)	0.0067** (0.0030)	0.0062** (0.0025)	0.0067** (0.0028)	0.0058** (0.0024)	0.0071*** (0.0027)
PM2.5 X Bowler PM2.5 (IPL Seasons 2008-2014)	-0.0012 (0.0013)					
PM2.5 X Bowler Team Stadium PM2.5 (Preseason)		-0.00043 (0.00046)				
PM2.5 X Bowler Team Stadium PM2.5 (1998-2007)			-0.000038 (0.000038)			
PM2.5 X Bowler Team Stadium PM2.5 (1998-2007, IPL Months)				-0.000049 (0.000046)		
PM2.5 X Bowler Team Stadium PM2.5 (2008-2022)					-0.000026 (0.000032)	
PM2.5 X Bowler Team Stadium PM2.5 (2008-2022, IPL Months)						-0.000063 (0.000048)
Weather controls	✓	✓	✓	✓	✓	✓
Bowler FE	✓					
Bowling Team-by-year FE		✓	✓	✓	✓	✓
Striker FE	✓	✓	✓	✓	✓	✓
Stadium-by-year FE	✓	✓	✓	✓	✓	✓
Over FE	✓	✓	✓	✓	✓	✓
Innings FE	✓	✓	✓	✓	✓	✓
<i>N</i>	53,607	183,558	183,558	183,558	183,558	183,558
<i>R</i> ²	0.055	0.047	0.047	0.047	0.047	0.047

Notes. The outcome variable is a binary indicator equal to 1 if at least one run is scored on a delivery and 0 otherwise. Standard errors are clustered two-way at the match and bowler level. Column (1) restricts the sample to bowlers who appear in both the first and second half of the panel (first half: 2008-2014, second half: 2015-2022) and analyzing their performance in the second half using their mean PM2.5 exposure during IPL games in the first half. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table H4: PM2.5 exposure and run-scoring probability: alternate specification with bowler-batter pair fixed effects

	(1) 1 (At least one run scored)	(2)
Match-day PM2.5	0.0042* (0.0022)	
Q2 (Match-day PM2.5)		0.012* (0.0064)
Q3 (Match-day PM2.5)		0.0077 (0.0080)
Q4 (Match-day PM2.5)		0.022** (0.010)
Q5 (Match-day PM2.5)		0.035*** (0.012)
Weather controls	✓	✓
Home stadium FE	✓	✓
Bowler-batter pair FE	✓	✓
Stadium-by-year FE	✓	✓
Innings FE	✓	✓
Over FE	✓	✓
<i>N</i>	181,556	181,556
<i>R</i> ²	0.15	0.15

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). PM2.5 is measured in $10 \mu g/m^3$. Quantiles 1 through 5 of PM2.5 are separated at 27, 34, 41, and $53 \mu g/m^3$, respectively. Columns (1) presents results from regressions of this run indicator on match-day PM2.5 levels. Columns (2) present results from regressions using PM2.5 quintile indicators, where the lowest quintile (Q1) is the omitted category. Both columns include fixed effects for bowler-batter pairs, stadium-by-year, home stadium, innings, and over. They also include controls for weather conditions including temperature, temperature squared, relative humidity, precipitation, solar radiation, and wind speed. 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 H5: PM2.5 exposure and run-scoring probability (restricted to observations with ground PM2.5 monitors)

	(1)	(2)	(3)	(4)	(5)	(6)
	$\mathbb{1}$ (At least one run scored)					
Match-day PM2.5	0.0030*** (0.00090)	0.0021 (0.0015)	0.0020 (0.0014)			
Q2 (Match-day PM2.5)				-0.00089 (0.012)	-0.0040 (0.012)	0.00016 (0.010)
Q3 (Match-day PM2.5)				0.00043 (0.012)	-0.0067 (0.012)	-0.0050 (0.010)
Q4 (Match-day PM2.5)				0.0033 (0.014)	-0.0088 (0.017)	-0.0080 (0.013)
Q5 (Match-day PM2.5)				0.024* (0.013)	0.0067 (0.020)	0.0030 (0.016)
Weather controls		✓	✓		✓	✓
Bowler FE			✓			✓
Batter FE			✓			✓
Stadium-by-year FE			✓			✓
Home stadium FE			✓			✓
Innings FE			✓			✓
Over FE			✓			✓
N	50,355	50,355	50,342	50,355	50,355	50,342
R^2	0.00043	0.00067	0.054	0.00037	0.00067	0.054

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). PM2.5, measured in $10 \mu g/m^3$, are 24-hour averages reported from the US AirNow air quality monitoring network at 5 U.S. consulates in Chennai, Kolkata, New Delhi (the embassy), Mumbai, and Hyderabad. Distances between the ground monitor at the consulate and the cricket stadium in each of these 5 respective cities ranges from 1.63 to 23.4 km with a mean of 10.9 km (median 11.0 km). Quantiles 1 through 5 of PM2.5 (as measured at ground monitors) are separated at 24, 33, 43, and $62 \mu g/m^3$, respectively. Columns (1–3) present results from regressions of this run indicator on match-day PM2.5 levels (measured in $10 \mu g/m^3$). Columns (4–6) present results from regressions using PM2.5 quintile indicators, where the lowest quintile (Q1) is the omitted category. Columns (3) and (6) include fixed effects for individual batters, bowlers, stadium-by-year, home stadium, innings, and over. Columns (2), (3), (5) and (6) include controls for weather conditions including temperature, temperature squared, relative humidity, precipitation, solar radiation, and wind speed. Following [Correia \(2015\)](#), 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 H6: PM2.5 exposure and delivery speed (all bowlers)

	(1)	(2)	(3)	(4)	(5)	(6)
	Delivery speed (km/h)					
Match-day PM2.5	0.29 (0.26)	0.45* (0.27)	0.020 (0.048)			
Q2 (Match-day PM2.5)				1.39 (1.01)	0.81 (0.98)	-0.10 (0.19)
Q3 (Match-day PM2.5)				1.25 (0.98)	0.77 (0.93)	-0.22 (0.21)
Q4 (Match-day PM2.5)				1.79* (1.03)	1.87* (1.07)	-0.094 (0.24)
Q5 (Match-day PM2.5)				1.83 (1.65)	2.42 (1.75)	-0.21 (0.26)
Weather controls		✓	✓		✓	✓
Bowler FE			✓			✓
Batter FE			✓			✓
Stadium-by-year FE			✓			✓
Home stadium FE			✓			✓
Innings FE			✓			✓
Over FE			✓			✓
<i>N</i>	113,975	113,975	113,965	113,975	113,975	113,965
<i>R</i> ²	0.00077	0.0036	0.88	0.00095	0.0034	0.88

Notes. The outcome is the measured delivery speed in kilometres per hour (mean 116.2). PM2.5 is measured in $10 \mu\text{g}/\text{m}^3$. Quintiles 1 through 5 of match-day PM2.5 are separated at 27, 34, 41, and $53 \mu\text{g}/\text{m}^3$, respectively. Columns (1)–(3) regress delivery speed on linear match-day PM2.5; columns (4)–(6) use PM2.5 quintile indicators, with the lowest quintile (Q1) omitted. Columns (3) and (6) include fixed effects for individual batters, bowlers, stadium-by-year, home stadium, innings, and over, plus controls for weather (temperature, temperature squared, relative humidity, precipitation, solar radiation, and wind speed); columns (2) and (5) include the weather controls only. Following [Correia \(2015\)](#), singleton observations are dropped in columns (3) and (6). The sample comprises deliveries from Hawk-Eye-matched matches with a valid measured ball speed. Standard errors (in parentheses) are two-way clustered at the match and bowler levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table H7: PM2.5 exposure and pitch length (all bowlers)

	(1)	(2)	(3)	(4)	(5)	(6)
	Pitch length (m, larger = shorter)					
Match-day PM2.5	0.023 (0.014)	-0.0052 (0.016)	-0.019 (0.012)			
Q2 (Match-day PM2.5)				0.066 (0.066)	0.011 (0.065)	-0.083* (0.046)
Q3 (Match-day PM2.5)				0.094 (0.067)	-0.018 (0.066)	-0.14*** (0.048)
Q4 (Match-day PM2.5)				0.17** (0.071)	-0.0084 (0.077)	-0.16*** (0.058)
Q5 (Match-day PM2.5)				0.15 (0.091)	-0.052 (0.11)	-0.21*** (0.067)
Weather controls		✓	✓		✓	✓
Bowler FE			✓			✓
Batter FE			✓			✓
Stadium-by-year FE			✓			✓
Home stadium FE			✓			✓
Innings FE			✓			✓
Over FE			✓			✓
N	116,414	116,414	116,403	116,414	116,414	116,403
R^2	0.00029	0.0011	0.20	0.00048	0.0011	0.20

Notes. The outcome is the delivery's pitch length in metres, measured as distance from the batter's stumps so that larger values are shorter and a negative coefficient indicates fuller deliveries (mean 6.36). PM2.5 is measured in $10 \mu g/m^3$. Quintiles 1 through 5 of match-day PM2.5 are separated at 27, 34, 41, and 53 $\mu g/m^3$, respectively. Columns (1)–(3) regress pitch length on linear match-day PM2.5; columns (4)–(6) use PM2.5 quintile indicators, with the lowest quintile (Q1) omitted. Columns (3) and (6) include fixed effects for individual batters, bowlers, stadium-by-year, home stadium, innings, and over, plus controls for weather (temperature, temperature squared, relative humidity, precipitation, solar radiation, and wind speed); columns (2) and (5) include the weather controls only. Following [Correia \(2015\)](#), singleton observations are dropped in columns (3) and (6). The sample comprises deliveries from Hawk-Eye-matched matches with a physically valid tracked landing point. Standard errors (in parentheses) are two-way clustered at the match and bowler levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table H8: PM2.5 exposure and pitch length (pace bowlers)

	(1)	(2)	(3)	(4)	(5)	(6)
	Pitch length (m, larger = shorter)					
Match-day PM2.5	0.018 (0.013)	0.0028 (0.018)	-0.032** (0.015)			
Q2 (Match-day PM2.5)				0.065 (0.071)	0.042 (0.073)	-0.078 (0.064)
Q3 (Match-day PM2.5)				0.036 (0.080)	-0.013 (0.081)	-0.19*** (0.068)
Q4 (Match-day PM2.5)				0.097 (0.077)	0.010 (0.086)	-0.19** (0.077)
Q5 (Match-day PM2.5)				0.13 (0.084)	0.018 (0.11)	-0.28*** (0.082)
Weather controls		✓	✓		✓	✓
Bowler FE			✓			✓
Batter FE			✓			✓
Stadium-by-year FE			✓			✓
Home stadium FE			✓			✓
Innings FE			✓			✓
Over FE			✓			✓
<i>N</i>	80,926	80,926	80,913	80,926	80,926	80,913
<i>R</i> ²	0.00015	0.00058	0.15	0.00022	0.00062	0.15

Notes. The outcome is the delivery's pitch length in metres, measured as distance from the batter's stumps so that larger values are shorter and a negative coefficient indicates fuller deliveries (mean 6.88); the sample is restricted to pace bowlers (fast and medium seam). PM2.5 is measured in $10 \mu g/m^3$. Quintiles 1 through 5 of match-day PM2.5 are separated at 27, 34, 41, and 53 $\mu g/m^3$, respectively. Columns (1)–(3) regress pitch length on linear match-day PM2.5; columns (4)–(6) use PM2.5 quintile indicators, with the lowest quintile (Q1) omitted. Columns (3) and (6) include fixed effects for individual batters, bowlers, stadium-by-year, home stadium, innings, and over, plus controls for weather (temperature, temperature squared, relative humidity, precipitation, solar radiation, and wind speed); columns (2) and (5) include the weather controls only. Following [Correia \(2015\)](#), singleton observations are dropped in columns (3) and (6). The sample comprises pace-bowler deliveries from Hawk-Eye-matched matches with a physically valid tracked landing point. Standard errors (in parentheses) are two-way clustered at the match and bowler levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table H9: Fast bowlers: PM2.5 exposure and run-scoring probability

	(1) 1 (At least one run scored)
Match-day PM2.5	0.0038* (0.0020)
Match-day PM2.5 X Fast bowler	0.00017 (0.0014)
Weather controls	✓
Home stadium FE	✓
Bowler FE	✓
Batter FE	✓
Stadium-by-year FE	✓
Home stadium FE	✓
Innings FE	✓
Over FE	✓
N	178,452
R^2	0.052

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). PM2.5 is measured in $10 \mu g/m^3$. Fast is a dummy variable equal to 1 if the bowler is a fast bowler; 0 if otherwise. 61.6% of bowlers are fast bowlers. The categorization is unobserved for 12 bowlers; 5,103 observations associated with these bowlers are dropped. Columns (1) presents results from a regression of this run indicator on match-day PM2.5 levels (measured in $10 \mu g/m^3$). It includes fixed effects for individual batters, bowlers, stadium-by-year, home stadium, innings, and over. It includes controls for weather conditions including temperature, temperature squared, relative humidity, precipitation, solar radiation, and wind speed. Following [Correia \(2015\)](#), 17 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 H10: South Asian bowlers: PM2.5 exposure and run-scoring probability

	(1) 1 (At least one run scored)
Match-day PM2.5	0.0046** (0.0018)
Match-day PM2.5 X South Asian bowler	-0.00097 (0.0012)
Weather controls	✓
Home stadium FE	✓
Bowler FE	✓
Batter FE	✓
Stadium-by-year FE	✓
Home stadium FE	✓
Innings FE	✓
Over FE	✓
N	178,459
R^2	0.052

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). PM2.5 is measured in $10 \mu g/m^3$. South Asian bowler is a dummy variable equal to 1 if the bowler plays on a national cricket team in a South Asian country; 0 if otherwise. 60.45% of bowlers are South Asian by this categorization. The categorization is unobserved for 11 bowlers; 5,096 observations associated with these bowlers are dropped. Columns (1) presents results from a regression of this run indicator on match-day PM2.5 levels (measured in $10 \mu g/m^3$). It includes fixed effects for individual batters, bowlers, stadium-by-year, home stadium, innings, and over. It includes controls for weather conditions including temperature, temperature squared, relative humidity, precipitation, solar radiation, and wind speed. Following [Correia \(2015\)](#), 17 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 H11: Adaptation to PM_{2.5} Exposure (Ordered Logit)

	(1)	(2)	(3)
	Number of runs scored		
Match-day PM _{2.5}	0.0017** (0.00082)	0.0027 (0.0018)	0.0059** (0.0023)
Past 30-day PM _{2.5}		0.0025 (0.0017)	
Match-day PM _{2.5} X Past 30-day PM _{2.5}		-0.000023 (0.000032)	
Match-day PM _{2.5} X Career PM _{2.5}			-0.000094** (0.000046)
Weather controls	✓	✓	✓
Bowler FE	✓	✓	✓
Batter FE	✓	✓	✓
Stadium-by-year FE	✓	✓	✓
Home stadium FE	✓	✓	✓
Innings FE	✓	✓	✓
Over FE	✓	✓	✓
<i>N</i>	183,572	183,572	183,572

Notes. The outcome variable is the number of runs scored (0 to 6). Regressions are estimated using ordered logit as in Equation F.1. Past 30-day PM_{2.5} is the bowler's mean PM_{2.5} exposure over the preceding 30 days. Career PM_{2.5} is defined as the mean PM_{2.5} in all of a bowler's games in the IPL. Standard errors (in parentheses) are two-way clustered at the match and bowler levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table H12: Short-term adaptation to PM2.5 exposure when match-day PM2.5 is high

	(1) 1 (At least one run scored)	(2)
Match PM2.5	0.0036** (0.0018)	-0.0077 (0.0066)
1 (Past 30-day PM2.5 > Match PM2.5)	-0.00094 (0.013)	-0.050** (0.024)
1 (Past 30-day PM2.5 > Match PM2.5) X PM2.5	-0.00079 (0.0030)	0.012* (0.0060)
Q5 (Match PM2.5)		-0.032 (0.035)
Q5 (Match PM2.5) X PM2.5		0.0099 (0.0071)
Q5 (Match PM2.5) X 1 (Past 30-day PM2.5 > Match PM2.5)		0.14** (0.064)
Q5 (Match PM2.5) X 1 (Past 30-day PM2.5 > Match PM2.5) X PM2.5		-0.029*** (0.011)
Weather controls	✓	✓
Home stadium FE	✓	✓
Stadium-by-year FE	✓	✓
Over FE	✓	✓
Innings FE	✓	✓
Bowler FE	✓	✓
Batter FE	✓	✓
N	183,556	183,556
R^2	0.052	0.052

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). Match PM2.5 is the PM2.5 concentration on the match day. Past 30-day PM2.5 is the bowler's mean PM2.5 exposure over the preceding 30 days. Column (1) includes an indicator for whether the bowler's 30-day mean exceeds match-day PM2.5 and interacts this indicator with continuous match-day PM2.5. Column (2) adds the triple interaction of this indicator with a top-quintile match-day PM2.5 indicator. Standard errors are two-way clustered by match and bowler. Following [Correia \(2015\)](#), 16 singleton observations are dropped. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table H13: Long-term adaptation to PM2.5 exposure when match-day PM2.5 is high

	(1) 1 (At least one run scored)	(2)
Match PM2.5	0.0039** (0.0018)	-0.0081 (0.0077)
1 (Career PM2.5 > Match PM2.5)	-0.0027 (0.016)	-0.056* (0.032)
1 (Career PM2.5 > Match PM2.5) X PM2.5	0.00050 (0.0039)	0.013* (0.0076)
Q5 (Match PM2.5)		-0.037 (0.039)
Q5 (Match PM2.5) X PM2.5		0.010 (0.0082)
Q5 (Match PM2.5) X 1 (Career PM2.5 > Match PM2.5)		0.81** (0.38)
Q5 (Match PM2.5) X 1 (Career PM2.5 > Match PM2.5) X PM2.5		-0.15** (0.066)
Weather controls	✓	✓
Home stadium FE	✓	✓
Stadium-by-year FE	✓	✓
Over FE	✓	✓
Innings FE	✓	✓
Bowler FE	✓	✓
Batter FE	✓	✓
N	183,556	183,556
R^2	0.052	0.052

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). Column (1) includes an indicator for whether the bowler's career mean PM2.5 exceeds match-day PM2.5 and interacts this indicator with continuous match-day PM2.5. Column (2) adds the triple interaction of this indicator with a top-quintile match-day PM2.5 indicator. Standard errors are two-way clustered by match and bowler. Following [Correia \(2015\)](#), 16 singleton observations are dropped. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table H14: Short-term adaptation to PM2.5 exposure: alternate specification with batter exposure

	(1) 1 (At least one run scored)
Match PM2.5	0.012** (0.0062)
Past 30-day PM2.5 (bowler)	0.0065* (0.0036)
Match PM2.5 X Past 30-day PM2.5 (bowler)	-0.00072 (0.00073)
Past 30-day PM2.5 (batter)	0.0070** (0.0034)
Match PM2.5 X Past 30-day PM2.5 (batter)	-0.00097 (0.00063)
Weather controls	✓
Home stadium FE	✓
Stadium-by-year FE	✓
Over FE	✓
Innings FE	✓
Bowler FE	✓
Batter FE	✓
N	183,556
R^2	0.052

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). Match PM2.5 is the PM2.5 concentration on the match day. Past 30-day PM2.5 is the bowler's (batter's) mean PM2.5 exposure over the preceding 30 days. Column (1) includes both measures in levels and their interaction. Standard errors are two-way clustered by match and bowler. Following [Correia \(2015\)](#), 16 singleton observations are dropped. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table H15: Long-term adaptation to PM2.5 exposure: alternate specification with batter exposure

	(1) 1 (At least one run scored)
Match PM2.5	0.014* (0.0081)
Match PM2.5 X Career PM2.5 (bowler)	-0.0021* (0.0011)
Match PM2.5 X Career PM2.5 (batter)	-0.00027 (0.0011)
Weather controls	✓
Home stadium FE	✓
Stadium-by-year FE	✓
Over FE	✓
Innings FE	✓
Bowler FE	✓
Batter FE	✓
N	183,556
R^2	0.052

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). Match PM2.5 is the PM2.5 concentration on the match day. Career PM2.5 is the bowler's (batter's) mean PM2.5 exposure over all matches played in the cricket league. Column (1) includes the interaction of both with PM2.5 on the day of the match. Standard errors are two-way clustered by match and bowler. Following [Correia \(2015\)](#), 16 singleton observations are dropped.

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

Appendix references

- BARTLETT, R. M. (2003): “The science and medicine of cricket: an overview and update,” *Journal of Sports Sciences*, 21, 733–752, publisher: Routledge.
- BELLONI, A., V. CHERNOZHUKOV, AND C. HANSEN (2014): “Inference on Treatment Effects after Selection among High-Dimensional Controls,” *The Review of Economic Studies*, 81, 608–650.
- CHEN, D., F. MAYVANEH, M. BAAGHIDEH, A. ENTEZARI, H. C. HO, Q. XIANG, A. JIAO, F. ZHANG, K. HU, G. CHEN, Q. ZHAO, S. SUN, AND Y. ZHANG (2020): “Utilizing daily excessive concentration hours to estimate cardiovascular mortality and years of life lost attributable to fine particulate matter in Tehran, Iran,” *Science of The Total Environment*, 703, 134909.
- DELL, M., B. F. JONES, AND B. A. OLKEN (2014): “What Do We Learn from the Weather? The New Climate-Economy Literature,” *Journal of Economic Literature*, 52, 740–798.
- DODSON, R. E., E. A. HOUSEMAN, J. I. LEVY, J. D. SPENGLER, J. P. SHINE, AND D. H. BENNETT (2007): “Measured and modeled personal exposures to and risks from volatile organic compounds,” *Environmental Science & Technology*, 41, 8498–8505.
- GARCIA, J., D. H. BENNETT, D. TANCREDI, M. B. SCHENKER, D. MITCHELL, S. J. REYNOLDS, AND F. M. MITLOEHNER (2013): “Occupational exposure to particulate matter and endotoxin for California dairy workers,” *International Journal of Hygiene and Environmental Health*, 216, 56–62.
- HAWK-EYE (2022): “HawkeyeStats,” Available at: <https://github.com/alittlefitness/HawkeyeStats>. Accessed June 22, 2026.
- KETTERER, B., B. COLES, AND D. J. MEYER (1983): “The role of glutathione in detoxication,” *Environmental Health Perspectives*, 49, 59–69, publisher: Environmental Health Perspectives.
- LIN, H., X. WANG, Z. M. QIAN, S. GUO, Z. YAO, M. G. VAUGHN, G. DONG, T. LIU, J. XIAO, X. LI, W. ZENG, Y. XU, AND W. MA (2018): “Daily exceedance concentration hours: A novel indicator to measure acute cardiovascular effects of PM_{2.5} in six Chinese subtropical cities,” *Environment International*, 111, 117–123.
- MONEYBALL (2025): “MoneyBall – The Wage Calculator of Indian Professional leagues,” .
- NOAKES, T. AND J. DURANDT (2000): “Physiological requirements of cricket,” *Journal of Sports Sciences*, 18, 919–929.
- PETERSEN, C. J., D. PYNE, B. DAWSON, M. PORTUS, AND A. KELLETT (2010): “Movement patterns in cricket vary by both position and game format,” *Journal of Sports Sciences*, 28, 45–52.

- PLOPPER, C. G., L. S. VAN WINKLE, M. V. FANUCCHI, S. R. C. MALBURG, S. J. NISHIO, A. CHANG, AND A. R. BUCKPITT (2001): “Early Events in Naphthalene-Induced Acute Clara Cell Toxicity,” *American Journal of Respiratory Cell and Molecular Biology*, 24, 272–281, publisher: American Thoracic Society - AJRCMB.
- TIMES, T. E. (2022): “ipl valuation: IPL crosses \$10 billion valuation to become a decacorn: D and P Advisory - The Economic Times,” .
- WANG, S., M. ZHANG, H. ZHAO, P. WANG, S. H. KOTA, Q. FU, C. LIU, AND H. ZHANG (2024): “Reconstructing long-term (1980–2022) daily ground particulate matter concentrations in India (LongPMInd),” *Earth System Science Data*, 16, 3565–3577.
- WEST, J. A. A., L. S. VAN WINKLE, D. MORIN, C. A. FLESCHNER, H. J. FORMAN, AND C. G. PLOPPER (2003): “Repeated inhalation exposures to the bioactivated cytotoxicant naphthalene (NA) produce airway-specific Clara cell tolerance in mice,” *Toxicological Sciences: An Official Journal of the Society of Toxicology*, 75, 161–168.
- WORLD HEALTH ORGANIZATION (2021): “WHO global air quality guidelines: particulate matter (PM_{2.5} and PM₁₀), ozone, nitrogen dioxide, sulfur dioxide and carbon monoxide,” Tech. rep.
- XIAO, D., W. GUO, D. XU, J. CHEN, Z. LIANG, AND X. ZHANG (2022): “Three Exposure Metrics for Fine Particulate Matter Associated With Outpatient Visits for Acute Lower Respiratory Infection Among Children in Guangzhou, China,” *Frontiers in Public Health*, 10, 876496.