Journal of Environmental Economics and Management 122 (2023) 102886

Contents lists available at ScienceDirect

Journal of Environmental Economics and Management

journal homepage: www.elsevier.com/locate/jeem

Air pollution kills competition: Evidence from eSports☆

Jiawei Mo[a,1], Zenan Wu[a,1], Ye Yuan[b,*,1]

[a] School of Economics, Peking University, China
[b] School of Economics, Institute for Global Health and Development, Peking University, China

ARTICLE INFO

JEL classification:
Q51
Q53
C72

Keywords:
Air pollution
Competition
Strategic interaction

ABSTRACT

This article investigates how environmental adversity affects competitive performance in cognitive-intensive settings. Using a comprehensive dataset of professional eSports tournaments and match-hour variation of fine particulate matters, we find robust evidence that pollution kills competition. Specifically, higher air pollution levels diminish the performance and winning odds of the weaker team in a matchup while boosting that of the stronger team, widening the gap between them. We document two operating channels: (i) pollution leads to heterogeneous performance-reducing effects contingent on a team's relative strength against their opponent, rather than its absolute competitiveness; and (ii) a weaker team adjusts their strategic decision-making differently in a polluted environment compared to their stronger counterparts. Our findings elucidate the distributional impact of environmental adversity and underscore its influence on strategic decision-making.

Introduction

Since the seminal work of Graff Zivin and Neidell (2012), environmental economists have investigated how environmental adversity affects human cognitive and physical productivity (see, e.g., Dominici et al., 2014; Chang et al., 2016, 2019; Archsmith et al., 2018; He et al., 2019; Park et al., 2020; Adhvaryu et al., 2022; Park, 2022). Nonetheless, most studies focus on independent decision-making contexts, whereas the consequences of environmental adversity in competition—where players are reflexively entangled—have rarely been examined. The impact of environmental adversity in competitive settings deserves careful investigation because its effect on a competition's outcome is multifaceted and unclear a priori: On the one hand, environmental adversity may have heterogeneous health impacts on the cognitive functioning of different players, whether they make decisions independently or in competition. On the other hand, environmental adversity may affect the strategic decision-making between competitors: Players need to factor in not only the impact of environmental adversity on their own performance but also that on their competitors when making decisions. To the best of our knowledge, this latter mechanism remains largely unexplored and we aim to fill this void.

☆ We are grateful to Co-Editor-in-Chief Roger H. von Haefen and two anonymous referees for detailed comments that significantly benefited this article. We thank Shihe Fu, Jingfeng Lu, Shiko Maruyama, and seminar/conference participants at various universities for helpful discussions, suggestions, and comments. Any errors are ours. We also thank Peiyuan Zhang and the other student research assistants at Peking University for their outstanding contributions to the data collection for this research project. We thank the National Natural Science Foundation of China (Nos. 72222002, 72173002, 71803003, 72103001, and 72203004); the Wu Jiapei Foundation of the China Information Economics Society (No. E21100383); and the Research Seed Fund of the School of Economics, Peking University, for financial support. The authors declare no financial support from or held position at any organization that has interests or is relevant to this article.

* Corresponding author.
E-mail addresses: jwmo@pku.edu.cn (J. Mo), zenan@pku.edu.cn (Z. Wu), yuanye.econ@pku.edu.cn (Y. Yuan).
[1] Co-first authors.

https://doi.org/10.1016/j.jeem.2023.102886
Received 12 June 2023
Available online 28 September 2023
0095-0696/

This paper studies the implications of air pollution—the world's greatest environmental health threat— in a contest setting in which final outcomes are based on all players' competitive relative performance.[2] We study the impact of air pollution not only on equilibrium performance outcomes but also on players' decision-making in competition. We focus on a contest setting for two reasons. First, contest generates distinctively rich and intricate strategic interactions. As Dixit (1987) demonstrates, players' best responses are often nonmonotone in contest: A player's efforts may optimally increase or decrease when her rival increases effort, depending on her relative standing to the rival.[3] Second and importantly, prior studies on air pollution and labor productivity mainly focus on the absolute measure of performance; however, in a contest, prizes are allocated based on relative performance, and many measurable outcomes—e.g., win or loss, and a range of performance measures—are inherently relative.[4] A contest environment thus enables us to explicitly study the distributional implications of air pollution.

Our setting is the League of Legends (LoL) Professional League, the world's most popular electronic sports (eSports) tournament. Like many professional sports, LoL holds regular tournament seasons every year and the champion wins a substantial prize. Each match consists of two phases: (i) a preparation phase, in which each team decides on five active players and each player chooses a champion (avatar); and (ii) a competition phase, in which players battle on a standard game map using their chosen champions and destroy the rival's homebase to win the match (see a game map in Appendix Figure B1). The match is extremely intensive and highly strategic. All players are professionals and all in-game decisions—from the pre-battle selection of players and champions to specific battle tactics—are planned, practiced, and deliberately executed.

The LoL tournament provides a desirable empirical setting to study the impact of air pollution in competition. First, the match schedule is predetermined and published weeks before the commencement of each season. It is thus independent of subsequent variations in air pollution or any unobserved factors. Second, multiple matches are held on each match date. This allows us to exploit the plausibly random *hourly* variation of fine particulate matters (PM2.5) across matches. All players compete in a large indoor stadium, so players in a given match are exposed to the same level of air pollution, but are unaffected by weather conditions. Third, each match demands extremely intensive cognitive engagement—e.g., attention, memory, dynamic learning, and strategic planning (Granic et al., 2014; Stafford and Dewar, 2014)—and requires minimum physical input.[5] Overall, we exploit this quasi-experimental setting to investigate the impact of increased short-term exposure to air pollution on competitive performance in a highly rewarding, cognitive-intensive contest. We obtain administrative match statistics for all matches in China's LoL Professional League from 2017 to 2021, merged with detailed records of air pollution at the hour of each match.

We find that a higher level of air pollution enhances the performance of the stronger team in a matchup and hampers that of the weaker team, regardless of a team's absolute strength. In particular, a 10 $\mu g/m^3$ increase in PM2.5 (or 0.36 standard deviations (SD) of PM2.5 in the sample period) statistically significantly increases the winning probability of the stronger team—which depends on both teams' play—by 1 percentage point (pp). This effect is economically meaningful: A 1 SD increase in PM2.5 widens the gap in winning probabilities between teams by 5.5 pp—which sets two rivals apart by 12.3 percentiles in the seasonal team ranking, holding air quality in other matches constant. We next turn to the set of performance measures—such as each team's kills, assists, and gold—which are again jointly determined by both teams' plays. Although these measures are not zero-sum in nature as win or loss, we find a consistent pattern: Air pollution widens the gap in these performance measures between rivals. Moreover, the magnitude of this gap-widening effect depends on the difference in strength between rival teams: The gap-widening effect is more pronounced when the difference in strength becomes greater; when teams are on par, the effect becomes negligible. These results altogether suggest that the balance of a match is more tilted in favor of the relatively stronger team, and as a result, the whole tournament is more lopsided in a more polluted environment. We validate these findings in various robustness checks.

We provide additional evidence that air pollution kills competition. First, under higher air pollution, the stronger team is more likely to achieve multiple kills of rival team's champions, resembling a scoring spree in basketball and a 40-love game in tennis. Such a killing spree delivers a huge blow to the losing team's resources and spirit and a huge boost to the winning team's, and usually leads to a landslide defeat of the losing team. The distributional impact of air pollution on multiple kills can explain 56% of the distributional impact on final win or loss. Second, we predict a match's outcome based on two teams' ex ante competitiveness level—i.e., we predict a team with a higher competitiveness level will win—and define an accuracy indicator if the predicted win or loss is the same as the actual one. We show that higher air pollution statistically significantly increases the prediction accuracy, which suggests that high pollution significantly reduces the uncertainty and suspense of the competition. Lastly, higher air pollution reduces the overall intensity of competition, measured by the summed performance metrics from both teams.

We proceed to explore two channels that may drive such a distributional effect of air pollution in competition. First, air pollution may have a direct heterogeneous impact on a player's cognitive performance. While prior studies have found heterogeneous cognitive impacts across predetermined individual-specific and job-specific traits, such as gender (Graff Zivin et al., 2020; Ebenstein et al., 2016); ability (Roth, 2021; La Nauze and Severnini, 2021); and experience (Krebs and Luechinger, 2021), we find that in competitive

[2] This setting stands in contrast to independent single-player decision-making and resembles many competitive events ranging from school admissions to personnel promotion, electoral competitions, arms races between nations, business project bidding, lobbying, R&D races, advertising campaigns, and sporting events. See Fu and Wu (2019) for a recent survey of theoretical studies of contests.

[3] Consider the tortoise and the hare. When the tortoise reduces its effort, the hare is tempted to reduce its effort, since a less competitive opponent allows it to slack off without suffering lower winning odds. In contrast, the hare's shirking would instead give hope to the tortoise and motivate it to further step up its effort.

[4] Take a soccer game as an example. While both teams may be handicapped by exposure to air pollution, a team's final score—a key observable measurement of performance—may increase or decrease because it depends on both teams' plays during the match.

[5] Each player competes on a uniformly configured computer with keyboard and mouse.

settings the heterogeneity of treatment effect is with respect to a team's relative strength against a match-specific opponent. This large, relative-strength dependent effect of air pollution remains intact after accounting for a team's absolute strength and its interaction with PM2.5 levels. Moreover, this heterogeneous impact is not alleviated by potential pollution acclimation—i.e., teams from more polluted home cities may be less affected by elevated pollution levels in the tournament host city. In particular, the coefficients of interest remain robust when considering (i) whether a team trains in a more polluted home city than the host city, (ii) whether it trains in a more polluted home city than the rival team, or (iii) whether it competes in its home city.

Second, a player in a strategic setting may respond not only directly to a cognitive impact of air pollution on her performance, but also indirectly to her opponent's responses to air pollution. We investigate air pollution's impact on players' strategic interactions—a channel that naturally arises in a competitive setting but has yet to be formally discussed in the literature of air pollution. We first present evidence that players are aware of the level of air pollution. We then exploit the preparation phase—a unique, standalone phase of the eSports match—in which each team decides strategically on the team setup and champion choices. While we are unable to observe each team's decision-making in the competition phase, as is true in most competitive settings, we can do so in the preparation phase. We construct four measures of a team's decisions: (i) total decision time, (ii) frequency of the pick-and-switch of champions, (iii) indicator of adopting the most frequently used team lineup, and (iv) indicator of picking the most frequently used champion. We find that a team's decision on the choice of lineup and champions varies when exposed to higher pollution, and the variation again depends on its relative strength against its rival. In particular, when exposed to a higher level of air pollution, the weaker team in a matchup statistically significantly increases its decision time, increases the intensity of changing champions before the final choice, and becomes more likely to adopt more aggressive tactics—e.g., adopting a less frequently used team lineup and champions. In contrast, these patterns are not present for the stronger team, regardless of its absolute competitiveness. Lastly, we develop a stylized contest model to elaborate on the role of air pollution in shaping equilibrium outcomes through its impact on teams' strategic interactions. Our results altogether validate the impact of air pollution on strategic decision-making between teams in competitive settings.

In summary, we have shown that air pollution gives the stronger team a competitive edge against its weaker rival in a cognitive-intensive, competitive environment. Environmental adversity tends to reduce the uncertainty of the competition. Our findings have two opposing policy implications for the non-health impacts of air pollution in competition. If the purpose of competition is to select and reward the highest-ability team, then environmental adversity would tilt the balance of the competition in favor of selecting out the highest-ability team. However, if uncertainty and suspense—which are crucial for the eSports industry in increasing viewership and sponsorship—are the vital elements for a competition, then a higher level of air pollution tends to defeat this purpose.

Related literature Our research is naturally linked to the large literature that examines the impact of air pollution on individual's well-being and economic and societal outcomes beyond commonly measured health indicators such as hospitalization and mortality. An emerging literature has delved into the causal relationship between air pollution and various aspects of cognitive decision-making and performance, including labor productivity (Graff Zivin and Neidell, 2012; Chang et al., 2016, 2019; Adhvaryu et al., 2022; He et al., 2019; Borgschulte et al., 2018), students' exam results (Graff Zivin et al., 2020; Roth, 2021), and decision quality in high-skilled professions such as judges, chess players, and financial investigators (Dong et al., 2021; Kahn and Li, 2020; Archsmith et al., 2018; Künn et al., 2023). While it is important to distinguish between the impacts of pollution on physical health and cognitive performance, the underlying mechanism for both types of adverse impacts is rooted in physical health factors. The prevailing consensus in this literature is that air pollution can affect cognitive functioning primarily through its physical harms (Aguilar-Gomez et al., 2022), such as causing irritation of the respiratory system, disruption of oxygenation in cells, and inflammation in the brain Peeples (2020).

Our study unveils a novel, nonhealth mechanism, the strategic interactions, through which air pollution can shape individual decision-making and equilibrium outcomes in competitive contexts. Our study complements the existing literature in two fundamental ways. First, unlike traditional single-agent decision-making settings where players (individuals or firms) operate in isolation, we focus on competitive environments where multiple rivals vie for a reward. This setting inherently involves strategic interactions among players, who must factor in the detrimental effects of air pollution on both their own performance and that of their opponents. Second, our work highlights the distributional effects of air pollution in competition. Rather than uniformly impairing all parties, air pollution might bolster the relative performance of some while hindering others. This notion of air pollution enhancing relative performance in certain scenarios is novel in the existing literature. Moreover, air pollution may deepen the underlying gap in ability or resources between rivaling parties, tilting the playing field in favor of the more advantaged, and widening the outcome inequalities. Our findings shed light on how environmental adversity can exacerbate workplace inequalities across a diverse array of real-life competitive settings.

Our study also contributes to the understanding of the heterogeneous effects of air pollution. While previous research has examined pollution's heterogeneous effects mainly as supplementary evidence to a baseline average effect, our study delves into the implication of pollution's heterogeneous impacts more comprehensively in competitive settings. In physical health outcomes, such as disease incidence and hospitalization, prior studies generally observe that air pollution has a greater adverse impact on the more physically vulnerable. However, in cognitive-intensive settings, the evidence is more mixed. For instance, studies on high-stakes exams by Graff Zivin et al. (2020) and Roth (2021) find that air pollution disproportionately affects high-ability students, whereas Ebenstein et al. (2016) find the opposite, with a stronger impact on low-ability students. Examining an online brain-training game, Krebs and Luechinger (2021) discover that higher pollution hampers the performance of skilled players more than beginners, whereas La Nauze and Severnini (2021) document a greater impact on those with lower skill proficiency.

In multi-player competitive contexts, evidence is scarce. Our study is closely related to the recent work of Künn et al. (2023), who investigate how air pollution affects chess players' cognitive performance in chess tournaments. Our work complements Künn et al. (2023) but differs in several aspects. First, we focus on exploring the distributional impact of air pollution in competition, while Künn et al. (2023) primarily examine how air pollution undermines cognitive performance. Second, while Künn et al. (2023) primarily analyze one aspect of player performance, namely errors in chess moves,[6] we provide novel evidence on pollution's effect on measures of players' efforts, such as decision time and selections of team lineup and champions, in addition to a broad range of performance measures. Third, our findings on how air pollution reduces suspense and unpredictability of competition and unbalances the playing field between asymmetric players hold important policy implications for various real-world competitive settings.

Lastly, our paper contributes to the thin empirical literature on contests. Brown (2011) uses panel data from professional golf tournaments to test the superstar effect. Boudreau et al. (2016) study a software development contest through the lens of contest design and find that a contestant's performance response to added competitors varies across contestants of different abilities. Malueg and Yates (2010) and Liu et al. (2023) study best-of-three contests in professional tennis and provide evidence of strategic momentum in dynamic contests. In a setting similar to ours, Liu et al. (2023) show that heat and air quality affect players' willingness to fight on, and the prevalence of prolonged contests drops sharply when the ambient environment deteriorates. We show that a more adverse ambient environment tilts the balance of the contest in favor of the stronger and reduces the degree of suspense.

The rest of the article is organized as follows. "Background and data" describes the background and data source of our empirical investigation. "Main results" presents estimation results on the average and distributional effects of air pollution. "Robustness checks" presents robustness analyses. "Mechanism" discusses the importance of relative standing and strategic interactions in our empirical setting. "Conclusion" concludes.

Background and data

In this section, we introduce the eSports context of our study, key features of the LoL tournament, and the game mechanics that make it an ideal setting for our empirical investigation. We also describe the data structure of LoL tournaments in China, which our subsequent analyses rely on.

Background

Esports industry ESports is a rapidly growing form of video game-based team sports in a professional tournament setting. It has attracted a huge global audience and generated total revenue that outperforms many traditional sports, such as Major League Baseball (MLB) and the National Basketball Association (NBA).[7] China is the leading eSports market, which grossed $360 million in 2021 and accounted for nearly a third of worldwide eSports revenues. The United States is the second largest market, followed by Western Europe.

LoL is one of the fastest growing—and currently the world's largest—eSports game. Developed and published by Riot Games, it had amassed a player base of over 80 million active monthly players and grossed over $1.75 billion worldwide in 2020. The game had over 7000 professional players and a prize pool of over $79 million in 2020.[8]

Lol gameplays LoL has a clear game objective and well-defined rules. In each LoL match, two teams of five players compete against each other. Each match consists of two phases, a preparation phase and a competition phase. In the preparation phase, each team decides on the roster of five active players and each player chooses a champion from a pool of available champions. Each champion has a set of unique abilities, which can counter certain champions effectively and be countered. It is crucial that teams carefully and deliberately select their champions for the battle. After champion selection, players head into the competition phase on a standard map (see Appendix Figure B1). In the competition phase, each player controls their champion (avatar) from an isometric perspective to battle against the rival team. All champions spawn and respawn, if killed, in their homebase (the diagonal corners on the game map). Team members collaborate to kill champions of the rival team and defeat neutral minions on the map to earn experience and gold for upgrades, and push through the rival's defensive turrets to attack on the rival's homebase. A team wins if the rival's homebase is destroyed or the rival surrenders. The match sets no time limit, but is fast paced and generally ends in 30 min. More details of game mechanics are provided in Appendix E.2.

Gameplay in LoL tournaments is strategic. All players are full-time professionals. Teams invest extensively in player management, tactical training, and teamwork. Most players play a single role in a team—like professional athletes in other team sports such as basketball—with limited role swapping. All in-game strategies—ranging from choosing the appropriate roster of champions to detailed tactics to achieve specific objectives—are planned, trained, and rigorously executed during a match. In summary, strategic gameplay is at the core of a tournament match.

[6] Künn et al. (2023) employ a chess engine algorithm to evaluate a player's performance in each move, which considers both players' previous moves and identifies an "optimal move". They evaluate a player's decision quality based on deviations from this optimal move.

[7] The global eSports audience reached 532 million in 2022, and is expected to reach 577 million in 2024. The global eSports market was valued at US$1.39 billion in 2022; the market is expected to grow at an annual rate of 24.8–27.2% from 2022 to 2025, according to Goldman Sachs Investment Research, NewZoo survey (2022 Global ESports Market Report).

[8] In comparison, the NBA Championship had a total prize pool of $13 million in 2018, the Masters (golf) $11 million, Tour de France $2.8 million, Melbourne Cup $6.2 million, and Confederations Cup $20 million. For more discussion of the eSports industry, see Appendix E.1.

Empirical setting The professional LoL league in China, referred to as the League of Legends Pro League (LPL), provides the empirical context for this study. LPL is the largest regional LoL tournament.[9] The first LPL season started in 2013. Since then, two seasons (spring and summer) are held each year. Each season has regular-season games and playoffs. All teams compete in a single round robin in the regular season, and the top ranked teams enter the playoff and compete in elimination. As of the 2021 spring season, 17 teams were competing for the LPL championship. The playoff champion receives 40% of the prize pool, which was 3.5 million RMB ($0.54 million, based on $1 = 6.5 RMB) in the 2019 summer season.

The tournament schedule and hosting cities are predetermined and published weeks before the season starts. The spring season starts in January and the summer season in June; each lasts about 10 weeks. Each season is jointly hosted by three to five cities. By 2021, 11 cities had hosted the tournament; Shanghai is the most frequent host city. Appendix Table A1, Columns (1) and (2) tabulates the number and frequency of matches hosted by different cities, respectively. Columns (3) and (4) tabulates the number and frequency of home cities of all LPL teams in our sample period. Shanghai is also the most frequent home city (for 12 out of 27 teams).

Data source

LPL match data We obtain the administrative database of match statistics for all LPL tournament matches from the official LPL website.[10] The database covers the universe of all 2638 LPL matches held in 11 different cities across 561 match dates from Jan 2017 to July 2021.[11] The publicly available match statistics encompass two sets of information: (i) post-match performance statistics for the competition phase and (ii) pre-match statistics on player and champion selection from the preparation phase. Post-match statistics are recorded for 508 professional full-time players (all males) from 27 teams.[12] Available post-match variables include win or loss, the number of kills (landing the last hit on a fallen rival champion) and assists (contributing to damaging a fallen rival champion); the amount of gold earned (a composite measure of in-game scores, earned by defeating rival champions and neutral minions); match duration; and a set of other match-specific performance metrics. Appendix Figure B2 depicts an auto-generated summary of key performance measures after a typical match. Detailed variable definition and game mechanics are presented in Appendix E.

We also obtain four pre-match variables from the preparation phase: decision time (i.e., the amount of time each player takes to finalize their choice of champion), the frequency of pick-and-switch before the final decision, the roster of five active players, and each player's final choice of champion by the end of the preparation phase. We manually collect the first two variables from video clips of each LPL match,[13] and obtain the latter two from the official match database. These variables enable us to assess a team's pre-match strategic decision-making.

Air pollution Air pollution is the world's largest environmental health threat and accounts for 7 million deaths around the world each year (Lelieveld et al., 2015). Particulate matter—especially particles below 2.5 μm in diameter (PM2.5)—are the main air pollutants and pose the greatest threat since these tiny particles penetrate deep into the lungs and bloodstream and affect the respiratory, vascular, and brain systems (Block et al., 2012; Peeples, 2020).

Data on PM2.5 and other major air pollutants are obtained from the China National Environmental Monitoring Center (CNEMC). We retrieve hourly concentrations of PM2.5 for all hosting stadiums from 2017 to 2021 based on the nearest national monitoring stations.[14] We then match the hourly level of PM2.5 to each match in our LPL database. PM2.5 is the most important air pollutant in China. It can easily penetrate buildings (Huang et al., 2007; Chen and Zhao, 2011; Nadali et al., 2020) and cannot be effectively reduced by standard air-conditioning systems (MacNeill et al., 2012). The indoor–outdoor ratio of PM2.5 commonly ranges 0.6 to 0.9 and can be close to one in indoor environments with frequent air exchange, such as in stadiums with open doors and windows (Chen and Zhao, 2011). We use the outdoor level of PM2.5 to proxy for indoor exposure to primary air pollutants during the match. The average level of match-hour PM2.5 is 36 $\mu g/m^3$ during our sample period, with a maximum level of 258 $\mu g/m^3$ and a SD of 28 $\mu g/m^3$. The average PM2.5 level was more than twice the WHO guideline of 15 $\mu g/m^3$ for daily exposure (World Health Organization, 2021).

The level of PM2.5 exhibited substantial variations across cities (Appendix Figure B3) and over time, ranging from 1.3 to 248.5 $\mu g/m^3$ over the sample period. The 50th, 75th, and 90th percentiles of the change in mean PM2.5 concentration from one match day to the next are −0.95, 13.2, and 29.6 $\mu g/m^3$, respectively; those of the change from one match to the next within the same day are 0.47, 2.95, and 6.40 $\mu g/m^3$, respectively. Fig. 1 presents hourly variations in PM2.5 in Shanghai (the most frequent host city) over the sample period (Panel A) and over a typical month in the regular season (Panel B). The figure demonstrates substantial fluctuations in the level of PM2.5 across dates as well as across matches within the same day. The high-frequency fluctuations of PM2.5 provide a source of exogenous variation to identify the causal impact of short-term pollution exposure on teams' competitive performance in LPL tournaments independent of any socioeconomic or weather-related factors.

[9] LoL operates 12 regional professional tournaments internationally. The top four are China, North America, Europe, and South Korea.

[10] See https://lpl.qq.com/es/schedule.shtml (in Chinese). Accessed on 2023-09-01.

[11] Our sample excludes online matches due to the COVID-19 pandemic in the spring season of 2020.

[12] Some teams were disbanded and new teams added to the league over this period. Moreover, on rare occasions, teams may change ownership and team names. We treat these teams as new additions after an ownership change.

[13] We recruited a team of 20 college students to watch the video clip of each LPL match and note down the decision time and the frequency of pick-and-switch for each player in the preparation phase. We exclude 12 matches due to incomplete video recording of the preparation phase.

[14] Because all hosting stadiums are located in the city center, we are able to locate at least one pollution monitoring station within a 5 km radius for more than 95% of stadiums.

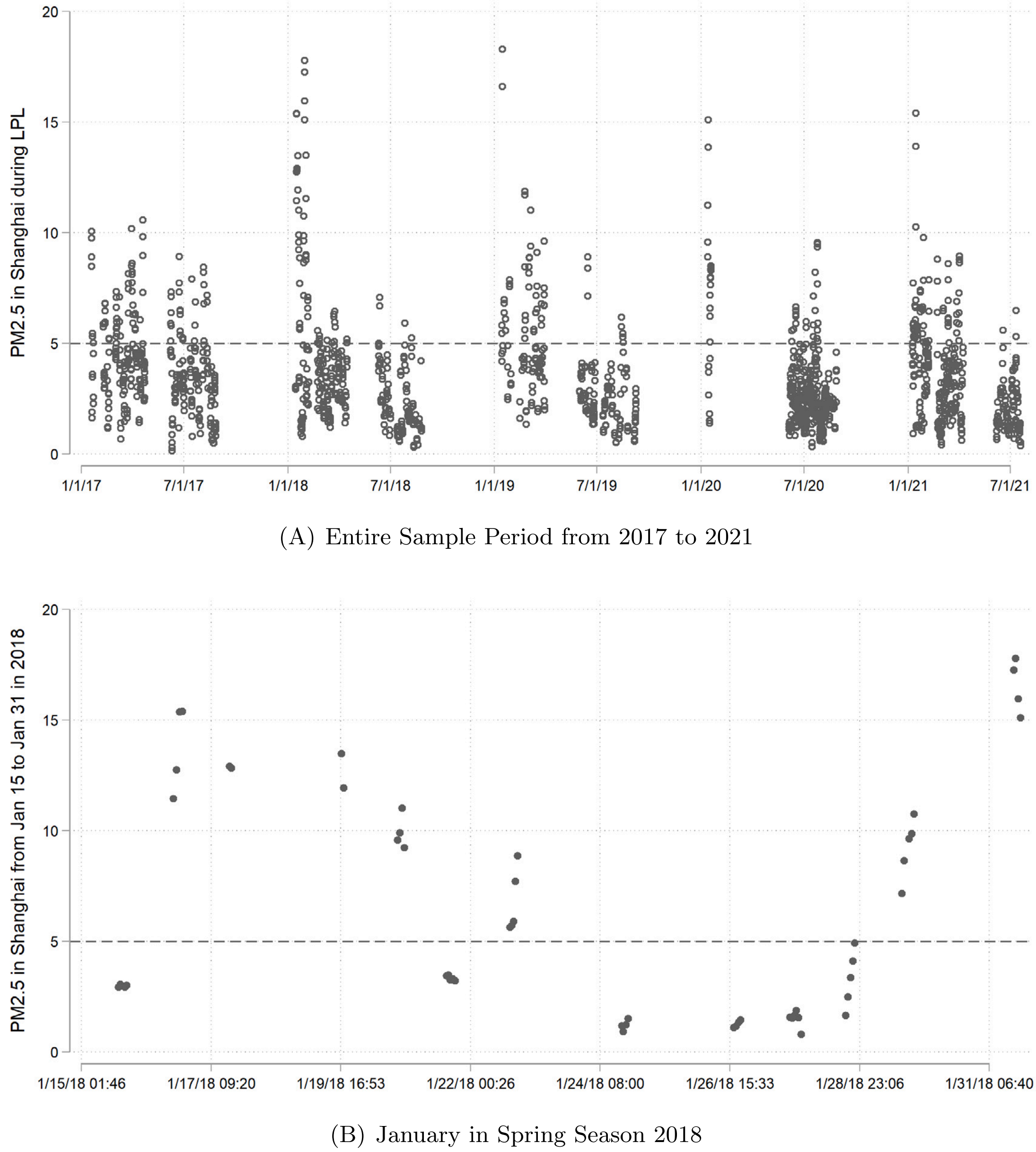


Fig. 1. Temporal variation in PM2.5 in Shanghai.
Notes: This figure presents the temporal variation in PM2.5 in Shanghai across LPL match hours. Each data point represents the level of PM2.5 during a particular match. Panel A presents the variation in PM2.5 across the entire sample period; Panel B presents the variation in PM2.5 across match hours in the spring season of 2018. Unit of PM2.5 is 10 $\mu g/m^3$.

We also retrieve weather information from the China Meteorological Data Service Center and use the inverse-distance weighting algorithm to convert weather variables from station to city level. These variables include temperature, precipitation, sunshine, humidity, wind speed, and an indicator for bad weather.[15]

Summary statistics The analytical sample contains all professional LPL tournament matches from the spring season of 2017 to the summer season of 2021. The sample contains 26,380 match-player observations and, equivalently, 5,276 match-team observations

[15] The indicator for bad weather equals to one if any of the weather variables—temperature, precipitation, sunshine, humidity, and wind speed—exceeds 90% percentile cutoff of sample values.

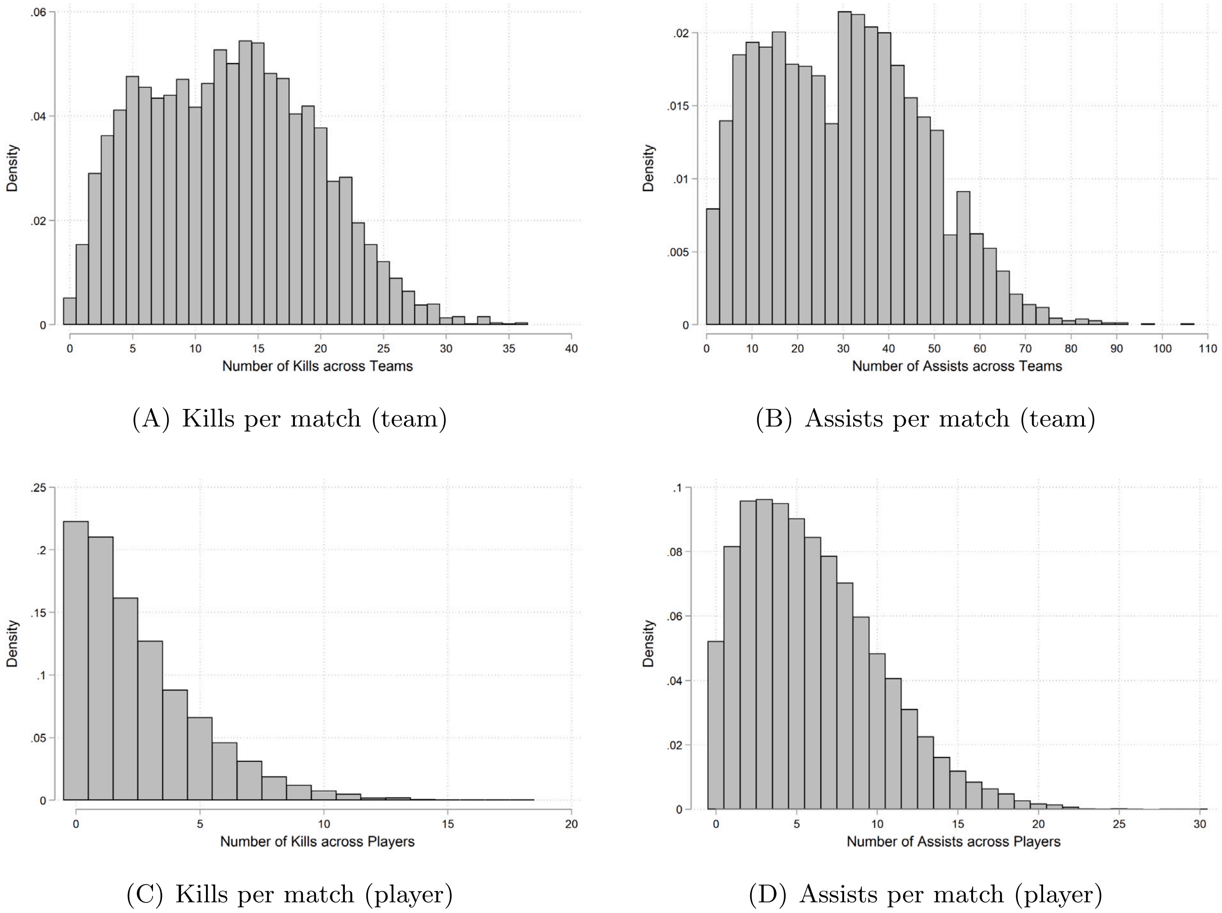


Fig. 2. Histogram of kills and assists per match for players and teams.
Notes: This figure presents the histogram of key performance metrics for teams and players. Panels A and B depict the distribution of kills and assists per match for teams, respectively; Panels C and D show the distribution of kills and assists per match for players, respectively.

from 2638 matches in the official database. We exclude 54 observations, or 1% of the sample, due to missing hourly PM2.5 records from monitoring stations, resulting in an analytical sample of 5,222 observations.

Table 1 presents summary statistics of each team's competitive performance during the competition phase (Panel A), pre-match statistics during the preparation phase (Panel B), and the level of main air pollutants during the match hour (Panel C).[16]

In the competition phase, the average winning probability is 0.5 with a standard deviation of 0.5 for all teams, as expected. A match lasts 33 min on average. Teams on average score 12.7 kills and 30.0 assists per match. We also compute the performance metrics per 10 min as measures of teams' efficiency in competitive performance. Teams score 3.9 kills and 9.2 assists per 10 min. There is substantial heterogeneity in performance across teams and players. Fig. 2 depicts the histograms of kills and assists per match at both team and player level. Panel A shows that top-performing teams score more than 30 kills in a match, while the bottom 10% of teams score below 5. Similarly, the distribution of team assists per match is also right-skewed (Panel B). At player level, the distributions of kills and assists per match—as depicted in Panels C and D, respectively—are more widespread and right-skewed than at team level.

In the preparation phase, a player takes an average of 17.7 s to finalize his choice of champion (the time limit is 30 s), and changes the initial choice by 0.64 times before the final decision. Each team has one most frequently used lineup that represents the highest level of experience and teamwork; each player has a set of six most preferred and frequently used champions. A team has an average probability of 0.31 of choosing a less frequently used lineup, and a player has a probability of 0.09 of choosing a less frequently used champion. The sample size for decision time and the frequency of pick-and-switch is 4% smaller than that of performance metrics from the official database because video recording were missing or incomplete for some matches or failed to show players' decision process due to broadcasting issues.

[16] Appendix Table A2 presents summary statistics at player level. In a subsequent discussion, we present estimation results at team level and relegate corresponding results at player level to the appendix. All results are consistent.

Table 1
Data description.

Variable	Mean	S.D.	Min	Max	Obs
Panel A: Measures of Team Performance in Competition Phase					
Win	0.50	0.50	0	1	5,276
Kill	12.69	6.70	0	36	5,276
Assist	30.05	17.28	0	107	5,276
Gold	59,195	13,137	22,524	122,536	5,276
Kill per 10 min	3.93	2.18	0	14.13	5,276
Assist per 10 min	9.23	5.40	0	32.86	5,276
Gold per 10 min	18,028	1,952	13,449	23,579	5,276
Match time (min)	32.8	6.5	15.6	67.9	5,276
Panel B: Measures of Team Decision in Preparation Phase					
Decision time (s)	17.74	4.43	2.75	30	5,006
Frequency of pick-and-switch	0.64	0.80	0	14.5	5,002
Using less frequent lineup	0.31	0.46	0	1	5,276
Using less frequent champion	0.09	0.29	0	1	26,380
Panel C: Descriptive Statistics of Air Pollution					
PM2.5 (10 μg/m^3)	3.57	2.77	0.10	24.85	5,222
PM10 (10 μg/m^3)	5.50	3.50	0.3	28.58	5,186
AQI (10 μg/m^3)	5.94	3.44	0.83	29.85	5,222

Notes: This table presents summary statistics. Kill is defined as the number of times a player has landed the killing blow on a fallen rival champion; assist is the number of times a player has contributed damages to a fallen rival champion; and gold is the amount of gold earned by defeating rival champions and neutral minions. Decision time is the time a player takes to choose a champion in the preparation phase; and the frequency of pick-and-switch is the number of times a player change the choice of champion before the final decision. Using less frequent lineup is an indicator that a team is not adopting the most frequently used lineup of five active players. Using less frequent champion is an indicator that a player is not using one of his six most frequently used champions (at player level, with larger sample size). PM2.5 is the concentration of airborne particulate matters with diameter less than 2.5 micrometers. PM10 is the concentration of airborne particulate matters with diameter less than 10 micrometers. AQI is the air quality index that measures the overall concentration of six main air pollutants: PM2.5, PM10, O3, CO, NO2, and SO2.

Table 2
Average effects of PM2.5 on match outcome and team performance.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Total			Per 10 Mins		
	Win	Kill	Assist	Gold	Kill	Assist	Gold
$PM2.5$	−0.000	−0.015	−0.138	−116.915	0.004	−0.019	−1.208
	(0.004)	(0.052)	(0.132)	(93.539)	(0.015)	(0.039)	(16.046)
Team-Pair FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Match-Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City×Year×Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-Week and Holiday FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,222	5,222	5,222	5,222	5,222	5,222	5,222
R-squares	0.195	0.207	0.182	0.228	0.238	0.206	0.230
Mean Dep. Var.	0.5	12.7	30.1	59,159	3.93	9.23	18,028

Notes: This table presents the average effects of PM2.5 on team's competitive performance. The dependent variable is the indicator of win (Column 1), the number of kills, assists, and gold (Columns 2–4), and their per-10-minute counterparts (Columns 5–7). $PM2.5$ is the level of PM2.5 (in 10 μg/m^3) at the hour of the match. Regressions control for team-pair fixed effects, match-type fixed effects, city-by-year-by-month fixed effects, and day-of-week and public holiday fixed effects. Mean of dependent variables are presented in the last row. Further details are specified in "Distributional impact of air pollution in competition". Robust standard errors in parentheses are clustered at team-by-season level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

As for exposure to air pollution during the match hour, the average concentrations of PM2.5, PM10, and AQI were 35.7, 55.0, and 59.4 μg/m^3, respectively. The average pollution exposure in LPL tournaments was higher than the WHO safety standard (the 24-hour standard is 15 μg/m^3 for PM2.5 and 45 μg/m^3 for PM10 (World Health Organization, 2021)). In particular, about 21% of matches were held in a highly polluted environment considered to be "very unhealthy" (PM2.5 ≥ 50 μg/m^3).

Main results

Average impact of air pollution in competition

We start by estimating the average effect of air pollution on team performance and match outcomes in the highly cognitive-intensive competition. We exploit the plausibly exogenous variation in PM2.5 at the hour of the match to identify the causal impact of air pollution on each team's competitive performance. Specifically, we estimate the following specification:

$$Y_{ijct} = \alpha + \beta PM2.5_{ct} + TeamPair_{ij} + MatchType_{ct} + City \times Year \times Month_{ct} + DoW_t + PH_t + \mu_{ijct}. \tag{1}$$

Y_{ijct} measures the competitive performance of team i against rival j in a match held in city c at time t, which includes an indicator of win or loss, the number of kills, the number of assists, the amount of gold earned, and corresponding metrics per 10 min. $PM2.5_{ct}$ measures the match-hour level of PM2.5 (in unit of 10 μg/m^3),[17] which is our primary measure of air pollution. We include a comprehensive set of fixed effects (FEs): team pair FEs ($TeamPair_{ij}$); match type FE ($MatchType_{ct}$)—i.e., whether the match is regular season or playoffs; city-by-year-by-month FEs ($City \times Year \times Month_{ct}$); day-of-week FEs ($DoW_t$); and public holidays FEs (PH_t).[18] Finally, μ_{ijct} is an idiosyncratic error term. We cluster standard errors at team-by-season level to allow for autocorrelation of team performance across matches in the same season.

Estimation results are reported in Table 2. The most notable and seemingly counterintuitive pattern is that a higher concentration of PM2.5 has a small and statistically insignificant effect on match outcome, measured by a team's win or loss (Column 1) and the set of team's performance metrics, including team's total kills (Column 2), total assists (Column 3), total gold earned (Column 4), and the corresponding performance metrics per 10 min (Columns 5 to 7). This pattern of "no average effect" is similarly documented when we estimate Eq. (1) at player level (see Appendix Table A3). This pattern stands in contrast to the host of large adverse impacts of air pollution on labor productivity, cognitive functioning, and athlete performance commonly documented in prior studies on air pollution (see, e.g., Dominici et al., 2014; Chang et al., 2016, 2019; Archsmith et al., 2018; He et al., 2019; Park et al., 2020; Adhvaryu et al., 2022; Park, 2022; Künn et al., 2023). An explanation is clearly warranted.

We hypothesize that air pollution leads to opposite effects on the two rival teams that cancel out, so that the average effects are mixed in sign, small in magnitude, and statistically insignificant. In such a scenario, one side of the competition would benefit from the more severe air pollution while the other side suffers. In addition, air pollution may substantially reduce or widen the gap between opposing teams, depending on which side of the competition air pollution benefits. We proceed to investigate the distributional impact of air pollution in competition.

Distributional impact of air pollution in competition

Graphical evidence We first explore the graphical pattern of the relationship between teams' performance metrics and pollution exposure, and show that the direction of the relationship depends critically on a team's relative standing against the rival in a matchup.

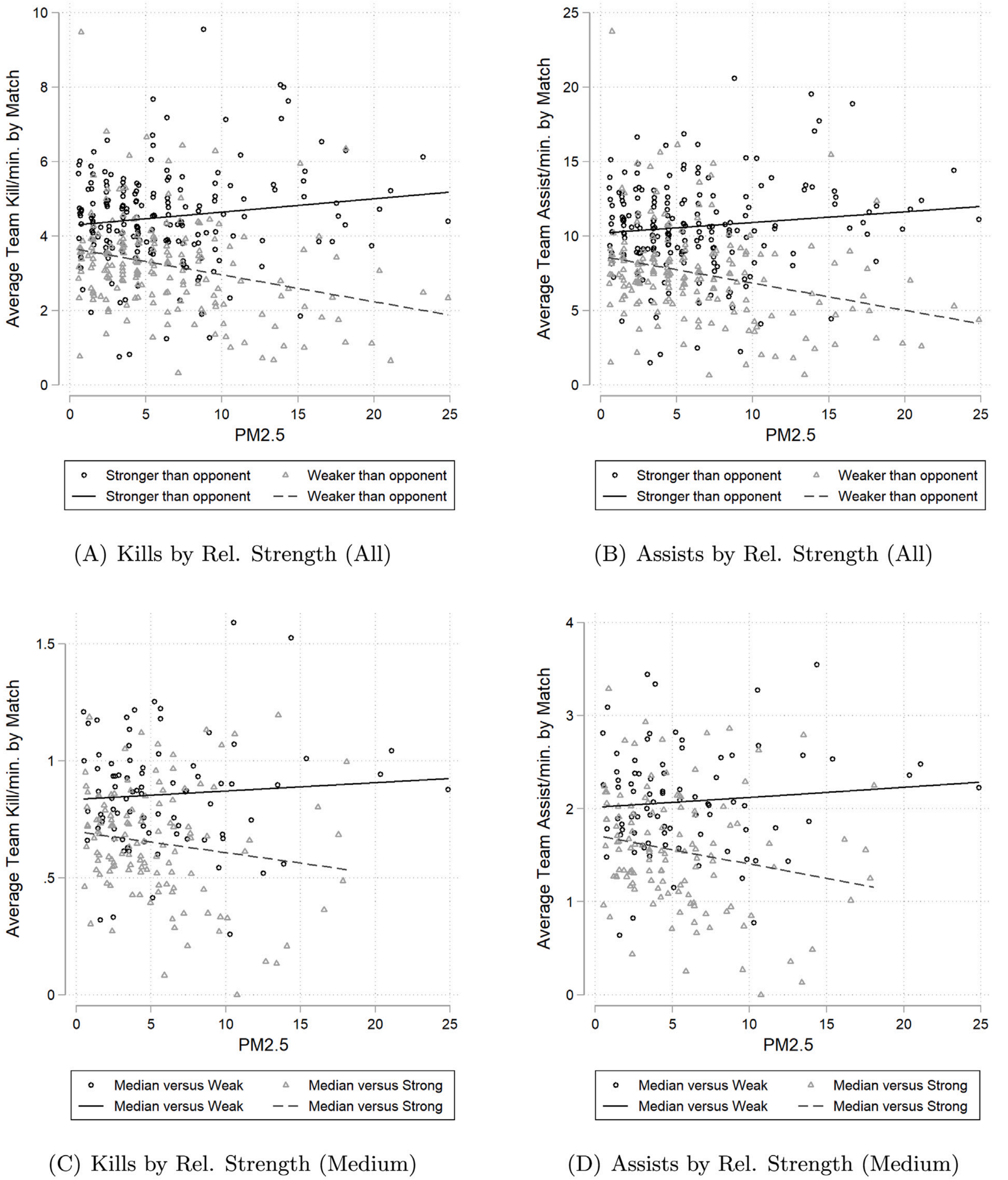
We find a clear visual pattern that the direction of the relationship between a team's performance and its pollution exposure depends on whether it is stronger than its rival in the matchup. Fig. 3 depicts the scatter plot of the team's kills and assists per 10 minutes against its PM2.5 exposure in two separate cases: when a team competes against a stronger rival and when it competes against a weaker one. We define a team as stronger than its rival if its average winning rate in a given tournament season is higher than its rival's. Panels A and B plot kills and assists, respectively. The figures show that the stronger team performs better in both kills and assists in a more polluted environment, whereas the weaker team performs significantly worse.

This pattern is consistent when we fix a group of medium-ranked teams (in terms of average winning rates) and plot their performance against stronger rivals (ranked above the 75th percentile) and against weaker rivals (ranked below the 25th percentile). Fig. 3, Panels C and D, show that air pollution enhances the performance of these medium teams against weaker rivals, and impairs their performance against stronger rivals. Overall, Fig. 3 demonstrates that the relative standing of a team with respect to its rival determines the impact of air pollution on match outcomes.

Baseline specification We now formally establish that air pollution has a large, distributional impact on a team's competitive performance, which crucially hinges on whether the team is stronger or weaker than its rival in a given matchup. As suggested by the graphical evidence, the effect of air pollution on a team's equilibrium outcomes may depend on its relative standing with respect to the opposing team in a matchup. We estimate the distributional effects of PM2.5 on match outcomes with respect to a team's relative standing against its rival using

[17] For ease of interpretation, we measure the level of PM2.5 in unit of 10 μg/m^3 throughout our analyses.

[18] Note that all independent variables in Eq. (1) are exogenous to a team's choices. We do not control for player-specific factors, such as the lineup of active players and their chosen champions, because these are choice variables that could be part of a team's responses to pollution exposure as well as to the rival team's strategy. We exploit the choice of players and champions as dependent variables to test for the impact of air pollution on a team's strategic interactions in "Strategic interactions".



(A) Kills by Rel. Strength (All)

(B) Assists by Rel. Strength (All)

(C) Kills by Rel. Strength (Medium)

(D) Assists by Rel. Strength (Medium)

Fig. 3. Relationship between team performance and air pollution.
Notes: This figure presents the scatter plot and linear fit of team performance against the match-hour level of PM2.5. Panel A presents the relationship between the team's kills per 10 min and the level of air pollution. Dark circles represent the stronger team and gray triangles represent the weaker team. See Eq. (3) for the definition of team strength. Panel B presents the relationship of assists per 10 min. Panels C and D fix to a group of medium-ranked teams and present the relationship between these teams' kills and assists per 10 min and the level of air pollution when competing against a weaker rival (dark circles) and a stronger rival (gray triangles). Unit of PM2.5 is 10 $\mu g/m^3$.

Table 3
Distributional effects of PM2.5 on team performance by relative strength.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Total			Per 10 Mins		
	Win	Kill	Assist	Gold	Kill	Assist	Gold
$PM2.5$	−0.009**	−0.150**	−0.478***	−255.159**	−0.040**	−0.128***	−46.948***
	(0.004)	(0.058)	(0.145)	(124.707)	(0.017)	(0.043)	(17.734)
$PM2.5 \times Rel.Strong$	0.019***	0.268***	0.680***	276.489*	0.088***	0.218***	91.479***
	(0.006)	(0.068)	(0.167)	(155.445)	(0.020)	(0.050)	(22.221)
Team-Pair FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Match-Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City×Year×Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-Week and Holiday FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,222	5,222	5,222	5,222	5,222	5,222	5,222
R-squares	0.197	0.209	0.185	0.228	0.240	0.208	0.234
Mean Dep. Var.	0.5	12.7	30.1	59,159	3.93	9.23	18,028

Notes: This table presents the distributional effects of PM2.5 on team's competitive performance. The dependent variable is the indicator of win (Column 1), the number of kills, assists, and gold (Columns 2–4), and their per-10-minute counterparts (Columns 5–7). $PM2.5$ is the level of PM2.5 (in 10 μg/m^3) at the hour of the match. $Rel.Strong$ is a dummy variable indicating the team's competitiveness index ranks higher than the rival team in the matchup. Team's competitiveness is computed as the team fixed effects from Eq. (3). Regressions control for team-pair fixed effects, match-type fixed effects, city-by-year-by-month fixed effects, and day-of-week and public holiday fixed effects. Mean of dependent variables are presented in the last row. Further details are specified in "Distributional impact of air pollution in competition". Robust standard errors in parentheses are clustered at team-by-season level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

$$\begin{aligned} Y_{ijct} = {}& \alpha + \beta PM2.5_{ct} + \gamma PM2.5_{ct} \times Rel.Strong_{ij} + TeamPair_{ij} + MatchType_{ct} \\ & + City \times Year \times Month_{ct} + DoW_t + PH_t + \mu_{ijct}. \end{aligned} \tag{2}$$

Our key variable of interest, the stronger-than-rival dummy $Rel.Strong_{ij}$, equals one if team i is stronger than its rival j in a matchup and zero otherwise. We define a team's strength relative to its opponent based on a competitiveness index. We aim to construct a measure for a team's baseline competitiveness by partialling out environmental and match-specific factors. Specifically, we measure a team's competitiveness index by regressing the following equation in the sample of regular-season matches:

$$\begin{aligned} Win_{ijpct} = {}& \delta_i + \eta_j + \delta_i \times \eta_j + Player_p + Champ_h + Role_r + \beta PM2.5_{ct} + MatchType_{ct} \\ & + City \times Year \times Month_{ct} + DoW_t + PH_t + \mu_{ijpct}, \end{aligned} \tag{3}$$

where Win_{ijpct} is the dummy of win, δ_i and η_j are self-team and rival-team fixed effects, respectively, and the regression is estimated at player level. The estimate of δ_i measures team i's (standardized) baseline winning rate across all matches after removing the influence of competing against different rivals across matches and other match-specific factors, such as the choice of players ($Player_p$), champions ($Champ_h$), the player's role on the team ($Role_r$),[19] pollution exposure, and unobservable city and time factors ($City{\times}Year{\times}Month_{ct}$, DoW_t, and PH_t). The underlying premise is that if a team has higher innate ability than its rival, it outperforms its rival on average across regular-season matches.[20] After obtaining the fitted value for all δ_i's, we define $Rel.Strong_{ij} = 1$ if $\hat{\delta}_i > \hat{\delta}_j$—i.e., team i has a competitive edge against team j.

We also adopt two alternative methods to compute a team's competitiveness index. One is based on a more parsimonious specification to estimate team FEs (δ_i) at team level: $Win_{ijct} = \delta_i + \eta_j + MatchType_{ct} + City_c + Year_t + Month_t + \mu_{ijct}$. The other is a team's average winning rate in all regular-reason matches. The competitiveness indices from these three methods are highly correlated and the corresponding index-based rankings of teams are almost identical (see Appendix Table A4).

With the relative strength of a team to its rival defined in each match, we estimate the baseline estimation model Eq. (2). The coefficients of interest are β and γ: The former measures the effect of a 10 μg/m^3 increase in PM2.5 on the competitive performance of the weaker team in the matchup, and the latter measures the difference in the effect of air pollution on the stronger team relative to the weaker. Positive estimates of β and γ both indicate better competitive performance. The sign of γ underscores the effect of air pollution on the relative performance of opposing teams. Two scenarios may occur: Higher air pollution balances the playing field and reduces the gap between teams, which implies that $\beta > 0$ and $\gamma < 0$, or the opposite—higher air pollution tilts the odds in the stronger team's favor and magnifies the gap between teams, which implies that $\beta < 0$ and $\gamma > 0$.

Baseline estimation results Table 3 presents baseline results based on Eq. (2), which delineate a clear opposite pattern: When a team is weaker in a matchup, a 10 μg/m^3 increase in PM2.5 concentration significantly reduces its performance in kills, assists, and gold

[19] Each of the five players in a team has a specific role. See Appendix Section E.2.3 for details.

[20] The regular season is a round-robin tournament in which each team competes against all other teams exactly once.

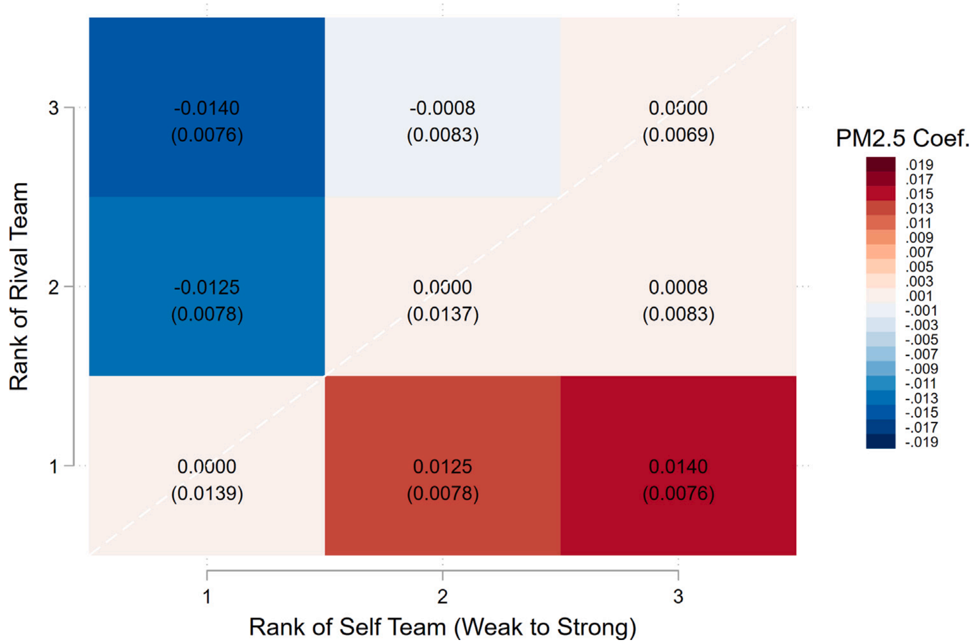


Fig. 4. Effect of PM2.5 on win or Loss in 3 × 3 combinations of team pairs.
Notes: This figure presents the estimated effect of air pollution on a team's winning probability in 3 × 3 cases of team pairs. We define three dummies for team strength—i.e., ranked at the top, middle, or bottom one-third in team competitiveness index ($\hat{\delta}$ in Eq. (3))—and generate 3 × 3 mutually exclusive groups of self-versus-rival team pairs. We plot the estimated effect of air pollution on the probability of winning in each group of team pairs. Robust standard errors are reported in parentheses.

earned, and results in a statistically significantly 1 pp drop in winning probability. In contrast, the stronger team experiences a statistically significant increase in kills, assists, and gold earned, and a (mechanically) 1 pp increase in winning probability. We refer to such an opposite impact on opposing teams as the distributional effect of air pollution.

The estimated distributional effect on a team's winning probability is economically meaningful: A 1 SD increase in PM2.5 (27.7 $\mu g/m^3$) creates an additional 5.54 pp gap in winning probability between teams—which would set two teams apart by 12.3 percentiles in the season's team rankings, holding pollution exposure for other teams constant.[21] Had air quality deteriorated during all matches in the tournament, the tournament would be more lopsided and teams' average winning rates more polarized.

The above results indicate that air pollution widens the performance gap between teams. We quantify the performance gap more directly as the difference in kills, assists, and gold earned between the stronger and weaker teams. Appendix Table A5 estimates the effect of air pollution on this measure of performance gap at the match level and shows that air pollution significantly enlarges the gap in these three dimensions of teams' competitive performance.

In addition, air pollution's the gap-widening effect grows stronger if the underlying gap in rivals' strength becomes larger. In contrast, when two teams are on par, the effect of air pollution becomes negligible. We estimate a specification similar to Eq. (2) by replacing the dummy $Rel.Strong_{ij}$ with a continuous measure of the gap in innate competitiveness between teams, $Gap_{ij} = \hat{\delta}_i - \hat{\delta}_j$:

$$\begin{aligned} Y_{ijct} = {} & \alpha + \beta PM2.5_{ct} + \gamma PM2.5_{ct} \times Gap_{ij} + TeamPair_{ij} + MatchType_{ct} \\ & + City \times Year \times Month_{ct} + DoW_t + PH_t + \mu_{ijct}. \end{aligned} \tag{4}$$

Two remarks are in order. First, the coefficient of the interaction term, γ, measures the incremental effect of air pollution on a team's performance if a team's competitiveness gap widens slightly. Table 4 shows that the estimates of γ are all positive and statistically significant, which suggests that teams with a larger advantage in baseline competitiveness over a rival perform significantly better in a more polluted environment.

Second, the coefficient of β measures the effect of air pollution in the scenario in which two teams are on par—i.e., $Gap_{ij} = 0$ in Eq. (4). Table 4 shows that the estimates of β are zero and statistically insignificant, which implies that air pollution no longer affects match outcomes for homogeneous rivals.

We further illustrate the lack of any effect of air pollution on homogeneous rivals in Fig. 4. We define three dummies for a team's strength—ranked at the top, middle, or bottom one-third in teams' competitiveness index $\hat{\delta}$—and generate 3 × 3 mutually

[21] Given that the range of average winning probabilities in the data is between 20 and 65 pp, an additional 5.54 pp gap in winning probability corresponds to 12.3 (= 5.54/(65 − 20)) percentiles in rankings.

Table 4
Distributional effects of PM2.5 on team performance by competitiveness gap.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Total			Per 10 Mins		
	Win	Kill	Assist	Gold	Kill	Assist	Gold
$PM2.5$	−0.000	−0.015	−0.138	−116.915	0.004	−0.019	−1.208
	(0.004)	(0.048)	(0.120)	(88.588)	(0.014)	(0.036)	(14.489)
$PM2.5 \times Gap$	0.063***	0.720***	1.917***	820.610*	0.215***	0.558***	250.688***
	(0.017)	(0.231)	(0.582)	(449.739)	(0.072)	(0.179)	(67.617)
Team-Pair FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Match-Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City×Year×Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-Week and Holiday FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,222	5,222	5,222	5,222	5,222	5,222	5,222
R-squares	0.197	0.208	0.184	0.228	0.239	0.207	0.232
Mean Dep. Var.	0.5	12.7	30.1	59,159	3.93	9.23	18,028

Notes: This table presents the distributional effects of PM2.5 on team's competitive performance. The dependent variable is the indicator of win (Column 1), the number of kills, assists, and gold (Columns 2–4), and their per-10-minute counterparts (Columns 5–7). $PM2.5$ is the level of PM2.5 (in 10 μg/m^3) at the hour of the match. Regressions control for team-pair fixed effects, match-type fixed effects, city-by-year-by-month fixed effects, and day-of-week and public holiday fixed effects. Gap is the competitiveness gap measured as the difference of competitiveness index between a team and its rival. Team's competitiveness is computed as the team fixed effects from Eq. (3). Further details are specified in "Distributional impact of air pollution in competition". Robust standard errors in parentheses are clustered at team-by-season level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

exclusive groups of self-versus-rival team pairs. We estimate the effect of air pollution in each pair. The figure plots the 3×3 matrix of coefficient estimates and shows that when a team competes against a similarly ranked rival—i.e., the diagonal of the coefficient matrix—the effect of air pollution on the team's winning probability is always zero and statistically insignificant. The other entries of the 3×3 matrix show consistently that, when two teams' baseline competitiveness differ by a greater extent, the gap-widening effect of air pollution on team's performance grows even greater.

Additional evidence of air pollution killing competition

Thus far, we have found that air pollution has distributional effects on opposing teams in competition: Air pollution magnifies the underlying gap between rivals, and its effect is muted when rivals are on par. Together, these results suggest that the balance of a match will be more tilted and the whole tournament more lopsided in a more polluted environment. Put differently, air pollution kills the game by substantially reducing uncertainty and suspense. We provide further evidence.

First, air pollution raises the likelihood of a landslide victory for the stronger team. We exploit a specific LOL game mechanism, in which the whole match's most exciting and most highlighted "battle-of-the-game" moment occurs when a team kills multiple rival players and in some cases, even wipes out the entire rival team. Such moment resembles a 20–0 scoring frenzy in basketball or a hitless innings streak in baseball, which triggers a huge morale boost for the winning side. Such a moment generally occurs in the second half or at the end of the match, usually followed by a landslide victory for the team that achieves multiple kills or a wipe-out.[22]

Appendix Table A6 shows that a 10 μg/m^3 increase in PM2.5 levels significantly increased the likelihood of multiple kills for the stronger team by 1 pp relative to the weaker team. This higher chance of achieving multiple kills can explain about 52.6% of the gap in the winning rate for the stronger team (52.6%=1/1.90, see Column 1 of Table 3). Consistently, both the frequency of multiple kills and the share of multiple kills in total kills increased statistically significantly for the stronger team under more severe air pollution.

Second, air pollution reduces the unpredictability of the match. We predict the match outcome (win or loss) based on the ranking of team's competitiveness index (see Eq. (3)). Specifically, we define five quantiles of the competitiveness index and predict a team to be the winner of the match if it has a higher quantile than the rival team. We then define an indicator of prediction accuracy if the predicted outcome is the same as the actual outcome. We regress this accuracy indicator on the level of PM2.5 in the baseline specification.

Appendix Table A7 shows that higher PM2.5 significantly increases the prediction accuracy. Column 1 shows that a 10 μg/m^3 increase in PM2.5 increases the prediction accuracy by 1.2% against a sample mean accuracy of 60.8%. In addition, Column 2 shows that the suspense-reducing effect of air pollution becomes more pronounced when the underlying gap in teams' competitiveness

22 The LPL game mechanics facilitates a victory by multi-kills or wipe-out. As a match progresses, fallen champions have longer respawn times. Consequently, when multiple players in a team are defeated or a whole team is wiped out, their home base is left undefended and the opposing team can easily capitalize this window of opportunity and end the game swiftly. The multi-kills and wipe-out moment of a match is always highlighted in the live stream and serves as a key element in boosting viewership and sponsorship for LPL.

becomes greater. Column 3 shows that air pollution has no effect on prediction accuracy when two teams are on par. These patterns are consistent with our finding in Table 4 that air pollution widens the performance gap between teams and has no effect when two teams are on par. The results are robust in Columns 4 to 6 when we re-predict the match outcome directly using teams' competitiveness index as opposed to the quantiles of the index.

Lastly, air pollution reduces the intensity of competition, measured by the summed performance metrics of both teams. Appendix Table A8 shows that air pollution reduces the total kills, assists, and damages dealt to all champions during a match, as well as the metrics per 10 min. This demonstrates that while air pollution may have a positive distributional effect on the stronger team's performance, it ultimately diminishes the overall performance of both teams. This observation is consistent with the extensive literature highlighting the adverse effects of air pollution on individual's cognitive function and labor productivity (see, e.g., Archsmith et al., 2018; Kahn and Li, 2020; Graff Zivin and Neidell, 2012; Chang et al., 2019; Borgschulte et al., 2018).

In summary, we have shown that air pollution gives the relatively stronger team a competitive edge against its rival and significantly reduces the uncertainty of the game. The policy implications are twofold. If the purpose of the tournament is selection efficiency—i.e., to select and reward the most competitive team—then a higher level of air pollution would tilt the balance of the game in favor of the stronger team in each match and eventually the strongest team of the tournament. However, if the purpose of the tournament is to create more suspense—which is critical for the eSports industry to increase viewership and game revenue—then a higher level of air pollution is more likely to decrease suspense and defeat this purpose.

Robustness checks

In this section, we conduct a comprehensive set of analytical tests to justify our identification assumption and validate the robustness of the baseline results. In the next section, we proceed to discuss the mechanisms that drive the distributional impact of air pollution in competition. Interested readers can move on to "Mechanism".

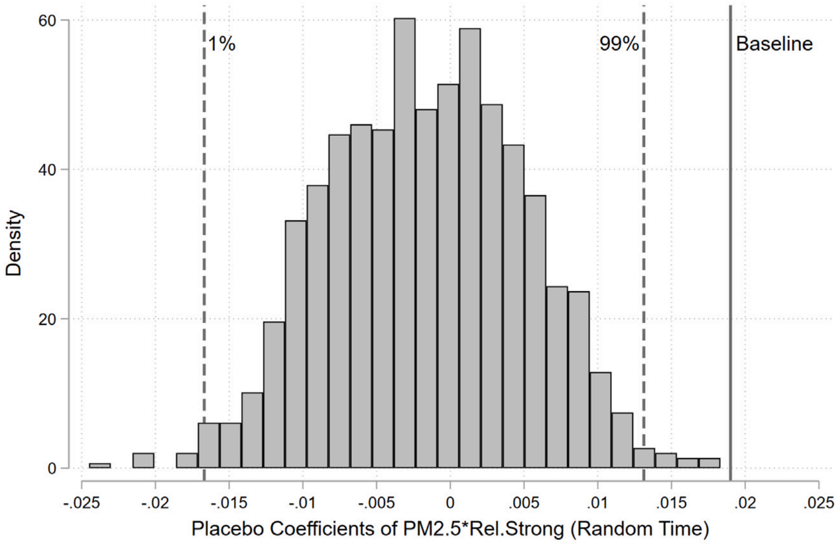
Threats to causal interpretation Although the match schedule in tournaments is predetermined and the hourly variation in PM2.5 across matches is plausibly exogenous, there remain several potential threats to a causal interpretation of the estimated effects of air pollution.

First, tournament hosts may have incentives to deliberately arrange certain matchups according to last-season records—e.g., a rematch between last-season championship contenders—on weekends or public holidays in order to increase viewership and sponsorship. Air pollution levels may also be systematically higher or lower during weekends and/or public holidays. This may create a spurious correlation between match outcomes and the level of air pollution. Therefore, in our baseline specification (Eq. (2)), we have controlled for day-of-week FEs and public holiday FEs. Additionally, we show that match outcomes between each pair of teams from the last season are uncorrelated with the pollution exposure during current-season matches of the same pair of teams (Appendix Table A9 and Appendix Figure B4). Additional analyses, discussions, figures, and tables are relegated to an online appendix.

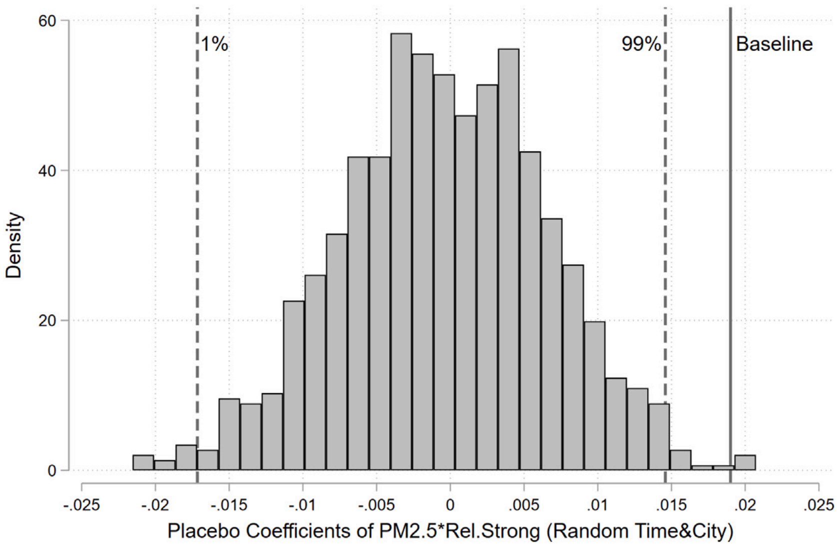
Air pollution levels can vary throughout the day (Fig. 1, Panel B), and players' cognitive performances might also fluctuate based on the hour of the match. For instance, players may perform better in the morning when they are well-rested, compared to during late-night matches, and such pattern may be more (or less) pronounced for higher-ability players. Consequently, the gap in performance between stronger and weaker teams might systematically differ based on the match hour. This systematic difference could introduce confounders in our identification of the causal effect of air pollution. To address this, we include hour-of-day FEs in the estimation as a robustness check. Essentially, we utilize the variation in PM2.5 levels between the same pair of teams, in the same city, year, month, and hour of the day, but on different days of the month to establish the causal link between pollution exposure and players' performance. Such variation of PM2.5 originates from a limited number of matchups in our sample. Considering that tournament schedule is determined quasi-randomly, it is uncommon for matchups between a specific pair of teams to be scheduled at the same hour across different dates. Nevertheless, Appendix Table A10 shows that estimation results are consistent with the baseline, suggesting that our identification in the baseline specification is largely based on the exogenous variation of air pollution independent of hour-of-the-day fluctuations.

Despite controlling for city-by-year-by-month FEs in the baseline specification, there might still exist unobservable city-specific, date-specific factors—e.g., local city social events, unexpected pre-match traffic jams—that may affect a player's mood and health before or during the match and correlate with the local pollution level. These unobservables may create omitted variable bias. We deal with such city-by-date confounding factors by including city-by-date FEs in the baseline regression. This eliminates the influence of any socioeconomic or weather factors that might vary across cities and match dates. We exploit only the within-team-pair, within-city, within-date variations in PM2.5 across match hours for identification. However, with only a subset of variations in PM2.5, the effect it identifies does not represent all teams and is less precisely estimated. It is reassuring that results of this restrictive specification are consistent with our baseline (Appendix Table A11).

We also rule out the influence of a dynamic discouragement effect that might arise between sequential tournament matches. Previous studies find that losing an earlier match in the tournament series may negatively affect players'/teams' performance in later matches, which creates a dynamic discouragement effect (Malueg and Yates, 2010; Liu et al., 2023). Pollution exposure during earlier matches may have dynamic effects on later matches. In LPL tournaments, each match series is either best of three (regular season) or best of five (playoffs). We create a set of dummies to interact the current match order in a given match series with the dummy of win or loss of earlier matches. We reestimate the baseline regression by controlling for this set of dummies to control for potential pollution-induced discouragement effects. Results remain robust (Appendix Table A12).



(A) Random Match Time



(B) Random Match Time and Locations

Fig. 5. Placebo Test using randomized match time and locations.
Notes: This figure plots estimated coefficients from two placebo tests. Panel A plots the histogram of coefficient estimate of γ from Eq. (2) after randomly assigning the match time (and correspondingly the level of PM2.5) to matches in actual match locations. Panel B plots the histogram of coefficient estimate of γ by randomly assigning both match time and match locations. The dependent variable is the indicator for winning. In each panel, a placebo regression of Eq. (2) is repeated 1,000 times. Dashed vertical lines represent 99% confidence intervals and solid vertical lines represent the benchmark estimate (γ) from Table 3, Column 1.

Placebo tests We conduct two placebo tests. First, we randomly assign the level of PM2.5 across matches held in the same city. The underlying premise is straightforward: A team's performance should not vary systematically with falsely generated pollution exposure. Using this randomly generated PM2.5 variable, a placebo test is conducted based on Eq. (2) and repeated 1,000 times. Fig. 5, Panel A plots the distribution of the estimated placebo coefficients (γ) from the 1,000 runs along with the benchmark estimate (solid line). As shown in the figure, the placebo coefficients are centered at zero and the benchmark coefficient of 0.019 lies outside the 99% confidence interval of placebo coefficients. Second, we conduct a similar placebo test by randomly assigning the level of PM2.5 across matches and across cities. We repeat this practice 1,000 times and plot the distribution of the estimated coefficients in Panel B. Again, the benchmark coefficient is significantly different from placebo coefficients. To summarize, the placebo tests demonstrate that a team's performance is only affected by exposure to PM2.5 during the actual match, and not by counterfactual variations in pollution across time or location.

Controlling for weather conditions One potential concern is that the fluctuation in weather conditions may affect individuals' moods and health (Berry et al., 2010; Cunningham, 1979) and also correlate with the variation in outdoor air pollution. Despite the fact that all hosting stadiums in our sample are fully covered and air-conditioned, fluctuations in weather before the match, such as heavy rain or extreme heat, may still have residual impacts on players' performance. To isolate the impact of air pollution on players' performance from weather-related factors, we control for a rich set of weather conditions, including flexible bins of temperature (as is standard in the literature; see, e.g., Deschênes and Greenstone, 2011), precipitation, sunshine, humidity, and wind speed, as well as an indicator for bad weather (see Footnote 15). The results are almost identical to the benchmark (Appendix Table A13), which implies that weather-related factors do not affect our estimation of the causal effect of air pollution on players' and teams' performance.

Player-level results We validate baseline results at player level. We estimate Eqs. (2) and (4) at player level and control for a set of player-specific factors—i.e., player FEs, champion FEs, and role-of-team FEs—and cluster standard errors at player-season level. The results are consistent (see Appendix Tables A14 and A15): All coefficients are quantitatively similar to those in team-level estimation, and are estimated more precisely due to the larger sample size.

Alternative measures of air pollution We check the robustness of the distributional effects of air pollution by adopting alternative measures of air pollution: PM10, SO2, and AQI. PM10 is the second most important source of airborne PM in China (the first being PM2.5) and can penetrate indoors.[23] SO2 is the most important gaseous pollutant and AQI combines the concentration values of all six main air pollutants. Appendix Table A16, Columns (1) to (3), present the estimation results using PM10, SO2, and AQI, respectively, as measures of air pollution. The results depict a consistent pattern of the distributional effects of air pollution on teams' competitive performance.

It is noteworthy that a specification based on ozone (O3) can be used as a placebo test. Outdoor ozone is formed mainly under sufficient sunshine and heat and decomposes naturally and quickly in sheltered and cool indoor environments (Weschler, 2000), which makes staying indoors an effective means of reducing ozone exposure. Because all tournament stadiums are covered and air-conditioned, we expect the variation of outdoor ozone to have no effect on team performance or match outcomes. The results in Appendix Table A16, Column (4) confirm our expectation. Similarly, Chang et al. (2016) find that higher outdoor PM2.5 lowers productivity for indoor workers at a pear-packing plant, but outdoor ozone has no effect on this indoor plant.

Pre-match and post-match exposure to air pollution We check whether the level of air pollution before or after the actual match day affects a team's competitive performance. Appendix Table A17 shows that after controlling for the concurrent level of air pollution during the match, fluctuations in air pollution 1, 3, 5, and 7 days before/after the match day do not have discernible effects on match outcomes. In other words, match-hour exposure to air pollution is the primary factor that affects a player's and team's competitive performance.

Nonlinear effects of air pollution Last, we consider the nonlinearity of pollution's impact on teams' competitive performance. We estimate a dose–response relationship by replacing the continuous $PM2.5$ term in Eq. (2) with evenly spaced bins of PM2.5 levels (in 25 $\mu g/m^3$). This allows for a flexibly nonlinear relationship between a team's competitive performance and PM2.5 levels. Appendix Figure B5 plots the estimated nonlinear impacts on the stronger team and weaker team in Panels A and B, respectively. The $0-10$ $\mu g/m^3$ bin is the omitted category. Appendix Figure B5, Panel A shows that the performance-enhancing effect of pollution on the stronger team is small when the concentration of PM2.5 is lower than 50 $\mu g/m^3$; rises moderately and flattens out when PM2.5 concentration rises from 50 to 100 $\mu g/m^3$, then rises sharply and is estimated to be statistically significant when the concentration exceeds 100 $\mu g/m^3$.[24] Panel B shows an almost symmetrical and opposite pattern for the weaker team. Regression results are reported in Appendix Table A18.

Mechanism

Thus far, we have presented robust evidence that a higher level of air pollution severely hampers the performance of the weaker team in competition but improves that of the stronger team, and leads to an elitist competition outcome. In this section we explore the factors that give rise to this pattern of the distributional impact of air pollution.

[23] PM10 has an indoor–outdoor ratio that commonly ranges from 0.3 to 0.8 (Chen and Zhao, 2011; Nadali et al., 2020).

[24] A similar pattern of nonlinear dose responses to air pollution is commonly observed in epidemiological studies (see, e.g., Kampa and Castanas, 2008) and economics studies (see, e.g., Chang et al., 2019).

Table 5
Testing relative vs. absolute strength as source of distributional effects of air pollution.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Total			Per 10 Mins		
	Win	Kill	Assist	Gold	Kill	Assist	Gold
$PM2.5$	−0.011**	−0.206***	−0.635***	−395.353***	−0.048**	−0.154***	−53.047**
	(0.006)	(0.068)	(0.176)	(124.217)	(0.021)	(0.054)	(22.282)
$PM2.5 \times Rel.Strong$	0.017**	0.203**	0.498**	113.791	0.080***	0.188***	84.402***
	(0.007)	(0.087)	(0.201)	(177.201)	(0.027)	(0.063)	(27.759)
$PM2.5 \times Abs.Strong$	0.005	0.137	0.381	340.781**	0.019	0.063	14.825
	(0.008)	(0.097)	(0.236)	(162.738)	(0.031)	(0.074)	(31.845)
Team-Pair FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Match-Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City×Year×Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-Week and Holiday FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,222	5,222	5,222	5,222	5,222	5,222	5,222
R-squares	0.197	0.209	0.185	0.229	0.240	0.208	0.234

Notes: This table tests the distributional effects of PM2.5 on team's competitive performance with respect to team's relative strength vs. absolute strength against the rival team. The dependent variable is the indicator of win (Column 1), the number of kills, assists, and gold (Columns 2–4), and their per-10-minute counterparts (Columns 5–7). $PM2.5$ is the level of PM2.5 (in 10 $\mu g/m^3$) at the hour of the match. Regressions control for team-pair fixed effects, match-type fixed effects, city-by-year-by-month fixed effects, and day-of-week and public holiday fixed effects. $Rel.Strong$ is a dummy variable indicating the team's competitiveness is higher than the rival team in the matchup. $Abs.Strong$ is a dummy variable indicating the team's competitiveness is higher than the medium among all teams. Team's competitiveness is computed as the team fixed effects from Eq. (3). Further details are specified in "Distributional impact of air pollution in competition". Robust standard errors in parentheses are clustered at team-by-season level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Heterogeneous impact based on relative strength

The first and foremost factor is that air pollution may have more adverse health impacts on the weaker team. Prior research mostly assesses the heterogeneous health impacts of air pollution based on certain personal characteristics, such as age, gender, ability, and experience (Zhang et al., 2018; Guo and Fu, 2019; Graff Zivin and Neidell, 2012; Chang et al., 2016, 2019). We present evidence that the distributional effect of air pollution depends on a team's relative strength with respect to its rival in a specific matchup rather than its own absolute strength. Importantly, such interdependence would not arise in settings of independent decision-making. Specifically, we estimate

$$\begin{aligned} Y_{ijct} &= \alpha + \beta PM2.5_{ct} + \gamma PM2.5_{ct} \times Rel.Strong_{ij} + \eta PM2.5_{ct} \times Abs.Strong_{i} + TeamPair_{ij} \\ &\quad + MatchType_{ct} + City \times Year \times Month_{ct} + DoW_t + PH_t + \mu_{ijct}. \end{aligned} \tag{5}$$

$Abs.Strong_i$ indicates a team's absolute strength, which equals one if team i's competitiveness index is higher than half of all teams (see "Distributional impact of air pollution in competition") and zero otherwise. $Rel.Strong_{ij}$ equals one if team i's competitiveness index is higher than its rival j and zero otherwise, the same as in Eq. (2).

Table 5 reports estimation results. The estimated coefficients of γ are quantitatively similar to the benchmark in Table 3 and statistically significant. The estimated coefficients of η, however, are smaller in magnitude and generally insignificant. For example, in terms of winning probability (Column 1), for a team that is absolutely weak and weaker than its rival ($Abs.Strong = 0$ and $Rel.Strong = 0$, the reference group), a 10 $\mu g/m^3$ increase in PM2.5 significantly reduces its winning probability by 1.1 pp. In comparison, a team that is absolutely weak but stronger than its rival ($Abs.Strong = 0$ and $Rel.Strong = 1$) gains a relative 1.7 pp increase in winning probability. However, a team that is absolutely strong but weaker than its rival ($Abs.Strong = 1$ and $Rel.Strong = 0$) performs similarly to the reference group when air pollution increases. The same pattern holds for performance measures of kills, assists, and gold earned (Columns 2–4) and per-10-min performance measures (Columns 5–7).

Overall, Table 5 demonstrates that the distributional effect of air pollution is mainly driven by the relative difference in a team's strength against its rival rather than the level of its own absolute strength. This pattern is consistent in a similar, highly cognitive-intensive competitive setting in German national chess tournaments. Künn et al. (2023) investigate the impact of indoor air pollution on top chess players' errors in play and find a larger adverse impact on the weaker player, whose ex ante national chess ranking is lower than their opponent; in contrast, air pollution has no effect on the stronger player. This relative-strength dependent heterogeneous impact of air pollution enriches our understanding of the health channel that underlies the cognitive impacts (Aguilar-Gomez et al., 2022). Results from Künn et al. (2023) and our study confirms that how air pollution affects a player's cognitive functioning in competition differs from a setting in which the outcome depends only on a single player's ability and choice.

Pollution acclimation

Teams who frequently train in cities with high levels of air pollution might develop resilience to the adverse effect of air pollution during tournament matches.[25,26] Similarly, teams who train in cities with higher levels of air pollution than their rival team may develop more such pollution acclimation. In addition, teams competing in their home city might be accustomed to the local air pollution levels and thus less affected by fluctuations in air pollution during matches played there. Next, we show that the heterogeneous impact of air pollution we identify is not alleviated by the aforementioned potential pollution acclimation effects.[27]

We first show that our main findings are robust to the potential pollution acclimation for teams from cities with a higher average air pollution level than the host city. We introduce an indicator variable ($HomeAcclimation_{ict}$) for team i whose home city has a higher average air pollution level than the average pollution level in host city c on the match date t.[28] We also include its interaction term with the match-hour PM2.5 level. Appendix Table A19, Panel (A) reports the estimation results, which show that the acclimation effects, represented by the coefficients of the interaction term, are small in magnitude, mixed in sign, and statistically insignificant for various dimensions of match performance. Moreover, Panel (B) shows that our key coefficient of interest, γ, in Eq. (2)—which quantifies the distributional effect of air pollution—remains similar in magnitude and statistical significance to the baseline results (e.g., 0.018 vs. 0.019 for the winning rate, as shown in Table 3) after controlling for the pollution acclimation effect.

We then assess the role of relative pollution acclimation between rival teams. We define an indicator variable ($Rel.HomePolluted_{ij}$) for team i whose home city has a higher average air pollution level than the rival team j. We also include its interaction term with the match-hour PM2.5 level. Appendix Table A20 reports the estimation results. Similarly, the coefficients of the interaction terms are small and statistically insignificant.

Third, we investigate the possibility of a home advantage. Teams competing in their home city may be more adapted to the local air pollution level and variations. We define an indicator variable ($HomeAdvantage_{ict}$) for team i whose home city is the host city c on the match date t. We also include its interaction with the match-hour PM2.5 level. Appendix Table A21 reports the estimation results. Again, the coefficients of the interaction term are generally negative, small in magnitude, and statistically insignificant for various measures of team performance. The estimates of the distributional impact of air pollution, γ, remain similar to the baseline.

In summary, results presented in Appendix Tables A19 to A21 demonstrate that pollution acclimation effect is unlikely to mitigate the observed distributional impact of air pollution on team performance. This finding is consistent with that presented in Table A17 and suggests that the distributional impact is primarily driven by instantaneous pollution exposure at the hour of the match rather than prior pollution exposure.

Strategic interactions

Strategic interactions are an essential component in competition. Players may respond endogenously to the cognitive impact of air pollution on their performance as well as to their opponent's competitive responses to air pollution. We therefore expect that air pollution may affect team's strategic decision-making.

We investigate how air pollution affects teams' strategic decision-making. We first provide suggestive evidence that players are aware of the level of air pollution, which is a necessary condition for air pollution's impact on strategic interactions. We then exploit a unique LPL setting to confirm the impact of air pollution on teams'/players' strategic decision-making. Lastly, we build a stylized contest model to highlight the role of strategic interactions in competition and elaborate on how air pollution affects competitive outcomes through strategic interactions.

Awareness of air pollution and its health effects A necessary condition for players to respond strategically to exposure to air pollution is that they are aware of air pollution and its health costs. In contemporaneous China, there is extensive evidence that the public is aware of air pollution and its damage to health (Barwick et al., 2019), and households are willing to pay for defensive means to reduce their pollution exposure (Ito and Zhang, 2020; Zhang and Mu, 2018). The general public has substantially raised their awareness of and attention to air pollution after China's Clean Air Action Plan was enacted in 2013 (Barwick et al., 2019).[29]

Fig. 6 presents evidence on public awareness of and attention to air pollution during our sample period. The figure shows that daily online searching for pollution-related keywords closely tracked the daily variation in PM2.5. Panels A to C plot the daily Baidu

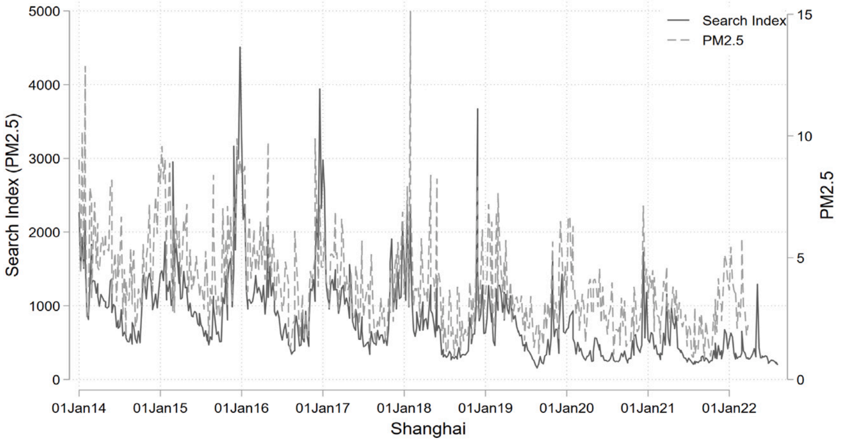
[25] We thank an anonymous referee for suggesting investigation of acclimation impacts of pollution exposure.

[26] Qin et al. (2022) find evidence suggesting that professional football players are less affected by the adverse impacts of air pollution if their home city has a higher average pollution level relative to the pollution level during the match. To the best of our knowledge, there has been no evidence on the existence of a pollution acclimation effect in a highly cognitive-intensive environment.

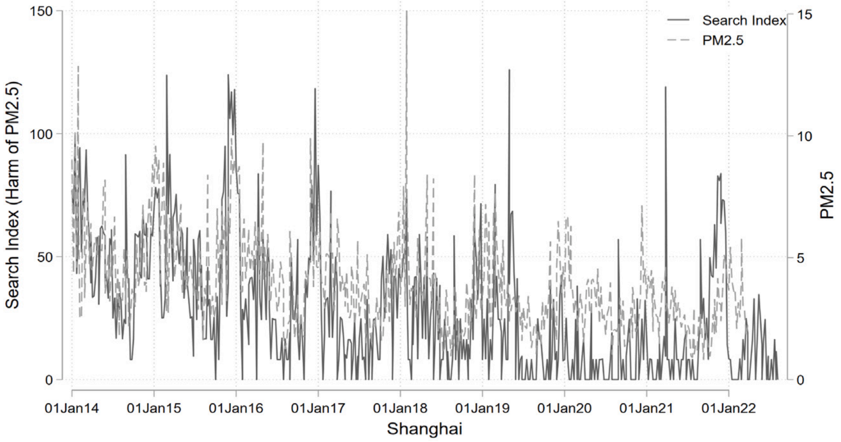
[27] It is important to note that pollution acclimation serves as a potential explanation for our baseline findings, rather than a confounding factor for causal inference.

[28] We collect information on the homebase city for all 27 LPL teams in our sample by first going through the official website of each LPL team. If a team has no official website, we obtain information on their registration city as homebase city from Baidu Baike (China's Wikipedia). Appendix Table A1, Columns 3 and 4 present the distribution of homebase cities.

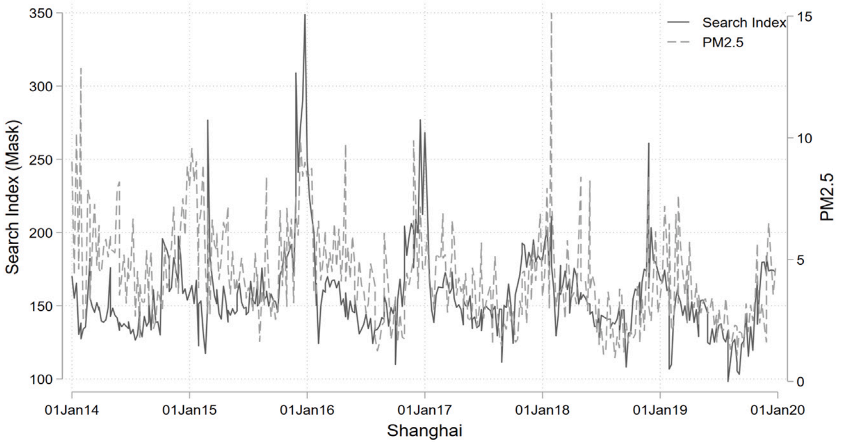
[29] In 2013, the Chinese government launched a national campaign to fight air pollution. The campaign set up subcity-level monitoring of air pollutants and released real-time pollution data to the public. Since then, news outlets and mobile apps started reporting real-time air pollution levels on an hourly basis. This has raised public awareness of air pollution and its health impacts and encouraged public engagement in pollution monitoring and control. See Barwick et al. (2019) and Greenstone et al. (2021) for a detailed account of the institutional background of pollution monitoring and real-time reporting in China since 2013 and discussion of recent studies on public awareness and avoidance of air pollution in the last decade.



(A) Search for the level of PM2.5



(B) Search for the health damages of PM2.5



(C) Search for PM2.5-proof face mask

Fig. 6. Comovement between pollution-related search and PM2.5 in Shanghai.

Notes: This figure depicts the temporal pattern of daily Baidu search volume of pollution-related keywords with daily level of PM2.5 in Shanghai. Unit of PM2.5 is 10 $\mu g/m^3$. Panel A presents the search for keywords related to the level of PM2.5, Panel B for the health damages of PM2.5, and Panel C for PM2.5-proof face mask. The figure shows that search intensity for PM2.5-related keywords increases as the PM2.5 level increases.

Table 6
Effects of air pollution on decision time and pick-and-switch.

	(1)	(2)	(3)	(4)
Panel A: Dependent Variable: Decision Time				
$PM2.5$	−0.041	−0.068	−0.089	−0.084
	(0.146)	(0.146)	(0.148)	(0.146)
$PM2.5 \times Abs.\ Weak$		0.071		−0.034
		(0.058)		(0.075)
$PM2.5 \times Rel.\ Weak$			0.096***	0.112**
			(0.035)	(0.046)
Observations	5,006	5,006	5,006	5,006
R-squares	0.371	0.371	0.372	0.372
Panel B: Dependent Variable: Log Frequency of Pick-and-switch				
$PM2.5$	0.0053	0.0032	0.0014	0.0018
	(0.0134)	(0.0138)	(0.0138)	(0.0139)
$PM2.5 \times Abs.\ Weak$		0.0056		−0.0030
		(0.0064)		(0.0078)
$PM2.5 \times Rel.\ Weak$			0.0078**	0.0092**
			(0.0039)	(0.0045)
Observations	5,002	5,002	5,002	5,002
R-squares	0.426	0.427	0.427	0.427

Notes: This table tests the effects of PM2.5 on team's and player's decision-making in the preparation phase of the match. The dependent variable in Panel A is the time a player takes to finalize his choice of champion; and the dependent variable in Panel B is the number of times a player changes his choice of champion before the final decision. $PM2.5$ is the level of PM2.5 (in 10 μg/m^3) at the hour of the match near the match stadium. $Rel.Weak$ indicates that the team's competitiveness is lower than the rival team. $Abs.Weak$ indicates that the team's competitiveness is lower than half of all teams. See the computation of team's competitiveness in Eq. (3). All regressions control for team-pair fixed effects, match-type fixed effects, city-by-year-by-month fixed effects, and day-of-week and public holiday fixed effects. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

search volume for the top three keywords—PM2.5 (the main pollutant), the health damages of PM2.5 (health cost), and PM2.5-proof face mask (pollution avoidance), respectively—against the daily level of PM2.5.[30] All panels show strong comovement between keyword search volume and the pollution level. Appendix Figure B6 presents the scatter plot of daily search volume against PM2.5 in our sample, and Appendix Table A22 presents corresponding regression results after controlling for year-month-week fixed effects. All evidence shows that the public is aware of daily changes in PM2.5 and the damage to health of exposure to severe pollution.

Pollution's impact on strategic interactions We assess pollution's impact on teams' strategic interactions by exploiting a unique, standalone phase of an LPL match—the preparation phase. This phase is designed to let each team choose an active lineup of five players and each player choose his champion for the upcoming battle in the competition phase. The choice is made under time pressure: Each player has up to 30 s to pick any unpicked champion in the pool and is allowed to switch his champion with another teammate. The choice of champion is finalized upon confirmation or when time runs out. Unlike the competition phase, a team's decisions in the preparation phase can be directly observed, so we can assess how teams change their decision-making—rather than equilibrium battle outcome—in response to higher air pollution. Decision-making in this preparation phase is highly strategic and interactive in nature: A team decides on players and a player chooses a champion while forming expectations on what the rival team might choose and anticipating the effect of its own choice on the rival's decision. Teams and players take turns choosing and fully internalize the impacts of air pollution on their choices and their opponent's choices.

We observe two direct measures of teams' and players' decisions: (i) the decision time each player takes to finalize his choice of champion and (ii) the frequency of pick-and-switch during this decision process (both averaged at team level). Moreover, observing the final decision of players' champions and teams' lineup, we define two additional variables based on each player's and team's prior history of games: (i) an indicator of whether a team chooses its most frequently used lineup of active players, and (ii) an indicator of whether a player chooses his most frequently used set of champions. In contrast to performance metrics in the competition phase—e.g., kills and assists—which are realized equilibrium outcomes, these four measures are a direct measure of a player's and a team's strategic decisions in pre-battle tactics, and thus enable us to investigate the impact of air pollution on strategic decision-making.

Table 6 shows that air pollution's effect on decision time and the frequency of pick-and-switch depends on a team's relative strength against its rival in a matchup. We first analyze a team's decision time and report the estimation results in Panel A. Column (4), based on Eq. (5) with $Rel.Strong$ and $Abs.Strong$, shows that the weaker team increases its decision time by 0.112 s when facing

[30] Baidu is the most widely used search engine in China; it publishes daily search indices that summarize the total number of queries for top keywords. The search index is generated using an algorithm similar to Google Trends (Vaughan and Chen, 2015).

Table 7
Effects of air pollution on team's choice of lineup and player's choice of champion.

	(1)	(2)	(3)	(4)
Panel A: Dependent Variable: Dummy for Using Less Frequent Team Lineup				
$PM2.5$	−0.007*	−0.010*	−0.015***	−0.015***
	(0.004)	(0.005)	(0.005)	(0.005)
$PM2.5 \times Abs.\ Weak$		0.010		−0.001
		(0.008)		(0.010)
$PM2.5 \times Rel.\ Weak$			0.016**	0.016**
			(0.007)	(0.008)
Observations	5,222	5,222	5,222	5,222
R-squares	0.350	0.350	0.351	0.351
Panel B: Dependent Variable: Dummy for Using Less Frequent Champion				
$PM2.5$	0.0004	−0.0001	−0.0010	−0.0010
	(0.0010)	(0.0012)	(0.0012)	(0.0013)
$PM2.5 \times Abs.\ Weak$		0.0016		−0.0002
		(0.0018)		(0.0020)
$PM2.5 \times Rel.\ Weak$			0.0029**	0.0030*
			(0.0014)	(0.0016)
Observations	26,092	26,092	26,092	26,092
R-squares	0.0993	0.0994	0.0995	0.0995

Notes: This table tests the effects of PM2.5 on team's and player's decision-making in the preparation phase of the match. The dependent variable in Panel A is the indicator for using a lineup that is not the most frequently used one; the dependent variable in Panel B is the indicator for a player choosing a champion that is not one of the most frequently used six champions. $PM2.5$ is the level of PM2.5 (in 10 μg/m^3) at the hour of the match near the match stadium. $Rel.Weak$ indicates that the team's competitiveness is lower than the rival team. $Abs.Weak$ indicates that the team's competitiveness is lower than half of all teams. See the computation of team's competitiveness in Eq. (3). Team-level regressions in Panel A control for team-pair fixed effects, match-type fixed effects, city-by-year-by-month fixed effects, and day-of-week and public holiday fixed effects. Player-level regressions in Panel B additionally control for player FEs and role-of-team FEs. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

a 10 μg/m^3 increase in PM2.5 during the match hour. Such an effect of air pollution on decision time is not exhibited by teams who are absolutely weak but stronger than their rival. This result is robust when we normalize the decision time by each team's seasonwide standard deviation of decision time. Appendix Table A23, Panel A shows that the weaker team increases its decision time by 0.025 SD for each 10 μg/m^3 increase in PM2.5.

Considering that a higher frequency of pick-and-switch implies greater effort in decision-making, we investigate the effect of air pollution on a team's frequency of pick-and-switch in Table 6, Panel B. Results confirm that air pollution increases a team's frequency of pick-and-switch if it is weaker than its rival in a matchup. Given that the frequency of pick-and-switch is highly right-skewed in distribution (see Appendix Figure B7), we take the log of the variable. We find that the weaker team increases its average frequency of pick-and-switch by 0.92% for each 10 μg/m^3 increase in PM2.5. Results remain robust when we normalize the frequency of pick-and-switch by a team's seasonwide SD of this frequency. Appendix Table A23, Panel B shows that the weaker team increases its frequency of pick-and-switch by 0.026 SD for each 10 μg/m^3 increase in PM2.5.

We then construct two proxies for whether a team adopts a more conservative or aggressive strategy based on a team's choice of active players and a player's choice of a champion, respectively. We define an indicator of an aggressive team strategy if a team chooses a less frequently used lineup of active players, and an indicator of an aggressive player strategy if a player chooses a less frequently played champion. In general, each team has one frequently used lineup that represents the highest level of experience and teamwork. Similarly, each player has a set of most preferred and frequently used champions.[31] However, since teams frequently compete against each other, each team's and player's most frequent choice is commonly known by all other teams. As a result, choosing the most frequently used lineup or champion would be a safe and conservative strategy, but can be expected and countered by the rival. In contrast, choosing a less frequently used lineup or champion may surprise the rival and catch them off guard, but at the same time be risky and aggressive in a competitive match. Choosing a less frequently used lineup or champion thus requires more team coordination and strategic planning. We investigate whether and how a higher level of air pollution may interfere with teams' decisions in deploying a more aggressive player lineup and champions.

Table 7 shows that air pollution changes a team's decision on the choice of players and champions, and the magnitude and the direction of such changes depend on a team's relative strength against its rival. Table 7, Column (4), based on the specification

[31] We define for each player the most frequently used 6 champions over the sample period as this player's set of frequently played champions. Most players have 5 to 6 frequently used champions for the purpose of flexibility of choice and team strategy.

of Eq. (5), shows that when facing a higher level of PM2.5, the weaker team has a higher probability of adopting a less frequently used lineup (Panel A) and choosing less frequently used champions (Panel B). This suggests that a more polluted environment renders the weaker team more likely to adopt an aggressive strategy, whereas the stronger team tends to stick to a more conservative one. This pattern of a team's strategic decisions on the choice of lineup and champions is consistent with the pattern for decision time and the frequency of pick-and-switch.

Overall, Tables 6 and 7 show that in the preparation phase the weaker team in a matchup adjusts their strategic decision-making differently in a polluted environment compared with the stronger opponent. These results confirm the impact of air pollution on the strategic decision-making of teams in competition.

A stylized contest model

We elaborate on the impact of air pollution on players' decisions and the equilibrium outcome in a simple two-player asymmetric contest model. The purpose of the model is to elucidate the role of strategic interaction in shaping players' decisions in contests and how air pollution may affect equilibrium outcomes through its impact on strategic interactions. We briefly discuss the setup, intuition, and takeaway of the model here and relegate the details to Appendix Section A.

Consider a simple contest with two risk-neutral teams, indexed by $i \in \{s, w\}$. To win the prize—e.g., a trophy, prize, and/or the opportunity to proceed to the next stage—teams simultaneously submit their effort entry $x_i \geq 0$. A lottery contest success function (CSF) captures the probabilistic nature of the equilibrium outcome of the contest: Fixing an effort profile $(x_s, x_w) > (0, 0)$, team i wins with a probability $p_i(x_s, x_w) = x_i/(x_s + x_w)$.[32]

Following Moldovanu and Sela (2001, 2006) and Moldovanu et al. (2007), team i's effort cost takes the form of $c(x_i)/a_i$, where $a_i > 0$ measures the team's innate ability or absolute strength and $c(\cdot)$ is a strictly increasing and weakly convex function with $c(0) = 0$. A larger a_i means that team $i \in \{s, w\}$ is of higher ability. Without loss of generality, we assume $a_s \geq a_w$.

Air pollution affects a team's effort cost function. More specifically, higher air pollution increases an individual's marginal cost on effort. Note that a team in a contest will adjust its equilibrium effort not only to a change in the marginal cost of its own effort, but also in response to how the rival team adjusts their effort in response to pollution. Therefore, air pollution affects the equilibrium outcome by varying teams' strategic interactions.

Our analysis leads to two propositions.[33] First, pollution's impact on team's equilibrium effort in contest is less than straightforward, due to an competition effect triggered by the strategic interactions between teams. We show that air pollution does not always reduce effort and may instead enhance the weak team's effort incentive (Appendix Propositions 1 and 2). This result is due to the nonmonotonicity in teams' best responses (Dixit, 1987), as stated in the introduction. Intuitively, a direct cost effect is triggered by higher air pollution—i.e., by the extra marginal cost—and both teams tend to cut back on their effort. However, they may respond differently to their opponents' reduction in effort. The favorite tends to further slack off when the underdog reduces effort; as a result, the favorite reduces its equilibrium effort unambiguously under higher pollution. In contrast, the underdog is encouraged to step up effort in response to the favorite's slacking off, which leads to an ambiguous overall effect of air pollution on the underdog's equilibrium effort. In particular, when the indirect competition effect outweighs the direct cost effect, the weak team would step up its effort in the equilibrium when the air quality deteriorates. This result may explain our empirical finding on a team's decisions in the preparation phase, whereby the weaker team adopts a more effortful, aggressive tactic in its team lineup and champion choices when air quality worsens during the match hour.

Second, whether the stronger team is more likely to win upon a negative air-quality shock hinges crucially on how air pollution varies the contest environment (Appendix Proposition 3 and Appendix Remark 1). In other words, air pollution could lead to either a more elitist distributional outcome—i.e., the favorite ends up with higher winning odds—or the opposite, depending on how air pollution affects the marginal effort cost function and the relative strength between players in the matchup (which affects the magnitude of the competition effect). In empirical analyses of LPL match outcomes, we find that air pollution would increase the winning probability of the stronger team.[34] Consistent with the model's prediction in symmetric contests, the gap-widening effect becomes negligible when teams are on par.

Conclusion

Our study illuminates the intricate effect of air pollution on players' decisions and equilibrium outcomes in a contest setting. We exploit a player-team-match dataset of a professional eSports tournament merged with hourly air-quality conditions to investigate the effect of air pollution on team performance and match outcome. We find a robust, distributional effect of air pollution on team performance that leads to a more elitist match outcome. We show that the distributional effect of air pollution is driven by the relative difference in team strength with respect to its rival rather than the level of its own strength. Air pollution tilts the competitive balance of the match and magnifies the gap in strength between teams and has zero effect between homogeneous rivals. In addition, air pollution reduces the unpredictability of the match and lowers the intensity of competition.

[32] In the case in which both teams exert zero effort—i.e., $(x_s, x_w) = (0, 0)$—teams win with equal probability.

[33] See details in Appendix Section A and proofs in Appendix Section B.

[34] A caveat worth noting is that we do not rule out the channel of a heterogeneous impact of air pollution on team performance. Our empirical findings can be driven by both the pathophysiological pathway on teams' cognitive performance and the effect on the strategic interactions of teams' efforts.

We propose players' strategic interactions as an important pathway by which air pollution affects equilibrium competition outcomes. We study this novel channel in both empirics and theory. In particular, based on observed player and team decision-making in a unique preparation phase of the eSports matches, we find that the weaker team in a matchup increases effort in decision-making and adopts more aggressive pre-battle tactics under a more polluted environment. This presents evidence on air pollution's impact on teams' strategic interactions in a highly competitive contest environment.

Although our analyses focus on a specific (eSports) contest setting, we believe that the nature of its cognitive engagement and strategic interactions can be embodied in other real-life high-skilled competitive environments. Our work thus opens up avenues for research on the implications of environmental adversity in strategic environments.

Declaration of competing interest

The authors declare no conflict of interest.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jeem.2023.102886.

References

Adhvaryu, A., Kala, N., Nyshadham, A., 2022. Management and shocks to worker productivity. J. Polit. Econ. 130 (1), 1–47.
Aguilar-Gomez, S., Dwyer, H., Graff Zivin, J., Neidell, M., 2022. This is air: The "nonhealth" effects of air pollution. Annu. Rev. Res. Econ. 14, 403–425.
Archsmith, J., Heyes, A., Saberian, S., 2018. Air quality and error quantity: Pollution and performance in a high-skilled, quality-focused occupation. J. Assoc. Environ. Res. Econ. 5 (4), 827–863.
Barwick, P.J., Li, S., Lin, L., Zou, E., 2019. From Fog to Smog: The Value of Pollution Information. Technical Report, National Bureau of Economic Research.
Berry, H.L., Bowen, K., Kjellstrom, T., 2010. Climate change and mental health: A causal pathways framework. Int. J. Public Health 55 (2), 123–132.
Block, M.L., Elder, A., Auten, R.L., Bilbo, S.D., Chen, H., Chen, J.-C., Cory-Slechta, D.A., Costa, D., Diaz-Sanchez, D., Dorman, D.C., et al., 2012. The outdoor air pollution and brain health workshop. Neurotoxicology 33 (5), 972–984.
Borgschulte, M., Molitor, D., Zou, E., 2018. Air Pollution and the Labor Market: Evidence from Wildfire Smoke. Working Paper.
Boudreau, K.J., Lakhani, K.R., Menietti, M., 2016. Performance responses to competition across skill levels in rank-order tournaments: Field evidence and implications for tournament design. Rand J. Econ. 47 (1), 140–165.
Brown, J., 2011. Quitters never win: The (adverse) incentive effects of competing with superstars. J. Polit. Econ. 119 (5), 982–1013.
Chang, T., Graff Zivin, J., Gross, T., Neidell, M., 2016. Particulate pollution and the productivity of pear packers. Am. Econ. J. Econ. Policy 8 (3), 141–169.
Chang, T.Y., Graff Zivin, J., Gross, T., Neidell, M., 2019. The effect of pollution on worker productivity: Evidence from call center workers in China. Am. Econ. J. Appl. Econ. 11 (1), 151–172.
Chen, C., Zhao, B., 2011. Review of relationship between indoor and outdoor particles: I/O ratio, infiltration factor and penetration factor. Atmos. Environ. 45 (2), 275–288.
Cunningham, M.R., 1979. Weather, mood, and helping behavior: Quasi experiments with the sunshine samaritan. J. Personal. Soc. Psychol. 37 (11), 1947.
Deschênes, O., Greenstone, M., 2011. Climate change, mortality, and adaptation: Evidence from annual fluctuations in weather in the US. Am. Econ. J. Appl. Econ. 3 (4), 152–185.
Dixit, A., 1987. Strategic behavior in contests. Amer. Econ. Rev. 77 (5), 891–898.
Dominici, F., Greenstone, M., Sunstein, C.R., 2014. Particulate matter matters. Science 344 (6181), 257–259.
Dong, R., Fisman, R., Wang, Y., Xu, N., 2021. Air pollution, affect, and forecasting bias: Evidence from Chinese financial analysts. J. Financ. Econ. 139 (3), 971–984.
Ebenstein, A., Lavy, V., Roth, S., 2016. The long-run economic consequences of high-stakes examinations: Evidence from transitory variation in pollution. Am. Econ. J. Appl. Econ. 8 (4), 36–65.
Fu, Q., Wu, Z., 2019. Contests: Theory and topics. In: Oxford Research Encyclopedia of Economics and Finance.
Graff Zivin, J., Liu, T., Song, Y., Tang, Q., Zhang, P., 2020. The unintended impacts of agricultural fires: Human capital in China. J. Dev. Econ. 147, 102560.
Graff Zivin, J., Neidell, M., 2012. The impact of pollution on worker productivity. Amer. Econ. Rev. 102 (7), 3652–3673.
Granic, I., Lobel, A., Engels, R.C., 2014. The benefits of playing video games. Am. Psychol. 69 (1), 66–78.
Greenstone, M., He, G., Li, S., Zou, E.Y., 2021. China's war on pollution: Evidence from the first 5 years. Rev. Environ. Econ. Policy 15 (2), 281–299.
Guo, M., Fu, S., 2019. Running with a mask? The effect of air pollution on marathon runners' performance. J. Sports Econ. 20 (7), 903–928.
He, J., Liu, H., Salvo, A., 2019. Severe air pollution and labor productivity: Evidence from industrial towns in China. Am. Econ. J. Appl. Econ. 11 (1), 173–201.
Huang, H., Cao, J., Lee, S., Zou, C., Chen, X., Fan, S., et al., 2007. Spatial variation and relationship of indoor/outdoor PM2. 5 at residential homes in Guangzhou city, China. Aerosol Air Qual. Res. 7 (4), 518–530.
Ito, K., Zhang, S., 2020. Willingness to pay for clean air: Evidence from air purifier markets in China. J. Polit. Econ. 128 (5), 1627–1672.
Kahn, M.E., Li, P., 2020. Air pollution lowers high skill public sector worker productivity in China. Environ. Res. Lett. 15 (8), 084003.
Kampa, M., Castanas, E., 2008. Human health effects of air pollution. Environ. Pollut. 151 (2), 362–367.
Krebs, B., Luechinger, S., 2021. Air Pollution, Cognitive Performance, and the Role of Task Proficiency. Working Paper.
Künn, S., Palacios, J., Pestel, N., 2023. Indoor air quality and strategic decision making. Manage. Sci.
La Nauze, A., Severnini, E.R., 2021. Air Pollution and Adult Cognition: Evidence from Brain Training. Technical Report, National Bureau of Economic Research.
Lelieveld, J., Evans, J.S., Fnais, M., Giannadaki, D., Pozzer, A., 2015. The contribution of outdoor air pollution sources to premature mortality on a global scale. Nature 525 (7569), 367–371.
Liu, H., Lu, J., Salvo, A., 2023. Willingness to fight on: Environmental quality in dynamic contests. Rand J. Econ. 54 (2), 189–239.
MacNeill, M., Wallace, L., Kearney, J., Allen, R., Van Ryswyk, K., Judek, S., Xu, X., Wheeler, A., 2012. Factors influencing variability in the infiltration of PM2.5 mass and its components. Atmos. Environ. 61, 518–532.
Malueg, D.A., Yates, A.J., 2010. Testing contest theory: Evidence from best-of-three tennis matches. Rev. Econ. Stat. 92 (3), 689–692.
Moldovanu, B., Sela, A., 2001. The optimal allocation of prizes in contests. Amer. Econ. Rev. 91 (3), 542–558.
Moldovanu, B., Sela, A., 2006. Contest architecture. J. Econom. Theory 126 (1), 70–96.
Moldovanu, B., Sela, A., Shi, X., 2007. Contests for status. J. Polit. Econ. 115 (2), 338–363.
Nadali, A., Arfaeinia, H., Asadgol, Z., Fahiminia, M., 2020. Indoor and outdoor concentration of PM10, PM2. 5 and PM1 in residential building and evaluation of negative air ions (NAIs) in indoor PM removal. Environ. Pollut. Bioavailab. 32 (1), 47–55.

Park, R.J., 2022. Hot temperature and high-stakes performance. J. Hum. Resour. 57 (2), 400–434.
Park, R.J., Goodman, J., Hurwitz, M., Smith, J., 2020. Heat and learning. Am. Econ. J. Econ. Policy 12 (2), 306–339.
Peeples, L., 2020. How air pollution threatens brain health. Proc. Natl. Acad. Sci. 117 (25), 13856–13860.
Qin, Y., Wu, J., Zhang, R., 2022. Can professional football players adapt to air pollution? Evidence from China. J. Sports Econ. 23 (3), 277–300.
Roth, S., 2021. The Effect of Indoor Air Pollution on Cognitive Performance: Evidence from the UK. Working Paper.
Stafford, T., Dewar, M., 2014. Tracing the trajectory of skill learning with a very large sample of online game players. Psychol. Sci. 25 (2), 511–518.
Vaughan, L., Chen, Y., 2015. Data mining from web search queries: A comparison of google trends and baidu index. J. Assoc. Inf. Sci. Technol. 66 (1), 13–22.
Weschler, C.J., 2000. Ozone in indoor environments: concentration and chemistry. Indoor Air 10 (4), 269–288.
World Health Organization, 2021. WHO Global Air Quality Guidelines: Particulate Matter (PM2.5 and PM10), Ozone, Nitrogen Dioxide, Sulfur Dioxide and Carbon Monoxide. World Health Organization.
Zhang, X., Chen, X., Zhang, X., 2018. The impact of exposure to air pollution on cognitive performance. Proc. Natl. Acad. Sci. 115 (37), 9193–9197.
Zhang, J., Mu, Q., 2018. Air pollution and defensive expenditures: Evidence from particulate-filtering facemasks. J. Environ. Econ. Manag. 92, 517–536.