Air Pollution Kills Competition: Evidence from ESports

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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.

Keywords: Air Pollution; Competition; Strategic Interaction.

JEL Codes: Q51; Q53; C72.

1 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.

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.[1] 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.[2] 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

1. 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.

2. 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.

relative performance, and many measurable outcomes—e.g., win or loss, and a range of performance measures—are inherently relative.[3] 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.[4] 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

3. 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.

4. Each player competes on a uniformly configured computer with keyboard and mouse.

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 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,[5] 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. (2022) 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. (2022) 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. Section 2 describes the background and data source of our empirical investigation. Section 3 presents estimation results on the average and distributional effects of air pollution. Section 4 presents robustness analyses. Section 5 discusses the importance of relative standing and strategic interactions in our empirical setting. Section 6 concludes.

2 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

5. 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.

on.

2.1 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).[6] 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 $7,000$ professional players and a prize pool of over $79 million in 2020.[7]

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

6. 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).

7. 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.

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 minutes. 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.

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.[8] 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).

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

2.2 Data Source

LPL Match Data We obtain the administrative database of match statistics for all LPL tournament matches from the official LPL website.[9] The database covers the universe of all 2,638 LPL matches held in 11 different cities across 561 match dates from Jan 2017 to July 2021.[10] 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.[11] 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,[12] 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 microns 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

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

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

11. 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.

12. 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.

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.[13] 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 (WHO, 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. Figure 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.

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

13. 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.

indicator for bad weather.[14]

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 from 2,638 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).[15]

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 minutes on average. Teams on average score 12.7 kills and 30.0 assists per match. We also compute the performance metrics per 10 minutes as measures of teams' efficiency in competitive performance. Teams score 3.9 kills and 9.2 assists per 10 minutes. There is substantial heterogeneity in performance across teams and players. Figure 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 seconds to finalize his choice of champion (the time limit is 30 seconds), 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

14. 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.

15. 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.

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.

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 $\mu g/m^3$, respectively. The average pollution exposure in LPL tournaments was higher than the WHO safety standard (the 24-hour standard is 15 $\mu g/m^3$ for PM2.5 and 45 $\mu g/m^3$ for PM10 (WHO, 2021)). In particular, about 21% of matches were held in a highly polluted environment considered to be "very unhealthy" (PM2.5 $\geq 50\mu g/m^3$).

3 Main Results

3.1 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:

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

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 minutes. $PM2.5_{ct}$ measures the match-hour level of PM2.5 (in unit of 10 $\mu g/m^3$),[16] 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).[17] Finally,

16. For ease of interpretation, we measure the level of PM2.5 in unit of 10 $\mu g/m^3$ throughout our analyses.

17. Note that all independent variables in Equation (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

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 minutes (Columns 5 to 7). This pattern of "no average effect" is similarly documented when we estimate Equation (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.

3.2 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. Figure 3 depicts the scatter plot of the team's kills and assists per 10 minutes against its PM2.5 exposure in

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 Section 5.3.

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). Figure 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, Figure 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

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

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 ($Role_r$),[18] 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.[19] 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 Equation (2). The coefficients of interest are β and γ: The former measures the effect of a 10 $\mu g/m^3$ 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

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

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

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 Equation (2), which delineate a clear opposite pattern: When a team is weaker in a matchup, a 10 $\mu g/m^3$ increase in PM2.5 concentration significantly reduces its performance in kills, assists, and gold 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.[20] 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 Equation (2) by replacing the dummy $Rel.Strong_{ij}$ with a continuous measure of the gap in innate competitiveness between teams, $Gap_{ij} = \hat{\delta}_i - \hat{\delta}_j$:

$$Y_{ijct} = \alpha + \beta PM2.5_{ct} + \gamma PM2.5_{ct} \times Gap_{ij} + TeamPair_{ij} + MatchType_{ct}$$

20. 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.

$$+ City \times Year \times Month_{ct} + DoW_t + PH_t + \mu_{ijct}. \tag{4}$$

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 Equation (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 Figure 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 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.

3.3 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.[21]

Appendix Table A6 shows that a 10 $\mu g/m^3$ 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 Equation 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 $\mu g/m^3$ 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 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'

21. 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.

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 minutes. 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.

4 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 Section 5.

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 (Equation 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 (Figure 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., 2022). 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).

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 Equation (2) and repeated $1,000$ times. Figure 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 14). 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 Equations (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.[22] 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

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

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 Equation (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 $\mu g/m^3$.[23] Panel B shows an almost symmetrical and opposite pattern for the weaker team. Regression results are reported in Appendix Table A18.

23. 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).

5 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.

5.1 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

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

$Abs.Strong_i$ indicates a team's absolute strength, which equals one if team i's competitiveness index is higher than half of all teams (see Section 3.2) 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 Equation (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.

5.2 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.[24,25] 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

24. We thank an anonymous referee for suggesting investigation of acclimation impacts of pollution exposure.

25. 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.

aforementioned potential pollution acclimation effects.[26]

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.[27] 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 Equation (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

26. 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.

27. 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.

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.

5.3 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).[28]

Figure 6 presents evidence on public awareness of and attention to air pollution during our

28. 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.

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 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.[29] 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 seconds 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

29. 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).

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 Equation (5) with *Rel.Strong* and *Abs.Strong*, shows that the weaker team increases its decision time by 0.112 seconds when facing a 10 $\mu g/m^3$ 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 $\mu g/m^3$ 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 $\mu g/m^3$ 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 $\mu g/m^3$ 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.[30] 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 of Equation (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.

5.4 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

30. 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.

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 $p_i(x_s, x_w) = x_i/(x_s + x_w)$.[31]

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.[32] 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.

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

32. See details in Appendix Section A and proofs in Appendix Section B.

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.[33] Consistent with the model's prediction in symmetric contests, the gap-widening effect becomes negligible when teams are on par.

6 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.

33. 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.

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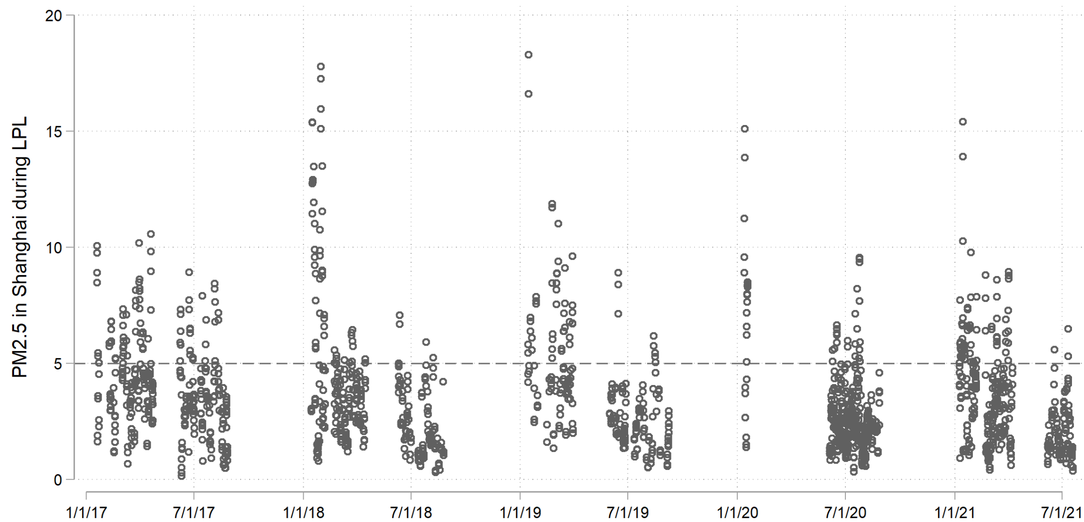
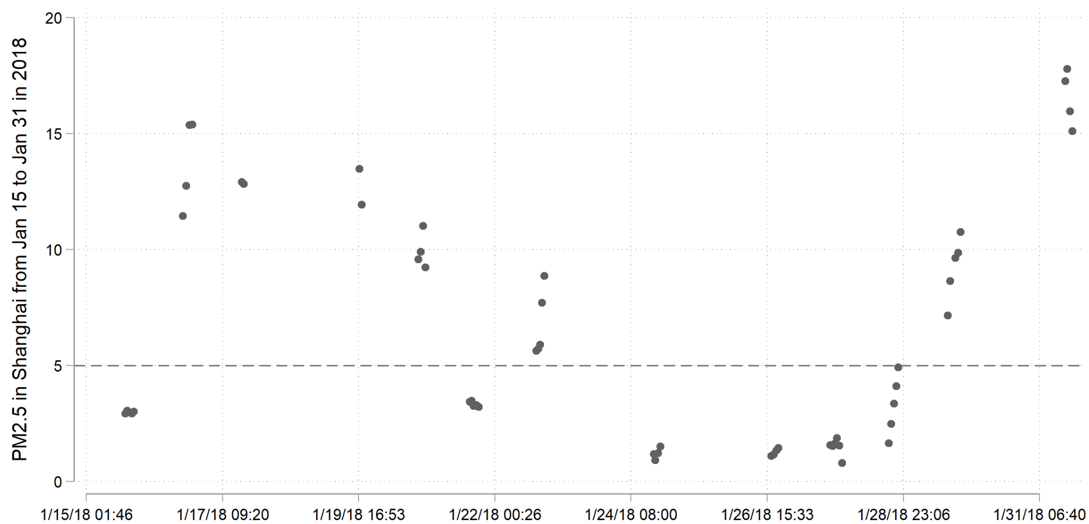
7 Figures



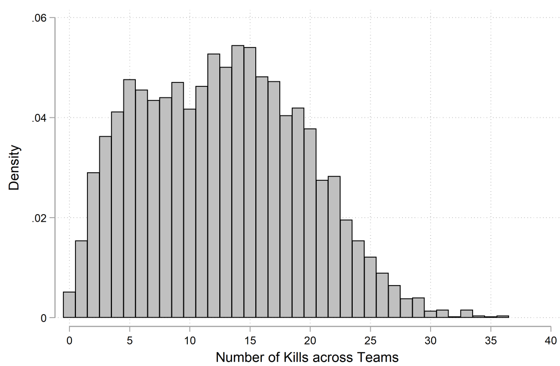
(A) Entire Sample Period from 2017 to 2021



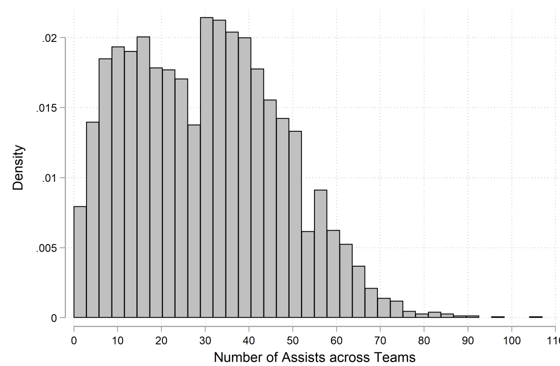
(B) January in Spring Season 2018

FIGURE 1
Temporal Variation in PM2.5 in Shanghai

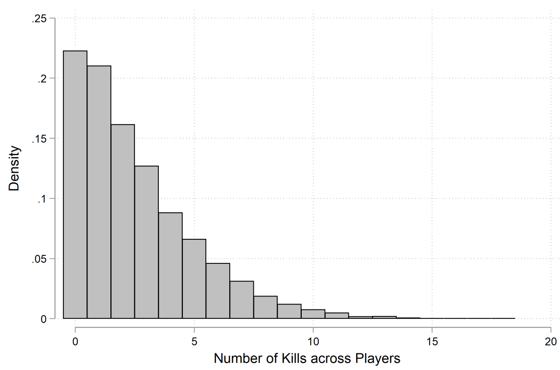
Notes: This figure presents the temporal variation in PM2.5 in Shanghai across LPL match hours. Each data point represents the level of PM2.5 during a particular match. Panel A presents the variation in PM2.5 across the entire sample period; Panel B presents the variation in PM2.5 across match hours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



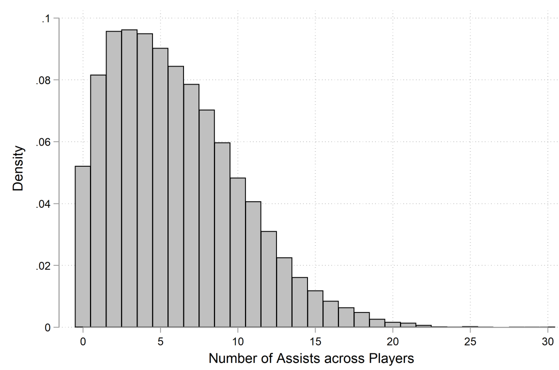
(A) Kills per match (team)



(B) Assists per match (team)



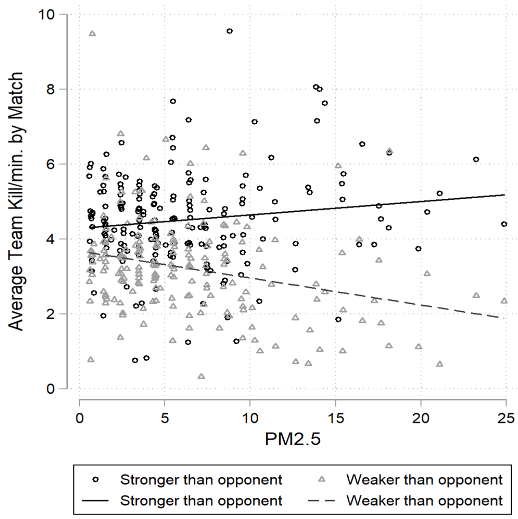
(C) Kills per match (player)



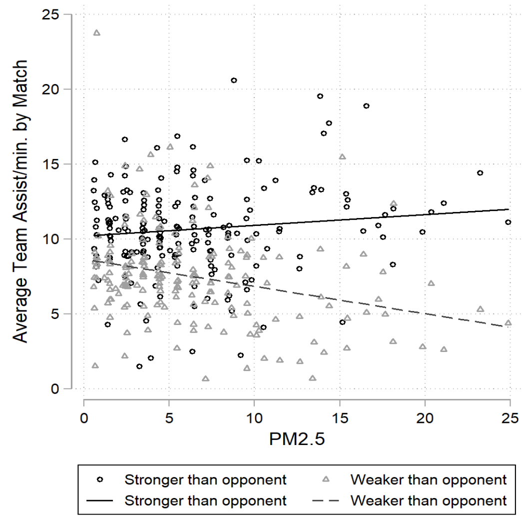
(D) Assists per match (player)

FIGURE 2
Histogram of Kills and Assists per Match for Players and Teams

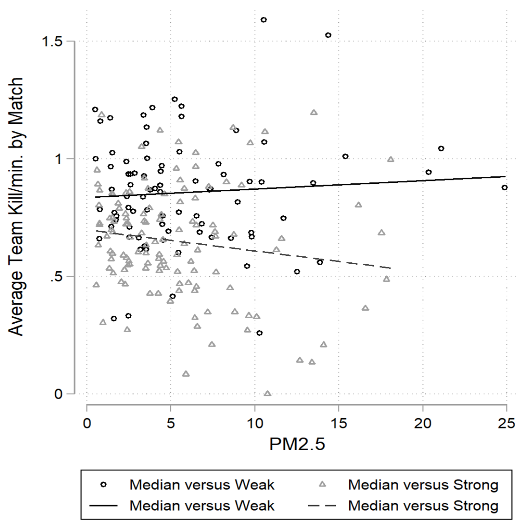
Notes: This figure presents the histogram of key performance metrics for teams and players. Panels A and B depict the distribution of kills and assists per match for teams, respectively; Panels C and D show the distribution of kills and assists per match for players, respectively.



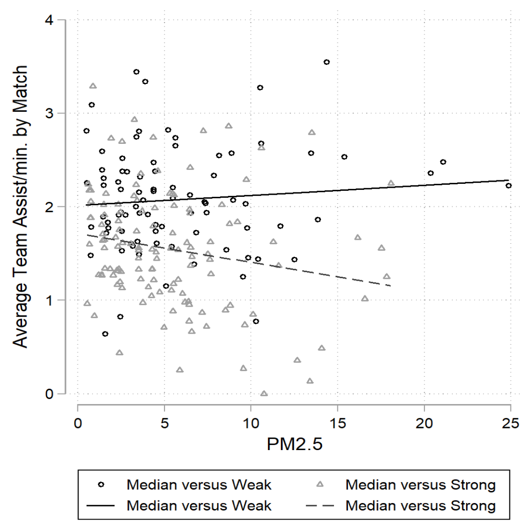
(A) Kills by Rel. Strength (All)



(B) Assists by Rel. Strength (All)



(C) Kills by Rel. Strength (Medium)



(D) Assists by Rel. Strength (Medium)

FIGURE 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 minutes and the level of air pollution. Dark circles represent the stronger team and gray triangles represent the weaker team. See Equation (3) for the definition of team strength. Panel B presents the relationship of assists per 10 minutes. Panels C and D fix to a group of medium-ranked teams and present the relationship between these teams' kills and assists per 10 minutes 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 $\mu g/m^3$.

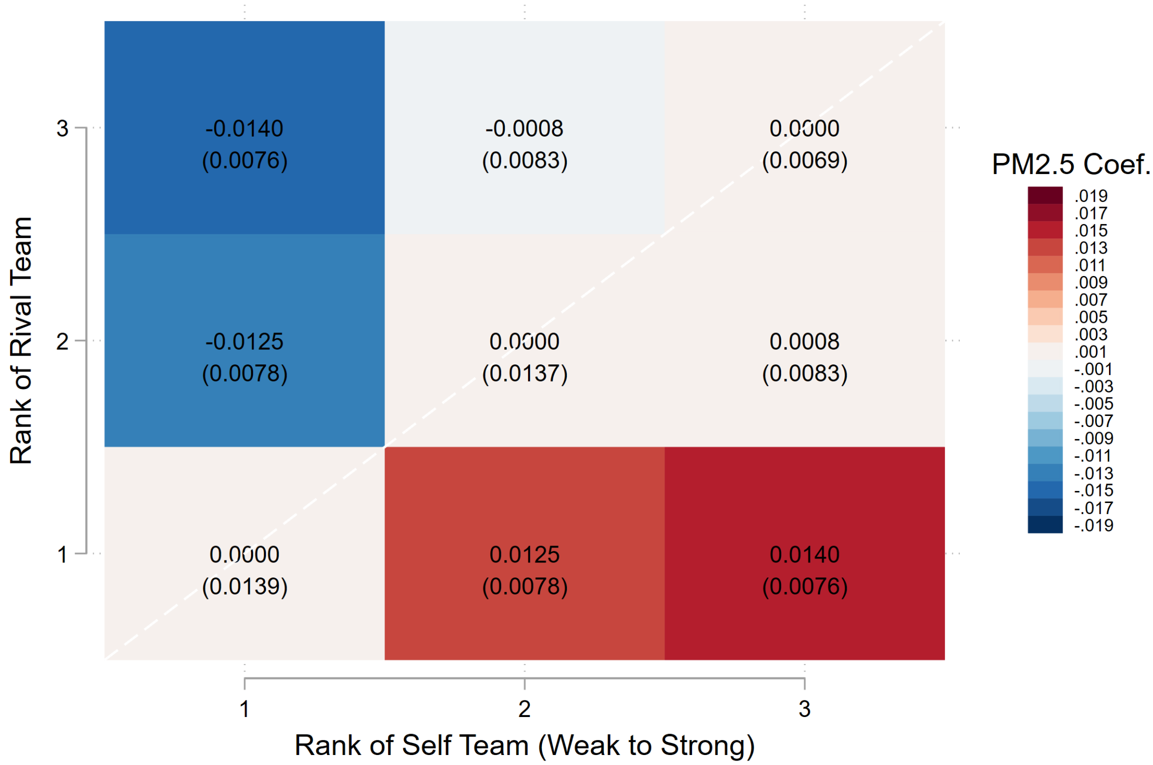
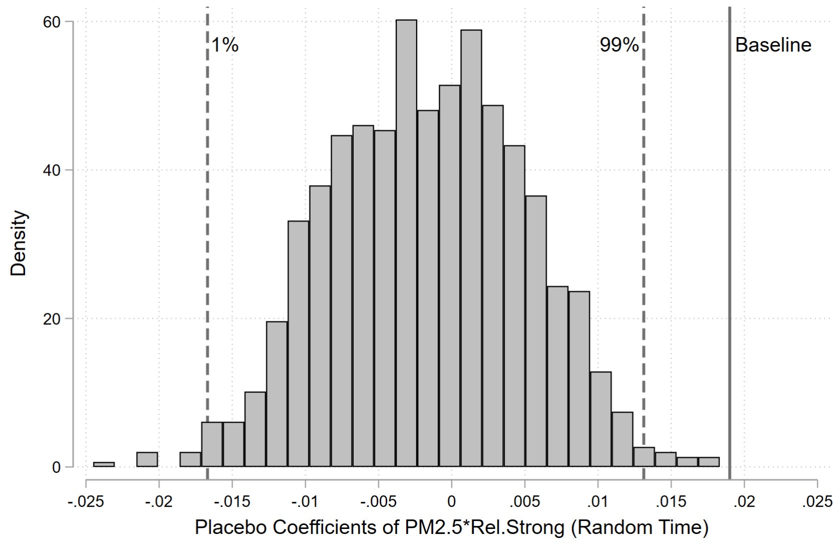


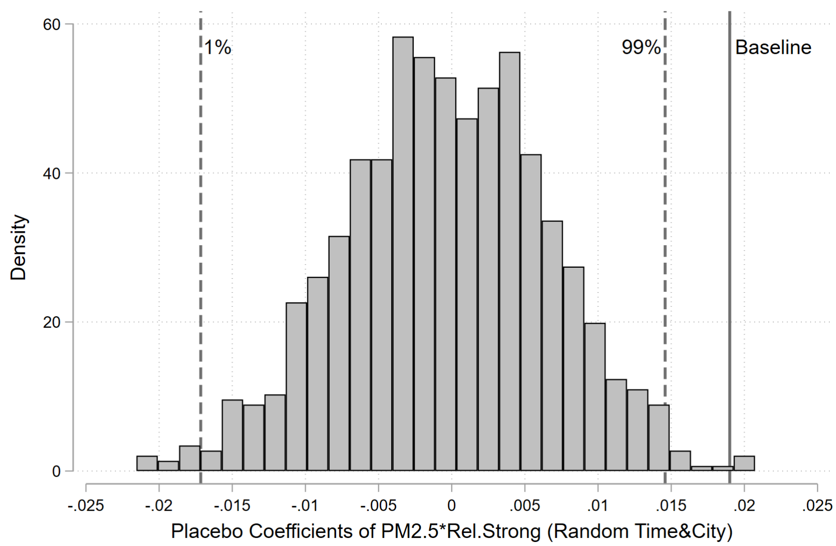
FIGURE 4

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 Equation (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.



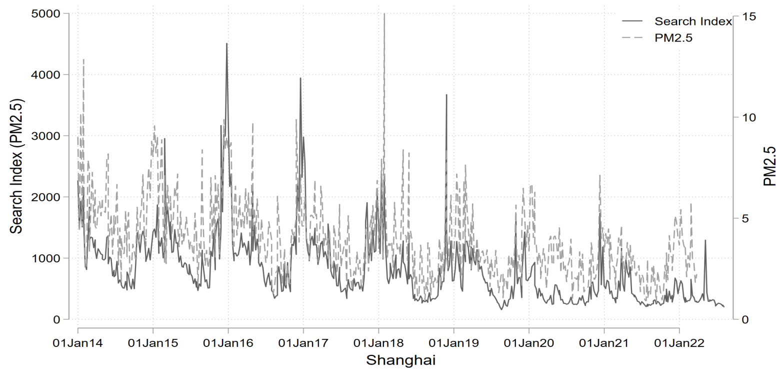
(A) Random Match Time



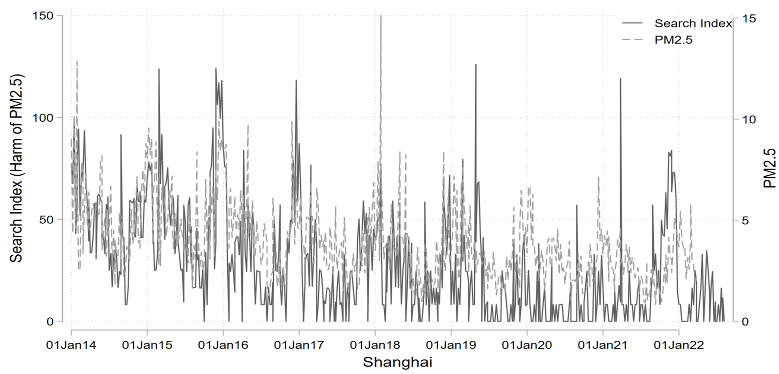
(B) Random Match Time and Locations

FIGURE 5
Placebo Test Using Randomized Match Time and Locations

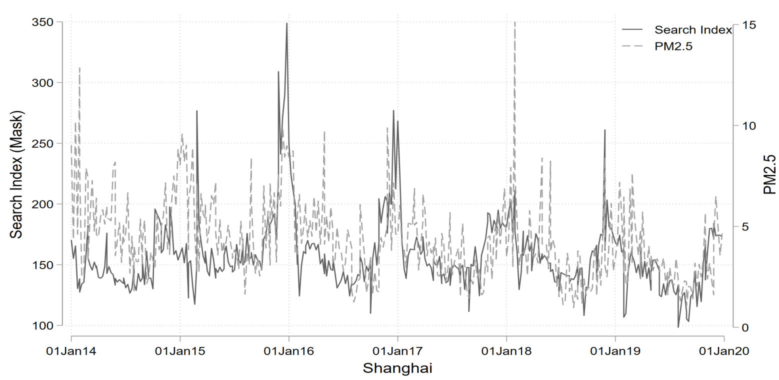
Notes: This figure plots estimated coefficients from two placebo tests. Panel A plots the histogram of coefficient estimate of γ from Equation (2) after randomly assigning the match time (and correspondingly the level of PM2.5) to matches in actual match locations. Panel B plots the histogram of coefficient 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 Equation (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.



(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

FIGURE 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.

8 Tables

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 (sec.)	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 ($10\mu g/m^3$)	3.57	2.77	0.10	24.85	5,222
PM10 ($10\mu g/m^3$)	5.50	3.50	0.3	28.58	5,186
AQI ($10\mu g/m^3$)	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 $\mu g/m^3$) 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. Mean of dependent variables are presented in the last row. Further details are specified in Section 3.2. Robust standard errors in parentheses are clustered at team-by-season level. *** p <0.01, ** p <0.05, * p <0.1.

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 $\mu g/m^3$) 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 Equation (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 Section 3.2. Robust standard errors in parentheses are clustered at team-by-season level. *** p <0.01, ** p <0.05, * p <0.1.

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 $\mu g/m^3$) 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. *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 Equation (3). Further details are specified in Section 3.2. Robust standard errors in parentheses are clustered at team-by-season level. *** p <0.01, ** p <0.05, * p <0.1.

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 Equation (3). Further details are specified in Section 3.2. Robust standard errors in parentheses are clustered at team-by-season level. *** p <0.01, ** p <0.05, * p <0.1.

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 $\mu g/m^3$) 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 Equation (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.

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 $\mu g/m^3$) 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 Equation (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.

Air Pollution Kills Competition: Evidence from ESports

ONLINE APPENDIX

(Not Intended for Publication)

In this appendix, we collect the analyses, discussions, figures, and tables omitted from the main text.[34]

Appendix A A Stylized Contest Model

In this section, we elaborate on the impact of air pollution on players' decisions and the equilibrium outcome in a simple contest model with asymmetric players. To better connect our model to later empirical analyses, we refer to player(s) as team(s) throughout the section. Our analysis demonstrates that (i) air pollution does not always lead to negative consequences, and may in fact increase the weak team's effort incentive in a game-theoretic environment, and (ii) 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 (or teams' adaptability to air pollution).

A.1 Model Setup

Consider a contest with two risk-neutral teams, indexed by $i \in \{s, w\}$. The two teams vie for a prize—e.g., a trophy, championship prize, and/or the opportunity to proceed to the next stage—by exerting irreversible efforts simultaneously. The prize carries a common monetary value, which we normalize to unity. Further, we assume a lottery contest success function (CSF) to capture the probabilistic nature of competition: Fixing an effort profile $(x_s, x_w) \geq (0, 0)$, team i wins with a probability

$$p_i(x_s, x_w) = \begin{cases} x_i/(x_s + x_w) & \text{if } x_s + x_w > 0, \\ 1/2 & \text{if } x_s + x_w = 0. \end{cases}$$

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 $a_i > 0$ refers to the team's ability and $c(\cdot)$ is a strictly increasing and weakly convex function with $c(0) = 0$. Note that a large a_i means that team i is of high ability and vice versa. Without loss of generality, we assume $a_s \geq a_w$.

Given the effort pair (x_s, x_w), team i's expected payoff is

$$\pi_i(x_s, x_w) := p_i(x_s, x_w) - c(x_i)/a_i, i \in \{s, w\}.$$

The $c(\cdot)$ function, together with teams' ability profile (a_s, a_w), defines a simultaneous-move contest game, which we denote by $\langle c(\cdot), (a_s, a_w) \rangle$. By Szidarovszky and Okuguchi (1997) and Cornes and Hartley (2005), there exists a unique pure-strategy equilibrium of the above contest game, which lays a foundation for our subsequent analysis.

For simplicity, we abstract away the free-riding problem within team members in the model laid out above by assuming that a representative player acts on behalf of each team. In Appendix C,

34. This note is not self-contained; it is the online appendix of the paper "Air Pollution Kills Competition: Evidence from ESports."

we extend the model to allow each team to consist of multiple homogeneous players and show that all of our results remain unchanged.

A.2 Analysis

Next, we examine the impact of a change in air quality on each team's equilibrium effort and winning probability. Numerous studies have documented the damaging effects of air pollution. For example, Zhang et al. (2018) estimate the contemporaneous and cumulative impacts of air pollution on cognition and show that air pollution impedes cognitive performance. Put differently, it becomes more costly for an agent to achieve the same cognitive performance as air pollution worsens. Inspired by these findings, we model air pollution as an increase in a team's marginal effort cost. More formally, we assume that the deterioration of air quality results in a change in the $c(\cdot)$ function from $c_1(\cdot)$ to $c_2(\cdot)$, with $c_1'(x) < c_2'(x)$ for all $x > 0$.[35]

Remark 1 ***(Impact of Air Pollution in Symmetric Contests)*** *Analysis of the case in which the two teams have the same ability—i.e., $a_s = a_w$—is straightforward. It can be verified that both teams exert the same amount of effort in the unique equilibrium, and thus the two teams have equal probabilities of winning regardless of the level of air pollution. Further, each team's effort in the symmetric equilibrium decreases as $c(\cdot)$ changes from $c_1(\cdot)$ to $c_2(\cdot)$.*

In what follows, we focus on the case in which the two teams have different abilities.

A.2.1 Impact of Air Pollution on Equilibrium Effort

We first analyze the equilibrium individual effort and aggregate effort. For notational convenience, denote team i's equilibrium effort under contest $\langle c_\ell(\cdot), (a_s, a_w)\rangle$ by $x^*_{i,\ell}$, with $\ell \in \{1, 2\}$. Further, define $X^*_\ell := \sum_{i=1}^{2} x^*_{i,\ell}$. Three propositions are in order. All proofs are provided in Appendix B.

Proposition 1 ***(Impact of Air Pollution on Equilibrium Effort)*** *Suppose that the two teams are heterogeneous—i.e., $a_s > a_w$—and consider two strictly increasing and weakly convex functions $c_1(\cdot)$ and $c_2(\cdot)$, with $c_1(0) = c_2(0) = 0$ and $c_1'(x) < c_2'(x)$ for all $x > 0$. The following statements hold as $c(\cdot)$ changes from $c_1(\cdot)$ to $c_2(\cdot)$:*

(i) The strong team's equilibrium effort always decreases, i.e., $x^*_{s,1} > x^*_{s,2}$;

(ii) The weak team's equilibrium effort may either increase or decrease—i.e., both $x^*_{w,1} < x^*_{w,2}$ and $x^*_{w,1} > x^*_{w,2}$ are possible—depending on $c_1(\cdot)$, $c_2(\cdot)$, and (a_s, a_w);

(iii) The aggregate effort of the contest unambiguously decreases, i.e., $X^*_1 > X^*_2$.

By Proposition 1(i), the strong team's effort incentive is dampened when the air quality decreases. The same pattern can be observed for aggregate effort. By Proposition 1(iii), despite the potential effort boost from the weak team, the overall impact of air pollution on the aggregate effort elicited from the competition is clear-cut and negative.

Importantly, the proposition indicates that air pollution does not always lead to negative consequences in a strategic environment. Proposition 1(ii) predicts that the impact of air pollution on the weak team's effort incentive is ambiguous. As previously stated, two effects naturally arise. There

35. In our model, each team realizes the impact of air pollution on its cost function. We will present empirical support for players' awareness of air pollution and its health effects in Section 5.3.

is a direct cost effect: Air pollution is counterproductive by nature and the elevated (marginal) cost discourages both teams' efforts. On the other hand, the direct cost effect would trigger an indirect competition effect that comes into play through the reflexive interaction between teams, since each must adjust its effort choice in response to the change in the effort of its opponent. In a typical contest setting, opponents' efforts are strategic complements to the strong team and strategic substitutes to the weak team. In our context, the concession of the weak team allows the strong team to slack off because of the strategic complementarity, since a lower effort may still render him equally likely to win; a less aggressive strong team—due to the direct cost effect—further incentivizes the weak team to step up its effort because of the strategic substitutability. Note that both the cost and competition effects weaken the strong team's effort incentive, and hence it would reduce effort unambiguously, as stated in Proposition 1(i). In contrast, the weak team's effort choice is subject to competing forces. 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.

To proceed, let $\overline{x} := c_1^{-1}(a_s)$. Evidently, choosing an effort level that exceeds $\overline{x}$ yields a negative expected payoff regardless of the opponent's effort level—which is strictly dominated by choosing zero effort—and thus a team's equilibrium effort must lie between 0 and $\overline{x}$. Define $\delta(x) := c_2(x) - c_1(x)$ and $r_1 := \inf_{x\in[0,\overline{x}]} x\delta''(x)/\delta'(x)$. Similarly, define $\mathcal{C}(x;\lambda) := c_1(x) + \lambda\delta(x)$, with $\lambda \in [0,1]$, and $r_2 := \sup_{x\in[0,\overline{x}],\lambda\in[0,1]} x\frac{\partial^2\mathcal{C}(x;\lambda)}{\partial x^2}/\frac{\partial\mathcal{C}(x;\lambda)}{\partial x}$. It follows immediately that $c_1(x) = \mathcal{C}(x;0)$ and $c_2(x) = \mathcal{C}(x;1)$. Note that r_1 and r_2 provide an intuitive measure of the curvature of $\delta(\cdot)$ and $\mathcal{C}(\cdot;\lambda)$, respectively.

Our next result spells out sufficient conditions for the weak team's equilibrium effort level to increase or decrease upon a deterioration of the air quality.[36]

Proposition 2 ***(Impact of Air Pollution on the Weak Team's Incentive)*** *Suppose that the two teams are heterogeneous—i.e., $a_s > a_w$—and consider two strictly increasing and weakly convex functions $c_1(\cdot)$ and $c_2(\cdot)$, with $c_1(0) = c_2(0) = 0$ and $c_1'(x) < c_2'(x)$ for all $x > 0$. The following statements hold as $c(\cdot)$ changes from $c_1(\cdot)$ to $c_2(\cdot)$:*

(i) Suppose that $\delta''(x) \leq 0$ for all $x \in (0,\overline{x}]$. Then the weak team's equilibrium effort decreases—i.e., $x^*_{w,1} > x^*_{w,2}$.

(ii) Suppose that $\delta''(x) > 0$ for all $x \in (0,\overline{x}]$. Then the weak team's equilibrium effort increases—i.e., $x^*_{w,1} < x^*_{w,2}$—if $r_1 \geq 1$ and

$$\left(\frac{a_s}{a_w}\right)^{\frac{r_1-1}{r_2+1}}\left[\left(\frac{a_s}{a_w}\right)^{\frac{1}{r_2+1}} - 1\right] > r_2\left(\frac{a_s}{a_w}\right)^{\frac{1}{r_2+1}} + r_2 + 2. \tag{6}$$

By Proposition 2, whether the deterioration of the air quality increases or decreases the weak team's equilibrium effort crucially depends on the shape/curvature of the $\delta(\cdot)$ function, i.e., the difference between $c_2(\cdot)$ and $c_1(\cdot)$. Intuitively, a convex effort cost function automatically handicaps the strong team because of its higher effort level, which in turn levels the playing field and fuels competition. When the $\delta(\cdot)$ function is weakly concave, a team is gradually adapted to the increased air pollution level as it continues to increase its effort. Given that the strong team always exerts more effort than the weak one in equilibrium, the equalizing effect triggered by the convexity of the effort cost function tends to lose its appeal, which limits the aforementioned competition effect. As

36. In Appendix D, we construct a parameterized setting with a linear quadratic effort cost function to illustrate how the conditions established in Propositions 2 and 3 translate into the parameters of the effort cost function.

a result, the direction of the weak team's effort response is mainly driven by the direct cost effect and thus decreases, as predicted by Proposition 2(i).

Proposition 2(ii) can again be explained in light of the rationale outlined above. Note that r_1 specifies the lower bound of the convexity of $\delta(\cdot)$ and r_2 gives the upper bound of the convexity of $\mathcal{C}(\cdot;\lambda)$, which we construct based on $c_1(\cdot)$ and $c_2(\cdot)$. The convexity of $\delta(\cdot)$ automatically holds for $r_1 \geq 1$, and condition (6) is likely to be satisfied when (i) a_s/a_w is large; (ii) r_1 is large; and (iii) r_2 is small. Intuitively, the equalizing effect triggered by the convex effort cost function becomes greater when the contest is more asymmetric—i.e., when the ability ratio a_s/a_w is large. Further, this role is magnified when a team becomes less adapted to air pollution as it increases effort—i.e., when $\delta(\cdot)$ is getting more convex—and when the equalizing effect triggered by the convexity of the effort cost function is relative small—i.e., when $\mathcal{C}(\cdot;\lambda)$ is getting less convex.

A.2.2 Impact of Air Pollution on Equilibrium Winning Probabilities

Next, we consider the impact of an air-quality shock on each team's winning probability. Denote team i's equilibrium winning probability under contest $\langle c_\ell(\cdot),(a_s,a_w)\rangle$ by $p^*_{i,\ell} := x^*_{i,\ell}/X^*_\ell$, with $\ell \in \{1,2\}$. Propositions 1 and 2 already shed some light on the comparative statics. Recall by Proposition 1, that $x^*_{s,1} > x^*_{s,2}$ and $X^*_1 > X^*_2$. In addition, $x^*_{w,1} < x^*_{w,2}$ by Proposition 2(ii) if $r_1 \geq 1$ and condition (6) is satisfied. Together, these imply that $p^*_{s,1} = 1 - p^*_{w,1} = 1 - x^*_{w,1}/X^*_1 > 1 - x^*_{w,2}/X^*_2 = 1 - p^*_{w,2} = p^*_{s,2}$—i.e., the strong team is less likely to win as the air quality deteriorates. However, it remains unknown whether the strong team's equilibrium winning probability would increase in the case in which air pollution discourages both teams' effort incentive—e.g., where $\delta''(x) \leq 0$ for all $x \geq 0$, as required in Proposition 2(ii).

Define $\psi(x;\lambda) := \big[\frac{\partial \mathcal{C}(x;\lambda)}{\partial x} + x\frac{\partial^2 \mathcal{C}(x;\lambda)}{\partial x^2}\big]/\delta'(x)$. Our next result demonstrates that the strong team's equilibrium winning probability may increase or decrease and provides sufficient conditions for each possibility to arise.

Proposition 3 ***(Impact of Air Pollution on Equilibrium Winning Probabilities)*** *Suppose that the two teams are heterogeneous—i.e., $a_s > a_w$—and consider two strictly increasing and weakly convex functions $c_1(\cdot)$ and $c_2(\cdot)$, with $c_1(0) = c_2(0) = 0$ and $c_1'(x) < c_2'(x)$ for all $x > 0$. The following statements hold as $c(\cdot)$ changes from $c_1(\cdot)$ to $c_2(\cdot)$:*

(i) If $\psi(x;\lambda)$ is strictly increasing in x for all $\lambda \in [0,1]$, then $p^*_{s,1} < p^*_{s,2}$.

(ii) If $\psi(x;\lambda)$ is strictly decreasing in x for all $\lambda \in [0,1]$, then $p^*_{s,1} > p^*_{s,2}$.[37]

By Proposition 3, the comparative statics of each team's equilibrium winning probability depends sensitively on the monotonicity of $\psi(\cdot;\lambda)$, which is closely related to the curvatures of $c_1(\cdot)$ and $\delta(\cdot)$. To better understand the intuition, we illustrate with a parameterized example. Set $c_1(x) = \frac{1}{2}x^2$ and $\delta(x) = \frac{1}{k}x^k$, with $k \geq 1$. Simple algebra would then verify that $\mathcal{C}(x;\lambda) = \frac{1}{2}x^2 + \lambda\frac{1}{k}x^k$ and thus $\psi(x;\lambda) = \lambda k + 2x^{2-k}$. Evidently, the monotonicity of $\psi(\cdot;\lambda)$ relies on the comparison between k and 2, i.e., the convexity of $\delta(\cdot)$ and that of $c_1(\cdot)$. When $\delta(\cdot)$ is more convex—i.e, $k > 2$—air pollution erodes the advantage of the strong team as an equalizing device and evens the odds, which leads to $p^*_{s,1} > p^*_{s,2}$. Similarly, when $\delta(\cdot)$ is less convex—i.e, $k < 2$—air pollution further tilts the playing field in favor of the strong team and increases its winning probability, i.e., $p^*_{s,1} < p^*_{s,2}$.

37. It is straightforward to verify that $p^*_{s,1} = p^*_{s,2}$ if $\psi(x;\lambda)$ is constant with respect to x for all $\lambda \in [0,1]$, which occurs when (i) $c_\ell(x) = \alpha_\ell x$, with $\alpha_2 > \alpha_1 > 0$, or (ii) $c_\ell(x) = \beta_\ell \frac{x^2}{2}$, with $\beta_2 > \beta_1 > 0$.

Proposition 3 demonstrates that the strong team's equilibrium winning probability may increase or decrease in a more polluted environment, depending on the convexity of the cost function as well as the change in cost function due to the air-quality shock. More generally, the distributional effect of air pollution on equilibrium outcomes is theoretically indeterminant. We next employ data from the world's largest eSports tournament and exploit its quasi-experimental setting to investigate the distributional effects of air pollution.

Appendix B Proofs

Proof of Proposition 1

Proof. Part (ii) of the proposition follows from Proposition 2, and it suffices to prove parts (i) and (iii). The equilibrium effort pair under contest $\langle c(\cdot), (a_s, a_w)\rangle$, which we denoted by (x_s^*, x_w^*), is governed by the first-order conditions $\frac{\partial \pi_s(x_s, x_w^*)}{\partial x_s}\big|_{x_s = x_s^*} = 0$ and $\frac{\partial \pi_w(x_s^*, x_w)}{\partial x_w}\big|_{x_w = x_w^*} = 0$, which can be rewritten as follows:

$$a_s p_{w,\ell}^* = X_\ell^* c_\ell'(x_{s,\ell}^*),\ a_w p_{s,\ell}^* = X_\ell^* c_\ell'(x_{w,\ell}^*),\ \text{for } \ell \in \{1,2\}, \tag{7}$$

where $p_{i,\ell}^* := x_{i,\ell}^*/X_\ell^*$ is team i's equilibrium winning probability under contest $\langle c_\ell(\cdot), (a_s, a_w)\rangle$, as defined in the main text.

We first show $X_1^* > X_2^*$. Suppose, to the contrary, that $X_1^* \leq X_2^*$. Then we must have $p_{s,1}^* > p_{s,2}^*$; otherwise, we have that

$$a_s(1 - p_{s,1}^*) = X_1^* c_1'(X_1^* p_{s,1}^*) \leq X_2^* c_2'(X_2^* p_{s,2}^*) = a_s(1 - p_{s,2}^*),$$

where the two equalities follow from (7) and inequality from the postulated $X_1^* \leq X_2^*$, $p_{s,1}^* \leq p_{s,2}^*$, and the definition of $c_1(\cdot)$ and $c_2(\cdot)$. A contradiction. Similarly, we can show $p_{w,1}^* > p_{w,2}^*$ if $X_1^* \leq X_2^*$. Together, these imply that

$$1 = p_{s,1}^* + p_{w,1}^* > p_{s,2}^* + p_{w,2}^* = 1,$$

which is a contradiction.

Next, we show that $x_{s,1}^* > x_{s,2}^*$. It is straightforward to verify that $p_{s,\ell}^* > \frac{1}{2} > p_{w,\ell}^*$ for $\ell \in \{1,2\}$ given $a_s > a_w$. If $p_{s,1}^* \geq p_{s,2}^*$, then $x_{s,1}^* = X_1^* p_{s,1}^* > X_2^* p_{s,2}^* = x_{s,2}^*$. If $p_{s,1}^* < p_{s,2}^*$, then we have that

$$\begin{aligned} x_{s,1}^* c_1'(x_{s,1}^*) = p_{s,1}^* X_1^* c_1'(x_{s,1}^*) &= a_s p_{s,1}^* p_{w,1}^* \\ &> a_s p_{s,2}^* p_{w,2}^* = p_{s,2}^* X_2^* c_2'(x_{s,2}^*) = x_{s,2}^* c_2'(x_{s,2}^*) > x_{s,2}^* c_1'(x_{s,2}^*), \end{aligned}$$

where the first and fourth equalities follow from the definition of $p_{i,\ell}^*$; the second and third equalities from (7); the first inequality from $p_{w,\ell}^* = 1 - p_{s,\ell}^*$ and $p_{s,1}^* < p_{s,2}^*$; and the last inequality from the assumption that $c_2'(x) > c_1'(x)$ for all $x > 0$. The above condition, together with the weak convexity of $c_1(\cdot)$, again implies $x_{s,1}^* > x_{s,2}^*$. This concludes the proof. ■

Proof of Proposition 2

Proof. Fixing $\lambda \in [0,1]$, $\mathcal{C}(x;\lambda) := c_1(x) + \lambda\delta(x) = \lambda c_2(x) + (1-\lambda)c_1(x)$ is an increasing and convex function of x. Denote the equilibrium effort pair under contest $\langle \mathcal{C}(x;\lambda), (a_s, a_w)\rangle$ by $\big(x_s^*(\lambda), x_w^*(\lambda)\big)$.

It is evident that $x_{w,1}^* = x_w^*(0)$ and $x_{w,2}^* = x_w^*(1)$. Further, (7) can be rewritten as follows:

$$\frac{a_s x_w^*(\lambda)}{\left[x_s^*(\lambda) + x_w^*(\lambda)\right]^2} = \frac{\partial \mathcal{C}\left(x_s^*(\lambda);\lambda\right)}{\partial x}, \tag{8}$$

$$\frac{a_w x_s^*(\lambda)}{\left[x_s^*(\lambda) + x_w^*(\lambda)\right]^2} = \frac{\partial \mathcal{C}\left(x_w^*(\lambda);\lambda\right)}{\partial x}. \tag{9}$$

Taking derivative of (8) and (9) with respect to λ yields that

$$(x_w^*)'(\lambda) = \frac{1}{\mathcal{M}}\left\{\frac{\delta'\left(x_s^*(\lambda)\right)\frac{\partial \mathcal{C}\left(x_w^*(\lambda);\lambda\right)}{\partial x}\left[x_s^*(\lambda) - x_w^*(\lambda)\right]}{x_s^*(\lambda)\left[x_s^*(\lambda) + x_w^*(\lambda)\right]} - \delta'\left(x_w^*(\lambda)\right)\left[\frac{\partial^2 \mathcal{C}\left(x_w^*(\lambda);\lambda\right)}{\partial x^2} + \frac{2\frac{\partial \mathcal{C}\left(x_w^*(\lambda);\lambda\right)}{\partial x}}{x_s^*(\lambda) + x_w^*(\lambda)}\right]\right\},$$

where

$$\mathcal{M} := \underbrace{\left[\frac{\partial^2 \mathcal{C}\left(x_w^*(\lambda);\lambda\right)}{\partial x^2} + \frac{2\frac{\partial \mathcal{C}\left(x_w^*(\lambda);\lambda\right)}{\partial x}}{x_s^*(\lambda) + x_w^*(\lambda)}\right]}_{>0} \times \underbrace{\left[\frac{\partial^2 \mathcal{C}\left(x_s^*(\lambda);\lambda\right)}{\partial x^2} + \frac{2\frac{\partial \mathcal{C}\left(x_s^*(\lambda);\lambda\right)}{\partial x}}{x_s^*(\lambda) + x_w^*(\lambda)}\right]}_{>0} + \underbrace{\frac{\frac{\partial \mathcal{C}\left(x_s^*(\lambda);\lambda\right)}{\partial x}\frac{\partial \mathcal{C}\left(x_w^*(\lambda);\lambda\right)}{\partial x}\left[x_s^*(\lambda) - x_w^*(\lambda)\right]^2}{x_s^*(\lambda)x_w^*(\lambda)\left[x_s^*(\lambda) + x_w^*(\lambda)\right]^2}}_{>0} > 0.$$

Therefore, $(x_w^*)'(\lambda) > 0$ is equivalent to

$$\underbrace{\frac{\delta'\left(x_s^*(\lambda)\right)}{\delta'\left(x_w^*(\lambda)\right)} \times \frac{x_s^*(\lambda) - x_w^*(\lambda)}{x_s^*(\lambda) + x_w^*(\lambda)}}_{\mathcal{LHS}} > \underbrace{\frac{x_s^*(\lambda)}{x_w^*(\lambda)} \times \left[\frac{x_w^*(\lambda)\frac{\partial^2 \mathcal{C}\left(x_w^*(\lambda);\lambda\right)}{\partial x^2}}{\frac{\partial \mathcal{C}\left(x_w^*(\lambda);\lambda\right)}{\partial x}} + \frac{2x_w^*(\lambda)}{x_s^*(\lambda) + x_w^*(\lambda)}\right]}_{\mathcal{RHS}}.$$

We first prove part (i) of the proposition. Suppose that $\delta''(x) \leq 0$ for all $x \in [0, \overline{x}]$. Then we can obtain

$$\mathcal{LHS} \leq \frac{x_s^*(\lambda) - x_w^*(\lambda)}{x_s^*(\lambda) + x_w^*(\lambda)} < \frac{2x_s^*(\lambda)}{x_s^*(\lambda) + x_w^*(\lambda)} \leq \mathcal{RHS},$$

where the first two inequalities follow from the weak concavity of $\delta(\cdot)$ and $x_s^*(\lambda) > x_w^*(\lambda) > 0$ and the last inequality from the convexity of $\mathcal{C}(\cdot;\lambda)$. Therefore, $x_w^*(\lambda)$ is decreasing in λ for $\lambda \in [0,1]$, which in turn implies that $x_{w,2}^* = x_w^*(1) < x_w^*(0) = x_{w,1}^*$.

Next, we prove part (ii). For notational convenience, define $k(\lambda) := x_s^*(\lambda)/x_w^*(\lambda) > 1$. Recall

$r_2 := \sup_{x\in[0,\overline{x}],\lambda\in[0,1]} x\frac{\partial^2\mathcal{C}(x;\lambda)}{\partial x^2}\Big/\frac{\partial\mathcal{C}(x;\lambda)}{\partial x}$. Then $\mathcal{RHS}$ can be bounded from above by

$$\mathcal{RHS} \equiv \frac{x_s^*(\lambda)}{x_w^*(\lambda)} \times \left[\frac{x_w^*(\lambda)\frac{\partial^2\mathcal{C}\left(x_w^*(\lambda);\lambda\right)}{\partial x^2}}{\frac{\partial\mathcal{C}\left(x_w^*(\lambda);\lambda\right)}{\partial x}} + \frac{2x_w^*(\lambda)}{x_s^*(\lambda)+x_w^*(\lambda)} \right] \leq k(\lambda) \times \left(r_2 + \frac{2}{k(\lambda)+1} \right). \tag{10}$$

Further, it follows from $\frac{\partial^2\mathcal{C}(x;\lambda)}{\partial x^2}\Big/\frac{\partial\mathcal{C}(x;\lambda)}{\partial x} \leq r_2/x$ for $x \in \left[x_w^*(\lambda), x_s^*(\lambda)\right]$ that

$$\begin{aligned}\ln\left(\frac{\partial\mathcal{C}(x_s^*(\lambda);\lambda)}{\partial x}\right) - \ln\left(\frac{\partial\mathcal{C}(x_w^*(\lambda);\lambda)}{\partial x}\right) &= \int_{x_w^*(\lambda)}^{x_s^*(\lambda)} \frac{\frac{\partial^2\mathcal{C}(x;\lambda)}{\partial x^2}}{\frac{\partial\mathcal{C}(x;\lambda)}{\partial x}} dx \\ &\leq \int_{x_w^*(\lambda)}^{x_s^*(\lambda)} \frac{r_2}{x} dx = r_2\left[\ln\left(x_s^*(\lambda)\right) - \ln\left(x_w^*(\lambda)\right)\right].\end{aligned}$$

The above inequality, together with (8) and (9), implies that

$$\frac{a_s}{a_w} = \frac{x_s^*(\lambda)}{x_w^*(\lambda)} \times \frac{\frac{\partial\mathcal{C}\left(x_s^*(\lambda);\lambda\right)}{\partial x}}{\frac{\partial\mathcal{C}\left(x_w^*(\lambda);\lambda\right)}{\partial x}} \leq \left[\frac{x_s^*(\lambda)}{x_w^*(\lambda)}\right]^{r_2+1} \implies k(\lambda) \geq \left(\frac{a_s}{a_w}\right)^{\frac{1}{r_2+1}}. \tag{11}$$

By the same argument, we can obtain

$$\frac{\delta'\left(x_s^*(\lambda)\right)}{\delta'\left(x_w^*(\lambda)\right)} \geq \left[k(\lambda)\right]^{r_1},$$

where $r_1 := \inf_{x\in[0,\overline{x}]} x\delta''(x)/\delta'(x)$. Therefore, $\mathcal{LHS}$ can be bounded from below by

$$\mathcal{LHS} \equiv \frac{\delta'\left(x_s^*(\lambda)\right)}{\delta'\left(x_w^*(\lambda)\right)} \times \frac{x_s^*(\lambda)-x_w^*(\lambda)}{x_s^*(\lambda)+x_w^*(\lambda)} \geq \left[k(\lambda)\right]^{r_1} \times \frac{k(\lambda)-1}{k(\lambda)+1}. \tag{12}$$

Combining (10) and (12), we can obtain that

$$\begin{aligned}\mathcal{RHS} - \mathcal{LHS} &\leq k(\lambda) \times \left(r_2 + \frac{2}{k(\lambda)+1}\right) - \left[k(\lambda)\right]^{r_1} \times \frac{k(\lambda)-1}{k(\lambda)+1} \\ &= k(\lambda) \times \left[\left(r_2 + \frac{2}{k(\lambda)+1}\right) - \left[k(\lambda)\right]^{r_1-1} \times \frac{k(\lambda)-1}{k(\lambda)+1}\right] \\ &\leq k(\lambda) \times \underbrace{\left[\left(r_2 + \frac{2}{\left(\frac{a_s}{a_w}\right)^{\frac{1}{r_2+1}}+1}\right) - \left(\frac{a_s}{a_w}\right)^{\frac{r_1-1}{r_2+1}} \times \frac{\left(\frac{a_s}{a_w}\right)^{\frac{1}{r_2+1}}-1}{\left(\frac{a_s}{a_w}\right)^{\frac{1}{r_2+1}}+1}\right]}_{\mathcal{G}},\end{aligned}$$

where the last inequality follows from $r_1 \geq 1$ and (11). Carrying out the algebra, $\mathcal{G} < 0$ is equivalent to

$$\left(\frac{a_s}{a_w}\right)^{\frac{r_1-1}{r_2+1}}\left[\left(\frac{a_s}{a_w}\right)^{\frac{1}{r_2+1}} - 1\right] > r_2\left(\frac{a_s}{a_w}\right)^{\frac{1}{r_2+1}} + r_2 + 2,$$

which corresponds to (6) required in part (ii) of the proposition. To summarize, if $r_1 \geq 1$ and (6) is satisfied, then $(x_w^*)'(\lambda) > 0$ for all $\lambda \in [0,1]$, which in turn implies that $x_{w,2}^* = x_w^*(1) > x_w^*(0) = x_{w,1}^*$ and concludes the proof. ■

Proof of Proposition 3

Proof. Recall $\mathcal{C}(x;\lambda) := c_1(x) + \lambda\delta(x)$ and that we denote the equilibrium effort pair under contest $\langle \mathcal{C}(x;\lambda), (a_s, a_w)\rangle$ by $\big(x_s^*(\lambda), x_w^*(\lambda)\big)$ in the proof of Proposition 2. For notational convenience, denote the resultant total effort and the corresponding equilibrium winning probabilities by $X^*(\lambda)$ and $\big(p_s^*(\lambda), p_w^*(\lambda)\big)$, respectively. The first-order conditions (8) and (9) can be rewritten as follows:

$$a_s p_w^*(\lambda) = X^*(\lambda)\frac{\partial \mathcal{C}\left(X^*(\lambda)p_s^*(\lambda);\lambda\right)}{\partial x},$$
$$a_w p_s^*(\lambda) = X^*(\lambda)\frac{\partial \mathcal{C}\left(X^*(\lambda)p_w^*(\lambda);\lambda\right)}{\partial x}.$$

Taking derivative of the above two equations with respect to λ and exploiting the fact that $dp_s^*(\lambda)/d\lambda = -dp_w^*(\lambda)/d\lambda$, we can obtain that

$$\frac{dp_s^*(\lambda)}{d\lambda} = \frac{X^*(\lambda)\delta'\left(x_s^*(\lambda)\right)\delta'\left(x_w^*(\lambda)\right)\left[\psi\left(x_s^*(\lambda);\lambda\right) - \psi\left(x_w^*(\lambda);\lambda\right)\right]}{\mathcal{Q}},$$

where

$$\mathcal{Q} := \underbrace{\left\{a_w + \left[X^*(\lambda)\right]^2 \times \frac{\partial^2 \mathcal{C}(x_w^*(\lambda);\lambda)}{\partial x^2}\right\}}_{>0}\underbrace{\psi\left(x_s^*(\lambda);\lambda\right)}_{>0}\underbrace{\delta'\left(x_s^*(\lambda)\right)}_{>0}$$
$$+\underbrace{\left\{a_s + \left[X^*(\lambda)\right]^2 \frac{\partial^2 \mathcal{C}(x_s^*(\lambda);\lambda)}{\partial x^2}\right\}}_{>0}\underbrace{\psi\left(x_w^*(\lambda);\lambda\right)}_{>0}\underbrace{\delta'\left(x_w^*(\lambda)\right)}_{>0} > 0.$$

Therefore, $dp_s^*(\lambda)/d\lambda > 0$ is equivalent to

$$\psi\left(x_s^*(\lambda);\lambda\right) > \psi\left(x_w^*(\lambda);\lambda\right).$$

Suppose that $\psi(x;\lambda)$ strictly increases with x for all $\lambda \in [0,1]$. It follows immediately from $x_s^*(\lambda) > x_w^*(\lambda)$ that $\psi\left(x_s^*(\lambda);\lambda\right) > \psi\left(x_w^*(\lambda);\lambda\right)$ and thus $dp_s^*(\lambda)/d\lambda > 0$. Therefore, we can obtain that $p_{s,2}^* = p_s^*(1) > x_s^*(0) = p_{s,1}^*$. Similarly, we can show $p_{s,2}^* < p_{s,1}^*$ if $\psi(x;\lambda)$ strictly decreases with x for all $\lambda \in [0,1]$. This concludes the proof. ■

Appendix C Multiple Players on Each Team

In the baseline model, we assume that a representative player acts on behalf of each team. Next, we extend the model to allow for multiple players within a team and show that all of our results continue to hold. To distinguish between the two settings, we call the former an individual contest and the latter a group contest.

Suppose that each team has $n \geq 2$ identical individual players. The players on team $i \in \{s,w\}$ are indexed by $ij \in \{i1,\ldots,in\}$. Players in both teams simultaneously and independently choose effort levels $x_{ij} \geq 0$. The cost of effort x_{ij} to player ij is $\tilde{c}(x_{ij})/\tilde{a}_i$, where $\tilde{a}_i > 0$ represents the team's ability and $\tilde{c}(\cdot)$ is a strictly increasing and weakly convex function with $\tilde{c}(0) = 0$. The value an individual player receives from winning the contest is again normalized to unity.

Following Kolmar and Rommeswinkel (2013); Brookins et al. (2018); and Crutzen et al. (2020), we assume that the probability of team $i \in \{s, w\}$ winning the contest given the effort profile $(\boldsymbol{x}_s, \boldsymbol{x}_w) := \langle (x_{s1}, \ldots, x_{sn}), (x_{w1}, \ldots, x_{wn}) \rangle$ is

$$\tilde{p}_i(\boldsymbol{x}_s, \boldsymbol{x}_w) = \begin{cases} \widetilde{\mathcal{X}}_i / (\widetilde{\mathcal{X}}_s + \widetilde{\mathcal{X}}_w) & \text{if } \widetilde{\mathcal{X}}_s + \widetilde{\mathcal{X}}_w > 0, \\ 1/2 & \text{if } \widetilde{\mathcal{X}}_s + \widetilde{\mathcal{X}}_w = 0, \end{cases}$$

where $\widetilde{\mathcal{X}}_i$ is given by the constant elasticity of substitution (CES) aggregation function of the efforts exerted by individual team members. That is,[38]

$$\widetilde{\mathcal{X}}_i := \left(\frac{1}{n} \sum_{j=1}^{n} x_{ij}^{\rho} \right)^{1/\rho}, \text{ for } i \in \{s, w\}, \text{ with } \rho < 1.$$

The parameter $1 - \rho$ measures the degree of complementarity between individual efforts within a team.

The expected payoff of player ij is

$$\tilde{\pi}_{ij}(\boldsymbol{x}_s, \boldsymbol{x}_w) := \tilde{p}_i(\boldsymbol{x}_s, \boldsymbol{x}_w) - \tilde{c}(x_{ij})/\tilde{a}_i, i \in \{s, w\}, j \in \{1, \ldots, n\}.$$

The function $\tilde{c}(\cdot)$, together with teams' ability profile $(\tilde{a}_s, \tilde{a}_w)$ and the number of players in each team $n \geq 2$, defines a simultaneous-move group contest game, which we denote by $\langle \tilde{c}(\cdot), (\tilde{a}_s, \tilde{a}_w), n \rangle$. Denote player ij's equilibrium effort by $\tilde{x}_{ij}^*$. Recall that the individual contest game analyzed in the main text is denoted by $\langle c(\cdot), (a_s, a_w) \rangle$. The following result ensues.

Proposition 4 *There exists a unique pure-strategy equilibrium of the group contest game* $\langle \tilde{c}(\cdot), (\tilde{a}_s, \tilde{a}_w), n \rangle$, *in which all individual players on each team remain active and exert the same amount of effort—i.e.,* $\tilde{x}_{i1}^* = \cdots = \tilde{x}_{in}^* =: \tilde{x}_i^* > 0$ *for* $i \in \{s, w\}$. *Furthermore,* $\tilde{x}_i^* = x_i^*$ *for* $i \in \{s, w\}$, *where* x_i^* *is the equilibrium effort of team* i *under the individual contest* $\langle c(\cdot), (a_s, a_w) \rangle = \langle \tilde{c}(x), (\tilde{a}_s/n, \tilde{a}_w/n) \rangle$.

Proof. We first show that all individual players must exert the same amount of effort in equilibrium. Fix two arbitrary players ij and ij', with $i \in \{s, w\}$, $j, j' \in \{1, \ldots, n\}$, and $j \neq j'$. It is straightforward to verify that an individual player must remain active in equilibrium. Therefore, the following first-order conditions must be satisfied in equilibrium:

$$\frac{\tilde{a}_i \left(\widetilde{\mathcal{X}}_s + \widetilde{\mathcal{X}}_w - \widetilde{\mathcal{X}}_i \right)}{\left(\widetilde{\mathcal{X}}_s + \widetilde{\mathcal{X}}_w \right)^2} \times \left. \frac{\partial \widetilde{\mathcal{X}}_i}{\partial \tilde{x}_{ij}} \right|_{\tilde{x}_{ij} = \tilde{x}_{ij}^*} = \tilde{c}'(\tilde{x}_{ij}^*), \tag{13}$$

and

$$\frac{\tilde{a}_i \left(\widetilde{\mathcal{X}}_s + \widetilde{\mathcal{X}}_w - \widetilde{\mathcal{X}}_i \right)}{\left(\widetilde{\mathcal{X}}_s + \widetilde{\mathcal{X}}_w \right)^2} \times \left. \frac{\partial \widetilde{\mathcal{X}}_i}{\partial \tilde{x}_{ij'}} \right|_{\tilde{x}_{ij'} = \tilde{x}_{ij'}^*} = \tilde{c}'(\tilde{x}_{ij'}^*), \tag{14}$$

Suppose, to the contrary, that $\tilde{x}_{ij}^* \neq \tilde{x}_{ij'}^*$. Without loss of generality, assume $\tilde{x}_{ij}^* > \tilde{x}_{ij'}^*$. It can

38. See also Ray et al. (2007) and Cornes and Hartley (2007) for the use of CES production functions.

then be verified that $\partial\widetilde{\mathcal{X}}_i/\partial\tilde{x}_{ij}|_{\tilde{x}_{ij}=\tilde{x}^*_{ij}} < \partial\widetilde{\mathcal{X}}_i/\partial\tilde{x}_{ij'}|_{\tilde{x}_{ij'}=\tilde{x}^*_{ij'}}$ and $\tilde{c}'(\tilde{x}^*_{ij}) \geq \tilde{c}'(\tilde{x}^*_{ij'})$, from which we can obtain

$$\tilde{c}'(\tilde{x}^*_{ij})\Big/\frac{\partial\widetilde{\mathcal{X}}_i}{\partial\tilde{x}_{ij}}\Big|_{\tilde{x}_{ij}=\tilde{x}^*_{ij}} > \tilde{c}'(\tilde{x}^*_{ij'})\Big/\frac{\partial\widetilde{\mathcal{X}}_i}{\partial\tilde{x}_{ij'}}\Big|_{\tilde{x}_{ij'}=\tilde{x}^*_{ij'}}. \tag{15}$$

However, combining (13) and (14) yields that

$$\tilde{c}'(\tilde{x}^*_{ij})\Big/\frac{\partial\widetilde{\mathcal{X}}_i}{\partial\tilde{x}_{ij}}\Big|_{\tilde{x}_{ij}=\tilde{x}^*_{ij}} = \tilde{c}'(\tilde{x}^*_{ij'})\Big/\frac{\partial\widetilde{\mathcal{X}}_i}{\partial\tilde{x}_{ij'}}\Big|_{\tilde{x}_{ij'}=\tilde{x}^*_{ij'}},$$

which contradicts (15). Therefore, we must have $\tilde{x}^*_{ij} = \tilde{x}^*_{ij'}$.

Next, substituting $\tilde{x}^*_i := \tilde{x}^*_{i1} = \cdots = \tilde{x}^*_{in}$ into (13) or (14) yields that

$$\frac{\tilde{a}_i}{n} \times \frac{\tilde{x}^*_s + \tilde{x}^*_w - \tilde{x}^*_i}{(\tilde{x}^*_s + \tilde{x}^*_w)^2} = \tilde{c}'(\tilde{x}^*_i), \text{ for } i \in \{s, w\}. \tag{16}$$

Note that the equilibrium effort of team i in the baseline model in the main text is governed by

$$a_i \times \frac{x^*_s + x^*_w - x^*_i}{(x^*_s + x^*_w)^2} = \tilde{c}'(x^*_i), \text{ for } i \in \{s, w\}. \tag{17}$$

Comparing (16) and (17), it is straightforward to see that $\tilde{x}^*_i = x^*_i$ for $i \in \{s, w\}$, where x^*_i in the equilibrium effort of team i under individual contest $\langle c(\cdot), (a_s, a_w)\rangle = \langle \tilde{c}(x), (\tilde{a}_s/n, \tilde{a}_w/n)\rangle$. This concludes the proof. ■

By Proposition 4, the results established under individual contests in the main text remain intact under group contests in which each team consists of two or more homogeneous players.

Appendix D Linear Quadratic Effort Cost

Example 1 ***(Linear Quadratic Effort Cost)*** *Suppose that the two teams are heterogeneous—i.e., $a_s > a_w$—and the $c_\ell(\cdot)$ function takes the form $c_\ell(x) = \alpha_\ell x + \beta_\ell \frac{x^2}{2}$, with $\alpha_2 \geq \alpha_1 \geq 0$, $\beta_2 \geq \beta_1 \geq 0$, and $\ell \in \{1, 2\}$. The following statements hold:*

- *(i) Suppose that $\alpha_2 > \alpha_1 = 0$ and $\beta_2 = \beta_1 > 0$. In other words, we start with a quadratic $c_1(\cdot)$ function and add a linear component to obtain $c_2(\cdot)$. Then $\delta(x) = (\alpha_2 - \alpha_1)x$ is linear and thus $\delta''(x) = 0$. By Proposition 2(i), we can obtain $x^*_{w,1} > x^*_{w,2}$.*
- *(ii) Suppose that $\alpha_2 = \alpha_1 > 0$ and $\beta_2 > \beta_1 = 0$. That is, we start with a linear $c_1(\cdot)$ function and add a quadratic term to obtain $c_2(\cdot)$. Then $\delta(x) = (\beta_2 - \beta_1)\frac{x^2}{2}$ is convex and $\overline{x} = a_s$, from which we can obtain $r_1 = \inf_{x\in[0,\overline{x}]} x\delta''(x)/\delta'(x) = 1$ and $r_2 = \sup_{x\in[0,a_s],\lambda\in[0,1]} \frac{\beta_2\lambda x}{\alpha_2+\beta_2\lambda x} = \frac{\beta_2 a_s}{\alpha_2+\beta_2 a_s}$. Note that r_2 degenerates to zero as β_2 approaches zero. With slight abuse of notation, denote the equilibrium effort profile under $c_2(\cdot) = \alpha_2 x + \beta_2\frac{x^2}{2}$ by $\big(x^*_s(\beta_2), x^*_w(\beta_2)\big)$. It follows immediately that $x^*_{w,1} = x^*_w(0)$ and $x^*_{w,2} = x^*_w(\beta_2)$. We can show that $(x^*_w)'(0) > 0$ if and only if $a_s/a_w > 3$.*

Proof. First-order conditions (8) and (9) can be expressed as follows:

$$\frac{a_s x^*_w(\beta_2)}{\big[x^*_s(\beta_2) + x^*_w(\beta_2)\big]^2} = \alpha + \beta_2 x^*_s(\beta_2), \tag{18}$$

$$\frac{a_w x_s^*(\beta_2)}{\left[x_s^*(\beta_2)+x_w^*(\beta_2)\right]^2}=\alpha+\beta_2 x_w^*(\beta_2). \tag{19}$$

Next, we show that $(x_w^*)'(0)>0$ if and only if $a_s/a_s>3$.

Substituting $\beta_2=0$ into (18) and (19) yields that

$$\frac{a_s x_w^*(0)}{\left[x_s^*(0)+x_w^*(0)\right]^2}=\alpha, \tag{20}$$

$$\frac{a_w x_s^*(0)}{\left[x_s^*(0)+x_w^*(0)\right]^2}=\alpha. \tag{21}$$

Taking the derivatives of (18) and (19) with respect to β_2 at $\beta_2=0$ yields that

$$\frac{a_s x_w^*(0)}{\left[x_s^*(0)+x_w^*(0)\right]^2}\times\left\{\frac{(x_w^*)'(0)}{x_w^*(0)}-\frac{2\left[(x_s^*)'(0)+(x_w^*)'(0)\right]}{x_s^*(0)+x_w^*(0)}\right\}=x_s^*(0), \tag{22}$$

$$\frac{a_w x_w^*(0)}{\left[x_w^*(0)+x_w^*(0)\right]^2}\times\left\{\frac{(x_s^*)'(0)}{x_s^*(0)}-\frac{2\left[(x_s^*)'(0)+(x_w^*)'(0)\right]}{x_s^*(0)+x_w^*(0)}\right\}=x_w^*(0). \tag{23}$$

Combining (20), (21), (22), and (23), we have that

$$\frac{(x_w^*)'(0)}{x_w^*(0)}-\frac{2\left[(x_s^*)'(0)+(x_w^*)'(0)\right]}{x_s^*(0)+x_w^*(0)}=\frac{x_s^*(0)}{\alpha},$$

$$\frac{(x_s^*)'(0)}{x_s^*(0)}-\frac{2\left[(x_s^*)'(0)+(x_w^*)'(0)\right]}{x_s^*(0)+x_w^*(0)}=\frac{x_w^*(0)}{\alpha},$$

from which we can obtain that

$$(x_w^*)'(0)=\frac{x_s^*(0)x_w^*(0)\left[x_s^*(0)-3x_w^*(0)\right]}{\alpha\left[x_s^*(0)+x_w^*(0)\right]}.$$

Note that $x_s^*(0)/x_w^*(0)=a_s/a_w$ from (20) and (21). Therefore, $(x_w^*)'(0)>0$ if and only if $x_s^*(0)/x_w^*(0)>3$, which is equivalent to $a_s/a_w>3$. This concludes the proof. ■

Next, we demonstrate how the conditions established in Proposition 3 translate into the parameters of the linear quadratic effort cost function. Simple algebra would verify

$$\psi(x;\lambda)=\frac{\frac{\partial\mathcal{C}(x;\lambda)}{\partial x}+x\frac{\partial^2\mathcal{C}(x;\lambda)}{\partial x^2}}{\delta'(x)}=\frac{\left[\alpha_1+\lambda(\alpha_2-\alpha_1)\right]+2\left[\beta_1+\lambda(\beta_2-\beta_1)\right]x}{(\alpha_2-\alpha_1)+(\beta_2-\beta_1)x}.$$

Example 1 ***(Continued, Linear Quadratic Effort Cost)*** *The following statements hold:*

(i) Suppose that $\alpha_2>\alpha_1=0$ and $\beta_2=\beta_1>0$. Then $\psi(x;\lambda)=\left(\frac{\alpha_1}{\alpha_2-\alpha_1}+\lambda\right)+\frac{2\beta_1}{\alpha_2-\alpha_1}x$, which strictly increases with x. By Proposition 3(i), we have that $p_{s,1}^*<p_{s,2}^*$.

(ii) Suppose that $\alpha_2=\alpha_1>0$ and $\beta_2>\beta_1=0$. Then $\psi(x;\lambda)=2\left(\frac{\beta_1}{\beta_2-\beta_1}+\lambda\right)+\frac{\alpha_1}{(\beta_2-\beta_1)x}$, which strictly decreases with x. By Proposition 3(ii), we have that $p_{s,1}^*>p_{s,2}^*$.

Appendix E Background and Game Mechanics of LoL

E.1 The ESports Industry

ESports is a rapidly growing form of video game-based team sports in a professional competitive tournament setting. In general, competitors play video games while being watched by a live audience as well as millions more online. The global eSports audience reached 474 million in 2021, and is expected to reach 577 million in 2024. Goldman Sachs predicts that by 2022, the market for eSports will be $2.96 billion,[39] which has already exceeded those of several traditional sports markets, including Major League Baseball (MLB) and the National Basketball Association (NBA). The prize money in top eSports tournaments is also comparable to traditional sports. The most viewed tournament, the International 2019—which took place in Shanghai—has a total prize pool of $34.3 million.[40] China is the leading market for eSports, grossing a total of $360 million in 2021, owing to the popularity of eSports among millennial youth and government support.[41] The United States is the second largest eSports market, with total revenues at $243 million in 2021, followed by Western Europe at $206 million.

Compared with traditional sports, eSports has its fair share of professional players, commentators, and celebrities. Leading players, like their more traditional star athlete counterparts, become LeBron-like superstars to digital native millennial audiences that find them more directly relatable. According to a recent report by Forbes, League of Legends superstar Faker, for example, makes more than $2 million annually—and that number does not include sponsorship revenues.

E.2 LoL Game Mechanics

E.2.1 Overview

League of Legends (LoL) is a multiplayer online battle arena (MOBA) game. Like other eSports games and traditional sports, LoL has a clear game objective and well-defined rules. Two teams of five players compete against each other. A team wins when the opponent's homebase is destroyed or when the opponent surrenders. The match sets no fixed time limit, but is very fast paced. In our data of top-tier tournament matches, a match lasts 33 mins on average, and ranges from 16 mins to 68 mins.

At the beginning of the game, each player takes turns selecting their champion (avatar), which has unique abilities and base statistics such as health, speed, and strength. The roster of champions is balanced in the sense that each champion has strengths and weaknesses, and may counter certain champions and be countered. Upon finishing champion selection, all champions are placed on a large symmetrical map, called the Summoner's Rift, and the competition begins.

E.2.2 The Battle Map

Figure B1 shows the map layout and basic game mechanics. All champions spawn—and respawn if killed—in their team's homebase; the homebases are located at the opposing corners of the map

39. See the Goldman Sachs report entitled "ESports: From Wild West to Mainstream" at https://www.goldmansachs.com/insights/pages/infographics/e-sports/report.pdf.

40. The NBA Championship has a total prize pool of $13 million in 2018, Masters (golf) $11 million, Tour de France $2.8 million, Melbourne Cup $6.2 million, and Confederations Cup $20 million.

41. For example, Hangzhou, the capital of Zhejiang Province in Eastern China, plans to build 14 eSports facilities before 2022 and is expected to invest up to RMB 15.5 billion (USD 2.22 billion). This investment is expected to make it the eSports capital of the world. Moreover, Hangzhou is going to host the Asian Games in 2022, in which eSports is already an official medal event.

and are defended by turrets and AI-controlled minions.

The map has three lanes: a top lane, a middle diagonal lane, and a bottom lane. They separately cut through the top, middle, and bottom portions of the map. Moreover, each of the lanes is home to a specific type of champion: Although this is not required, the game has developed an almost universal metagame, and now most team tactics have agreed on which champion type is prioritized for each lane.

In between these lanes is a jungle full of neutral monsters. Players kill the opposing team's champions, minions, and neutral monsters to earn gold that can be used to purchase in-game items to boost their champion's abilities and other aspects of gameplay.

E.2.3 Role of Champion

The LoL game community has developed an almost universal metagame for each role of the team. The five team members fall into five roles: top-laner, attack damage carry (ADC), support, jungler, and mid-laner. The top-laner is the solo defensive player of the team who holds against the high-powered attack duo from the enemy's bottom lane. The bottom lane usually consists of two players, the ADC and the support. The ADC is essentially the firepower of the team, but is also the most vulnerable one. The support is ADC's safety guard, providing him with healing and shields and setting up kills. The jungler is the assassin; she plays in the jungle rather than in any lane, killing neutral monsters, and hiding and waiting for the opportunity to pop into a lane to give his teammates a competitive edge over the opposing team. The mid-laner is the do-it-all member of the team, and generally plays solo in the early game but is prepared to help the other lanes if the jungler is dead or preoccupied.

E.2.4 Phases of Game

A game is split into two phases, a preparation phase when teams choose active players and players choose champions, and a competition phase when the competition begins.

The Preparation Phase This is the pre-match phase. Teams first decide on the roster of five active players. Then, players from both teams take turns banning and picking champions. Each player can choose to ban one champion (5 bans per team) from the champion pool before picking their own champion. In professional matches in which teams are familiar with each other, champions that rival players can play exceptionally well are strategically banned to deter the pick. Players may also pick a champion not for their own good, but to secure it for their teammates, or simply prevent it from being picked by the rival team. Each team is allowed to swap champions between teammates at the end of the preparation phase. Considering that champions have different skills, some of which counter other champions or have been countered, this makes the banning and picking of champions extremely strategic in this pre-match phase. After the picking is finished, team members have a chance to swap champions with teammates before heading into competition.

The Competition Phase At the beginning of the competition phase, players enter their designated lanes or areas, battle against their opponent counterparts, kill enemy minions for gold, and try to get an advantage over the enemy laners when possible. Junglers run around to help their laners; they also reconnoitre the map so that their team can have a better idea of what the enemy is doing. At this point, players are weaker than the defensive turrets on the map so that it is hard for either them to push into the enemy's territory.

After players have grown stronger and the first few turrets have been taken down, the mid-game tends to revolve around the two major neutral monsters—the Drakes and the Baron, both of which reward massive gold and team perks. Teams often fight over these mid-game objectives as five-man units, trying to both deny these monsters to the enemy and win them for themselves.

In the late game, most champions have reached their maximum strength and the game becomes one of cat-and-mouse. Even a small mistake can lead to a near-instant victory for the enemy. As such, the late game is spent mostly trying to gain more vision around the map in an attempt to catch enemies or to sneak a kill on the Baron without enemy interference.

E.3 LoL Tournaments in China

The League of Legends Pro League (LPL) is the top-tier LoL professional tournament in China and the world's largest professional LOL tournament. The first season of LPL was in 2013. Since then, each year hosts two tournament seasons, in spring and summer. Each LPL season has regular-season games and playoffs, and the format is similar to other popular sports events such as the NBA. In the regular season, all teams compete in a single round robin—i.e., each team competes against all other teams in turn. Matches are all best of three and the winner takes one point. Top teams from the regular season advance to the playoffs. Playoff matches are best of five. Teams compete by elimination. The final winner takes about 40% of the prize pool, which totaled 3.5 million RMB in the 2019 summer season. Overall, the LPL tournament is held in a format similar to other competitive leagues such as the NBA and NFL. We collect game statistics from all matches of LPL regular seasons and playoffs from 2017 to 2021.

The list of host cities is determined prior to the regular season. Three to five cities jointly host each season. From 2017 to 2021, 11 cities have hosted the tournament. Shanghai has hosted most LPL tournament games so far (64%). Appendix Table A1 tabulates the number of matches hosted by different cities. The tournament schedule is also predetermined, including both the match date and the pairing of teams. The spring season starts in January and the summer season in June, and both last about 10 weeks.

All regular season and playoff matches are hosted in large indoor stadiums. We collect the location of the hosting stadiums and match them to the nearest national air pollution monitoring stations. All stadiums have standard temperature control systems. However, air pollutants, and PM2.5 in particular, exchanged between outdoor and indoor environments are not filtered. The environmental literature documents that PM2.5 penetrate indoors, with an indoor-outdoor ratio ranging from 0.6 to 0.9 (Huang et al., 2007; Chen and Zhao, 2011; Nadali et al., 2020). We use the level of hourly reported outdoor PM2.5 from the nearest national monitoring stations as the proxy for the level of indoor PM2.5 players were exposed to during the game.

Appendix F Tables

TABLE A1
Number of Historical Matches Held and Homebase of Teams Across Cities

	(1)	(2)		(3)	(4)
Host City	Num. Matches	Share	HomeBase City	Num. Teams	Share
Shanghai	1,689	64.03	Shanghai	12	44.44
Hangzhou	212	8.04	Beijing	3	11.11
Beijing	203	7.70	Wuhan	3	11.11
Xi'an	128	4.85	Shenzhen	2	7.41
Chongqing	126	4.78	Suzhou	2	7.41
Chengdu	120	4.55	Guangzhou	1	3.7
Suzhou	76	2.88	Chengdu	1	3.7
Shenzhen	53	2.01	Hangzhou	1	3.7
Nanjing	16	0.61	Xi'an	1	3.7
Guangzhou	12	0.45	Chongqing	1	3.7
Foshan	3	0.11			
Total	816	100	Total	27	100

Notes: This table presents the total number of historical LPL matches held and homebase of teams across cities during the sample period from 2017 to 2021 (10 spring seasons and 10 summer seasons).

TABLE A2
Summary Statistics for Player Performance

Variable	(1) Mean	(2) S.D.	(3) Min	(4) Max
Panel A: Measures of Player Decision in Competition Phase				
Win	0.50	0.50	0	1
Kill	2.54	2.48	0	18
Assist	6.01	4.17	0	30
Death	2.54	1.79	0	13
Gold	11,839	3,556	3,311	40,511
Kill per 10 min.	0.79	0.78	0	6.79
Assist per 10 min.	1.85	1.31	0	11.73
Gold per 10 min.	3,607	811	1,737	6,526
Panel B: Measures of Player Decision in Preparation Phase				
Decision time (sec.)	17.74	8.39	0	30
Frequency of pick-and-switch	0.64	1.63	0	28
Using less frequent champion	0.09	0.29	0	1

Notes: This table presents summary statistics of performance metrics at player level. Panel A presents the post-game statistics at the competition phase; Panel B presents the pre-game statistics at the preparation phase. See variable definitions in Table 1.

TABLE A3
Average Effects of PM2.5 on Player Performance

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Total			Per 10 Mins	
	Win	Kill	Assist	Gold	Kill	Assist	Gold
$PM2.5$	-0.001	-0.007	-0.035***	-28.182***	-0.000	-0.006	-1.871
	(0.002)	(0.007)	(0.013)	(8.896)	(0.002)	(0.004)	(1.713)
Player FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Champion FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Role FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
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	26,090	26,090	26,090	26,090	26,090	26,090	26,090
R-squares	0.229	0.304	0.263	0.502	0.308	0.279	0.710

Notes: This table presents the average effects of the level of PM2.5 on metrics of competitive performance of individual player. The dependent variable is the indicator for winning (Column 1), the total amount of kills, assists, and gold (Columns 2-4), and their per-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 near the match stadium. The player-level regressions across columns control for player fixed effects, champion fixed effects, role-of-team fixed effects, team pair fixed effects, match-type fixed effects, city-by-year-by-month fixed effects, and day-of-week and public holiday fixed effects. Robust standard errors in parentheses are clustered at player-by-season level. *** p <0.01, ** p <0.05, * p <0.1.

TABLE A4
Correlation of Measures of Team's Competitiveness

Panel A: Correlation of Competitiveness Index

	Competitiveness (Model 1)	Competitiveness (Model 2)	Competitiveness (Model 3)
Competitiveness (Model 1)	1		
Competitiveness (Model 2)	0.9955	1	
Competitiveness (Model 3)	0.7231	0.7087	1

Panel B: Correlation of Team Ranking based on Competitiveness Index

	Team Rank (Model 1)	Team Rank (Model 2)	Team Rank (Model 3)
Team Rank (Model 1)	1		
Team Rank (Model 2)	1	1	
Team Rank (Model 3)	0.8516	0.8516	1

Notes: This table presents the correlation of measures of team's relative competitiveness (Panel A) and the correlation of indicators for the stronger team, defined as the team's competitiveness being higher than the sample median (Panel B). Model 1 computes the competitiveness using each team's average winning rate in all regular-season games. Model 2 computes the competitiveness as the computed team fixed effect ($\hat{\delta}_i$) from regressing $Win_{ijct} = \delta_i + \eta_j + City_c + Year_t + Month_t + \mu_{ijct}$. Model 3 computes the competitiveness as the computed team fixed effect ($\hat{\delta}_i$) using Equation (3). See Equation (3) for discussion of the three models.

TABLE A5
Effects of PM2.5 on Teams' Performance Gap

	(1)	(2)	(3)	(4)	(5)	(6)
	Gap in total			Gap in every 10 mins		
	Kill	Assist	Gold	Kill	Assist	Gold
$PM2.5$	0.100**	0.182*	74.350*	0.038**	0.073*	30.520*
	(0.049)	(0.109)	(43.146)	(0.018)	(0.040)	(16.958)
Team-Pair FE	Yes	Yes	Yes	Yes	Yes	Yes
Match-Type FE	Yes	Yes	Yes	Yes	Yes	Yes
City×Year and Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-Week and Holiday FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,611	2,611	2,611	2,611	2,611	2,611
R-squares	0.139	0.133	0.159	0.160	0.141	0.155
Mean of Gaps	9.17	23.80	10265.8	3.01	7.71	3330.5

Notes: This table presents the effects of PM2.5 on teams' performance gap. The dependent variable is the absolute difference in measures of competitive performance between teams in a matchup, including the total number of kills, assists, and gold in a match (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 and month fixed effects, and day-of-week and public holiday fixed effects. Further details are specified in Equation (2). Robust standard errors in parentheses are clustered at team-pair level. *** p <0.01, ** p <0.05, * p <0.1.

TABLE A6
Distributional Effects of PM2.5 on Multiple Kills

	(1) Any multiple kills	(2) Number of multiple kills	(3) Share of multiple kills in total kills
$PM2.5$	-0.0057	-0.0736*	-0.0030
	(0.0050)	(0.0377)	(0.0024)
$PM2.5 \times Rel.Strong$	0.0100*	0.1169***	0.0046*
	(0.0058)	(0.0408)	(0.0027)
Team-pair FE	Yes	Yes	Yes
Match-Type FE	Yes	Yes	Yes
City×Year×Month FE	Yes	Yes	Yes
Day-of-Week and Holiday FE	Yes	Yes	Yes
Observations	5,222	5,222	5,194
R-squares	0.1679	0.1696	0.1498
Mean Dep. Var.	0.663	3.926	0.251

Notes: This table presents the distributional effects of PM2.5 on team's likelihood of achieving multiple kills in competition. The dependent variable is the indicator of multiple kills (Column 1), the number of multiple kills (Columns 2-4), and the share of multiple kills in total number of kills (Column 3). $PM2.5$ 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. Team's competitiveness is computed as the team fixed effects from Equation (3). Further details are specified in Section 3.2. Robust standard errors in parentheses are clustered at team-by-season level. *** p <0.01, ** p <0.05, * p <0.1.

TABLE A7
Effects of PM2.5 on the Prediction Accuracy of Match Outcome

	(1)	(2)	(3)	(4)	(5)	(6)
	Predicted outcome being the same as actual outcome					
	Prediction by Quantile Ranking			Prediction by Competitiveness Index		
	Full Sample	Exclude Same Quantiles	Same Quantiles	Full Sample	Exclude Similar Competitiveness	Similar Competitiveness
$PM2.5$	0.0119***	0.0130***	0.0000	0.0143***	0.0158***	0.0089
	(0.0033)	(0.0036)	(0.0155)	(0.0033)	(0.0038)	(0.0115)
Team-Pair FE	Yes	Yes	Yes	Yes	Yes	Yes
Match-Type FE	Yes	Yes	Yes	Yes	Yes	Yes
City×Year×Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-Week and Holiday FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,222	4,286	936	5,222	4,176	1,046
R-squares	0.2057	0.2276	0.1158	0.2033	0.2326	0.2933
Mean Dep. Var.	0.608	0.620	0.500	0.619	0.630	0.582

Notes: This table shows that 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 Equation 3). In Columns (1) to (3), we define five quantiles of the competitiveness index, and predict a team to be the winner of the match if a team has a higher quantile than the rival team. In Column (4), we predict a team would win the match if having a higher competitiveness index than its rival. In Columns (5) and (6), we define two teams have similar competitiveness if the difference of their indices is smaller than 20th percentile. We then define an indicator of prediction accuracy if predicted outcome is the same as the actual outcome. $PM2.5$ 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. Robust standard errors in parentheses are clustered at team-by-season level. *** p <0.01, ** p <0.05, * p <0.1.

TABLE A8
Effects of PM2.5 on Match Intensity

	(1)	(2)	(3)	(4)	(5)	(6)
	Total (both teams combined)			Total per 10 mins		
	Kill	Assist	Damages to champions	Kill	Assist	Damages to champions
$PM2.5$	-0.155**	-0.453**	-938.130**	-0.021	-0.071	-34.193**
	(0.077)	(0.192)	(372.125)	(0.022)	(0.052)	(13.666)
Team-Pair FE	Yes	Yes	Yes	Yes	Yes	Yes
Match-Type FE	Yes	Yes	Yes	Yes	Yes	Yes
City×Year and Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-Week and Holiday FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,611	2,611	2,611	2,611	2,611	2,611
R-squares	0.052	0.035	0.054	0.103	0.072	0.055

Notes: This table presents the effects of PM2.5 on match intensity. The dependent variable is the summed performance metrics from both teams in a matchup, including the total number of kills, assists, and damages dealt to champions (Columns 1-3), and their per-10-minute counterparts (Columns 4-6). $PM2.5$ 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 and month fixed effects, and day-of-week and public holiday fixed effects. Further details are specified in Equation (2). Robust standard errors in parentheses are clustered at team-by-season level. *** p <0.01, ** p <0.05, * p <0.1.

TABLE A9
Correlation of Last-season Performance and Current-season Pollution

	(1)	(2)	(3)
	Average Performance in Last Season Against the Same Rival		
	Win	Kill/min	Assist/min
PM2.5 in Current Season	-0.00022	0.00012	0.00071
	(0.00059)	(0.00041)	(0.00104)
Team-Pair FE	Yes	Yes	Yes
Observations	1,450	1,450	1,450
R-squared	0.515	0.579	0.532

Notes: This table presents the correlation between a team's average performance with respect to a rival in the last season and the level of PM2.5 in the current season. Robust standard errors in parentheses are clustered at the team level. *** p <0.01, ** p <0.05, * p <0.1.

TABLE A10
Robustness to Inclusion of Hour-of-Day FEs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Total			Per 10 Mins	
	Win	Kill	Assist	Gold	Kill	Assist	Gold
$PM2.5$	-0.009**	-0.150**	-0.475***	-271.828**	-0.039**	-0.124***	-46.930***
	(0.004)	(0.060)	(0.151)	(118.724)	(0.018)	(0.045)	(17.980)
$PM2.5 \times Rel.Strong$	0.019***	0.268***	0.680***	276.489*	0.088***	0.218***	91.479***
	(0.006)	(0.069)	(0.170)	(144.277)	(0.021)	(0.051)	(22.305)
Hour-of-Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
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	0.213	0.186	0.234	0.248	0.212	0.235

Notes: This table tests the robustness of our baseline results after additionally controlling for the hour-of-day FEs. 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 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 Equation (3). Further details are specified in Section 3.2. Robust standard errors in parentheses are clustered at team-by-season level. *** p <0.01, ** p <0.05, * p <0.1.

TABLE A11
Robustness to the Inclusion of City-by-date FEs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Total			Per 10 Mins	
	Win	Kill	Assist	Gold	Kill	Assist	Gold
$PM2.5$	-0.009	-0.400*	-1.174*	-786.805**	-0.076	-0.237	-78.659
	(0.016)	(0.229)	(0.597)	(371.112)	(0.067)	(0.175)	(58.177)
$PM2.5 \times Rel.Strong$	0.019***	0.268***	0.680***	276.489***	0.088***	0.218***	91.479***
	(0.006)	(0.059)	(0.152)	(74.069)	(0.020)	(0.050)	(22.760)
Team-Pair FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Match-Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City×Date 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	0.315	0.294	0.423	0.327	0.292	0.258

Notes: This table presents the distributional effects of PM2.5 on team's competitive performance after including the city-by-date FEs. 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. $Rel.Strong$ 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 Equation (3). Regressions control for team-pair fixed effects, match-type fixed effects, city-by-date fixed effects, and day-of-week and public holiday fixed effects. Further details are specified in Equation (2). Robust standard errors in parentheses are clustered at team-by-season level. *** p <0.01, ** p <0.05, * p <0.1.

TABLE A12

Robustness to Controlling for Dynamic Effects from Previous Matches

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Total			Per 10 Mins	
	Win	Kill	Assist	Gold	Kill	Assist	Gold
$PM2.5$	-0.009**	-0.149**	-0.474***	-252.739**	-0.039**	-0.126***	-46.173**
	(0.004)	(0.058)	(0.144)	(125.097)	(0.017)	(0.042)	(17.874)
$PM2.5 \times Rel.Strong$	0.019***	0.261***	0.660***	273.946*	0.085***	0.209***	89.555***
	(0.006)	(0.069)	(0.169)	(155.581)	(0.020)	(0.051)	(22.475)
MatchOrder×LastWin FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
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	0.198	0.216	0.189	0.232	0.252	0.216	0.235

Notes: This table presents the distributional effects of the level of PM2.5 on metrics of competitive performance of individual player (Panel A) and team (Panel B). The player-level regression is specified in Equation (2). The dependent variable is the indicator for winning (Column 1), the total amount of kills, assists, and gold (Columns 2-4), and their per-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 near the match stadium. $Rel.Strong$ is a dummy variable indicating the team's competitiveness is higher than the rival team in the matchup. Each team's competitiveness is computed as the team fixed effects from Equation (3). See table notes in Table 3 for regression specifications. *** p <0.01, ** p <0.05, * p <0.1.

TABLE A13
Robustness Check with the Inclusion of Weather Conditions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Total			Per 10 Mins	
	Win	Kill	Assist	Gold	Kill	Assist	Gold
$PM2.5$	-0.010*	-0.156**	-0.486***	-270.050*	-0.041**	-0.129***	-47.787**
	(0.005)	(0.067)	(0.165)	(147.973)	(0.019)	(0.048)	(21.556)
$PM2.5 \times Rel.Strong$	0.021***	0.263***	0.670***	282.268*	0.086***	0.215***	92.808***
	(0.006)	(0.071)	(0.174)	(167.150)	(0.020)	(0.051)	(23.612)
Weather Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
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	4,126	4,126	4,126	4,126	4,126	4,126	4,126
R-squares	0.185	0.217	0.192	0.215	0.243	0.211	0.221

Notes: This table presents the distributional effects of PM2.5 on team's competitive performance after including the set of weather conditions. 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. $Rel.Strong$ 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 Equation (3). Weather controls include flexible bins of temperature, precipitation, sunshine, humidity, wind speed, as well as an indicator for bad weather. The indicator equals one if any of the weather variables—i.e., temperature, precipitation, sunshine, humidity, and wind speed—exceeds 90% percentile cutoff of sample values and zero otherwise. 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. Further details are specified in Equation (2). Robust standard errors in parentheses are clustered at team-by-season level. *** p <0.01, ** p <0.05, * p <0.1.

TABLE A14
Distributional Effects of PM2.5 on Player Performance

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Total			Per 10 Mins	
	Win	Kill	Assist	Gold	Kill	Assist	Gold
$PM2.5$	-0.011***	-0.037***	-0.102***	-56.550***	-0.011***	-0.028***	-11.983***
	(0.002)	(0.008)	(0.015)	(12.091)	(0.002)	(0.005)	(2.032)
$PM2.5 \times Rel.Strong$	0.019***	0.060***	0.134***	55.897***	0.020***	0.044***	19.925***
	(0.002)	(0.011)	(0.018)	(15.282)	(0.003)	(0.006)	(2.599)
Player FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Champion FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Role FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
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	26,090	26,090	26,090	26,090	26,090	26,090	26,090
R-squares	0.231	0.305	0.264	0.503	0.309	0.281	0.711

Notes: This table presents the results of regressing Equation (2) at player level and controlling for player FEs, champion FEs, and the role of team FEs. Robust standard errors in parentheses are clustered at player-by-season level. *** p <0.01, ** p <0.05, * p <0.1.

TABLE A15
Distributional Effects of PM2.5 on Player Performance

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Total			Per 10 Mins	
	Win	Kill	Assist	Gold	Kill	Assist	Gold
$PM2.5$	-0.001	-0.007	-0.036***	-28.660***	-0.001	-0.007*	-2.029
	(0.002)	(0.007)	(0.012)	(8.513)	(0.002)	(0.004)	(1.597)
$PM2.5 \times Gap$	0.068***	0.174***	0.397***	187.724***	0.054***	0.120***	62.310***
	(0.007)	(0.038)	(0.066)	(47.708)	(0.012)	(0.021)	(8.287)
Player FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Champion FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Role FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
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	26,090	26,090	26,090	26,090	26,090	26,090	26,090
R-squares	0.231	0.305	0.264	0.503	0.309	0.280	0.711

Notes: This table presents the results of regressing Equation (4) at player level and controlling for player FEs, champion FEs, and the role of team FEs. Robust standard errors in parentheses are clustered at player-by-season level. *** p <0.01, ** p <0.05, * p <0.1.

TABLE A16
Effects of Air Pollution on Competitive Performance Using the Concentration of Other Main Air Pollutants

	(1)	(2)	(3)	(4)
	Dependent variable: Win			
Type of Air Pollutant	PM10	AQI	SO2	O3
Pollutant	-0.011***	-0.008**	-0.049	-0.001
	(0.004)	(0.004)	(0.034)	(0.002)
Pollutant × *Rel.Strong*	0.021***	0.017***	0.099***	0.002
	(0.005)	(0.004)	(0.035)	(0.003)
Team-Pair FE	Yes	Yes	Yes	Yes
Match-Type FE	Yes	Yes	Yes	Yes
City×Year×Month FE	Yes	Yes	Yes	Yes
Day-of-Week and Holiday FE	Yes	Yes	Yes	Yes
Observations	5,186	5,222	5,222	5,222
R-squares	0.199	0.197	0.196	0.195

Notes: This table presents the effects of the level of other main air pollutants on a team's winning probability. The dependent variable is the indicator for winning. *Pollutant* is the concentration level of PM10, AQI, SO2 and O3 in Columns (1) to (4), respectively. *Rel.Strong* is a dummy variable indicating that the team's competitiveness is higher than the rival team in the matchup. Each team's competitiveness is computed as the team fixed effects from Equation (3). See Section 3.2 for regression specifications. *** p <0.01, ** p <0.05, * p <0.1.

TABLE A17
Effect of Pre-match and Post-match Air Pollution on the Match Outcome

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Prior to Match Day				Post Match Day			
	7-Day	5-Day	3-Day	1-Day	1-Day	3-Day	5-Day	7-Day
$Placebo\_PM2.5$	-0.003	0.000	0.002	0.000	-0.001	0.004	-0.000	0.001
	(0.009)	(0.009)	(0.006)	(0.005)	(0.006)	(0.008)	(0.010)	(0.015)
$Placebo\_PM2.5 \times Rel.Strong$	0.006	-0.000	-0.004	-0.001	0.001	-0.009	0.000	-0.002
	(0.008)	(0.008)	(0.007)	(0.007)	(0.008)	(0.009)	(0.009)	(0.011)
Control for concurrent PM2.5	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Team-Pair FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Match-Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City×Year×Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-Week and Holiday FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,052	5,108	5,158	5,186	5,182	5,148	5,092	5,038
R-squares	0.202	0.199	0.199	0.198	0.198	0.199	0.200	0.199

Notes: This table presents the placebo test on the effect of pre-match and post-match air pollution exposure on a team's winning probability. The dependent variable is the indicator for winning. Placebo $PM2.5$ is defined as the match-hour PM2.5 level (in 10 $\mu g/m^3$) 1 day, 3 days, 5 days, and 7 days before and after the actual match. $Rel.Strong$ is a dummy variable indicating the team's competitiveness is higher than the rival team in the matchup. Each team's competitiveness is computed as the team fixed effects from Equation (3). *** p <0.01, ** p <0.05, * p <0.1.

TABLE A18
Nonlinear Distributional Effects of PM2.5 on Team Performance

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Total			Per 10 Mins	
	Win	Kill	Assist	Gold	Kill	Assist	Gold
PM2.5[1,2.5)×*Rel.Weak*	-0.019	-0.443	-2.057	716.547	-0.207	-0.803	-104.198
	(0.051)	(0.664)	(1.775)	(1,068.029)	(0.232)	(0.608)	(198.997)
PM2.5[2.5,5)×*Rel.Weak*	-0.018	-0.406	-1.973	479.229	-0.197	-0.728	-147.345
	(0.050)	(0.666)	(1.799)	(1,089.683)	(0.227)	(0.604)	(189.224)
PM2.5[5,7.5)×*Rel.Weak*	-0.059	-0.801	-3.226*	-349.704	-0.276	-1.059*	-308.726
	(0.055)	(0.716)	(1.888)	(1,365.470)	(0.244)	(0.638)	(218.814)
PM2.5[7.5,10)×*Rel.Weak*	-0.060	-1.360	-4.744*	-1,711.136	-0.359	-1.254	-241.551
	(0.062)	(0.921)	(2.428)	(1,521.545)	(0.299)	(0.780)	(250.569)
PM2.5[10,25)×*Rel.Weak*	-0.188**	-2.888***	-9.976***	-5,042.388***	-0.805**	-2.832***	-885.988**
	(0.090)	(1.110)	(2.829)	(1,880.961)	(0.357)	(0.923)	(342.395)
PM2.5[1,2.5)×*Rel.Strong*	0.019	0.122	-0.579	1,086.857	-0.002	-0.326	34.007
	(0.049)	(0.676)	(1.870)	(1,136.775)	(0.225)	(0.605)	(192.575)
PM2.5[2.5,5)×*Rel.Strong*	0.018	0.168	-0.514	1,094.237	0.019	-0.255	83.814
	(0.045)	(0.710)	(1.952)	(1,057.574)	(0.235)	(0.637)	(193.015)
PM2.5[5,7.5)×*Rel.Strong*	0.059	1.182*	2.036	1,400.090	0.356	0.567	277.072
	(0.053)	(0.705)	(1.914)	(1,182.243)	(0.260)	(0.681)	(224.817)
PM2.5[7.5,10)×*Rel.Strong*	0.060	0.072	-1.488	-535.684	0.177	-0.075	247.654
	(0.065)	(0.792)	(2.144)	(1,275.176)	(0.268)	(0.689)	(254.106)
PM2.5[10,25)×*Rel.Strong*	0.188**	1.768*	1.438	-364.145	0.757**	0.850	641.603*
	(0.087)	(0.989)	(2.707)	(1,784.611)	(0.360)	(0.951)	(341.504)
FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,222	5,222	5,222	5,222	5,222	5,222	5,222
R-squares	0.198	0.210	0.186	0.229	0.241	0.209	0.234

Notes: This table presents the nonlinear distributional effects of the level of PM2.5 on metrics for a team's competitive performance. The dependent variable is the indicator for winning (Column 1), the total amount of kills, assists, and gold (Columns 2-4), and their per-10-minute counterparts (Columns 5-7). $PM[1, 2.5)$ is the indicator for the level of PM2.5 being within the range 10-25 $\mu g/m^3$, $PM[2.5, 5)$ for the range 25-50 $\mu g/m^3$, and so on. *Stronger* is a dummy variable indicating that the team's competitiveness is higher than the rival team in the matchup. Each team's competitiveness is computed as the team fixed effects from Equation (3). The full set of FEs are controlled for. See Section 3.2 for details. *** p <0.01, ** p <0.05, * p <0.1.

TABLE A19
Acclimation Effects of PM2.5 on Team Performance: Home More Polluted Than Host City

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Total			Per 10 Mins	
	Win	Kill	Assist	Gold	Kill	Assist	Gold
Panel A							
$PM2.5$	-0.002	-0.010	-0.141	-139.203	0.008	-0.013	-0.657
	(0.005)	(0.063)	(0.157)	(107.428)	(0.019)	(0.046)	(18.911)
$HomeAcclimation$	0.034	0.687	0.728	265.003	0.298	0.434	332.361*
	(0.049)	(0.585)	(1.445)	(1,150.921)	(0.185)	(0.456)	(196.324)
$PM2.5 \times HomeAcclimation$	0.007	-0.018	0.007	67.054	-0.013	-0.019	-2.857
	(0.007)	(0.085)	(0.224)	(161.887)	(0.026)	(0.069)	(27.645)
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	0.231
Panel B							
$PM2.5$	-0.011**	-0.135**	-0.456***	-264.631**	-0.033*	-0.115**	-42.858**
	(0.005)	(0.064)	(0.157)	(125.431)	(0.019)	(0.046)	(18.958)
$PM2.5 \times Rel.Strong$	0.018***	0.270***	0.684***	271.961*	0.090***	0.221***	91.504***
	(0.006)	(0.068)	(0.169)	(159.370)	(0.020)	(0.051)	(22.540)
$HomeAcclimation$	0.039	0.757	0.905	335.339	0.321*	0.491	356.027*
	(0.048)	(0.573)	(1.414)	(1,136.359)	(0.183)	(0.450)	(191.243)
$PM2.5 \times HomeAcclimation$	0.005	-0.050	-0.074	34.614	-0.024	-0.045	-13.772
	(0.006)	(0.078)	(0.205)	(157.205)	(0.024)	(0.064)	(24.630)
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	0.241	0.208	0.234

Notes: This table presents the acclimation 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 $\mu g/m^3$) at the hour of the match. $HomeAcclimation$ is a dummy variable indicating that the team's home city has a higher average air pollution level than the daily average pollution level in host city on the match date. $Rel.Strong$ 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 Equation (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. Further details are specified in Section 3.2. Robust standard errors in parentheses are clustered at team-by-season level. *** p <0.01, ** p <0.05, * p <0.1.

TABLE A20
Acclimation Effects of PM2.5 on Team Performance: Home More Polluted Than Rival's Home

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Total			Per 10 Mins	
	Win	Kill	Assist	Gold	Kill	Assist	Gold
Panel A							
$PM2.5$	-0.001	-0.012	-0.157	-109.186	0.008	-0.019	1.139
	(0.005)	(0.064)	(0.158)	(104.892)	(0.019)	(0.048)	(19.696)
$PM2.5 \times Rel.HomePolluted$	0.003	-0.009	0.049	-19.947	-0.010	-0.000	-6.057
	(0.006)	(0.083)	(0.210)	(142.893)	(0.026)	(0.066)	(26.021)
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
Panel B							
$PM2.5$	-0.011**	-0.150**	-0.509***	-251.511**	-0.037*	-0.132***	-45.961**
	(0.005)	(0.066)	(0.162)	(122.816)	(0.020)	(0.050)	(20.103)
$PM2.5 \times Rel.Strong$	0.019***	0.268***	0.683***	276.171*	0.088***	0.219***	91.393***
	(0.006)	(0.068)	(0.167)	(154.233)	(0.020)	(0.050)	(22.154)
$PM2.5 \times Rel.HomePolluted$	0.004	0.001	0.076	-9.007	-0.007	0.009	-2.437
	(0.006)	(0.075)	(0.190)	(133.408)	(0.024)	(0.060)	(23.217)
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

Notes: This table presents the acclimation 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 $\mu g/m^3$) at the hour of the match. $Rel.HomePolluted$ is a dummy variable indicating that the team's home city has a higher average air pollution level than the rival team. $Rel.Strong$ 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 Equation (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. Further details are specified in Section 3.2. Robust standard errors in parentheses are clustered at team-by-season level. *** p <0.01, ** p <0.05, * p <0.1.

TABLE A21
Home-advantage Effects of PM2.5 on Team Performance

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Total			Per 10 Mins	
	Win	Kill	Assist	Gold	Kill	Assist	Gold
Panel A							
$PM2.5$	0.005	0.036	-0.006	-49.927	0.018	0.016	15.200
	(0.005)	(0.058)	(0.156)	(109.058)	(0.017)	(0.046)	(17.819)
$HomeAdvantage$	-0.017	-0.192	-0.189	9.865	-0.098	-0.164	-119.164
	(0.032)	(0.360)	(0.897)	(589.411)	(0.125)	(0.301)	(130.463)
$PM2.5 \times HomeAdvantage$	-0.011*	-0.115*	-0.297*	-150.877	-0.030	-0.077	-36.408
	(0.006)	(0.067)	(0.163)	(116.119)	(0.024)	(0.056)	(23.292)
Observations	5,222	5,222	5,222	5,222	5,222	5,222	5,222
R-squares	0.196	0.208	0.183	0.228	0.239	0.206	0.232
Panel B							
$PM2.5$	-0.006	-0.120*	-0.402**	-206.008	-0.035*	-0.114**	-38.101*
	(0.006)	(0.071)	(0.179)	(144.919)	(0.021)	(0.053)	(21.881)
$PM2.5 \times Rel.Strong$	0.017***	0.252***	0.639***	251.922	0.085***	0.209***	86.031***
	(0.006)	(0.072)	(0.174)	(158.346)	(0.022)	(0.053)	(23.527)
$HomeAdvantage$	-0.031	-0.391	-0.694	-189.272	-0.165	-0.329	-187.170
	(0.032)	(0.357)	(0.881)	(581.570)	(0.124)	(0.294)	(126.719)
$PM2.5 \times HomeAdvantage$	-0.006	-0.046	-0.123	-82.159	-0.007	-0.020	-12.941
	(0.006)	(0.070)	(0.166)	(114.016)	(0.025)	(0.057)	(23.325)
Observations	5,222	5,222	5,222	5,222	5,222	5,222	5,222
R-squares	0.198	0.210	0.185	0.228	0.241	0.209	0.235

Notes: This table presents the acclimation 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 $\mu g/m^3$) at the hour of the match. $HomeAdvantage$ is a dummy variable indicating that the team's home city is the host city on the match date. $Rel.Strong$ 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 Equation (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. Further details are specified in Section 3.2. Robust standard errors in parentheses are clustered at team-by-season level. *** p <0.01, ** p <0.05, * p <0.1.

TABLE A22
Effects of PM2.5 on Online Search Activities for Pollution-related Keywords

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	Search for PM2.5		Search for Harm of PM2.5		Search for Face Mask	
PM2.5	167.8***		3.604***		7.611***	
	(4.883)		(0.271)		(1.097)	
Severe (PM2.5>75 $\mu g/m^3$)		744.6***		17.56***		27.47***
		(49.58)		(2.433)		(9.700)
Year×Month×Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,025	3,025	3,025	3,025	3,025	3,025
R-squared	0.760	0.678	0.514	0.491	0.884	0.882

Notes: This table presents the effects of PM2.5 (in 10 $\mu g/m^3$) and an indicator of severe air pollution (PM2.5>75 $\mu g/m^3$) on online search activities for pollution-related keywords. Columns (1) and (2) present the search for the level of PM2.5, Columns (3) and (4) for the health damages of PM2.5, and Columns (5) and (6) for PM2.5-proof face mask. Robust standard errors in parentheses are clustered at team-by-season level. *** p <0.01, ** p <0.05, * p <0.1.

TABLE A23
Effects of Air Pollution on Decision Time and Pick-and-switch

	(1)	(2)	(3)	(4)
Panel A: Dependent Variable: Decision Time (normalized by S.D.)				
$PM2.5$	-0.006	-0.012	-0.017	-0.016
	(0.034)	(0.034)	(0.035)	(0.034)
$PM2.5 \times Abs.\ Weak$		0.017		-0.007
		(0.013)		(0.017)
$PM2.5 \times Rel.\ Weak$			0.022***	0.025**
			(0.008)	(0.010)
Observations	5,006	5,006	5,006	5,006
R-squares	0.434	0.435	0.435	0.435
Panel B: Dependent Variable: Frequency of Pick-and-switch (normalized by S.D.)				
$PM2.5$	0.016	0.010	0.005	0.006
	(0.038)	(0.039)	(0.039)	(0.039)
$PM2.5 \times Abs.\ Weak$		0.018		-0.006
		(0.020)		(0.024)
$PM2.5 \times Rel.\ Weak$			0.023*	0.026*
			(0.012)	(0.013)
Observations	5,002	5,002	5,002	5,002
R-squares	0.350	0.350	0.351	0.351

Notes: This table tests the effects of PM2.5 on team and player efforts 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 $\mu g/m^3$) 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 Equation (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.

Appendix G Figures

FIGURE B1
Map for LoL Games

Notes: This figure presents the map layout for LoL games. The diagonal corners at the bottom left and upper right, respectively, are the homebase for the two rival teams. Defensive turrets are positioned along the top, middle, and bottom lanes, while neutral minions spawn in the jungles.

FIGURE B2
Post-game Statistics for LoL Games

Notes: This figure presents the post-game statistics for a standard LoL match.

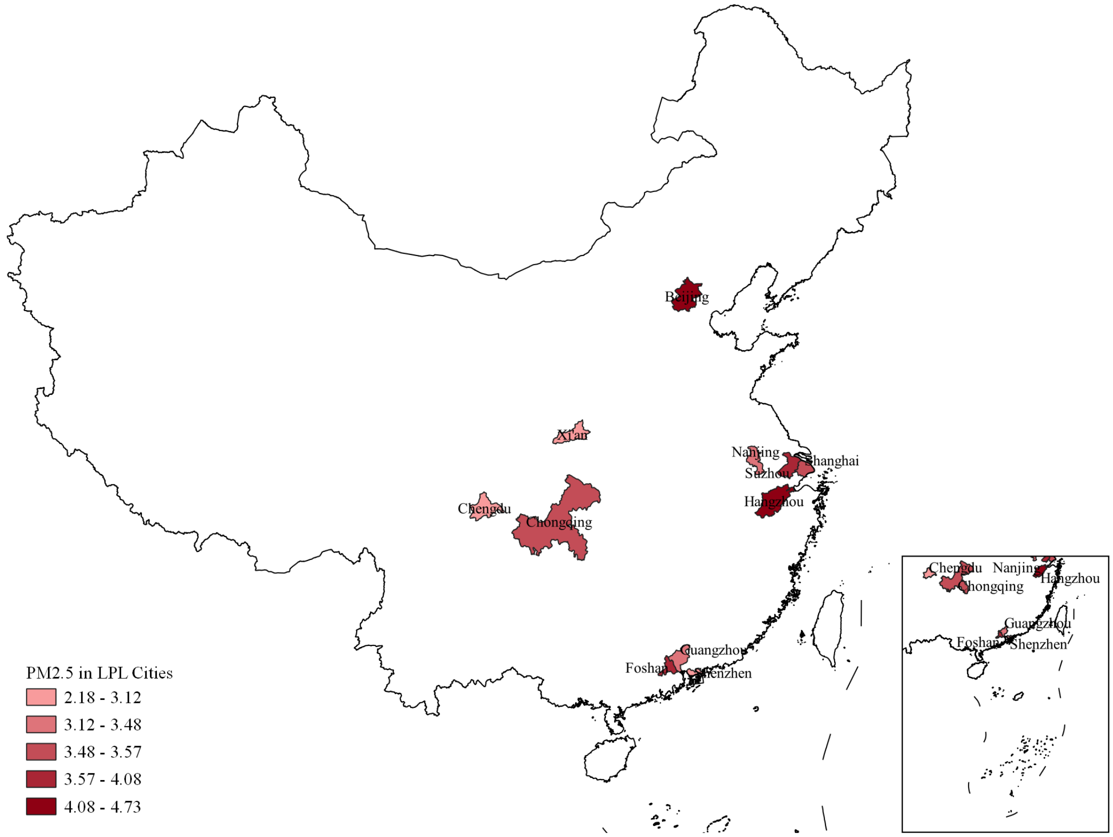


FIGURE B3
Average Concentration of PM2.5 in LPL Hosting Cities

Notes: This figure presents the spatial distribution of average concentrations of PM2.5 in LPL hosting cities during the sample period (from 2017 to 2021). Unit of PM2.5 is 10 $\mu g/m^3$.

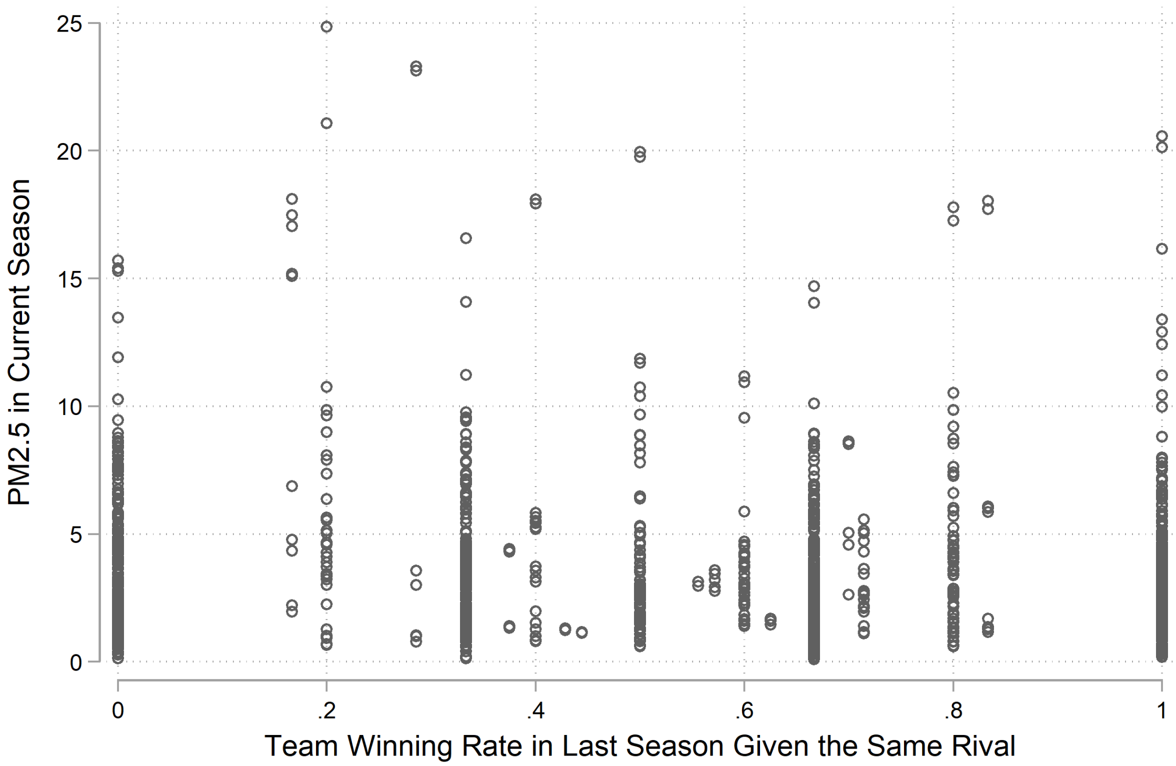
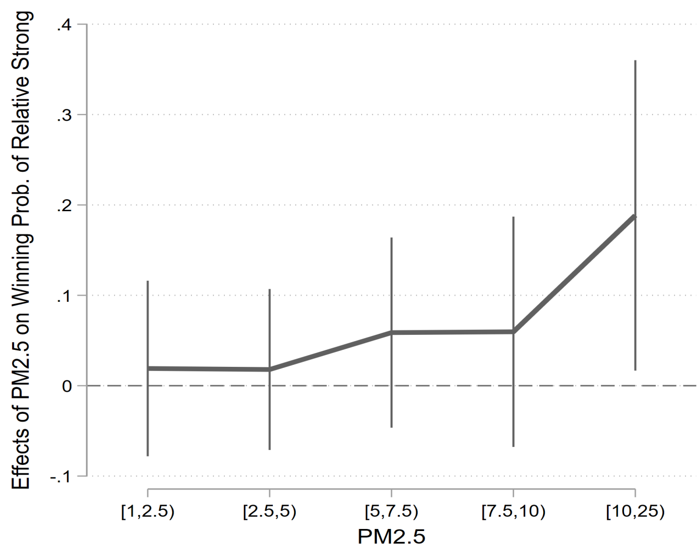
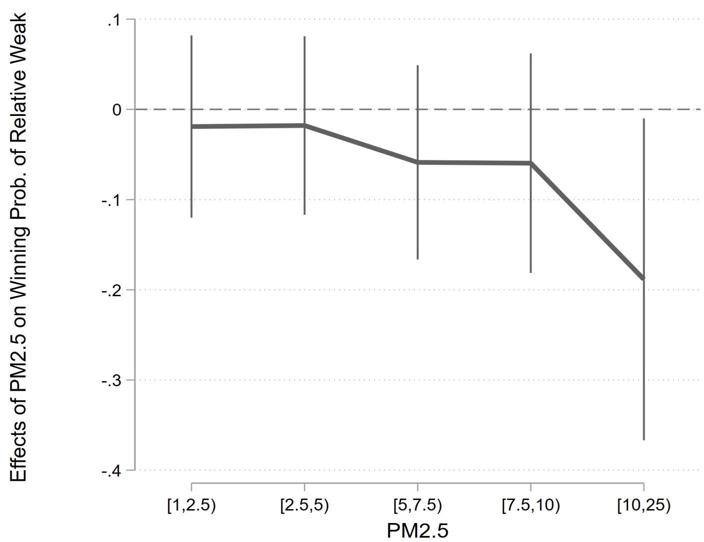


FIGURE B4
Falsification Test of Winning Rate in Last Season and PM2.5 in Current Game

Notes: This figure presents the distribution of each team's average winning rate against different rival teams in the last season to the level of PM2.5 on the match day in this season, given the same rival team. Unit of PM2.5 is 10 $\mu g/m^3$.



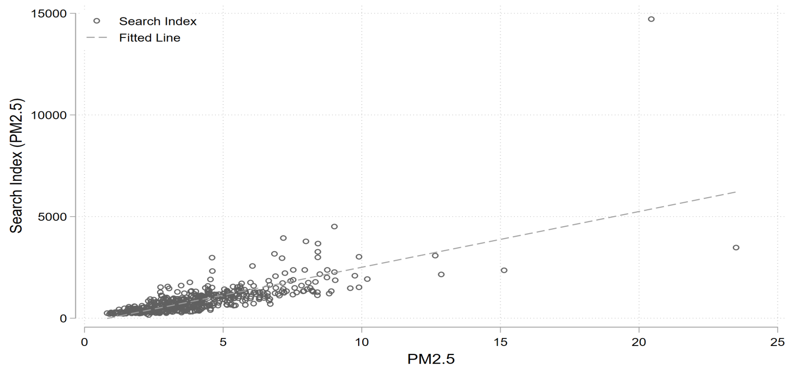
(A) Nonlinear Effects on the Stronger Team



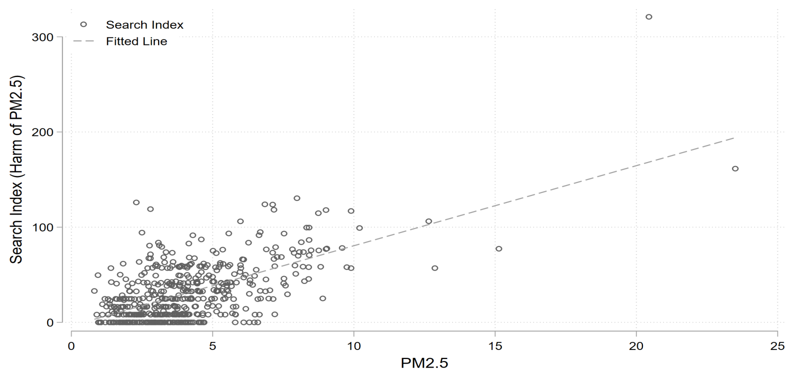
(B) Nonlinear Effects on the Weaker Team

FIGURE B5
Nonlinear Effects of Air Pollution on Competitive Performance

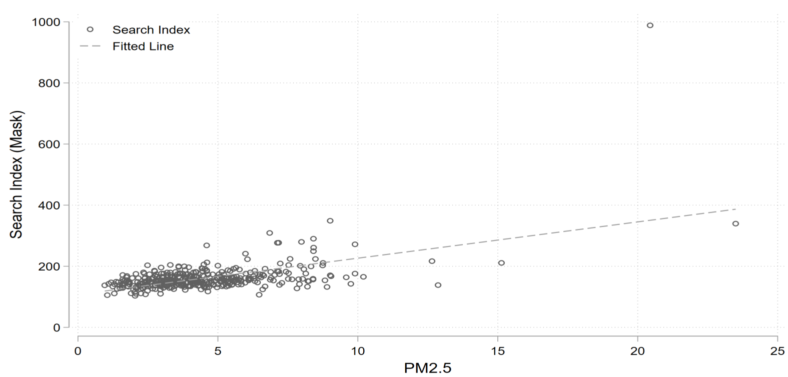
Notes: This figure presents the nonlinear distributional effects of air pollution on a team's competitive performance. Panel A plots the nonlinear effects of air pollution on the competitive performance of the stronger team in the matchup; Panel B plots the nonlinear effects on the weaker team. Detailed regression results are reported in Appendix Table A18. Unit of PM2.5 is 10 $\mu g/m^3$.



(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

FIGURE B6
Scatter Plot of Pollution-related Search and PM2.5

Notes: This figure depicts the scatter plot of daily Baidu search volume of pollution-related keywords against daily level of PM2.5 in our analytical sample. Panel A presents the search for the level of PM2.5, Panel B for the health damages of PM2.5, and Panel C for PM2.5-proof face mask. Unit of PM2.5 is 10 $\mu g/m^3$.

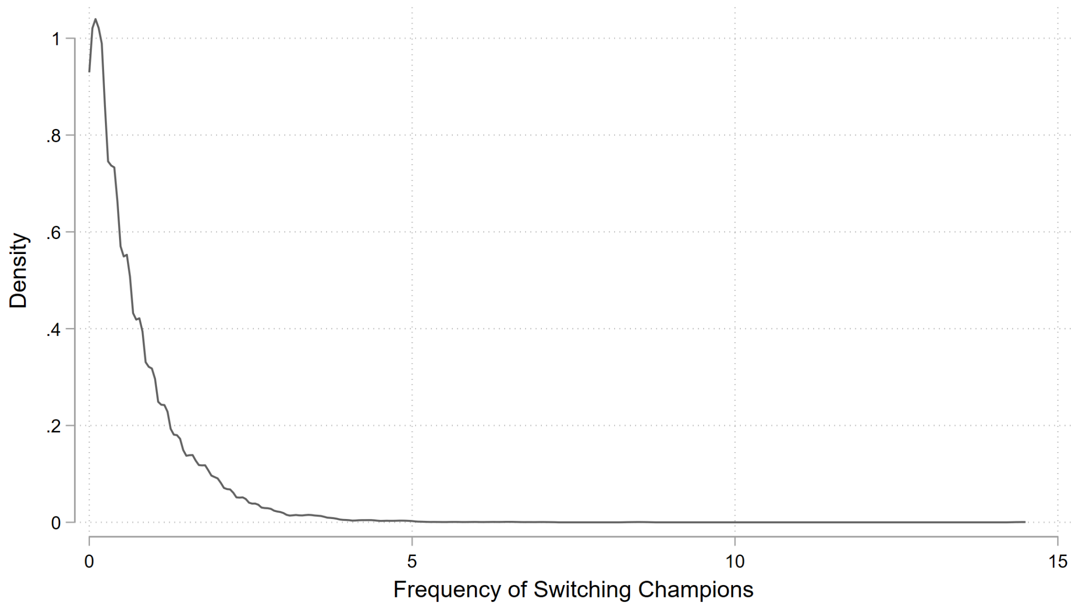


FIGURE B7
Distribution of the Number of Pick-and-switch in a Match

Notes: This figure presents the distribution of the number of pick-and-switch of a player in a given match. In the preparation phase of the match, each player in the team is allowed to pick a champion and change his choice by any number of times within a 30-second time limit.