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 findings suggest 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, indicating 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 which, 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 (PM2.5) above the World Health Organization (2021) safety guideline of 5 $\mu g\,m^{-3}$ (Rentschler and Leonova, 2023). Beyond its well-documented health impacts, PM2.5 exposure degrades labor productivity, constraining economic growth (Graff Zivin and Neidell, 2012). These productivity losses are likely to be particularly large for the 2.8 billion people exposed to hazardous annual average PM2.5 levels above 35 $\mu g\,m^{-3}$. Although a large literature has examined productivity impacts of PM2.5 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, much 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 PM2.5 than for those accustomed to cleaner air. While recent studies have begun to document non-linearities in the PM2.5–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 is largely unexplored.

We fill this gap by asking a central question: Does the marginal effect of contemporaneous PM2.5 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 to it. We examine this question using detailed performance data from professional cricket athletes in India, a high-pollution setting with average PM2.5 levels over five times higher than those typical in the US. We choose this setting because the structure of the Indian Premier League (IPL) cricket league provides quasi-experimental variation in both contemporaneous and long-term PM2.5 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. The IPL's strict salary-cap rules also help decouple pollution exposure from player ability (ESPN, 2024), strengthening our identification strategy.[1] Additionally, cricket is particularly informative because each play 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 PM2.5 estimates for each stadium (Wang et al., 2024).[2] Our setting offers unusually rich variation: PM2.5 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.

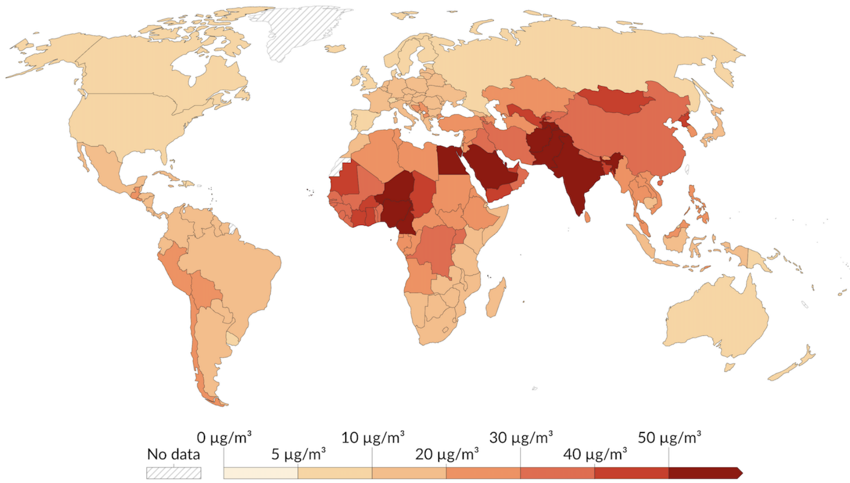
We report four main findings. First, pollution significantly reduces worker performance: a 10 $\mu g\, m^{-3}$ increase in PM2.5—equivalent to half a standard deviation—increases the probability that a bowler concedes a run—indicating poor performance for the bowler—by 0.41 percentage points (1.01%). Because run-scoring arises from bowler–batter interactions, this asymmetry indicates that pollution disproportionately impairs bowlers. This finding is aligned with the medical literature, which establishes respiration as the primary channel through which exposure to particulate matter air pollution occurs (Hamanaka and Mutlu, 2025): bowlers have much higher levels of exertion and respiration rates relative to batters, who engage in 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

[1] Our identifying assumption for measuring how the effect of contemporaneous pollution shocks varies by long-term pollution exposure requires that long-term pollution exposure is not correlated with player ability. To ensure fair competition amongst teams, the IPL sets a limit for how much each team can spend on player salaries—a proxy for their ability—thereby supporting the assumption that player quality is roughly equal across teams and not systematically correlated with air pollution levels at home stadiums.

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

Figure 1: Average Annual PM2.5 Concentrations in 2019



Notes. Figure displays annual average PM2.5 concentrations (population-weighted) in 2019 (WHO, 2025).

in developing countries but rarely studied. At lower pollution levels, run-scoring probabilities do not change significantly, suggesting that both worker types are similarly affected until exposures become extreme. Third, workers adapt to long-term pollution. 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. Fourth, we find suggestive evidence of shorter-term adaptation: exposure in the prior month reduces marginal effects by up to 50%, although these estimates are not statistically significant.

The institutional rules of cricket and a recently developed machine learning air pollution data product enable us to answer questions previously unexplored in the literature. Existing research on pollution and productivity 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 US 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.

Prior work has largely left adaptation to chronic pollution unexplored. Among the ten studies above, only He et al. (2019) examine exposure beyond a week. Yet in many developing countries, workers face persistently high pollution, making it essential to understand how accumulated exposure shapes responses to short-term shocks.

We make three main contributions to this literature. First, we provide among the first 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, and substantially outperforms conventional satellite-based measures such as MODIS AOD in the country's highly variable pollution conditions (Wang et al., 2024).

Second, we document substantial non-linearities in pollution's dose–response relationship, concentrated at extreme exposure levels. Because our outcomes reflect relative performance in a two-person production task, we can isolate which types of work activities are most susceptible to pollution—an important advantage over settings that observe 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 largely unidentified 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. Our design thus extends epidemiological insights on long-term pollution exposure (Schwartz, 2000; Zanobetti et al., 2002; Wei et al., 2021) to the labor productivity domain, where elasticities may differ substantially.

As a corollary, we also shed light on the tension between performance and health effects of accumulated exposure. Although long-term PM2.5 exposure entails large health costs (Orellano et al., 2024), we find that it also partially buffers workers against acute shocks. We emphasize, however, that the 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 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. Finally, the asymmetric impacts we document across physical tasks underscore the importance of considering occupational exposure differences when designing air quality and workplace health policies.

This paper proceeds as follows. Section 2 describes our cricket setting. 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 Institutional detail

Cricket provides an advantageous setting for studying the impact of air quality on physical labor productivity because players perform specialized roles, resulting in differing susceptibility to PM2.5 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 pollution on cricket players are thus economically important in their own right. In addition, the clean causal identification and 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.

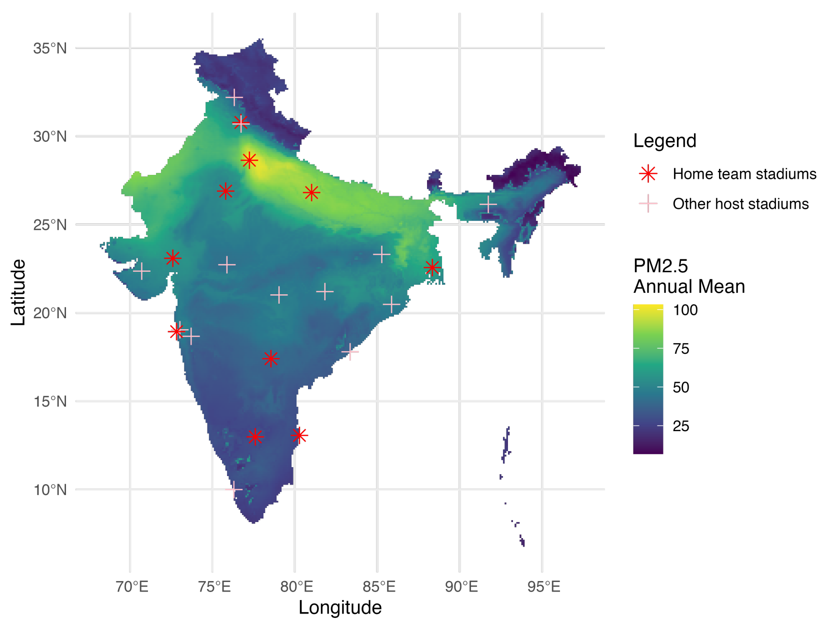
The IPL's structure and characteristics create two distinct sources of variation that make it particularly valuable for studying air quality impacts on worker productivity. First, the IPL operates as a franchise system with ten teams based in different cities: Chennai, Delhi, Ahmedabad, Kolkata, Lucknow, 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

[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.

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 PM2.5 exposure is not correlated with team quality as indicated by the proportion of matches that teams win (Figure 3). 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.

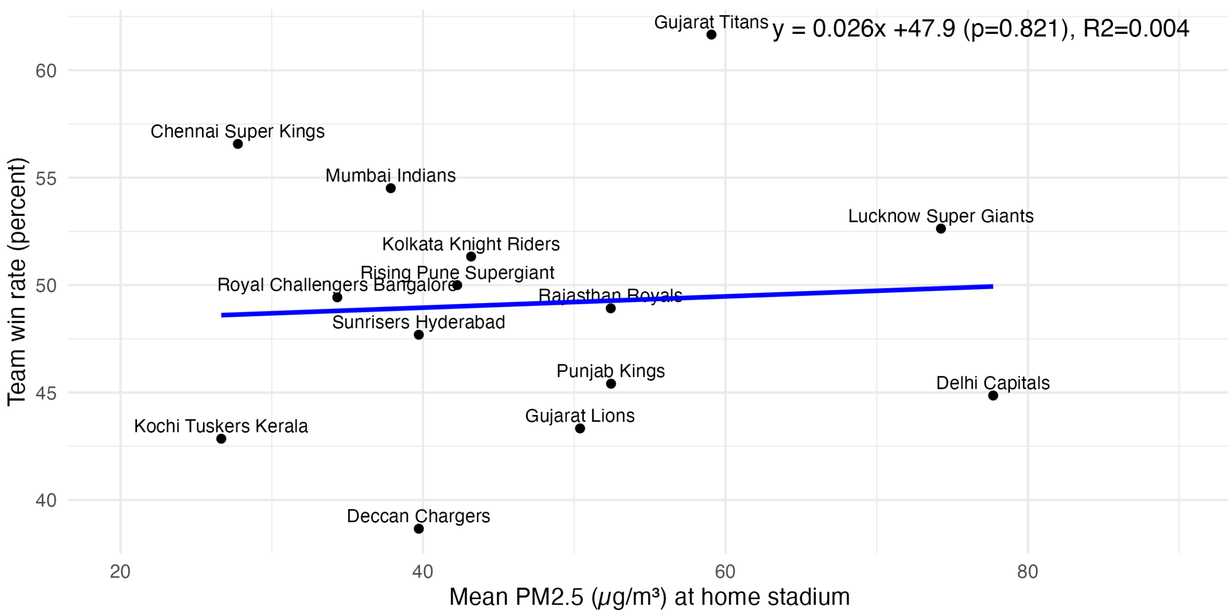
Figure 2: Geographic distribution of cricket stadiums and PM2.5 in the IPL



Notes. This figure shows annual mean PM2.5 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.

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,

Figure 3: Team quality is not correlated with long-term PM2.5 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 PM2.5 at the team's home stadium. Average PM2.5 is defined as the mean level of PM2.5 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 PM2.5 is robust to alternative definitions of long-term PM2.5, such as including non-IPL months, or including PM2.5 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.

plants their front foot with ground reaction forces between 2.4 and 5.8 times their body weight, and decelerates rapidly after ball release (Bartlett, 2003). In Twenty20 cricket, fast bowlers perform approximately 23 sprints per hour of play, with significantly less recovery time between high-intensity efforts compared to other positions (Petersen et al., 2010). During bowling spells, heart rates can reach 180–190 beats per minute, and in hot conditions, bowlers have recorded sweat rates up to 1.5 liters per hour, comparable to marathon runners (Noakes and Durandt, 2000).

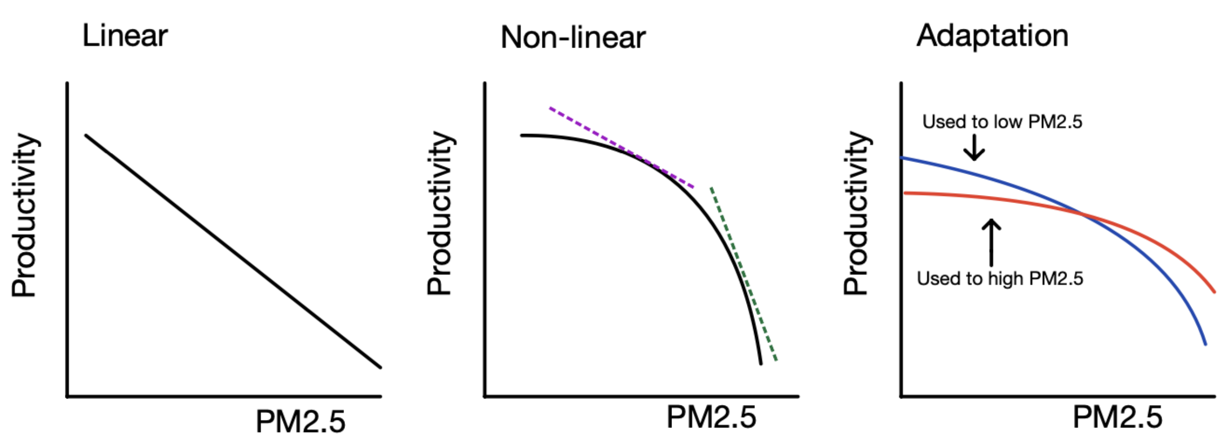
For batters, the physical requirements combine intermittent high-intensity running with periods of technical performance (Noakes and Durandt, 2000), surrounded by periods of rest. In Twenty20 cricket, batters perform approximately 15 sprints per hour (Petersen et al., 2010). The activity pattern, however, is highly intermittent: mean heart rates during a day's cricket rarely exceed 128 beats per minute for batters. Over a complete Twenty20 innings, batters cover approximately 3.5 kilometers in total distance—a relatively small amount considering that innings 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.

Together, these features of professional cricket in India create a uniquely suitable setting for studying air quality's effects on worker productivity across multiple temporal dimensions. Match schedules in the IPL are predetermined and beyond teams' control, creating plausibly exogenous variation in short-term exposure through day-of-match pollution levels. The IPL's geographic dispersion provides variation in medium-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.

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.

Figure 4: Dose response of performance to pollution



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.[5] 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).[6]

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

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

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 pollution with a longer-term average exposure in our empirical specifications, we can begin to disentangle the short- and long-run effects. In the next section, we outline the physiological basis for why the short-run effect may be mediated by long-run exposure.

3.1 Physiological basis for adaptation

While the notion of adaptation is not new to the environmental 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.

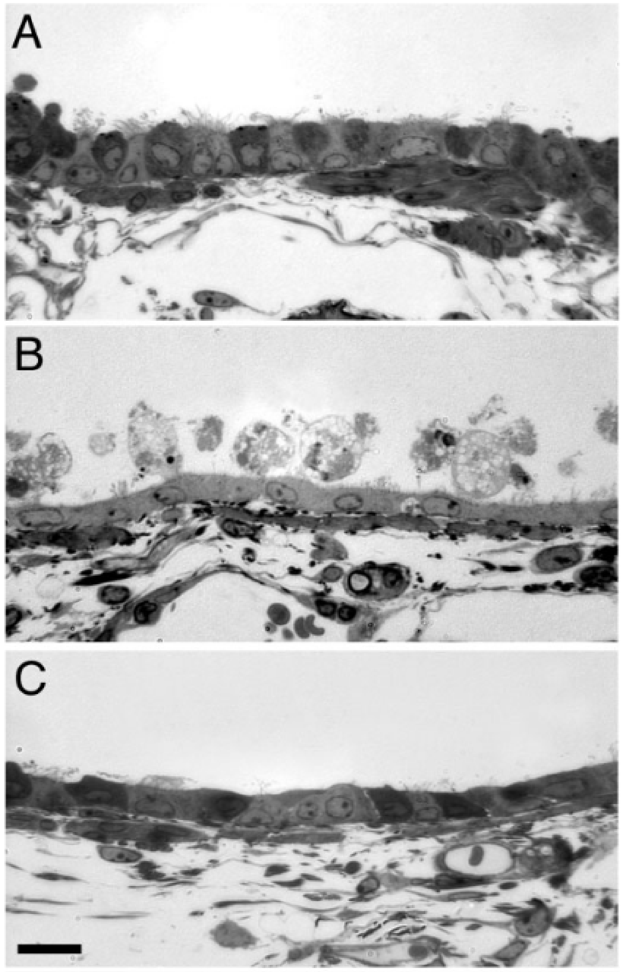
Using randomized controlled trials exposing mice to varying levels of air pollution over time, the environmental toxicology literature has established that mice become resistant to the acute damages of pollution with repeated exposure (West et al., 2003; Kültz et al., 2015; Lee et al., 2018). Cells in 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 that resides in cells within the lining of the walls of the lungs and respiratory tract (i.e., the epithilial lining). 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.

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 5 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.

Figure 5: 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.

4 Data

We combine three data sources to study the effect of PM2.5 on cricket player performance: detailed ball-by-ball performance data from 773 IPL matches in India[7] spanning 2008–2022; high-resolution daily air pollution measures from both ground monitors and satellite-based

[7]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.

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.[8] 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 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

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

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.

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	–	–
Bowlers in sample	575	–	–
Players in sample	619	–	Bowlers may play as bowlers
Bowlers per team per game	5.9	6	Range: 2 to 9
Deliveries per bowler per match	20.1	24	Range: 1 to 34

Our analytic sample contains 773 games in the IPL from 2008-2022 that took place in India.[9] 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,[10] resulting in a theoretical 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 Air quality

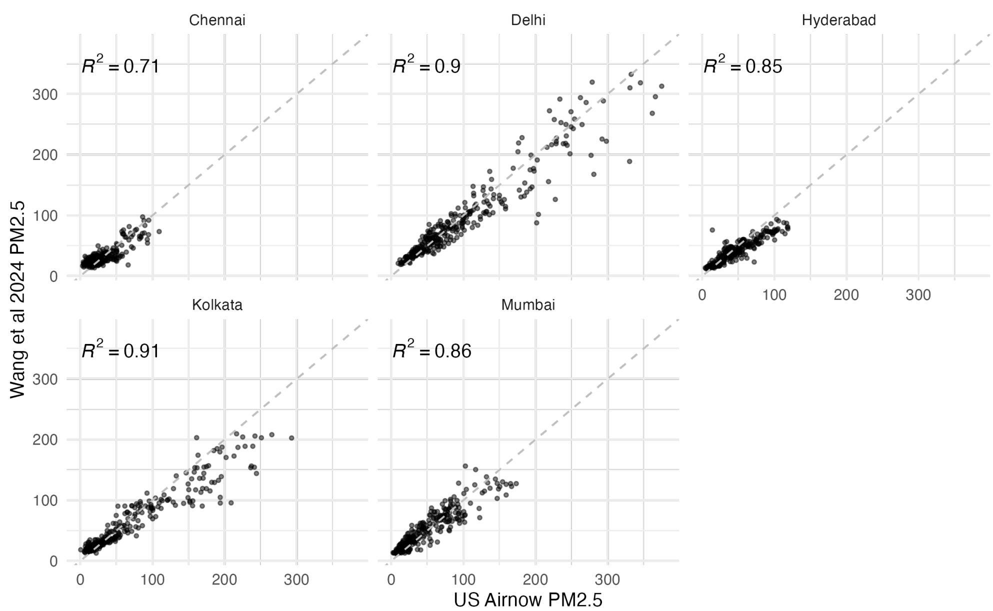
Our primary source of air pollution data comes from Wang et al. (2024), who provide daily estimates of ground-level fine particulate matter (PM2.5) concentrations at a 10km $\times$ 10km

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

[10]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.")

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 6, which demonstrates a strong correlation between the Wang et al. (2024) dataset and ground readings. By contrast, Figure A.1 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 PM2.5 concentrations.

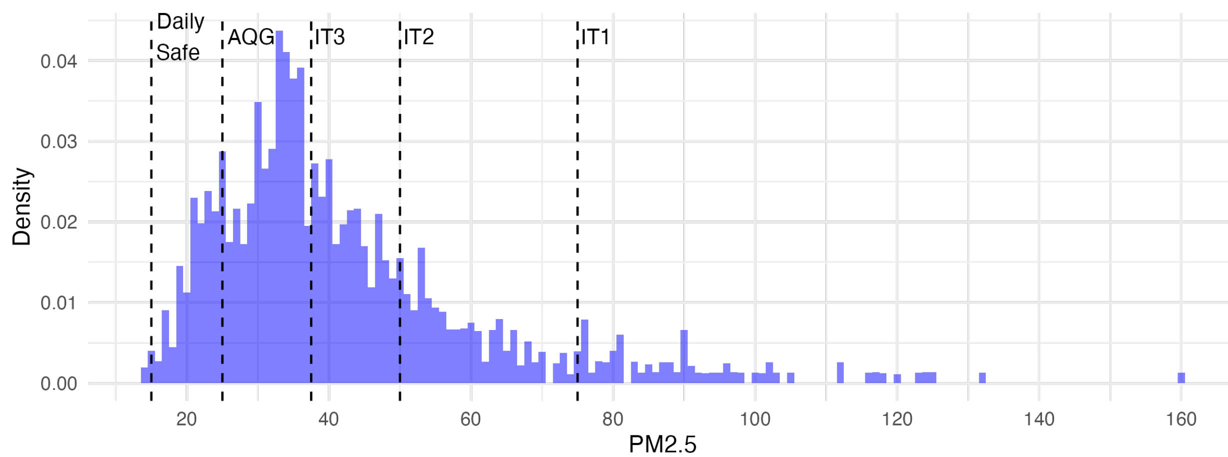
Figure 6: U.S. Airnow vs. Wang et al. (2024) Daily PM2.5



Notes. This figure displays the correlation between Wang et al. (2024) estimates of PM2.5 and ground observations of PM2.5 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 PM2.5. 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.

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 PM2.5 in IPL games is dramatically higher than PM2.5 in high-income countries, with a mean PM2.5 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 7, World Health Organization (2021)). These PM2.5 concentrations are orders of magnitude higher than annual average PM2.5 concentrations in, for exmaple, the U.S., which ranged from 7-9 $\mu g\, m^{-3}$ in 2013-2023.

Figure 7: IPL Game PM2.5 Distribution with WHO Thresholds Indicated



Notes. This figure shows the distribution of PM2.5 at IPL games in the period 2008-2022 with WHO thresholds for daily PM2.5 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 PM2.5 associated with higher short-term mortality risk (World Health Organization, 2021).

4.3 Weather

Particulate matter is not the only meteorological factor that may affect performance in cricket; the weather may do so as well. PM2.5 concentrations themselves are a product of many meteorological factors, including temperature, humidity,[11] 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

[11] 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).

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 $\times$ 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. 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 case for a batter.[12]

[12] 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.

5.1 Main specification

We examine the relationship between match-day PM2.5 levels and run-scoring probability with our baseline specification:

$$R_{ij\ell t} = \beta \text{PM2.5}_{\ell d} + \mathbf{X}'_{\ell d}\phi + \psi_j + \phi_i + \delta_{\ell y} + \theta_n + \eta_o + \Lambda_i + \Delta_j + \varepsilon_{ij\ell t} \tag{2}$$

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 PM2.5 levels (measured in 10 $\mu g\, m^{-3}$) on run-scoring probability.[13] 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) (there are two innings per game), over fixed effects (η_o) (there are 20 overs per inning), dummy variables for whether the stadium is the home stadium for the batter (Λ_i) or bowler (Δ_j),[14] and 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, solar radiation, and wind speed.

Identification in Equation 2 comes from the fact that cricket matches are scheduled well in advance (before reliable air pollution forecasts are available) and cannot be rescheduled due to pollution levels, making match-day PM2.5 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 at the match and bowler level to account

[13]The standard measure of PM2.5 is 1 $\mu g\, m^{-3}$. When measured in these units, the effects we observe are very small in magnitude. Given the distribution of PM2.5 in our sample (see Figure 7), measuring PM2.5 in 10 $\mu g\, m^{-3}$ is appropriate. The effect sizes we observe are similar to those of other studies that measure effects in 10 $\mu g\, m^{-3}$ (Adhvaryu et al., 2022).

[14]Note that some matches are played at stadiums that are a home stadium for neither time, which prevents these two terms from being collinear.

for potential serial correlation in performance for bowlers and the fact that pollution exposure is observed for each match. Additionally, 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.

5.2 Non-linear effects

To examine potential non-linearities in the pollution-performance relationship, we also estimate the following specification replacing the continuous PM2.5 measure with indicators for PM2.5 quantiles:

$$R_{ij\ell t} = \sum_{k=2}^{5} \beta_k Q_k \left(\text{PM2.5}_{\ell d}\right) + \mathbf{X}'_{\ell d}\phi + \psi_j + \phi_i + \delta_{\ell y} + \theta_n + \eta_o + \Lambda_i + \Delta_j + \varepsilon_{ij\ell t} \tag{3}$$

where $Q_k(\text{PM2.5}_{\ell d})$ represents indicators for the second through fifth quintiles of match-day PM2.5, with the lowest quintile serving as the reference category.

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

$$R_{ij\ell t} = \sum_{j=0}^{p} \beta_j (\text{PM2.5}^{j}_{\ell d}) + \sum_{k=1}^{N} \beta_{p+k} (\text{PM2.5}_{\ell d} - \tau_k)^p \mathbf{1}\{\text{PM2.5}_{\ell d} \geq \tau_k\} + \mathbf{X}'_{\ell d}\phi + \psi_j + \varepsilon_{ij\ell t} \tag{4}$$

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 Defining past exposure to PM2.5

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 PM2.5 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 8 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.

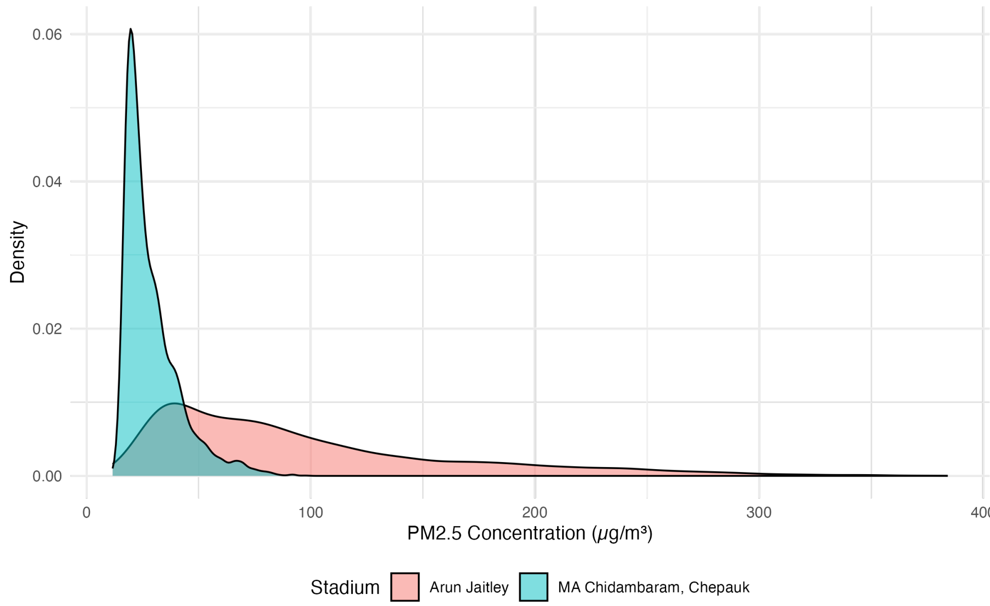
5.3.1 Medium-term exposure

We ground our definition of long-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[15]—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 PM2.5:

[15] 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.

Figure 8: Probability Density Functions of PM2.5 in Two Example Stadiums



Notes. This figure displays the probability density function (PDF) of PM2.5 concentration in two example stadiums with divergent distributions of PM2.5.

1. Mean PM2.5 over past X days

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

2. Number of days in past X days where PM2.5 was above Z threshold

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

$$PM2.5_{J(j)d} = \sum_{d=1}^{X}\mathbf{1}(PM2.5_{J(j)d} > Z) \tag{6}$$

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

$$PM2.5_{J(j)d} = \sum_{d=1}^{X}[\mathbf{1}(PM2.5_{J(j)d} > Z)](PM2.5_{dj} - Z) \tag{7}$$

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 PM2.5 exposure to teams

1. If the team plays a match on a given day, we assign the PM2.5 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 PM2.5 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 PM2.5 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 PM2.5 for their home stadium.

Figure 9 shows the distribution of PM2.5 exposure histories for each of the eight teams with the highest numbers of matches in the IPL as of 2022.[16] In Figure 10, we compare the PM2.5 estimates assigned to teams (based on their travel itinerary, as described above) as

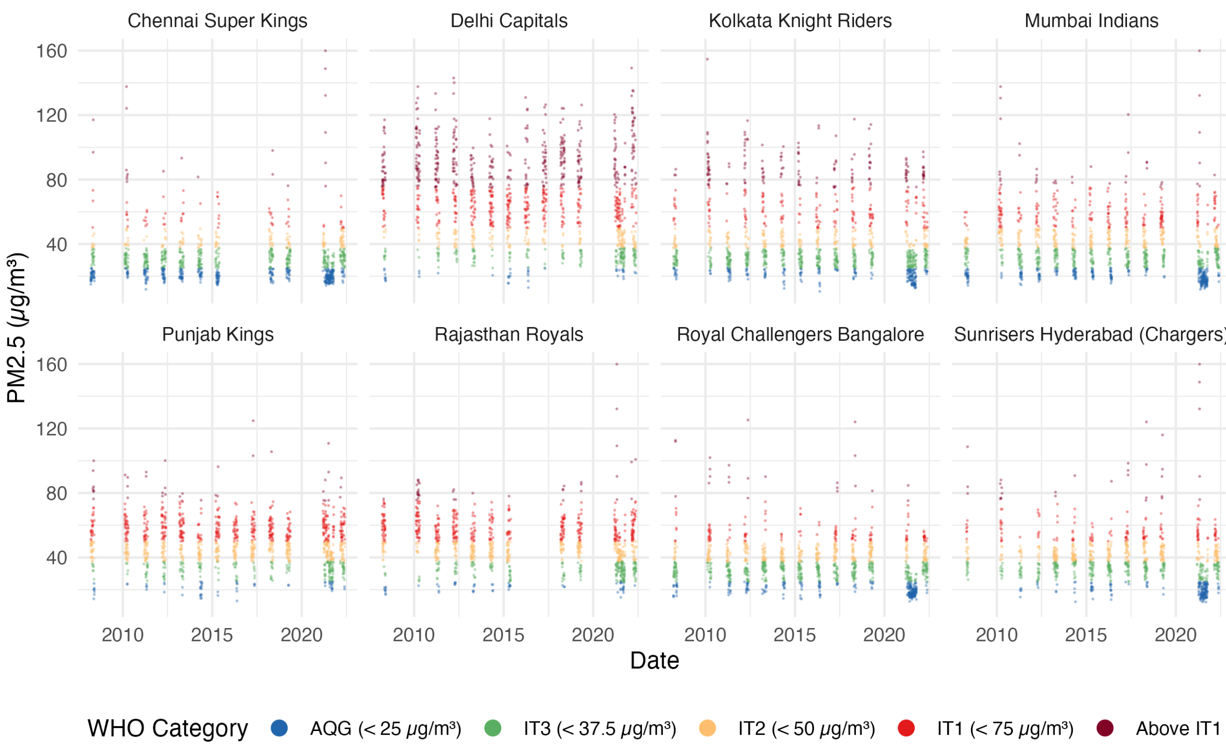
[16]We combine the PM2.5 exposure histories for teams that changed names across seasons but retained the same home city and stadium; the graph shows the most recent name of each team.

opposed to the PM2.5 at their home stadium. The red line shows the level of PM2.5 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 PM2.5 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 5, 6, 7 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 PM2.5 may affect the body. Use of the measure in Equation 5 would suggest that the mean level of exposure in the past, say, 30 days is meaningful. Measuring the mean, however, may gloss 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 5 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.

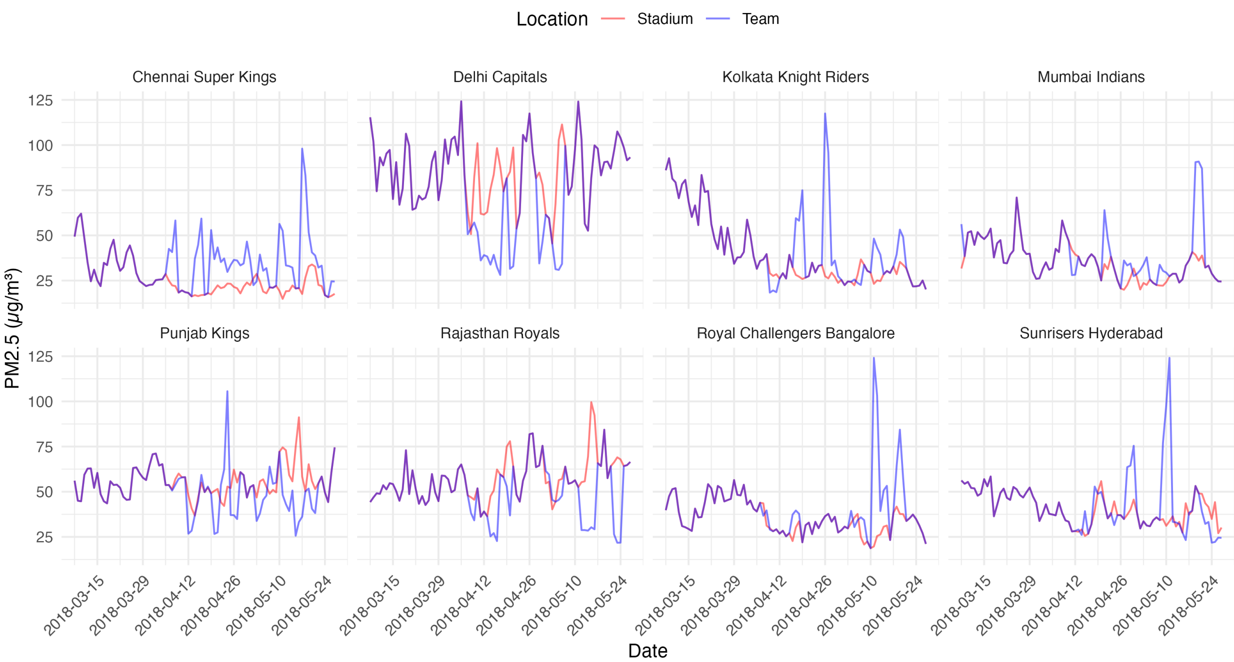
The measure in Equation 6 corrects for this coarseness to some extent by counting how many "bad" days of pollution there were for a team in a given time window, where "bad" is a threshold that can be adjusted. The underlying idea that there is a certain threshold

Figure 9: Team PM2.5 Exposure Histories in IPL, 2008-2022



Notes. This figure displays the PM2.5 exposure history of each IPL team in the years 2008-2022. Teams are assumed to be exposed to the level of PM2.5 in their home stadium, unless they are playing a match at an away stadium, in which case they are exposed to the PM2.5 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 PM2.5 exposure between seasons, leading to blank spaces between the clusters of dots for each season.

Figure 10: Team PM2.5 Exposure vs. Home Stadium PM2.5 Exposure in 2018



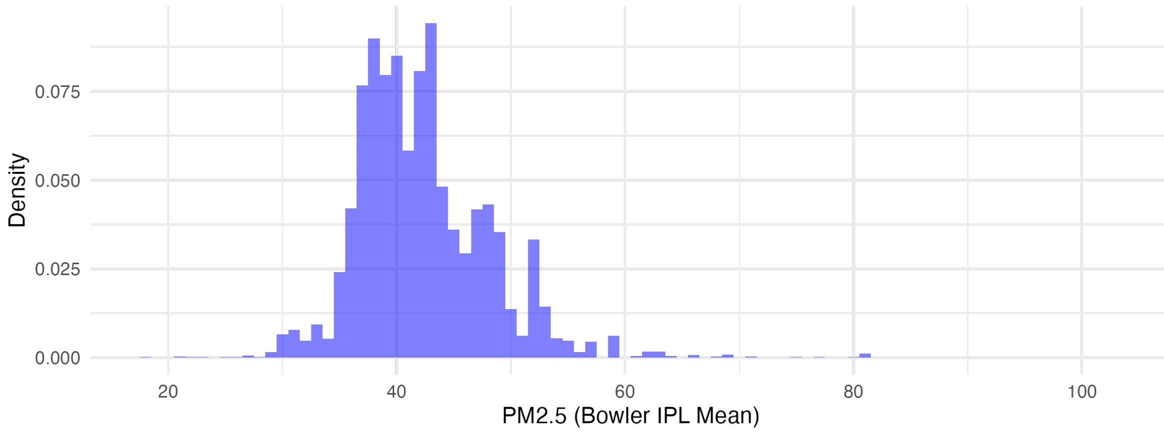
Notes. This figure compares the PM2.5 estimates assigned to teams (based on their travel itinerary, as in Section 5.3.1) relative to the PM2.5 at their home stadium. The red line shows the level of PM2.5 exposure at the team's home stadium whereas the blue line shows the PM2.5 exposure for each team taking into account their away games and travel schedule.

beyond which exposure to PM2.5 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 6 would be 15 in the alternating case and 0 in the consistent case.

The measure in Equation 7 is a further refinement of that in Equation 6—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 PM2.5 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 7 relative to Equation 6 is that Equation 7 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.

Figure 11: Histogram of Bowler PM2.5 Mean in IPL Games 2008-2022



Notes. This figure displays the distribution of bowler mean PM2.5 defined as the mean PM2.5 exposure across all games for a given bowler in the IPL 2008-2022 (i.e. PM2.5_{j0} in Equation 11).

5.3.2 Long-term exposure

In addition to the measures of past exposure in Section 5.3.1 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. This measure is displayed in Figure 11. 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. However, it is likely that pollution exposure during cricket matches themselves contributes to a bowler's ability to tolerate pollution while playing cricket, and this measure appropriately captures that type of exposure.

Table 2 presents six additional alternative definitions of long-term PM2.5. Our preferred definition for long-term exposure to PM2.5 is the mean exposure to PM2.5 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 PM2.5 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 PM2.5 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 PM2.5 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.[17] 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.

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

5.4 Hetereogeneity in the short-run effect of PM2.5 by past PM2.5 exposure

We hypothesize that short-run responses to PM2.5 levels on the day of the match vary by how much pollution a cricket player is exposed to in the past. To quantify this effect, we interact the realization of pollution in the day and location of the match, $\text{PM2.5}_{\ell d}$, with past exposure. The medium-term exposure levels defined in Section 5.3.1 vary at the team-match level whereas the long-term exposure levels defined in Section 5.3.2 vary at the bowler (or bowler-season) level. Each measure therefore requires a slightly different econometric specification to correctly identify the extent to which past exposure mediates the harms of present exposure.

Beginning with the medium-term measure in Equation 5, we estimate:

$$\begin{aligned} R_{ij\ell t} = {} & \beta_1 \text{PM2.5}_{\ell d} + \beta_2 \text{PM2.5}_{\ell d} \times \text{PM2.5}_{J(j)d} + \beta_3 \text{PM2.5}_{J(j)d} \\ & + \mathbf{X}'_{\ell d}\phi + \psi_j + \phi_i + \delta_{\ell y} + \theta_n + \eta_o + \Lambda_i + \Delta_j + \varepsilon_{ij\ell t} \end{aligned} \tag{8}$$

where $\text{PM2.5}_{J(j)d}$ is defined as the mean level of PM2.5 exposure in the past X days from day d for bowler j who is on team J, and other variables are as defined in Equation 2. We include the full interaction of present PM2.5 and past PM2.5 to disambiguate the level-effect of past PM2.5 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.

We estimate analogous equations for the measure in Equation 6

$$\begin{aligned} R_{ij\ell t} = {} & \beta_1 \text{PM2.5}_{\ell d} + \beta_2 \text{PM2.5}_{\ell d} \times \sum_{d=1}^{X} \mathbf{1}(PM2.5_{J(j)d} > Z) + \sum_{d=1}^{X} \mathbf{1}(PM2.5_{J(j)d} > Z) \\ & + \mathbf{X}'_{\ell d}\phi + \psi_j + \phi_i + \delta_{\ell y} + \theta_n + \eta_o + \Lambda_i + \Delta_j + \varepsilon_{ij\ell t} \end{aligned} \tag{9}$$

and the measure in Equation 7:

$$
\begin{aligned}
R_{ij\ell t} = \beta_1 \mathrm{PM2.5}_{\ell d} + \beta_2 \mathrm{PM2.5}_{\ell d} \times \sum_{d=1}^{X} [\mathbf{1}(PM2.5_{dj} > Z)](PM2.5_{dj} - Z) \\
+ \sum_{d=1}^{X} [\mathbf{1}(PM2.5_{dj} > Z)](PM2.5_{dj} - Z) \\
+ \mathbf{X}'_{\ell d}\phi + \psi_j + \phi_i + \delta_{\ell y} + \theta_n + \eta_o + \Lambda_i + \Delta_j + \varepsilon_{ij\ell t}.
\end{aligned} \tag{10}
$$

For the measure of long-term exposure that is fixed for each bowler in Section 5.3.2, we estimate:

$$
R_{ij\ell t} = \beta_1 \mathrm{PM2.5}_{\ell d} + \beta_2 \mathrm{PM2.5}_{\ell d} \times \mathrm{PM2.5}_{j0} + \mathbf{X}'_{\ell d}\phi + \psi_j + \phi_i + \delta_{\ell y} + \theta_n + \eta_o + \varepsilon_{ij\ell t} \tag{11}
$$

where $\mathrm{PM2.5}_{j0}$ is long-term exposure to pollution for a given bowler, and other variables are as defined in Equation 2. 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 PM2.5 exposure in the medium-term—which vary across time—in Equation 11, we omit the term for past exposure, $\mathrm{PM2.5}_{j0}$, from the estimation since it is fixed within bowler and therefore would be collinear with bowler fixed effects.

5.5 Robustness: alternative measures of long-term PM2.5

Table 2: 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.

We estimate Equation 11 for the long-term definitions of PM2.5 in rows 1 and 2 of Table 2. 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 PM2.5 to each bowler changes depending on what team they are on in each year.[18] We estimate the slightly modified specification:

$$R_{ij\ell t} = \beta_1 \text{PM2.5}_{\ell d} + \beta_2 \text{PM2.5}_{\ell d} \times \text{PM2.5}_{j0} + \mathbf{X}'_{\ell d}\phi + \psi_{yJ(j,y)} + \delta_{\ell y} + \theta_n + \eta_o + \varepsilon_{ij\ell t} \quad (12)$$

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.

[18] 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.

6 Results

Our empirical analysis establishes four main findings. First, air pollution significantly impairs worker productivity, with a 10 $\mu g\, m^{-3}$ increase in PM2.5 reducing performance by 1.01%. 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 throughout their career, partially buffering acute impacts. Fourth, this adaptation comes at a cost: accumulated exposure itself degrades baseline performance, and the protective effect only dominates harm under extremely rare pollution conditions.

6.1 Baseline effects of air pollution on performance

Table 3 presents estimates of how match-day PM2.5 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 PM2.5—equal to one half a standard deviation[19]—increases the probability that a bowler concedes a run by 0.41 percentage points ($p < 0.05$). Given a baseline run-scoring probability of 59.9%, this represents a 1.01% increase in the likelihood of a bowler conceding a run. 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.

This effect is both economically meaningful and robust across specifications. Adding weather controls in column 2 reduces the coefficient to 0.27 percentage points, reflecting omitted variable bias: PM2.5 and humidity are negatively correlated ($\rho = -0.62$) while run-scoring decreases with humidity, and PM2.5 and temperature are positively correlated ($\rho =$

[19]The mean PM2.5 level in our sample is 42.3 with a standard deviation of 20.0 and a range of 14.2 to 159.9 $\mu g\, m^{-3}$.

Table 3: 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		✓	✓		✓	✓
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. 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

0.22) while run-scoring increases with temperature.[20] Including comprehensive fixed effects restores the coefficient to 0.41 percentage points, indicating that pollution's effect operates largely independently once we control for factors determining each delivery's outcome.[21]

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

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 3 replace the continuous PM2.5 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 PM2.5 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.

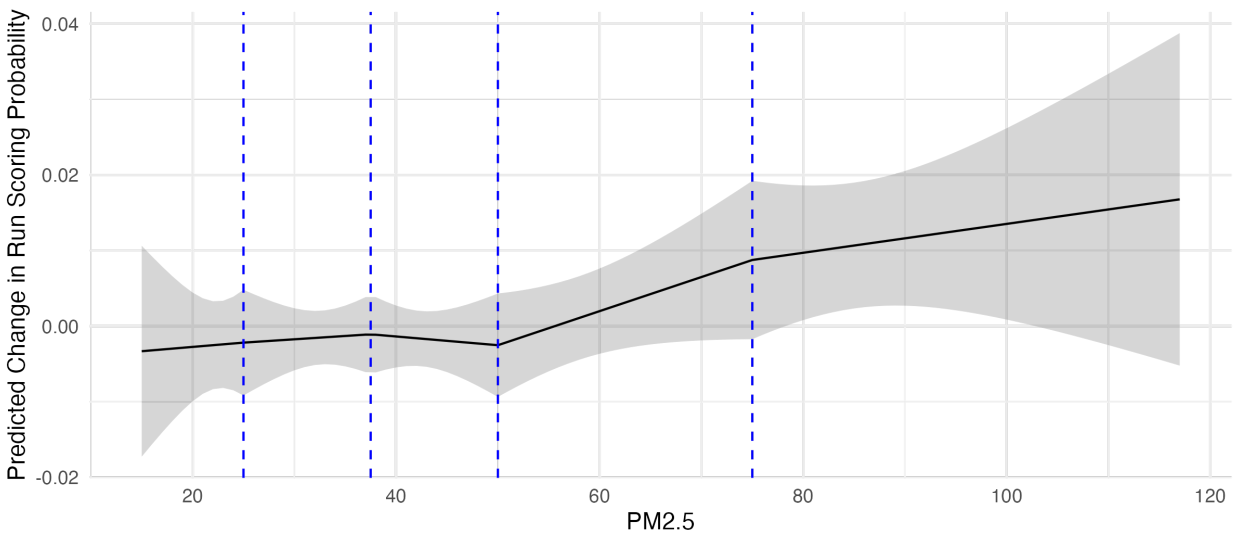
This non-linearity is striking given that even our lowest quintile (0–27 $\mu g\, m^{-3}$) substantially exceeds the WHO's 15 $\mu g\, m^{-3}$ daily limit, and the second quintile (27–34 $\mu g\, m^{-3}$) is more than double WHO guidelines. The absence of significant effects in quintiles 2–4, despite 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

[20]See Table A.1 for raw correlations between run-scoring, PM2.5, and all weather variables.

[21]This result is also confirmed using the PDS LASSO method proposed in Belloni et al. (2014); see Section B.2 for details.

developing countries but rarely observed in settings typically studied.

Figure 12: Effect of PM2.5 on Run Probability (Linear Spline, WHO Thresholds)



Notes. Figure displays predicted changes in run-scoring probability as a function of match-day PM2.5 estimated using Equation 4 with $p = 1$ and knots at WHO targets: 25, 37.5, 50, and 75 $\mu g\, m^{-3}$. Dashed lines indicate knot locations.

Figures 12 confirms this pattern using the spline specification in Equation 4.[22] The dose–response function remains relatively flat through moderate pollution levels before steepening markedly above 50 $\mu g\, m^{-3}$. 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.

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 long-term exposure histories.

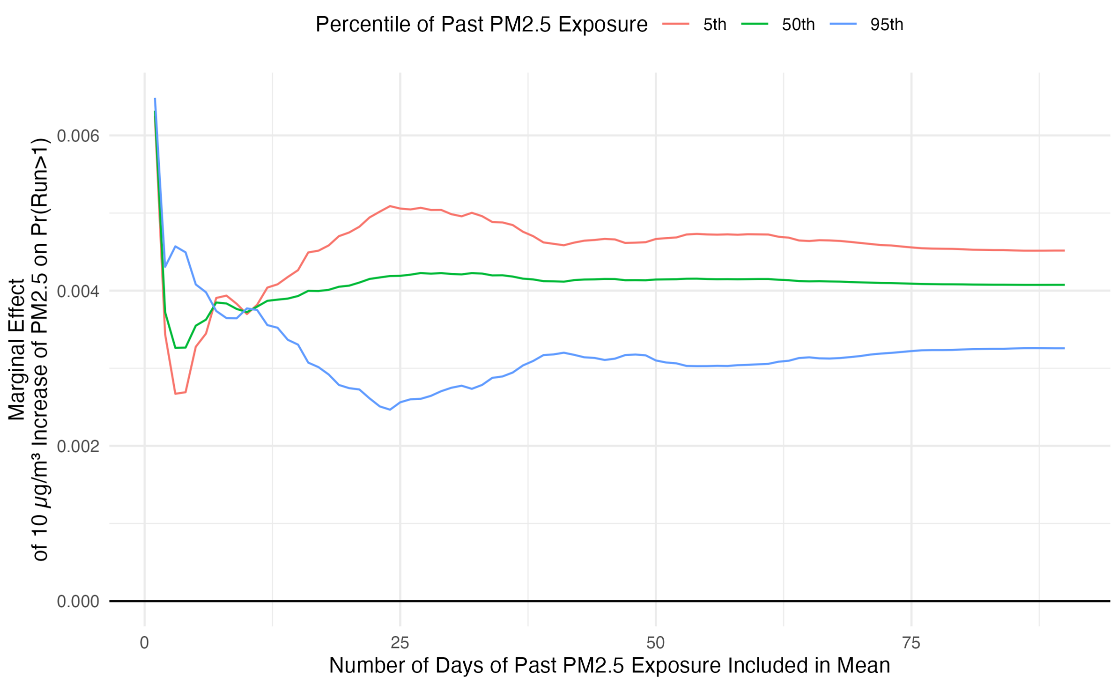
[22]As an additional robustness check, we estimate the spline specification in Equation 4 using a restricted cubic spline with knots at quintiles and find qualitatively similar results; see Figure A.3.

6.3.1 Temporal dynamics: Medium-term adaptation

We begin by examining adaptation to recent exposure, testing three measures of a bowler's pollution in the period immediately preceding a match: mean exposure, days above thresholds, and cumulative exposure above thresholds (Equations 5–7). We vary lookback windows from 1 to 90 days and pollution thresholds from 25 to 75 µg m^{-3}.

Figure 13 plots how the marginal effect of match-day PM2.5 varies with past exposure and lookback window length. For bowlers at the 95th percentile of past exposure, the marginal effect is substantially smaller—as low as 0.25 percentage points—with the strongest attenuation using 20–30 day windows. Figure A.6 shows this adaptation effect peaks at 24 days, where highly exposed bowlers experience marginal effects 41% smaller than those at the median.

Figure 13: Marginal Effect of PM2.5 on Run Probability for Varying Exposure Windows



Notes. Figure shows the marginal effect of a 10 µg m^{-3} increase in match-day PM2.5 for bowlers at the 5th, 50th, and 95th percentiles of past exposure.

Table 4 demonstrates consistency across measurement approaches. Mean exposure peaks

Table 4: Medium-term adaptation effects: magnitude and time window across measures

Measure	**Threshold**	**Days (largest effect)**	**Magnitude (%)**
30-day Mean (Equation 5)	–	24	41.1
Days Above Thresholds (Equation 6)	25	90	55.0
	37.5	81	68.6
	50	32	54.0
	75	24	81.5
Degree-Day Measures (Equation 7)	25	24	40.5
	37.5	24	42.7
	50	24	40.3
	75	24	44.3

at 24 days (41%), days above 50 $\mu g\, m^{-3}$ at 32 days (54%), and cumulative above 50 $\mu g\, m^{-3}$ at 24 days (40%). This convergence on a 24–32 day window provides confidence we are capturing a real phenomenon rather than statistical artifact. Notably, adaptation is twice as large (82%) when counting days above 75 $\mu g\, m^{-3}$, suggesting particular responsiveness to extreme episodes—consistent with medical evidence on antioxidant upregulation following severe exposures.

Table 5 column 6 presents our preferred specification using mean exposure over 30 days. The coefficient on match-day PM2.5 is 0.66 percentage points while the coefficient on 30-day mean is 0.61 percentage points—statistically indistinguishable ($p = 0.81$). 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, consistent with findings that repeated exposure makes lungs "refractory to further injury" (West et al., 2003).

The interaction term is $-0.00055\,(p = 0.38)$. Though not statistically significant, Figure 14 reveals economic significance: at low past exposure (20 $\mu g\, m^{-3}$), match-day pollution increases run-scoring by approximately 1.0 percentage point; at high past exposure (80 $\mu g\, m^{-3}$), the effect is only 0.5 percentage points—a 50% reduction demonstrating meaningful

Table 5: Evidence of Adaptation to Air Pollution

	(1)	(2)	(3)	(4)	(5)	(6)
		$\mathbb{1}$ (At least one run scored)				
Contemporaneous PM2.5	0.0027*	0.0042***	0.0042**	0.0041**	0.013**	0.0066*
	(0.0014)	(0.0016)	(0.0016)	(0.0017)	(0.0052)	(0.0034)
Contemporaneous PM2.5 X Career PM2.5					-0.0020*	
					(0.0011)	
Past 30-day PM2.5						0.0061*
						(0.0034)
Contemporaneous PM2.5 X Past 30-day PM2.5						-0.00055
						(0.00063)
Weather controls		✓	✓	✓	✓	✓
Home stadium dummies		✓	✓	✓	✓	✓
Stadium-by-year FE			✓	✓	✓	✓
Over FE			✓	✓	✓	✓
Innings FE				✓	✓	✓
Bowler FE					✓	✓
Batter FE					✓	✓
N	183,572	183,558	183,558	183,556	183,556	183,556
R^2	0.00041	0.046	0.046	0.052	0.052	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. Past PM2.5 is defined as the mean PM2.5 exposure for the bowler in the past 30 days. Standard errors are clustered two-way at the match and bowler level. Following Correia (2015), 14 singleton observations are dropped in columns (2) and (3) and 16 singleton observations are dropped in columns (4)-(6). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

adaptation.

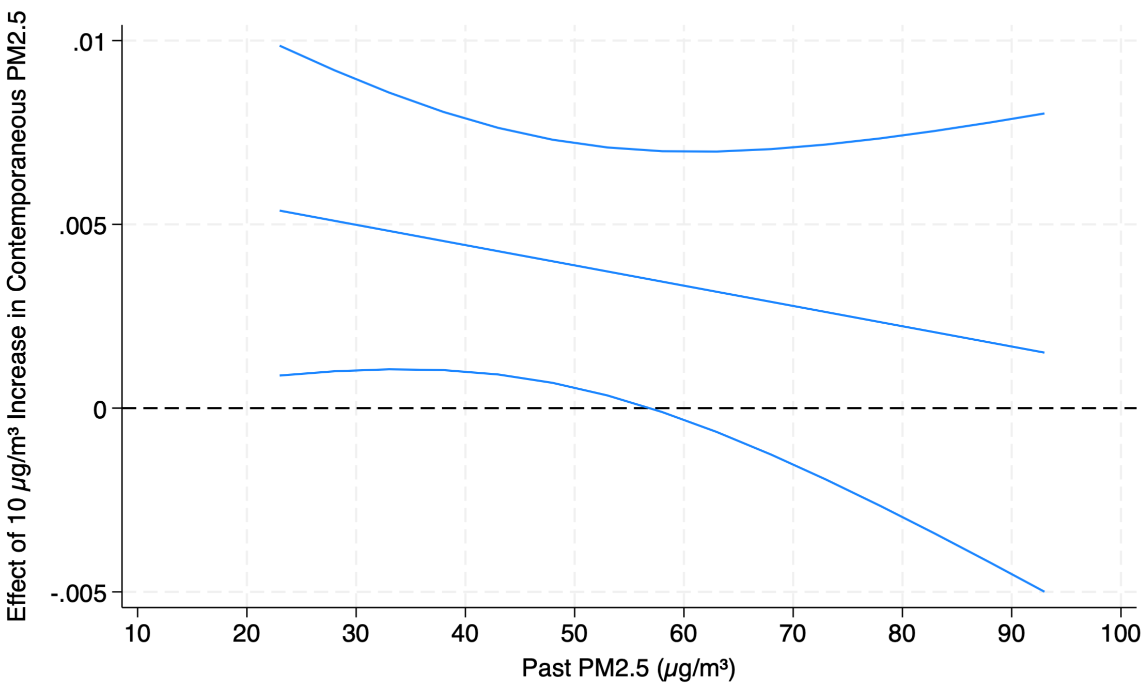
6.3.2 Long-term adaptation across career exposure

Column (5) of Table 5 examines adaptation to career-length exposure, defined as each bowler's mean across all IPL matches. Column 5 shows the interaction coefficient is -0.0020 ($p < 0.10$), indicating bowlers with higher career-average exposure exhibit smaller responses to match-day pollution. At zero career exposure, the marginal effect is 1.3 percentage points. At the sample mean (42.6 $\mu\text{g m}^{-3}$), it is 0.49 percentage points. At high career exposure (60 $\mu\text{g m}^{-3}$), it attenuates close to zero, though remaining weakly positive.

Figure 15 displays this relationship across observed career exposures. For bowlers at the 95th percentile of long-term exposure (70.6 $\mu\text{g m}^{-3}$ average), the marginal effect of match-day PM2.5 is 0.27 percentage points, compared to 0.42 percentage points for bowlers with median exposure (44.0 $\mu\text{g m}^{-3}$)—a 36% reduction in the acute response.

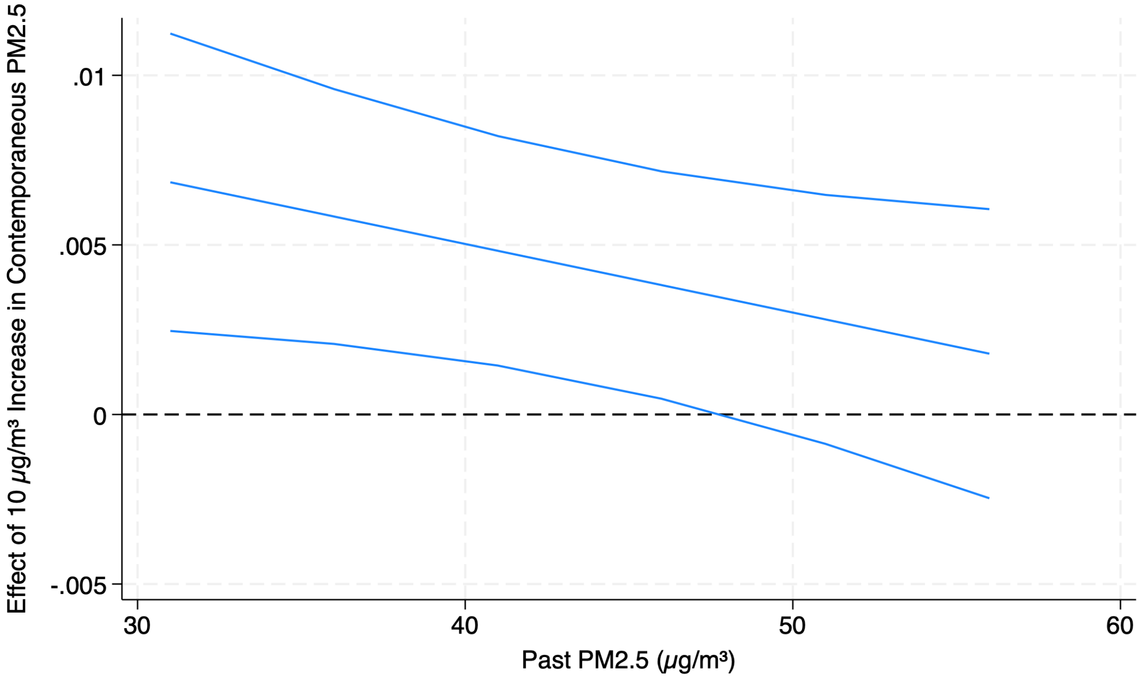
Table A.3 examines robustness using place-based measures (team home stadium pollution) rather than person-specific career averages. While interaction coefficients remain consistently

Figure 14: Marginal Effect of Match-Day PM2.5 by Recent Pollution Exposure



Notes. This figure plots the marginal effect of a 10 $\mu g\,m^{-3}$ increase in match-day PM2.5 as a function of mean PM2.5 exposure over the prior 30 days.

Figure 15: Marginal Effect of Match-Day PM2.5 by Career Pollution Exposure



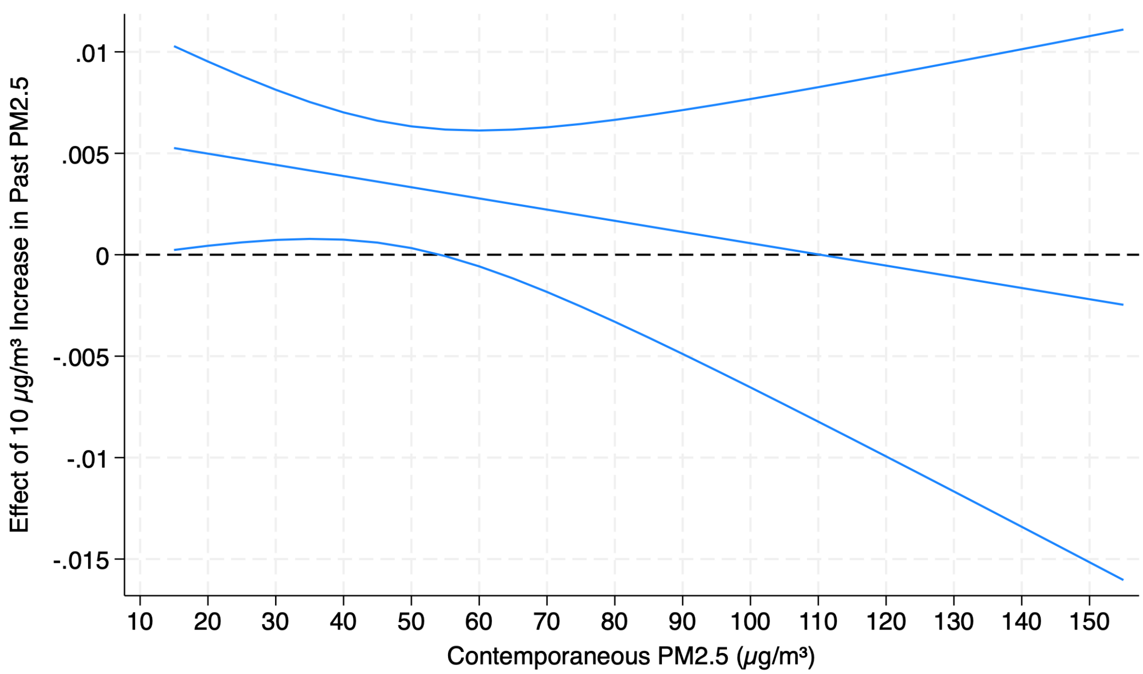
Notes. This figure plots the marginal effect of a 10 $\mu g\,m^{-3}$ increase in match-day PM2.5 as a function of career-average PM2.5 exposure.

negative, they become smaller and statistically insignificant. This pattern suggests that measurement matters critically: person-specific measures capturing actual cumulative exposure based on their movements over time result in larger adaptation effects than place-based measures.

6.4 The tradeoff between adaptation and cumulative harm

Our findings document both harm and adaptation, raising a critical question: does adaptation ever outweigh cumulative damage? Figure 16 addresses this by plotting the marginal effect of past 30-day exposure on current performance as a function of match-day pollution.

Figure 16: Marginal Effect of Past PM2.5 on Pr(Run) by Contemporaneous PM2.5



Notes. This figure plots the marginal effect (with 95% confidence intervals) of past PM2.5, defined as the 30-day mean as in Equation 5, on the probability of run-scoring for varying levels of contemporaneous PM2.5 as estimated in Equation 8.

At low match-day pollution (20–40 $\mu g\, m^{-3}$), past exposure unambiguously harms performance. As match-day pollution rises above 60–70 $\mu g\, m^{-3}$, the marginal effect declines, crossing zero around 110 $\mu g\, m^{-3}$. Beyond this threshold, past exposure becomes protective by providing resilience against extremely high acute exposure.

However, this crossover occurs at extraordinarily high levels—only 1.8% of deliveries exceed 110 $\mu g\,m^{-3}$, more than seven times WHO guidelines and among the most polluted conditions worldwide. The widening confidence intervals reflect this data sparsity. While we find suggestive evidence that adaptation can eventually overcome cumulative harm, this threshold lies far above conditions most workers experience even in heavily polluted settings.

For the vast majority of exposure scenarios, both acute and chronic pollution impair productivity, even as adaptation moderates the acute response. Past pollution harms performance through direct cumulative damage while simultaneously necessitating costly adaptation that only partially offsets acute impacts.

7 Discussion and conclusion

These results paint a consistent picture of how air pollution affects labor productivity in a setting that combines aspects of physical and cognitive performance. First, pollution has significant effects on worker performance, with particularly strong impacts at high exposure levels. Second, these effects are asymmetric across player roles: the baseline results in Table 3 show that pollution increases run-scoring probability, suggesting bowlers are more affected than batters. The results in Table 5 show that bowlers are less-harmed by high pollution on match-day when they are used to higher levels of pollution in the long-run, all else equal. Together, these preliminary findings suggest that the acute effects of pollution are mediated by past exposure. We emphasize, however, that long-term exposure to air pollution still worsens productivity—as well as health–over the long-term, counteracting this positive side-effect in the short-term.

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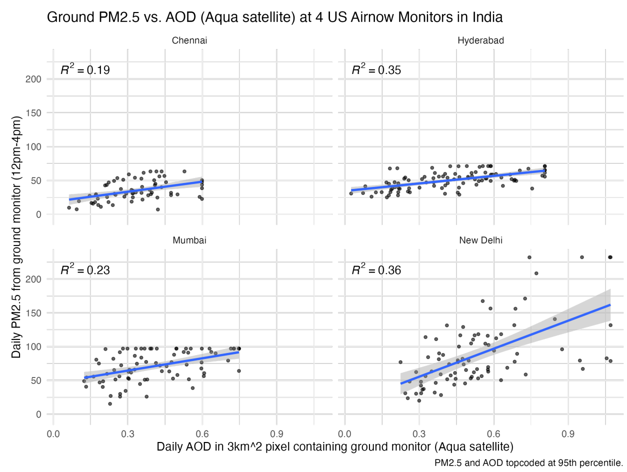
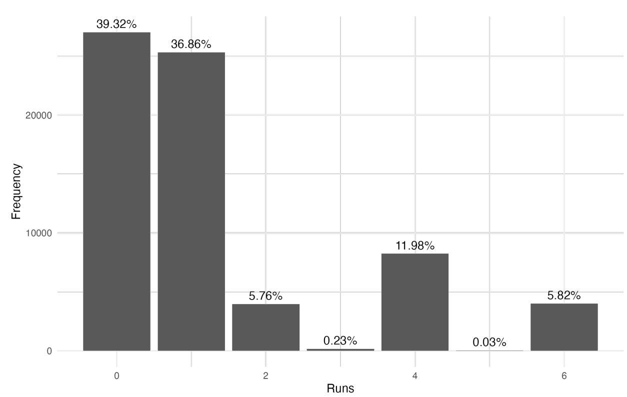
A Appendix: Tables and Figures

Figure A.1: 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 PM2.5 at five cities with a U.S. AirNow ground monitor. Each dot represents a daily mean value of PM2.5. AOD is calculated as the mean AOD in the 3km x 3km pixel containing the ground monitor. Both PM2.5 and AOD are topcoded at the 95th percentile.

Figure A.2: Histogram of Runs



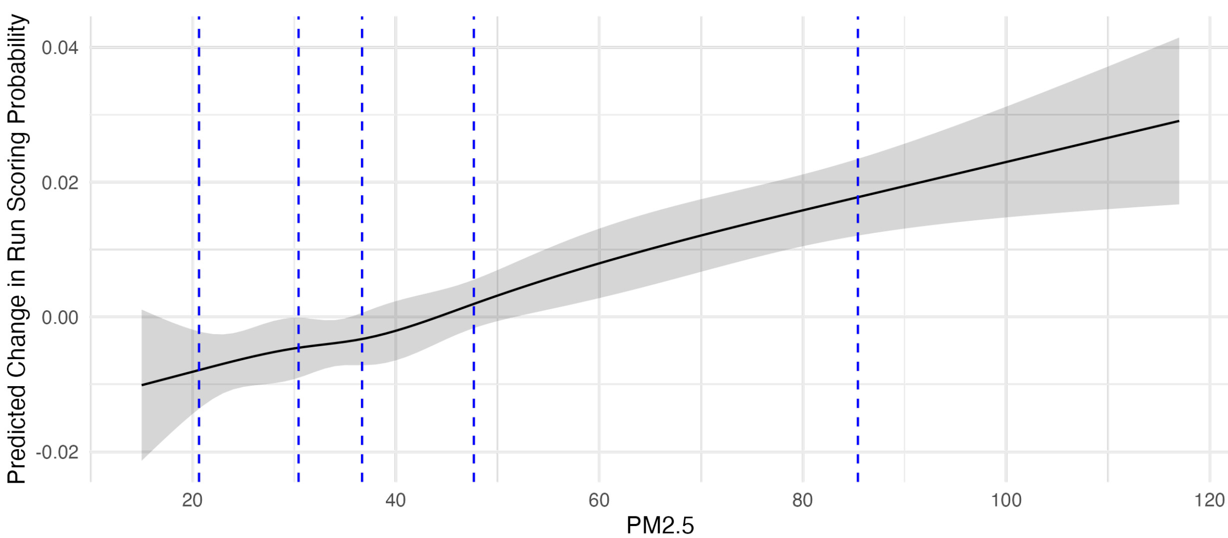
Notes. This figure shows the distribution of the outcome variable (runs scored) in our analysis.

Table A.1: 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.3: Effect of PM2.5 on Run Probability (Restricted Cubic Spline, Quantile Knots)



Notes. Figure displays predicted changes in run-scoring probability as a function of match-day PM2.5 estimated using Equation 4 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: 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.2: Evidence of Adaptation to Air Pollution Climates (Ordered Logit)

	(1)	(2)	(3)	(4)	(5)	(6)
	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 (0 to 6). 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

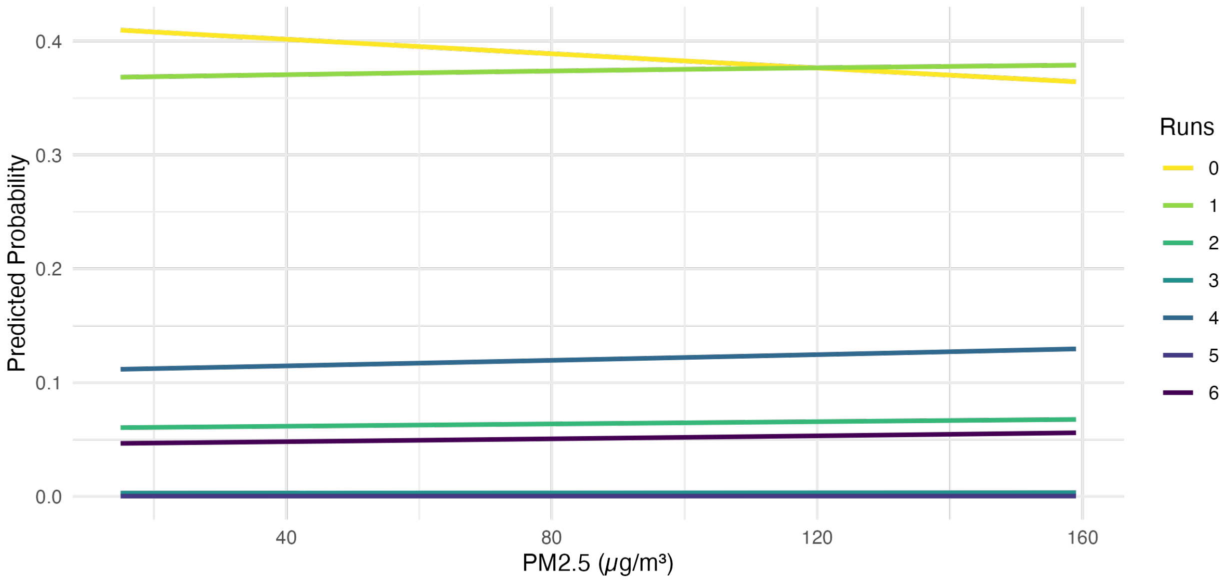


Figure A.4: Predicted Probability of Scoring 0, 1, 2, 3, 4, 5, or 6 runs by PM2.5

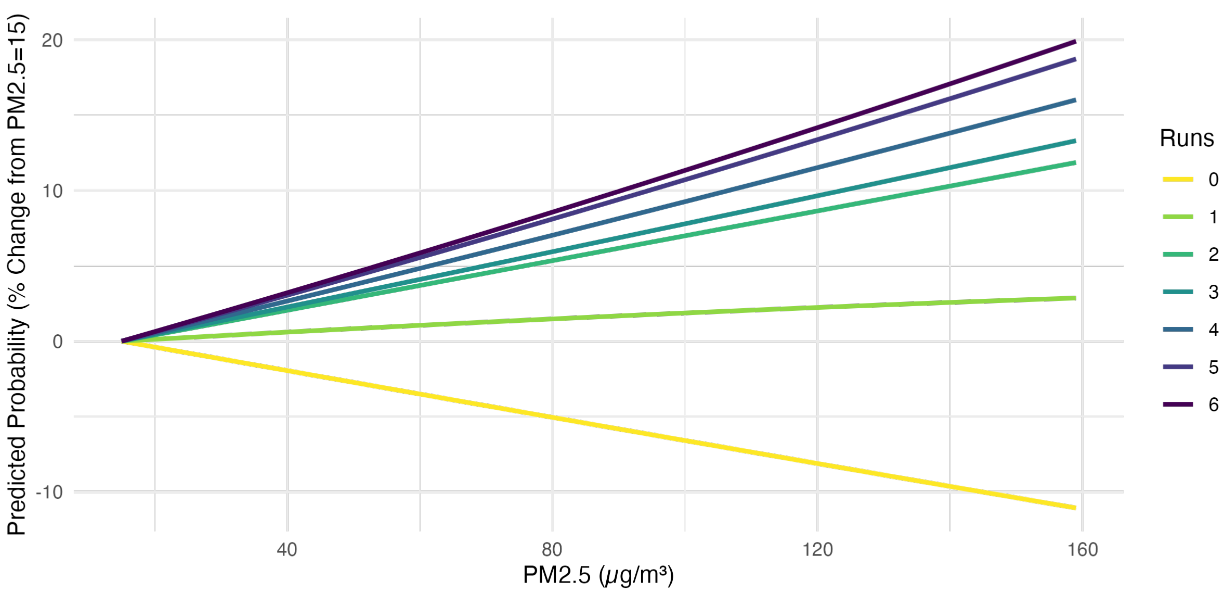
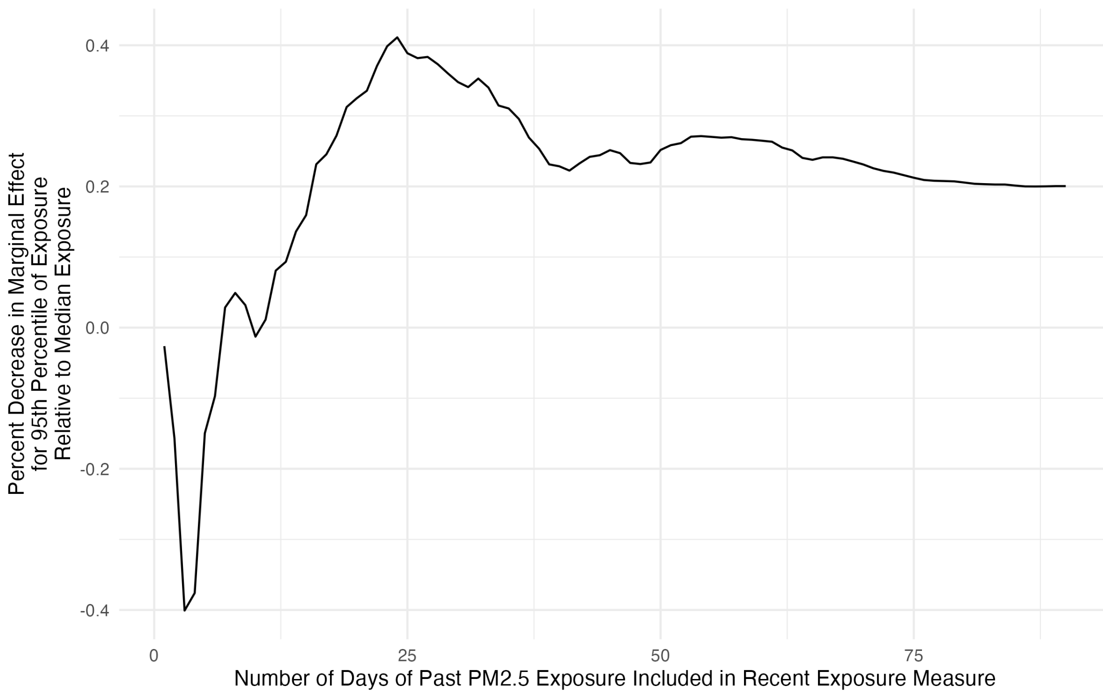


Figure A.5: Change in Predicted Probability of Scoring 0, 1, 2, 3, 4, 5, or 6 runs by PM2.5

Notes. These figures report graphically the results from Equation 14. Figure A.4 shows the predicted probability of scoring each number of runs given varying levels of game PM2.5. Figure A.5 presents the same results, but scaled relative to the predicted probabilities when PM2.5 is 15 $\mu g\,m^{-3}$.

Figure A.6: 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 PM2.5 on run-scoring for for the Y^{th} percentiles of mean past exposure to PM2.5. Marginal effects are estimated from Equation 8. The effect peaks when these lines are furthest apart.

B Appendix: Additional Robustness Checks

B.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.

$$\log\left(\frac{P(R_{ij\ell t} \leq r)}{P(R_{ij\ell t} > r)}\right) = \beta_1 \text{PM2.5}_{\ell d} + \beta_2 \text{PM2.5}_{\ell d} \times \text{PM2.5}_{j0} + \mathbf{X}'_{\ell d}\phi + \psi_j + \delta_{\ell y} + \theta_n + \eta_o + \varepsilon_{ij\ell t} \quad (13)$$

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

$$\log\left(\frac{P(R_{ij\ell t} \leq r)}{P(R_{ij\ell t} > r)}\right) = \beta_1 \text{PM2.5}_{\ell d} + \varepsilon_{ij\ell t}. \quad (14)$$

The results estimating Equation 13 are reported in Table A.2 and are qualitatively similar to those estimating analogous regressions in Table 5. Figures A.4 and A.5 report graphically the results of results estimating Equation 14.

B.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 PM2.5 and directly affect performance.

We implement Post-Double Selection (PDS) Lasso (Belloni et al., 2014) with PM2.5 as the treatment variable, regressing run-scoring on 35 potential controls: home stadium dummies, linear and quadratic weather terms, pairwise weather interactions, and PM2.5-weather interactions. The procedure selects no controls as outcome predictors but identifies two PM2.5 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 PM2.5'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.