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DISCUSSION PAPER SERIES

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ABSTRACT

Indoor Air Quality and Cognitive Performance*

This paper studies the causal impact of indoor air quality on the cognitive performance of individuals using data from official chess tournaments. We use a chess engine to evaluate the quality of moves made by individual players and merge this information with measures of air quality inside the tournament venue. The results show that poor indoor air quality hampers cognitive performance significantly. We find that an increase in the indoor concentration of fine particulate matter (PM2.5) by 10 μg/m3 increases a player's probability of making an erroneous move by 26.3%. The impact increases in both magnitude and statistical significance with rising time pressure. The effect of the indoor concentration of carbon dioxide (CO2) is smaller and only matters during phases of the game when decisions are taken under high time stress. Exploiting temporal as well as spatial variation in outdoor pollution, we provide evidence suggesting a short-term and transitory effect of fine particulate matter on cognition.

JEL Classification: D91, I1, J24, Q50, Z20

Keywords: indoor air quality, cognition, worker productivity, chess

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1 Introduction

Environmental pollution is estimated to be responsible for nine million premature deaths annually (Landrigan et al., 2018). While most countries impose strict regulations on the emission of air pollutants to improve ambient air quality, the current calculations of societal cost of air pollution may be substantially underestimated as a growing body of evidence in health sciences suggests that exposure to poor air quality may also have harmful immediate and lasting impacts on the human brain, ultimately lowering individuals' cognitive abilities (Underwood, 2017). Exposure to air pollution alone has been shown to have severe health consequences which may translate into adverse effects on human capital formation and labor market outcomes in the short and long run (Graff Zivin and Neidell, 2013, 2018).[1] These physiological effects on human cognition may have severe consequences for individual performance in complex cognitive tasks.

This paper examines the causal impact of indoor air quality on the cognitive performance of individuals using data from chess tournaments. Chess provides an ideal setting to study the relationship between environmental conditions and individuals' cognition. Chess is a complex and cognitively demanding activity (Vaci et al., 2019), where individuals face strong incentives to exert high effort and which involves strategic decision making under time pressure. The quality of cognitive performance can be objectively evaluated at high frequency using a chess engine as a benchmark. In addition, our study uses measures of air quality from inside the room where individuals are executing the tasks, which provides unambiguous information on players' exposure to environmental conditions.

We use a unique panel dataset on the performance of chess players obtained from tournaments held in Germany in 2017, 2018 and 2019. The data contain detailed information on about 30,000 moves made by 121 players in 596 games. Each tournament edition comprises seven rounds over a period of eight weeks, which provides us with sufficient natural variation in indoor air quality. Players' skills range from beginner to advanced levels. All players have strong incentives to perform well throughout the tournament as the outcomes in each game count for their official chess rating score, which is a matter of prestige among chess players and has implications for future competitions. In addition, monetary prizes provide pecuniary incentives. We make use of a state of the art chess engine to measure the quality of players' decisions. The chess engine evaluates actual moves made by the players and compares them to moves deemed optimal according to its algorithm. Based on the engine's output we construct two outcome variables: (i) a binary indicator for moves annotated as an error and (ii) the magnitude of the error.

[1] Air pollution increases direct medical costs, such as hospitalizations and pharmaceutical expenses (Schlenker and Walker, 2016; Deschenes et al., 2017). Further, students perform worse in high-stakes examinations (Ebenstein et al., 2016) and workers spent less time on the job when ambient air pollution is higher (Hanna and Oliva, 2015; Aragón et al., 2017). Similarly, extremely warm days lead to a reduction in working hours (Graff Zivin and Neidell, 2014).

Our identification strategy exploits the panel structure of the data. We observe the performance of the same individuals playing multiple games against different opponents in the exact same venue, at the same time of the day, but under varying levels of indoor air quality which are beyond the control of the players. In order to accurately assign players' exposure to air quality, we installed sensors inside the tournament venue continuously measuring indoor environmental conditions. We focus on the concentration of fine particulate matter with a diameter smaller than 2.5 micrometers (PM2.5), which may penetrate deep into the lungs and brains. Evidence from epidemiology and toxicology suggests that exposure to air pollution can hinder cognition by causing inflammatory reactions (Underwood, 2017; Kumar, 2018) and by reducing the transportation of oxygen to the brain (Bernstein et al., 2004). In addition to particulate pollution, we study potential effects of variation in the concentration of carbon dioxide (CO2). High levels of CO2 have been linked to dizziness, headache or fatigue (Stankovic et al., 2016). In addition, we control for other environmental conditions such as temperature, humidity and noise.

Overall, our results show that indoor concentration of fine particles significantly deteriorates cognitive performance. Exploiting within-player variation in air quality and controlling for year, round, and move fixed effects, and a set of control variables including other environmental conditions, we find that an increase in fine particulate pollution (PM2.5) of ten micrograms per cubic meter (10 $\mu g/m^3$), about three quarters of a standard deviation in the sample, leads to a 2.1 percentage point increase in the probability of making a meaningful error. This corresponds to an increase by 26.3% relative to the sample mean. We do not find evidence for effects of the observed variation in carbon dioxide in the full sample of moves.

In addition, the high frequency of our performance measures allows to examine effect heterogeneity with respect to time pressure as the tournament rules set a time restriction. In all games in our sample, each player has to complete the first 40 moves within a time limit of 110 minutes. This implies that, when approaching move 40, move decisions can be assumed to be made under relative time pressure, compared to other phases of the game. The impact of PM2.5 increases in both magnitude and statistical significance with increasing time pressure, with the most pronounced effect shortly before move 40. In contrast, the effect of CO2 is smaller in magnitude and is only statistically significant just before the time control is applied. This suggests that poor air quality harms the performance of players particularly if acting under time pressure. Moreover, we find older individuals' performance being more sensitive to poor air quality, and an increased effect of pollution if players are faced with a stronger opponent, which may be in itself a more stressful situation.

Finally, we explore the role of outdoor pollution in shaping indoor conditions. The variation in indoor particulate pollution largely reflects levels of air pollution in the (outdoor) vicinity of the tournament site, coming from automobile exhaust or industrial emissions. Using outdoor pollution measures stemming from nearby air quality stations, we find very similar results suggesting that the identified effects are indeed due to particulate pollution rather than other potential sources. Exploiting temporal and spatial variation in outdoor pollution, we find evidence for short-term and transitory effects of particulate matter on cognition.

Several sensitivity checks show the high robustness of our 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 due to the exposure to air pollutants per se, but are rather driven by other potential channels which are correlated with the outdoor emission sources. Moreover, we check the impact of ozone levels and run several specification tests and sample restrictions. The results are robust to all of these tests, which makes us confident that our findings provide evidence for a physiological channel through which air quality affects cognitive performance.

This paper makes the following contributions to the literature. First, we complement the growing economics literature on productivity losses resulting from working in disadvantageous environments characterized by poor air quality. Most of the existing quasi-experimental evidence is based on routine manual occupations, such as agriculture or factory workers (Graff Zivin and Neidell, 2012; Chang et al., 2016), where individual output is easy to quantify.[2] Our understanding of how environmental hazards affect the performance of workers in cognitive or analytical professions, where the value added of a worker tends to be much harder to quantify, is still limited. Previous studies in the field use measures such as quantity rates (e.g., number of calls handled per hour, Chang et al., 2019), judges' decision time (Kahn and Li, 2019) or uptime (percent of time in a day that a trader is at his desk trading, Meyer and Pagel, 2017) to measure the added value of a worker. Little is known about how the final quality of the tasks or decisions undertaken by cognitive workers is affected by adverse environmental conditions. Archsmith et al. (2018) provide initial evidence by studying the propensity of professional baseball umpires to make incorrect calls. The results of our paper contribute to this literature by examining a setting where individuals are confronted with highly demanding complex cognitive tasks involving strategic decision making under varying levels of time pressure and with strong incentives to perform well. Using objective outcome measures reflecting the quality of the cognitive task, we show for the first time that detrimental effects of poor air quality on cognition are transitory and being most pronounced if decisions are taken under time pressure. Therefore, our findings are likely to have strong implications for high-skilled office workers executing non-routine cognitive tasks under time pressure. The roles of these tasks are gaining more and more importance in developed labor markets and are mainly represented in professional, managerial, technical, and creative occupations (Autor and Price, 2013).

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

Second, the levels of indoor air quality we observe are rather moderate and therefore our results are not driven by extreme levels of air pollution frequently observed in countries like China or India. This implies that high-skill human cognition is already affected by moderate variation in particulate pollution and CO2 concentration if acting under time pressure. In addition, since the variation of indoor air pollution is largely driven by outdoor emission sources our results have important implications for environmental policy-making. Quantifying the benefits of improving air quality by regulating emissions from traffic or industrial activity has to expand beyond major health impacts that result in hospitalizations or death and additionally take into account more subtle effects on labor productivity and human capital accumulation (Graff Zivin and Neidell, 2018). Our findings further suggest that the economic damage of air pollution in terms of forgone worker productivity may differ depending on the study context. In our setting, the negative impact of poor air quality mainly arises if acting under time pressure, which is commonly present in economic activities. The transitory nature of the effects suggests that it is worth for institutions investing in clean working environments for their workers.

Third, our study design allows us to analyze the impact on cognitive performance caused by individuals' exposure to *indoor* air quality while existing studies in the field of environmental economics predominately rely on outdoor measures (e.g. Kahn and Li, 2019; Chang et al., 2019; Meyer and Pagel, 2017). The availability of a nearby outdoor station allows us to reproduce our indoor results using outdoor measures which validates previous findings relying on outdoor pollution measures to predict indoor activities.

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 present our empirical strategy. The results are presented and discussed in section 4 and robustness checks 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 cognitive performance. Chess is a two-player strategic board game in which players alternately make moves with pieces on the chess board.[3] 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 player runs out of time. In addition, the players can agree upon a draw at any time during the game.

Chess is a very complex, strategic, and computational activity, and has been heavily deployed

[3]For details on the game of chess see the chess handbook as provided by the *World Chess Federation* (FIDE): `https://www.fide.com/fide/handbook.html?id=171view=article`.

by cognitive psychologists for investigating different strategic and cognitive aspects of human thinking, such as perception, memory, and problem solving (e.g. Charness, 1992). Burgoyne et al. (2016) provide empirical proof for the relationship between chess skills and general cognitive skills such as fluid reasoning, comprehension knowledge, short-term memory, and processing speed. In recent years, economists started using chess to analyze human behavior due its computational nature and the cognitive power of chess players (see, e.g., Palacios-Huerta and Volij, 2009; Gerdes and Gränsmark, 2010; Levitt et al., 2011; Backhus et al., 2016).

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 the year.[4] Each tournament edition comprises seven rounds over an eight-week period with each round taking place on a Monday night starting at 6:00pm and lasting until the last game is over.[5] Figure A.1 in the 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.[6] The tournament format follows the "Swiss system", a non-eliminating 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' pre-tournament chess rating scores indicating their strength as well as their performance during the tournament.[7]

Chess rating scores are calculated based on the performance in games against other players. Winning (losing) a game results in an improvement (a 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

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

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

[6] Most participants are from the same city or from the surrounding region.

[7] 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 (i.e., the player just below the median score) 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. This implies that, 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.

applied for the assignment of fixtures in the tournaments is the German chess federation's rating score *DWZ* (*Deutsche Wertungszahl*).[8] This score is equivalent to the international *Elo* rating system as used by the world chess federation FIDE, also for assigning titles like "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 are submitted to the chess federation for a recalculation of players' rating scores based on their results.[9] Hence, all players participating in the tournaments have 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 which determines fixtures in future competitions. In addition, pecuniary incentives are offered. The winner of the tournament receives a cash prize of 400 euros. The participants ranked 2nd to 4th receive prizes of 300, 150, and 100 euros respectively, and extra prizes are awarded for the best-ranked players among the youth, the senior, and the female players (70 euros each), as well as for the best team (60 euros).

2.2 Measurement of cognitive performance

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 $m \in \{1, \dots, M_g\}$, where 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 to players and is essential to evaluate positions in chess software.[10] 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 have information on the evolution of the game based on

[8] 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.

[9] 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.

[10] 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 while 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.

players' hand-written notation (see Figure A.2 in the appendix for an example), which has been digitized by the tournament organizers.[11] We use the chess engine *Stockfish* to assess the quality of each move in the tournaments.[12] In theory, for each move, a particular move option optimizes the pawn metric given the situation on the chess board. Figuring out 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 have resulted from the computer's optimally suggested move. The pawn-metric difference between the human player and the computer can be viewed as an error:

$$Error_{igm} = |C_{igm}^{computer}| - |C_{igm}^{player}| \tag{1}$$

In the empirical analysis, we look at player-move specific errors as an outcome variable that may be affected by disadvantageous air quality to which the players are exposed. We remove the first 14 moves of each game, which can be assumed to represent the opening game for which players usually have an established plan and are hence less affected by air quality (Backhus et al., 2016). Furthermore, 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 is a very rare event and because we are mainly interested in the errors associated with the air quality, and therefore the positive side of the error distribution, we redefine negative cases as zero (0.7% of the sample). Panel A in Figure 1 displays the relationship between the average error per player and her *Elo* rating score, showing a clear negative relationship between the two. A statistically significant and negative correlation also exists between a player's *Elo* rating score and her mean error ($\rho = -0.51$, p-value $= 0.00$).

[Insert Figure 1 about here]

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. This 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. 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

[11] Both players are obliged to document the evolution of moves and have to hand in the hand-written notation to the tournament organizer immediately after the game is completed.

[12] More precisely, we use the chess engine Stockfish 9 64-bits with a current *Elo* rating score of 3548 (`http://ccrl.chessdom.com/ccrl/404/`). The highest *Elo* rating score by a human is 2882, achieved in 2014 by the current chess world champion Magnus Carlsen.

not be played weakening the chances of the player to consolidate her position or win the game. Given her 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. The chess engine detects and annotates these errors. Panel B in Figure 1 displays the relationship between the average number of moves annotated as errors per player and the player's *Elo* rating score, showing a clear negative relationship between the two. The correlation between the average number of annotated meaningful errors per player (the sum of strategic mistakes and blunders) and her *Elo* rating score is -0.63 (p-value $= 0.00$).

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, she loses the game.

This gives each player a time budget to allocate to each move in the game, implying that 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. Figure A.3 in the appendix 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 approaching the time control as the average time per move decreases clearly for moves 36–40. Furthermore, Figure A.4 in the appendix 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 that 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 set-up 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

During all editions of the tournament, the organizers granted us permission to measure indoor environmental conditions throughout all tournament rounds inside the venue, a large church community hall in a suburban residential area. 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, i.e., studying the effect of indoor environmental conditions on chess players' performance.[13]

Our measures of indoor air quality – the concentrations of fine particulate matter (PM2.5) and carbon dioxide (CO2) – were gathered from three real-time web-connected sensors located inside the tournament venue (see Figure A.5 in the appendix for an example).[14] The sensors measure the parameters of interest (as well as temperature, noise and humidity) every minute and upload the measurements to a cloud server.

[INSERT FIGURE 2 ABOUT HERE]

Figure 2 shows the distribution of the two parameters of interest over the seven rounds across the three editions of the tournament (2017, 2018 and 2019). The levels of CO2 range between 1,000 and 2,400 ppm with a mean value of about 1,500 ppm. These levels are above critical thresholds presented in the literature as detrimental for human cognition, for example, 1,000 or 1,500 ppm (Allen et al., 2016). The average level in our sample for PM2.5 is 27.1 $\mu g/m^3$, slightly above the European target of 25 $\mu g/m^3$ set by the European Environmental Agency (EEA, 2018). Note that important differences exist in the measurements of these parameters for the same rounds between the three years. In addition, no clear trend appears in the changes of the parameters between the years, but the changes in air quality between years are seemingly random. These differences are crucial for our estimation strategy, based on within-player and round variation of errors.

2.5 Descriptive statistics

Our data follow 121 players over a maximum of 21 matches. A total of 62 players (51%) participate in at least two editions of the tournament; out of which 34 (28%) participate 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

[13] 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, we put signs next to each sensor explaining that the device was measuring indoor environmental conditions and should not be moved.

[14] We used two *Foobot* sensors and one *Netatmo* indoor sensor.

only two official matches in her 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 the *Elo* rating score 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 the chess association 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.

[Insert Table 1 and Figure 3 about here]

Focusing on the game-specific characteristics (Panel B in Table 1), we can see that games in our sample last around three hours on average. This length is similar to the average exposure time in epidemiological studies exploring the effect of CO2 or temperature on cognition (e.g. Satish et al., 2012). In our study, the average game duration is sufficiently long to expect the exposure time of participants is sufficient to uncover an effect of the air quality on their cognitive abilities. The average length of the games in our sample is around the 40 moves threshold (see Figure A.4 in the appendix 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

Our goal is to estimate the effect of indoor air quality on the quality of the decisions undertaken by chess players. Our study setting has a number of features that allow us to identify the effect of environmental stressors on cognitive performance. First, players are executing the same (cognitive) 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 is exogenously determined by the tournament rules. Thus, participants have no control over the environmental conditions that they are exposed to during their games nor the opponents they play in a given round.

Second, we have objective measures of individual cognitive performance by evaluating each move in our sample of games. The chess engine is able to detect meaningful errors in the moves undertaken by the players. In addition, we build a continuous measure of the magnitude of an error by comparing the advantage reached with the actual move of the player with the maximum (pawn) advantage that a player could have reached if she had undertaken the best possible move.

The evaluation of the move quality is specific to the player's move and is not influenced in any way by the opponent.

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 disappears over the course of the game.

Finally, all players in our sample face strong incentives to exert high effort, because the performance in each game of the tournaments counts for their chess rating score. Therefore, the incentive structure in our setting deviates from the structure in non-incentivized lab experiments or survey-based studies in which participants' payoffs are not determined by their performance in the proposed tasks. By contrast, our participants are highly motivated to perform to the best of their abilities.

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

$$Y_{ijtrm} = \alpha + \delta IAQ_{tr} + \beta X_{ijtrm} + \eta_i + \gamma_t + \lambda_r + \theta_m + V_{ijtrm}, \tag{2}$$

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

We include a set of time-varying controls, (i) capturing the indoor temperature[15], noise and humidity, (ii) describing the differences in skills between opponents in a given game, (iii) the points earned over the tournament by the player, and (iv) the initial advantage of the player before executing the move, pawn metric $C^{player}_{ijtr,m-1}$. We describe the differences in skills between the opponents with the variable $EloDiff_{ijt}$ that denotes the player-opponent difference in terms of the *Elo* rating score to control for initial performance differences among the two players, measured at the beginning of the tournament. We include the level variable $EloDiff_{ijt}$ as well as its squared term. η_i, γ_t, λ_r, and θ_m are individual, year, round and move fixed effects, respectively.

[15] The main specification includes temperature linearly. We also checked a non-linear specification of temperature as a control variable which does not change the results.

The term IAQ_{tr} includes the two indoor air quality measures: (i) the concentration of fine particulate matter (PM2.5) and (ii) the carbon dioxide (CO2) concentration. All measures are included as the mean value of the prevailing conditions as measured during the second hour of the tournament rounds (N=21). Whereas PM2.5 is relatively stable during the tournament rounds, CO2 concentration varies with the number of people in the room, namely, increasing (decreasing) at the start (end) of the tournament. Therefore, we decided to take the mean within the second hour of the tournament (as indicated by the dashed lines in Figure 2) to avoid lower values at the beginning/end of the tournament polluting the measure.[16] Finally, the error term V_{ijtrm} is clustered at the day (round $\times$ year) level to allow for arbitrary correlation within tournament days. However, given the low number of clusters in our study (N=21) potentially violating the large-sample assumptions, we additionally provide the p-values based on wild bootstrap clusters as recommended by Cameron et al. (2008).

The parameter of interest is denoted by δ, which measures the impact of prevailing indoor air quality IAQ_{tr} on the outcome variable. In such a setting, the main identifying assumption is that particulate pollution and CO2 are assigned as good as random after including the rich set of fixed effects. Thus, we identify the parameter of interest by observing identical individuals playing against different opponents under varying levels indoor air quality across tournament editions (years) of the same round of the tournament.

4 Results

We present the results on the impact of indoor air quality on the performance of chess players in four stages: In a first step, the results based on the full sample are presented in section 4.1, where we estimate equation (2) using all moves in the games of the sample. In the second step, we split the sample into subsamples based on the status of a game, i.e., the move number to investigate effect heterogeneity with respect to time pressure. Players have a total of 110 minutes for the first 40 moves, inducing higher time pressure once they approach the 40th move than at the beginning of the match. The results for different move levels are presented in section 4.2. Third, we analyze effect heterogeneity with respect to individual and game characteristics in section 4.3. In a fourth step, we use outdoor pollution measurements to validate our main results and to generate evidence on the timing of the effect in section 4.4. Finally, we provide a discussion of our findings in the context of previous findings in section 4.5.

[16] In section 5 we show that taking the mean within the second as well as third hour of the tournament does not change the results in sign and magnitude.

4.1 Pooled estimation

Table 2 presents the estimated coefficients $\hat{\delta}$ associated with indoor air quality in equation (2) using all moves in our sample. Panel A presents the estimation results using the probability of making a meaningful error as the outcome variable. Panel B shows the results for the magnitude of our continuous error measure. Columns (1) to (4) show estimates for the impact of the air quality variables (PM2.5 and CO2) separately, whereby columns (1) and (2) excludes and columns (3) and (4) include the game-specific control variables. All regressions include the full set of fixed effects. The last column shows the results of a joint regression including the air quality measures, other environmental control variables, the full set of fixed effects and all control variables. The standard errors are clustered at the day level (round × year) and presented in parentheses. In addition, we provide the p-values based on wild bootstrap clusters in squared brackets.[17]

[Insert Table 2 about here]

The estimation results for the air quality parameters indicate that only the level of PM2.5 in the room is associated with the probability of making a meaningful error. This result holds across the different specifications considered in the analysis, i.e., columns (1), (3) and (5). The results of our main specification (5) indicate a 10 $\mu g/m^3$ increase in PM2.5 raises the probability of a player making a meaningful error by 2.1 percentage points in a given move of a game. This effect corresponds to an 26.3% increase given the average probability of making a meaningful error in our sample of 8.0% (see Panel C in Table 1). The estimate is statistically significant at the 1%-level based on the analytical standard errors. The p-value of 0.079 based on the wild bootstrapping method shows a statistical significance at the 10%-level. In Panel B of Table 2, we present the analysis for the magnitude of those errors. Focusing on specification (5), we find that a 10 $\mu g/m^3$ increase in PM2.5 leads to a 10.6% increase in the error measure. While the analytical standard errors indicate statistical significance at the 1%-level, the bootstrapped p-value of 0.202 rejects the statistical significance at conventional levels. With respect to CO2 concentration, we neither find any significant effects on the probability of making a meaningful error (Panel A) nor on the magnitude of the error (Panel B) in any of the specifications considered in the analysis, i.e., columns (2), (4) and (5).

4.2 Effect heterogeneity with respect to time pressure

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. In this section, we estimate equation (2) for four different subsamples of move intervals within games,

[17] We calculate the p-values using the *boottest.ado* command in *STATA* (see Roodman et al., 2019).

i.e., moves 15–20 (21% of the sample), 21–30 (35%), 31–40 (23%), and moves >40 moves (21%). Decisions taken within the interval of moves 31–40 can be assumed to be taken under relative time pressure, compared to the other categories given the low expected time left to execute the required 40 moves to stay in the game. In our sample, 40.4% percent of the games last more than 40 moves.

[Insert Figure 4 about here]

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). All regressions contain individual, year, round, and move fixed effects, both air quality measures as well as the other environmental control measures, and the full set of game-specific control variables. The dots represent 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).

First, we focus on the results concerning the effect of air quality on the probability of making a meaningful error (Panel A in Figure 4). We observe a clear pattern for the case of PM2.5. The estimated coefficients increase in size and statistical significance the closer the game gets to the 40th move. This finding suggests that the effects displayed in Table 2 are mainly driven by the moves close to move 40, when the time control takes place. Focusing on the move category 31–40, we find a 10 $\mu g/m^3$ increase in the levels of PM2.5 in the room leads to an increase in the probability of making a meaningful error by 3.2 percentage points (p-value=0.02). 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). The confidence intervals confirm statistical significance of the parameter.

While we find no statistically significant effect in the pooled regression, CO2 concentration does affect the performance of the players shortly before the time control. For the move category 31–40, we find that a 100 ppm increase in CO2 leads to an increase in the probability of making a meaningful error by 0.6 percentage points, which is also statistically significant at the 5%-level (p-value=0.03). The magnitude of this effect is about half the size compared to the impact of fine particulate matter when expressing the effect sizes per standard deviation of the PM2.5 and CO2 distributions.

Second, we focus on the impact of air quality on the magnitude of the error. Panel B in Figure 4 shows the estimated coefficient $\hat{\delta}$ of equation (2) using $Ln(error)$ as the outcome variable. We observe the same pattern as in Panel A, i.e., the estimated coefficients increase in size the closer the game gets to the 40th move. However, none of the parameters are estimated to be statistically significant at the 10%-level.

4.3 Effect heterogeneity with respect to individual and game characteristics

In a final step, we analyze potential effect heterogeneity with respect to individuals' age, as well as the ex ante probability of winning the game calculated based on the difference in the *Elo* rating score between the players (reflecting the tightness of a game). Table 3 shows the estimated parameters within each subsample with respect to the probability of making a meaningful error in columns (1) and (2) and the magnitude of the error in columns (3) and (4). Thereby, we show the results for both the pooled sample in columns (1) and (3) and the subsample containing only the moves within the move category 31–40 moves in columns (2) and (4). All regressions contain individual, year, round, and move fixed effects, all environmental control variables, and the full set of game-specific control variables.

[Insert Table 3 about here]

With respect to age, we divide the sample into three age groups according to the terciles of the age distribution. The effects of PM2.5 pollution are strongest for the middle age category (about 51–62 years old). The effects are statistically significant within the pooled sample as well as the subsample containing 31–40 moves. For CO2 concentration, we see the strongest effects for the oldest age category (>62 years old) when performing under time pressure. This evidence suggest that the cognitive performance of older individuals is particularly sensitive to poor air quality.

Considering the tightness of the game, the impact of PM2.5 pollution becomes more pronounced when players face an ex ante higher probability to lose the game, i.e., playing against a stronger opponent. Similar to the results on time pressure, this suggests that players' performance is particularly sensitive to air pollution if they have to act under certain pressure. Air pollution does not affect the players' performance when playing against a weaker opponent. We do not observe any clear pattern in the coefficients associated with CO2.

4.4 Outdoor pollution

This section investigates the role of outdoor pollution in explaining the impairment of players' performance. While high levels of CO2 arise from indoors due to the presence of the players, the PM2.5 pollution results from outdoor sources. Therefore, we re-estimate our main results by using outdoor pollution values instead of the indoor PM2.5 measure to validate our main results because we should find a correlation with outdoor pollution if our effects are indeed triggered by PM2.5. At the same time, this is informative about the role of buildings and to what extent they are able to protect people against air pollution. This will particularly add knowledge about the validity of previous studies in the field of environmental economics predominantly relying on outdoor measures (except for Roth, 2018). In a second step, we exploit temporal and spatial variation in the outdoor pollution measure to provide more insights on the timing of the effect.

Outdoor values. Similar to existing studies (e.g., Park, 2018; Ebenstein et al., 2016), we retrieve information on outdoor pollution from an air quality sensor close to the tournament venue (about 3.8 kilometers, see Figure A.6 in the appendix). The outdoor pollution is measured during the same time interval as the indoor measures, i.e., during the second hour of the tournament rounds. However, for pollution, we have to rely on PM10 because PM2.5 is not available for the outdoor measurement.[18]

[Insert Figure 5 about here]

Figure 5 shows the results when we use the outdoor measure of PM10 instead of the indoor measure of PM2.5 as the treatment. We find a very similar pattern for the coefficients on outdoor PM10, compared to our main results using indoor PM2.5 (see Figure 4). This is mostly attributable to the high correlation between the two pollution measures of 0.76 in our sample. As said before, the finding validates our results based on the indoor PM2.5 measure, and provides evidence on the validity of previous findings in the literature relying on outdoor pollution measures to evaluate indoor activities.

Lagged and lead outdoor pollution values. The previous exercise proves 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.[19] 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 levels of PM10 corresponding to the second hour of the tournament rounds (7:00pm–8:00pm) in the two preceding ($t-2$ and $t-1$) and two following days ($t+1$ and $t+2$). In addition, we include the pollution levels in the early (6:00am–9:00am) and late morning (9:00am–12:00am) of the same day of the tournament round.

[Insert Figure 6 about here]

Focusing on the most pronounced results from above using the subsample of moves 31–40, Figure 6 shows the results of seven separate regressions including the outdoor pollution values at different times around the time of the tournament rounds. The positive relationship between the

[18] Unfortunately, the outdoor measurement of PM2.5 is only available as the daily mean for every second day, so we decided to rely on the PM10 measurement instead.

[19] Given the lack of indoor measurements on the days before and after the tournament rounds, we need to rely on outdoor PM10 levels.

level of pollution and the error measures is strongest when we use the PM10 value measured at the exact time of the tournament. All other estimates are statistically insignificant. This finding suggests a short-term and transitory effect of particulate matter on the performance 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 the lag PM10 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.

Spatial variation in pollution values. Next to the temporal variation, we exploit spatial variation in the outdoor pollution measure given that multiple air quality stations are available within different distances to the tournament venue. We have four other stations available within the city of the tournament venue. Figure A.6 in the appendix shows a map with the exact location of the stations. Station 1 is the main station as used before. In addition, we have stations 2 and 3 located in the city center, and station 4 located next to a larger highway interchange close to the tournament venue. Moreover, we retrieved data from an outdoor sensor located in nearby city (station 5, about 30 km away) which is not shown on the map.

[INSERT FIGURE 7 ABOUT HERE]

Figure 7 shows the estimated coefficients for outdoor PM10 as retrieved from the different stations using the subsample of 31–40 moves. The stations within the city (station 1–4) yield very similar results, while the PM10 values stemming from the station in a nearby city (station 5) yield insignificant estimates. This finding suggests that it is indeed the local pollution that triggers the impairment of players' performance, validating our results and supporting the hypothesis of a short-term and transitory effect of particulate pollution on cognition.

4.5 Discussion of results in context of previous findings

Previous studies have found a negative effect of CO2 on the cognitive performance of adults. However, the level at which CO2 impairs cognitive performance and the exact mechanisms for cognitive impairments remain unclear. In a lab experiment, Allen et al. (2016) show that levels beyond 1,500 ppm have a detrimental effect on the performance of 24 adults in a simulated management task, using 500 ppm as a baseline. Zhang et al. (2015) reduce the air supply in the chamber to let subjects be exposed to 3,000 ppm of CO2. The authors find a cognitive impairment in the subjects at 3,000 ppm. The distribution of values of CO2 observed in our study differs from the distributions in lab experiments. Our baseline ($minCO2 = 1,179$ ppm) is twice the 500 ppm value commonly used in the literature as the reference CO2 level. We only find a negative effect of CO2 concentration on the presence of errors if acting under time stress.

Evidence on the impact of air pollution on cognitive performance of adults is increasing. Ebenstein et al. (2016) find that a 10-unit increase in daily PM2.5 (AQI) leads to an increase of two percentage points in the probability of failing a high-stakes exam. In our pooled sample, we find comparable effects with 10 $\mu g/m^3$ increase resulting in a 2.1 percentage points increase in the probability of making a meaningful error. Importantly, we find that the overall effect is driven by moves taken under time pressure. The impact of PM2.5 is largest at the move interval shortly before the time control. An increase of 10 $\mu g/m^3$ in PM2.5 leads to a 3.2 percentage points increase in the probability of making meaningful errors. When looking at continuous variables of performance, we see heterogeneity in the elasticities of pollution on performance.[20] Among manual workers, the highest elasticity is 0.260, estimated in a US sample of agriculture workers (Graff Zivin and Neidell, 2012). For China, Kahn and Li (2019) estimate the elasticity of PM2.5 in a sample of highly skilled public workers, finding elasticities between 0.179 and 0.243. In our pooled sample, we find a 0.273 (0.196) elasticity associated with PM2.5 (PM10). When restricting the sample to the move interval shortly before the time control, we observe that the elasticity increases to 0.517 for PM2.5 and 0.356 for PM10, suggesting the effect of PM on cognitive performance is exacerbated and only present under time pressure.

In sum, we find a negative impact of PM2.5 and CO2 on the quality of tasks of our subjects if acting under time stress. The estimated impact of PM2.5 in the full sample is similar to the estimates of the literature and become larger in the sample of moves just before the time control.

5 Sensitivity analysis

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: (i) We additionally control for traffic density and ozone levels, (ii) change the timing of the measurement of the indoor air quality measures during the tournament rounds, and (iii) restrict the sample by removing games with 40 moves or less. All specifications include the full set of fixed effects, and control variables as regressors.

Potential confounding factors. We test the sensitivity of our results with respect to two potential confounding factors, i.e., traffic density and ozone. First, traffic density around the tournament venue creates PM2.5 pollution and at the same time might affect players' cognition directly as they may be stressed by 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 (4:00pm–6:00pm), which are relevant for players commuting by car to the tournament venue. Table A.2 in the

[20] See Kahn and Li (2019) for an overview of the elasticities found in previous studies.

appendix shows the results including the total length (in km) of traffic jams within this time period as an additional control variable. The results are highly robust and hardly change once traffic density is included as an additional control variable.

Second, we test whether the estimated effects are due to general pollution or are specific to particulate matter pollution. Therefore, we include the average level of ozone as measured at the close-by outdoor air quality station during the tournament rounds in the main empirical model, together with PM10 and the rest of the environmental measures (equation (2)). Figure A.7 in the appendix shows the estimated coefficients associated with outdoor levels of PM10 and ozone. Although the coefficient associated with PM10 remains unchanged, ozone never has a statistically significant effect in our sample. This finding supports the hypothesis that the estimated impacts of air pollution are mainly driven by the level of particles.

Timing of the measurement of indoor air quality. We further test the sensitivity of the results with respect to the timing of the measurement of the indoor air quality. In the main analysis, we include the environmental measures as the mean value during the second hour of the tournament rounds. We do this in order to avoid a biased measurement for CO2 concentration due to lower values at the beginning/end of the tournament, as it is correlated with the number of people in the room. We now extend this period of measurement to the third hour of the tournament to test the sensitivity of our results. A consideration beyond three hours is not sensible given that more than 50% of the games last less than three hours, and therefore many players are not in the tournament hall anymore.

Figure A.8 in the appendix presents the results using the mean values of PM2.5 and CO2 as measured during the second and third hour of the tournament rounds. The estimates are very similar to our main results in size and significance (compare to Figure 4).

Attrition. In our sample, a number of games end before reaching the 40th move, when the time control takes 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 subsection, we present the estimation results restricting our sample to those games that last at least 40 moves and hence pass the time threshold.

Figure A.9 in the appendix presents the estimation results of the main equations for the sample of games lasting at least 40 moves. The results suggest that the main findings from section 4 are not driven by the games that finish before the time control is implemented. The coefficients for the move category 31–40 moves increase in size for both outcome variables. The confidence intervals for such coefficients are slightly larger compared to the main sample but still indicate statistical significance, even for the magnitude of the error (Panel B).

6 Conclusion

In this paper, we investigate the impact of air quality on human cognition by examining the performance of chess players at tournaments under different levels of air quality. Chess requires players to use their cognitive skills intensively and to decide strategically. Due to the computational nature of the game of chess, the cognitive performance of players can be measured objectively by comparing the quality of a player's actual moves with those moves proposed by a chess computer. In addition, chess players at tournaments have strong intrinsic as well as extrinsic motivation to exert high effort.

By using this setting, we contribute to the existing literature on the effects of environmental conditions on human (cognitive) productivity, which so far have relied on using simulated office tasks in lab settings, and field studies focusing on routine manual occupations or workers' availability to execute tasks (or uptime) in non-routine cognitive occupations. In addition, most studies are based on outdoor measurements of the environment that are likely to deviate from the actual environmental conditions (office) workers are exposed to during the working day. In our study, we were able to install measurement sensors recording the indoor air quality to which the players were exposed during the tournaments.

The results consistently show that poor air quality harms players' performance in cognitive tasks. The impact is most pronounced when players are acting under time pressure. For the pooled sample we find that a 10 $\mu g/m^3$ increase in the levels of PM2.5 in the room leads to a 2.1 percentage point increase in the probability of making a meaningful error. The effect increases to 3.2 percentage points for the move category 31–40 moves, which is closest to the time control. While the estimated elasticity of 0.273 for pollution on the magnitude of the error in the pooled sample is similar to existing estimates within the literature, it doubles to 0.517 if decisions are taken under time pressure. For CO2 concentration the impact is only statistically significant within the move category 31–40 moves. We find that a 300 ppm increase in CO2 (about one standard deviation) leads to an increase in the probability of making a meaningful error by 1.8 percentage points. The magnitude of this effect is about half the size compared to the impact of fine particulate matter when expressing the effect sizes per standard deviation of the PM2.5 and CO2 distributions. We further find older individuals being most affected by poor air quality, and an increased effect of pollution if players have to play against a stronger opponent which may represent a more stressful situation in itself. Finally, exploiting temporal and spatial variation in outdoor pollution, we provide evidence suggesting a short-term and transitory effect of particulate matter on cognition.

Given that our measures of indoor air quality are within a moderate range, resembling usual conditions humans are usually exposed to during their daily life, we argue that our findings can be extrapolated to different setups where individuals are required to make complex decisions or execute cognitive tasks under time pressure. For the labor market, given the type of cognitive task chess players have to perform our results may have strong implications for the productivity of high-skilled office workers, in particular, for those executing non-routine cognitive tasks requiring problem-solving skills. Due to technological change, the role of these tasks is steadily rising in developed labor markets and is represented in professional, managerial, technical, and creative occupations (Autor and Price, 2013).

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Tables and Figures

Table 1: Descriptive statistics

	N (1)	mean (2)	sd (3)	min (4)	max (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 (in years)	121	52.62	17.20	18	89
Female	121	0.05	0.22	0	1
B. Game-specific characteristics					
Total number of moves	596	38.45	14.41	15	98
Total duration (in minutes)	596	171.40	54.92	43	343
Draw game	596	0.18			
Player-opponent difference in					
Elo rating score	596	293.50	187.40	2	1,265
Age (in years)	596	18.26	14.00	0	66
C. Move-specific characteristics					
Meaningful error	29,517	0.08	0.28	0	1
Error if > 0	12,742	1.55	5.06	0.01	90.25
D. Environmental conditions (round level)[a)]					
Temperature (in °C)	21	24.32	2.15	21.77	28.75
CO2 (in ppm)	21	1,511	338.80	967.20	2,393
PM2.5 (in $\mu g/m3$)	21	27.15	13.19	14.03	69.75
Humidity (in %)	21	47.36	1.21	45.33	49.92
Noise (in decibels)	21	48.64	5.08	39.72	58.23

a) Environmental measures are mean values of the prevailing conditions as measured during second hour of the tournament round.

Table 2: Impact of indoor environmental quality on performance of chess players

	(1)	(2)	(3)	(4)	(5)
Panel A: Meaningful error					
PM2.5 (in 10 $\mu g/m3$)	0.014***		0.014***		0.021***
	(0.002)		(0.002)		(0.003)
	[0.060]		[0.093]		[0.077]
CO2 (in 100 ppm)		-0.001		-0.001	0.001
		(0.001)		(0.001)	(0.001)
		[0.821]		[0.718]	[0.576]
Environmental control variables					
Temperature (in ℃)					0.000
					(0.002)
					[0.958]
Humidity (in %)					-0.000
					(0.001)
					[0.425]
Noise (in decibels)					-0.013**
					(0.005)
					[0.426]
Observations	29,517	29,517	29,517	29,517	29,517
Adjusted R-squared	0.037	0.036	0.041	0.040	0.041
Panel B: Ln(error)					
PM2.5 (in 10 $\mu g/m3$)	0.082***		0.081***		0.106***
	(0.018)		(0.018)		(0.030)
	[0.091]		[0.168]		[0.202]
CO2 (in 100 ppm)		-0.004		-0.002	0.006
		(0.008)		(0.008)	(0.011)
		[0.892]		[0.863]	[0.682]
Environmental control variables					
Temperature (in ℃)					0.010
					(0.019)
					[0.955]
Humidity (in %)					-0.006
					(0.007)
					[0.517]
Noise (in decibels)					-0.047
					(0.037)
					[0.609]
Observations	12,742	12,742	12,742	12,742	12,742
Adjusted R-squared	0.117	0.115	0.125	0.124	0.125
Player FE	YES	YES	YES	YES	YES
Tournament FE	YES	YES	YES	YES	YES
Round FE	YES	YES	YES	YES	YES
Move FE	YES	YES	YES	YES	YES
Game-specific controls	NO	NO	YES	YES	YES

Note: */**/*** indicate statistical significance at the 10%/5%/1% levels. Standard errors are in parentheses and clustered at the day level (round × year). P-values calculated using wild bootstrap (*boottest.ado*) and are reported in squared brackets. Each panel presents the regression on different outcomes. The binary outcome variable "meaningful error" takes the value of 1 if the move is marked as a meaningful error by the chess engine and zero otherwise. Each column displays the results of a separate regression. All regressions include the full set of game-specific control variables: (i) difference in the *ELO* rating score between the player and the opponent (as well as its squared term), (ii) the number of points achieved during the tournament, and (iii) the actual status of the game before the move, namely, the pawn metric of the previous move by the opponent ($C^{opponent}_{jtrm-1}$).

Table 3: Effect heterogeneity with respect to individual and game characteristics

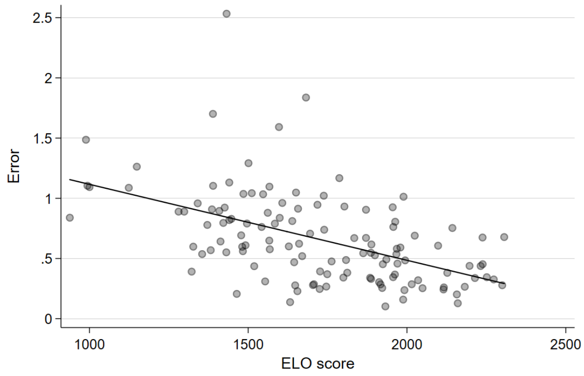
	(1) Meaningful Error Pool sample	(2) Meaningful Error Moves 30-40	(3) Ln(error) Pool sample	(4) Ln(error) Moves 30-40
Age 18-50				
CO2 (in 100 ppm)	-0.000	-0.004	-0.019	-0.065**
	(0.002)	(0.002)	(0.015)	(0.025)
	[0.839]	[0.720]	[0.718]	[0.524]
PM2.5 (in 10 $\mu g/m3$)	0.015*	0.012	0.083	0.050
	(0.007)	(0.013)	(0.065)	(0.106)
	[0.134]	[0.152]	[0.333]	[0.277]
Observations	9,600	2,087	3,820	858
Adjusted R-squared	0.036	0.032	0.126	0.126
Age 51-62				
CO2 (in 100 ppm)	0.003*	0.008***	0.011	0.034
	(0.001)	(0.003)	(0.012)	(0.022)
	[0.323]	[0.095]	[0.642]	[0.257]
PM2.5 (in 10 $\mu g/m3$)	0.036***	0.059***	0.191***	0.183
	(0.007)	(0.015)	(0.064)	(0.119)
	[0.035]	[0.006]	[0.172]	[0.037]
Observations	10,772	2,387	4,780	1,084
Adjusted R-squared	0.046	0.057	0.123	0.128
Age $>$ 62				
CO2 (in 100 ppm)	-0.001	0.015***	0.013	0.097***
	(0.002)	(0.005)	(0.019)	(0.024)
	[0.903]	[0.045]	[0.684]	[0.020]
PM2.5 (in 10 $\mu g/m3$)	0.011	0.051***	0.059	0.191*
	(0.007)	(0.013)	(0.058)	(0.098)
	[0.549]	[0.141]	[0.637]	[0.154]
Observations	9,145	2,054	4,142	892
Adjusted R-squared	0.050	0.048	0.141	0.101
Probability to win$^{a)}$ $<$ 0.5				
CO2 (in 100 ppm)	-0.001	0.008**	-0.010	0.030
	(0.002)	(0.003)	(0.010)	(0.018)
	[0.867]	[0.099]	[0.846]	[0.118]
PM2.5 (in 10 $\mu g/m3$)	0.028***	0.072***	0.095***	0.247**
	(0.006)	(0.015)	(0.032)	(0.088)
	[0.089]	[0.031]	[0.037]	[0.016]
Observations	14,752	3,262	6,842	1,515
Adjusted R-squared	0.044	0.067	0.136	0.150
Probability to win$^{a)}$ $>$ 0.5				
CO2 (in 100 ppm)	0.002	0.010	0.038**	0.213***
	(0.003)	(0.008)	(0.016)	(0.071)
	[0.609]	[0.780]	[0.961]	[0.044]
PM2.5 (in 10 $\mu g/m3$)	0.030*	0.123***	0.203	1.188***
	(0.016)	(0.026)	(0.149)	(0.376)
	[0.697]	[0.393]	[0.776]	[0.372]
Observations	6,640	1,490	2,757	606
Adjusted R-squared	0.047	0.061	0.156	0.179
Player FE	YES	YES	YES	YES
Tournament FE	YES	YES	YES	YES
Round FE	YES	YES	YES	YES
Move FE	YES	YES	YES	YES

Note: */**/*** indicate statistical significance at the 10%/5%/1% levels. Standard errors are in parentheses and clustered at the day level (round × year). P-values calculated using wild bootstrap (*boottest.ado*) and are reported in squared brackets. Each panel presents the regression on different outcomes. The binary outcome variable "meaningful error" takes the value of 1 if the move is marked as a meaningful error by the chess engine and zero otherwise. Each column displays the results of a separate regression. All regressions include the full set of game-specific control variables: (i) difference in the *ELO* rating score between the player and the opponent (as well as its squared term), (ii) the number of points achieved during the tournament, and (iii) the actual status of the game before the move, namely, the pawn metric of the previous move by the opponent ($C^{opponent}_{jtrm-1}$).

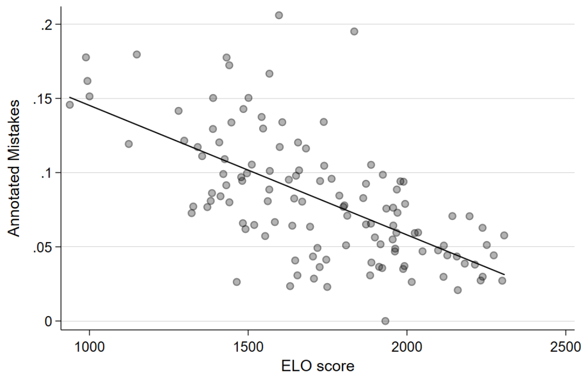
a) Probability of winning is calculated based on the difference in the *Elo* score between the player and the opponent: $Prob(win) = 1/(1 + 10^{(-diff_{Elo}/400)})$.

Figure 1: Player skills and average move performance

Panel A. Average error and player *ELO* rating score

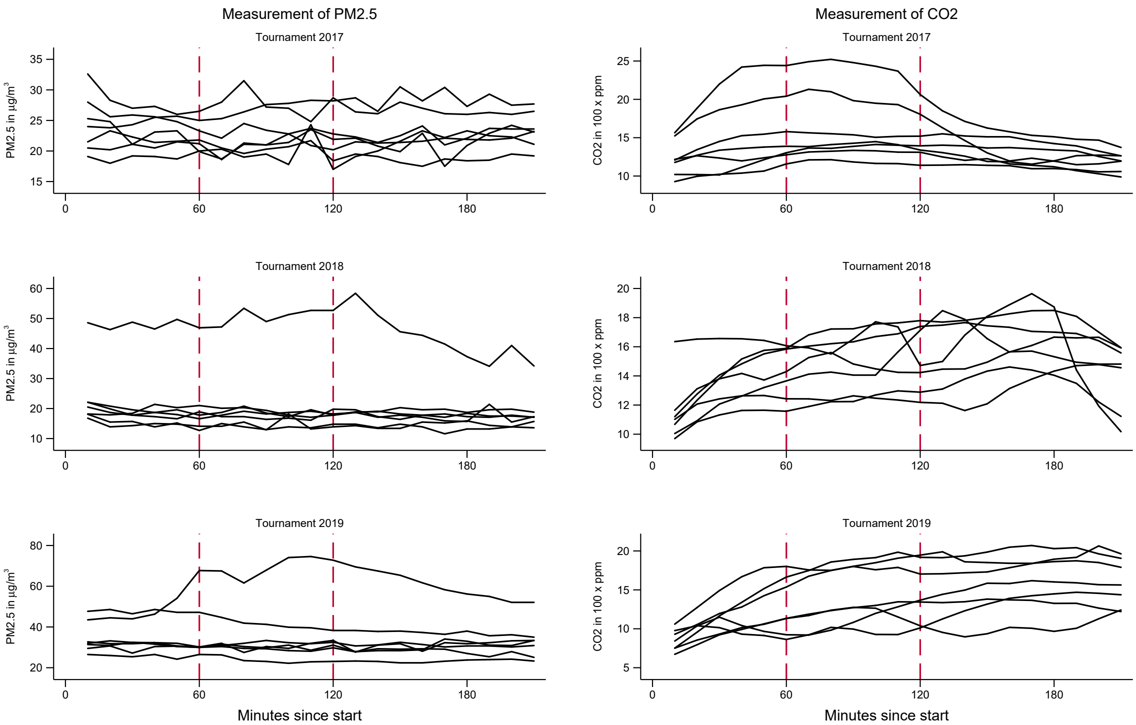


Panel B. Average number of meaningful errors and player *ELO* rating score



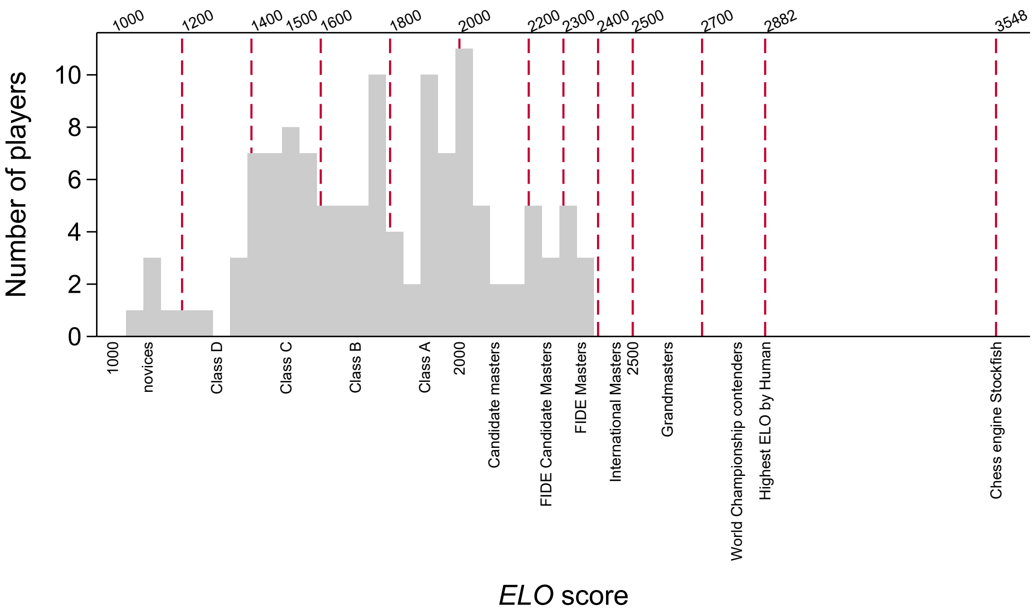
Note: Each dot in the figures represents a player, the figures display the average error of a player (Panel A) or the average number of annotated errors (Panel B) in the vertical axis, and the average *ELO* rating score of the player over the two tournaments in the sample in the horizontal axis. The error measure is defined in equation 1. The annotated errors are defined as the sum of moves labeled as mistakes and blunders. The Pearson correlation between the error measure [annotated error] and the *ELO* rating score is -0.54 (p-value=0.00) [-0.62 (p-value=0.00)]. The correlation between the player average of the two move-performance measures is 0.72 (p-value=0.00).

Figure 2: Distribution of indoor air quality measures during the tournament rounds



Note: The solid black lines indicate the distribution of the environmental measures during the seven rounds within a tournament. The calculation of the mean values of the environmental measures as used in the regression analysis are calculated based on observations during the second hour of the tournament rounds, as indicated by the dashed lines.

Figure 3: Distribution of players' *Elo* rating score



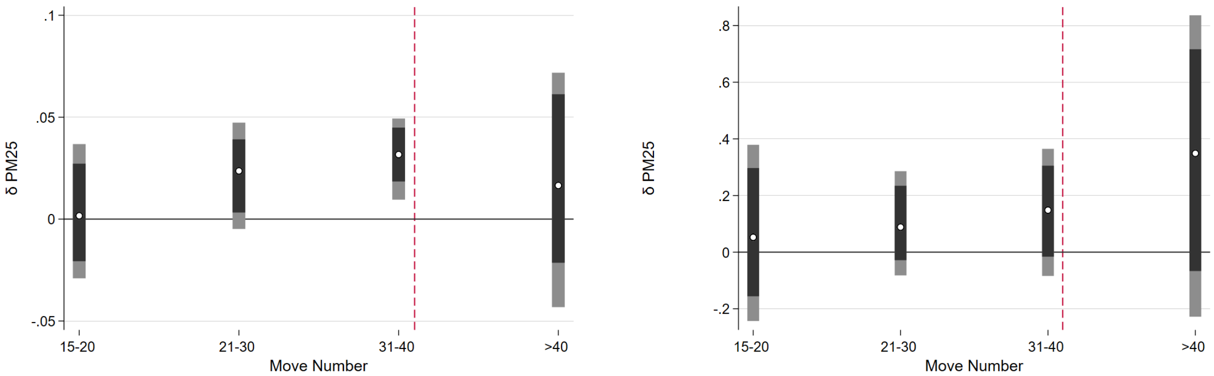
Note: The players' Elo score is calculated by adding 100 to the players' DWZ score in order to make the scores comparable to the FIDE system.

Figure 4: Impact of indoor environmental quality on performance of chess players by move level

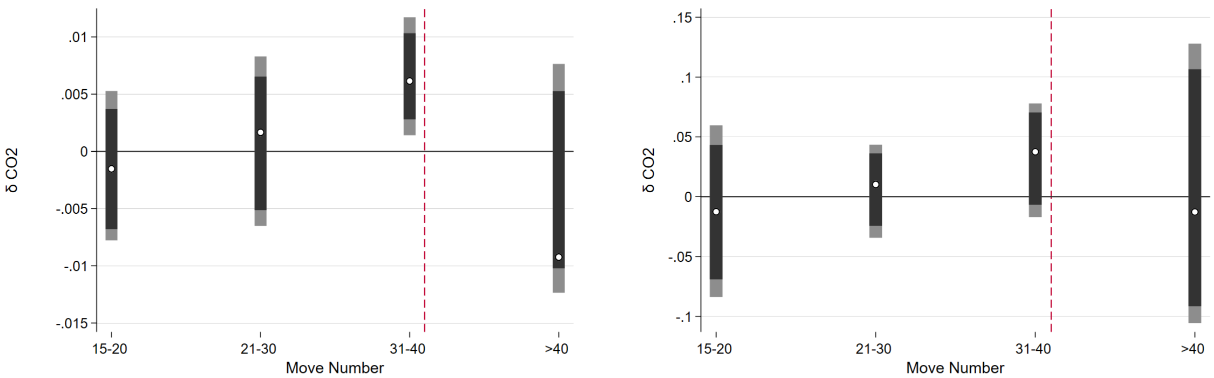
Panel A: Meaningful error

Panel B: Ln(error)

PM2.5 (in 10 $\mu g/m3$)



CO2 concentration (in 100 ppm)

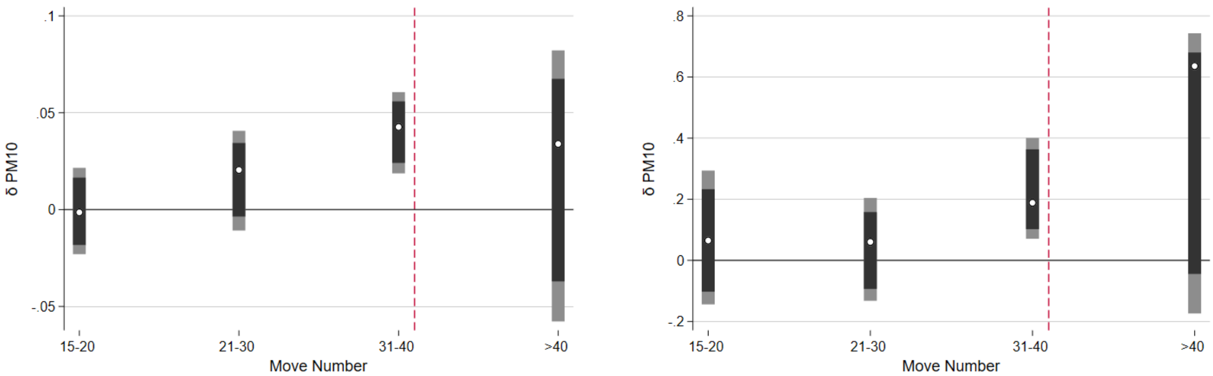


Note: The figure shows the estimated coefficient of joint regressions including PM2.5 and CO2. We divided the total sample of moves into subsamples with respect to the number of moves within a game (horizontal axis). The vertical, dashed red line indicates the occurrence of the time restriction during the game. Each panel presents the regression on different outcomes. The binary outcome variable "meaningful error" takes the value of 1 if the move is marked as a meaningful error by the chess engine, and zero otherwise. 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 of the previous move by the opponent ($C^{opponent}_{jtrm-1}$).

Figure 5: Using outdoor pollution measure

Panel A: Meaningful error | Panel B: Ln(error)

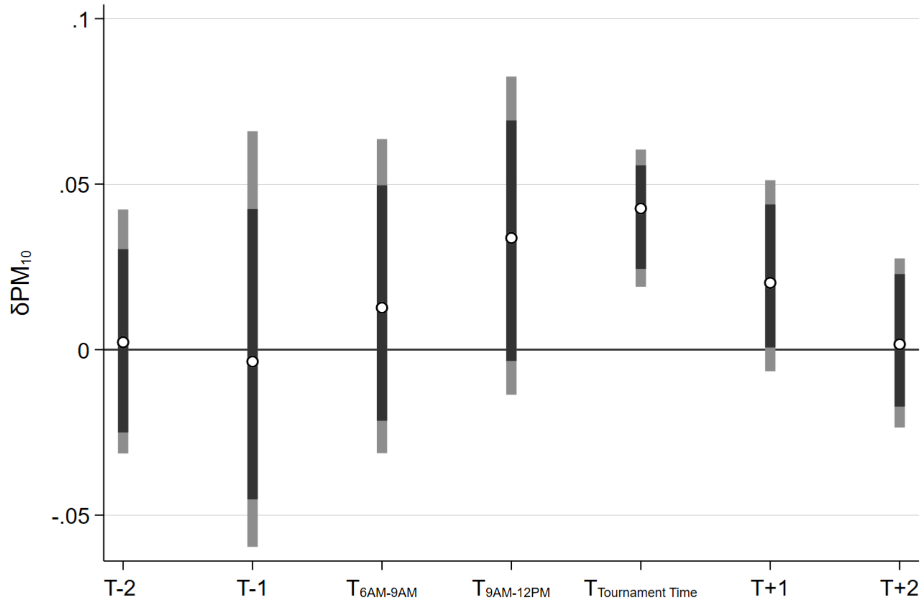
Outdoor PM10 (in 10 $\mu g/m3$)



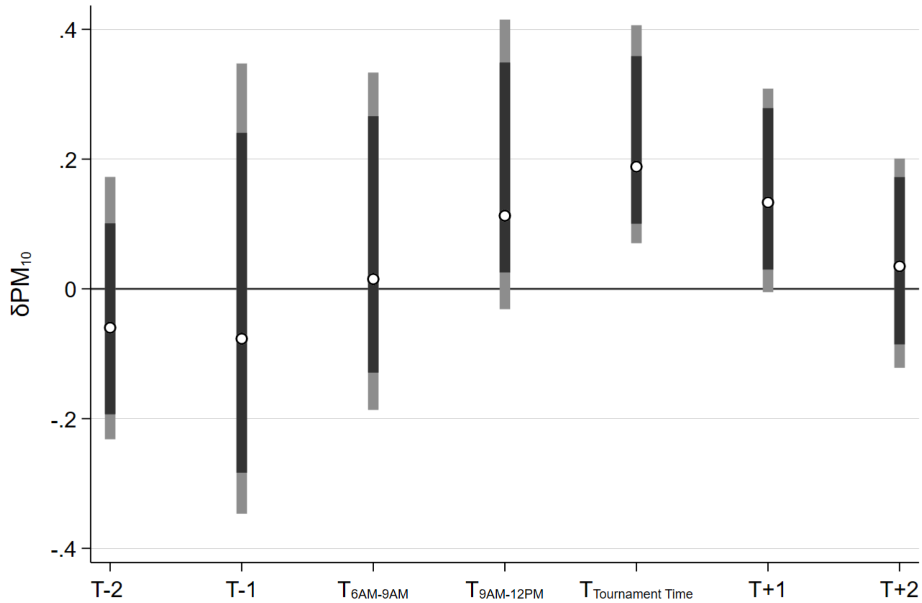
Note: The figure shows the estimated coefficients of joint regressions including PM10 and CO2. We divided the total sample of moves into subsamples with respect to the number of moves within a game (horizontal axis). The vertical, dashed red line indicates the occurrence of the time restriction during the game. Each panel presents the regression on different outcomes. The binary outcome variable “meaningful error” takes on the value one if the move is marked as a meaningful error by the chess engine and zero otherwise. 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 of the previous move by the opponent ($C^{opponent}_{jtrm-1}$).

Figure 6: Lagged and lead pollution values

Panel A: Meaningful error



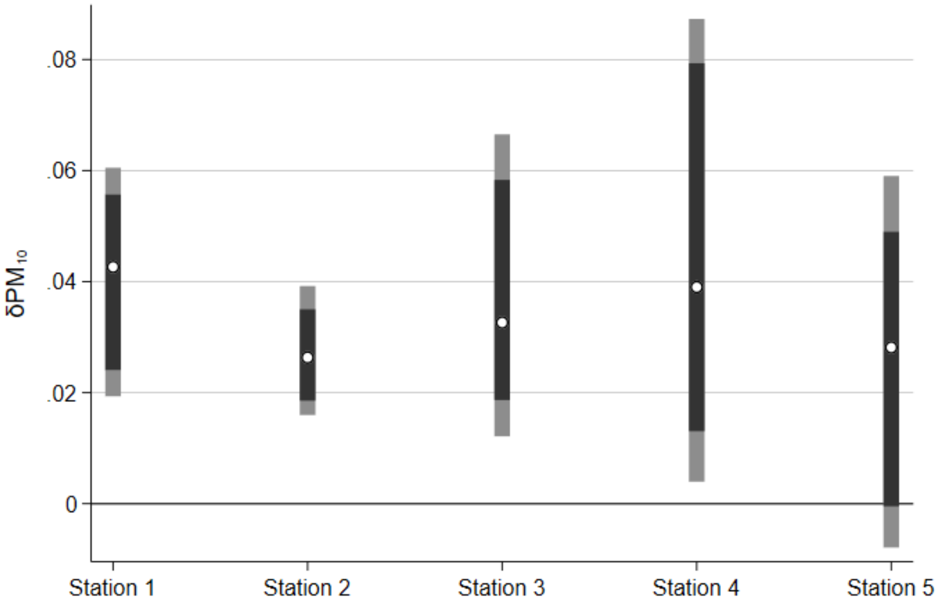
Panel B: Ln(error)



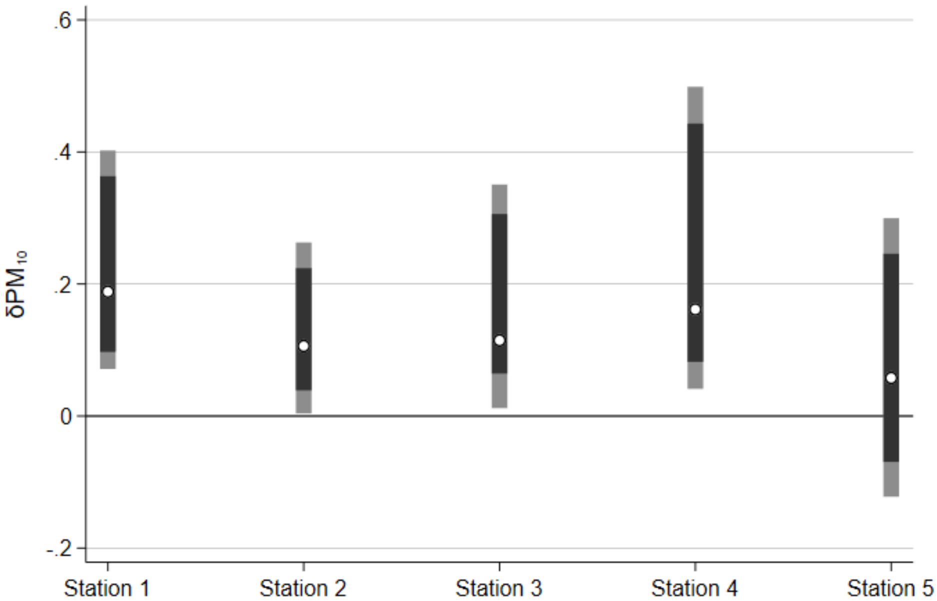
Note: The figure shows the estimated coefficients of separate regressions with different lags and leads of outdoor PM10 using the subsample with 31-40 moves. Each panel presents the regression on different outcomes. The binary outcome variable "meaningful error" takes on the value one if the move is marked as a meaningful error by the chess engine and zero otherwise. 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 CO2 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 ($C^{opponent}_{jtrm-1}$).

Figure 7: Spatial variation in outdoor pollution values

Panel A: Meaningful error



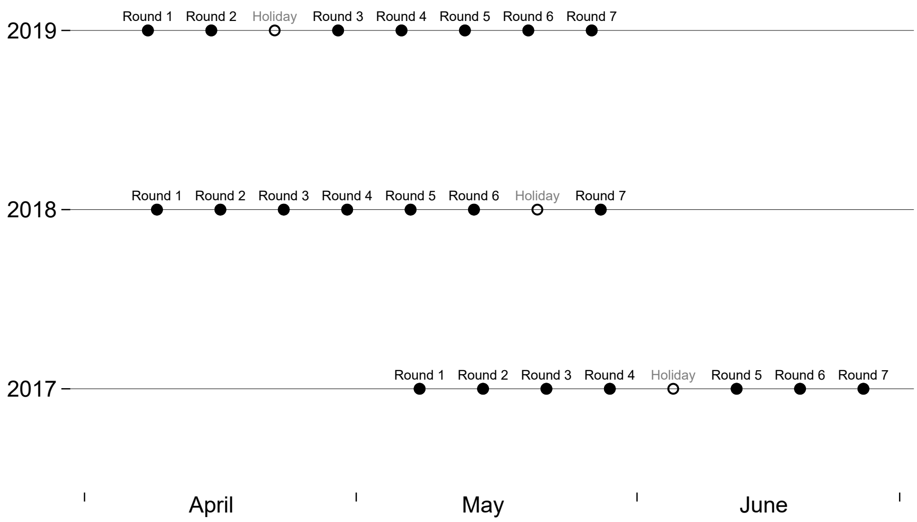
Panel B: Ln(error)



Note: The figure shows the estimated coefficients of separate regressions using outdoor PM10 as retrieved from different stations and estimated based on the subsample with 31-40 moves. Figure A.6 in the appendix shows a map with the exact location of the stations within the city (Station 1-5). Station 5 is located in another nearby city (about 30 km). Each panel presents the regression on different outcomes. The binary outcome variable "meaningful error" takes on the value one if the move is marked as a meaningful error by the chess engine and zero otherwise. 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 CO2 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 ($C^{opponent}_{jtrm-1}$).

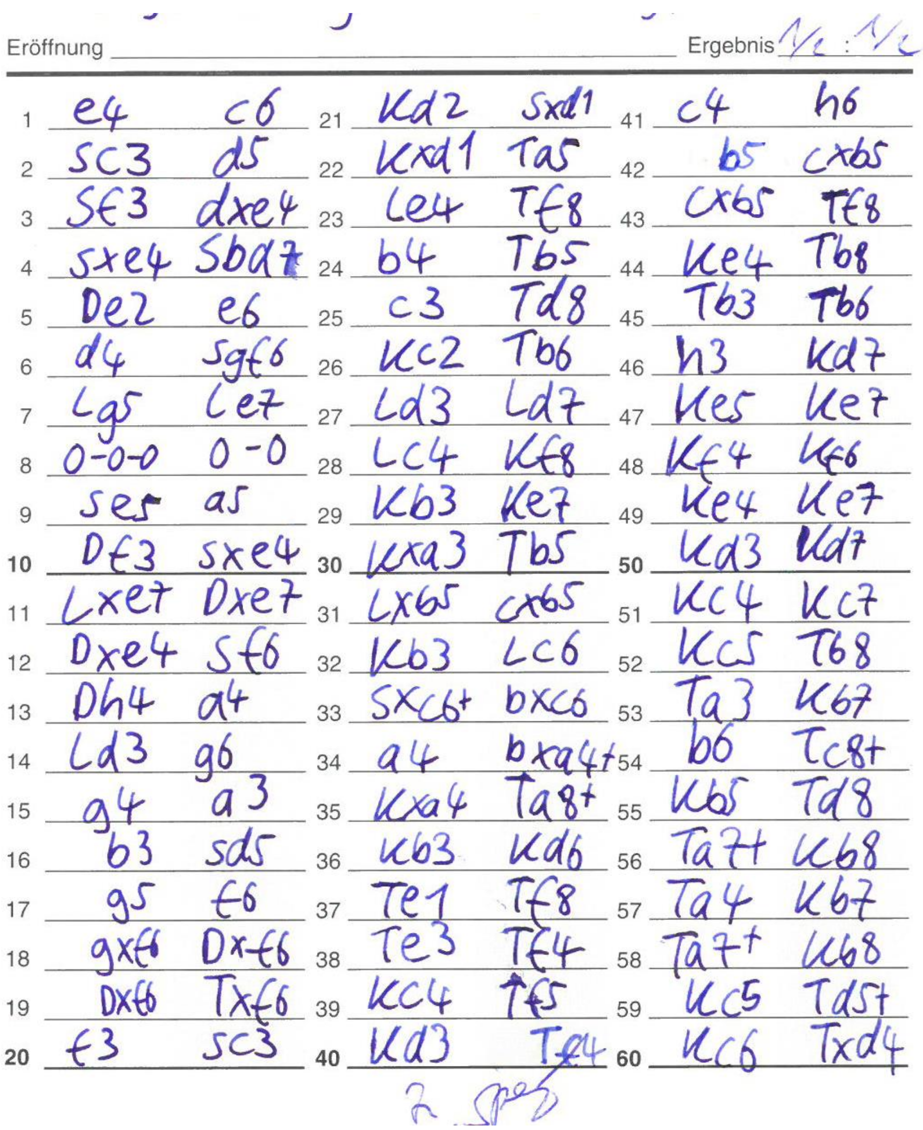
A Appendix

Figure A.1: Timing and setting of the chess tournaments



Note: This diagram illustrates the timing and setting of the observed tournaments. Each tournament consists of seven rounds, played every Monday, 6:00pm (local time).

Figure A.2: Example of players' hand-written game notation

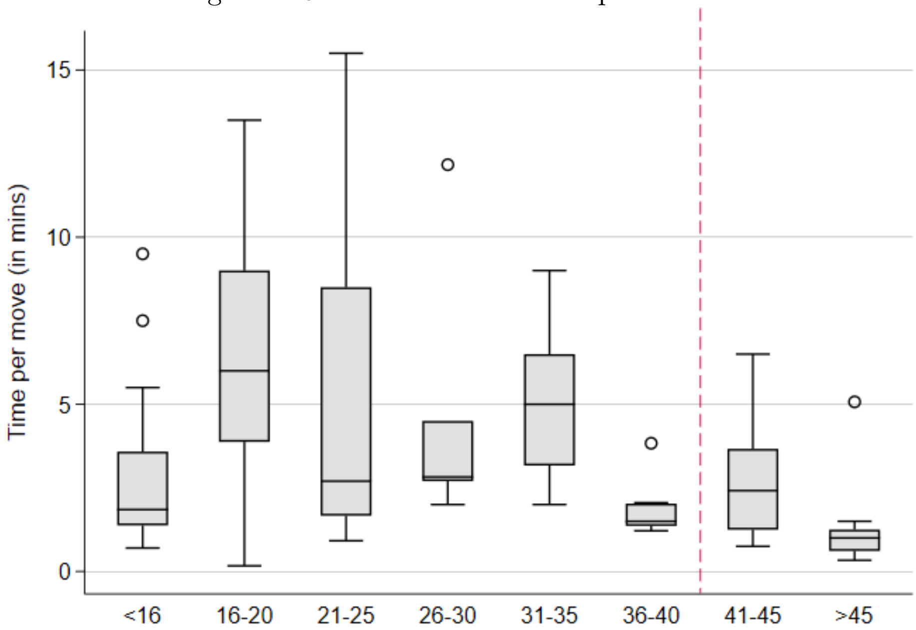


Eröffnung ______ Ergebnis 1/2 : 1/2

1	e4	c6	21	Kd2	Sxd1	41	c4	h6
2	Sc3	d5	22	Kxd1	Ta5	42	b5	cxb5
3	Sf3	dxe4	23	Le4	Tf8	43	cxb5	Tf8
4	Sxe4	Sbd7	24	b4	Tb5	44	Ke4	Tb8
5	De2	e6	25	c3	Td8	45	Tb3	Tb6
6	d4	Sgf6	26	Kc2	Tb6	46	h3	Kd7
7	Lg5	Le7	27	Ld3	Ld7	47	Ke5	Ke7
8	0-0-0	0-0	28	Lc4	Kf8	48	Kf4	Kf6
9	Se5	a5	29	Kb3	Ke7	49	Ke4	Ke7
10	Df3	Sxe4	30	Kxa3	Tb5	50	Kd3	Kd7
11	Lxe7	Dxe7	31	Lxb5	cxb5	51	Kc4	Kc7
12	Dxe4	Sf6	32	Kb3	Lc6	52	Kc5	Tb8
13	Dh4	a4	33	Sxc6+	bxc6	53	Ta3	Kb7
14	Ld3	g6	34	a4	bxa4+	54	b6	Tc8+
15	g4	a3	35	Kxa4	Ta8+	55	Kb5	Td8
16	b3	Sd5	36	Kb3	Kd6	56	Ta7+	Kb8
17	g5	f6	37	Te1	Tf8	57	Ta4	Kb7
18	gxf6	Dxf6	38	Te3	Tf4	58	Ta7+	Kb8
19	Dxf6	Txf6	39	Kc4	Tf5	59	Kc5	Td5+
20	f3	Sc3	40	Kd3	Tf4	60	Kc6	Txd4

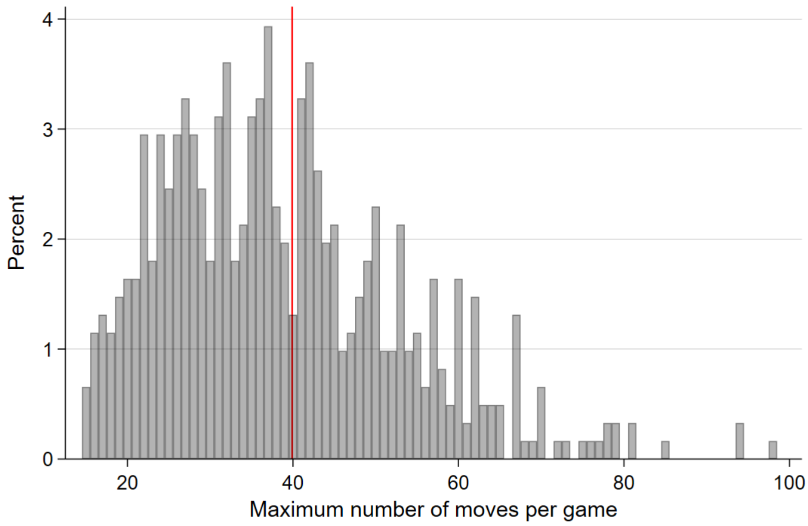
Note: This picture shows an example of the hand-written documentation as filled in during each game within the chess tournament. The documentation has been digitized by the tournament organizers.

Figure A.3: Distribution of time per move



Note: This diagram shows the distribution of remaining time (in minutes) in clock for a given move. The evidence was collected based on a sample of 63 games played during the 2019 tournament edition.

Figure A.4: Distribution of total number of moves per game

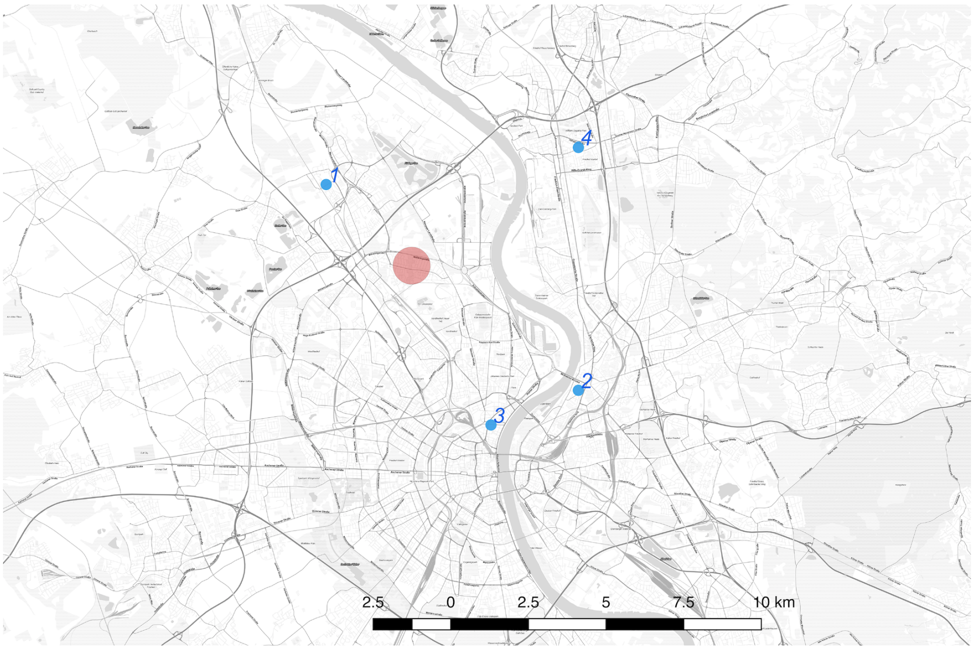


Note: This diagram shows the distribution of the total number of moves for all the games in our sample.

Figure A.5: Example for sensor location

Note: This picture illustrates the placement of one sensor measuring the indoor environmental quality. In total, three sensors were placed across the room on separate tables.

Figure A.6: Location of weather and air quality stations within the city of the tournament



Note: This picture shows a map of the city where the observed chess tournaments took place. The red dot indicates the location of the tournament venue. The blue dots indicate the location of the available air quality stations. Station 1 is the main station used to retrieve the outdoor pollution values (about 3.8 km away from the tournament venue).

Table A.1: Elasticity of air pollution on *Error*

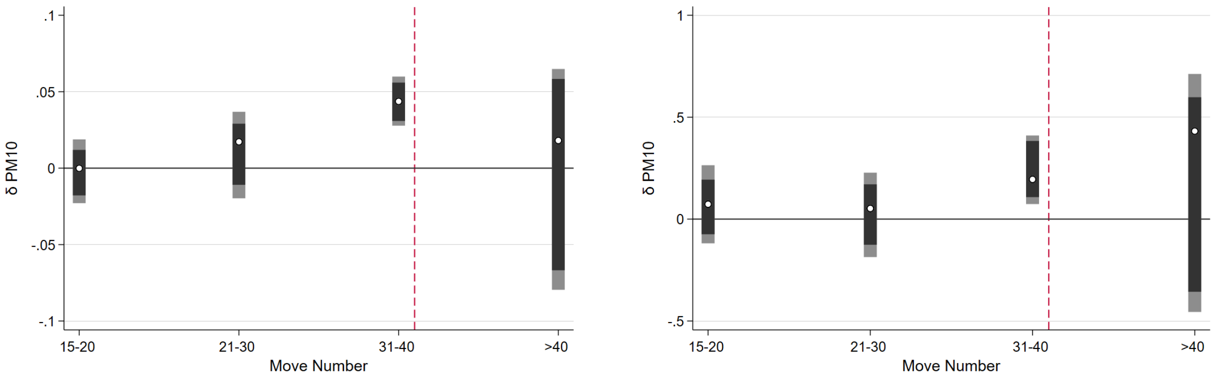
	(1) Pooled	(2) 30-40 moves	(3) Pooled	(4) 30-40 moves
Indoor ln(PM25)	0.273***	0.517***		
	(0.082)	(0.129)		
	[0.268]	[0.112]		
Outdoor ln(PM10)			0.196**	0.356***
			(0.072)	(0.111)
			[0.197]	[0.008]
Observations	12,742	2,834	12,742	2,834
Player FE	YES	YES	YES	YES
Tournament FE	YES	YES	YES	YES
Round FE	YES	YES	YES	YES
Move FE	YES	YES	YES	YES
Controls	YES	YES	YES	YES

Note: */**/*** indicate statistical significance at the 10%/5%/1% levels. Standard errors are in parentheses and clustered at the game level. P-values calculated using wild bootstrap (*boottest.ado*) and are reported in squared brackets. All regressions presented in the table include all the environmental parameters and the full set of control variables: (i) difference in the *ELO* rating score between the player and the opponent (as well as its squared term), (ii) the number of points achieved during the tournament, and (iii) the actual status of the game before the move, namely, the pawn metric of the previous move by the opponent ($C_{jtrm-1}^{opponent}$).

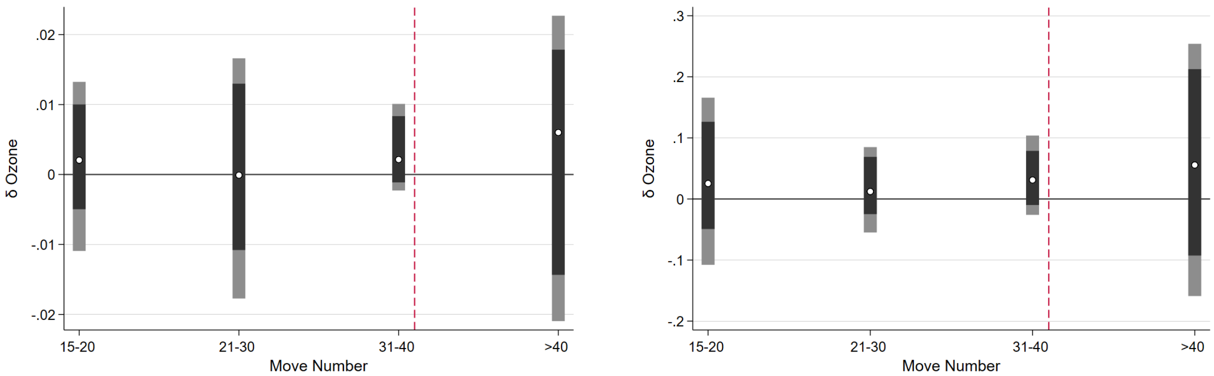
Figure A.7: Robustness: Inclusion of ozone

Panel A: Meaningful error | Panel B: Ln(error)

Outdoor PM10 (in 10 $\mu g/m3$)



Ozone (in ppm)



Note: The figure shows the estimated coefficients of joint regressions including PM10, ozone and CO2. We divided the total sample of moves into subsamples with respect to the number of moves within a game (horizontal axis). The vertical, dashed red line indicates the occurrence of the time restriction during the game. Each panel presents the regression on different outcomes. The binary outcome variable "meaningful error" takes on the value one if the move is marked as a meaningful error by the chess engine and zero otherwise. 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 of the previous move by the opponent ($C^{opponent}_{jtrm-1}$).

Table A.2: Robustness: Inclusion of traffic controls

	Pooled	30-40 moves	Pooled	30-40 moves	Pooled	30-40 moves	Pooled	30-40 moves
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Meaningful error				***Panel B: Ln(error)***			
PM2.5 (in 10 $\mu g/m3$)	0.021***	0.032***	0.021***	0.030***	0.106***	0.148***	0.109***	0.146***
	(0.003)	(0.006)	(0.003)	(0.006)	(0.030)	(0.048)	(0.028)	(0.048)
	[0.076]	[0.022]	[0.101]	[0.016]	[0.201]	[0.120]	[0.183]	[0.173]
Traffic density 4-6pm (jams in total km)	NO	NO	YES	YES	NO	NO	YES	YES
Observations	29,517	6,528	29,517	6,528	12,742	2,834	12,742	2,834
Player FE	YES	YES	YES	YES	YES	YES	YES	YES
Tournament FE	YES	YES	YES	YES	YES	YES	YES	YES
Round FE	YES	YES	YES	YES	YES	YES	YES	YES
Move FE	YES	YES	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES	YES	YES

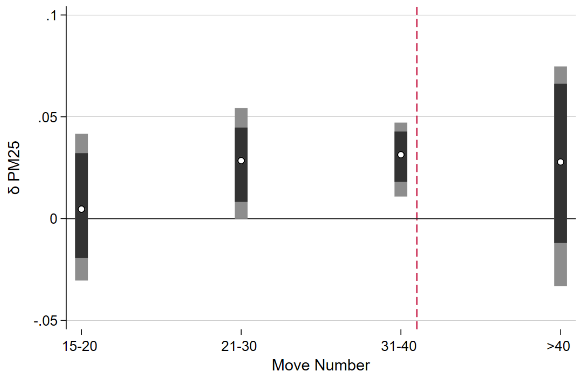
Note: */**/*** indicate statistical significance at the 10%/5%/1% levels. Standard errors are in parentheses and clustered at the day level (round × year). P-values are calculated using wild bootstrap (*boottest.ado*) and are reported in squared brackets.

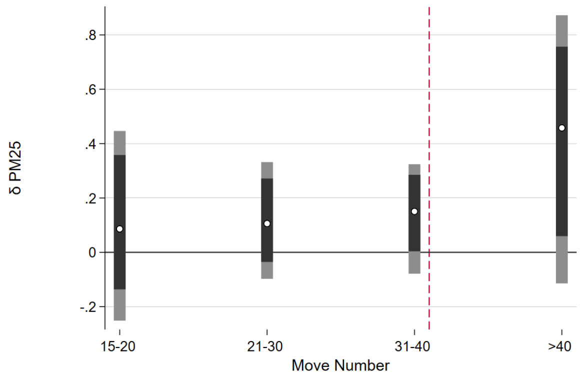
Figure A.8: Robustness: Using mean values of air quality during second and third hour of the tournament

Panel A: Meaningful error

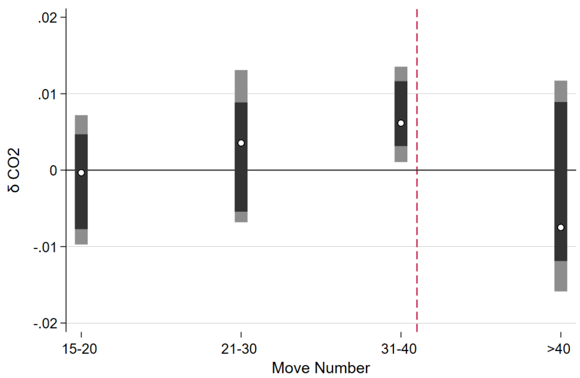
Panel B: Ln(error)

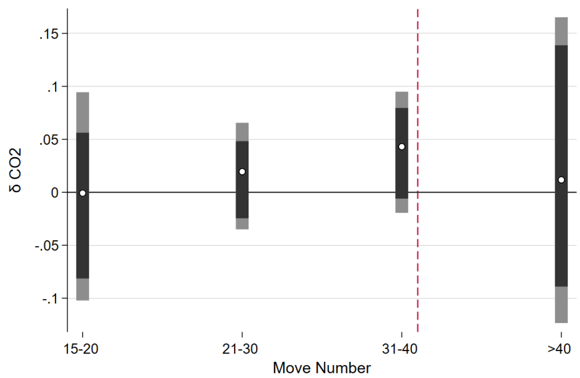
PM2.5 (in 10 µg/m3)





CO2 concentration (in 100 ppm)





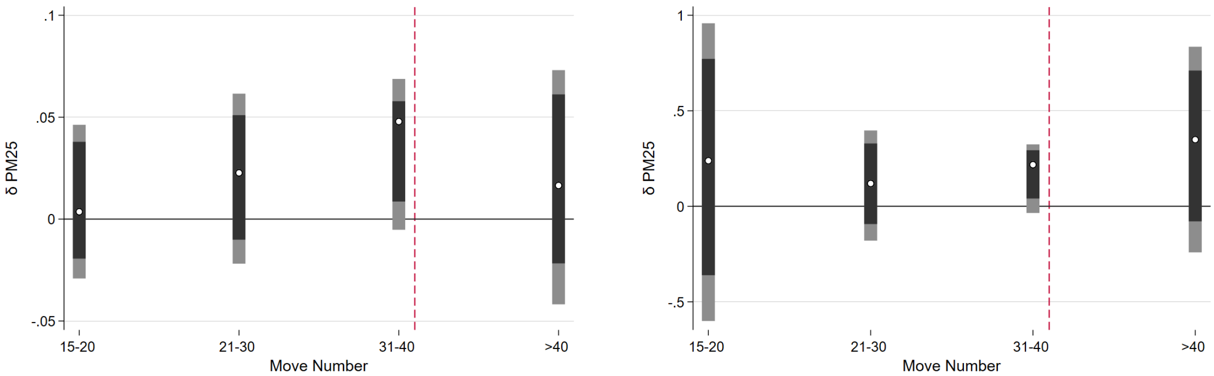
Note: The figure shows the estimated coefficients of joint regressions including PM2.5 and CO2. We divided the total sample of moves into subsamples with respect to the number of moves within a game (horizontal axis). The vertical, dashed red line indicates the occurrence of the time restriction during the game. Each panel presents the regression on different outcomes. The binary outcome variable "meaningful error" takes on the value one if the move is marked as a meaningful error by the chess engine and zero otherwise. 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 of the previous move by the opponent ($C^{opponent}_{jtrm-1}$).

Figure A.9: Robustness: Only games with > 40 moves per player

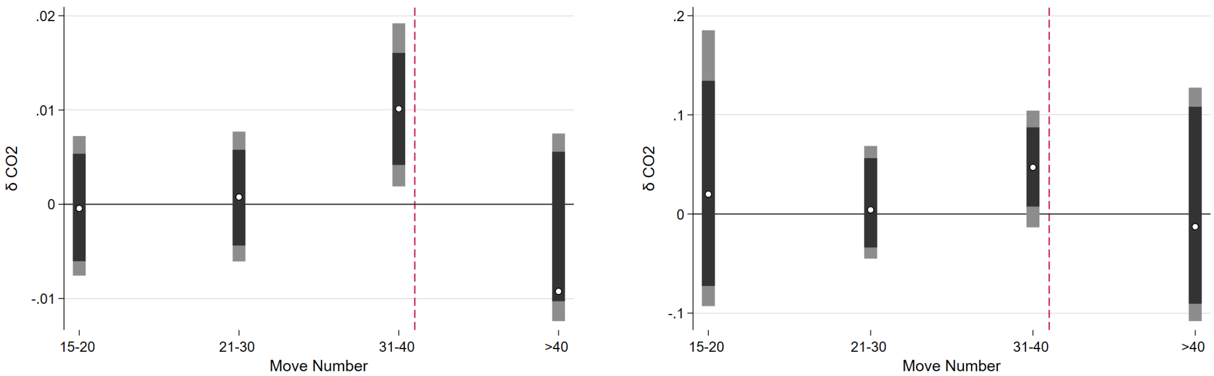
Panel A: Meaningful error

Panel B: Ln(error)

PM2.5 (in 10 µg/m3)



CO2 concentration (in 100 ppm)



Note: The figure shows the estimated coefficients of joint regressions including PM2.5 and CO2. We divided the total sample of moves into subsamples with respect to the number of moves within a game (horizontal axis). The vertical, dashed red line indicates the occurrence of the time restriction during the game. Each panel presents the regression on different outcomes. The binary outcome variable "meaningful error" takes on the value one if the move is marked as a meaningful error by the chess engine and zero otherwise. 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 of the previous move by the opponent ($C^{opponent}_{jtrm-1}$).