Management Science

Publication details, including instructions for authors and subscription information:
http://pubsonline.informs.org

Indoor Air Quality and Strategic Decision Making

Steffen Künn, Juan Palacios, Nico Pestel

To cite this article:
Steffen Künn, Juan Palacios, Nico Pestel (2023) Indoor Air Quality and Strategic Decision Making. Management Science 69(9):5354-5377. https://doi.org/10.1287/mnsc.2022.4643

informs
https://pubsonline.informs.org/journal/mnsc

MANAGEMENT SCIENCE
Vol. 69, No. 9, September 2023, pp. 5354–5377
ISSN 0025-1909 (print), ISSN 1526-5501 (online)

Indoor Air Quality and Strategic Decision Making

Steffen Künn,[a,b,c] **Juan Palacios,**[b,d,e,*] **Nico Pestel**[a,b,f]

[a] Research Centre for Education and the Labour Market, Maastricht University, 6200 MD Maastricht, Netherlands; [b] Institute of Labor Economics, 53113 Bonn, Germany; [c] School of Business and Economics, Department of Economics, Maastricht University, 6211 LM, Maastricht, Netherlands; [d] Center for Real Estate, Massachusetts Institute of Technology, Cambridge, Massachusetts 02139; [e] School of Business and Economics, Department of Finance, Maastricht University, 6211 LM, Maastricht, Netherlands; [f] Center of Economic Studies CESifo, 81679 Munich, Germany

*Corresponding author

Contact: s.kuenn@maastrichtuniversity.nl (SK); jpalacio@mit.edu, https://orcid.org/0000-0003-4234-5114 (JP); n.pestel@maastrichtuniversity.nl, https://orcid.org/0000-0003-0062-9514 (NP)

Received: March 20, 2021
Revised: April 23, 2022
Accepted: June 14, 2022
Published Online in Articles in Advance: January 26, 2023

https://doi.org/10.1287/mnsc.2022.4643

Abstract. Decision making on the job is becoming increasingly important in the labor market, in which there is an unprecedented rise in demand for workers with problem-solving and critical-thinking skills. This paper investigates how indoor air quality affects the quality of strategic decision making based on data from official chess tournaments. Our main analysis relies on a unique data set linking the readings of air-quality monitors inside the tournament room to the quality of 30,000 moves, each of them objectively evaluated by a powerful artificial intelligence–based chess engine. The results show that poor indoor air quality hampers players' decision making. We find that an increase in the indoor concentration of fine particulate matter ($PM_{2.5}$) by 10 $\mu g/m^3$ (corresponding to 75% of a standard deviation in our sample) increases a player's probability of making an erroneous move by 26.3%. The decomposition of the effects by different stages of the game shows that time pressure amplifies the damage of poor air quality to the players' decisions. We implement a number of robustness checks and conduct a replication exercise with analogous move-quality data from games in the top national league showing the strength of our results. The results highlight the costs of poor air quality for highly skilled professionals faced with strategic decisions under time pressure.

History: Accepted by Prof. Yan Chen, behavioral economics and decision analysis.

Funding: The authors gratefully acknowledge the financial support from the Graduate School of Business and Economics at Maastricht University as well as the Institute of Labor Economics Bonn.
Supplemental Material: The online appendix and data are available at https://doi.org/10.1287/mnsc.2022.4643.

Keywords: indoor air quality • pollution • strategic decision making • chess

1. Introduction

Strategic decision making is crucial in the workplace and is growing in importance as part of a general trend toward high-skill labor (Acemoglu and Restrepo 2019, Binder and Bound 2019).[1] In the United States, about one third of recent job vacancies listed decision making in their job description (Deming 2021). Firms are increasingly demanding problem solving and critical thinking skills among their employees to support optimal decision making in complex environments (Atalay et al. 2020). Strategic decision making is considered to be particularly consequential for the long-term success and survival of firms (Nagelkerk and Henry 1990, Baum and Wally 2003, Hortaçsu et al. 2019) because it leads to meaningful reallocation of resources (Eisenhardt 1989). It is, thus, crucial to understand the factors that influence strategic decision making in the workplace and can lead to erroneous strategic decisions.

One factor that likely influences the quality of strategic decision making in the workplace but is largely overlooked is indoor air quality. Air pollution is known to have serious negative implications for cognition and brain health. Long-term exposure to air pollution is associated with severe brain damage, dementia, and accelerating cognitive decline over the lifetime (Underwood 2017). Acute exposure to air pollution can result in neuro-inflammation and brain oxidative stress (Calderon-Garciduenas et al. 2015), which is shown to have a range of psychological impacts, including cognitive malfunctioning (for an extensive literature review on the impact of pollution on (cognitive) performance see Lu 2020, Aguilar-Gomez et al. 2022).[2] Once cognitive performance is negatively influenced, strategic decision making is likely to also suffer from poor air quality. This is because, unsurprisingly, cognitive performance is associated with individuals' ability to make better decisions in strategic settings: individuals with higher cognitive skills make fewer strategic errors and learn faster in new strategic environments (Burnham et al. 2009, Bayer and Renou 2016, Gill and Prowse 2016).[3] However, despite this theoretical link between air quality and strategic decision making, empirical evidence is lacking.

The lack of evidence on the effects of air quality on strategic decision making is likely a result of three key challenges. First, objective measures on the quality of decisions are scarce and lack comparability across occupations (Acemoglu and Autor 2011). Second, the mobility of decision makers across locations hinders the assignment of individual exposure to pollution. Finally, strategic decisions are predominantly carried out indoors, where actual exposure of individuals might differ substantially from outdoor conditions covered by widely used data from air-quality monitoring networks.

In this paper, we investigate the implications of exposure to poor (indoor) air quality for strategic decision making. We compile a unique panel data set that links systematic evaluations of move decisions made by chess players during real chess tournaments to the readings of indoor air-quality monitors installed inside the tournament venue. Chess offers a unique laboratory to evaluate how air pollution hinders skilled individuals making strategic decisions in nonroutine settings. There is a large overlap in the skills required to excel in chess and those in strategic decision making. Deciding on a move in a chess game is a complex cognitive task, which requires individuals to engage their intuition, perception, and problem-solving skills (Chase and Simon 1973, Simon and Chase 1973, Charness 1992, Moxley et al. 2012).[4] Intuition helps players to reduce considerably the set of alternatives, which they analyze in depth, evaluating all possible follow-up scenarios (Simon and Chase 1973). In their evaluation, players rely heavily on their problem-solving skills and backward induction. Professional players devote a large part of their career to finding optimal strategies for chess positions using this reasoning and are often considered by researchers in economics and behavioral science as expert decision makers in strategic settings (e.g., Palacios-Huerta and Volij 2009, Gerdes and Gränsmark 2010, Levitt et al. 2011, Backhus et al. 2016, Strittmatter et al. 2020).

The data contain comprehensive information on more than 30,000 moves from 121 players in 609 games in three official tournaments held in Germany in 2017–2019. Each tournament comprised seven rounds over a period of eight weeks, which provides us with sufficient natural variation in air quality. In each round, the chess tournaments have a predefined system to allocate players to opponents. We use Stockfish, a powerful open-source artificial intelligence chess engine to evaluate each move in our data set and generate our main performance indicators. The chess engine systematically evaluates the players' actual moves by benchmarking them against moves deemed optimal based on the chess engine's algorithm.[5] Based on the output from the chess engine, we generate a binary indicator for moves annotated as an error by the engine and a continuous measure describing the differences in chances to win the game between the player's and computer's moves. These two outcomes are complementary, covering the likelihood and magnitude of errors made by players in a given move decision. The evaluation of each player's move is fully independent of the player's opponent and the previous moves of the player. Each move in a game is conceived as an independent "chess puzzle," in which players need to find the best solution as proposed by the chess engine. Players in our sample face strong intrinsic and extrinsic incentives to perform well.[6]

Our identification strategy exploits the panel structure of the data. We evaluate the move quality of the same individual playing multiple games at the same venue on the same day of the week at the same time of day but under varying levels of indoor air quality, which are beyond the control of the players. To assess players' exposure to poor air quality, we installed three sensors inside the tournament venue, and they continuously measure indoor environmental conditions. We evaluate air quality based on the concentration of fine particulate matter with a diameter smaller than 2.5 micrometers ($PM_{2.5}$), which is one of the most common indicators for air pollution in health science and economic studies. $PM_{2.5}$ consists of microscopic solid or liquid droplets that can penetrate indoor environments and be inhaled and enter deep into the lungs and bloodstream, introducing well-documented serious risks to the human body (Cohen et al. 2017). Ultimately, particulate matter affects the functioning of the brain via inflammatory responses and oxidative stress in the lungs and central nervous system (Lodovici and Bigagli 2011, Peeples 2020) and may affect humans beyond health, hindering their performance or influencing their behavior (Aguilar-Gomez et al. 2022). Finally, and importantly for our study setting, there are a number of recent studies that document the filtration of $PM_{2.5}$ indoors, ultimately harming individuals in those buildings (e.g., Chang et al. 2016).[7]

Overall, our findings show that indoor concentrations of $PM_{2.5}$ significantly worsen the ability of subjects in selecting the optimal move. Exploiting within-player variation in air quality and controlling for year, round, and move fixed effects and a set of control variables including other indoor and outdoor environmental factors (i.e., temperature, humidity, and noise), we find that an increase in $PM_{2.5}$ of 10 micrograms per cubic meter (75% of the standard deviation of $PM_{2.5}$ in our sample) leads to a 2.1 percentage point increase in the probability of making a meaningful error. This corresponds to an increase of 26.3% relative to the average proportion of errors in our sample.

Our results highlight that time pressure exacerbates the impact of poor air quality on performance. In our setting, each player has a fixed time budget for the first 40 moves. Time pressure arises as the game proceeds and the remaining time approaches zero. The high frequency of our data allows us to examine the presence of differential effects of air pollution under different levels of time stress.[8] Our results indicate that the impact of $PM_{2.5}$ increases with time pressure with the most pronounced effect shortly before the time control at move 40. This finding suggests that poor air quality harms performance of players, particularly when acting under time pressure. The results of a heterogeneity analysis indicate that weaker players were especially harmed by poor air quality in phases of the game with a limited time budget. This provides the first evidence that air pollution exacerbates inequalities among skilled individuals, particularly impacting initially disadvantaged groups in competitive settings.

Several sensitivity checks show the robustness of the results. In particular, we control for levels of traffic congestion on tournament days to address concerns that our estimation results for indoor air quality are not a result of exposure to air pollutants per se, but are rather driven by other potential factors correlated with the outdoor emission sources (e.g., stress from traffic jams). Moreover, we check the robustness to attrition and nonlinear inclusion of weather controls. The results are robust to all of these tests, which provide supportive evidence for a physiological channel whereby air quality affects the decision making of players.

We document the role of outdoor pollution in shaping indoor conditions. The variation in indoor fine particles largely reflects levels of air pollution in the (outdoor) vicinity of the tournament site, coming from automobile exhaust or industrial emissions.[9] Using outdoor air pollution measures from nearby air-quality stations, we find similar performance drops to those based on our indoor measures, suggesting the identified effects are indeed a result of particulate pollution rather than other potential sources. Exploiting intraday variation in outdoor pollution, we find evidence for short-term and transitory effects of particulate matter.

In a final step, we conducted a replication exercise with analogous move-quality data from the top national league in Germany (i.e., Chess Bundesliga). The replication data set combines data from tournament venues across the country with outdoor PM pollution measurements over the period from 2003 to 2019. Consistent with our main results, the analysis in the sample of the top league displays a significant and sizable increase in the likelihood of making meaningful mistakes, especially when players are in the stage of the game proceeding the time control. This emphasizes that our main results are valid beyond the studied tournament location and time period and are relevant for a cohort of players ranked among the strongest in the world. Finally, we implement an instrumental variable (IV) approach that exploits variation in air pollution exposure driven by changes in wind directions (Deryugina et al. 2019). The IV estimates show the same pattern as those in our main analysis, highlighting that our estimated pollution damages are not driven by confounding factors, such as economic activity, traffic conditions, or any other change in the daily life of players that could bias our results.

Our results contribute to the extensive literature on the determinants of worker performance (see Syverson 2011 for a review). More specifically, the results of this study enhance our understanding of how air quality affects workers' decision making quality in complex settings. Most of the existing evidence is based on routine manual occupations, such as agriculture or factory workers (Graff Zivin and Neidell 2012, Chang et al. 2016), in which individual output is easy to quantify.[10] Our understanding of how environmental hazards affect the performance of workers in nonroutine professions, in which a worker's value added tends to be much harder to quantify, is still rather limited. Initial studies use rate-based indicators (e.g., number of calls handled per hour; Chang et al. 2019) or time required to complete tasks (e.g., days required by a judge to reach a verdict; Kahn and Li 2020) as a proxy for performance. More recently, evidence from the financial sector indicates that investors exposed to polluted air tend to systematically underperform, obtaining lower returns on their investments, and are more prone to exhibit investment biases, such as the disposition effect, attention-driven buying behavior, or excessive trading (Heyes et al. 2016, Huang et al. 2020). Finally, this paper contributes to the growing literature investigating the impact of air pollution on cognitive and quality-focused tasks, covering cognitive tests (Zhang et al. 2017), high-stake examinations (Ebenstein et al. 2016, Roth 2016, Graff Zivin et al. 2020), or baseball umpires (Archsmith et al. 2018).[11] This is the first study to examine a setting closely resembling managerial occupations, in which individuals with high levels of expertise are faced with strategic decision making in a complex setting.

The high granularity of our performance data allows us to uncover the role of time pressure and expertise as important mechanisms influencing the severity of the impacts of poor air quality on decision making. Time pressure is common to many economic decisions and occupational tasks and may, in itself, affect the quality of decision making (Kocher and Sutter 2006, Kocher et al. 2013). Examples of environments that operate under time pressure include buying or selling stocks in financial markets, bargaining and negotiations, or urgent medical care. Sustained exposure to time stress is linked to burnouts and other health problems among executives, teachers, and other professionals. More recently, experimental evidence documents the detrimental effects of time pressure on human decision making, introducing behavioral biases and hindering individual performance in strategic tasks (Spiliopoulos and Ortmann 2018).[12] Our results are the first to document that time pressure increases the vulnerability of high-skill professionals to air pollution.

Finally, the findings of this paper have important implications for firms and policy. They highlight the benefits of investments in building infrastructure to protect workers against outside hazards and in improving indoor air quality. In addition to the positive health effects documented by previous literature, our results show that a clean indoor environment can improve the quality of strategic decisions made by high-skill workers, especially when they are working under high levels of time stress.

The remainder of our paper is organized as follows. In Section 2, we provide a description of the game of chess and its use by the scientific literature to understand human behavior and performance. In this section, we also explain the construction of our performance measures and the estimation sample. In Section 3, we outline our empirical strategy. The results are presented and discussed in Section 4, and validation exercises are shown in Section 5. Section 6 concludes.

2. Chess Tournaments: Background and Data

In this paper, we use data from official chess tournaments to study the impact of indoor air quality on strategic decision making. Chess is a two-player, strategic board game in which players, under perfect information, alternately make moves with pieces on the chess board.[13] A player wins the game if (i) the player checkmates the opponent's king; (ii) the opponent resigns; or (iii) in a game with time restrictions, the opponent runs out of time. In addition, the players can agree upon a draw at any time during the game.

The data used in this paper come from three chess tournaments in Germany. We received access to data on players' characteristics as well as all moves of each individual tournament game. Throughout the tournaments, we measured indoor environmental conditions at the venue.

2.1. Tournament Setup and Chess Rating Score

The tournaments were organized by a chess club in a major city in West Germany in May–June 2017, April–May 2018, and April–May 2019 as the club's main event of each year.[14] Each tournament edition comprised seven rounds over an eight-week period with each round taking place on a Monday night starting at 6 p.m. and lasting until the last game was over.[15] Figure A.1 in the online appendix illustrates the timing of the tournaments. Registration for the tournament was open to any chess player on a first-come, first-served basis conditional on paying the participation fee of 30 euros. The total number of participants was limited to about 80 players per tournament.[16] The tournament format follows the "Swiss system," a noneliminating tournament format commonly applied in chess competitions. In each round, players gain one point for a win, 0.5 for a draw, and zero for a defeat. The winner of the tournament is the player with the highest aggregate points earned in all rounds. The assignment of fixtures is based on players' pretournament chess rating scores indicating their strength as well as their performance during the tournament.[17]

Chess rating scores are calculated based on the performance in games against other players. Winning (losing) a game results in an improvement (decline) in the rating score, whereby the change in the rating score is larger in absolute terms for "unexpected" outcomes, for example, when a player with a much higher score than the opponent loses the game. The rating score applied for the assignment of fixtures in the tournaments is the German Chess Federation's rating score DWZ (Deutsche Wertungszahl).[18] This score is equivalent to the international Elo rating system used by the World Chess Federation (FIDE) also for assigning titles such as "international master" or "grandmaster." We use the internationally acknowledged term "Elo" rating score instead of DWZ in the remainder of the paper.

After each tournament in our sample, all game outcomes were submitted to the chess federation for a recalculation of players' rating scores based on their results.[19] Hence, all players participating in the tournaments had an incentive to perform well throughout all tournament rounds in order to improve their rating score, which is a matter of prestige among chess players and determines fixtures in future competitions. In addition, pecuniary incentives were offered. The winner of the tournament received a cash prize of 400 euros. The participants ranked second to fourth received prizes of 300, 150, and 100 euros, respectively, and extra prizes were awarded for the best-ranked players among the youth, senior, and female players (70 euros each) as well as for the best team (60 euros).

2.2. Assessment of Move Quality

We assess the performance of players in each tournament round based on the quality of moves undertaken by the player. A chess game g comprises M_g moves with two plies per move $m \in \{1, \ldots, M_g\}$, in which the player with the white pieces moves first. For any given stage of the game, the relative (dis)advantage for each player is evaluated by the so-called *pawn metric* C_{gm} based on the remaining pieces and their position on the board. Although it plays no formal role in the game, the pawn metric is useful for players to evaluate their own game performance and identifying errors after the match and is essential to evaluate positions in chess software.[20] The sign of this metric indicates which player is in the better position (i.e., is more likely to win the game) with $C_{gm} > 0$ ($C_{gm} < 0$) indicating advantage for white (black). For example, a pawn metric of –1 is interpreted as the player with the black pieces having an advantage equivalent to one extra pawn on the board relative to the opponent.

For each tournament game, we retrieved all moves based on players' handwritten notations, which were digitized by the tournament organizers. Both players are obliged to document each move and had to hand in the handwritten notation to the tournament organizer immediately after the game was completed.[21] We use the chess engine Stockfish to assess the quality of each move in the tournaments.[22] Stockfish has an Elo rating score of 3,548 and is consistently ranked first or near the top among chess engines (Acher and Esnault 2016, Alliot 2017), and it considerably outperforms every human player. The highest Elo rating score by a human is 2,882, achieved in 2014 by the current chess world champion Magnus Carlsen. Stockfish is commonly used by researchers to evaluate move decisions and performance of chess players (e.g., Strittmatter et al. 2020, Künn et al. 2021).

For a given situation on the chess board, a particular move option is optimal and can be found by backward induction. Based on a decision tree for all possible move options of a given sequence of moves ahead (search depth), the chess engine determines the best response in order to optimize the pawn metric given the current situation with which the player is faced (Strittmatter et al. 2020). Searching the best possible move is essentially a computational task for the human player. Therefore, we compare the pawn metric resulting from player i's actual move m in game g to the metric that would result from the computer's optimally suggested move. The pawn metric difference between the human player and the computer can be viewed as an error:

$$Error_{igm} = |C^{computer}_{igm}| - |C^{player}_{igm}|. \tag{1}$$

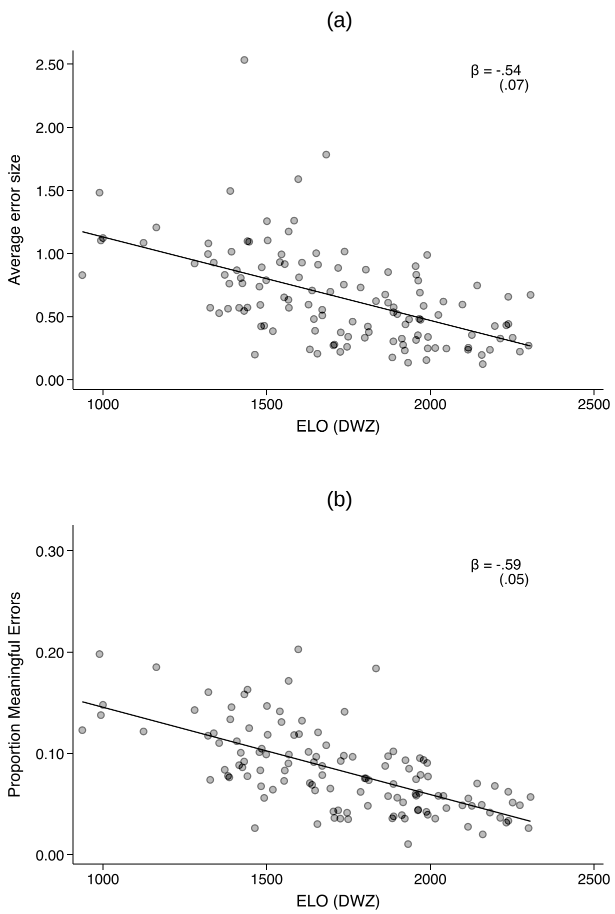
In the empirical analysis, we look at player-move-specific errors as our main outcome variable. We exclude from the analysis the first 14 moves of each game, which tend to be part of the opening of the game for which players follow preestablished chess-opening strategies and are, hence, not affected by the contemporaneous air quality (Backhus et al. 2016).[23] Expression (1) can take negative values when, at a given point in the game, the player makes a move that is evaluated to be better than the one proposed by the computer. This event is very rare, and because we are mainly interested in the errors associated with air quality and, therefore, the positive side of the error distribution, we redefine negative cases as zero (0.7% of our sample).

In addition to the continuous error measure, we explore the probability of an individual making a "meaningful error" based on the annotations of the chess engine. Chess engines are able to classify a certain move as a meaningful error based on the status of the game, the skill of the player, and the magnitude of the $Error_{igm}$. In particular, chess engines annotate a move m as meaningful error if the engine considers move m to be poor and should not be played, weakening the chances of the player consolidating the player's position or win the game. Given the player's skill level (Elo rating score), the player should be able to realize the move should not be played. The chess engine annotates two types of meaningful errors: (1) strategic mistakes and (2) tactical mistakes or blunders. The annotation of a move considered a strategic mistake describes a move that results in a loss of tempo or material for the player. These errors are considered strategic and not tactical. Blunders are severe errors that overlook a tactic from the opponent and usually result in an immediate loss in position with a substantial drop in the chances of the player winning or drawing the game. Using this binary outcome variable is particularly important because not every positive deviation from the optimal move proposed by the computer ($Error_{igm} > 0$) has a significant meaning for the game. For instance, some errors are minor without real consequences for the remainder of the game, or sometimes players create positive errors on purpose when they follow a risky strategy or try to force errors by the opponent. The chess engine detects and annotates these errors.

The chess engine provides an independent evaluation for each single move of player i. The only input for the assessment of a particular move is the position of pieces on the board. From that position, the chess engine evaluates all possible moves under the assumption of sequential best response. Intuitively, each move is an independent chess puzzle, in which players need to find the best solution as proposed by the engine. In particular, this assessment does not depend on previous moves of the opponent. This allows for an independent assessment of player quality, independent of the opponent's performance.

In a descriptive analysis, we assess the power of these move evaluations produced by the chess engine to predict player and game outcomes. Panel (a) in Figure 1 displays the relationship between the average error per player and the player's Elo rating score, showing a strong negative relationship between the two. A statistically significant and negative correlation also exists between a player's Elo rating score and the player's mean error (Pearson's $\rho = -0.51$, p-value $= 0.00$). Panel (b) in

Figure 1. Player Skills and Average Move Performance



Notes. (a) Average error and player Elo rating score. (b) Proportion of meaningful errors and player Elo rating score. Each dot in the figures represents a player; the figures display the average error of a player (panel (a)) or the player's proportion of meaningful errors detected by the chess engine (panel (b)) in the vertical axis and the average Elo rating score of the player over the two tournaments in the sample in the horizontal axis. The construction of the error measure is described in Equation (1). The figures include a fitted line and slope coefficient from a bivariate regression of the outcomes on player's Elo, using heteroskedasticity robust standard errors. The figure displays the standardized coefficients (β) associated with player's Elo and the associated standard errors (in parentheses). The Pearson correlation between the proportion of meaningful errors in the sample of moves of the player and the Elo rating score of the player is -0.62 (p-value = 0.00). The Pearson correlation between player's Elo and the average size of the player's errors is –0.54 (p-value = 0.00). The correlation between the player's average of the two move-performance measures is 0.72 (p-value = 0.00). Online Table A.2 describes how a higher proportion of errors and a larger average error size in a game predict the probability of losing the game for the player.

Figure 1 displays the relationship between the average proportion of moves annotated as errors per player and the player's Elo rating score. The relationship is even stronger than the continuous error measure (panel (a)), and the correlation between the average number of annotated meaningful errors per player (the sum of strategic mistakes and blunders) and the player's Elo rating score is larger at Pearson's $\rho = -0.63$ (p-value = 0.00). Finally, Online Table A.2 describes how a higher proportion of errors and a larger average error size in a game predict the probability of losing the game for the player.

2.3. Time Control

In each game, players face a time constraint (time control). Each player is allotted 90 minutes for the first 40 moves plus 30 seconds per completed move, resulting in a total time budget of 110 minutes for the first 40 moves. After completing move 40, players get an extra time allowance of 15 minutes, to be added to the time budget left at move 40 plus 30 seconds per completed move. The time limit is allotted to each player individually and enforced by chess clocks. In each round, the tournament organizer announces the start for all games taking place in the same venue at the same time. If a player does not complete 40 moves within the time limit, the player loses the game.

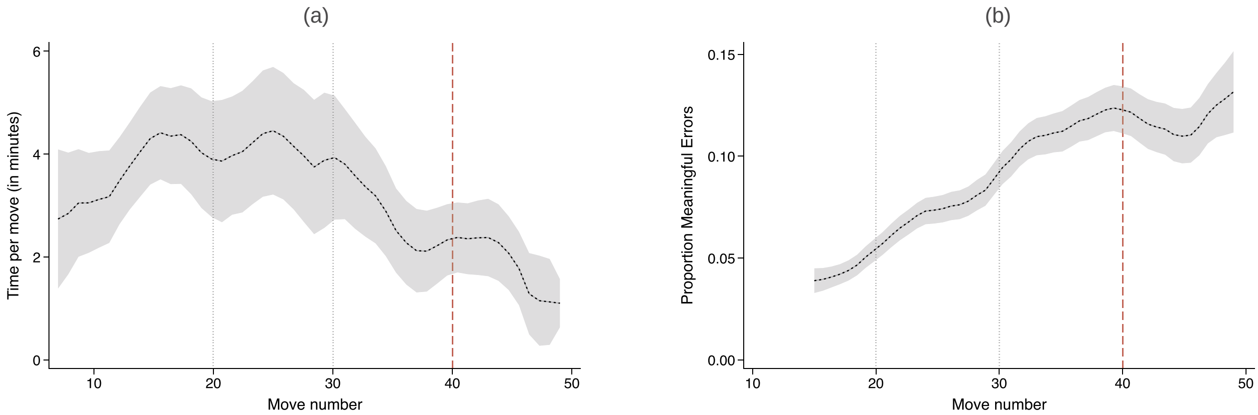
This setting gives each player a time budget to allocate to each move in the game, implying players may be under time pressure when they approach the 40th move and the time budget is reaching zero. To prevent losing the game altogether, a player then has to make move decisions substantially more quickly, potentially within seconds, which makes them more prone to making lower quality moves. Panel (a) in Figure 2 shows the distribution of the time per move for different move categories. It provides suggestive evidence for the hypothesis that players act under time pressure when they are approaching the time control as the average time per move decreases steadily from move 30 until move 40.

Furthermore, panel (a) in Figure 2 shows how the proportion of erroneous moves within a game peaks at move 40 when the time control takes place, suggesting that tighter time budget constraint harms the quality of move decisions.[24] Finally, Online Figure A.2 shows the distribution of the total number of moves for all the games in our sample. The histogram shows peaks in the number of games finished around the move constraint (40 moves), suggesting the imposed time constraint is binding, increasing the probability of ending a game right after the 40th move. In the empirical analysis, we exploit this feature of the tournament setup to test whether the indoor air quality during a game increases the effect of air quality on the probability of making errors when approaching the last move of the time control.

2.4. Measurement of Indoor Air Quality

In the empirical analysis, we use PM as the main indicator for indoor air quality, which is considered the biggest environmental risk to health (World Health Organization 2016). We focus on the concentration of fine particulate matter, microscopic solid or liquid particles with a diameter smaller than 2.5 micrometers ($PM_{2.5}$), which may penetrate indoor environments and enter deep into the lungs and bloodstream.[25]

Figure 2. (Color online) Time Pressure in Our Sample



Notes. (a) Average minutes per move. (b) Proportion of meaningful errors per move. The figure in panel (a) shows the average time (in minutes) used by players in the corresponding move of the game. The evidence was collected based on a sample of 63 games played during all rounds in the 2019 tournament edition. The figure in panel (b) shows the proportion of meaningful errors across moves in all games in our sample. Online Figure A.4 displays the average error size across moves in games in our sample.

The research team collected the data on indoor air pollution during the chess tournament. During all editions of the tournament, the organizers allowed us to measure indoor environmental conditions throughout all tournament rounds inside the venue, a large church community hall in a suburban residential area. The tournament venue is located in a clean neighborhood with moderate levels of pollution. The average levels of outdoor concentration of fine particles during the tournament days are moderate. The average levels are equivalent to 34% of the average 24-hour concentration in U.S. cities over the past decade (Environmental Protection Agency 2020), and they are just below the average of pollution levels retrieved from stations in the largest cities in Germany during the time of the tournament (see Online Figure A.4).

The sensors were installed before the start of each tournament round and removed after the last game was finished. The players were informed that the measurement was being undertaken for scientific purposes but not about the exact purpose of the study, that is, studying the effect of indoor environmental conditions on chess players' performance.[26]

The indoor environmental quality measurements are retrieved from three real-time web-connected sensors located inside the tournament venue: two Foobot sensors and one Netatmo indoor sensor. The $PM_{2.5}$ measurements come from the Foobot sensors. Previous studies in the field of atmospheric science show that Foobot yields precise estimates of $PM_{2.5}$ concentrations in rooms.[27] In addition, the Netatmo sensor measures CO_2, temperature, and humidity and noise in the room.[28] This indoor air-quality monitor is used by leading studies in the field of epidemiology and public health to evaluate the impact of ventilation rates on occupant cognitive outcomes (e.g., Allen et al. 2016). The sensors measure the parameters of interest every minute and upload the measurements to a cloud server.

We focus on the mean measurements of $PM_{2.5}$ during the second hour of each tournament round.[29] The average level in our sample for $PM_{2.5}$ is 27.1 $\mu g/m^3$ (see Table 1), slightly above the European target of 25 $\mu g/m^3$ set by the European Environmental Agency (2018). Indoor $PM_{2.5}$ levels are mainly determined by outdoor sources. Fine particles are emitted directly from either natural sources (e.g., volcanoes, dust storms, fires) or human action when burning fossil fuels from traffic, power plants, industry, etc. In addition, the level of particulate matter pollution is strongly influenced by meteorological and topographic conditions (Environmental Protection Agency 2009). Therefore, we contrast our results based on the indoor measurements with measurements of outdoor particulate matter pollution retrieved from official air quality stations (see Section 5 for the results of outdoor measurements).

2.5. Descriptive Statistics

Our data follow 121 players over a maximum of 21 matches. A total of 62 players (51%) participated in at least two editions of the tournament, out of which 34 (28%) participated in all three tournaments. Panel A of Table 1 shows summary statistics for player skills and demographic characteristics of the participants. Our sample is mainly composed of adult men who were, on average, 53 years old with a wide range of levels of expertise. The least experienced player has only two official matches in his records, and the most experienced player played 279 matches. The players also differ in their skill levels, according to the Elo rating score attached to their records. The Elo rating score of the most skilled player was more than twice as large as that

Table 1. Descriptive Statistics

	N (1)	Mean (2)	Standard deviation (3)	Minimum (4)	Maximum (5)
A. Player characteristics					
Elo rating score	121	1,685	313.80	938.30	2,281
Number of official matches played	121	80.75	65.27	2	279
Age, years	121	52.62	17.20	18	89
Female	121	0.05	0.22	0	1
B. Game-specific characteristics					
Total number of moves	609	38.85	14.58	15	98
Total duration, minutes	609	171.48	54.53	43	343
Draw game	609	0.19	0.39	0	1
Player–opponent difference in Elo rating score	609	294.49	187.17	2	1,265
Age, years	609	18.36	14.03	0	66
C. Move-specific characteristics					
Meaningful error	29,795	0.08	0.27	0	1
Error if >0	12,970	1.58	5.20	0.01	107.78
D. Round-specific characteristics[a]					
$PM_{2.5}$, $\mu g/m^3$	21	27.15	13.19	14.03	69.75
CO_2, ppm	21	1,511	338.80	967.20	2,393
Temperature, °C	21	24.32	2.15	21.77	28.75
Noise, decibels	21	47.36	1.21	45.33	49.92
Humidity, %	21	48.64	5.08	39.72	58.23
Outdoor PM_{10}, $\mu g/m^3$	21	18.74	10.92	10	48.17

Note. The table describes the main estimation sample.
[a]Round-specific characteristics display the mean values of the prevailing conditions as measured during the second hour of the tournament round.

of the least skilled player. In addition, Figure 3 shows the entire distribution of the Elo rating score of the players in the observed tournaments and compares the scores with the official ranks within FIDE. As the figure shows, we observe a wide range of skill levels ranging from beginners (novices) to advanced players (FIDE masters). In addition, the figure shows the Elo score of the chess engine Stockfish clearly dominating any human player.

Focusing on the game-specific characteristics (panel B in Table 1), we can see that games in our sample lasted around three hours on average. The average length of the games in our sample was around the 40-move threshold (see Online Figure A.2 for the full distribution of moves). About 18% of games finished in a draw. The distribution of our outcome measures is shown in panel C of Table 1. A total of 8% of the moves are annotated as meaningful errors. Moreover, 43% of the moves are considered suboptimal (positive error) with an average error rate of 1.55 pawns. Finally, panel D in Table 1 shows the distribution of the indoor environmental variables within the estimation sample.

3. Empirical Model

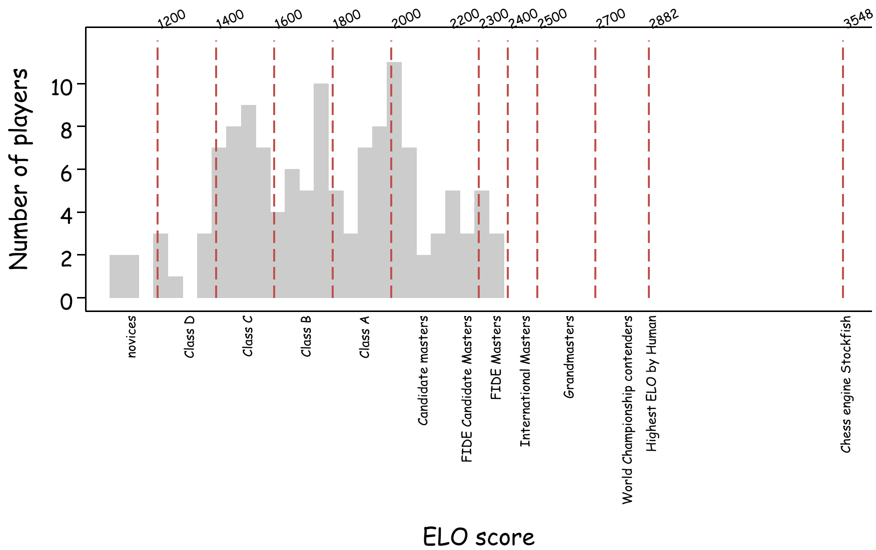
The goal of this paper is to estimate the causal effect of indoor air quality on the quality of strategic decisions undertaken by chess players. Our study setting has a number of features that allow us to identify the effect of environmental stressors on decision making. First, players were executing the same task repeatedly in the same venue, the same day of the week, and at the same time of the day. In addition, the selection of opponents for each of the games was exogenously determined by the tournament rules. Thus, participants had no control over the environmental conditions to which they were exposed during their games nor over the opponents they played in a given round. Second, we have objective measures of decision quality by evaluating each move by the players in our sample of games. Third, the high frequency of our outcome measures allows for the decomposition of the impact of air quality over different stages of the game. In particular, it allows us to test for differences in the magnitude of the impact as the time budget of players diminishes over the course of the game. Finally, all players in our sample faced strong incentives to exert high effort because the performance in each game of the tournaments counted toward their chess rating score. Therefore, the incentive structure in our setting deviates from the structure in nonincentivized laboratory experiments or survey-based studies in which participants' payoffs are not determined by their performance in the proposed tasks. By contrast, our participants were highly motivated to perform to the best of their abilities.

We follow a fixed-effects strategy and estimate the following linear model:

$$Y_{ijtrm} = \alpha + \delta PM2.5_{tr} + \boldsymbol{\beta X_{ijtrm}} + \eta_i + \gamma_t + \lambda_r + \theta_m + V_{ijtrm}, \quad (2)$$

where Y_{ijtrm} is the outcome variable measured in a

Figure 3. (Color online) Distribution of Players' Elo Rating Score



Note. The players' Elo score is calculated by adding 100 to the players' DWZ score in order to make the scores comparable to the FIDE system.

game between player i and opponent j in year t, round r at move m. We consider two main outcome variables to capture the frequency and the magnitude of errors. Our first outcome variable, *Meaningful Error*, is defined as a binary indicator taking the value of one if player i's move m is annotated as a meaningful error by the chess engine (strategic mistakes and blunders) and zero otherwise. We focus on annotated errors instead of using $Prob(Error > 0)$ because not every positive error has a significant meaning for the game (see Section 2.2 for details). The second outcome variable *Ln(Error)* is the natural logarithm of the continuous error measure, describing the difference in the pawn metric between the computer's optimal proposal and the player's actual move. See Equation (1) for a detailed description of the variable.

The parameter of interest is denoted by δ, which measures the impact of prevailing indoor concentration of $PM_{2.5}$ measured during the second hour of the tournament round r in year t on the outcome variable. Our main identifying assumption for estimating δ is that the exposure to indoor $PM_{2.5}$ is assigned exogenously to players as they do not have any control over the timing of the games nor the configuration of the venue where games take place. As move decisions in chess games are very complex and may be affected by a range of factors beyond particle concentrations, we further include a rich set of fixed effects and controls that may be spuriously correlated with measures of indoor air quality in order to retrieve the causal effect of $PM_{2.5}$ on our outcomes measuring the quality of strategic decision making of players.

Specifically, we include a rich set of round-, game-, and move-specific controls denoted by $\boldsymbol{X}_{ijtrm}$. First, it includes a rich set of environmental conditions in the tournament room, that is, temperature, concentration of CO_2, noise, and humidity, measured during tournament round r in year t.[30] The CO_2 and noise measures allow us to control for potential changes in the number and behavior of players across rounds. The noise sensor measures the background noise in the tournament venue, allowing us to capture any changes in noise levels in the neighborhood (e.g., traffic) or inside the venue that might disrupt the concentration of players. Indoor concentrations of CO_2 are a proxy for changes in the ventilation rates in the room, together with changes in the number and activity patterns of occupants, such as breathing patterns (e.g., Satish et al. 2012, Allen et al. 2016, Roth 2016).[31] Second, the set of controls includes the differences in skills between opponents in a given game, $EloDiff_{ijt}$, which denotes the initial difference in Elo rating score between the player and the opponent measured at the beginning of the tournament in year t. In the regression, we include the level variable $EloDiff_{ijt}$ as well as its squared term. In addition, we control for the points earned over the tournament by the player up to round r of the tournament in year t. Finally, we control for the initial advantage of the player before executing move m, the pawn metric $C^{player}_{ijtr,m-1}$, in the respective game. This variable reflects how tight the game is based on the ex ante situation on the chess board and, therefore, proxies how likely the game is to end in the upcoming moves.

In addition, we include a rich set of fixed effects. Individual player fixed effects η_i hold a player's ability and other time-invariant player characteristics constant over their games and moves part of the sample. This term also captures players' general health conditions, which may affect the sensitivity to air pollution. The term γ_t captures any year-specific impact on error-proneness that is uniform to all players, which may also include year-to-year changes in average pollution levels. Finally, fixed effects for tournament round λ_r and move θ_m

capture average dynamics over the course of a tournament edition and within a game, respectively. In particular, move fixed effects capture that, in specific phases of the game, for example, the so-called middle game or when approaching the time control at move 40, players may generally make more mistakes irrespective of the exposure to poor air quality (see Section 2.3 for a discussion). Hence, our main identifying assumption is that the remaining variation in $PM_{2.5}$ is assigned as good as random to chess players, allowing us to interpret the coefficients as the causal impact of poor indoor air quality on strategic decision making.

Finally, the error term V_{ijtrm} is clustered at the day (round × year) level to allow for arbitrary correlation within tournament days. Given the low number of clusters in our study ($n = 21$), potentially violating the large-sample assumptions, we base our inference on p-values based on wild bootstrap clusters as recommended by Cameron et al. (2008).[32]

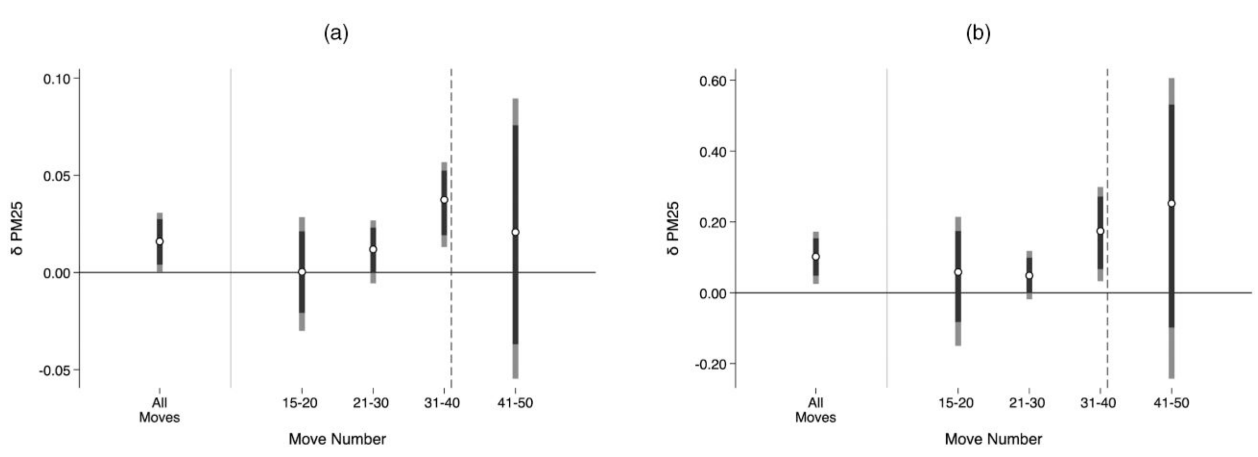
4. Effects of Indoor Air Quality on Move Decisions

We present the results on the impact of indoor air quality on the quality of chess players' moves in three stages: In a first step, we present our main results in Section 4.1, in which we estimate Equation (2) based on all moves in the games as well as subsamples representing different phases of a game in which players face varying time pressure. Players had a total of 110 minutes for the first 40 moves, inducing higher time pressure once they approached the 40th move than at the beginning of the match. Second, we analyze effect heterogeneity with respect to individual and game characteristics in Section 4.2. Third, we present a number of sensitivity analyses in Section 4.3.

4.1. Main Results

Figure 4 shows the estimated parameters for the air-quality measures with respect to the probability of making a meaningful error (panel (a)) and the magnitude of the error (panel (b)). Each bar represents the estimation results from separate regressions, each including a different sample of moves. First, we estimate our parameters of interest in the pooled sample, containing all moves in the games in our sample. Moreover, we define four different subsamples of move intervals within games, that is, moves 15–20 (21% of the sample), 21–30 (35%), 31–40 (23%), and >40 moves (21%). The time control regulations of the tournament rules induce time pressure, requiring players to make the first 40 moves within 110 minutes of the game; otherwise, they lose the game. Decisions taken within the interval of moves 31–40 are assumed to be taken under relative time pressure compared with the other categories given the low expected time left to execute the required 40 moves to stay in the game.[33] All regressions contain individual, year, round, and move fixed effects; air-quality and other environmental control measures; and the full set of game-specific control variables. The dots represent

Figure 4. Impact of Indoor Air Quality on Move Quality



Notes. (a) Likelihood of meaningful errors. (b) Size errors. The figure shows the estimated coefficient associated with $PM_{2.5}$ in Equation (2). We divided the total sample of moves into subsamples of moves within a game (horizontal axis). The vertical, dashed line indicates the occurrence of the time control during the chess game. For an overview of the changes in time per move in different phases of the game, see Figure 2. Each panel presents the regression on different outcomes. Panel (a) displays the estimation results of the analysis exploring changes in the likelihood of errors measured by a binary outcome variable "meaningful error," which takes the value of one if the move is marked as a meaningful error by the chess engine and zero otherwise. Panel (b) displays estimates in changes in the size of errors, using the natural logarithm of the $Error_{igm}$ (i.e., $\text{Ln}(Error_{igm})$). Dots represent point estimates. Black (gray) bars show the 90% (95%) confidence intervals calculated based on wild bootstrapping using boottest.ado. All regressions include individual, year, round, and move fixed effects as well as the full set of control variables: (i) indoor CO_2, temperature, humidity, and noise; (ii) difference in the Elo rating score between the player and the opponent (as well as its squared term); (iii) the number of points achieved during the tournament; and (iv) the actual status of the game before the move, namely, the pawn metric describing the situation on the chess board before the player makes the move ($C^{opponent}_{jtrm-1}$).

point estimates and the black (gray) bars show the 90% (95%) confidence intervals calculated based on wild bootstrap clusters as recommended by Cameron et al. (2008).[34]

Focusing first on the estimation results for $PM_{2.5}$, we see that the level of $PM_{2.5}$ in the room is associated with a higher probability of making a meaningful error (panel (a)). In the pooled sample (including all moves in the games), the results indicate that a 10 $\mu g/m^3$ increase in $PM_{2.5}$ raises the probability of a player making a meaningful error by 2.1 percentage points in a given move of a game: 26.3% of the baseline probability of making a meaningful error in our sample (i.e., 8.0%; see panel C in Table 1). In order to contextualize the impact of $PM_{2.5}$ on player performance, we benchmark the impacts of $PM_{2.5}$ with the coefficient associated with the player's ability rating (i.e., Elo).[35] In our sample, a standard deviation increase in air pollution equals a 66% standard deviation drop in the distribution of ability as described by the player's Elo score. Thus, a player being exposed to one standard deviation higher of $PM_{2.5}$ performs as a player with an ability 66% standard deviation lower (i.e., 220 Elo points lower) than the player's current ability level (i.e., current Elo rating).

The subsample analysis over the different phases of the game reveal the clear pattern that the impact of $PM_{2.5}$ increases the closer the game gets to the 40th move, when the time budget that players are granted per move in our sample tends to zero (see Section 2.3). This finding suggests that the effect in the pooled sample is mainly driven by the moves close to move 40 when the time control takes place. Focusing on the move category 31–40, we find that a 10 $\mu g/m^3$ increase in the levels of $PM_{2.5}$ in the room leads to a 3.2 percentage point increase in the probability of making a meaningful error. This effect is equivalent to a 27.6% increase given the average probability of making a meaningful error in our sample (11.3% for moves in this range). One might be concerned that the increasing effect of $PM_{2.5}$ over the course of the game might be alternatively explained by the rising complexity of moves. However, we argue that this is unlikely to explain the observed pattern because there is no indication that moves 21–30, 31–40, or 41–50 systematically differ in terms of move complexity. These move categories usually capture the so-called middle game of chess, which is most challenging as players can rely less on memorization of theoretical variations (i.e., book moves) than in the opening or end game. In the middle game, there is no evidence that the degree of complexity is systematically increasing with move number.

In panel (b) of Figure 4, we present the analysis for the magnitude of those errors. We find a similar pattern as for the binary outcome in panel (a). A 10 $\mu g/m^3$ increase in the levels of $PM_{2.5}$ significantly increases the size of an error by 10.8% among all erroneous moves and by 20.2% for erroneous moves in the interval of moves 31–40. It is important to note that our continuous error measure *Ln(error)* is only defined for erroneous moves (i.e., those moves in which the player's move is strictly worse than the computer's move) resulting in a significantly smaller sample size compared with the binary outcome variable that is observed for all moves in the sample (12,742 compared with 29,517 observations). In Online Figure A.6, we present the results based on the full sample of moves using the inverse hyperbolic sine transformation of the error size as an outcome showing a similar pattern to our main effects.[36]

4.2. Effect Heterogeneity with Respect to Player Relative Strength

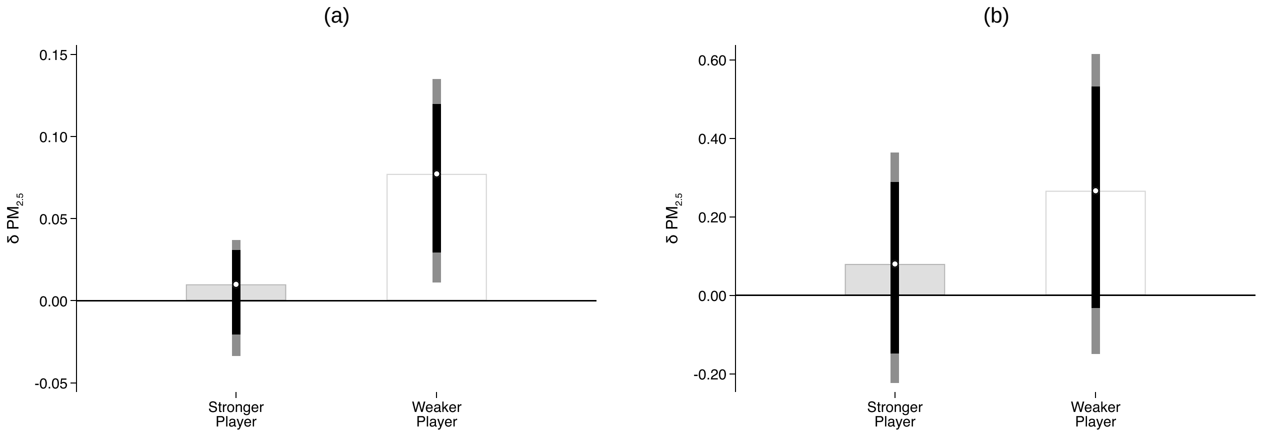
In a second step, we analyze potential effect heterogeneity with respect to individuals' skills based on the difference in the Elo rating score between the players, indicating the ex ante strength relative to the opponent. Figure 5 shows the standardized coefficients separately for the subsample of players with a ex ante lower and higher Elo rating scores than the opponent. For this analysis, we focus on the moves within the 31–40 moves category given that this is the stage of the game at which poor air quality has the highest effect on average.[37] Following our main analysis, all regressions contain individual, year, round, and move fixed effects; all environmental control variables; and the full set of game-specific control variables. Finally, to address inference concerns regarding multiple hypothesis testing, we additionally calculate adjusted p-values controlling for the familywise error rate following Jones et al. (2019).

The results indicate that the impact of $PM_{2.5}$ on the probability of making a meaningful error is larger among weaker players, that is, those playing against an opponent with higher Elo rating.[38] To address inference concerns regarding multiple hypothesis testing, we additionally calculate adjusted p-values controlling for the familywise error rate following Jones et al. (2019). The p-values after correction of multiple hypothesis testing confirm the robustness of the findings. We observe no effect of pollution among players that are facing a weaker opponent with an Elo score lower than the player. The effect pattern is still visible when using the continuous error measure as the outcome variable (panel (b)), but the results are not statistical significant.

4.3. Sensitivity Analyses

In this section, we present a number of sensitivity tests to check the robustness of our results. In particular, we reestimate the linear model as shown in Equation (2), introducing the following modifications: we (i) additionally control for traffic density as a potential confounder, (ii) restrict the sample by removing games with 40

Figure 5. Effect of Heterogeneity with Respect to Individual Ex Ante Player Relative Skill Strength



Notes. (a) Likelihood of meaningful errors. (b) Size errors. The figure shows the standardized estimated coefficients within two subsamples: (1) subsample of players with higher Elo score (i.e., "stronger player") than their opponent and (2) subsample of players with lower Elo score (i.e., "weaker player") than their opponent. The Elo score is a measure of expertise and skills of the player (see Section 2.1) for a description about the Elo score. Panel (a) displays the results for the outcome describing the probability of making a meaningful error in a given move measured with a binary outcome variable "meaningful error," which takes the value of one if the move is marked as a meaningful error by the chess engine and zero otherwise. Panel (b) describes the results for the magnitude of the error in panel (b), constructed using the natural logarithm of the $Error_{igm}$ (i.e., $\ln(Error_{igm})$). The sample is restricted to the stage of the game just before the time control takes place, that is, the 31–40 moves category. (For an overview of the changes in time per move in different phases of the game, see Figure 2.) All regressions contain individual, year, round, and move fixed effects; all environmental control variables; and the full set of game-specific control variables: (i) indoor CO_2 concentration, temperature, humidity, and noise; (ii) difference in the Elo rating score between the player and the opponent (as well as its squared term); (iii) the number of points achieved during the tournament; and (iv) the actual status of the game before the move, namely, the pawn metric describing the situation on the chess board before the player makes the move ($C^{opponent}_{jtrm-1}$). Dots represent point estimates. Black (gray) bars show the 90% (95%) confidence intervals calculated based on wild bootstrapping using boottest.ado. To address inference concerns regarding multiple hypothesis testing, we additionally calculate adjusted *p*-values controlling for the familywise error rate using wyoung.ado (following Jones et al. 2019): the adjusted *p*-values associated with $\delta_{PM2.5}$ in panel (a) (b) is 0.085 (0.400) in the subsample of weaker players and 0.811 (0.811) for the subsample of stronger players.

moves or fewer, (iii) test a nonlinear specification of temperature as a control, (iv) exclude CO_2 as a control, and (v) control for the presence of errors by the opponent in the preceding move. All specifications include the full set of fixed effects and control variables as regressors. Online Table A.3 summarizes the results of the sensitivity analysis. We focus on presenting results for our indoor measures $PM_{2.5}$ for the pooled sample as well as the restricted sample, including moves shortly before the time control (moves 31–40). To facilitate comparisons, the first two columns include the results of the main analysis.

4.3.1. Traffic Density as a Potential Confounding Factor. We test the sensitivity of our results with respect to local traffic density as a potential confounder. Traffic density around the tournament venue creates $PM_{2.5}$ pollution and, at the same time, might have affected players' cognition directly because they may have been stressed going through traffic jams (Sandi 2013). Based on official police records, we retrieved information on all traffic jams on highways and larger roads around the tournament venue within the two hours before the start of the tournament (4–6 p.m.), which are relevant for players commuting by car to the tournament venue. Columns (3) and (4) in Online Table A.3 show the results including the total length (in kilometers) of traffic jams within this time period as an additional control variable. The results are highly robust and hardly change compared with the main results as presented in columns (1) and (2).

4.3.2. Attrition. In our sample, a number of games ended before reaching the 40th move when the time control took place. Those games are likely to display differences in the number of errors in the earlier stages of the games that might lead to the early defeat of one of the players. These games might mislead our interpretation of the results, which might well be driven by those games finishing before the 40th move and not by the time pressure induced by the time control per se. In this section, we present the estimation results restricting our sample to those games that lasted at least 40 moves and, hence, passed the time threshold. Columns (5) and (6) in Online Table A.3 present the estimation results of the main equations for the sample of games lasting at least 40 moves. The results suggest the main findings from Section 4 are not driven by the games that finished before the time control was implemented. The coefficients slightly increase in size for both indoor air-quality measures as well as outcome variables. The significance of the results also increases, on average, but in particular for the magnitude of the error within the restricted sample containing moves 31–40.

4.3.3. Nonlinear Specification of Temperature. We test the inclusion of a nonlinear specification of temperature as a control variable as generally done within the literature (e.g., Graff Zivin and Neidell 2012, Ebenstein et al. 2016, Chang et al. 2019, Kahn and Li 2020). Therefore, we include temperature as a set of dummy variables describing the quartiles of the temperature distribution. Columns (7) and (8) in Online Table A.3 show the results. Most of the coefficients slightly increase in size and significance, in particular within the sample restricted to moves 31–40.

4.3.4. Impact of Indoor CO_2. In our main analysis, we include the average CO_2 levels (in ppm) in the tournament room as a control. Indoor CO_2 is commonly used in the building science field to measure ventilation rates or air exchange in rooms.[39] The levels of CO_2 in the room change as a response to the settings in the ventilation system of the building, opening or closing windows in the room, or changes in the number or activity levels of occupants in the room because changes in breathing patterns generate changes in CO_2 emissions. Therefore, this measure captures changes in numerous aspects of the room and occupants. Columns (9) and (10) in Online Table A.3 present our main estimates without including CO_2 as a control. The estimated coefficients are similar in magnitude and statistical significance, suggesting that our main results are not influenced by the inclusion of CO_2 as a control.

4.3.5. Impact of Opponent's Errors. In the main analysis, we interpret our estimates as a direct (physiological) impact of air pollution on the decision-making performance of players. Here, we test for the influence of psychological channels associated with opponent mistakes that might mediate the impacts of air pollution on decision quality of players. Columns (11) and (12) in Online Table A.3 show the estimated coefficients associated with $PM_{2.5}$ in Equation (2), adding as a control the presence of errors in the previous move of the opponent for the full sample of moves and stage of the game preceding the time control. The inclusion of this variable in the model aims to test for psychological channels mediating the effect of $PM_{2.5}$ on the decision-making performance of the players. The presence of errors by the opponent might trigger changes in the strategy of the player and ultimately influence the players' move quality. The results are almost identical to our main results, suggesting that these channels are not a major contributor to the estimated effects in this study. However, we cannot fully rule out the presence of other unobservable psychological channels in the behavior of opponent or player triggered by air pollution in the room beyond those mistakes.

5. Validation Exercises Using Outdoor Pollution Measures

This section provides a number of analyses testing the validity of the indoor sensor data, identification strategy, and external validity of the results presented in Section 4. First, in Section 5.1, we investigate the role of outdoor pollution in explaining the impairment of players' decision making indoors. The concentration of $PM_{2.5}$ in the tournament room originates from outdoor sources, and hence, we should be able to identify a link between outdoor pollution levels and player performance. Therefore, we reestimate our main results by using outdoor pollution values instead of the indoor $PM_{2.5}$ measure to validate our main results. At the same time, testing the impact of outdoor pollution measures on player performance indoors is informative about the role of buildings and to what extent they are able to protect people against air pollution.

The findings particularly add knowledge about the validity of previous studies in the field of environmental economics predominantly relying on outdoor measures.[40] In addition, the introduction of outdoor measures in the analysis allows for exploiting the temporal and spatial variation in the outdoor pollution measurements and run different falsification tests to mitigate concerns about potential confounding factors: (i) the temporal variation provides insights into the exact timing of the effect, and (ii) based on the spatial variation, we can show that the effects are indeed driven by local pollution.

Second, in Section 5.2, we replicate our results using large-scale data from the top national chess league in Germany (Bundesliga). This emphasizes that our results are valid even beyond the studied tournament, location, and cohort of players. The sample of Bundesliga players includes very sophisticated chess players, including some of the strongest in the world. Finally, we implement an IV strategy exploiting exogenous variation in air pollution driven by changes in wind direction in the location of the top national chess league venues in Section 5.3.

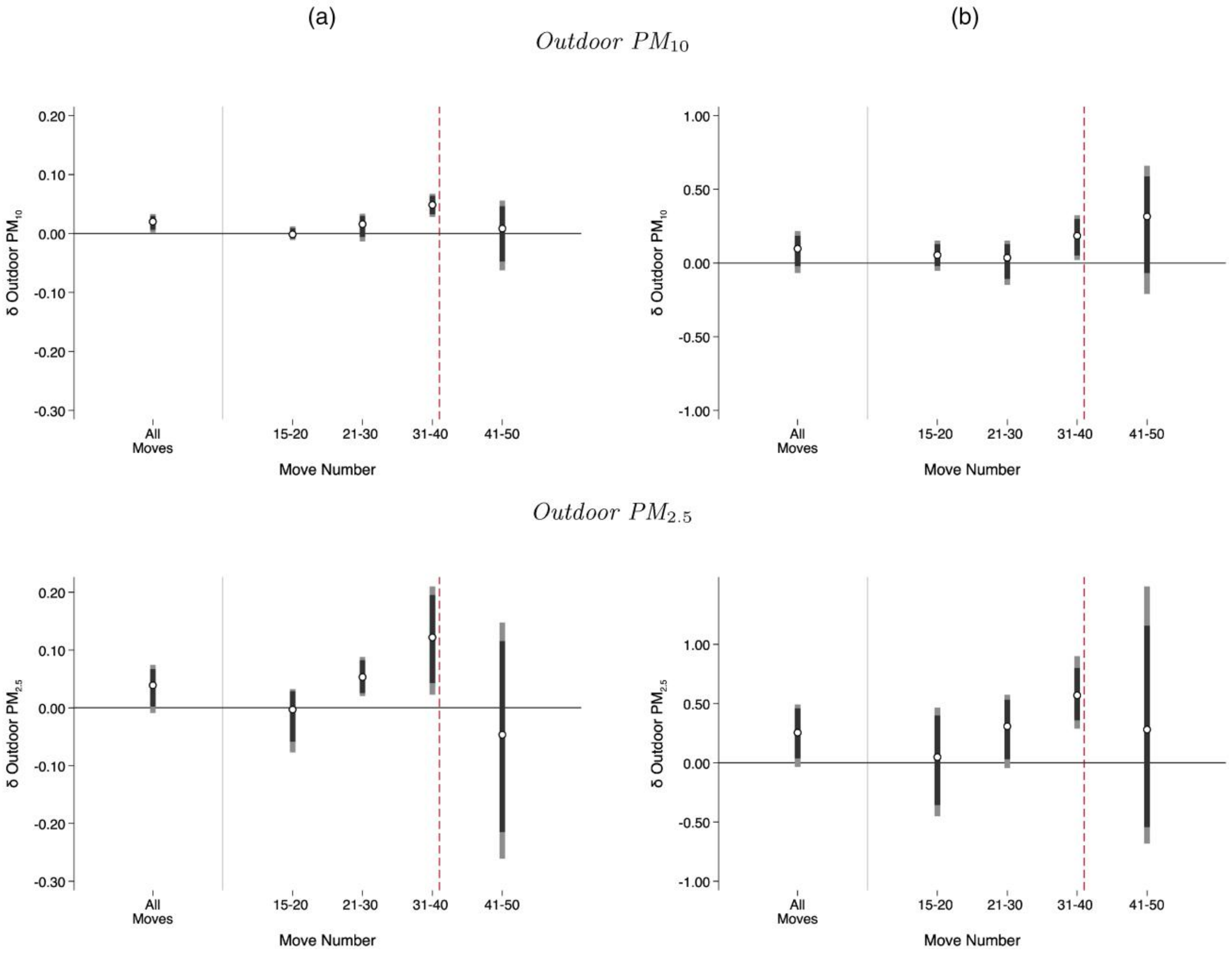
5.1. Outdoor PM Measurements

Similar to existing studies (e.g., Ebenstein et al. 2016), we retrieved information on outdoor pollution from an air-quality sensor close to the tournament venue (3.8 kilometers from the venue). The data are provided by the Federal Environment Agency (Umweltbundesamt), which operates a dense network of outdoor stations continuously measuring ambient air pollution across Germany. The outdoor pollution is measured during the same time interval as the indoor measures, namely, during the second hour of the tournament rounds.

Figure 6 shows the results when we use the outdoor measures of PM_{10} and $PM_{2.5}$ instead of the indoor measure of $PM_{2.5}$ as the treatment.[41] We find a very similar pattern for the coefficients on outdoor PM compared with our main results using indoor $PM_{2.5}$ (see Figure 4). The estimated effects of $PM_{2.5}$ are indeed larger than those associated with PM_{10}. This is consistent with the fact that $PM_{2.5}$ is an order of magnitude smaller and is able to penetrate the building in which the tournament took place.

Finally, we further test whether the estimated effects are due to general pollution, not directly emitted by traffic or factories, or are specific to particulate matter pollution. In particular, we include the average level of ozone as measured at the same outdoor air-quality station during the tournament rounds in the main empirical model, together with the rest of the environmental measures. Ozone is a product of complex chemical reactions between gases, such as nitrogen oxides and volatile organic compounds, in combination with heat and

Figure 6. (Color online) Impact of Outdoor Pollution on Move Quality



Notes. (a) Likelihood of meaningful errors. (b) Error size. The figure shows the estimated coefficients of outdoor levels of PM_{10}, top panels (in 10 $\mu g/m^3$), and $PM_{2.5}$, bottom panels (in 10 $\mu g/m^3$), on the move quality of players. We divided the total sample of moves into subsamples with respect to the number of moves within a game (horizontal axis). The vertical, dashed line indicates the occurrence of the time control during the game. (For an overview of the changes in time per move in different phases of the game, see Figure 2.) Each panel presents the regression on different outcomes. Panel (a) displays the results for the outcome describing the probability of making a meaningful error in a given move, measured with a binary outcome variable "meaningful error," which takes on the value of one if the move is marked as a meaningful error by the chess engine and zero otherwise . Panel (b) describes the results for the magnitude of the error in panel (b), constructed using the natural logarithm of the $Error_{igm}$ (i.e., $\ln(Error_{igm})$). Dots represent point estimates. Black (gray) bars show the 90% (95%) confidence intervals calculated based on wild bootstrapping using boottest.ado. All regressions include individual, year, round, and move fixed effects as well as the full set of control variables: (i) indoor temperature, humidity, and noise; (ii) difference in the Elo rating score between the player and the opponent (as well as its squared term); (iii) the number of points achieved during the tournament; and (iv) the actual status of the game before the move, namely, the pawn metric describing the situation on the chess board before the player makes the move ($C^{opponent}_{jtrm-1}$). In Online Figure A.6, we include the estimation results exploring the effect of ambient PM_{10} on performance including ozone as extra control and the estimation results of ozone on the performance of players.

sunlight (Graff Zivin and Neidell 2012). Online Figure A.8 shows the estimated coefficients associated with outdoor levels of ozone. Ozone has no statistically significant effect in our sample. This may be because ozone is a very unstable and reactive compound that breaks down very quickly indoors (Weschler 2000).

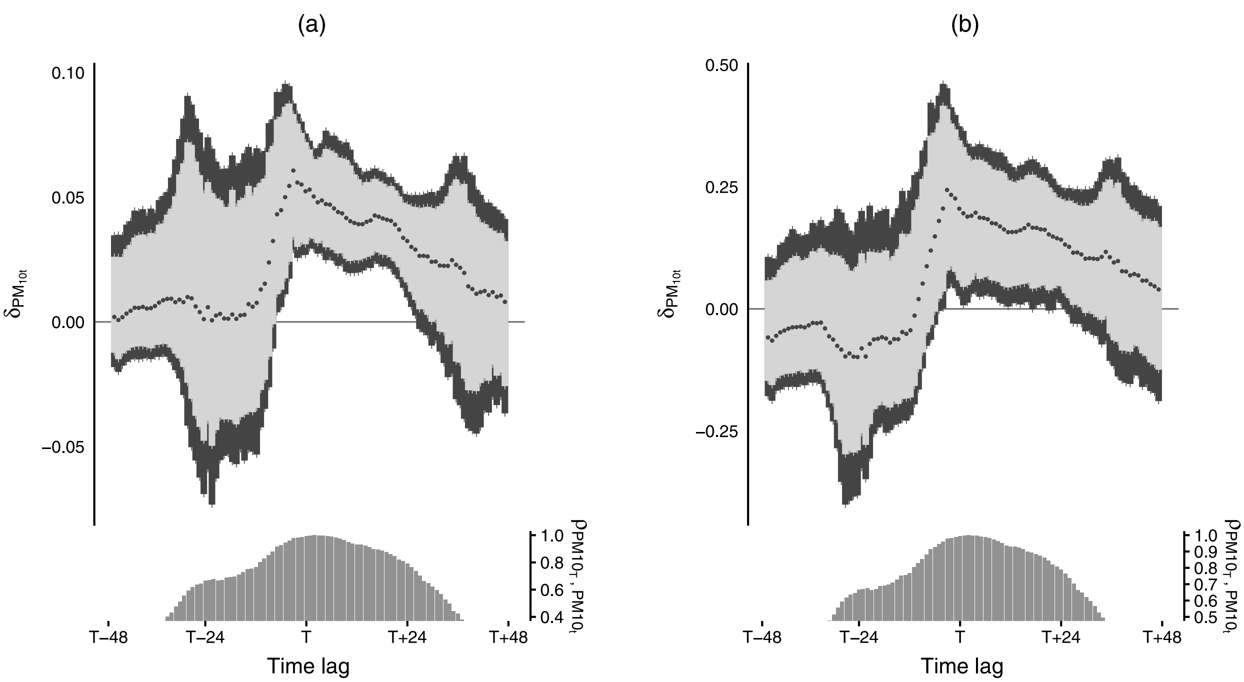
Consistent with our indoor measurements, the results on the outdoor pollution measures suggest the negative effect on players' performance is due to particulate matter pollution coming from outdoor pollution sources, and it is not explained by general outdoor pollution measured by ozone levels in the location of the tournament venue.

5.1.1. Lagged and Lead Outdoor Pollution Values. The previous exercise shows the validity of the results when using outdoor pollution. We now exploit the temporal variation in outdoor pollution, which is available in the high-frequency data as retrieved from the air-quality station nearby the tournament venue.[42] We present results of a specification test in which we estimate the relationship between the error measures and average outdoor pollution at times other than during the actual tournament rounds. In particular, we estimate a modified version of Equation (2) with misaligned pollution using the hourly levels of PM_{10}.

Focusing on the most pronounced results from earlier using the subsample of moves 31–40, Figure 7 shows the results of 97 separate regressions, including the consecutive hourly outdoor pollution values from 48 hours before to 48 hours after the time of the tournament rounds. The estimated impact of PM_{10} on our outcomes peaks at the time of the tournament, suggesting that the impact of air pollution on strategic decision making is driven by contemporaneous exposure. The figure shows significantly positive coefficients of PM_{10} from seven hours before the tournament. Similarly, the coefficients steadily go to zero as they move away from the tournament time, remaining insignificant after 24 hours.

This is in line with recent evidence that penetration of outdoor particles to the indoor environment occurs rapidly and almost entirely within five hours (Krebs et al. 2021). All other estimates are statistically insignificant. This finding suggests a short-term and transitory effect

Figure 7. Impact of PM_{10} on Move Quality in the Hours and Days Before and After the Games



Notes. (a) Likelihood of meaningful errors. (b) Error size. The figure shows the estimated coefficients of separate regressions with different lags and leads of outdoor PM_{10} in the 48 hours preceding and following the tournament time, using the subsample with 31-40 moves. Each panel presents the regression on different outcomes. Panel (a) displays the results for the outcome describing the probability of making a meaningful error in a given move, measured with a binary outcome variable "meaningful error," which takes on the value of one if the move is marked as a meaningful error by the chess engine and zero otherwise. Panel (b) describes the results for the magnitude of the error in panel (b), constructed using the natural logarithm of the $Error_{igm}$ (i.e., $\ln(Error_{igm})$). Dots represent point estimates. Black (gray) bars show the 90% (95%) confidence intervals calculated based on wild bootstrapping using boottest.ado. Both panels include at the bottom the correlation between the PM_{10} in the corresponding hour with the PM_{10} at the time of the tournament, $\rho(PM_{10\tau} PM_{10t})$ (i.e., the treatment variable in our main specification). All regressions include individual, year, round, and move fixed effects as well as the full set of control variables: (i) indoor CO_2 concentration, temperature, humidity, and noise; (ii) difference in the Elo rating score between the player and the opponent (as well as its squared term); (iii) the number of points achieved during the tournament; and (iv) the actual status of the game before the move, namely, the pawn metric of the previous move by the opponent ($C^{opponent}_{jtrm-1}$).

of particulate matter on the decision making of players. Moreover, it is supportive evidence that our results on the probability and magnitude of errors are driven by the transitory effect of pollution rather than by other explanations. The lack of effects of lagged PM_{10} beyond a few hours preceding the tournament indicates an absence of lagged health channels driving our performance measures. The absence of an effect for lead pollution offers further confirmation that our results are not driven by unobserved confounding factors. However, it is important to note that the high serial correlation hinders the analysis of accumulated exposure channels in our sample. At the bottom of each panel in Figure 7, we include a bar graph showing the correlation between the corresponding PM_{10} hourly measure and the PM_{10} levels at the time of the tournament. The figure shows that the Pearson correlation coefficients between the pollution at the time of the tournament and hourly measures of pollution up to 12 hours before the tournament are above 0.8 and remain at those high levels until 24 hours after the tournament.

5.1.2. Spatial Variation in Pollution Values. Next to the temporal variation, we exploit spatial variation in the outdoor pollution measure to show that our results are indeed driven by local pollution. We use data on outdoor PM concentrations at the exact same time as the tournament dates but measured by alternative air-quality stations. We build a comprehensive data set containing the PM_{10} measurements from all air-quality stations located in the 40 largest cities in Germany.[43] The actual city of the tournament venue is one of the largest cities in the country.

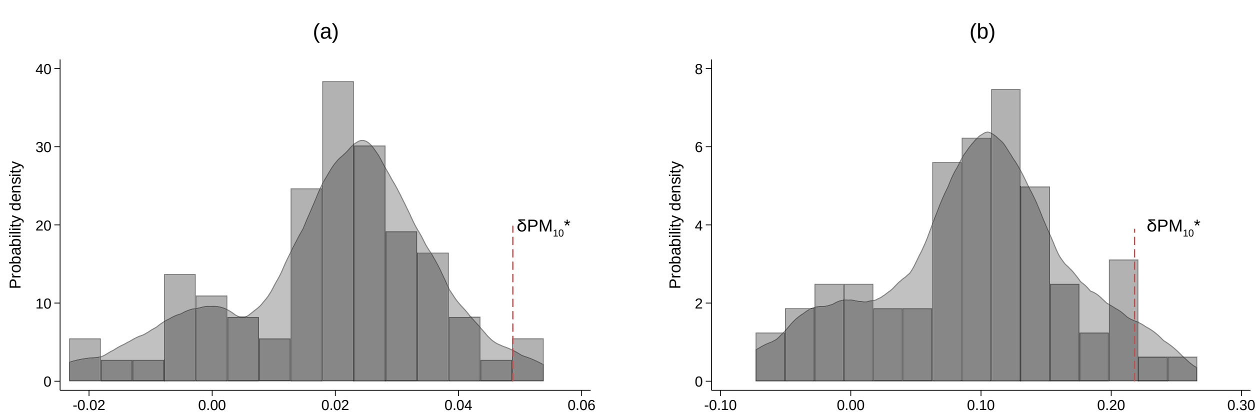
Figure 8 shows a histogram of the distribution of the resulting point estimates when using PM_{10} levels from alternative city locations. The point estimates based on the closest station to the tournament venue are indicated by a vertical dashed line. The figure shows that the point estimates obtained from the closest station to the venue are at the very top of the distribution, suggesting that local pollution indeed triggered the impairment of players' performance, validating our results and supporting the hypothesis that our main estimates are driven by a short-term exposure to particulate pollution.

The graph further shows that PM_{10} levels retrieved from other stations also yield mostly positive point estimates. This is not surprising as air pollution on a given day is positively correlated across locations within the country, especially given that 14 out of the 40 cities are within a radius of 100 km around the location of the tournament.

5.2. Replication Exercise Using Large-Scale Data from Top National Chess League

The main analysis in this manuscript relies on data from three editions of one tournament organized by one chess club in Germany. The organizers granted the research team access to deploy indoor air-quality sensors in the tournament room and shared with us all the move records in all games of the tournament and player characteristics (see Section 2 for details). This tournament provides a high-control setting, in which we can follow a

Figure 8. (Color online) Estimated Effects of PM_{10} from Every Air-Quality Station Located in the Largest 40 Cities in Germany



Notes. (a) Likelihood of meaningful errors. (b) Error size. The figure shows the histogram of estimated coefficients δ of Equation (2) using outdoor PM_{10} retrieved from sensor stations located in the 40 largest cities in Germany as well as from the closest sensor station to our tournament location (indicated by the dashed line and $\delta_{PM}*$). The sample is restricted to the subsample with 31–40 moves, the stage of the game just before the time control takes place. Each panel presents the results for a different outcome variable. Panel (a) displays the results for the outcome describing the probability of making a meaningful error in a given move, measured with a binary outcome variable "meaningful error," which takes on the value of one if the move is marked as a meaningful error by the chess engine and zero otherwise. Panel (b) describes the results for the magnitude of the error, constructed using the natural logarithm of the $Error_{igm}$ (i.e., $\ln(Error_{igm})$). All regressions include individual, year, round, and move fixed effects as well as the full set of control variables: (i) indoor CO_2 concentration, temperature, humidity, and noise; (ii) difference in the Elo rating score between the player and the opponent (as well as its squared term); (iii) the number of points achieved during the tournament; and (iv) the actual status of the game before the move, namely, the pawn metric of the previous move by the opponent ($C^{opponent}_{jtrm-1}$).

constant cohort of individuals, playing in the same room, always on Monday evenings in spring, under different levels of fine-particle concentrations. However, the reliance on one location, cohort, and tournament organizer might trigger concerns regarding the external validity of our findings.

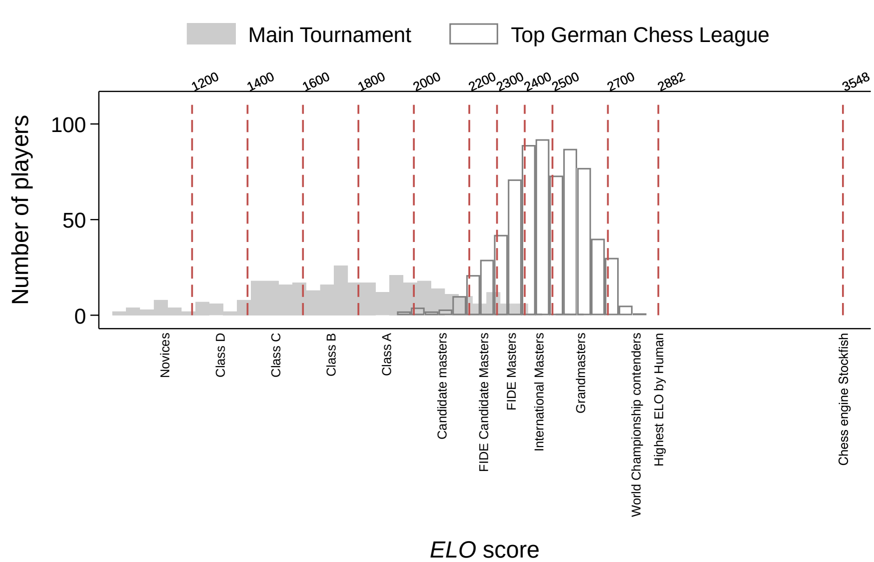
In this section, we present the results of a replication exercise, in which we mimic our main analysis using data on official games from the top national chess league in Germany (Bundesliga) over the period 2003–2019.[44] Germany's top league is considered one of the world's strongest chess competitions, attracting some of the strongest players in the world, including world champions, such as Magnus Carlsen. Figure 9 displays the distribution of Elo ratings in the sample of players in the top German league and compares it with the players' Elo ratings in our main tournament. The figure shows how the distribution of players in the top German league is mainly concentrated at levels obtained by international masters and grandmasters, indicating the much higher average strength of the Bundesliga players compared with the main sample.

We use the same chess engine as in our main analysis (Stockfish) to analyze the games from the top national chess league and analogously calculate the outcome variables for each move (see Section 2.2). Even the strongest player in our sample has an Elo rating that is 744 points (i.e., five times the standard deviation of the Elo rating in the Bundesliga sample) below the Elo rating of the chess engine, indicating that the moves selected by the engine are superior to those selected by any player in our sample.

In each season, the Bundesliga league includes 16 teams from all regions in Germany that compete against each other in seven rounds from September to May. Each round is held during a weekend with the games starting on Friday at 4 p.m., Saturday at 2 p.m., or Sunday at 10 a.m. In total, we observe 64 different locations in 26 cities in our final sample. The map in Online Figure A.10 shows the geographic distribution of locations across Germany alongside the tournament location we use in our main analysis. In order to reduce travel and accommodation costs, geographically close teams are paired, and two pairs meet at one location for each round. With 16 teams in total, we observe four different locations in each round. The nomination of players per team, the pairing of teams, the game schedule, and the round locations are determined before the start of the season. Finally, similar to our main setting, games in the Bundesliga are also subject to a time control by which players get a certain time budget (110–120 minutes) for the first 40 moves plus an extra time allowance afterward.

We construct a data set that mimics the setting in our main analysis, containing the universe of moves by each player in games played at the home venue over multiple rounds and years. In addition, we apply the same sample restrictions as in our main analysis, excluding the first 14 moves of each game, redefining negative errors as zero. We merge data on local outdoor PM_{10} pollution (extracted from the Federal Environment Agency; see Section 5.1) measured six hours before the tournament start to account for the lagged effect of pollution on strategic decision making as identified in the main

Figure 9. (Color online) Distribution of Players' Elo Rating Score in Main Tournament and Top German League



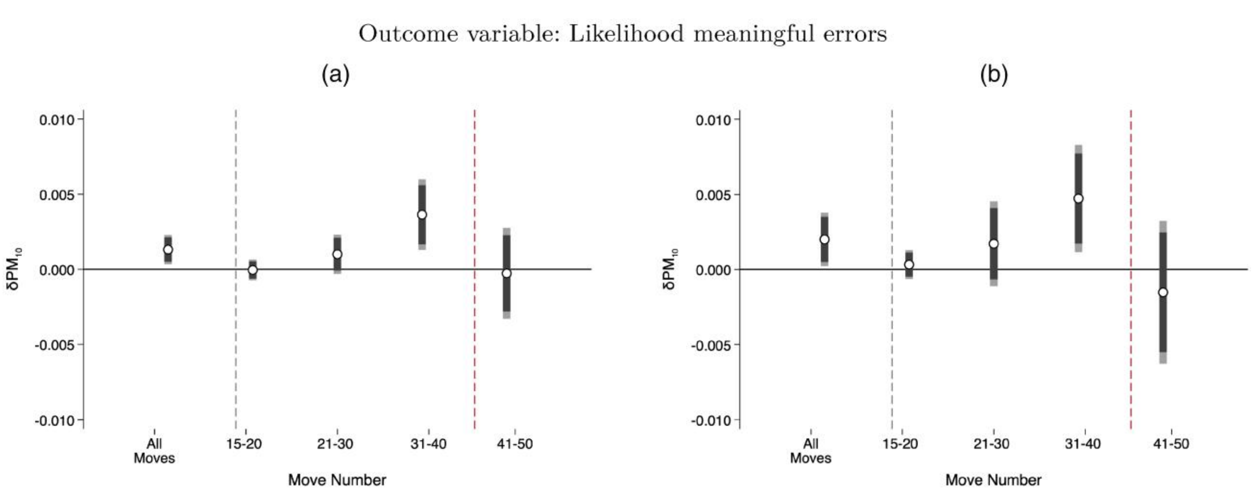
Notes. Figure displays the distribution of Elo rating score in our main sample (in gray), main tournament, and in the top German chess league (in white), that is, sample used for our replication exercise. The players' Elo score in our main sample is calculated by adding 100 to the players' DWZ score in order to make the scores comparable to the FIDE system.

analysis.[45] Given that we observe multiple sensor stations in urban areas (where the tournaments take place), we draw a radius of 10 km around each location and calculate the inverse distance-weighted mean pollution of all available monitors within that radius (similar to the approach by Currie and Neidell 2005, Archsmith et al. 2018, Isphording and Pestel 2021). In our final sample, we observe 473 players making 102,755 moves in 2,301 games between 2003 and 2019.[46] Online Table A.4 describes the sample of players, games, and moves included in the sample. The strength of the players in the top chess league is, on average, much higher than that of the players as observed in our main analysis (mean Elo rating score of 2,470 compared with 1,685). As a result, we also observe a lower probability to make a meaningful error (0.03 compared with 0.08) and smaller absolute errors (0.83 compared with 1.55) in the top chess league. Finally, we estimate the same empirical model as used for the main analysis (see Equation (2)) and additionally include opponent, location, and board fixed effects. The vector of time-varying controls includes outdoor temperature and humidity, the player–opponent difference in terms of Elo rating score as well as its squared term, and a measure capturing the initial advantage of the player before executing the move ($C^{player}_{ijtr,m-1}$).

Figure 10 shows the results based on the top national chess league data using the probability to make a meaningful error as the outcome variable.[47] Panel (a) of Figure 10 shows the results using ordinary least squares (OLS) estimation (Equation (2)). Panel (b) presents results from an IV estimation in which we instrument local pollution levels by wind direction (see Section 5.3 for a detailed description of the IV estimation and a description of the results).

Focusing on panel (a), we find the same pattern as in the main analysis. The impact of air pollution is positive and statistically significant for all moves but is strongest when games are approaching the time control in move 40 and players are expected to experience the highest time stress. Our estimates indicate that a 10 $\mu g/m^3$ increase in the levels of outdoor PM_{10} increases players' probability to make a meaningful error by 0.13 (0.36) percentage points for all moves (the move category 31–40). The effects for all moves and the move category 31–40 are statistically significant at the 1% level and correspond to a 5.4% (9%) increase compared with the average

Figure 10. (Color online) Impact of Outdoor PM_{10} on Move Quality Using Games of the German Top National Chess League



Kleibergen-Paap F-statistics

All	≤ 20	21-30	31-40	>40
36.14	37.83	34.49	28.16	19.55

Notes. (a) OLS estimation. (b) IV estimation. Panel (a) shows the estimated coefficient δ of Equation (2) based on separate regressions for each move category. The binary outcome variable "meaningful error" takes the value of one if the move is marked as a meaningful error by the chess engine and zero otherwise. The underlying sample consists of analyzed chess moves as played during official competitions of the top national chess league in Germany between 2003 and 2019 (see Section 5.2). PM_{10} outdoor pollution levels are measured six hours before the tournament start. Panel (b) shows the second stage estimation results using wind direction measured at six, seven, and eight hours before the tournament start to instrument for local outdoor PM_{10} pollution measured six hours before the tournament start. The Kleibergen–Paap *F*-statistic is presented below each figure, indicating a sufficiently large first stage estimation. Dots represent point estimates. Black (gray) bars show the 90% (95%) confidence intervals. Standard errors are clustered at the year, round, and location level. All regressions include individual, opponent, year, round, move, board, and location fixed effects as well as the full set of control variables: (i) outdoor temperature (dummy variables for each decile of the distribution) and humidity, (ii) the player–opponent difference in terms of the Elo rating score as well as its squared term, and (iii) the initial advantage of the player before executing the move ($C^{opponent}_{jtrm-1}$).

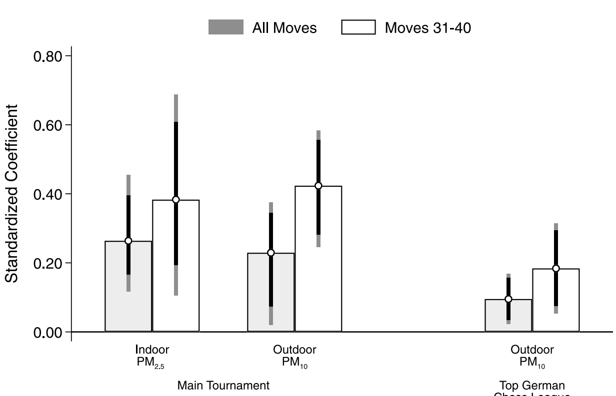
Management Science, 2023, vol. 69, no. 9, pp. 5354–5377, © 2023 The Author(s)

probability of making a meaningful error (in move interval 31–40).

5.2.1. Comparing Effects Between Main Tournament and Top National League. In Figure 11, we show a comparison of the magnitude of the results in the main tournament and our replication sample including the strongest chess players in the country. To facilitate the comparison across specifications, we standardize the coefficients associated with PM and display them in terms of the average baseline probability of making a meaningful error in the corresponding estimation sample. Thus, the coefficients are to be interpreted as the impact of a one standard deviation increase in PM pollution on the likelihood of making a meaningful error relative to the baseline probability in the corresponding sample.

The figure indicates that the magnitude of the impact of air pollution in both samples is economically significant, especially when players are choosing moves under a limited time budget. In the main tournament, a one standard deviation increase in PM leads to an increase in the probability of making a meaningful error equivalent to 26% of the baseline probability of making a meaningful error in the overall sample of moves and 38% when limiting the sample to moves just before the time control takes place. The results are almost identical in terms of magnitude and statistical significance when we use the readings from the closest outdoor air-quality station. In the sample of players from the top German chess league, a one standard deviation increase in PM leads to a smaller increase in errors by 9.5% of the sample's baseline probability of making a meaningful mistake. The effect increases to 18.4% when focusing on the stage of the game immediately before the time control. Therefore, the results in the top German league are smaller in magnitude than those in the main analysis, which is in line with the results presented in the heterogeneity analysis in Section 4.2, which describes that the effects are smaller for stronger players. In sum, the results consistently show that air pollution significantly hinders the ability of players to select optimal moves, especially when these individuals face time pressure. This result is visible in our main tournament and in the top national chess league in Germany, in which the average player is substantially stronger. This supports the external validity of the tournament sample and highlights the implications of air pollution for strategic decision making over the entire distribution of skill levels or expertise.

Figure 11. Comparison Impact Size of Air Pollution on Move Quality Across Samples for the Likelihood of Making a Meaningful Error



Notes. The figure shows the standardized estimated PM coefficients on the probability of making a meaningful error for each subsample separately. Gray bars represent the results using the full sample of moves, and white bars display the coefficients for the subsample of moves from the 31st to 40th move of the game, just before the time control takes place. We display the results for four different specifications. From left to right: (1) "Indoor $PM_{2.5}$" bars describe the PM estimates based on our indoor air-quality monitor, deployed at the tournament room in the main tournament; (2) "Outdoor PM_{10}" describes the results for the main tournament using the readings from the closest outdoor air-quality station; (3) the last pair of bars describe the estimates based on games in "the top German league" using readings from air-quality stations near tournament venues. The outcome variable "meaningful error" takes on the value of one if the move is marked as a meaningful error by the chess engine and zero otherwise. Dots describe point estimates. Black (gray) error bars show the 90% (95%) confidence intervals.

5.3. Wind Direction as Exogenous Source of Variation

Finally, the main empirical approach in this paper relies on the general variation in air pollution across days regardless of the source inducing changes in the exposure of players to air pollution. In a final test, we exploit the rich spatial and temporal variation in the Bundesliga data to implement an IV approach, in which we exploit location-specific variation in wind directions driving variation in pollution exposure to estimate the impact of PM_{10} pollution on players' decision making.

The IV approach helps to single out the effect of PM_{10} pollution by overcoming problems of omitted variables bias (e.g., changes in local economy or traffic causing stress to players) or measurement error. Measurement error can be of concern in our Bundesliga data because our PM readings do not come from an air-quality monitor in the tournament room, but from the interpolation of weighted average readings of PM_{10} stations within a 10-km radius of the tournament location. In this analysis, we adopt the widely used IV approach proposed by Deryugina et al. (2019), exploiting the exogenous and largely imperceptible variation in wind directions to predict local outdoor PM_{10} pollution levels. Wind direction can be expected to affect the level of air pollution in a given location because of its physical and economic geography. For example, a tournament venue to the west of a polluter (e.g., industrial area, highway) experiences higher PM_{10} pollution levels on days with wind blowing from the east than on days with west wind. At the same time, the wind direction on a particular day can be considered exogenous to local economic conditions as well as any factor influencing the measurement error in pollution (Deryugina et al. 2019).

In the first stage, we regress the local PM_{10} pollution in the vicinity of the tournament venues (10-km radius) measured six hours before the tournament start on a set of binary instruments, which are interactions of local wind direction and regional indicators. Specifically, we follow Deryugina et al. (2019) and include the local wind direction measured six hours before the tournament start as well as two lags as to account for the geographical distance between the wind sensor and the sensor station measuring PM_{10} pollution. Location-specific wind directions are retrieved from the German Meteorological Service (Deutscher Wetterdienst) and are measured at the wind station closest to the tournament location within a maximum radius of 50 km. We create four binary indicators taking a value of one when the wind is blowing from the northeast, southeast, northwest or southwest, respectively, and zero otherwise. Clearly, the wind direction may have differential effects on PM_{10} pollution across different locations depending on geographical and economic circumstances. Therefore, we interact the four local wind direction indicators with regional binary indicators to allow for different pollution effects of local wind direction across regions in Germany. In order to reduce the computational burden of the IV estimation and to increase statistical power, we assign Bundesliga locations to 12 regions across Germany, which are based on the federal states.[48] Finally, the IV estimation includes the identical set of fixed effects and control variables as in the OLS estimation (see Section 5.2 for full description).

The Kleibergen–Paap *F*-statistics, included in a table at the bottom of panel (b) of Figure 10, confirm a sufficiently strong first stage estimation within each subsample (i.e., $F - statistic > 10$). The estimates based on the IV strategy are presented in panel (b) of Figure 10. The figure shows the same pattern as in the main fixed effects estimation strategy (panel (a)). The magnitude of the instrumented effects is slightly larger than the OLS results with the strongest effects of PM_{10} taking place in the stage just before the time control. In sum, the IV results underline the validity of the main analysis and support the notion that the reduction in players' performance is indeed explained by direct exposure to PM and not because of confounding factors.

6. Conclusion

In this paper, we investigate the impact of indoor air quality on strategic decision making using data from official chess tournaments, a high-stakes setting in which individuals make complex decisions under time pressure. The selection of moves in chess demands the intensive use of problem solving, creativity, and intuition. These skills are in considerable demand in modern labor markets and are difficult to automate. The results consistently show that exposure to poor air quality harms player performance in those tasks. For the pooled sample, we find that a 10 $\mu g/m^3$ increase in the levels of $PM_{2.5}$ in the room leads to a 2.1 percentage point increase in the probability of making a meaningful error. Our results document the critical role of time stress in moderating the impacts of air pollution on individual performance. The extent of the effect increases to 3.2 percentage points for the 31–40 moves category, which is closest to the time control when players tend to have rather limited time to select their move. During that stage of the game, we find some evidence of an increase in the magnitude of errors. A 10 $\mu g/m^3$ increase in the levels of $PM_{2.5}$ increases the size of an error by 20.2%. Finally, subgroup analyses indicate that less skilled subjects were most affected by poor air quality, thus exacerbating ex ante inequalities between players.

To place these results in context, it is instructive to compare them to performance estimates found in prior research that focuses on other types of economic outcomes. Ebenstein et al. (2016) find that a 10-unit increase in daily $PM_{2.5}$ leads to a two percentage point increase in the probability of failing a high-stakes exam. Similarly, Heyes et al. (2016) documents a 2.6 percentage point increase in the probability of incorrect calls by baseball empires associated with a 10-unit increase in 12-hour $PM_{2.5}$. In our pooled sample, we find effects within the range of those estimates. However, when focusing on the stage of the game with high time pressure for players, just before the time control, the pollution effects are magnified. An increase of 10 $\mu g/m^3$ in $PM_{2.5}$ leads to a 3.2 percentage point increase in the probability of making meaningful errors in our sample.

A similar pattern emerges when comparing the elasticity of the size of errors in our sample with the elasticities displayed in previous studies.[49] Among manual workers, the highest elasticity is 0.260, estimated in a U.S. sample of agriculture workers (Graff Zivin and Neidell 2012). For China, Kahn and Li (2020) estimate the elasticity of $PM_{2.5}$ in a sample of highly skilled public workers and find elasticities between 0.179 and 0.243. Similarly, in our pooled sample, we find 0.281 elasticity associated with $PM_{2.5}$. When restricting the sample to the move interval shortly before the time control, we observe that the elasticity increases to 0.548 for $PM_{2.5}$, 2.25 times larger than the largest elasticity documented in previous studies.

Our results have important implications for firms and policy. The results highlight the relevance of indoor air quality for strategic decision making, an integral aspect of management in firms and a critical factor influencing the survival of firms in competitive environments. In addition, our estimates provide compelling evidence of the damages of deficient air filtration in office buildings

Management Science, 2023, vol. 69, no. 9, pp. 5354–5377, © 2023 The Author(s)

or any other indoor space where individuals are required to undertake strategic decisions. Performance damage is visible even in a clean city with relatively low levels of air pollution. The average levels of outdoor concentration of fine particles during the tournament days are relatively low: 36% of the average 24-hour concentration standard set by the European Environmental Agency. The need to isolate indoor workplaces from fine particles ($PM_{2.5}$) is becoming even more pressing in different areas of the world given the increase in frequency in recent years of high-pollution events, such as wildfires, near a high concentration of cognitive workers in California or South East Asia. The presence of such environmental hazards, therefore, increase the need to protect workers against such hazards using air filters or any other technology to enhance indoor air quality where these individuals make their decisions.

Acknowledgments

The authors thank Thomas Dohmen, Joshua Graff Zivin, Michael Greenstone, Erez Yoeli, Jackson Lu, Piet Eichholtz, Nils Kok, Matthew Neidell, Jonas Radbruch, Albert Saiz, and Christian Seel as well as seminar participants at Institute of Labor Economics Bonn, Massachusetts Institute of Technology, Maastricht University, the 2019 annual meetings of the European Association of Labour Economists, and the European Society of Population Economics for their helpful comments and suggestions. The authors are also grateful to three anonymous reviewers and the editor for their suggestions that helped to further improve the paper. Rafael Suchy, Sergej Bechtoldt, and Nicolas Meys provided excellent research assistance in collecting the data.

Endnotes

[1] Researchers in cognitive psychology describe strategic decision making as complex decisions that require problem identification, alternatives generation, and evaluation (Schwenk 1988). Strategic decisions require individuals to develop adaptation and anticipation in complex cognitive processes (Wally and Baum 1994, Rustichini 2015, Gill and Prowse 2016), often under pressing time-constrained environments (Bourgeois and Eisenhardt 1988, Eisenhardt 1989).

[2] Ultimately, exposure to air pollution may hinder the performance of individuals in cognitive tests (Ebenstein et al. 2016, Roth 2016, Zhang et al. 2018).

[3] Similarly, there is mounting evidence in the management literature highlighting the influence of education and other proxies for cognitive skills on the performance of managers, suggesting that more skilled managers make better decisions and represent a key component of firm productivity (Bloom and Van Reenen 2010, Goldfarb and Xiao 2011, Hortaçsu et al. 2019).

[4] Chess has been used since the 1970s in the field of cognitive psychology and neuroscience as the ideal environment for the study of complex cognitive processes (Charness 1992).

[5] Numerous studies in the fields of economics and cognitive psychology rely on this method to examine determinants of decision making and cognitive performance (e.g., Moxley et al. 2012, Strittmatter et al. 2020).

[6] Chess tournaments have a clear incentive scheme. In addition to monetary incentives, each official game influences the player's Elo rating, the main indicator of prestige among chess players with implications for future competitions. All chess associations apply a well-developed tool to evaluate players' quality. The Elo (1978) skill rating (Elo) considers the historical results of all official games of each player and is regarded as a "gold standard" of individual differences in skill-development research (Charness 1992). In addition, monetary prizes provide pecuniary incentives.

[7] Finally, $PM_{2.5}$ is a key target of numerous regulatory efforts by environmental agencies to guide their policies and set standards in air pollution (Currie and Walker 2019).

[8] In chess, the ability to maintain move quality under a limited time budget is considered to be a cornerstone skill for players. Time pressure limits players' ability to calculate variations and recognize meaningful patterns on the board (Sigman et al. 2010), and it is widely viewed in chess as a major differentiating indicator of skills and expertise among chess players because decisions made under time pressure are more heavily influenced by intuition (Wright 1974). The quality of moves of the more skillful tends to suffer less under time pressure than that of their less skilled counterparts (Calderwood et al. 1988).

[9] The Pearson correlation between contemporaneous indoor and outdoor fine particles of 0.92 (p-value < 0.001) reflects the high correspondence between the two (see Online Table A.1).

[10] In addition, Lichter et al. (2017) shows that air pollution negatively affects the (physical) performance of professional soccer players.

[11] Comparing our estimates with the findings of previous studies suggests that complex cognitive tasks are heavily affected by exposure to poor air quality, especially when undertaken under time pressure. The magnitude and elasticities associated with pollution damage and the elasticities of our results lay within the top of the distribution of estimates documented by studies in the field for the pooled sample.

[12] Recent experiments in economics studies document the influence of time pressure on the performance of individual search behavior (Ibanez et al. 2009), decision making under risk (Kocher et al. 2013), consumer choice (Reutskaja et al. 2011), valuation of alternatives (Armel and Rangel 2008), cooperation in public games (Rand 2016), and the ability of individuals to play Nash equilibrium in a centipede game (Kocher and Sutter 2006).

[13] For details on the game of chess, see the chess handbook provided by FIDE: https://www.fide.com/fide/handbook.html?id=171view=article.

[14] Further activities are participation in regional championship competitions, smaller scale internal tournaments, and regular training meetings.

[15] The weekly tournament rounds were paused for one week because of the public holidays Whit Monday (in 2017) and Easter Monday (in 2018 and 2019).

[16] Most participants (about 80%) are from the same city or from the surrounding region. Moreover, 70% of all participants signed up for the tournament at least one month in advance. Hence, we can rule out that participation is endogenous to outdoor environmental conditions just before the tournament. After having registered, participants may not show up for particular tournament rounds, which results in a loss. We do not find any evidence that nonappearance is affected by outdoor air pollution.

[17] Before the first round, all players are ranked based on their rating score. The ranking is then divided into the upper and lower half of the score distribution. In the first round, the highest ranked player of the upper half (i.e., the player with the highest score overall) plays against the highest ranked player of the bottom half and so on. After round one, fixtures are assigned in the same way but separately among the groups of players equal on points earned during the tournament. Therefore, by construction, the difference in rating scores between opponents is relatively high in the first round and typically becomes smaller in subsequent rounds because players with a higher score are more likely to win, especially when the difference is large.

[18] The DWZ rating system works as follows: Chess player *i* is assigned a cardinal rating score $Z_{i,g}$ reflecting the player's strength before game *g* against opponent *j*. The outcome of game *g* determines the change in the score between games *g* and $g+1$ according to the following formula: $Z_{i,g+1} = Z_{i,g} + \alpha_{i,g}[y_{i,g} - E(y_{i,g}|\Delta Z_{ij,g})]$, where the *actual* outcome for player *i* in game *g* is $y_{i,g} \in \{1, 0.5, 0\}$ for win, draw, or defeat, whereas the *expected* outcome is defined as $E(y_{i,g}|\Delta Z_{ij,g}) = \frac{1}{1+10^{(-\Delta Z_{ij,g}/400)}}$ based on the difference between players' scores, $\Delta Z_{ij,g} = Z_{i,g} - Z_{j,g}$, as well as a factor $\alpha_{i,g}$ depending on player *i*'s score level, experience, and age. See https://www.schachbund.de/dwz.html for details.

[19] The club has to pay a fee for the recalculation of participating players' scores, which is less expensive for the German DWZ score than for the international Elo score, which is why the organizers decided to only apply the DWZ score.

[20] The metric values the remaining pieces on the board relative to a pawn, determining how valuable a piece is strategically. For example, knights and bishops are typically valued three times a pawn, whereas the queen is valued at nine times a pawn. In addition, the value of a piece on the board differs depending on its position. See https://chess.fandom.com/wiki/Centipawn for details.

[21] Players are obliged to write down each individual move immediately, which rules out that documentation suffers from recollection errors.

[22] More precisely, we use the chess engine Stockfish 9 64-bits (http://ccrl.chessdom.com/ccrl/404/).

[23] For a description of game openings, see https://en.wikipedia.org/wiki/Chess_opening_book.

[24] Online Figure A.3 displays the average error across moves in the game, showing the same pattern as the discrete measure of move quality.

[25] In addition to hampering cognitive performance by causing inflammatory responses and oxidative stress in the lungs and the central nervous system (Lodovici and Bigagli 2011), $PM_{2.5}$ may also affect decision making by increasing the occurrence of headaches and depression (Lim et al. 2012), reducing people's happiness and well-being (Luechinger 2009, Levinson 2012, Zheng et al. 2019) and increasing anxiety (Trushna et al. 2021).

[26] Just before the start of the first rounds, the main organizer of the tournaments informed all players about the presence of the sensors and that they should not be touched. In addition, the research team put signs next to each sensor explaining that the device was measuring indoor environmental conditions and should not be moved.

[27] In laboratory tests, Sousan et al. (2017) assess the linear relationship and bias of monitor measurements and mass concentrations of $PM_{2.5}$ for different air-quality monitors. The authors conclude that the Foobot sensor exhibited the best performance with a highly linear response between measurements and particle mass concentrations (i.e., PM measurements).

[28] The measurements of temperature, humidity, and to a certain extent noise obviously also reflect outdoor (weather) conditions. Note that there was not a single tournament day with rainfall at the tournament location.

[29] Online Figure A.5 shows that the level of indoor $PM_{2.5}$ during the tournaments is relatively constant.

[30] Thermal conditions might comove with air pollution and are shown in previous studies to affect cognitive performance (e.g., Graff Zivin et al. 2018, Park et al. 2020).

[31] Different settings in the ventilation system in the room might alter the filtration of air particles in the room. Higher ventilation rates without proper filtration allow a higher number of particles to enter the tournament venue. In a robustness check, we exclude CO_2 from the regression, showing that the $PM_{2.5}$ estimates remain stable after excluding this variable from the regression.

[32] In the online appendix, we show the robustness of our results to the inclusion of double clustering at round and player levels to account for any residual heteroscedasticity within moves by the same player (Online Table A.3). The table shows no major differences in the significance levels of our estimated impacts of PM in the main analysis, supporting that most of the meaningful individual specific heteroscedasticity in the covariance matrix was captured in the fixed effects (Cameron and Miller 2015, Abadie et al. 2017) and, therefore, decided to use standard errors clustered at the round level in our main analysis.

[33] In our sample, 40.4% of the games lasted more than 40 moves. We find that our results are not driven by selective attrition; see Section 4.3.

[34] We calculate the *p*-values using the boottest command in Stata (see Roodman et al. 2019).

[35] To estimate the changes in the probability of making an error with player's ability, we reestimate our main specification (Equation (2)) including the player's Elo as a regressor. The comparison between the coefficient associated with Elo and $PM_{2.5}$ is based on their standardized coefficients.

[36] The hyperbolic sine transformation is a method frequently used in applied econometrics to derive elasticities, reduce heteroscedasticity, or reduce the effect of outliers when the original variable includes zeros or negative values (Bellemare and Wichman 2020, Aihounton and Henningsen 2021).

[37] Results for the full sample of moves display the same patterns.

[38] Note that the categories are defined based on the player's Elo rating score, and hence, we cannot disentangle whether the effect arises because such players are weaker in this specific game or weak in general.

[39] CO_2 is a colorless, odorless gas commonly used as an indicator of airflow and room ventilation in the building science literature and widely used in official guidelines to measure ventilation rates and set indoor air quality standards in office buildings, schools, and other public buildings (American Society of Heating, Refrigerating and Air Conditioning Engineers 2013). High levels of CO_2 are linked to dizziness, headache, or fatigue (Stankovic et al. 2016) and lower performance in cognitive tasks in controlled laboratory studies (Allen et al. 2016, Du et al. 2020). In a secondary analysis, we explore the impact of CO_2 on our main outcomes. The results indicate a marginal effect on performance. However, it is important to note that the lack of data in our study about the source of variation hinders any causal interpretation of these parameters (results included in Online Figure A.7).

[40] A notable exception in the study by Roth (2016), who deployed sensors in university classrooms in London to test the effect of indoor PM on test scores.

[41] Whereas PM_{10} is available at the hourly level, the Federal Environmental Agency only provides daily averages of $PM_{2.5}$.

[42] Given the lack of indoor measurements on the days before and after the tournament rounds, we need to rely on outdoor PM_{10} levels. In addition, we have to rely on PM_{10} because the outdoor measurement of $PM_{2.5}$ is not available at an hourly frequency. $PM_{2.5}$ measurements are only available at daily levels.

[43] The network of stations associated with $PM_{2.5}$ is substantially smaller. Distribution of estimates using all $PM_{2.5}$ stations in Germany on the day of the tournament are presented in Online Figure A.9.

[44] The sample spans the first season in which digital records of moves are available (2003/2004) to the last season available at the time of writing before the interruption of the competition by the COVID-19 pandemic (2018/2019).

[45] We tested different lags of PM_{10} and find that the effect of PM_{10} on players' performance peaks at lag 6. We restrict the analysis to PM_{10} because outdoor $PM_{2.5}$ pollution is not available before 2009.

[46] Because of missing episodes in the air-quality station data, we have to remove about one third of the initial sample. We additionally removed missing values in the outcome and control variables (3% of the sample).

[47] Results regarding the error size can be found in Online Figure A.11.

[48] Germany consists of 16 federal states, but we merged the three city-states of Berlin, Hamburg, and Bremen as well as the small state of Saarland with their larger neighboring states in our analysis. This means that we use 36 binary indicators as instruments, resulting from interactions of the 12 binary regional indicators and three wind directions (with southwest being the reference category).

[49] See Kahn and Li (2020) for an overview of the elasticities found in previous studies.

References

Abadie A, Athey S, Imbens GW, Wooldridge J (2017) When should you adjust standard errors for clustering? Technical report, National Bureau of Economic Research, Cambridge, MA.

Acemoglu D, Autor D (2011) *Skills, Tasks and Technologies: Implications for Employment and Earnings*, vol. 4 (Elsevier, North Holland).

Acemoglu D, Restrepo P (2019) Automation and new tasks: How technology displaces and reinstates labor. *J. Econom. Perspect.* 33(2):3–30.

Acher M, Esnault F (2016) Large-scale analysis of chess games with chess engines: A preliminary report. Preprint, submitted April 28, https://arxiv.org/abs/1607.04186.

Aguilar-Gomez S, Dwyer H, Graff Zivin JS, Neidell MJ (2022) This is air: The "non-health" effects of air pollution. NBER Working Paper No. 29848, National Bureau of Economic Research, Cambridge, MA.

Aihounton GB, Henningsen A (2021) Units of measurement and the inverse hyperbolic sine transformation. *Econom. J.* 24(2): 334–351.

Allen JG, MacNaughton P, Satish U, Santanam S, Vallarino J, Spengler JD (2016) Associations of cognitive function scores with carbon dioxide, ventilation, and volatile organic compound exposures in office workers: A controlled exposure study of green and conventional office environments. *Environ. Health Perspect.* 124(6): 805–812.

Alliot J-M (2017) Who is the master? *ICGA J.* 39(1):3–43.

American Society of Heating, Refrigerating and Air Conditioning Engineers (2013) *Ventilation for Acceptable Indoor Air Quality* (American Society of Heating, Refrigerating and Air Conditioning Engineers, Atlanta).

Archsmith J, Heyes A, Saberian S (2018) Air quality and error quantity: Pollution and performance in a high-skilled, quality-focused occupation. *J. Assoc. Environ. Resource Econom.* 5(4):827–863.

Armel KC, Rangel A (2008) The impact of computation time and experience on decision values. *Amer. Econom. Rev.* 98(2): 163–168.

Atalay E, Phongthiengtham P, Sotelo S, Tannenbaum D (2020) The evolution of work in the United States. *Amer. Econom. J. Appl. Econom.* 12(2):1–34.

Backhus P, Cubel M, Guid M, Sánchez-Pages S, Lopez Manas E (2016) Gender, competition and performance: Evidence from real tournaments. Working paper, Institut d'Economia de Barcelona, Spain.

Baum JR, Wally S (2003) Strategic decision speed and firm performance. *Strategic Management J.* 24(11):1107–1129.

Bayer R-C, Renou L (2016) Logical abilities and behavior in strategic-form games. *J. Econom. Psych.* 56(1):39–59.

Bellemare MF, Wichman CJ (2020) Elasticities and the inverse hyperbolic sine transformation. *Oxford Bull. Econom. Statist.* 82(1):50–61.

Binder AJ, Bound J (2019) The declining labor market prospects of less-educated men. *J. Econom. Perspect.* 33(2):163–190.

Bloom N, Van Reenen J (2010) Why do management practices differ across firms and countries? *J. Econom. Perspect.* 24(1):203–224.

Bourgeois LJ, Eisenhardt KM (1988) Strategic decision processes in high velocity environments: Four cases in the microcomputer industry. *Management Sci.* 34(7):816–835.

Burnham TC, Cesarini D, Johannesson M, Lichtenstein P, Wallace B (2009) Higher cognitive ability is associated with lower entries in a p-beauty contest. *J. Econom. Behav. Organ.* 72(1):171–175.

Calderon-Garciduenas L, Calderon-Garciduenas A, Torres-Jardon R, Avila-Ramirez J, Kulesza RJ, Angiulli AD (2015) Air pollution and your brain: What do you need to know right now. *Primary Health Care Res. Development* 16(4):329–345.

Calderwood R, Klein G, Crandall B (1988) Time pressure, skill, and move quality in chess. *Amer. J. Psych.* 101(4):481–493.

Cameron AC, Miller DL (2015) A practitioner's guide to cluster-robust inference. *J. Human Resources* 50(2):317–372.

Cameron AC, Gelbach JB, Miller DL (2008) Bootstrap-based improvements for inference with clustered errors. *Rev. Econom. Statist.* 90(3):414–427.

Chang T, Graff Zivin J, Gross T, Neidell M (2016) Particulate pollution and the productivity of pear packers. *Amer. Econom. J. Econom. Policy* 8(3):141–169.

Chang T, Graff Zivin J, Gross T, Neidell M (2019) The effect of pollution on worker productivity: Evidence from call center workers in China. *Amer. Econom. J. Appl. Econom.* 11(1):151–172.

Charness N (1992) The impact of chess research on cognitive science. *Psych. Res.* 54(1):4–9.

Chase WG, Simon HA (1973) Perception in chess. *Cognitive Psych.* 4(1):55–81.

Cohen AJ, Brauer M, Burnett R, Anderson HR, Frostad J, Estep K, Balakrishnan K, et al. (2017) Estimates and 25-year trends of the global burden of disease attributable to ambient air pollution: An analysis of data from the Global Burden of Diseases Study 2015. *Lancet* 389(10082):1907–1918.

Currie J, Neidell M (2005) Air pollution and infant health: What can we learn from California's recent experience? *Quart. J. Econom.* 120(3):1003–1030.

Currie J, Walker R (2019) What do economists have to say about the Clean Air Act 50 years after the establishment of the Environmental Protection Agency? *J. Econom. Perspect.* 33(4):3–26.

Deming DJ (2021) The growing importance of decision-making on the job. NBER Working Paper No. 28733, National Bureau of Economic Research, Cambridge, MA.

Deryugina T, Heutel G, Miller NH, Molitor D, Reif J (2019) The mortality and medical costs of air pollution: Evidence from changes in wind direction. *Amer. Econom. Rev.* 109(12): 4178–4219.

Du B, Tandoc M, Mack ML, Siegel JA (2020) Indoor CO_2 concentrations and cognitive function: A critical review. *Indoor Air* 30(6):1067–1082.

Ebenstein A, Lavy V, Roth S (2016) The long run economic consequences of high-stakes examinations: Evidence from transitory variation in pollution. *Amer. Econom. J. Appl. Econom.* 8(4):36–65.

Eisenhardt KM (1989) Making fast strategic decisions in high-velocity environments. *Acad. Management J.* 32(3):543–576.

Elo AE (1978) *The Rating of Chess Players, Past and Present* (Arco Publishing, Inc., New York).

Environmental Protection Agency (2009) Integrated science assessment for particulate matter. Technical report, Washington, DC.

Environmental Protection Agency (2020) Environmental Protection Agency's annual air trends report, Washington, DC.

European Environment Agency (2018) Air quality in Europe—2018 report. Technical report, Luxembourg.

Gerdes C, Gränsmark P (2010) Strategic behavior across gender: A comparison of female and male expert chess players. *Labour Econom.* 17(5):766–775.

Gill D, Prowse V (2016) Cognitive ability, character skills, and learning to play equilibrium: A level-k analysis. *J. Political Econom.* 124(6):1619–1676.

Goldfarb A, Xiao M (2011) Who thinks about the competition? Managerial ability and strategic entry in US local telephone markets. *Amer. Econom. Rev.* 101(7):3130–3161.

Graff Zivin J, Neidell M (2012) The impact of pollution on worker productivity. *Amer. Econom. Rev.* 102(7):3652–3673.

Graff Zivin J, Hsiang SM, Neidell M (2018) Temperature and human capital in the short and long run. *J. Assoc. Environ. Resource Econom.* 5(1):77–105.

Graff Zivin J, Liu T, Song Y, Tang Q, Zhang P (2020) The unintended impacts of agricultural fires: Human capital in China. *J. Development Econom.* 147:102560.

Heyes A, Neidell M, Saberian S (2016) The effect of air pollution on investor behavior: Evidence from the S&P500. NBER Working Paper No. 22753, National Bureau of Economic Research, Cambridge, MA.

Hortaçsu A, Luco F, Puller SL, Zhu D (2019) Does strategic ability affect efficiency? Evidence from electricity markets. *Amer. Econom. Rev.* 109(12):4302–4342.

Huang J, Xu N, Yu H (2020) Pollution and performance: Do investors make worse trades on hazy days? *Management Sci.* 66(10): 4455–4476.

Ibanez M, Czermak S, Sutter M (2009) Searching for a better deal—On the influence of group decision making, time pressure and gender on search behavior. *J. Econom. Psych.* 30(1):1–10.

Isphording IE, Pestel N (2021) Pandemic meets pollution: Poor air quality increases deaths by COVID-19. *J. Environ. Econom. Management* 108(July):102448.

Jones D, Molitor D, Reif J (2019) What do workplace wellness programs do? Evidence from the Illinois workplace wellness study. *Quart. J. Econom.* 134(4):1747–1791.

Kahn ME, Li P (2020) Air pollution lowers high skill public sector worker productivity in China. *Environ. Res. Lett.* 15(8):084003.

Kocher MG, Sutter M (2006) Time is money: Time pressure, incentives, and the quality of decision-making. *J. Econom. Behav. Organ.* 61(3):375–392.

Kocher MG, Pahlke J, Trautmann ST (2013) Tempus fugit: Time pressure in risky decisions. *Management Sci.* 59(10):2380–2391.

Krebs B, Burney J, Graff Zivin J, Neidell M (2021) Using crowdsourced data to assess the temporal and spatial relationship between indoor and outdoor particulate matter. *Environ. Sci. Tech.* 55(9):6107–6115.

Künn S, Seel C, Zegners D (2021) Cognitive performance in remote work-evidence from professional chess. *Econom. J. (London)* 132(643):1218–1232.

Levinson A (2012) Valuing public goods using happiness data: The case of air quality. *J. Public Econom.* 96(9–10):869–880.

Levitt SD, List JA, Sadoff SE (2011) Checkmate: Exploring backward induction among chess players. *Amer. Econom. Rev.* 101(2):975–990.

Lichter A, Pestel N, Sommer E (2017) Productivity effects of air pollution: Evidence from professional soccer. *Labour Econom.* 48(October): 54–66.

Lim Y-H, Kim H, Kim JH, Bae S, Park HY, Hong Y-C (2012) Air pollution and symptoms of depression in elderly adults. *Environ. Health Perspect.* 120(7):1023–1028.

Lodovici M, Bigagli E (2011) Oxidative stress and air pollution exposure. *J. Toxicology* 2011:487074–487074.

Lu JG (2020) Air pollution: A systematic review of its psychological, economic, and social effects. *Current Opinion Psych.* 32:52–65.

Luechinger S (2009) Valuing air quality using the life satisfaction approach. *Econom. J. (London).* 119(536):482–515.

Moxley JH, Anders Ericsson K, Charness N, Krampe RT (2012) The role of intuition and deliberative thinking in experts' superior tactical decision-making. *Cognition* 124(1):72–78.

Nagelkerk JM, Henry BM (1990) Strategic decision making. *J. Nursing Admin.* 20(7–8):18–23.

Palacios-Huerta I, Volij O (2009) Field centipedes. *Amer. Econom. Rev.* 99(4):1619–1635.

Park RJ, Goodman J, Hurwitz M, Smith J (2020) Heat and learning. *Amer. Econom. J. Econom. Policy* 12(2):306–339.

Peeples L (2020) How air pollution threatens brain health. *Proc. Natl. Acad. Sci. USA* 117(25):13856–13860.

Rand DG (2016) Cooperation, fast and slow: Meta-analytic evidence for a theory of social heuristics and self-interested deliberation. *Psych. Sci.* 27(9):1192–1206.

Reutskaja E, Nagel R, Camerer CF, Rangel A (2011) Search dynamics in consumer choice under time pressure: An eye–tracking study. *Amer. Econom. Rev.* 101(2):900–926.

Roodman D, MacKinnon JG, Nielsen MØ, Webb MD (2019) Fast and wild: Bootstrap inference in Stata using boottest. *Stata J.* 19(1):4–60.

Roth S (2016) The contemporaneous effect of indoor air pollution on cognitive performance: Evidence from the UK. Unpublished manuscript.

Rustichini A (2015) The role of intelligence in economic decision making. *Current Opinion Behav. Sci.* 5:32–36.

Sandi C (2013) Stress and cognition. *Wiley Interdisciplinary Rev. Cognitive Sci.* 4(3):245–261.

Satish U, Mendell MJ, Shekhar K, Hotchi T, Sullivan D, Streufert S, Fisk WJ (2012) Is CO_2 an indoor pollutant? Direct effects of low-to-moderate CO_2 concentrations on human decision-making performance. *Environ. Health Perspect.* 120(12):1671–1677.

Schwenk CR (1988) The cognitive perspective on strategic decision making. *J. Management Stud.* 25(1):41–55.

Sigman M, Etchemendy P, Slezak DF, Cecchi GA (2010) Response time distributions in rapid chess: A large-scale decision making experiment. *Frontiers Neuroscience* 4:1–12.

Simon H, Chase W (1973) Skill in chess. *Amer. Sci.* 61(4):394–403.

Sousan S, Koehler K, Hallett L, Peters TM (2017) Evaluation of consumer monitors to measure particulate matter. *J. Aerosol Sci.* 107:123–133.

Spiliopoulos L, Ortmann A (2018) The BCD of response time analysis in experimental economics. *Experiment. Econom.* 21:383–433.

Stankovic A, Alexander D, Oman CM, Schneiderman J (2016) A review of cognitive and behavioral effects of increased carbon dioxide exposure in humans. NASA/TM-2016-219277, 1–24.

Strittmatter A, Sunde U, Zegners D (2020) Life cycle patterns of cognitive performance over the long run. *Proc. Natl. Acad. Sci. USA* 117(44):27255–27261.

Syverson C (2011) What determines productivity? *J. Econom. Literature* 49(2):326–365.

Trushna T, Dhiman V, Raj D, Tiwari RR (2021) Effects of ambient air pollution on psychological stress and anxiety disorder: A systematic review and meta-analysis of epidemiological evidence. *Rev. Environ. Health* 36(4):501–521.

Underwood E (2017) The polluted brain. *Sci.* 355(6323):342–345.

Wally S, Baum JR (1994) Personal and structural determinants of the pace of strategic decision making. *Acad. Management J.* 37(4):932–956.

Weschler C (2000) Ozone in indoor environments: Concentration and chemistry. *Indoor Air* 10(4):269–288.

World Health Organization (2016) Burning opportunity: Clean household energy for health, sustainable development, and wellbeing of women and children, 113. https://www.who.int/publications/i/item/burning-opportunity-clean-household-energy-for-health-sustainable-development-and-wellbeing-of-women-and-children.

Wright P (1974) The harassed decision maker: Time pressures, distractions, and the use of evidence. *J. Appl. Psych.* 59(5):555–561.

Zhang X, Chen X, Zhang X (2018) The impact of exposure to air pollution on cognitive performance. *Proc. Natl. Acad. Sci. USA* 115(37):9193–9197.

Zhang X, Wargocki P, Lian Z, Thyregod C (2017) Effects of exposure to carbon dioxide and bioeffluents on perceived air quality, self-assessed acute health symptoms, and cognitive performance. *Indoor Air* 27(1):47–64.

Zheng S, Wang J, Sun C, Zhang X, Kahn ME (2019) Air pollution lowers Chinese urbanites' expressed happiness on social media. *Nature Human Behav.* 3(3):237–243.