

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

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Appendix A Bowler and batter physical demands

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% 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 B Glutathione's role in cellular adaptation to repeated pollution exposure

B.1 Physiological mechanism: increased glutathione production

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 H4 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). The key insight is that the mice who were exposed over seven 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.

B.2 Empirical tests of glutathione-driven tolerance

In 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.

While 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. West et al. (2002) identifies glutathione as a mechanism for tolerance. 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 H4 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).)

Appendix C Conceptual framework

First, the marginal effect of pollution on performance may vary with the level of pollution. As depicted in the left panel of Figure H1, 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 levels.⁶³

Second, the effect of pollution may vary systematically across individuals based on their typical exposure levels, consistent with adaptation.⁶⁴ The right panel of Figure H1 illustrates how

⁶³Alternatively, the relationship could be convex, though the key insight remains: there is little theoretical justification for assuming constant marginal effects across all pollution levels.

⁶⁴Conceptually, 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.

performance might differ between individuals accustomed to high versus low pollution levels.⁶⁵ 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.

Appendix D Validating Wang et al. (2024) PM_{2.5} estimates

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). (Wang et al. (2024) use ground monitor readings from India’s Central Pollution Control Board to train their model.) Figure H7 demonstrates a strong correlation between the Wang et al. (2024) dataset and ground readings. By contrast, Figure H8 reports the results of an analogous exercise with aerosol optical depth (AOD) from the Moderate Resolution Imaging Spectroradiometer (MODIS), and shows a much weaker correlation. We therefore choose Wang et al. (2024) as our source of data for PM_{2.5} concentrations. In both validation exercises, we compare estimates from the data product in the cell containing the U.S. AirNow ground monitor. For Wang et al. (2024), these are 10 km × 10 km grid cells. For MODIS AOD, these are 3 km × 3 km grid cells.

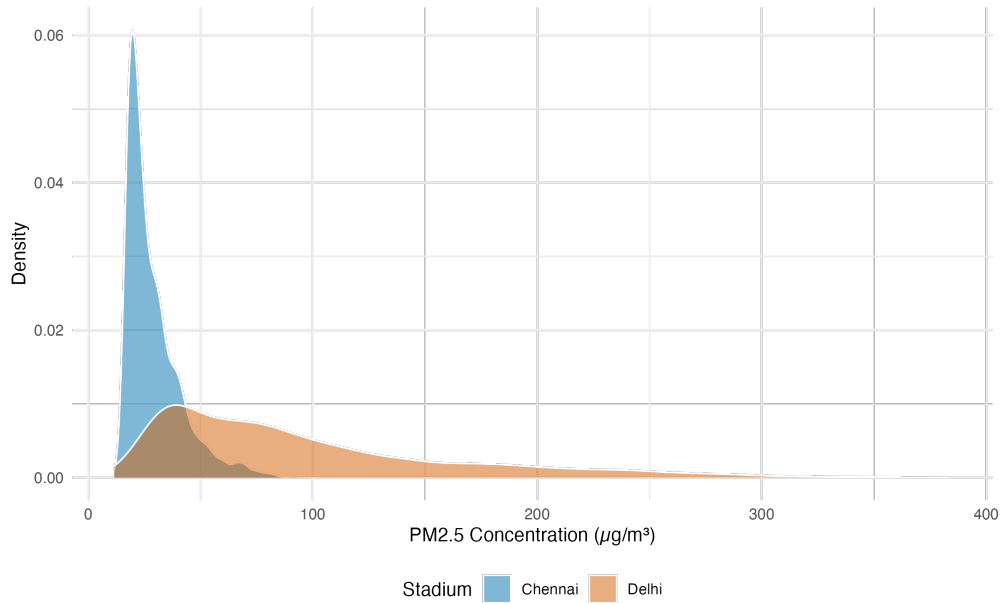
Appendix E Measuring past exposure to PM_{2.5}

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 2). For example, in Figure E1 we see that although there is a common support of the probability mass at low pollution levels, 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

⁶⁵Similarly, we could categorize damage functions into different tasks, with different damage functions for each type of task.

Figure E1: 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}.

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 0.97,⁶⁶ 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 exposure, discuss the advantages and drawbacks of each, and make a recommendation for how to measure this consistently in similar settings.

⁶⁶The 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.

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

In addition to the measure of exposure defined in Section 4.3.1,

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

we define two alternative measures of short-term past exposure:

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

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

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

$$P_{J(j)d} = \sum_{d=1}^T [\mathbf{1}(P_{J(j)\tau} > Z)] (P_{j\tau} - Z) \quad (\text{F.3})$$

We note that the measures in Equations F.2, F.3 are piece-wise linear functions of the measure in Equation F.1. 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 F.1 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 F.1 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 F.2 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 F.2 would be 15 in the alternating case and 0 in the consistent case.

The measure in Equation F.3 is a further refinement of that in Equation F.2—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 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 F.3 relative to Equation F.2 is that Equation F.3 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.

For matches early in each season, the lookback window extends into the pre-season period, during which we assume teams are present at their home stadiums; we extend back 30 days before the season start, so that a 30-day window is always complete.⁶⁷ This assumption reflects the fact that teams tend to start training in their home stadiums several weeks before the season starts.

Note that we report results for the mean measure in Equation F.1 only, with its horizon determined by the distributed-lag specification of Section 5.3 (Table 4) rather than by a search over windows. The count and degree-day measures are defined here to make explicit the alternative hypotheses about how past exposure may operate.

Appendix G Additional robustness checks

G.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 estimate two models that incorporate variation in the number of runs scored. The first is an OLS regression where the outcome is the number of runs scored per delivery. Second, we 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:

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

where $R_{ij\ell t}$ is the number of runs scored ($R_{ij\ell t} \in \{0, 1, 2, 3, 4, 5, 6\}$). The OLS model results are reported in Table I12. The results estimating Equation G.1 are reported in Table I13. Both sets of results are qualitatively similar to those estimating analogous regressions in Tables 2, 5 and 6.

⁶⁷For windows longer than 30 days, this would truncate the lookback for matches within the first weeks of a season and mechanically lower the count variables in Equations F.2 and F.3; with $T = 30$ the truncation does not bind.

G.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 $PM_{2.5}$ and directly affect performance.

We implement Post-Double Selection (PDS) Lasso (Belloni et al., 2014) with $PM_{2.5}$ 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 one $PM_{2.5}$ predictor: humidity-wind interactions. The final regression yields a coefficient of 0.41 percentage points ($p < 0.01$), similar in magnitude to our baseline result of 0.42 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 (21.7 °C to 37.3 °C with a mean of 29.5 °C) where heat stress might substantially impair performance.

G.3 Robustness: alternative measures of long-term past exposure to $PM_{2.5}$

Table I17 presents seven alternative definitions of long-term $PM_{2.5}$. Our preferred definition for long-term exposure to $PM_{2.5}$ is the mean exposure to $PM_{2.5}$ 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 $PM_{2.5}$ 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 $PM_{2.5}$ 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 five rows of the table report means of $PM_{2.5}$ in the location of the home-stadium for a given IPL team. There are 15 teams that have been in the IPL over 2008–2022.⁶⁸ 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. The final row uses the mean $PM_{2.5}$ at the team’s home stadium over the 21 days before each season’s start, which varies by team-season rather than by team. These measures all assign long-term pollution to a bowler on the

⁶⁸Two pairs (Deccan Chargers and Sunrisers Hyderabad; Pune Warriors and Rising Pune Supergiant) share a home stadium.

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 I18 for the long-term definitions of $PM_{2.5}$ in row 2 of Table I17 (column 1); the definition in row 1 is our main specification (Table 6). For the definitions in rows 3–7, we alter the specification to include bowling team-by-year fixed effects instead of bowler fixed effects, since the assignment of long-term $PM_{2.5}$ to each bowler changes depending on what team they are on in each year.⁶⁹ We estimate the slightly modified specification:

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

where $\psi_{yJ(j,y)}$ 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 .

⁶⁹Note 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.

Appendix H Additional figures

Figure H1: Dose response of performance to pollution

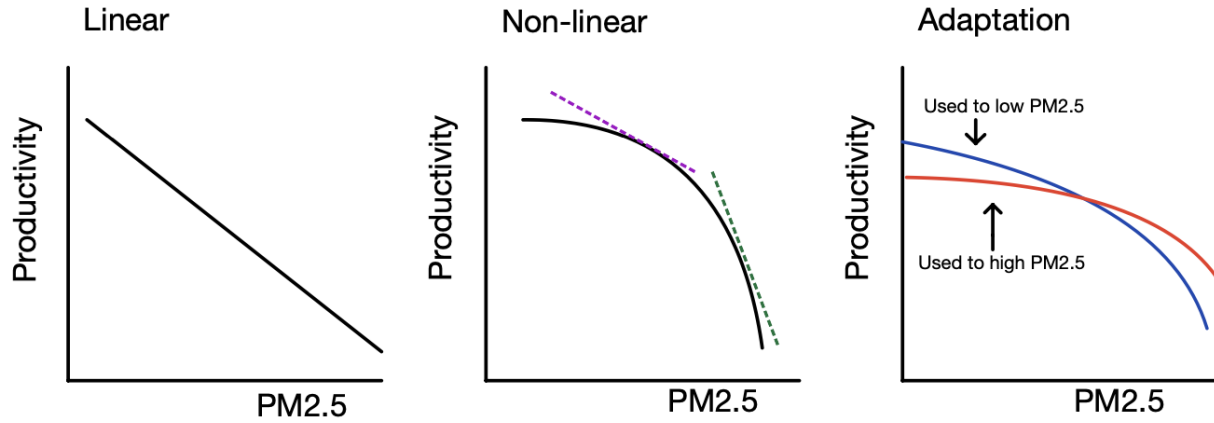
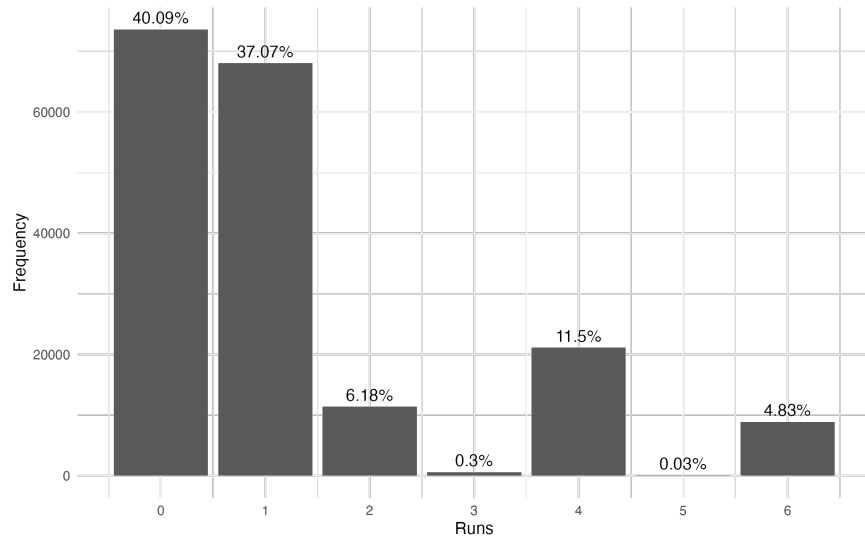
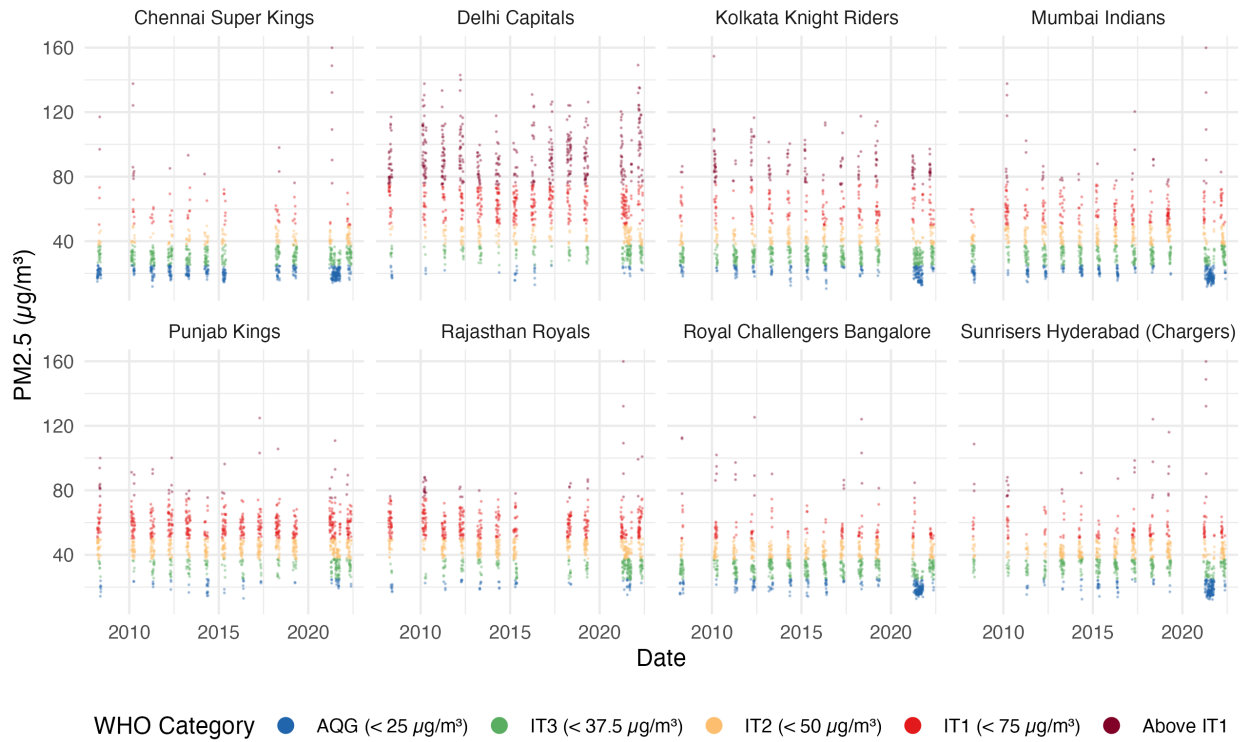


Figure H2: Histogram of runs



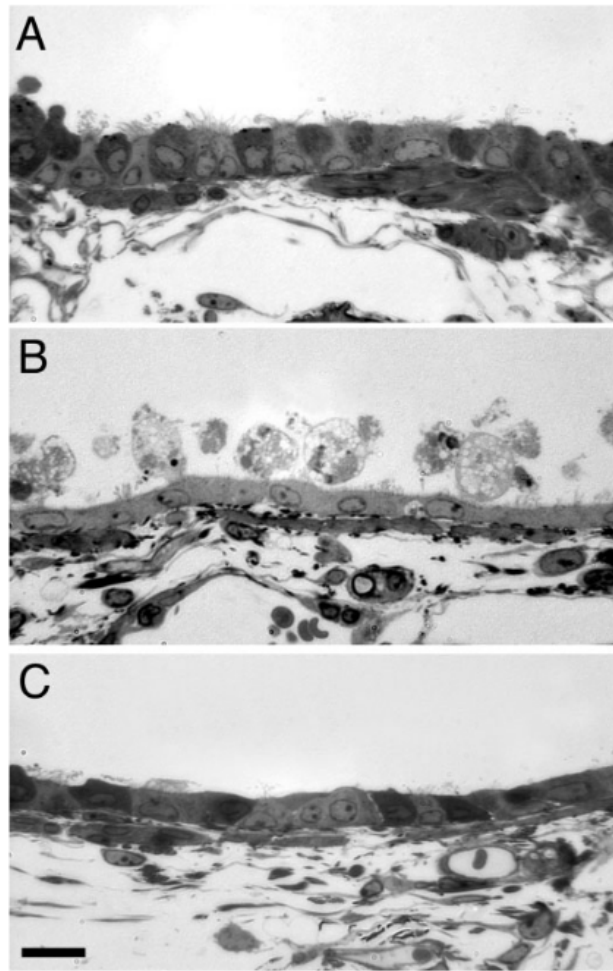
Notes. This figure shows the distribution of the outcome variable (runs scored) in our analysis. The unit of observation is a delivery (N=183,572).

Figure H3: Team PM_{2.5} exposure histories in IPL, 2008–2022



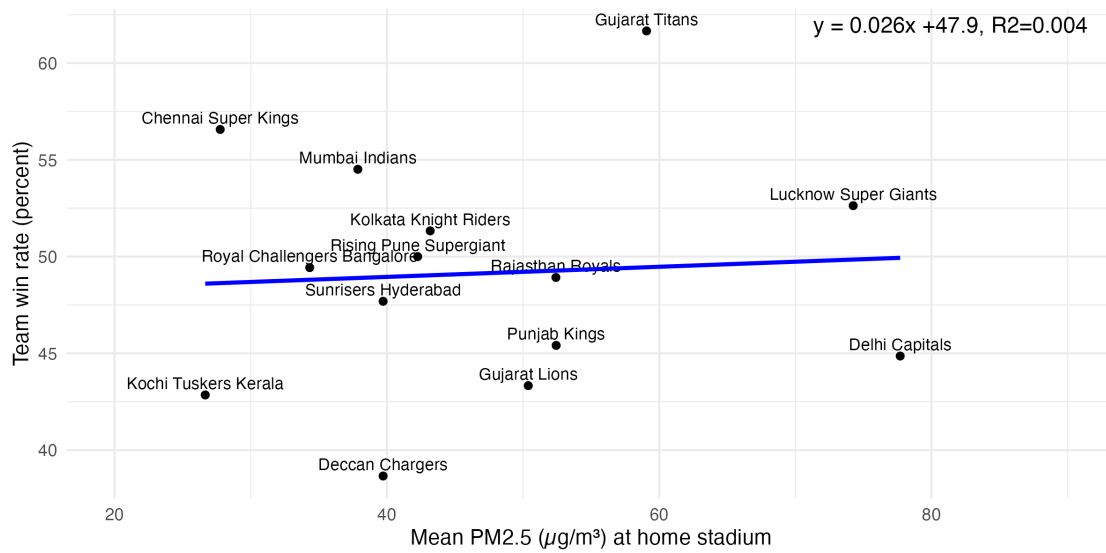
Notes. This figure displays the PM_{2.5} exposure history of each IPL team in the years 2008–2022. Teams are assumed to be exposed to the level of PM_{2.5} in their home stadium, unless they are playing a match at an away stadium, in which case they are exposed to the PM_{2.5} at that location. The IPL 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 H4: Cellular adaptation to repeated exposure to air pollution



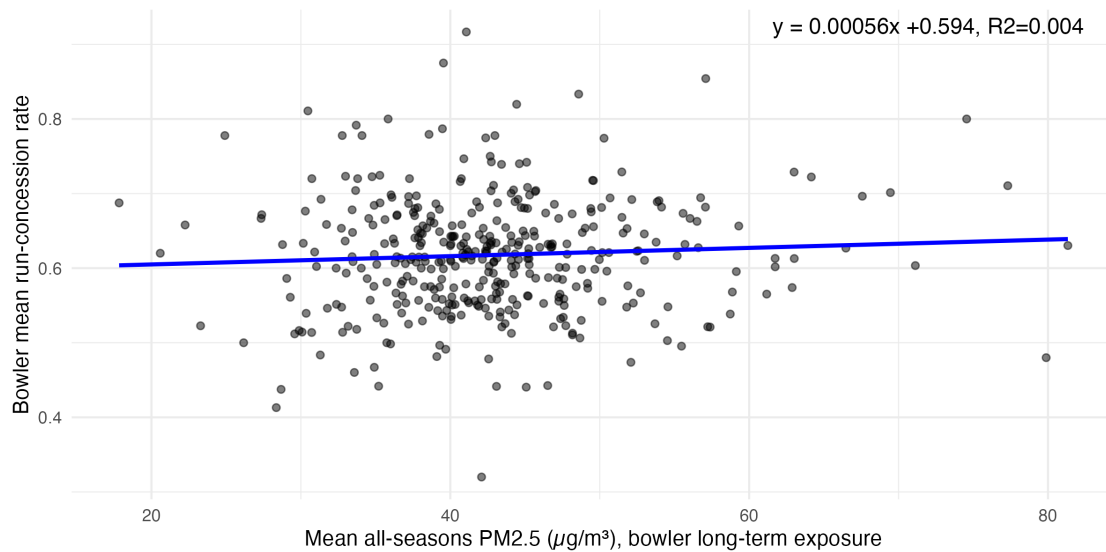
Notes. This figure, reproduced from [West et al. \(2003\)](#), displays three panels of microscopic images of cells in the lungs of mice. Panel A shows cells from mice that were in the control group and breathed clean air throughout the experiment. Panel B shows cells from mice from the treatment group 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 H5: Team quality is not correlated with long-term PM_{2.5} exposure



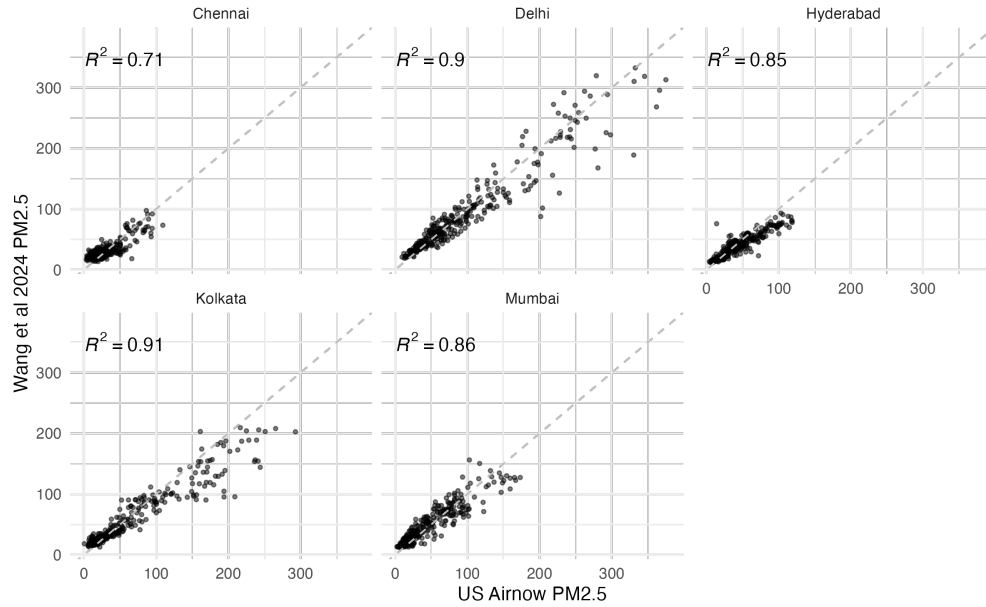
Notes. This figure shows the win rate (number of matches won out of all matches played) for IPL teams as plotted against the average PM_{2.5} at the team's home stadium. Average PM_{2.5} is defined as the mean level of PM_{2.5} at the team's home stadium during March, April, and May (the months when 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 H6: Bowler quality is not correlated with long-term PM_{2.5} exposure



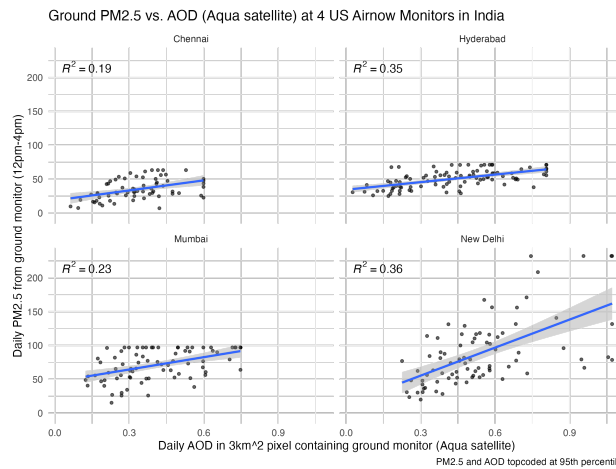
Notes. This figure shows the run-concession rate (number of deliveries that result in a run divided by the total number deliveries) for bowlers as plotted against the average PM_{2.5} the bowler is exposed to across all matches in the IPL (i.e., career PM_{2.5} in Equation 8). Bowlers who deliver fewer 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 H7: U.S. AirNow vs. Wang et al. (2024) daily PM_{2.5}



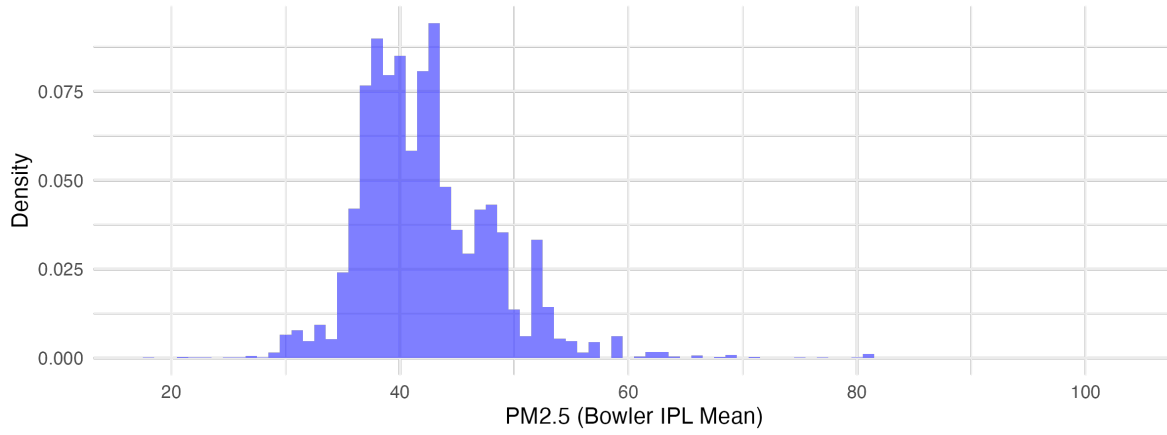
Notes. This figure displays the correlation between Wang et al. (2024) estimates of PM_{2.5} and ground observations of PM_{2.5} at five cities with a U.S. AirNow ground monitor, a network of high-quality monitors that are calibrated to EPA standards. Each dot represents a daily mean value of PM_{2.5}. The 45 degree line is shown for reference. Values of Wang et al. (2024) PM_{2.5} are taken from the 10 km × 10 km 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 H8: U.S. AirNow vs. MODIS AOD



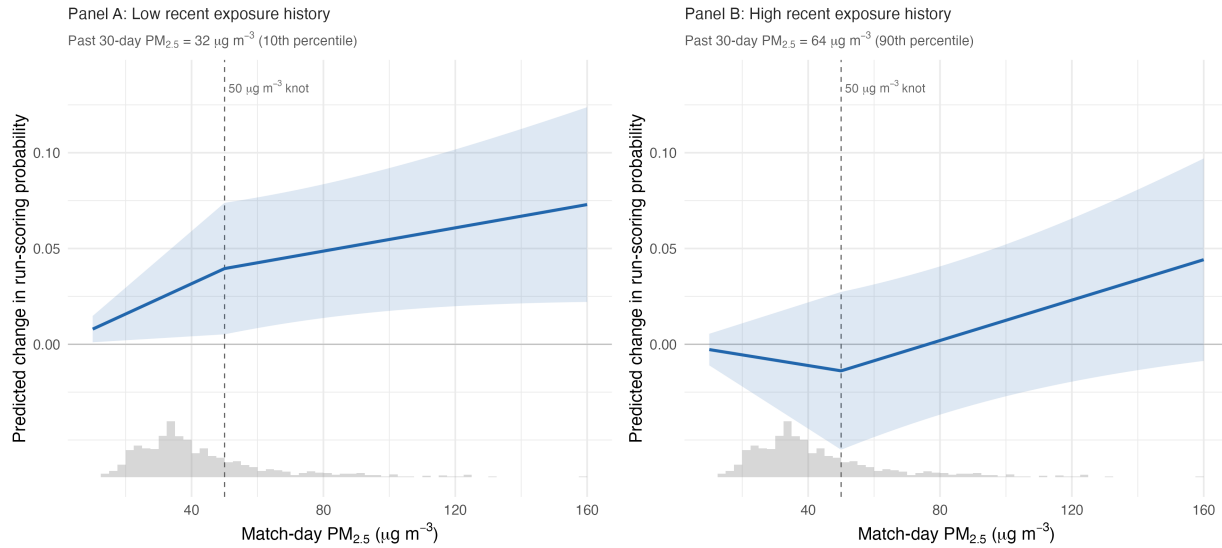
Notes. This figure displays the correlation between Aerosol Optical Depth from the MODIS Aqua satellite (which passes over India approximately once per day in the afternoon) with ground observations of PM_{2.5} at five cities with a U.S. AirNow ground monitor. Each dot represents a daily mean value of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

Figure H9: Histogram of bowler career PM_{2.5} mean in IPL matches 2008–2022



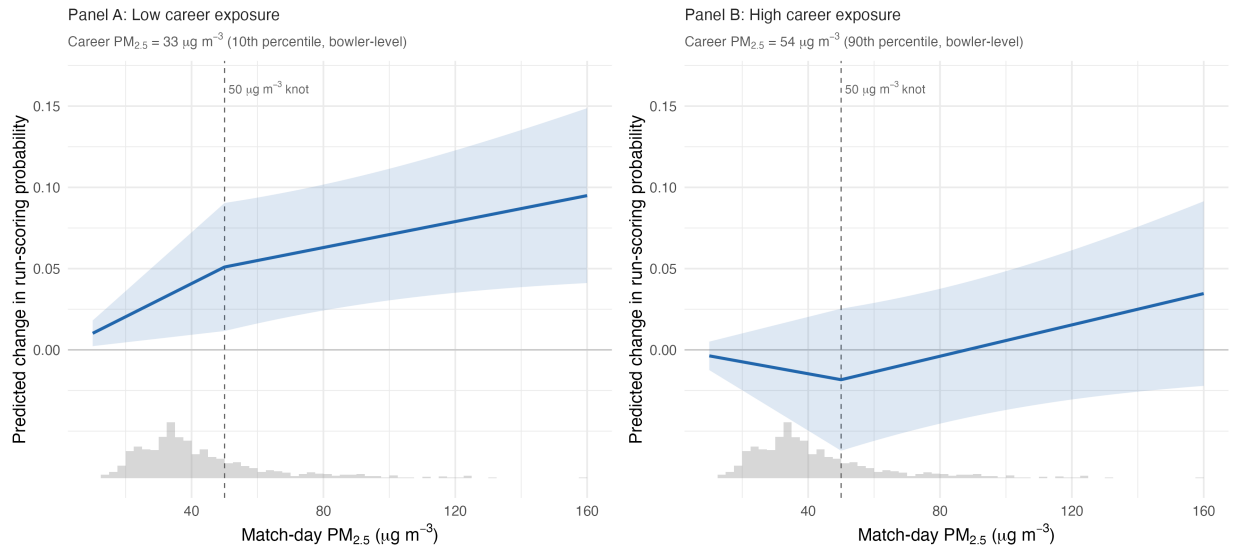
Notes. This figure displays the distribution of bowler mean PM_{2.5} defined as the mean PM_{2.5} exposure across all matches for a given bowler in the IPL 2008–2022 (i.e., $\bar{P}_{j0}$ in Equation 8).

Figure H10: Adaptation to PM_{2.5} by short-term exposure history



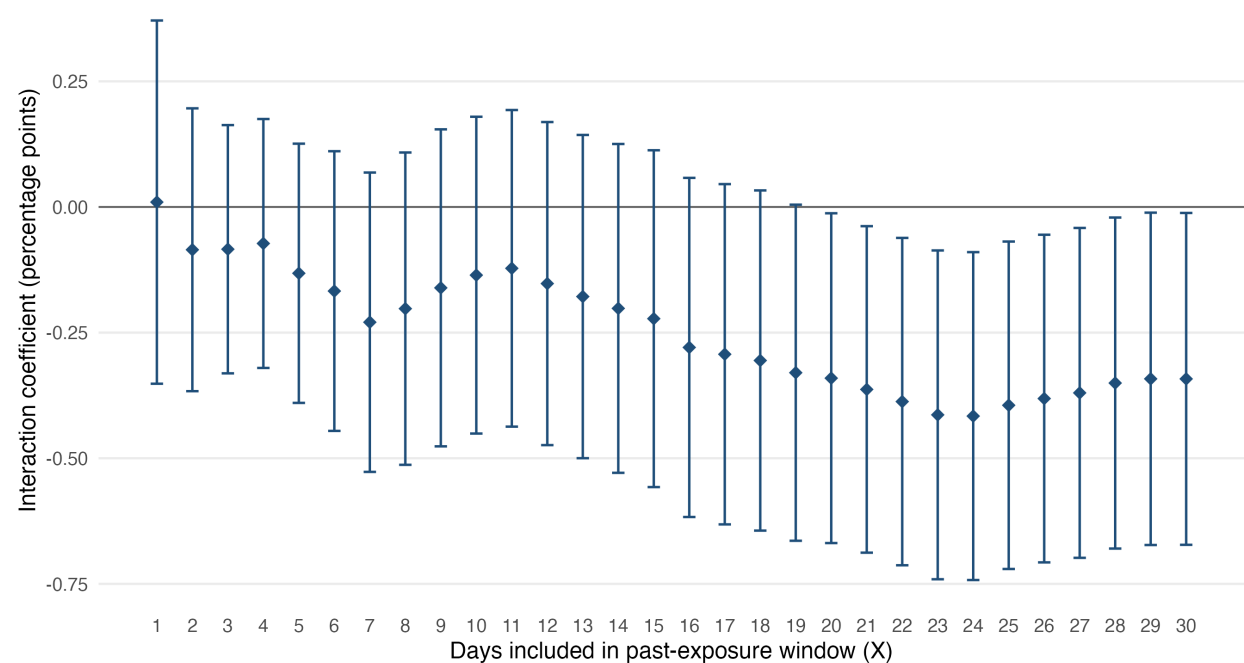
Notes. This figure plots the model-implied effect of match-day PM_{2.5} on run-scoring probability, relative to PM_{2.5} = 0, holding past 30-day PM_{2.5} exposure fixed at its 10th percentile (Panel A) or 90th percentile (Panel B) across deliveries. Effects come from a linear spline in match-day PM_{2.5} with a single knot at 50 µg m⁻³, interacted with past 30-day PM_{2.5}, with weather controls and fixed effects for stadium-by-year, bowler, batter, innings, month, and over phase. Shaded bands are 90% confidence intervals from standard errors two-way clustered by match and bowler. Tick marks along the x-axis show the distribution of match-day PM_{2.5} in the estimation sample.

Figure H11: Adaptation to PM_{2.5} by career exposure history



Notes. This figure plots the model-implied effect of match-day PM_{2.5} on run-scoring probability, relative to PM_{2.5} = 0, holding a bowler's career PM_{2.5} exposure (mean across all IPL matches) fixed at its 10th percentile (Panel A) or 90th percentile (Panel B) across bowlers. Effects come from a linear spline in match-day PM_{2.5} with a single knot at 50 μg m⁻³, interacted with career PM_{2.5} (which enters the interaction only, since it is bowler-constant and otherwise absorbed by the bowler fixed effect), with weather controls and fixed effects for stadium-by-year, bowler, batter, innings, month, and over phase. Shaded bands are 90% confidence intervals from standard errors two-way clustered by match and bowler. Tick marks along the x-axis show the distribution of match-day PM_{2.5} in the estimation sample.

Figure H12: Robustness of short-term adaptation across varying past-exposure windows



Notes. Figure plots point estimates and 95% confidence intervals for the coefficient on the interaction term “0–50 $\mu\text{g m}^{-3} \times \text{Past } X\text{-day PM}_{2.5}$ ” as in Table 5 for X ranging from 1 to 30.

Appendix I Additional tables

Table I1: PM_{2.5} and weather correlation matrix

	Run	PM _{2.5}	Temperature	Precipitation	Radiation	Wind	Humidity
Run	1	0.017	0.007	-0.002	0.003	0.001	-0.014
PM _{2.5}	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. PM_{2.5} and weather variables are measured at the match-level.

Table I2: PM_{2.5} exposure and run-scoring probability: adding day-of-week fixed effects

	(1)	(2)	(3)	(4)	(5)
		Linear		Quintiles	Spline
	ℙ (At least one run scored)				
Match-day PM _{2.5}	0.0041*** (0.0010)	0.0027* (0.0014)	0.0040** (0.0017)		
Q2 (Match-day PM _{2.5})				0.0083 (0.0060)	
Q3 (Match-day PM _{2.5})				0.010 (0.0070)	
Q4 (Match-day PM _{2.5})				0.014 (0.0090)	
Q5 (Match-day PM _{2.5})				0.028*** (0.010)	
Match-day PM _{2.5} between 0 and 50 µg m ⁻³					0.0043 (0.0037)
Match-day PM _{2.5} between 50 and 160 µg m ⁻³					0.0038* (0.0020)
Weather controls		✓	✓	✓	✓
Bowler FE			✓	✓	✓
Batter FE			✓	✓	✓
Stadium-by-year FE			✓	✓	✓
Month FE			✓	✓	✓
Home stadium FE			✓	✓	✓
Innings FE			✓	✓	✓
Over phase FE			✓	✓	✓
Day-of-week FE			✓	✓	✓
N	183,572	183,572	183,556	183,556	183,556
R ²	0.00028	0.00039	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 (mean 0.599). All PM_{2.5} variables are measured in 10 µg m⁻³. Quintile 1 of match-day PM_{2.5} is 14-27; Quintile 2 is 27-34, Quintile 3 is 34-41, Quintile 4 is 41-53, and Quintile 5 is 53-160 µg m⁻³. Columns (1–3) enter match-day PM_{2.5} linearly, adding weather controls in column (2) and fixed effects in column (3). Column (4) replaces the linear term with PM_{2.5} quintile indicators, where the lowest quintile (Q1) is the omitted category. Column (5) instead enters match-day PM_{2.5} as a continuous piecewise-linear spline with a single knot at 50 µg m⁻³. Columns (1)–(2) are identical to the corresponding columns of Table 2, since neither carries any fixed effects yet. Columns (2)–(5) include controls for weather conditions including temperature, temperature squared, relative humidity, wind speed, precipitation, atmospheric pressure, and solar radiation. Columns (3)–(5) additionally include fixed effects for individual bowlers, batters, stadium-by-year, month, innings, and over phase and, unlike Table 2, for the day of week of the match. Match-day PM_{2.5} is orthogonal to day of week ($p = 0.986$, a joint test conditional on stadium-by-season fixed effects), so this row checks whether Table 2's estimates are sensitive to scheduling patterns rather than testing for a substantively new confound. Following [Correia \(2015\)](#), 16 singleton observations are dropped in columns (3)–(5). Standard errors (in parentheses) are two-way clustered at the match and bowler levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table I3: PM_{2.5} and bowler-specific outcomes, pace and spin bowlers: per-over fixed effects

	(1) No-ball (=1)	(2)	(3) Length (m)	(4)	(5) Speed (km/h)	(6)
	Linear	Quintile	Linear	Quintile	Linear	Quintile
<i>Panel A. Pace bowlers only</i>						
Match-day PM _{2.5}	0.00046** (0.00020)		-0.02534* (0.01523)		0.09643 (0.06601)	
Q2 (Match-day PM _{2.5})		0.00093 (0.00090)		-0.12151* (0.06480)		0.02253 (0.23399)
Q3 (Match-day PM _{2.5})		0.00170* (0.00097)		-0.20463*** (0.06997)		-0.06866 (0.25666)
Q4 (Match-day PM _{2.5})		0.00304*** (0.00106)		-0.23251*** (0.07962)		0.12297 (0.28551)
Q5 (Match-day PM _{2.5})		0.00287** (0.00111)		-0.28731*** (0.08762)		0.34882 (0.31745)
Outcome mean	0.0053	0.0053	6.8770	6.8770	127.7380	127.7380
N	118,508	118,508	80,913	80,913	79,346	79,346
R ²	0.0137	0.0137	0.1492	0.1494	0.7027	0.7027
<i>Panel B. Spin bowlers only</i>						
Match-day PM _{2.5}	-0.00011 (0.00016)		-0.00144 (0.01375)		-0.00886 (0.05865)	
Q2 (Match-day PM _{2.5})		0.00101* (0.00053)		-0.07242* (0.04338)		-0.33202 (0.29127)
Q3 (Match-day PM _{2.5})		0.00084 (0.00051)		-0.01967 (0.05008)		-0.57915** (0.28985)
Q4 (Match-day PM _{2.5})		0.00116 (0.00103)		-0.04706 (0.07042)		-0.50099 (0.36734)
Q5 (Match-day PM _{2.5})		0.00025 (0.00118)		-0.01496 (0.10247)		-0.74104* (0.38370)
Outcome mean	0.0014	0.0014	5.1843	5.1843	90.5525	90.5525
N	59,926	59,926	35,477	35,477	34,605	34,605
R ²	0.0145	0.0145	0.0818	0.0819	0.3381	0.3385
Weather controls	✓	✓	✓	✓	✓	✓
Bowler, batter, stadium-by-year, month, home stadium, innings, and over FE	✓	✓	✓	✓	✓	✓

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

Table I4: PM_{2.5} and speed decline within a bowling spell

	All	Pace	Spin
	Delivery speed (km/h)		
Delivery number in spell	-0.06948*** (0.01987)	-0.14037*** (0.01999)	0.08913*** (0.02551)
PM _{2.5} × delivery number in spell	-0.00255 (0.00251)	-0.00037 (0.00297)	-0.00520 (0.00369)
<i>N</i>	113,975	79,360	34,615

Notes. The unit of observation is a delivery. The outcome is delivery speed in km/h. Each column represents a separate regression. A bowling spell is defined as a set of deliveries that a bowler delivers consecutively, without rest. The delivery number is defined as the sequential position within the bowler's spell (i.e. 1 for the 1st delivery within the spell, 2 for the second, etc.). Each column shows delivery speed regressed on delivery number and delivery number interacted with match-day PM_{2.5}. Each regression includes a fixed effect for each spell. Standard errors in parentheses are two-way clustered at the match and bowler levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table I5: Fast bowlers: PM_{2.5} exposure and run-scoring probability

	(1) 1 (At least one run scored)
Match-day PM _{2.5}	0.0039* (0.0020)
Match-day PM _{2.5} X Fast bowler	0.00029 (0.0014)
Weather controls	✓
Bowler FE	✓
Batter FE	✓
Stadium-by-year FE	✓
Month FE	✓
Home stadium FE	✓
Innings FE	✓
Over phase FE	✓
<i>N</i>	178,452
<i>R</i> ²	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 (mean 0.599). PM_{2.5} is measured in 10 µg 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 PM_{2.5} levels (measured in 10 µg m⁻³). It includes fixed effects for individual batters, bowlers, stadium-by-year, home stadium, month, innings, and over phase. It includes controls for weather conditions including temperature, temperature squared, relative humidity, precipitation, atmospheric pressure, 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 I6: PM_{2.5} exposure and run-scoring probability: alternate specification with bowler-batter pair fixed effects

	(1)	(2) Linear	(3)	(4) Quintiles	(5) Spline
	1 (At least one run scored)				
Match-day PM _{2.5}	0.0041*** (0.0010)	0.0027* (0.0014)	0.0040* (0.0023)		
Q2 (Match-day PM _{2.5})				0.012* (0.0064)	
Q3 (Match-day PM _{2.5})				0.0078 (0.0083)	
Q4 (Match-day PM _{2.5})				0.022** (0.011)	
Q5 (Match-day PM _{2.5})				0.036*** (0.013)	
Match-day PM _{2.5} between 0 and 50 µg m ⁻³					0.0061 (0.0045)
Match-day PM _{2.5} between 50 and 160 µg m ⁻³					0.0031 (0.0026)
Weather controls		✓	✓	✓	✓
Bowler-batter pair FE			✓	✓	✓
Stadium-by-year FE			✓	✓	✓
Month FE			✓	✓	✓
Home stadium FE			✓	✓	✓
Innings FE			✓	✓	✓
Over phase FE			✓	✓	✓
N	183,572	183,572	181,556	181,556	181,556
R ²	0.00028	0.00039	0.15	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). All PM_{2.5} variables are measured in 10 µg m⁻³. Quintile 1 of match-day PM_{2.5} is 14-27; Quintile 2 is 27-34, Quintile 3 is 34-41, Quintile 4 is 41-53, and Quintile 5 is 53-160 µg m⁻³. Columns (1)–(3) enter match-day PM_{2.5} linearly, adding weather controls in column (2) and fixed effects in column (3). Column (4) replaces the linear term with PM_{2.5} quintile indicators, where the lowest quintile (Q1) is the omitted category. Column (5) instead enters match-day PM_{2.5} as a continuous piecewise-linear spline with a single knot at 50 µg m⁻³. Columns (1)–(2) are identical to the corresponding columns of Table 2, since neither carries any fixed effects yet. Columns (3)–(5) replace the individual bowler and batter fixed effects with a single fixed effect for each bowler-batter pair, and additionally include fixed effects for stadium-by-year, month, home stadium, innings, and over phase. Columns (2)–(5) include controls for weather conditions including temperature, temperature squared, relative humidity, wind speed, precipitation, atmospheric pressure, and solar radiation. Following [Correia \(2015\)](#), 2,016 singleton observations are dropped in columns (3)–(5). Standard errors (in parentheses) are two-way clustered at the match and bowler levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table I7: Bowler experience and match-day PM_{2.5}

	(1) Share of bowlers with ≥ 3 prior IPL seasons
Match-day PM _{2.5}	0.00101 (0.00323)
Weather controls	✓
Stadium-by-year FE	✓
Team FE	✓
N	1,544
R^2	0.78166

Notes. The unit of observation is team-match (i.e. one row per team per match). The dependent variable is the share of a team's bowlers used in a match who have already completed at least 3 prior IPL seasons as of the match's season (mean 0.43). PM_{2.5} is measured in $10 \mu\text{g m}^{-3}$. The regression includes fixed effects for stadium-by-year and team, and controls for temperature, temperature squared, relative humidity, precipitation, atmospheric pressure, solar radiation, and wind speed. Standard errors (in parentheses) are clustered at the match level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table I8: Career PM_{2.5} exposure and order in the bowling sequence

	(1) Bowling order	(2) First in bowling order (0/1)
Match-day PM _{2.5}	-0.02932 (0.04008)	0.01287 (0.01004)
Match-day PM _{2.5} × Career PM _{2.5}	0.00584 (0.00878)	-0.00300 (0.00222)
Weather controls	✓	✓
Bowler FE	✓	✓
Stadium-by-year FE	✓	✓
Innings FE	✓	✓
<i>N</i>	9,097	9,097
<i>R</i> ²	0.53848	0.38284

Notes. The unit of observation is a bowler's spell. The outcome in column 1 is bowling order. Bowling order is defined as the rank of introduction (1 = first bowler used that innings, 2, second bowler used that innings, etc.; mean 3.49). The outcome in column 2 is an indicator for that takes the value 1 if bowling order is equal to 1; 0 otherwise (mean 0.17). PM_{2.5} variables are measured in 10 µg m⁻³. Career PM_{2.5} is the bowler's mean match-day PM_{2.5} across all matches played in the IPL. All columns include fixed effects for individual bowlers, stadium-by-year, and innings, and controls for temperature, temperature squared, relative humidity, precipitation, atmospheric pressure, solar radiation, and wind speed. Standard errors (in parentheses) are clustered at the match level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table I9: PM_{2.5} exposure and run-scoring probability (ground-monitor PM_{2.5})

	(1)	(2)	(3)	(4)	(5)
		Linear		Quintiles	Spline
	1 (At least one run scored)				
Match-day PM _{2.5}	0.0030*** (0.00090)	0.0021 (0.0015)	0.0018 (0.0015)		
Q2 (Match-day PM _{2.5})				-0.0033 (0.011)	
Q3 (Match-day PM _{2.5})				-0.0070 (0.011)	
Q4 (Match-day PM _{2.5})				-0.013 (0.014)	
Q5 (Match-day PM _{2.5})				-0.0048 (0.017)	
Match-day PM _{2.5} between 0 and 50 µg m ⁻³					-0.0029 (0.0045)
Match-day PM _{2.5} over 50 µg m ⁻³					0.0026* (0.0015)
Weather controls		✓	✓	✓	✓
Bowler FE			✓	✓	✓
Batter FE			✓	✓	✓
Stadium-by-year FE			✓	✓	✓
Month FE			✓	✓	✓
Home stadium FE			✓	✓	✓
Innings FE			✓	✓	✓
Over phase FE			✓	✓	✓
N	50,355	50,355	50,342	50,342	50,342
R ²	0.00043	0.00067	0.048	0.048	0.048

Notes. This table restricts observations to those from stadiums colocated with a ground PM_{2.5} monitor (N=50,355 vs. N=183,572 deliveries in the full sample). The outcome variable is a binary indicator equal to 1 if at least one run is scored on a delivery and 0 otherwise (mean 0.602 in this subsample). PM_{2.5}, measured in 10 µg 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). Quintile 1 of ground-monitor match-day PM_{2.5} is 7-24; Quintile 2 is 24-32, Quintile 3 is 33-43, Quintile 4 is 43-62, and Quintile 5 is 62-296 µg m⁻³. Columns (1–3) enter match-day PM_{2.5} linearly, adding weather controls in column (2) and fixed effects in column (3). Column (4) replaces the linear term with PM_{2.5} quintile indicators, where the lowest quintile (Q1) is the omitted category. Column (5) instead enters match-day PM_{2.5} as a continuous piecewise-linear spline with a single knot at 50 µg m⁻³, the same knot as Table 2's column (5). Columns (2)–(5) include controls for weather conditions including temperature, temperature squared, relative humidity, precipitation, atmospheric pressure, solar radiation, and wind speed. Columns (3)–(5) additionally include fixed effects for individual batters, bowlers, stadium-by-year, month, home stadium, innings, and over phase. Following [Correia \(2015\)](#), 13 singleton observations are dropped in columns (3)–(5). Standard errors (in parentheses) are two-way clustered at the match and bowler levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table I10: Almon distributed lag over 30 days: unrestricted lags and polynomial degrees 0 to 4

	(1)	(2)	(3)	(4)	(5)	(6)
	Unrestricted lags	Almon polynomial in lag order				
		$Q = 0$	$Q = 1$	$Q = 2$	$Q = 3$	$Q = 4$
		$\mathbb{1}$ (At least one run scored)				
Match-day $PM_{2.5}$	0.00672*** (0.00228)	0.00411** (0.00177)	0.00410** (0.00177)	0.00418** (0.00176)	0.00410** (0.00182)	0.00417** (0.00183)
<i>Cumulative effect of past exposure, lags 1 through:</i>						
10 days	-0.00136 (0.00275)	0.00119** (0.00053)	0.00128 (0.00148)	0.00088 (0.00152)	0.00097 (0.00153)	0.00097 (0.00153)
20 days	0.00148 (0.00326)	0.00239** (0.00107)	0.00248 (0.00179)	0.00266 (0.00187)	0.00277 (0.00188)	0.00259 (0.00208)
30 days (whole window)	-0.00018 (0.00300)	0.00358** (0.00160)	0.00360** (0.00160)	0.00343** (0.00163)	0.00353** (0.00165)	0.00344* (0.00175)
p : profile is degree Q	—	0.0567	0.0479	0.0525	0.0516	0.0395
R^2 given up vs col. (1)	—	0.00024	0.00024	0.00024	0.00024	0.00024
p : profile is flat	—	—	0.9519	0.8670	0.9474	0.9813
N	183,556	183,556	183,556	183,556	183,556	183,556
R^2	0.0474	0.0472	0.0472	0.0472	0.0472	0.0472
Weather controls	✓	✓	✓	✓	✓	✓
Bowler, batter, stadium-by-year, month, home stadium, innings, and over phase FE	✓	✓	✓	✓	✓	✓

Notes. The outcome variable is a binary indicator equal to 1 if at least one run is scored on a delivery and 0 otherwise (mean 0.599). All $PM_{2.5}$ variables are measured in $10 \mu g m^{-3}$. Every column is the specification of Table 2, column 3, plus the bowling team's $PM_{2.5}$ on each of the 30 days before the match; the columns differ only in what is assumed about the shape of the lag profile. Column (1) leaves the 30 lag coefficients β_s unrestricted. Columns (2) through (6) restrict the profile to a polynomial of degree Q in the lag index s , as in Equation 6; column (4), $Q = 2$, is the model reported in Table 4. Degree 0 is a flat profile, which is a regression on the simple 30-day mean of past exposure used elsewhere in the paper: its whole-window total, 0.00358, reproduces the coefficient on that mean estimated directly, 0.00358, to every reported digit. The cumulative rows report $\sum_{s=1}^k \beta_s$, the effect of raising $PM_{2.5}$ by $10 \mu g m^{-3}$ on each of the k days before the match; each is a linear combination of the estimated coefficients with a delta-method standard error. The orthonormal basis $g_0, \dots, g_Q$ of Equation 6 can be completed to a basis $g_0, \dots, g_{30-1}$ spanning all 30 lags, so column (1) is exactly reparameterised as a regression on 30 such terms and the degree- Q restriction is $\alpha_{Q+1} = \dots = \alpha_{30-1} = 0$. The first p -value tests that restriction against column (1) with a cluster-robust Wald F -test on $30 - 1 - Q$ degrees of freedom; the row beneath reports the R^2 of column (1) minus the column's own, the fit the restriction gives up. The second p -value is the joint test within each column that the shape terms $\alpha_1, \dots, \alpha_Q$ are zero, i.e. that no day in the window matters more than any other; it is undefined at degree 0. The whole-window total of the degree-2 model is statistically indistinguishable from the unrestricted sum in column (1) (Hausman-style $p = 0.151$). 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 I11: Contribution of days beyond k to the 30-day cumulative effect

	(1) Almon polynomial, $Q = 2$ ‡ (At least one run scored)	(2) Unrestricted lags
Cumulative effect of past exposure, lags 1–30	0.00343** (0.00163)	-0.00018 (0.00300)
<i>Panel A. Contribution of days $k + 1$ through 30, for k equal to:</i>		
5 days	0.00322** (0.00150)	0.00266 (0.00188)
10 days	0.00255 (0.00157)	0.00118 (0.00186)
15 days	0.00165 (0.00162)	0.00322 (0.00202)
20 days	0.00077 (0.00163)	-0.00167 (0.00192)
25 days	0.00014 (0.00125)	0.00045 (0.00169)
Joint test of the 5 rows (p)	0.1397	0.0442
degrees of freedom	3	5
<i>Panel B. Contribution of non-overlapping five-day blocks, days:</i>		
1–5	0.00021 (0.00109)	-0.00284 (0.00261)
6–10	0.00067 (0.00061)	0.00147 (0.00134)
11–15	0.00090 (0.00066)	-0.00204 (0.00179)
16–20	0.00088 (0.00059)	0.00489*** (0.00169)
21–25	0.00063 (0.00052)	-0.00212 (0.00162)
26–30	0.00014 (0.00125)	0.00045 (0.00169)
N	183,556	183,556
R^2	0.0472	0.0474
Weather controls	✓	✓
Bowler, batter, stadium-by-year, month, home stadium, innings, and over phase FE	✓	✓

Notes. The outcome variable is a binary indicator equal to 1 if at least one run is scored on a delivery and 0 otherwise (mean 0.599). All $PM_{2.5}$ variables are measured in $10 \mu g m^{-3}$. Both columns are the specification of Table 2, column 3, plus the bowling team's $PM_{2.5}$ on each of the 30 days before the match, with match-day $PM_{2.5}$ entering unrestricted. Column (1) restricts the lag profile to a polynomial of degree $Q = 2$ in the lag index s , as in Equation 6, and is the model of Table 4; column (2) leaves the 30 lag coefficients β_s unrestricted. The first row is the whole-window cumulative effect $\sum_{s=1}^{30} \beta_s$, the effect of raising $PM_{2.5}$ by $10 \mu g m^{-3}$ on each of the 30 days before the match. Panel A reports the part of that total contributed by the days beyond day k , so each row asks whether a window of k days would miss anything a 30-day window captures. Panel B reports the sum of the lag coefficients over non-overlapping five-day blocks and asks which days carry the effect. Every entry is a separate linear combination of the estimated coefficients with a delta-method standard error, not a difference of cumulative rows, whose standard errors carry no information about the covariance between two overlapping sums. The joint test in Panel A is a cluster-robust Wald test that all 5 contrasts are zero; in column (1) it has 3 rather than 5 degrees of freedom, because a degree-2 profile has only 3 free parameters and the contrasts cannot span more dimensions than that. With standard errors of the same order as the point estimates, a row that is not distinguishable from zero is a statement about power, not evidence that those days do not matter. A quadratic is symmetric about its vertex, so in column (1) the two end blocks of Panel B (days 1–5 and 26–30) are constrained by the functional form to be similar; column (2) imposes no shape and is reported for that reason, at the cost of precision: adjacent daily exposures are highly collinear, so its block sums alternate in sign from one block to the next and are better read through the joint test than one at a time. 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 I12: Adaptation to PM_{2.5} exposure, number of runs scored outcome

	(1)	(2)	(3)
	Number of runs scored		
Match-day PM _{2.5}	0.00095 (0.00058)	0.0019 (0.0012)	0.0051*** (0.0017)
Past 30-day PM _{2.5}		0.0019* (0.0010)	
Match-day PM _{2.5} X Past 30-day PM _{2.5}		-0.000019 (0.000018)	
Match-day PM _{2.5} X Career PM _{2.5}			-0.000092** (0.000036)
Weather controls	✓	✓	✓
Bowler FE	✓	✓	✓
Batter FE	✓	✓	✓
Stadium-by-year FE	✓	✓	✓
Month FE	✓	✓	✓
Home stadium FE	✓	✓	✓
Innings FE	✓	✓	✓
Over phase FE	✓	✓	✓
<i>N</i>	183,556	183,556	183,556
<i>R</i> ²	0.028	0.028	0.028

Notes. The outcome variable is the number of runs scored (0, 1, 2, 3, 4, 5, or 6; mean 1.25). PM_{2.5} is measured in $\mu\text{g m}^{-3}$. 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. Regressions include fixed effects for individual bowlers, batters, stadium-by-year, month, innings, and over phase. Regressions also include controls for weather conditions including temperature, temperature squared, relative humidity, wind speed, precipitation, atmospheric pressure, and solar radiation. Standard errors (in parentheses) are two-way clustered at the match and bowler levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table I13: Adaptation to PM_{2.5} exposure, number of runs scored (ordered logit)

	(1)	(2)	(3)
	Number of runs scored (ordered logit)		
Match-day PM _{2.5}	0.016* (0.0085)	0.027 (0.018)	0.056** (0.023)
Past 30-day PM _{2.5}		0.025 (0.017)	
Match-day PM _{2.5} X Past 30-day PM _{2.5}		-0.0024 (0.0032)	
Match-day PM _{2.5} X Career PM _{2.5}			-0.0090* (0.0047)
Weather controls	✓	✓	✓
Bowler FE	✓	✓	✓
Batter FE	✓	✓	✓
Stadium-by-year FE	✓	✓	✓
Month FE	✓	✓	✓
Home stadium FE	✓	✓	✓
Innings FE	✓	✓	✓
Over phase FE	✓	✓	✓
N	183,572	183,572	183,572

Notes. The outcome variable is the number of runs scored (0, 1, 2, 3, 4, 5, or 6; mean 1.25). Regressions are estimated using ordered logit as in Equation G.1. PM_{2.5} is measured in $\mu\text{g m}^{-3}$. 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. Regressions include fixed effects for individual bowlers, batters, stadium-by-year, month, innings, and over phase. Regressions also include controls for weather conditions including temperature, temperature squared, relative humidity, wind speed, precipitation, atmospheric pressure, and solar radiation. Standard errors (in parentheses) are two-way clustered at the match and bowler levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table I14: Adaptation to PM_{2.5} exposure: short-term

	(1) 1 (At least one run scored)	(2)
Match-day PM _{2.5}	0.00674* (0.00357)	
Past 30-day PM _{2.5}	0.00595* (0.00344)	0.00965** (0.00430)
Match-day PM _{2.5} × Past 30-day PM _{2.5}	-0.00053 (0.00065)	
Q2 (Match-day PM _{2.5})		0.01453 (0.01929)
Q3 (Match-day PM _{2.5})		0.03831* (0.02034)
Q4 (Match-day PM _{2.5})		0.04514* (0.02307)
Q5 (Match-day PM _{2.5})		0.07368*** (0.02550)
Q2 (Match-day PM _{2.5}) × Past 30-day PM _{2.5}		-0.00206 (0.00466)
Q3 (Match-day PM _{2.5}) × Past 30-day PM _{2.5}		-0.00693 (0.00473)
Q4 (Match-day PM _{2.5}) × Past 30-day PM _{2.5}		-0.00756 (0.00505)
Q5 (Match-day PM _{2.5}) × Past 30-day PM _{2.5}		-0.01032** (0.00518)
<i>Implied effect of match-day PM_{2.5}: linear slope in (1), Q5 vs. Q1 in (2)</i>		
Low exposure (p10)	0.00502** (0.00202)	0.04018*** (0.01248)
High exposure (p90)	0.00337 (0.00205)	0.00796 (0.01461)
<i>p</i> : high = low	0.419	0.047
<i>N</i>	183,556	183,556
<i>R</i> ²	0.0472	0.0472
Weather controls	✓	✓
Bowler, batter, stadium-by-year, month, home stadium, innings, and over phase FE	✓	✓

Notes. The dependent variable is an indicator equal to 1 if at least one run is scored on the delivery and 0 otherwise (mean 0.599). All PM_{2.5} variables are measured in 10 µg m⁻³. Past 30-day PM_{2.5} is the bowler's mean exposure over the preceding 30 days. Column (1) enters both linearly with their interaction; column (2) replaces match-day PM_{2.5} with quintile indicators (lowest quintile omitted), interacted with the 30-day mean. The panel below the coefficients reports the implied effect of match-day PM_{2.5} at the 10th and 90th percentile of past 30-day PM_{2.5} (32.5 and 63.7 µg m⁻³). *p*: high = low tests the interaction. Standard errors (in parentheses) are two-way clustered at the match and bowler levels. * *p* < 0.10, ** *p* < 0.05, *** *p* < 0.01.

Table I15: Adaptation to PM_{2.5} exposure: long-term

	(1) ℓ (At least one run scored)	(2)
Match-day PM _{2.5}	0.01289** (0.00537)	
Match-day PM _{2.5} × Career PM _{2.5}	-0.00193* (0.00116)	
Q2 (Match-day PM _{2.5})		-0.00557 (0.03456)
Q3 (Match-day PM _{2.5})		0.03546 (0.03412)
Q4 (Match-day PM _{2.5})		0.07731* (0.04048)
Q5 (Match-day PM _{2.5})		0.09761** (0.03884)
Q2 (Match-day PM _{2.5}) × Career PM _{2.5}		0.00307 (0.00834)
Q3 (Match-day PM _{2.5}) × Career PM _{2.5}		-0.00625 (0.00816)
Q4 (Match-day PM _{2.5}) × Career PM _{2.5}		-0.01517 (0.00932)
Q5 (Match-day PM _{2.5}) × Career PM _{2.5}		-0.01630* (0.00890)
<i>Implied effect of match-day PM_{2.5}: linear slope in (1), Q5 vs. Q1 in (2)</i>		
Low exposure (p10)	0.00656*** (0.00218)	0.04430*** (0.01341)
High exposure (p90)	0.00247 (0.00212)	0.00985 (0.01493)
<i>p</i> : high = low	0.096	0.068
<i>N</i>	183,556	183,556
<i>R</i> ²	0.0472	0.0472
Weather controls	✓	✓
Bowler, batter, stadium-by-year, month, home stadium, innings, and over phase FE	✓	✓

Notes. The dependent variable is an indicator equal to 1 if at least one run is scored on the delivery and 0 otherwise (mean 0.599). All PM_{2.5} variables are measured in 10 µg m⁻³. Career PM_{2.5} is a bowler's mean exposure across all IPL matches, entered continuously. Column (1) enters match-day PM_{2.5} linearly, interacted with career PM_{2.5}; column (2) replaces it with quintile indicators (lowest quintile omitted). The panel below the coefficients reports the implied effect of match-day PM_{2.5} at the 10th and 90th percentile of career PM_{2.5} (32.7 and 53.8 µg m⁻³). *p*: high = low tests the interaction. Standard errors (in parentheses) are two-way clustered at the match and bowler levels. * *p* < 0.10, ** *p* < 0.05, *** *p* < 0.01.

Table I16: Long-term adaptation to PM_{2.5} exposure: alternate specification with batter exposure

	(1) 1 (At least one run scored)
Match-day PM _{2.5}	0.015* (0.0081)
Match-day PM _{2.5} X Career PM _{2.5} (bowler)	-0.0020* (0.0012)
Match-day PM _{2.5} X Career PM _{2.5} (batter)	-0.00041 (0.0011)
Weather controls	✓
Home stadium FE	✓
Stadium-by-year FE	✓
Over phase FE	✓
Month FE	✓
Innings FE	✓
Bowler FE	✓
Batter FE	✓
<i>N</i>	183,556
<i>R</i> ²	0.047

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-day PM_{2.5} is measured in 10 µg m⁻³. Career PM_{2.5} is the bowler's (batter's) mean PM_{2.5} exposure over all matches played in the cricket league. Column (1) includes the interaction of both with PM_{2.5} on the day of the match. Column (1) includes controls for weather conditions including temperature, temperature squared, relative humidity, wind speed, precipitation, atmospheric pressure, and solar radiation, and indicators for whether the bowling and batting teams are at their home stadium, together with fixed effects for individual bowlers, batters, stadium-by-year, month, innings, and over phase. Standard errors (in parentheses) are two-way clustered at the match and bowler levels. Following [Correia \(2015\)](#), 16 singleton observations are dropped. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table I17: Summary statistics of long-run PM_{2.5} variables

Definition	Distinct values	Mean	SD	Min	Max
<i>Bowler PM_{2.5}</i>					
All IPL, 2008–2022	445	42.62	9.66	17.83	103.16
IPL, 2008–2014	136	40.50	7.48	22.76	69.13
<i>Team stadium PM_{2.5}</i>					
1998–2007	15	45.47	17.42	25.11	83.59
2008–2022	15	50.12	19.61	28.27	96.23
2008–2022, IPL months	15	46.67	14.86	26.66	77.70
1998–2007, IPL months	15	42.54	14.27	22.28	70.49
Preseason	110	51.08	15.14	23.44	100.13

Notes. This table reports summary statistics for seven alternative definitions of long-run PM_{2.5} exposure, computed at the level given by Distinct values. Bowler PM_{2.5} is a bowler's mean PM_{2.5} exposure across all IPL matches played, either over the full 2008–2022 sample or restricted to matches in 2008–2014 (for bowlers who also appear in 2015–2022). Team stadium PM_{2.5} is the mean PM_{2.5} at a team's home stadium over the indicated window; IPL months restricts to March–May. Preseason PM_{2.5} is the mean PM_{2.5} at a team's home stadium over the 21 days preceding that season's start.

Table I18: Robustness of long-term PM_{2.5} measures

	(1)	(2)	(3)	(4)	(5)	(6)
		ℙ (At least one run scored)				
Match-day PM _{2.5}	0.0056 (0.0060)	0.0068** (0.0030)	0.0066** (0.0026)	0.0073** (0.0029)	0.0061** (0.0025)	0.0078*** (0.0028)
PM _{2.5} X Bowler PM _{2.5} (IPL Seasons 2008–2014)	-0.0014 (0.0013)					
PM _{2.5} X Bowler Team Stadium PM _{2.5} (Preseason)		-0.00044 (0.00046)				
PM _{2.5} X Bowler Team Stadium PM _{2.5} (1998–2007)			-0.000041 (0.000039)			
PM _{2.5} X Bowler Team Stadium PM _{2.5} (1998–2007, IPL Months)				-0.000058 (0.000048)		
PM _{2.5} X Bowler Team Stadium PM _{2.5} (2008–2022)					-0.000029 (0.000033)	
PM _{2.5} X Bowler Team Stadium PM _{2.5} (2008–2022, IPL Months)						-0.000074 (0.000051)
Weather controls	✓	✓	✓	✓	✓	✓
Bowler FE	✓					
Bowling Team-by-year FE		✓	✓	✓	✓	✓
Batter FE	✓	✓	✓	✓	✓	✓
Stadium-by-year FE	✓	✓	✓	✓	✓	✓
Month FE	✓	✓	✓	✓	✓	✓
Innings FE	✓	✓	✓	✓	✓	✓
Over phase FE	✓	✓	✓	✓	✓	✓
<i>N</i>	53,607	183,558	183,558	183,558	183,558	183,558
<i>R</i> ²	0.048	0.042	0.042	0.042	0.042	0.042

Notes. The outcome variable is a binary indicator equal to 1 if at least one run is scored on a delivery and 0 otherwise. All columns include controls for weather conditions including temperature, temperature squared, relative humidity, wind speed, precipitation, atmospheric pressure, and solar radiation, and fixed effects for batter, stadium-by-year, month, innings, and over phase; column (1) additionally includes fixed effects for individual bowlers, while columns (2)–(6) include fixed effects for bowling teams-by-year in place of individual bowlers. Standard errors (in parentheses) are two-way clustered at the match and bowler levels. 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), analyzing their performance in the second half using their mean PM_{2.5} exposure during IPL games in the first half. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table I19: South Asian bowlers: PM_{2.5} exposure and run-scoring probability

	(1) 1 (At least one run scored)
Match-day PM _{2.5}	0.0049*** (0.0018)
Match-day PM _{2.5} X South Asian bowler	-0.0012 (0.0012)
Weather controls	✓
Bowler FE	✓
Batter FE	✓
Stadium-by-year FE	✓
Month FE	✓
Home stadium FE	✓
Innings FE	✓
Over phase FE	✓
<i>N</i>	178,459
<i>R</i> ²	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 (mean 0.599). PM_{2.5} is measured in 10 µg 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 PM_{2.5} levels (measured in 10 µg m⁻³). It includes fixed effects for individual batters, bowlers, stadium-by-year, home stadium, month, innings, and over phase. It includes controls for weather conditions including temperature, temperature squared, relative humidity, precipitation, atmospheric pressure, 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 I20: Short-career ladder for the long-term adaptation interaction

	(1) Bowlers in ≤ 1 season (168 bowlers)	(2) Bowlers in ≤ 2 seasons (248 bowlers)	(3) Bowlers in ≤ 3 seasons (292 bowlers)	(4) Bowlers in ≤ 5 seasons (364 bowlers)	(5) Bowlers in ≤ 8 seasons (413 bowlers)
ℙ (At least one run scored)					
Match-day $PM_{2.5}$	0.01561 (0.02254)	0.01152 (0.01143)	0.02715*** (0.01029)	0.01864** (0.00724)	0.01465** (0.00574)
Match-day $PM_{2.5} \times$ Career $PM_{2.5}$ (entire career)	-0.00395 (0.00382)	-0.00190 (0.00205)	-0.00485** (0.00200)	-0.00231 (0.00154)	-0.00225* (0.00123)
Weather controls	✓	✓	✓	✓	✓
Bowler FE	✓	✓	✓	✓	✓
Batter FE	✓	✓	✓	✓	✓
Stadium-by-year FE	✓	✓	✓	✓	✓
Month FE	✓	✓	✓	✓	✓
Innings FE	✓	✓	✓	✓	✓
Over phase FE	✓	✓	✓	✓	✓
N	11,859	25,983	38,915	73,980	123,010
R^2	0.10239	0.07957	0.06758	0.05356	0.04939

Notes. The dependent variable is an indicator equal to 1 if at least one run is scored on the delivery and 0 otherwise. $PM_{2.5}$ is measured in $10 \mu g m^{-3}$. Each column restricts the sample to bowlers whose entire IPL career is at most N seasons ($N = 1, 2, 3, 5$, or 8 , per column), keeping all of their seasons, and recomputes career $PM_{2.5}$ on that restricted sample. All columns include controls for temperature, temperature squared, relative humidity, wind speed, precipitation, atmospheric pressure, and solar radiation, and indicators for whether the bowling and batting teams are at their home stadium, together with fixed effects for individual bowlers, batters, stadium-by-year, month, innings, and over phase. Standard errors (in parentheses) are two-way clustered at the match and bowler levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table I21: Career-length ladder for the long-term adaptation interaction

	(1) Bowlers in ≥ 1 season (445 bowlers)	(2) Bowlers in ≥ 2 seasons (277 bowlers)	(3) Bowlers in ≥ 3 seasons (197 bowlers)	(4) Bowlers in ≥ 5 seasons (111 bowlers)	(5) Bowlers in ≥ 8 seasons (44 bowlers)
ℙ (At least one run scored)					
Match-day $PM_{2.5}$	0.01045 (0.00873)	0.02524*** (0.00679)	0.01552** (0.00640)	0.01563** (0.00763)	0.02622*** (0.00819)
Match-day $PM_{2.5} \times$ Career $PM_{2.5}$ (first N seasons)	-0.00086 (0.00154)	-0.00398*** (0.00136)	-0.00258* (0.00136)	-0.00249 (0.00162)	-0.00445** (0.00180)
Weather controls	✓	✓	✓	✓	✓
Bowler FE	✓	✓	✓	✓	✓
Batter FE	✓	✓	✓	✓	✓
Stadium-by-year FE	✓	✓	✓	✓	✓
Month FE	✓	✓	✓	✓	✓
Innings FE	✓	✓	✓	✓	✓
Over phase FE	✓	✓	✓	✓	✓
N	45,278	66,553	78,351	91,283	64,815
R^2	0.06712	0.05426	0.05055	0.04927	0.05337

Notes. The dependent variable is an indicator equal to 1 if at least one run is scored on the delivery and 0 otherwise. $PM_{2.5}$ is measured in $10 \mu g m^{-3}$. Each column restricts the sample to bowlers with at least N IPL seasons ($N = 1, 2, 3, 5$, or 8 , per column), keeping only their first N seasons of data, and recomputes career $PM_{2.5}$ on that restricted sample. All columns include controls for temperature, temperature squared, relative humidity, wind speed, precipitation, atmospheric pressure, and solar radiation, and indicators for whether the bowling and batting teams are at their home stadium, together with fixed effects for individual bowlers, batters, stadium-by-year, month, innings, and over phase. Standard errors (in parentheses) are two-way clustered at the match and bowler levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table I22: Long-term adaptation to PM_{2.5}, bowlers with at least 3 seasons, first 3 seasons only

	(1) Linear	(2) Spline, knot at 50 $\mu\text{g m}^{-3}$
	1 (At least one run scored)	
Match-day PM _{2.5}	0.01552** (0.00640)	
Match-day PM _{2.5} $\times$ Career PM _{2.5} (first 3 seasons)	-0.00258* (0.00136)	
Match-day PM _{2.5} between 0 and 50 $\mu\text{g m}^{-3}$		0.04096*** (0.01369)
Match-day PM _{2.5} between 50 and 160 $\mu\text{g m}^{-3}$		0.00264 (0.00937)
0–50 $\mu\text{g m}^{-3} \times$ Career PM _{2.5} (first 3 seasons)		-0.00909*** (0.00317)
50–160 $\mu\text{g m}^{-3} \times$ Career PM _{2.5} (first 3 seasons)		0.00038 (0.00197)
Weather controls	✓	✓
Bowler FE	✓	✓
Batter FE	✓	✓
Stadium-by-year FE	✓	✓
Month FE	✓	✓
Home stadium controls	✓	✓
Innings FE	✓	✓
Over phase FE	✓	✓
<i>N</i>	78,351	78,351
<i>R</i> ²	0.05	0.05
<i>p</i> : dose–response linear		0.05
<i>p</i> : no moderation	0.06	0.01
<i>p</i> : moderation constant across segments		0.03

Notes. The dependent variable is an indicator equal to 1 if at least one run is scored on the delivery and 0 otherwise. All PM_{2.5} variables are measured in $10 \mu\text{g m}^{-3}$. The sample is restricted to the 197 bowlers who appear in at least 3 IPL seasons, keeping only each bowler's first 3 seasons of data. Across all 445 bowlers, the mean career length is 3.2 seasons (median 2). Career PM_{2.5} is recomputed on this restricted sample, so it is each bowler's mean PM_{2.5} over his first 3 seasons only. In column (1), match-day PM_{2.5} and career PM_{2.5} are in levels and are interacted. Column (2) replaces the linear match-day dose with a continuous piecewise-linear spline with one knot at 50 $\mu\text{g m}^{-3}$ and interacts each segment slope with career PM_{2.5}. The reported *p*-values are for tests that: the two segment slopes are equal, so the dose–response is linear; there is no moderation; and the two interactions of column (2) are equal to one another. Both columns include controls for temperature, temperature squared, relative humidity, wind speed, precipitation, atmospheric pressure, and solar radiation, and indicators for whether the bowling and batting teams are at their home stadium, together with fixed effects for individual bowlers, batters, stadium-by-year, month, innings, and over phase. Following [Correia \(2015\)](#), 21 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 I23: IPL bowler entry and exit, by season

Season	First-time bowlers	Exiting bowlers
2008	98	32
2010	63	23
2011	44	30
2012	29	31
2013	29	38
2014	17	19
2015	17	18
2016	20	23
2017	24	28
2018	22	18
2019	26	34
2021	14	26
2022	42	n/a
Mean	34.23	26.67
S.d.	23.51	6.60
Min	14	18
Median	26.0	27.0
Max	98	38

Notes. A player is any bowler observed in an IPL delivery (match-player pairs, collapsed to one observation per player-season; team switches within a season are not treated as separate observations). A player is first-time in season s if s is the earliest season in which the player is observed. A player exits in season s if s is the player's last observed season and s is not the final season in the sample (the final season, 2022, is right-censored – exit status is unknown for players still active then – and is marked n/a and excluded from the summary panel below). Summary statistics are computed across the 13 seasons (first-time players) and 12 seasons excluding the final one (exits).

Table I24: Season-to-season retention probit (bowler-season panel)

	(1) 1 (bowls in the IPL next season)
Log deliveries this season	0.238*** (0.077)
Matches this season	0.071*** (0.019)
Run-concession rate this season	0.549 (0.555)
Runs conceded per delivery this season	-0.348** (0.144)
Wickets per 100 deliveries this season	0.008 (0.012)
Wides + no-balls per 100 deliveries this season	-0.003 (0.012)
Share of deliveries in powerplay	-0.178 (0.190)
Share of deliveries at the death	-0.381 (0.244)
Mean match-day PM _{2.5} this season	-0.019 (0.029)
Age	-0.051*** (0.009)
IPL seasons played so far (incl. this one)	0.059*** (0.021)
Pace bowler	-0.103 (0.094)
South Asia	0.170* (0.088)
Season dummies	✓
<i>N</i> (bowler-seasons)	1,403
Pseudo R^2	0.175
AUC (ROC)	0.773
Correctly classified (%)	72.3
Sensitivity (%)	85.9
Specificity (%)	46.5

Notes. One observation per bowler-season in the estimation panel (IPL seasons played in India, 2008–2022). The dependent variable is 1 if the bowler bowled at least one delivery in the following IPL season, measured in the full ball-by-ball record through 2024 and including the two seasons played outside India (2009, 2020), so it is defined for every panel season. All regressors are measured in the current season. AUC is the area under the receiver operating characteristic curve; correctly classified, sensitivity, and specificity are computed at the $\hat{p} \geq 0.5$ classification cutoff. Standard errors (in parentheses) are conventional probit standard errors. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table I25: Contemporaneous and career-adaptation estimates under sequential attrition weights

	(1)	(2)	(3)	(4)	(5)	(6)
	Contemporaneous		Linear $\times$ career		Spline $\times$ career	
	Unweighted	Seq. IPW	Unweighted	Seq. IPW	Unweighted	Seq. IPW
Match-day $PM_{2.5}$	0.00413** (0.00178)	0.01015*** (0.00364)	0.01002* (0.00511)	0.02246** (0.00887)		
Match-day $PM_{2.5}$ between 0 and $50 \mu g m^{-3}$					0.03034** (0.01394)	0.02991 (0.01855)
Match-day $PM_{2.5}$ between 50 and $160 \mu g m^{-3}$					-0.00092 (0.00756)	0.02206* (0.01220)
Match-day $PM_{2.5} \times$ Career $PM_{2.5}$			-0.00131 (0.00111)	-0.00278 (0.00175)		
0–50 $\mu g m^{-3} \times$ Career $PM_{2.5}$					-0.00635** (0.00321)	-0.00654 (0.00442)
50–160 $\mu g m^{-3} \times$ Career $PM_{2.5}$					0.00120 (0.00176)	-0.00191 (0.00272)
Weather and home-stadium controls	✓	✓	✓	✓	✓	✓
Bowler, batter, stadium-by-year, month, innings, over-phase FE	✓	✓	✓	✓	✓	✓
N	178,459	178,459	178,459	178,459	178,459	178,459
R^2	0.0472	0.0578	0.0473	0.0578	0.0473	0.0579
p : no moderation			0.24	0.11	0.13	0.09
p : cols (1)=(2)		0.04				
Weight: 99th pct.		25.7		25.7		25.7
Weight: max		150.8		150.8		150.8

Notes. The dependent variable is an indicator equal to 1 if at least one run is scored on the delivery. $PM_{2.5}$ variables are in $10 \mu g m^{-3}$. Columns (1)–(2) estimate the Table 2 column (3) specification; columns (3)–(6) the linear and spline career-adaptation specifications of Table 6, columns (1) and (2). Even-numbered columns weight each delivery by the sequential inverse-probability-of-retention weight $w_{is} = \prod_{t < s} 1/\hat{p}_{it}$, the product over the bowler's earlier observed seasons of the inverse predicted probability of returning the following season from the probit of Table I24 (weight 1 in the bowler's first season). Bowlers with a missing retention probability in any season are excluded from all columns. p : no moderation tests the interaction term(s); p : cols (1)=(2) tests whether the match-day $PM_{2.5}$ coefficient differs between columns (1) and (2); because both columns use the same deliveries under different weights, it is computed from a single stacked model in which every regressor and fixed effect is interacted with a column indicator, with standard errors two-way clustered at the match and bowler levels. Following Correia (2015), 17 singleton observations are dropped. Standard errors (in parentheses) are two-way clustered at the match and bowler levels and treat the weights as known. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table I26: Short-term adaptation to PM_{2.5}

	(1) Linear	(2) Spline, knot at 50 $\mu\text{g m}^{-3}$
	1 (At least one run scored)	
Match-day PM _{2.5}	0.00638* (0.00357)	
Past 20-day PM _{2.5}	0.00600* (0.00350)	0.01657** (0.00642)
Match-day PM _{2.5} $\times$ Past 20-day PM _{2.5}	-0.00049 (0.00068)	
Match-day PM _{2.5} between 0 and 50 $\mu\text{g m}^{-3}$		0.01836** (0.00789)
Match-day PM _{2.5} between 50 and 160 $\mu\text{g m}^{-3}$		0.00006 (0.00515)
0–50 $\mu\text{g m}^{-3} \times$ Past 20-day PM _{2.5}		-0.00341** (0.00167)
50–160 $\mu\text{g m}^{-3} \times$ Past 20-day PM _{2.5}		0.00085 (0.00110)
Weather controls	✓	✓
Bowler FE	✓	✓
Batter FE	✓	✓
Stadium-by-year FE	✓	✓
Month FE	✓	✓
Home stadium controls	✓	✓
Innings FE	✓	✓
Over phase FE	✓	✓
<i>N</i>	183,556	183,556
<i>R</i> ²	0.05	0.05
<i>p</i> : dose–response linear		0.10
<i>p</i> : no moderation	0.47	0.12
<i>p</i> : moderation constant across segments		0.08

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

Table I27: Short-term adaptation to PM_{2.5}

	(1) Linear	(2) Spline, knot at 50 $\mu\text{g m}^{-3}$
	1 (At least one run scored)	
Match-day PM _{2.5}	0.00726** (0.00366)	
Past 24-day PM _{2.5}	0.00678* (0.00351)	0.01947*** (0.00631)
Match-day PM _{2.5} $\times$ Past 24-day PM _{2.5}	-0.00066 (0.00068)	
Match-day PM _{2.5} between 0 and 50 $\mu\text{g m}^{-3}$		0.02186*** (0.00794)
Match-day PM _{2.5} between 50 and 160 $\mu\text{g m}^{-3}$		-0.00021 (0.00525)
0–50 $\mu\text{g m}^{-3} \times$ Past 24-day PM _{2.5}		-0.00416** (0.00166)
50–160 $\mu\text{g m}^{-3} \times$ Past 24-day PM _{2.5}		0.00091 (0.00111)
Weather controls	✓	✓
Bowler FE	✓	✓
Batter FE	✓	✓
Stadium-by-year FE	✓	✓
Month FE	✓	✓
Home stadium controls	✓	✓
Innings FE	✓	✓
Over phase FE	✓	✓
<i>N</i>	183,556	183,556
<i>R</i> ²	0.05	0.05
<i>p</i> : dose–response linear		0.05
<i>p</i> : no moderation	0.34	0.04
<i>p</i> : moderation constant across segments		0.04

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

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