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

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Abstract

Air pollution harms labor productivity, yet little is known about whether workers adapt to chronic exposure. We address this question using 14 years of individual-level performance data from India's premier cricket league, a setting characterized by some of the highest levels of particulate matter air pollution (PM2.5) and whose schedule and geography result in variation in both acute and chronic exposure histories. We pair these granular performance metrics with an India-specific machine learning data product that incorporates remotely sensed and ground-monitor measures of PM2.5. Our results reveal that both chronic and acute exposure to pollution are costly, but in different ways. A 10 microgram-per-cubic-meter increase in same-day PM2.5 concentration (half a standard deviation in our sample) reduces productivity by about 1 percent, with effects concentrated at the highest pollution levels, implying a nonlinear dose-response. The dose-response also exhibits surprising heterogeneity: same-day shocks harm those chronically exposed at the highest levels approximately 40 percent less than those with median exposure histories, indicating adaptation. Nevertheless, chronic exposure itself results in performance declines that, though smaller in magnitude than the declines resulting from same-day shocks, far outweigh any protective effect from adaptation. Our findings suggest that standard estimates from low-pollution environments do not capture the dynamics between acute and chronic exposure in high-pollution settings.

Keywords: Air pollution, labor productivity, adaptation
JEL codes: Q53, Q56, J24

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1 Introduction

Over 7.3 billion people—94% of the global population—are exposed to unsafe annual average concentrations of fine particulate matter ($PM_{2.5}$) above the World Health Organization (2021) safety guideline of 5 $\mu g\,m^{-3}$ (Rentschler and Leonova, 2023). Beyond its well-documented health impacts, $PM_{2.5}$ exposure degrades labor productivity, constraining economic growth (Graff Zivin and Neidell, 2012). These productivity losses are likely to be particularly severe for the 2.8 billion people exposed to hazardous annual average $PM_{2.5}$ levels above 35 $\mu g\,m^{-3}$. Yet while a substantial literature has examined productivity impacts of $PM_{2.5}$ exposure in low- and moderate-pollution settings such as the United States, where annual concentrations have remained below 10 $\mu g\,m^{-3}$ over the past decade, less is known about impacts at far higher exposure levels common across emerging economies.

Understanding productivity effects at high pollution levels is challenging for two reasons. First, dose–response relationships may be non-linear: marginal increases in exposure may have qualitatively different effects at high concentrations than at low ones. Second, workers' responses may depend on *accumulated* exposure: acute pollution shocks may alter productivity differently for workers chronically exposed to high $PM_{2.5}$ than for those accustomed to cleaner air. While recent studies have begun to document non-linearities in the $PM_{2.5}$–performance relationship in consistently high pollution settings (Arceo et al., 2016; Hoffmann and Rud, 2024), the question of whether these high levels of chronic exposure mediate workers' responses to contemporaneous pollution remains largely unexplored.

We fill this gap by asking a central question: Does the marginal effect of contemporaneous $PM_{2.5}$ exposure on labor productivity vary with accumulated past exposure? We find that it does and that—surprisingly—workers chronically exposed to high air pollution levels 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 extraordinarily rare pollution conditions.

We examine this question using detailed performance data from professional cricket athletes in India, a high-pollution setting where average $PM_{2.5}$ levels exceed five times those typical in the United States. Cricket provides an ideal laboratory for three reasons. First, the Indian Premier League (IPL) cricket league's structure generates quasi-experimental variation in both contemporaneous and long-term $PM_{2.5}$ exposure—a rare empirical feature. Specifically, match-day pollution varies across venues over time, while league rules assign players to teams located in cities with substantially different baseline pollution levels. Second, strict salary-cap rules help decouple pollution exposure from player ability (ESPN, 2024), strengthening our identification.[1] Third, each play in the game reflects a direct interaction between two "workers"—a bowler and a batter—allowing us to identify which types of tasks are most vulnerable to pollution exposure.

Our empirical approach combines ball-by-ball performance data from 773 IPL matches (spanning 2008–2022) with a novel machine learning-based dataset providing daily $PM_{2.5}$ estimates for each stadium (Wang et al., 2024).[2] Our setting offers unusually rich variation: $PM_{2.5}$ during matches averages 42 $\mu g\,m^{-3}$ and peaks at 160 $\mu g\,m^{-3}$—more than ten times the World Health Organization (2021) daily safe limit and representative of conditions faced by billions of workers in developing countries.

We report four main findings. First, pollution significantly reduces worker performance: a 10 $\mu g\,m^{-3}$ increase in $PM_{2.5}$—equivalent to half a standard deviation—increases the probability that a bowler concedes a run by 0.41 percentage points (a 0.68% increase relative to a mean probability of 59.9%). Because run-scoring reflects bowler–batter interactions, this positive relationship indicates that pollution disproportionately impairs bowlers relative to batters. This asymmetry is aligned with physiological evidence establishing respiration as the primary channel for particulate matter exposure (Hamanaka and Mutlu, 2025): bowlers have much higher levels of exertion and respiration rates relative to batters, who engage in

[1] Our identifying assumption requires that long-term pollution exposure is not systematically correlated with player ability. The IPL's salary cap—which limits how much each team can spend on player compensation—ensures that player quality is roughly equal across teams and not systematically related to home stadium pollution levels.

[2] A "ball" is analogous to a pitch in baseball.

more intermittent activity.

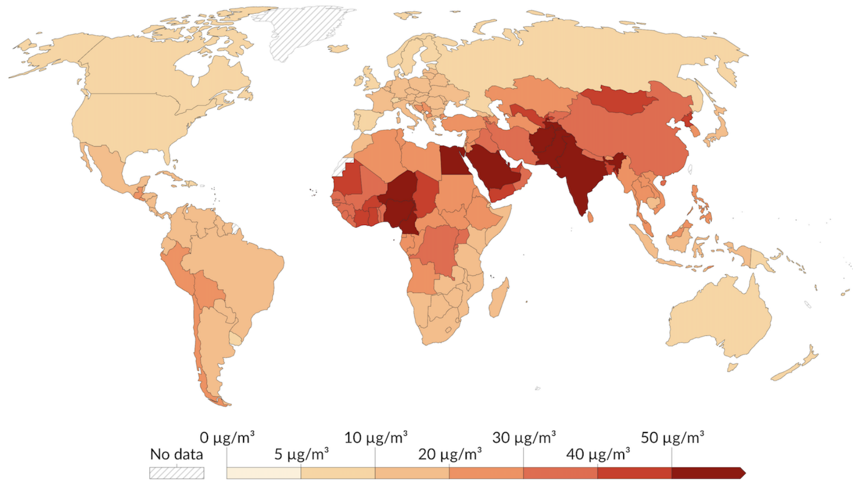
Second, these effects are highly non-linear. Impacts on relative bowler performance arise almost entirely in the highest pollution quintile (above 53 $\mu g\,m^{-3}$), exposure levels common in developing countries but rarely studied. At lower pollution levels, run-scoring probabilities do not change significantly, suggesting that extremely high exposures are required for task-specific effects to materialize.

Third, workers adapt to chronic pollution exposure over both short and long time horizons. Players with higher career-average PM2.5 exposure exhibit substantially smaller marginal responses to acute shocks—approximately 36% smaller for the most highly exposed players relative to those with median career exposure. Adaptation also emerges over shorter 30-day windows, with highly exposed bowlers experiencing marginal effects up to 41% smaller than those at the median. Critically, this adaptation is most pronounced when contemporaneous pollution is extremely high yet remains below workers' typical exposure levels.

Fourth, adaptation does not offset cumulative harm. Past pollution simultaneously degrades baseline performance and necessitates physiological adjustment. The protective effect of adaptation only dominates cumulative damage at extraordinarily rare pollution levels—above 110 $\mu g\,m^{-3}$, a threshold exceeded in just 1.8% of observations. For virtually all policy-relevant scenarios, both acute and chronic pollution unambiguously impair productivity.

These findings contribute to a literature on pollution and productivity that remains concentrated in low-pollution contexts. As noted by Aguilar-Gomez et al. (2022), half of the ten leading studies on pollution's physical productivity effects examine the United States or Europe (Archsmith et al., 2018; Chang et al., 2016; Graff Zivin and Neidell, 2012; Mullins, 2018), four examine China (Chang et al., 2019; He et al., 2019; Guo and Fu, 2019; Kahn and Li, 2020), and only one focuses on India (Adhvaryu et al., 2022). This geographic focus—disproportionately weighted to low-pollution environments—may obscure important non-linearities in dose–response relationships that only manifest in the high exposure ranges shown in Figure 1. Moreover, prior work has largely left adaptation to chronic pollution

Figure 1: Average Annual $PM_{2.5}$ Concentrations in 2019



Notes. Figure displays annual average $PM_{2.5}$ concentrations (population-weighted) in 2019 (WHO, 2025).

unexplored. Among these studies, only He et al. (2019) examine exposure beyond a week, despite the fact that workers in many developing countries face persistently high pollution.

We make three main contributions to this literature. First, we provide high-quality estimates of productivity effects in a persistently high-pollution environment. Prior work in India is limited by sparse ground monitoring networks–only five of twenty IPL stadiums had ground monitors during our sample period. We overcome this limitation using an India-specific machine learning-based dataset that fuses ground monitors and satellite data, substantially outperforming conventional satellite-based measures in India's highly variable pollution conditions (Wang et al., 2024).

Second, we document substantial non-linearities in pollution's dose–response relationship and identify which types of work activities are most susceptible. Because our outcomes reflect relative performance in a two-person production task, we can isolate task-specific vulnerabilities—an important advantage over settings observing only aggregate output. Our results caution against linear extrapolations from low-pollution settings and highlight heterogeneity across tasks with different physical and cognitive demands.

Third, we provide novel evidence on how long-term pollution exposure mediates productivity responses to acute pollution shocks. This relationship has been difficult to identify in existing studies, which typically examine workers in fixed locations and rely on instruments such as wind direction or thermal inversions (Chung et al., 2025; Hansen-Lewis, 2024; He et al., 2019; Hill et al., 2024; Merfeld, 2023). In contrast, the IPL's scheduling rules generate plausibly exogenous variation in both contemporaneous and accumulated exposure, allowing us to extend epidemiological insights on long-term pollution exposure (Schwartz, 2000; Wei et al., 2021; Zanobetti et al., 2002) to the labor productivity domain.

Our findings also illuminate the tension between performance and health effects of accumulated exposure. Although long-term $PM_{2.5}$ exposure entails large health costs (Orellano et al., 2024), we find that it also partially buffers workers against acute shocks. We emphasize, however, that cumulative performance losses from chronic exposure far outweigh this protective effect except under extremely rare high-pollution conditions. This trade-off is especially relevant for high-intensity activities with large returns to small performance improvements, including professional sports and financial trading, where pollution-induced mistakes can immediately affect outcomes (Heyes et al., 2016).

Our findings have direct implications for environmental policy in emerging economies. The sharp non-linearities in the dose–response relationship that we document imply that curbing extreme pollution episodes may generate disproportionately large productivity gains, particularly for occupations requiring sustained physical exertion and high respiration rates. At the same time, the evidence for adaptation that we observe suggests that workers in chronically polluted environments may exhibit partial resilience to acute shocks, albeit at the cost of degraded baseline performance. The asymmetric impacts we document across physical tasks underscore the importance of considering occupational exposure differences when designing air quality and workplace health policies. Most importantly, adaptation is not a solution to pollution; instead, it is evidence of workers' ongoing struggle against persistent environmental assault.

This paper proceeds as follows. Section 2 describes our cricket setting and the physiological mechanisms for adaptation to air pollution exposure. Section 3 develops a conceptual framework for non-linear and adaptation effects. Section 4 presents our data. Section 5 outlines our empirical strategy. Section 6 reports our results. Section 7 concludes.

2 Background

2.1 Institutional details of cricket

Cricket provides an advantageous setting for studying the impact of air quality on labor productivity because players perform specialized roles, resulting in differing susceptibility to $PM_{2.5}$ exposure throughout the game. A cricket match thus generates rich data on observable outputs that are affected by air pollution. At its core, 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. However, cricket is distinctive among team sports in that it features players in highly specialized roles who engage in what is essentially 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 (analagous 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.[3]

The Indian Premier League (IPL), founded in 2008, has emerged as the world's premier Twenty20 cricket competition and provides our empirical setting.[4] 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 league itself was valued at over $10 billion USD in 2022 (Times, 2022). The productivity effects of air

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

[4]Twenty20, 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 games can take days.

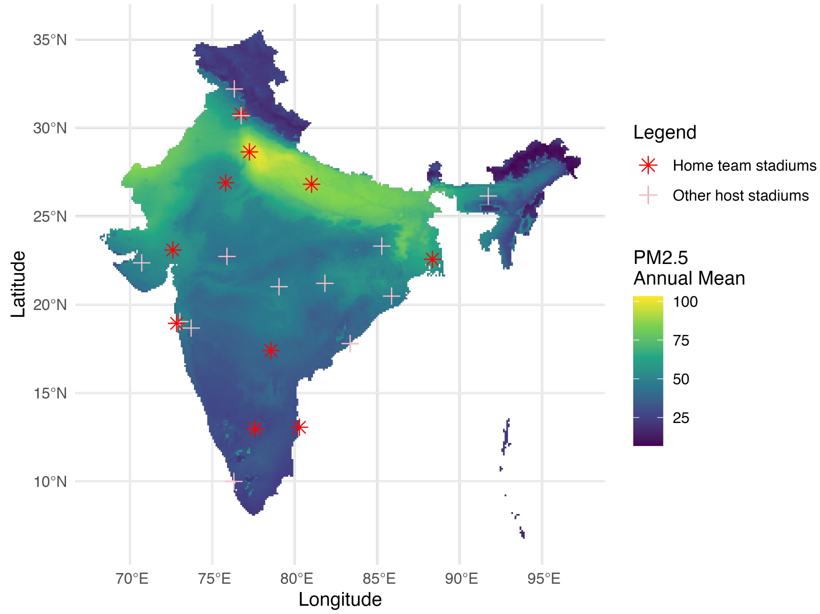
pollution on cricket players are thus economically important in their own right. In addition, the rich performance data that the IPL yields make it an ideal setting to understand some of the nuanced effects of pollution on performance, which can then be explored in further studies on other populations of workers.

The IPL's structure and characteristics create two distinct sources of variation that make it particularly valuable for studying air quality impacts on worker productivity. First, the IPL operates as a franchise system with ten teams based in different cities: Chennai, Delhi, Ahmedabad, Kolkata, Lucknow, Mumbai, Mullanpur, Jaipur, Bengalaru, and Hyderabad (Figure 2). These cities span India's diverse geography, from coastal regions to inland valleys, and vary substantially in their air quality due to differences in vehicle traffic, industrial activity, and natural features. This geographic dispersion creates variation in pollution exposure across team training locations, as indicated in the wide dispersion of pollution in Figure 2. Crucially for our analysis, this variation in $PM_{2.5}$ exposure is not correlated with team quality as indicated by the proportion of matches that teams win.[5] This lack of relationship makes sense given the fact 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 due to wealth.

Second, 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

[5] See Figure A.1 in the appendix.

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



Notes. This figure shows annual mean $PM_{2.5}$ across India in 2019 as estimated by Wang et al. (2024) and the locations of cricket stadiums used in the Indian Premier League (IPL) from 2008–2022. Red asterisks indicate home stadiums of the ten IPL franchise teams: Chennai Super Kings (Chennai), Delhi Capitals (New Delhi), Gujarat Titans (Ahmedabad), Kolkata Knight Riders (Kolkata), Lucknow Super Giants (Lucknow), Mumbai Indians (Mumbai), Punjab Kings (Mullanpur), Rajasthan Royals (Jaipur), Royal Challengers Bengaluru (Bengaluru), and Sunrisers Hyderabad (Hyderabad). Pink crosses indicate other stadiums that have hosted IPL matches during this period but are not permanent home venues for any current IPL team.

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 stretch on for about 1.5 hours. Only about 20 percent of this distance 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 bowler requirements, suggesting that bowlers may be more affected by air pollution than are batters.

Match schedules in the IPL are predetermined and beyond teams' control, so players cannot control pollution exposure by avoiding matches on days with high pollution. This scheduling system thus creates plausibly exogenous variation in short-term exposure through day-of-match pollution levels. The IPL's geographic dispersion provides variation in short- and long-term exposure through differences in baseline air quality across team locations, while the international composition of teams introduces variation in longer-term exposure through players' diverse origins. These temporal variations in pollution exposure, combined with the distinctly different physical demands placed on bowlers versus batters, allow us to examine how both acute and chronic exposure to air pollution affects workers performing different types of physical tasks. Moreover, the discrete nature of cricket's bowler–batter interactions generates rich data on individual performance, enabling precise measurement of productivity effects.

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.

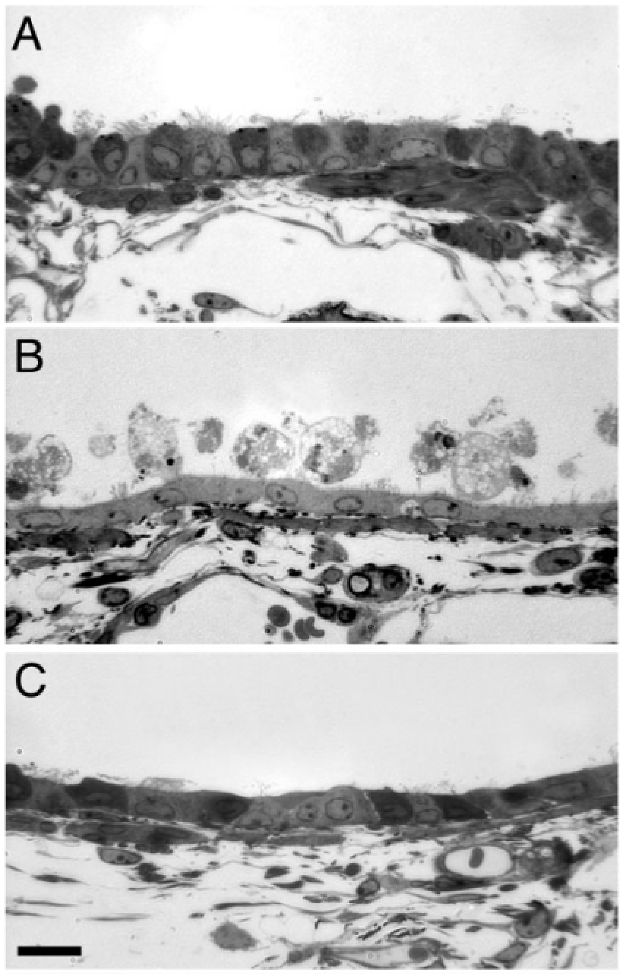
Using randomized controlled trials exposing mice to varying levels of air pollution over time, the environmental toxicology literature has established that mice become resistant to the acute damages of pollution with repeated exposure (West et al., 2003; Kültz et al., 2015; Lee et al., 2018). Cells in 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.

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. 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. See Appendix B for a detailed discussion of the biological mechanisms underlying this cellular adaptation.

To visualize the effects of this adaptation response, Figure 3 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.

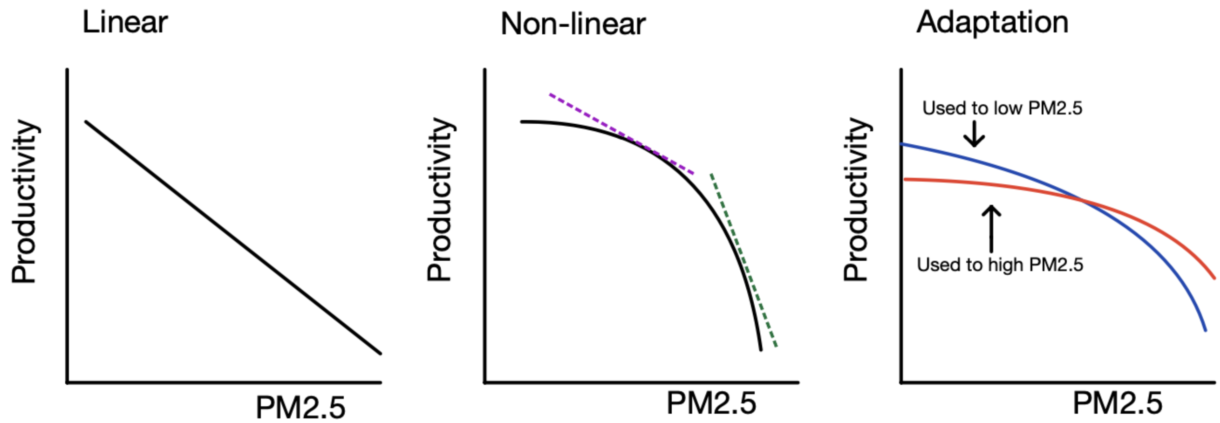
Studies have shown that this adaptation response occurs as quickly as after a week of repeated exposure to air pollution (West et al., 2003). However, little is known about how this response may amplify—or fade—over time. As a result, we explore exposure windows from 1 to 90 days to identify the lookback window that results in the largest magnitude of adaptation response in our empirical setting.

Figure 3: 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 4: Dose response of performance to pollution



3 Conceptual framework

While the negative effect of air pollution on performance is well documented (Aguilar-Gomez et al., 2022), the relationship between pollution and productivity is likely to be more nuanced than a simple linear decline. Our conceptual framework highlights three channels through which air pollution may affect worker performance. First, the negative impacts of air pollution on productivity may be non-linear, with potentially larger marginal effects at higher concentrations. Second, workers may adapt to chronic exposure through both behavioral responses (e.g., using protective equipment such as masks, or respiratory therapies such as inhalers or supplemental oxygen) and physiological changes, as suggested by medical research showing respiratory system adaptation to repeated pollution exposure (Dimeo et al., 1981; Hackney et al., 1977; Hamade and Tankersley, 2009). Third, pollution's impacts likely vary by task type, depending on the interplay of specific physical and cognitive requirements.

First, the marginal effect of pollution on performance may vary with the level of pollution itself. As depicted in the left panel of Figure 4, 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. Alternatively, the relationship could be convex, though the key insight remains: there is little theoretical justification for assuming constant marginal effects across all pollution levels.

Second, the effect of pollution may vary systematically across individuals based on their typical exposure levels. The right panel of Figure 4 illustrates how performance might differ between individuals accustomed to high versus low pollution levels.[6] 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.

There may be negative effects to performance resulting from cumulative physiological damage from long-term pollution exposure, though this need not be permanent as recovery may occur during periods of lower exposure. There also may be positive effects from acclimatization along several dimensions: behavioral (e.g., learning when and how to avoid pollution by wearing masks, using inhalers), physiological (e.g., changes in lung function) (Hackney et al., 1977; Hamade and Tankersley, 2009), and psychological (e.g., developing coping strategies for pollution-related discomfort).

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).[7]

Equation 1 decomposes the total effect of pollution on performance into its constituent parts:

$$\underbrace{\frac{\mathrm{d}F}{\mathrm{d}p}}_{\text{Long-run effect}} = \underbrace{\frac{\partial F}{\partial p}}_{\text{Short-run effect}} + \underbrace{\frac{\partial F}{\partial a}\frac{\mathrm{d}a}{\mathrm{d}p}}_{\text{Adaptation effect}} \tag{1}$$

Standard reduced-form estimates capture only the short-run effect $\frac{\partial F}{\partial p}$. By interacting current

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

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

pollution with a longer-term average exposure in our empirical specifications, we can begin to disentangle the short- and long-run effects.

4 Data

We combine three data sources to study the effect of $PM_{2.5}$ on cricket player performance: detailed ball-by-ball performance data from 773 IPL matches in India[8] spanning 2008–2022; high-resolution daily air pollution measures from both ground monitors and satellite-based estimates; and comprehensive weather controls. Our ball-by-ball data capture granular measures of player performance through specific bowler-batter interactions, while our pollution data allow us to precisely characterize both acute and chronic exposure patterns across India's diverse geography. The combination of these three datasets yields a rich analytical sample that allows us to examine the relationship between air quality and athletic performance while controlling for potentially confounding weather conditions. 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. Our sample covers IPL matches from the league's inaugural 2008 season through the 2022 season, comprising over 180,000 deliveries (analogous to pitches in baseball) across 773 matches matches.[9] 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 over number and the score).

We leverage the data's ball-by-ball granularity by defining our main outcome as a binary

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

[9] Cricsheet data are available at www.cricsheet.org.

Table 1: Summary Statistics from IPL Matches (2008–2022)

Statistic	**Mean**	**Median**	**Note**
Matches in India	773	–	–
Runs scored per match	298	302	Range: 51 to 448
Deliveries per match	237.5	244	Range: 51 to 263
Deliveries per match resulting in ≥ 1 run	142	146	60% of deliveries
Bowlers in sample	445	–	–
Batters in sample	575	–	–
Players in sample	619	–	Bowlers may play as batters
Bowlers per team per game	5.9	6	Range: 2 to 9
Deliveries per bowler per match	20.1	24	Range: 1 to 34
Number of seasons each bowler plays	3.2	2	Range: 1 to 12
Number of matches each bowler plays	20.5	10	Range: 1 to 151
Number of teams each bowler plays on	1.8	1	Range: 1 to 6

indicator for whether any runs were conceded on a given delivery. This 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 evolving match conditions. 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.

Our analytic sample contains 773 games in the IPL from 2008-2022 that took place in India.[10] Table 1 describes summary statistics from these games. Bowlers bowl a maximum of four overs per game, where an over consists of six legal deliveries,[11] resulting in a theoretical

[10] Some games took place outside India due to security concerns; we exclude these from our sample.

[11] A delivery can be classified as illegal several reasons, but they boil down to giving the bowler an unfair advantage against the batter (e.g., bowling the ball too far away from the batter, known as a "wide.")

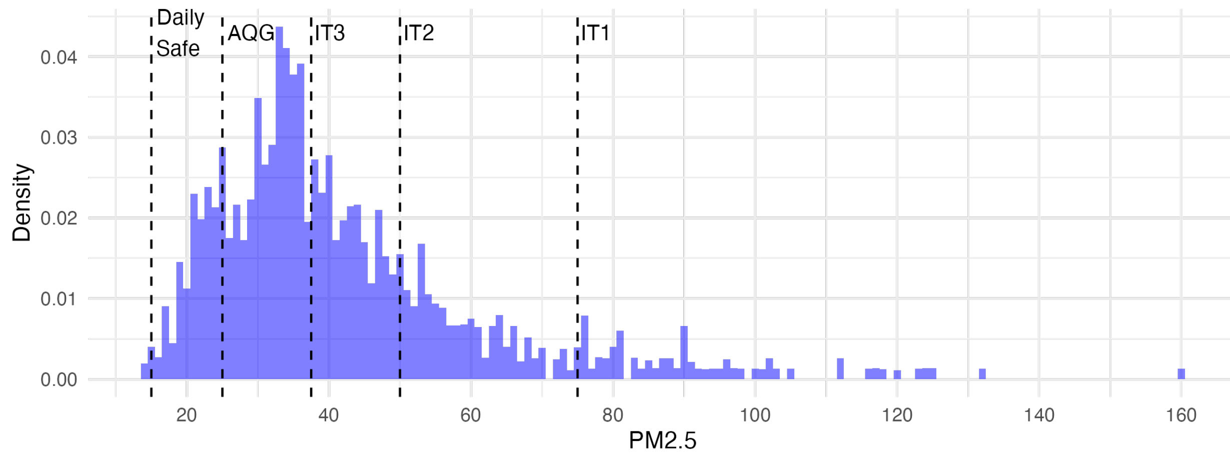
maximum of 24 legal deliveries per bowler in a game. Bowlers typically meet this threshold: the median number of deliveries per game for a bowler is 24. A match has two innings, where each inning consists of up to 20 overs. This means that a match may have up to $2 \times 20 \times 6 = 240$ legal deliveries which is approximately what we observe: the mean number of deliveries per match is 237.5 (median 244). That the number of deliveries per bowler exceeds 24 in some cases and that the number of delivieries per match exceeds 240 in some cases is a result of a handful of illegal deliveries in each match.

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 $\times$ 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 24 stadiums where IPL matches were played during our study period, including both the ten permanent home venues and fourteen additional stadiums that periodically hosted matches (Figure 2). We validate the Wang et al. (2024) data against the U.S. AirNow network in Figure A.4, which demonstrates a strong correlation between the Wang et al. (2024) dataset and ground readings. By contrast, Figure A.3 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.

Leveraging the Wang et al. (2024) data to gain complete coverage of all IPL games during our study period, we emphasize that the distribution of $PM_{2.5}$ in IPL games is dramatically higher than $PM_{2.5}$ in high-income countries, with a mean $PM_{2.5}$ concentration of 42 $\mu g\, m^{-3}$ on game day (median 37 $\mu g\, m^{-3}$), and a maximum of 160 $\mu g\, m^{-3}$—over 10 times the WHO safe daily limit (Figure 5, World Health Organization (2021)). These $PM_{2.5}$ concentrations are orders of magnitude higher than annual average $PM_{2.5}$ concentrations in, for exmaple,

Figure 5: IPL Game $PM_{2.5}$ Distribution with WHO Thresholds Indicated



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

the U.S., which ranged from 7-9 $\mu g\, m^{-3}$ in 2013-2023.

4.3 Defining past exposure to $PM_{2.5}$

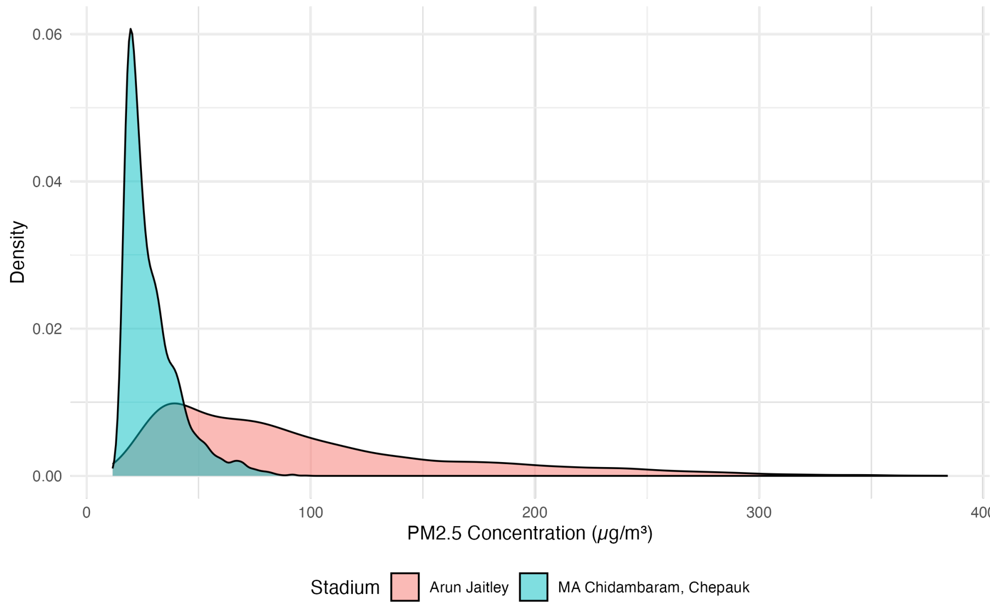
Our approach to exploring heterogeneity in the short-run effect of pollution by exposure to pollution in the long-run—suggesting a form of adaptation—connects to the climate economics literature which examines how long-term temperature averages in a specific region mediate short-term response to temperature changes (Dell et al., 2014; Mérel and Gammans, 2021; Mérel et al., 2024). However, unlike the climate literature which focuses almost exclusively on adaptation within spatial units (e.g. agricultural fields, Census tracts, or nations), we shift the unit of analysis to the person.

We build on the person-based approach to measuring pollution exposure histories in environmental toxicology (Dodson et al., 2007; Garcia et al., 2013). 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 average number of times each player switched teams is 1.4, with a range of 2 to 12 times. 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.

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 game at a stadium in a rival's city, they experience a new pollution climate where daily pollution realizations are not different realizations from the same distribution but realizations from a different distribution. This framework is consistent with the observed data indicating diverging average pollution levels across stadiums (Figure 2). For example, in Figure 6 we see that although there is a common support of the probability mass at low pollution levels, the Arun Jaitley stadium Delhi regularly experiences pollution levels that the stadium in Chepauk, Chennai never experiences.

Figure 6: 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 $PM_{2.5}$.

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[12]—we therefore flexibly adjust our time window from 1 to 90 days prior to the match.

We focus on three measure of past exposure to $PM_{2.5}$:

1. Mean $PM_{2.5}$ over past X days

$$PM2.5_{J(j)d} = \frac{1}{X}\sum_{d=1}^{X}\overline{PM2.5_{J(j)d}} \tag{2}$$

[12]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 beyond seven days are complicated which forced them to limit the time frame of their study.

2. Number of days in past X days where $PM_{2.5}$ was above Z threshold

   E.g. WHO thresholds i.e. $Z \in \{25, 37.5, 50, 75\}$

$$PM2.5_{J(j)d} = \sum_{d=1}^{X} \mathbf{1}(PM2.5_{J(j)d} > Z) \tag{3}$$

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

$$PM2.5_{J(j)d} = \sum_{d=1}^{X} [\mathbf{1}(PM2.5_{J(j)d} > Z)](PM2.5_{dj} - Z) \tag{4}$$

Since each of these measures extends into the past by at most three months and there is a nine-month gap between seasons of the IPL, these past-exposure measures are assigned at the level of the team, not that of the individual player. The team-level of assignment is reflected in the subscript $J(j)$, where J is a function that maps bowler j to team J.

To construct past exposure levels for each of these measures, we adopt a set of assumptions for assigning a team's exposure to pollution within a season for days on which a team does not play a match.

Rules for assigning $\mathbf{PM_{2.5}}$ exposure to teams

1. If the team plays a match on a given day, we assign the $PM_{2.5}$ for the 10x10km grid 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 $PM_{2.5}$ 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 $PM_{2.5}$ for the location of the previous match's stadium.

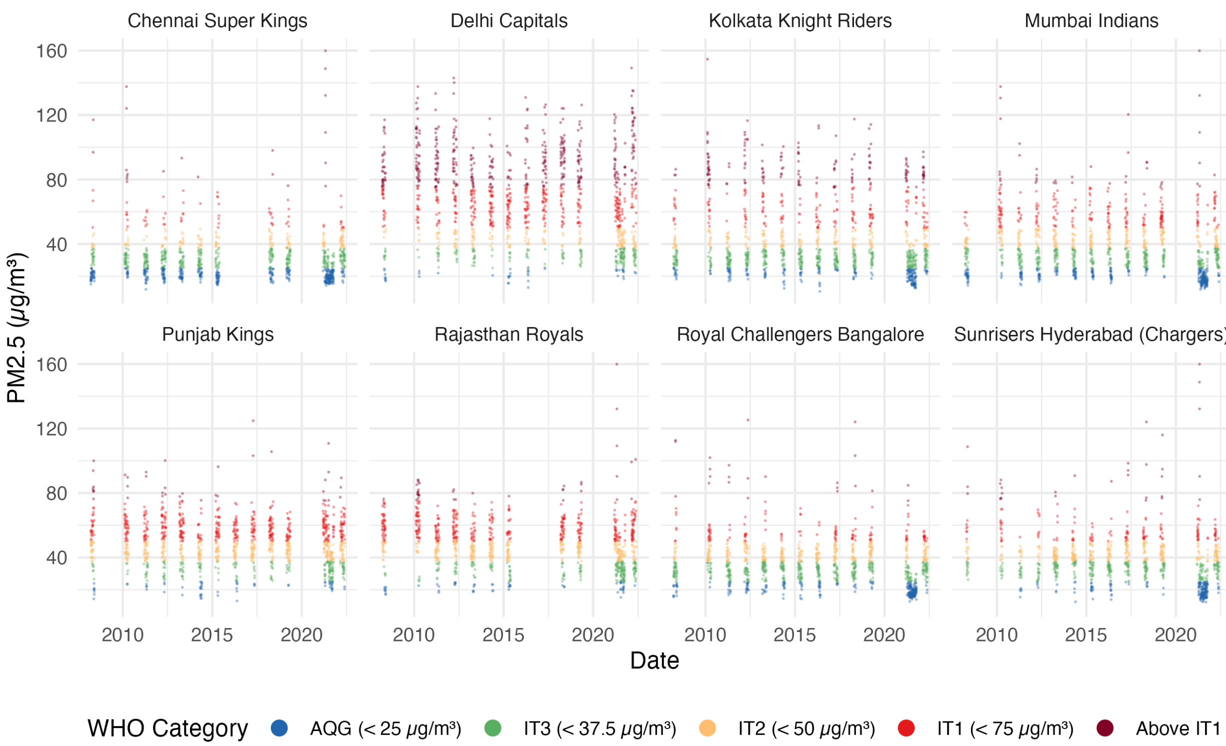
(c) If neither of these are the case (i.e., the team did not play a match the day before and will not play one the day after), we assign them the $PM_{2.5}$ for their home stadium.

Figure 7 shows the distribution of $PM_{2.5}$ exposure histories for each of the eight teams with the highest numbers of matches in the IPL as of 2022.[13] In Figure 8, we compare the $PM_{2.5}$ estimates assigned to teams (based on their travel itinerary, as described above) as opposed 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 where the team spends a disproportionate amount, though not all, of their time. The blue line shows the $PM_{2.5}$ exposure for each team taking into account their away games 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.

We note that the measures in Equations 2, 3, 4 are piece-wise linear functions of one another and 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 gloss

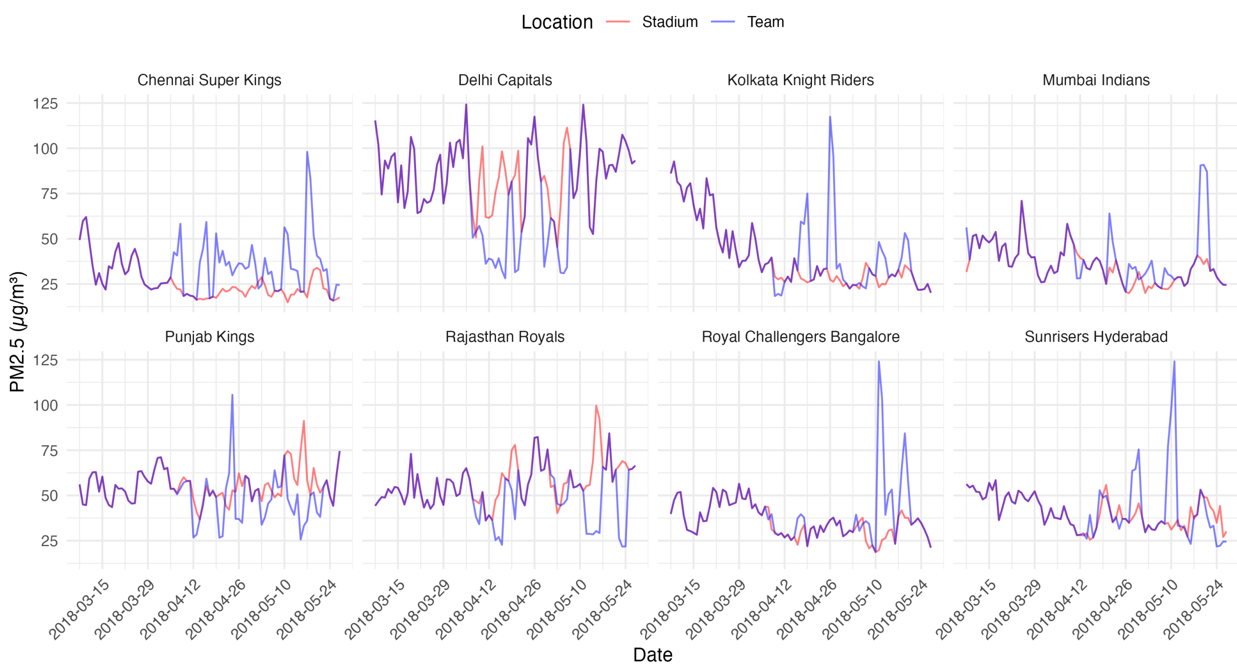
[13] We combine the $PM_{2.5}$ exposure histories for teams that changed names across seasons but retained the same home city and stadium; the graph shows the most recent name of each team.

Figure 7: 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 8: 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 games and travel schedule.

over 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 $\mu g\, m^{-3}$) and then a day with some of the most polluted air, say, 80 $\mu g\, m^{-3}$, the measure in Equation 2 would be 40 $\mu g\, m^{-3}$. This would be the same as that measure for someone who is exposed to days of exactly 40 $\mu g\, m^{-3}$ 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 3 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 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 $\mu g\, m^{-3}$, Interim Target 3 (37.5 $\mu g\, m^{-3}$), Interim Target 2 (50 $\mu g\, m^{-3}$) and Interim Target 1 (75 $\mu g\, m^{-3}$), and explore robustness of the measure to each threshold. Returning to the example above, using the threshold of 50 $\mu g\, m^{-3}$ would mean that the measure in Equation 3 would be 15 in the alternating case and 0 in the consistent case.

The measure in Equation 4 is a further refinement of that in Equation 3—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 $PM_{2.5}$ 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 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 $\mu g\, m^{-3}$, the team exposed to alternate 0 and 80 $\mu g\, m^{-3}$ days for 30 days would be assigned $30 \times 15 = 450$ for this measure, while the team exposed to 40 $\mu g\, m^{-3}$ consistently would be assigned 0. The advantage of Equation 4 relative to Equation 3 is that Equation 4 makes it possible to distinguish between a scenario where on the "high" days in the alternating scenario the high is, say, 55 $\mu g\,m^{-3}$ versus 80 $\mu g\,m^{-3}$. 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 this pollution exposure history for games early in each season, we extend back only 30 days prior to the season start. This decision reflects the fact that teams tend to only start to train in their home stadiums several weeks before the season starts.

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 games they play in the IPL. The distribution of this measure is displayed in Figure A.5. It 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 games 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 C.3, we explore alternative definitions of long-term $PM_{2.5}$ exposure.

4.4 Weather

Particulate matter is not the only meteorological factor that may affect performance in cricket; the weather may do so as well. $PM_{2.5}$ concentrations themselves are a product of many meteorological factors, including temperature, humidity,[14] and wind, and thus have substantial correlations (sometimes negative, sometimes positive) with each of these. We therefore include temperature, temperature-squared (to capture the non-linear effect of temperature on performance), humidity, precipitation, solar radiation, and wind speed in our regression specifications. We obtain 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 11km × 11km spatial resolution, enabling precise matching to match locations. These weather controls are crucial for our analysis as they may independently affect both cricket performance and pollution levels.

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 a binary indicator for whether a run is scored on each delivery as our primary outcome variable. This choice of dependent variable is motivated by three considerations. First, conditional on scoring, the distribution of runs is heavily concentrated at one run, with over 60 percent of scoring deliveries resulting in a single run (Figure A.2). Second, certain run values (particularly fours and sixes) are achieved through qualitatively different actions—hitting the ball to the boundary of the stadium rather than running between wickets (analogous to bases in baseball)—making a continuous measure potentially misleading.[15] Third, the binary outcome provides a clear interpretation: we can characterize the marginal effect of pollution as the change in probability of a bowler conceding (or batter scoring) a run, where a bowler conceding a run indicates poor performance while the opposite is the

[14] ERA5-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).

[15] In Appendix C.1 we specify and estimate ordered logit models that incorporate variation in the number of runs scored.

case for a batter.[16]

5.1 Baseline effects of air pollution on performance

We examine the relationship between match-day $\mathrm{PM}_{2.5}$ levels and run-scoring probability with our baseline specification:

$$R_{ij\ell t} = \beta \mathrm{PM}_{2.5\ell d} + \mathbf{X}'_{\ell d}\phi + \psi_j + \phi_i + \delta_{\ell y} + \theta_n + \eta_o + \Lambda_i + \Delta_j + \varepsilon_{ij\ell t} \tag{5}$$

where $R_{ij\ell t}$ is an indicator for whether a run is scored on a delivery from bowler j to batter i from ball-of-match t at location (stadium) ℓ. Our coefficient of interest is β, which captures the effect of match-day $\mathrm{PM}_{2.5}$ levels (measured in $10\ \mu\mathrm{g\,m^{-3}}$) on run-scoring probability.[17] 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 (θ_n), over fixed effects (η_o)[18], and dummy variables for whether the stadium is the home stadium for the batter (Λ_i) or bowler (Δ_j).[19] Bowler and batter fixed effects control for any time-invariant player-specific factors, stadium-by-year fixed effects account for venue-specific temporal trends that might correlate with both pollution levels and cricket performance, and innings and over fixed effects control for stage-of-game effects that could influence playing styles and strategies. The dummy variables for the home stadium of the bowler and batter account for home field advantage. A vector of weather controls for the day d and location ℓ of the match ($\mathbf{X}_{\ell d}$) including a linear and quadratic term for temperature, and linear terms for relative humidity, atmospheric pressure, precipitation,

[16] There 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.

[17] The standard measure of $\mathrm{PM}_{2.5}$ is $1\ \mu\mathrm{g\,m^{-3}}$. When measured in these units, the effects we observe are very small in magnitude. Given the distribution of $\mathrm{PM}_{2.5}$ in our sample (mean $42.3\ \mu\mathrm{g\,m^{-3}}$ and standard deviation $20.0\ \mu\mathrm{g\,m^{-3}}$; for full distribution see Figure 5), measuring $\mathrm{PM}_{2.5}$ in $10\ \mu\mathrm{g\,m^{-3}}$ is appropriate. The effect sizes we observe are similar to those of other studies that measure effects in $10\ \mu\mathrm{g\,m^{-3}}$ (Adhvaryu et al., 2022).

[18] There are typically two innings per game and 20 overs per inning.

[19] Note 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.

solar radiation, and wind speed.[20]

Intuitively, Equation 5 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. Identification in Equation 5 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 plausibly exogenous to player characteristics and performance potential. 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.

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 $\text{PM}_{2.5}$ quantiles:

$$R_{ij\ell t} = \sum_{k=2}^{5} \beta_k Q_k \left(\text{PM}_{2.5\ell d}\right) + \mathbf{X}'_{\ell d}\phi + \psi_j + \phi_i + \delta_{\ell y} + \theta_n + \eta_o + \Lambda_i + \Delta_j + \varepsilon_{ij\ell t} \tag{6}$$

where $Q_k(\text{PM}_{2.5\ell d})$ 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

[20] See Appendix C.2 for a more flexible approach to controlling for weather variables, interactions between weather variables, and interactions between $\text{PM}_{2.5}$ and weather variables.

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

$$R_{ij\ell t} = \sum_{j=0}^{p} \beta_j (\mathrm{PM_{2.5}}_{\ell d}^{j}) + \sum_{k=1}^{N} \beta_{p+k} (\mathrm{PM_{2.5}}_{\ell d} - \tau_k)^p \mathbf{1}\{\mathrm{PM_{2.5}}_{\ell d} \geq \tau_k\} + \mathbf{X}'_{\ell d}\phi + \psi_j + \varepsilon_{ij\ell t} \quad (7)$$

where we vary the number of knots N and the degree of the polynomial p. In the spline specification, we omit fixed effects other than bowler fixed effects to ease computation.

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

We hypothesize that the effect of match-day air pollution on performance varies by how much pollution a cricket player is exposed to in the past, consistent with adaptation. Our basic approach to quantify this dynamic is to interact the realization of pollution on match-day, $\mathrm{PM_{2.5}}_{\ell d}$, with a measure of the player's past exposure. We construct two categories of measures of past-exposure. The first category includes short-term measures that are measured on the timescale of days to weeks (see Section 4.3.1 for details). The second category includes measures that are measured in years (see Section 4.3.2 for details).

Since players switch teams across seasons,[21] we customize our econometric specifications to account for different units of measurement for past-exposure. For all measures, conceptually the ideal unit of measurement would be the person. However, for the short-term measures, since we assume that all players on the same team move together, this variable is effectively measured at the team-level. By contrast, our long-term measure of career exposure is player-specific. In the two following sections, we describe our estimation strategy for short-term exposure measures and long-term exposure measures, respectively.

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

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

$$\begin{aligned} R_{ij\ell t} = &\beta_1 \mathrm{PM}_{2.5\ell d} + \beta_2 \mathrm{PM}_{2.5\ell d} \times \mathrm{PM}_{2.5J(j)d} + \beta_3 \mathrm{PM}_{2.5J(j)d} \\ &+ \mathbf{X}'_{\ell d}\phi + \psi_j + \phi_i + \delta_{\ell y} + \theta_n + \eta_o + \Lambda_i + \Delta_j + \varepsilon_{ij\ell t} \end{aligned} \tag{8}$$

where $\mathrm{PM}_{2.5J(j)d}$ is any one of the three measures of short-term past exposure defined in Section 4.3.1 for bowler j on team J. Other variables are as defined in Equation 5. We include the full interaction of present $\mathrm{PM}_{2.5}$ and past $\mathrm{PM}_{2.5}$ to disambiguate the level-effect of past $\mathrm{PM}_{2.5}$ itself from the modulating effect that past exposure may have on the harms of present exposure. Importantly, because this measure of past exposure is not fixed for an individual, it is not collinear with bowler fixed effects.

Non-linearity in the heterogeneous effect By specifying a linear interaction term between two continuous variables, the specification in Equation 8 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. We take two distinct approaches to estimating this non-linearity. The first is to put current $\mathrm{PM}_{2.5}$ exposure into bins, while treating past exposure continuously. The second is to put past exposure into bins while treating present exposure continuously.

Binning current $\mathrm{PM}_{2.5}$ exposure 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 9:

$$\begin{aligned} R_{ij\ell t} = &\sum_{k=2}^{5} \beta_{1k} Q_k \left(\mathrm{PM}_{2.5\ell d}\right) + \sum_{k=2}^{5} \beta_{2k} Q_k \left(\mathrm{PM}_{2.5\ell d}\right) \times \mathrm{PM}_{2.5J(j)d} + \beta_3 \mathrm{PM}_{2.5J(j)d} \\ &+ \mathbf{X}'_{\ell d}\phi + \psi_j + \phi_i + \delta_{\ell y} + \theta_n + \eta_o + \Lambda_i + \Delta_j + \varepsilon_{ij\ell t}. \end{aligned} \tag{9}$$

This approach builds on the strategy to estimate non-linear effects of contemporaneous exposure in Equation 6, and the quintile notation is the same as in that equation.

Binning past $\mathbf{PM_{2.5}}$ exposure While Equation 9 treats past exposure to $PM_{2.5}$ as continuous and bins current $PM_{2.5}$ exposure, Equation 10 takes the opposite approach. In Equation 10, we dichotomize past exposure based on whether it exceeds match-day exposure and treat present exposure as continuous. However, we also 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.*

$$
\begin{aligned}
R_{ij\ell t} = {} & \beta_0 + \beta_1 \, \mathrm{PM}_{2.5\ell d} + \beta_2 \, Q5_{\ell d} + \beta_3 \, \mathbf{1}\big(\mathrm{PM}_{2.5J(j)d} > \mathrm{PM}_{2.5\ell d}\big) \\
& + \beta_4 \left(\mathrm{PM}_{2.5\ell d} \times Q5_{\ell d}\right) + \beta_5 \left(\mathrm{PM}_{2.5\ell d} \times \mathbf{1}(\mathrm{PM}_{2.5J(j)d} > \mathrm{PM}_{2.5\ell d})\right) \\
& + \beta_6 \left(Q5_{\ell d} \times \mathbf{1}(\mathrm{PM}_{2.5J(j)d} > \mathrm{PM}_{2.5\ell d})\right) \\
& + \beta_7 \left(\mathrm{PM}_{2.5\ell d} \times Q5_{\ell d} \times \mathbf{1}(\mathrm{PM}_{2.5J(j)d} > \mathrm{PM}_{2.5\ell d})\right) \\
& + \mathbf{X}'_{\ell d}\phi + \psi_j + \phi_i + \delta_{\ell y} + \theta_n + \eta_o + \Lambda_i + \Delta_j + \varepsilon_{ij\ell t}
\end{aligned}
\tag{10}
$$

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.

5.3.2 Long-term past exposure

For the measure of long-term exposure that is fixed for each bowler in Section 4.3.2, we estimate:

$$R_{ij\ell t} = \beta_1 \text{PM}_{2.5\ell d} + \beta_2 \text{PM}_{2.5\ell d} \times \text{PM}_{2.5j0} + \mathbf{X}'_{\ell d}\phi + \psi_j + \phi_i + \delta_{\ell y} + \theta_n + \eta_o + \Lambda_i + \Delta_j + \varepsilon_{ij\ell t} \quad (11)$$

where $\text{PM}_{2.5j0}$ is long-term exposure to pollution for a given bowler, and other variables are as defined in Equation 5. Identification in Equation 11 comes from the fact that different teams' home stadiums experience varying pollution levels, generating quasi-random variation in players' typical exposure levels. Unlike in the specifications for past $\text{PM}_{2.5}$ exposure in the short-term—which vary across time—in Equation 11, we omit the term for past exposure, $\text{PM}_{2.5j0}$, from the estimation since it is fixed within bowler and therefore would be collinear with bowler fixed effects.

6 Results

Our empirical analysis establishes four main findings. First, air pollution significantly impairs worker productivity, with a 10 $\mu\text{g}\,\text{m}^{-3}$ increase in $\text{PM}_{2.5}$ reducing performance by 0.68%. Second, these effects exhibit striking non-linearities, concentrated almost entirely in the highest pollution quintile—levels common in developing countries but rarely studied. Third, workers adapt to chronic pollution exposure, with evidence of both short-term adaptation (over approximately 30 days) and long-term adaptation (across career spans) that partially buffers acute impacts. Fourth, this adaptation comes at a cost: accumulated exposure itself degrades baseline performance, and the protective effect only dominates cumulative harm under extremely rare pollution conditions.

6.1 Baseline effects of air pollution on performance

Table 2 presents estimates of how match-day $PM_{2.5}$ exposure affects the probability of run-scoring. Our preferred specification (column 3) includes comprehensive fixed effects for bowlers, batters, stadium-by-year, innings, and overs, along with weather controls. A 10 $\mu g\,m^{-3}$ increase in $PM_{2.5}$—equal to one half a standard deviation—increases the probability that a bowler concedes a run by 0.41 percentage points ($p < 0.05$).[22] Given a baseline run-scoring probability of 59.9%, this represents a 0.68% increase in the probability of a bowler conceding a run.[23]

The robustness 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.[24] The comprehensive 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.[25]

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

[22] The mean $PM_{2.5}$ level in our sample is 42.3 with a standard deviation of 20.0 and a range of 14.2 to 159.9 $\mu g\,m^{-3}$.

[23] We view this effect as a lower bound on the total performance losses from pollution exposure: while pollution exposure likely impairs both bowlers and batters, our estimates capture only the net disadvantage for the bowler relative to the batter, not the absolute effect on each.

[24] See Table A.2 for raw correlations between run-scoring, $PM_{2.5}$, and all weather variables.

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

Table 2: PM2.5 exposure and run-scoring probability

	(1)	(2)	(3)	(4)	(5)	(6)
	$\mathbb{1}$ (At least one run scored)					
Match-day PM2.5	0.0041***	0.0027*	0.0041**			
	(0.0010)	(0.0014)	(0.0017)			
Q2 (Match-day PM2.5)				0.0027	0.0038	0.0072
				(0.0064)	(0.0069)	(0.0060)
Q3 (Match-day PM2.5)				0.00015	-0.00065	0.0099
				(0.0065)	(0.0073)	(0.0069)
Q4 (Match-day PM2.5)				0.0086	0.0047	0.013
				(0.0076)	(0.0096)	(0.0086)
Q5 (Match-day PM2.5)				0.023***	0.017	0.027***
				(0.0069)	(0.010)	(0.0099)
Weather controls		✓	✓		✓	✓
Home stadium dummies			✓			✓
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). 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 (1–3) present results from regressions of this run indicator on match-day PM2.5 levels (measured in 10 $\mu g/m^3$ per cubic meter). 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), 16 singleton observations are dropped in columns (3) and (6). Standard errors (in parentheses) are two-way clustered at the match and bowler levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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).

6.2 Non-linear effects at extreme pollution levels

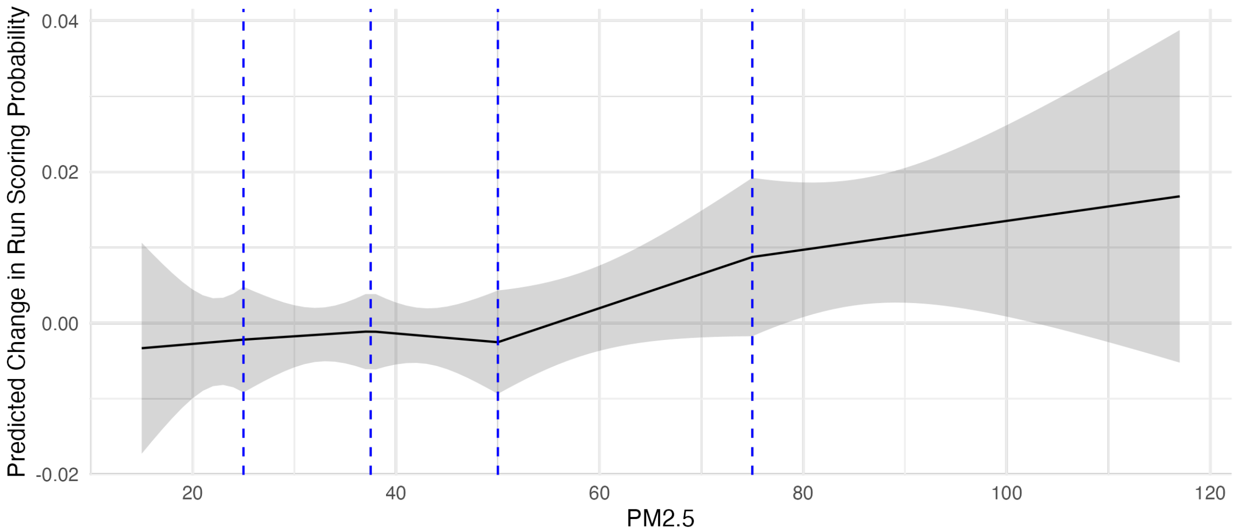
The average effect masks important non-linearities in the pollution–productivity relationship. Columns 4–6 of Table 2 replace the continuous $PM_{2.5}$ measure with quintile indicators, revealing that productivity impacts are concentrated at the highest exposure levels. In our preferred specification (column 6), only the fifth quintile shows a statistically significant effect: exposure to $PM_{2.5}$ above 53 $\mu g\,m^{-3}$ 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 striking given that even our lowest quintile (0–27 $\mu g\,m^{-3}$) substantially exceeds the WHO's 15 $\mu g\,m^{-3}$ daily limit, and the second quintile (27–34 $\mu g\,m^{-3}$) is more than double WHO guidelines. The absence of significant effects in quintiles 2–4, 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.

Figures 9 confirms this pattern using the spline specification in Equation 7. The dose–response function remains relatively flat through moderate pollution levels before steepening markedly above 50 $\mu g\,m^{-3}$.[26] This threshold effect has important implications: linear extrapolations from low-pollution studies would substantially mischaracterize productivity losses in high-pollution settings where billions of workers operate daily.

[26] As an additional robustness check, we estimate the spline specification in Equation 7 using a restricted cubic spline with knots at quintiles and find qualitatively similar results (Figure A.6).

Figure 9: Effect of $PM_{2.5}$ on Run Probability (Linear Spline, WHO Thresholds)



Notes. Figure displays predicted changes in run-scoring probability as a function of match-day $PM_{2.5}$ estimated using Equation 7 with $p = 1$ and knots at WHO targets: 25, 37.5, 50, and 75 $\mu g\, m^{-3}$. Dashed lines indicate knot locations.

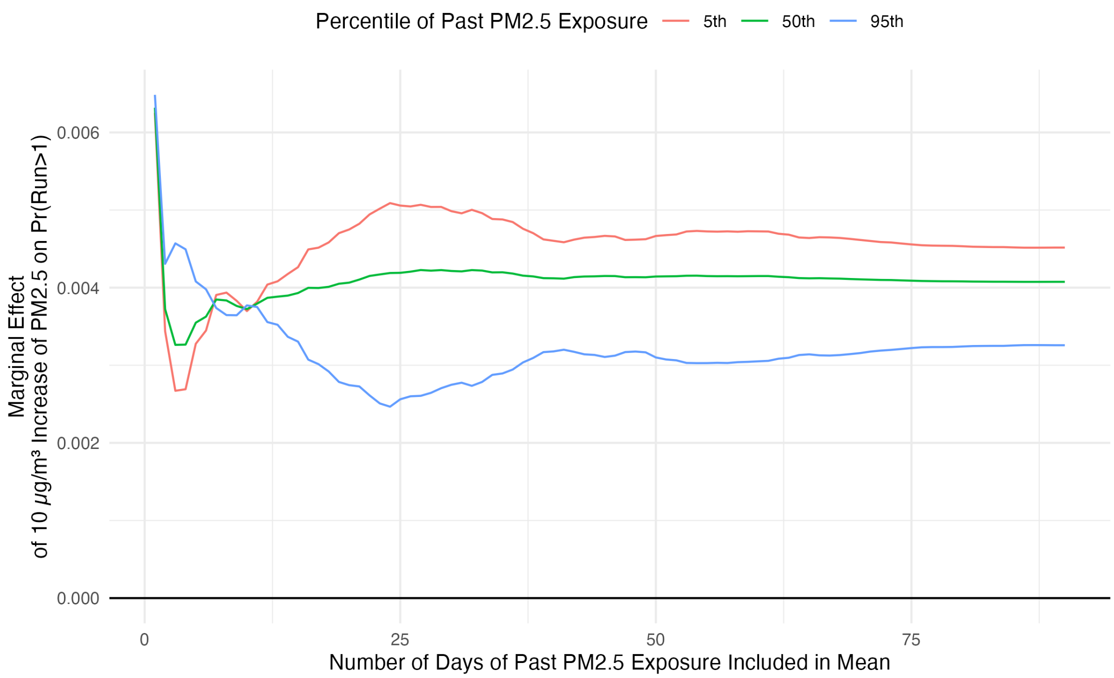
6.3 Evidence of adaptation to chronic exposure

We next examine whether workers adapt to chronic pollution exposure, potentially mitigating acute productivity losses. This analysis leverages unique variation in our setting: players are assigned to teams in cities with different baseline pollution through the IPL's salary cap and auction system, creating plausibly exogenous variation in short- and long-term exposure histories.

6.3.1 Temporal dynamics: Short-term adaptation

We begin by examining how recent pollution exposure affects sensitivity to match-day pollution, testing three measures of a bowler's pollution in the period immediately preceding a match: mean exposure (Equation 2), days above thresholds (Equations 3), and cumulative exposure above thresholds (Equation 4). For each measure, we vary lookback windows from 1 to 90 days and pollution thresholds from 25 to 75 $\mu g\, m^{-3}$, examining how the marginal effect of match-day $PM_{2.5}$ varies with past exposure levels.

Figure 10: 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 $\mu g\, m^{-3}$ 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 8.

Figure 10 illustrates this search using mean exposure. The marginal effect of match-day $PM_{2.5}$ varies with both past exposure and lookback window length. For bowlers at the 95th percentile of past exposure, the marginal effect is substantially attenuated—as low as 0.25 percentage points—with the strongest differential emerging using 20–30-day windows. This attenuation is most pronounced at 24 days, where the marginal effect for highly exposed bowlers is 41% smaller than for those at the median.[27]

Table 3 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 $\mu g\, m^{-3}$ (54%), and 24 days for cumulative above 50 $\mu g\, m^{-3}$ (40%). This convergence on a 24–32-day window—approximately one month—provides confidence we are capturing a real

[27]Figure A.8 presents an alternative visualization of how of the magnitude of this differential varies with the length of the lookback window.

Table 3: Differentials in marginal effect sizes for low- and high-exposure bowlers across three short-term exposure measures

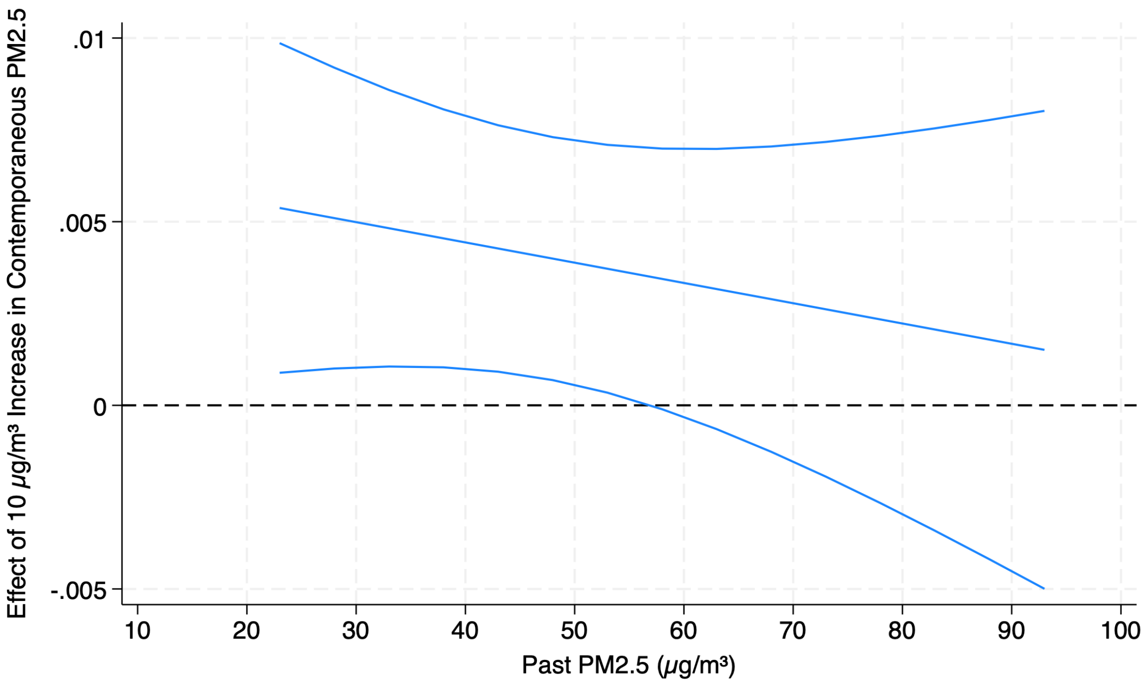
Exposure measure	**Window with largest differential (days)**	**Differential in marginal effects (%)**
Panel A. Mean Exposure (Eq. 2)		
Mean over window	24	41.1
Panel B. Days Above Threshold (Eq. 3)		
Count of days above 25 $\mu g\, m^{-3}$	90	55.0
Count of days above 37.5 $\mu g\, m^{-3}$	81	68.6
Count of days above 50 $\mu g\, m^{-3}$	32	54.0
Count of days above 75 $\mu g\, m^{-3}$	24	81.5
Panel C. Degree-Day Measures (Eq. 4)		
Cumulative PM2.5 exposure over 25 $\mu g\, m^{-3}$	24	40.5
Cumulative PM2.5 exposure over 37.5 $\mu g\, m^{-3}$	24	42.7
Cumulative PM2.5 exposure over 50 $\mu g\, m^{-3}$	24	40.3
Cumulative PM2.5 exposure over 75 $\mu g\, m^{-3}$	24	44.3

Notes. This table reports differentials in marginal effect sizes for low- and high-exposure bowlers for three measures of recent PM2.5 exposure: (i) the mean over the lookback window, (ii) the number of days above selected WHO thresholds, and (iii) degree-day measures defined relative to the same thresholds. For each measure, we vary the lookback window from 1 to 90 days; column 1 reports the window length that yields the maximum differential in marginal effects, and column 2 reports the percent difference in marginal effects. The differential in marginal effect is defined as $\big(ME_{p50} - ME_{p95}\big)/ME_{p50}$, where ME_{pY} denotes the marginal effect of match-day $PM_{2.5}$ evaluated at the Y^{th} percentile of past exposure for the corresponding measure. Marginal effects are estimated from Equation 8.

phenomenon rather than statistical artifact. Notably, the differential is twice as large (82%) when counting days above 75 $\mu g\, m^{-3}$, 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).

Having established the appropriate lookback window, Table 4 presents our main short-term adaptation results using the 30-day mean exposure measure. Column 1 estimates the baseline continuous specification, with both match-day $PM_{2.5}$ and past 30-day mean entering linearly alongside their interaction. The main effects are nearly identical: 0.66 percentage points for match-day $PM_{2.5}$ and 0.61 percentage points for the 30-day mean—statistically

Figure 11: Marginal Effect of Match-Day $PM_{2.5}$ by Past 30-day Mean $PM_{2.5}$



Notes. This figure plots the marginal effect (with 95% confidence intervals) of a 10 $\mu g\, m^{-3}$ 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 8 using the estimated coefficients in column 1 of Table 4.

indistinguishable from each other ($p = 0.81$). However, a 10 $\mu g\, m^{-3}$ 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 interaction term in column 1 is negative but not statistically significant ($p = 0.38$). However, Figure 11 reveals that this modest coefficient masks economically meaningful heterogeneity. At low recent exposure (20 $\mu g\, m^{-3}$), a 10 $\mu g\, m^{-3}$ increase in match-day pollution increases run-scoring by approximately 1.0 percentage point. At high recent exposure (80 $\mu g\, m^{-3}$), 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. Bowlers with higher recent pollution exposure are substantially less sensitive to acute pollution shocks.

Table 4: Short-term adaptation to PM2.5 exposure

	(1)	(2)	(3)
	$\mathbb{1}$ (At least one run scored)		
Match PM2.5	0.0066*		-0.0077
	(0.0034)		(0.0066)
Past 30-day PM2.5	0.0061*	0.0089**	
	(0.0034)	(0.0043)	
Match PM2.5 $\times$ Past 30-day PM2.5	-0.00055		
	(0.00063)		
Q2 (Match PM2.5)		0.0097	
		(0.019)	
Q3 (Match PM2.5)		0.034*	
		(0.021)	
Q4 (Match PM2.5)		0.041*	
		(0.023)	
Q5 (Match PM2.5)		0.069***	
		(0.025)	
Q2 (Match PM2.5) $\times$ Past 30-day PM2.5		-0.00099	
		(0.0046)	
Q3 (Match PM2.5) $\times$ Past 30-day PM2.5		-0.0060	
		(0.0048)	
Q4 (Match PM2.5) $\times$ Past 30-day PM2.5		-0.0068	
		(0.0051)	
Q5 (Match PM2.5) $\times$ Past 30-day PM2.5		-0.0095*	
		(0.0051)	
Q5 (Match PM2.5)			-0.032
			(0.035)
Q5 (Match PM2.5) $\times$ PM2.5			0.0099
			(0.0071)
$\mathbb{1}$ (Past 30-day PM2.5 > Match PM2.5)			-0.050**
			(0.024)
$\mathbb{1}$ (Past 30-day PM2.5 > Match PM2.5) $\times$ PM2.5			0.012*
			(0.0060)
Q5 (Match PM2.5) $\times$ $\mathbb{1}$ (Past 30-day PM2.5 > Match PM2.5)			0.14**
			(0.064)
Q5 (Match PM2.5) $\times$ $\mathbb{1}$ (Past 30-day PM2.5 > Match PM2.5) $\times$ PM2.5			-0.029***
			(0.011)
Weather controls	✓	✓	✓
Home stadium dummies	✓	✓	✓
Stadium-by-year FE	✓	✓	✓
Over FE	✓	✓	✓
Innings FE	✓	✓	✓
Bowler FE	✓	✓	✓
Batter FE	✓	✓	✓
N	183,556	183,556	183,556
R^2	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 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 both measures in levels and their interaction. Column (2) replaces match-day PM2.5 with quintile indicators (the lowest quintile omitted) and interacts them with past 30-day PM2.5. Column (3) replaces past 30-day PM2.5 with 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 and 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Column 2 of Table 4 examines whether this adaptation varies across the pollution distribution by replacing continuous match-day $PM_{2.5}$ with quintile indicators. The pattern aligns with our baseline non-linearity findings in Table 2: only the top quintile of match-day $PM_{2.5}$ 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 $\mu g\, m^{-3}$.

Lastly, column 3 provides an alternative lens on this interaction by discretizing past exposure rather than contemporaneous exposure. We create an indicator for whether a bowler's 30-day mean exceeds match-day $PM_{2.5}$ and interact it with both continuous match-day $PM_{2.5}$ and an indicator for top-quintile match-day $PM_{2.5}$. 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.

6.3.2 Long-term adaptation across career exposure

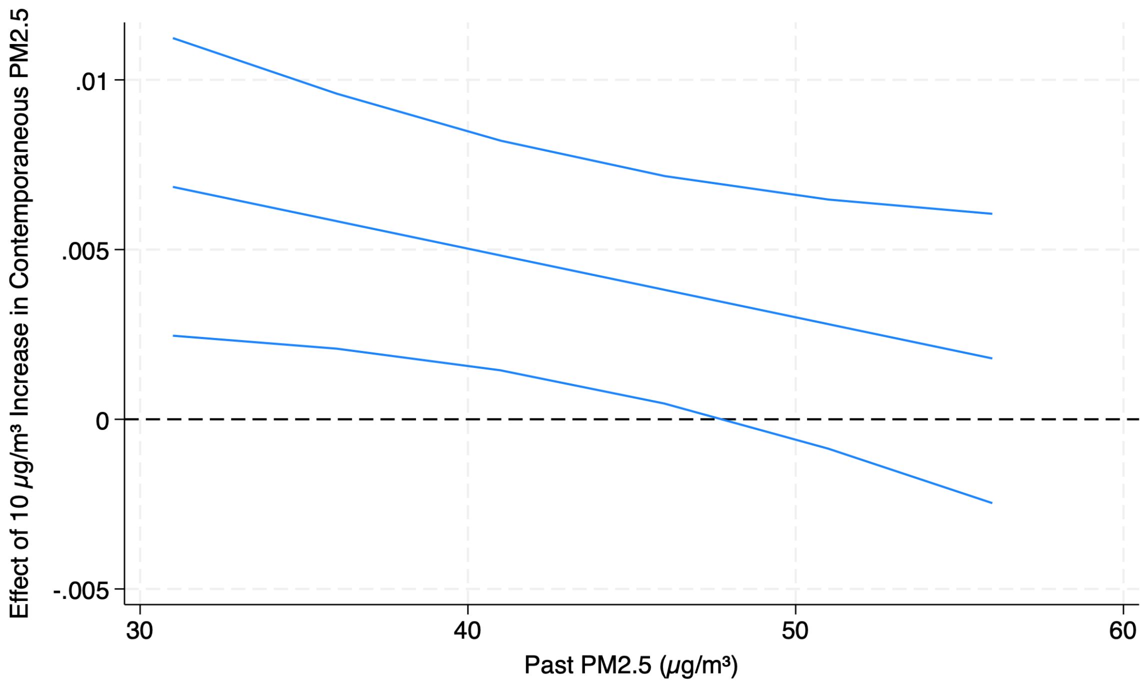
We now examine whether the adaptation patterns observed over 30-day windows extend to career-length exposure. Table 5 presents results using each bowler's mean $PM_{2.5}$ across all IPL matches as the measure of long-term exposure. Column 1 estimates the linear interaction specification parallel to our 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. The economic magnitude is substantial: at zero career exposure, the marginal effect is 1.3 percentage points; at the sample mean (42.3 $\mu g\, m^{-3}$), it falls to 0.49 percentage points; at high career exposure (60 $\mu g\, m^{-3}$), it attenuates close to zero, though remaining weakly positive.

Table 5: Long-term adaptation to PM2.5 exposure

	(1)	(2)	(3)
	$\mathbb{1}$ (At least one run scored)		
Match PM2.5	0.013**		-0.0081
	(0.0052)		(0.0077)
Match PM2.5 × Career PM2.5	-0.0020*		
	(0.0011)		
Q2 (Match PM2.5)		-0.011	
		(0.034)	
Q3 (Match PM2.5)		0.031	
		(0.034)	
Q4 (Match PM2.5)		0.076*	
		(0.039)	
Q5 (Match PM2.5)		0.097**	
		(0.037)	
Q2 (Match PM2.5) × Career PM2.5		0.0042	
		(0.0082)	
Q3 (Match PM2.5) × Career PM2.5		-0.0053	
		(0.0081)	
Q4 (Match PM2.5) × Career PM2.5		-0.015*	
		(0.0090)	
Q5 (Match PM2.5) × Career PM2.5		-0.016*	
		(0.0086)	
Q5 (Match PM2.5)			-0.037
			(0.039)
Q5 (Match PM2.5) × PM2.5			0.010
			(0.0082)
$\mathbb{1}$ (Career PM2.5 > Match PM2.5)			-0.056*
			(0.032)
$\mathbb{1}$ (Career PM2.5 > Match PM2.5) × PM2.5			0.013*
			(0.0076)
Q5 (Match PM2.5) × $\mathbb{1}$ (Career PM2.5 > Match PM2.5)			0.81**
			(0.38)
Q5 (Match PM2.5) × $\mathbb{1}$ (Career PM2.5 > Match PM2.5) × PM2.5			-0.15**
			(0.066)
Weather controls	✓	✓	✓
Home stadium dummies	✓	✓	✓
Stadium-by-year FE	✓	✓	✓
Over FE	✓	✓	✓
Innings FE	✓	✓	✓
Bowler FE	✓	✓	✓
Batter FE	✓	✓	✓
N	183,556	183,556	183,556
R^2	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 PM2.5 is the PM2.5 concentration on the match day. Career PM2.5 is the bowler's mean PM2.5 exposure over all matches played in the cricket league. Column (1) includes both measures in levels and their interaction. Column (2) replaces match-day PM2.5 with quintile indicators (the lowest quintile omitted) and interacts them with Career PM2.5. Column (3) replaces Career PM2.5 with 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 and 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 12: Marginal Effect of Match-Day $PM_{2.5}$ by Career $PM_{2.5}$ Exposure



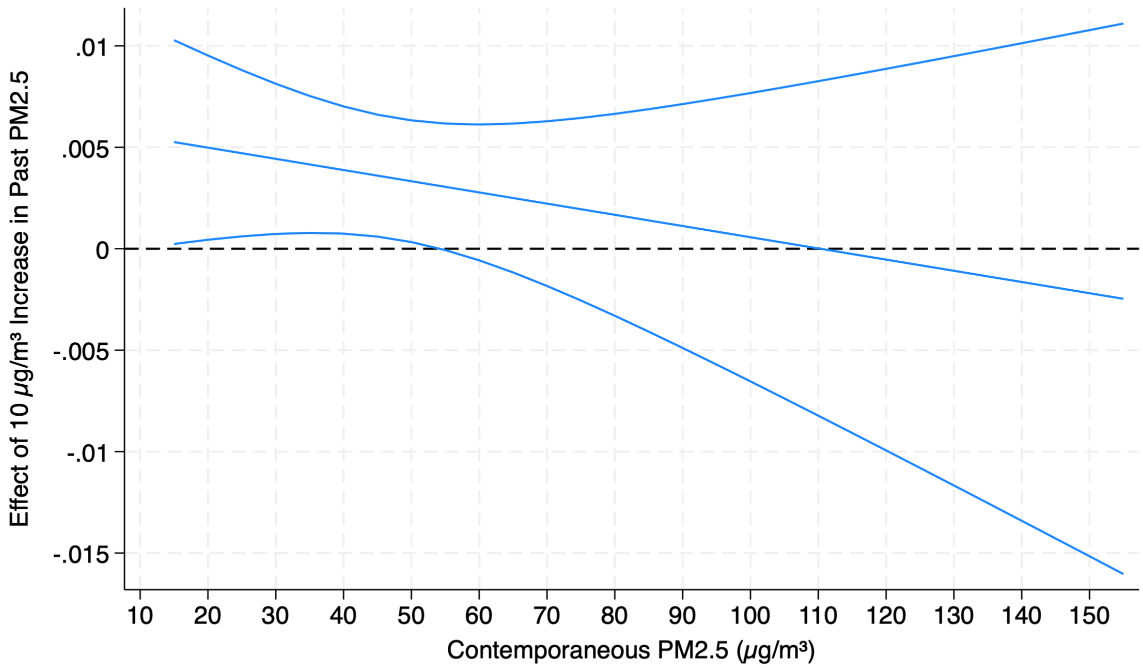
Notes. This figure plots the marginal effect (with 95% confidence intervals) of a 10 $\mu g\,m^{-3}$ increase in match-day $PM_{2.5}$ as a function of career-average $PM_{2.5}$ exposure. Marginal effects are computed from Equation 11 using the estimated coefficients in column 1 of Table 5.

Figure 12 visualizes this gradient across the observed distribution of career exposures. For bowlers at the 95th percentile of long-term exposure (70.6 $\mu g\,m^{-3}$ average), the marginal effect of match-day $PM_{2.5}$ is 0.27 percentage points, compared to 0.42 percentage points for bowlers with median exposure (44.0 $\mu g\,m^{-3}$)—a 36% reduction in the acute sensitivity.

Column 2 of Table 5 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.

Finally, column 3 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

Figure 13: Marginal Effect of Past 30-day Mean $PM_{2.5}$ by Match-Day $PM_{2.5}$



Notes. This figure 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 8 using the estimated coefficients in column 1 of Table 4.

-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.[28]

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 outweigh the cumulative damage?

[28]These 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 A.4).

Figure 13 addresses this by plotting 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 $\mu g\,m^{-3}$), 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 $\mu g\,m^{-3}$, this marginal effect declines, crossing zero around 110 $\mu g\,m^{-3}$. Beyond this threshold, the marginal effect becomes negative: past exposure is protective, providing resilience that dominates the cumulative harm when facing extremely high acute exposure.

However, this crossover occurs at extraordinarily rare pollution levels. Only 1.4% of matches (comprising 1.8% of deliveries) in our sample exceed 110 $\mu g\,m^{-3}$—more than seven times WHO daily guidelines and among the most polluted conditions observed anywhere in the world. The widening confidence intervals at these extreme levels reflect data sparsity and underscore the uncertainty surrounding estimates in this range. For the vast majority of observed pollution levels, both acute and chronic exposure impair productivity, even as adaptation moderates the acute response.

7 Discussion and conclusion

This paper documents how air pollution affects worker productivity in a high-pollution developing-country context, with three main contributions. First, we establish that pollution significantly impairs performance, with a 10 $\mu g\,m^{-3}$ increase in $PM_{2.5}$ reducing productivity by approximately 1%. Second, we show these effects exhibit striking non-linearities, concentrated almost entirely at extreme pollution levels common in developing countries but rarely studied—effects materialize primarily above 53 $\mu g\,m^{-3}$, well into ranges that billions of workers experience daily. Third, we provide evidence of both short-term (30-day) and long-term (career-spanning) adaptation that partially buffers acute impacts, though this adaptation comes at a substantial cost and provides only partial protection.

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 on adaptation reveals a more complex relationship between past and present pollution exposure than previous research has documented. Workers accustomed to higher pollution levels are substantially less sensitive to acute pollution shocks, with this protective effect strengthening over longer exposure horizons. Career-long adaptation provides significantly stronger buffering than recent 30-day adaptation alone. Critically, adaptation is most pronounced when workers face extremely high contemporaneous pollution that nonetheless remains below their typical exposure levels. This suggests that physiological and behavioral adjustments develop gradually through sustained exposure to elevated pollution.

However, adaptation does not resolve the productivity costs of pollution—it merely reveals how workers' bodies and behaviors respond to chronic harm. The central question is whether the protective benefits of adaptation outweigh the cumulative damage from sustained exposure. Our evidence indicates they do not. Past pollution simultaneously imposes two costs: direct cumulative damage to baseline performance and the physiological burden of developing and maintaining adaptive capacity. The protective effect only dominates cumulative harm at extraordinarily rare pollution levels above 110 $\mu g\, m^{-3}$—a threshold exceeded in just 1.8% of our observations and more than seven times WHO guidelines. 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 $\mu g\, m^{-3}$ produces larger marginal benefits than reducing exposure from 40 to 20 $\mu g\, m^{-3}$.

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, the fact that adaptation provides minimal net benefits underscores that chronic pollution exposure remains profoundly harmful even when workers develop physiological tolerance. The small protective effect is vastly outweighed by cumulative damage and the costs of adaptation itself. Our results therefore reinforce rather than undermine the case for aggressive pollution control in chronically polluted settings. Adaptation is not a solution to pollution; instead, it is evidence of the body's ongoing struggle against persistent environmental assault. For the billions of workers operating in high-pollution environments across the developing world, reducing pollution exposure remains the main path to protecting both productivity and long-term health.

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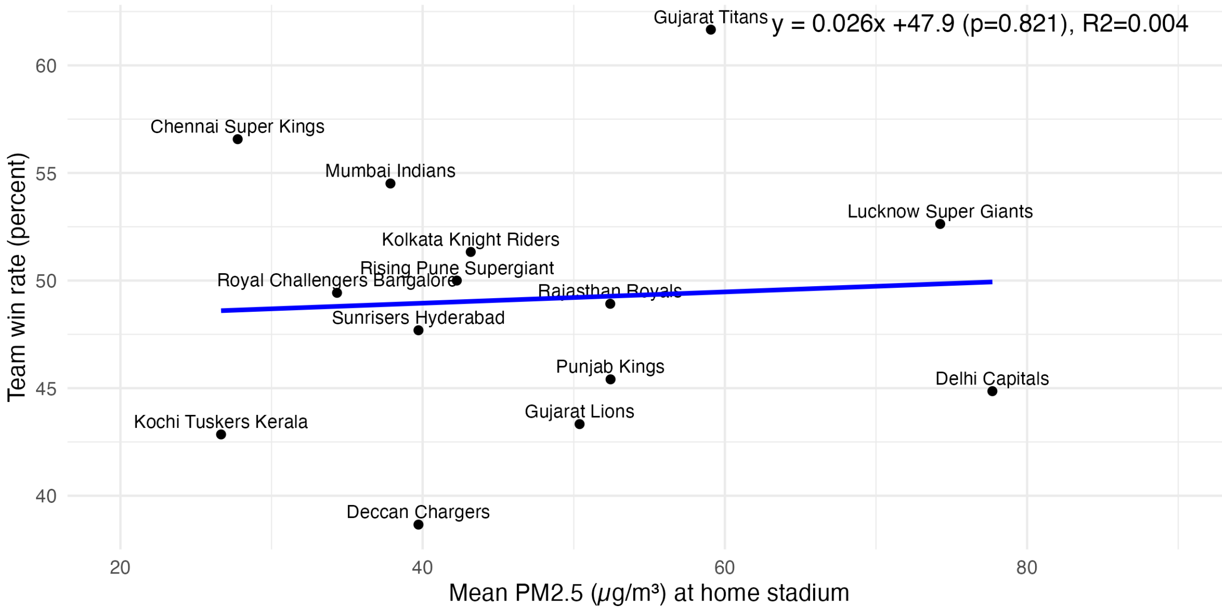
A Appendix: tables and figures

Figure A.1: Team quality is not correlated with long-term $PM_{2.5}$ exposure



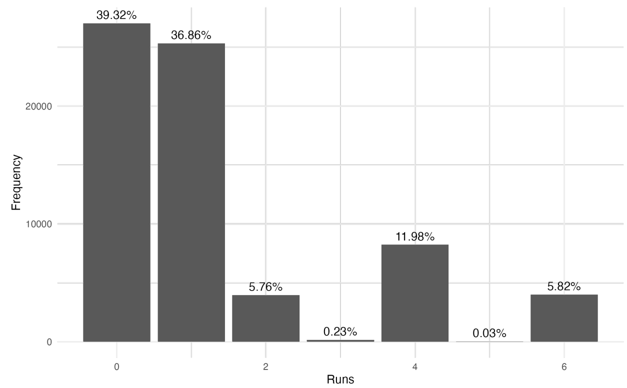
Notes. This figure shows the win rate (number of matches won out of all matches played) for IPL teams as plotted against the average $PM_{2.5}$ at the team's home stadium. Average $PM_{2.5}$ is defined as the mean level of $PM_{2.5}$ at the team's home stadium during March, April, and May (the months 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.

Table A.1: 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

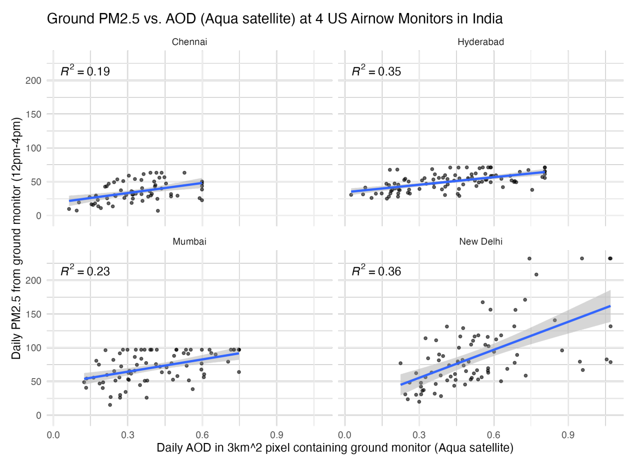
[a] All IPL. [b] IPL 2008-2014. [c] 1998-2007. [d] 2008-2022. [e] 2008-2022, IPL months. [f] 1998-2007, IPL months.
Notes. This table reports summary statistics for six alternative definitions of long-run PM2.5.

Figure A.2: Histogram of Runs



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

Figure A.3: U.S. Airnow vs. MODIS AOD



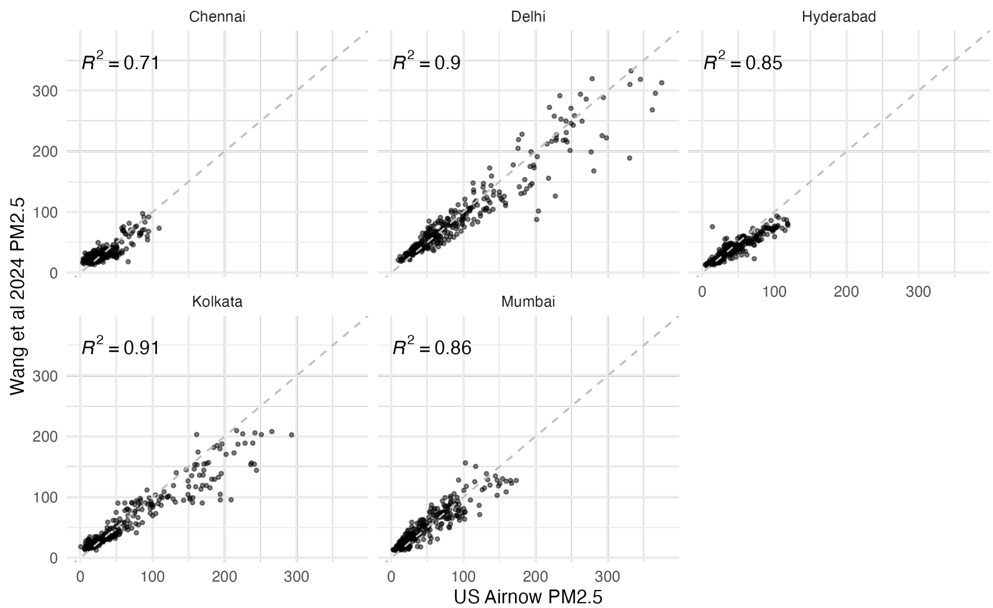
Notes. This figure displays the correlation between Aerosol Optical Depth from the MODIS Aqua satellite (which passes over India approximately once per day in the afternoon) with ground observations of $PM_{2.5}$ at five cities with a U.S. AirNow ground monitor. Each dot represents a daily mean value 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.

Table A.2: 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

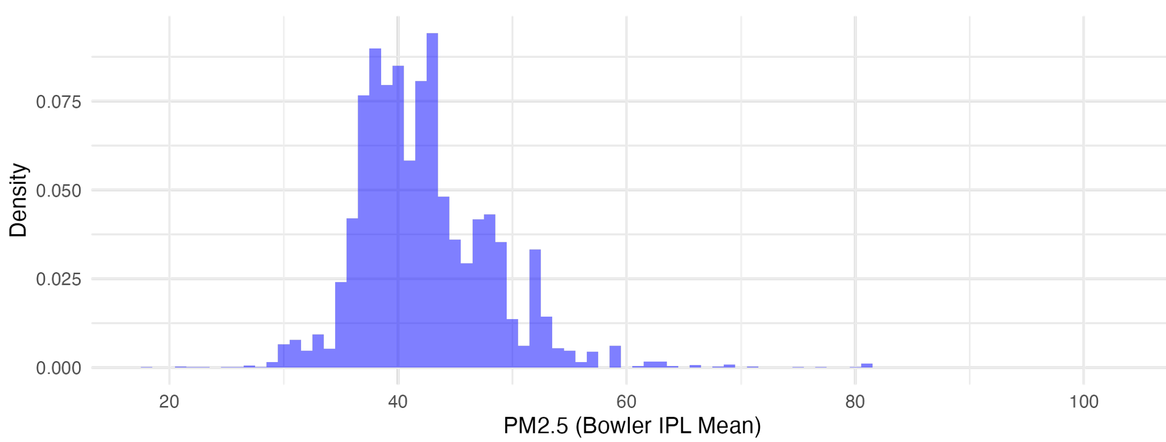
Notes: Run is a binary indicator equal to 1 if at least one run is scored on a delivery and 0 otherwise. Correlations computed from delivery-level data. PM2.5 and weather variables are measured at the match-level.

Figure A.4: U.S. Airnow vs. Wang et al. (2024) Daily $PM_{2.5}$



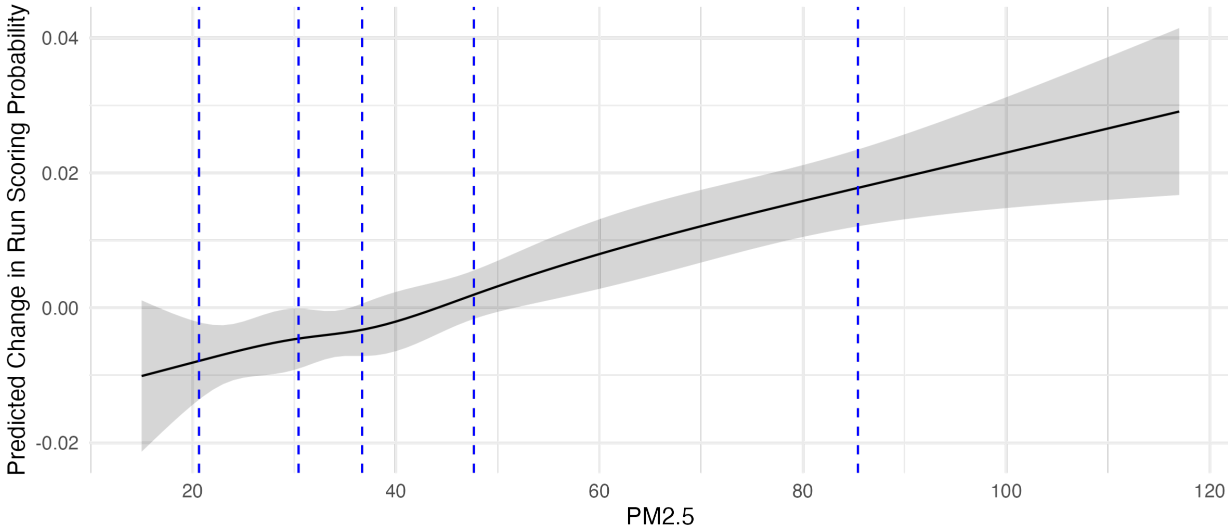
Notes. This figure displays the correlation between Wang et al. (2024) estimates of $PM_{2.5}$ and ground observations of $PM_{2.5}$ at five cities with a U.S. AirNow ground monitor, a network of high-quality monitors that are calibrated to EPA standards. Each dot represents a daily mean value of $PM_{2.5}$.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

Figure A.5: Histogram of Bowler $PM_{2.5}$ Mean in IPL Games 2008-2022



Notes. This figure displays the distribution of bowler mean $PM_{2.5}$ defined as the mean $PM_{2.5}$ exposure across all games for a given bowler in the IPL 2008-2022 (i.e. $PM_{2.5 j0}$ in Equation 11).

Figure A.6: Effect of $PM_{2.5}$ on Run Probability (Restricted Cubic Spline, Quantile Knots)



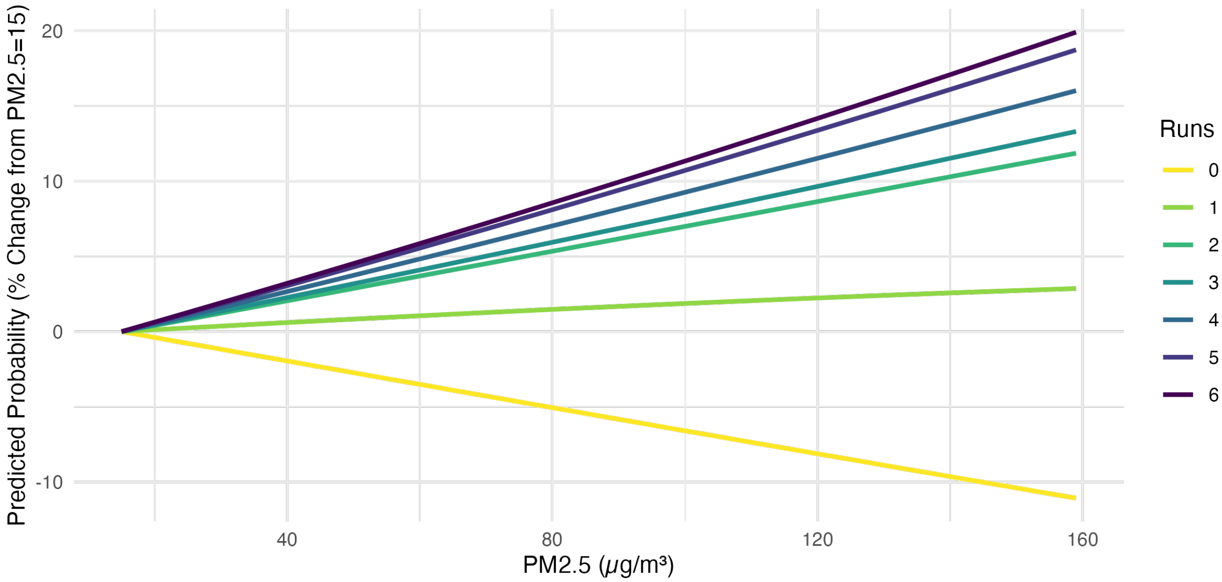
Notes. Figure displays predicted changes in run-scoring probability as a function of match-day $PM_{2.5}$ estimated using Equation 7 with $p = 3$ and knots at quintiles: 21, 30, 37, 48, and 85 $\mu g\, m^{-3}$. Dashed lines indicate knot locations.

Table A.3: Evidence of Adaptation to Air Pollution Climates (Ordered Logit)

	(1)	(2)	(3)	(4)	(5)	(6)
		$\mathbb{1}$ (At least one run scored)				
Match PM2.5	0.013***	0.013***	0.019***	0.021***	0.019***	0.075***
	(0.0027)	(0.0037)	(0.0054)	(0.0054)	(0.0055)	(0.020)
Match PM2.5 X Bowler PM2.5						-0.012***
						(0.0041)
Weather controls		✓	✓	✓	✓	✓
Stadium-by-year FE			✓	✓	✓	✓
Match innings FE			✓	✓	✓	✓
Over FE				✓	✓	✓
Bowler FE					✓	✓
N	183,572	183,572	183,572	183,572	183,572	183,572

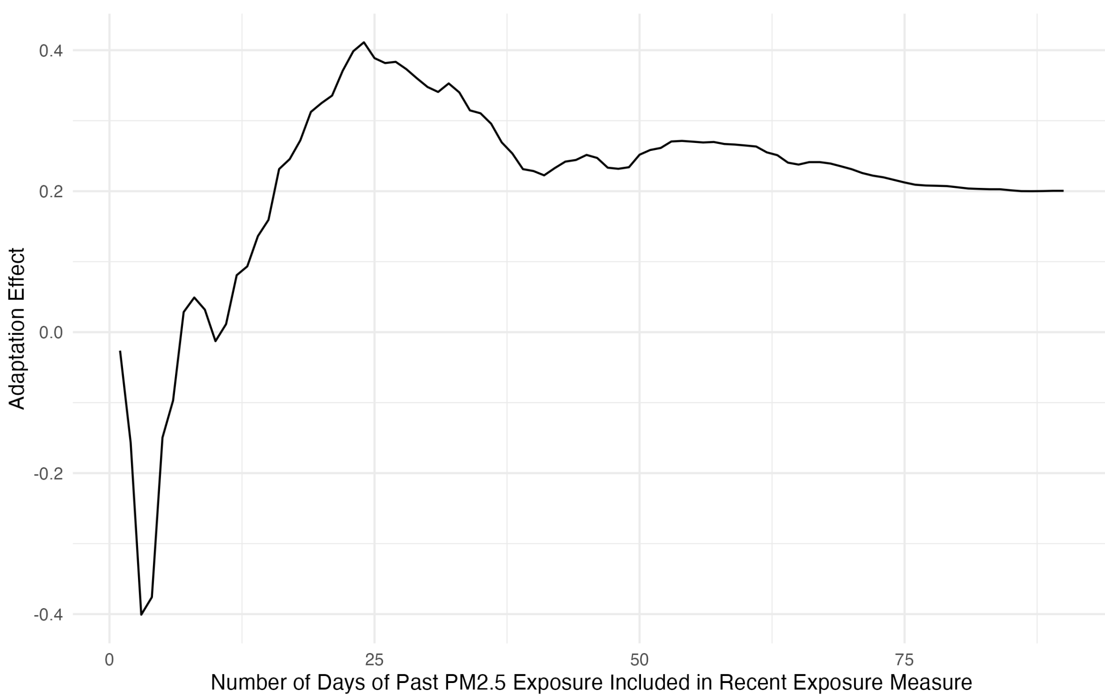
Notes. The outcome variable is the number of runs scored (range 0 to 6, mean 1.25). Regressions are estimated using ordered logit. Bowler PM2.5 is defined as the mean PM2.5 in all of bowler's games in the IPL. Standard errors clustered at the bowler level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure A.7: Change in Predicted Probability of Scoring 0, 1, 2, 3, 4, 5, or 6 runs by $PM_{2.5}$



Notes. This figures graphically reports the results from Equation 13. It shows how the predicted probability of scoring each number of runs changes (relative to a baseline probability when $PM_{2.5}$ is 15 $\mu g\, m^{-3}$) as a function of match-day $PM_{2.5}$.

Figure A.8: 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 for the Y^{th} percentiles of mean past exposure to $PM_{2.5}$. Marginal effects are estimated from Equation 8.

Table A.4: Robustness of Long-term PM2.5 Measures

	(1)	(2)	(3)	(4)	(5)	(6)
	𝟙 (At least one run scored)					
Match PM2.5	0.0052	0.0067**	0.0062**	0.0067**	0.0058**	0.0071***
	(0.0060)	(0.0030)	(0.0025)	(0.0028)	(0.0024)	(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	✓	✓	✓	✓	✓	✓
N	53,607	183,558	183,558	183,558	183,558	183,558
R^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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B Appendix: 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 3 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.

C Appendix: additional robustness checks

C.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 better performance for the team opposing the bowler.

$$\log\left(\frac{P(R_{ij\ell t} \leq r)}{P(R_{ij\ell t} > r)}\right) = \beta_1 \mathrm{PM}_{2.5\ell d} + \beta_2 \mathrm{PM}_{2.5\ell d} \times \mathrm{PM}_{2.5j0} + \mathbf{X}'_{\ell d}\phi + \psi_j + \delta_{\ell y} + \theta_n + \eta_o + \varepsilon_{ij\ell t} \quad (12)$$

where $R_{ij\ell t}$ is the number of runs scored ($\{0, 1, 2, 3, 4, 5, 6\}$). To ease computation and for our graphical presentation of results, we also estimate a simpler version of this equation with only bowler fixed effects:

$$\log\left(\frac{P(R_{ij\ell t} \leq r)}{P(R_{ij\ell t} > r)}\right) = \beta_1 \mathrm{PM}_{2.5\ell d} + \psi_j + \varepsilon_{ij\ell t}. \tag{13}$$

The results estimating Equation 12 are reported in Table A.3 and are qualitatively similar to those estimating analogous regressions in Tables 2 and 5. Figure A.7 reports graphically the results of results estimating Equation 13.

C.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 $\mathrm{PM}_{2.5}$ and directly affect performance.

We implement Post-Double Selection (PDS) Lasso (Belloni et al., 2014) with $\mathrm{PM}_{2.5}$ as the treatment variable, regressing run-scoring on 35 potential controls: home stadium dummies, linear and quadratic weather terms, pairwise weather interactions, and $\mathrm{PM}_{2.5}$-weather interactions. The procedure selects no controls as outcome predictors but identifies two $\mathrm{PM}_{2.5}$ predictors: temperature-humidity and humidity-wind interactions. The final regression yields a coefficient of 0.35 percentage points ($p < 0.01$), 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. Temperature's coefficient (0.14 percentage points, $p = 0.102$) is one-third $\mathrm{PM}_{2.5}$'s magnitude and statistically insignificant—striking given that matches occur in warm conditions (71–99 °F, mean 85 °F) where heat stress might substantially impair performance.

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

Table A.1 presents six additional alternative definitions of long-term $\mathrm{PM}_{2.5}$. Our preferred definition for long-term exposure to $\mathrm{PM}_{2.5}$ is the mean exposure to $\mathrm{PM}_{2.5}$ across all IPL games (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 $\mathrm{PM}_{2.5}$ exposure into past matches. However, if this results in classical measurement error, this noise in measurement would only attenuate results. In addition, we find that pollution levels are serially correlated within player.

In the second row, we calculate a similar measure, but instead of taking the mean across all games 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 games 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 $PM_{2.5}$ 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.[29] 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 games 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 definition of long-term exposure as robustness checks.

We estimate Equation 11 for the long-term definitions of $PM_{2.5}$ in rows 1 and 2 of Table A.1. 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 $PM_{2.5}$ to each bowler changes depending on what team they are on in each year.[30] We estimate the slightly modified specification:

$$R_{ij\ell t} = \beta_1 \text{PM}_{2.5\ell d} + \beta_2 \text{PM}_{2.5\ell d} \times \text{PM}_{2.5j0} + \mathbf{X}'_{\ell d}\phi + \psi_{yJ(j,y)} + \delta_{\ell y} + \theta_n + \eta_o + \varepsilon_{ij\ell t} \tag{14}$$

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

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

[30] Note 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 game 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.