Discussion Paper Series

IZA DP No. 18656

May 2026

Air Pollution and Cognitive Performance Under Varying Task Complexity

Max Kikken
Maastricht University

Steffen Künn
Maastricht University, ROA
and IZA@LISER

IZA DP No. 18656 May 2026

Air Pollution and Cognitive Performance Under Varying Task Complexity

Abstract

This paper studies how short-term variations in fine particulate matter (PM2.5) pollution affect cognitive performance across tasks of varying complexity. While prior work shows that pollution impairs performance in highly demanding cognitive settings, it remains unclear whether these effects extend to simpler tasks. We examine this question using data from official Rubik's Cube tournaments in the United States and India. Solving different cube sizes provides a natural proxy for task complexity, while solving time measures cognitive performance. To identify causal effects, we exploit exogenous variation in local PM2.5 generated by wind direction. We find that PM2.5 pollution has negligible effects on simple tasks but significantly slows performance on complex ones for tournaments in the United States. In India, where baseline PM2.5 levels are substantially higher, we find similar effect patterns but none of the effects are statistically significant. We show that this pattern is explained by diminishing marginal sensitivity to short-term PM2.5 shocks as baseline PM2.5 pollution levels increase. Our findings provide causal evidence that the cognitive costs of PM2.5 pollution depend critically on task complexity.

JEL classification

D64, D91, Z13, P16

Keywords

cognitive performance, air pollution, task complexity

Corresponding author

Max Kikken
m.kikken@maastrichtuniversity.nl

1 Introduction

Industrialization and urbanization over recent decades have led to persistently high levels of fine particulate matter ($PM_{2.5}$) in many parts of the world (Rai, 2016). $PM_{2.5}$ consists of liquid droplets and solids with a diameter of less than 2.5 micrometers (EPA, 2022). In addition to natural events such as storms and wildfires, these particulates are particularly emitted by fossil fuel combustion. Because of their extremely small size, $PM_{2.5}$ particles can enter the bloodstream and even cross the blood-brain barrier. Once in the body, they damage the lungs and other organs and impair brain functioning through inflammatory reactions (Calderón-Garcidueñas et al., 2015).

Evidence from epidemiology and health sciences documents substantial adverse effects of $PM_{2.5}$ exposure on physical health (Feng et al., 2016; X. Lu et al., 2015), mood and mental health (Pignon et al., 2022; Yin et al., 2018), risk preferences (K. Liu et al., 2024) and cognitive functioning (Ke et al., 2022; Thiankhaw et al., 2022). In addition to these findings, economists have recently begun evaluating the impact of PM pollution on worker performance and labor supply. One strand of research shows that $PM_{2.5}$ exposure reduces physical activity and labor supply (Chang et al., 2016; He and Ji, 2021; Wu et al., 2023), while another strand documents the adverse effect of short-term $PM_{2.5}$ shocks on cognitive performance in high-stakes and cognitively demanding settings. For example, Archsmith et al. (2018) study baseball referees, Künn et al. (2019) analyze chess players, and Sarmiento (2022) focuses on judicial workers.[1]

However, the analyzed tasks in this literature are typically highly complex and cognitively demanding, leaving it unclear whether pollution-induced performance losses also arise in tasks with lower cognitive demands. Understanding this distinction is important, e.g., for assessing the labor market consequences of air pollution, since most workers perform tasks of moderate or low cognitive complexity rather than the highly cognitive demanding activities studied in existing work (e.g., baseball umpires, chess players, or judges). We address this question by examining player performance at *Rubik's Cube* tournaments and provide the first direct evidence on how short-term $PM_{2.5}$ pollution

---

[1] Research has also emphasized heterogeneity in vulnerability. For instance, elderly individuals and those with lower cognitive ability experience stronger adverse effects (Künn et al., 2019; Zhang et al., 2018). Protective factors can also matter: leisure-time physical activity has been shown to mitigate the cognitive effects of pollution exposure (J. Liu et al., 2023).

shocks affect cognitive performance along the task complexity margin.

The empirical analysis relies on data from official *Rubik's Cube* tournaments organized by the *World Cube Association.* The Rubik's Cube is a three-dimensional combination puzzle with six faces that must be rotated and aligned until each face displays a single color. The objective of a player is to solve the cube as quickly as possible. We use solving time as a proxy for cognitive performance, as it reflects a range of cognitive skills applied in a competitive setting (Jonassen, 2000; Meinz et al., 2023). We use cube size as a natural proxy for task complexity because cognitive demands increase sharply across cube types due to exponential growth in combinatorial complexity and the planning and working-memory requirements associated with the solving process (Gupta, 2021; Jonassen, 2000; Meinz et al., 2023). Physical demands, by contrast, are modest and broadly similar across cube types. This setting constitutes a quasi-experimental design, as the same player repeatedly performs the same task at varying levels of complexity and $PM_{2.5}$ pollution. At the same time, the *Rubik's Cube* tournament setting is specialized, as it isolates a form of cognition (high-speed visuo-spatial sequential problem-solving under time pressure) and the extent to which our findings generalize to real-world work environments is not immediate and is discussed in detail in the conclusion.

The estimation sample includes 196 official *Rubik's Cube* tournaments involving 2,734 participants and held at 94 locations in India and the United States of America (US) between 2018 and 2022. We focus on these two countries to evaluate the robustness of our results across environments with moderate (US) and very high (India) baseline levels of $PM_{2.5}$ pollution. We merge official tournament data with information on local weather and pollution levels based on the exact location and timing of each tournament round. To address endogeneity concerns, we implement an instrumental variable strategy exploiting variation in local wind direction to predict players' exposure to $PM_{2.5}$ pollution.

The results show that the effect of short-term $PM_{2.5}$ exposure on players' performance increases with cube size and hence with task complexity. For tournaments in the US, a 10 $\mu g/m^3$ increase in $PM_{2.5}$ increases standardized solving time by about 0.03 standard deviations, a magnitude similar in order to pollution effects documented in other high-frequency cognitive environments (Archsmith et al., 2018; Künn et al., 2019). Moreover, pollution-induced performance penalties rise sharply with task complexity. $PM_{2.5}$ exposure has negligible effects on simple tasks (2×2×2 and 3×3×3) but increasingly large and statistically significant effects on more complex cubes (4×4×4 and 5×5×5).

For tournaments in India, where baseline $PM_{2.5}$ levels are substantially higher, we find a similar effect pattern but no statistically significant effects of short-term $PM_{2.5}$ exposure. We show that this pattern is explained by diminishing marginal sensitivity to pollution as baseline $PM_{2.5}$ exposure increases, and is unlikely to reflect alternative mechanisms, such as behavioral adaptations or selection into tournaments. Together, these findings suggest that in settings where physical demands are limited, the cognitive costs of $PM_{2.5}$ pollution are most relevant when performance depends on higher-order cognitive processes.

The remainder of this paper is structured as follows: Section 2 provides a detailed description of Rubik's Cubes and the tournament setting in which the observations take place. Section 3 describes the data. Section 4 discusses the research design. The results are presented in Section 5. Section 6 concludes.

2 Setting: Rubik's Cube tournaments

This section describes the Rubik's Cube tournament environment and explains why it provides a suitable setting to study how $PM_{2.5}$ pollution affects cognitive performance across tasks of varying complexity.

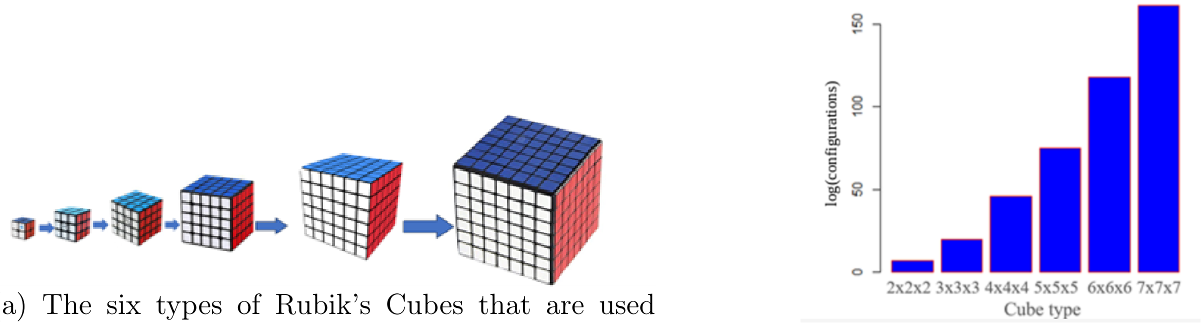
2.1 Rubik's Cube: the puzzle

Rubik's Cubes are cube-shaped three-dimensional puzzles that contain six colored faces arranged in $n \times n \times n$ layers. The objective is to rotate the layers until each face displays a uniform color. Official WCA competitions include six main cube types (2×2×2 through 7×7×7), each containing a different number of blocks (Figure 1a).[2] As cube size increases, the number of possible configurations grows exponentially, making it increasingly difficult to solve the puzzle. Figure 1b illustrates this gradient by showing that the logarithm of the number of possible configurations rises sharply with n.

---

[2] Rubik's Cubes also exist in other shapes, such as pyramids or dodecahedrons, although those types of puzzles are less often included in tournaments.

Figure 1: Rubik's cube types and combinatorial task complexity



(a) The six types of Rubik's Cubes that are used in official WCA tournaments: 2x2x2, 3x3x3, 4x4x4, 5x5x5, 6x6x6 and 7x7x7

(b) The log-number of possible configurations by cube type

Standardized algorithms allow players to solve the cube from any initial configuration. Solving the puzzle requires several cognitive abilities. During the inspection phase, players analyze the cube configuration and identify an efficient solving strategy, which relies on reasoning and fluid intelligence (Meinz et al., 2023). Once the inspection phase ends, participants must immediately begin solving their cube. The solving phase relies heavily on visual-spatial reasoning to anticipate the effects of successive rotations (Uttal et al., 2013), as well as working memory and processing speed to keep track of intermediate steps while selecting and executing the optimal next move (Meinz et al., 2023; S. Singh, Sandhu, et al., 2024).

Although all puzzles share the same basic objective and solving logic, their cognitive demands increase steeply with cube size due to the growing number of required reduction steps and algorithmic sequences. During tournaments, participants attempt to solve each cube as quickly as possible. Therefore, we use solving time as a proxy for cognitive performance, where shorter solving times reflect better performance.

2.2 Tournament setting

All Rubik's Cube tournaments in our study are organized by the *World Cube Association* (WCA). WCA competitions take place in more than 100 countries and follow standardized regulations governing the execution and documentation of the game, although certain organizational aspects are determined by local organizers. Each tournament is supervised by at least one WCA delegate who ensures that the event adheres to the WCA regulations.

Tournament-specific rules

Tournament organizers determine which cube types are included in each tournament. The order and timing of cube-type events vary across tournaments, and the number of rounds depends on the number of registered participants. Participants may compete in multiple cube types during the same tournament but must preregister for each cube type in advance. Last-minute registrations for tournaments or specific cube types are not allowed. In practice, registration typically closes about one week before the tournament.

During each round, participants will have one or more trials to solve a cube as quickly as possible. Participants competing in cube types 2x2x2, 3x3x3, 4x4x4 and 5x5x5 will have two trials in the cut-off rounds, and 5 trials in the final round, while participants playing cube types 6x6x6 and 7x7x7 will have one trial in the cut-off rounds and three trials in the final rounds. Only the fastest competitors advance to the final round.

Game-specific rules

At the start of each trial, the participants have 15 seconds to inspect the cube and plan their solving strategy. After the inspection period, the participant activates a timer and begins solving the cube. Each cube is randomly scrambled to ensure a unique configuration, preventing participants from simply repeating identical sequences of moves across trials. The solving time for each cube is recorded and judges are present to ensure that participants adhere to the official rules.

The WCA tournament environment provides several features that support a quasi-experimental research design: (i) The tournaments take place in a *controlled environment* governed by standardized rules. (ii) The preregistration for tournaments and cube types *mitigates selection bias* because participants select their events before the tournament and hence independently of local air pollution on the tournament day. (iii) *Participants are incentivized* to exert high effort due to intrinsic motivation such as ranking improvements as well as monetary and non-monetary rewards.[3] And finally, (iv) many players participate in multiple tournaments and compete in several cube types. This allows us to observe the same individuals repeatedly performing the same activity at different levels of task complexity and under varying levels of air pollution, creating a *natural experiment* for studying the relationship between $PM_{2.5}$ exposure and cognitive performance.

---

[3] The type of reward depends on the sponsor but is generally a monetary reward or medal/trophy.

3 Data

The empirical analysis relies on official WCA tournaments held in the US and India between November 2018 and December 2022.[4] Figure A1 in the appendix shows the exact tournament locations included in our sample, which are widely distributed across both countries. We focus on India and the US to compare the short-term effect of $\mathrm{PM}_{2.5}$ on cognitive performance across environments with high (India) and relatively low (US) baseline pollution levels. For instance, in 2019, 21 out of 30 of the most polluted cities in the world were in India (IQAir, 2019). We combine the administrative records from WCA tournaments with high-frequency environmental data drawn from government-operated monitoring networks in both countries. All data sources are merged using the exact timing and location of each tournament event.

3.1 Tournament data

The tournament data are retrieved from the website of the *World Cube Association* and contain participants identifiers, the exact tournament location, event timing, and performance outcomes for all official WCA tournaments held in India and the US between November 2018 and December 2022. The raw dataset comprises 195,904 observations at the round level, where each observation reports the average solving time across all trials for an individual who competed in a specific cube type in a specific round played at a specific tournament. Depending on the cube type and round, players have between 1 and 5 trials (see Section 2.2), with more than 98% of trials being valid (see Table A1 in the appendix).

We impose two sample restrictions: First, we remove tournaments without an available time schedule, as the schedule is required to determine the precise timing at which each player solved a specific cube type. We retrieve the time schedules using a data-scraping algorithm that collects all schedules from the WCA website for India and the US within the selected time frame. Second, we restrict the sample to individuals with experience in

---

[4] We focus on this period because, from November 2018 onward, all Rubik's Cube tournament data are reported in a uniform format including detailed time schedules with the date and hour of each event. Before November 2018, time schedules are often missing. No tournaments were held during the COVID-19 pandemic.

larger cube types, defined as having previously competed in cube type 5x5x5 or above at a WCA tournament. This restriction yields a more homogeneous sample of individuals who face meaningful variation in task complexity across cube types. After applying these restrictions, the final estimation sample includes 110,516 tournament-round observations with an observed date, time and location.

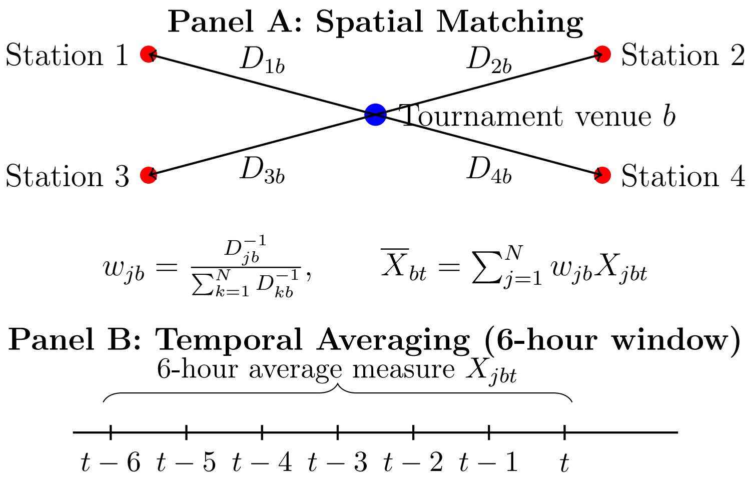
3.2 Environmental conditions

We obtain pollution and meteorological data from monitoring stations located near each tournament venue in the US and India. The data are retrieved from the *Indian Central Pollution Control Board* (CPCB), the *U.S. Environmental Protection Agency* (EPA), and the *National Oceanic and Atmospheric Administration* (NOAA). These data sets contain recordings of the local levels of $PM_{2.5}$, ozone, barometric pressure, wind direction, wind speed, relative humidity, total daily precipitation, and average daily outdoor temperature. All variables are measured at outdoor monitoring stations and are available at the hourly level, except total precipitation and outdoor temperature, which are measured at the day level.

To link the environmental data to the tournament data, we first construct 6-hour pre-event averages for each hourly variable. Specifically, for each tournament round we compute the mean of the six hourly readings preceding the start time of that round (Panel B in Figure 2). We use a 6-hour window for two reasons: First, penetration of outdoor $PM_{2.5}$ particles into indoor environments can take several hours (Krebs et al., 2021). Second, prior research suggests that the cognitive effects of $PM_{2.5}$ may occur with a short lag (Künn et al., 2019). Daily precipitation and daily outdoor temperature are assigned at the tournament-day level.

Second, we spatially match monitoring stations to tournament venues to get a precise estimate of the local conditions at the tournament hall. We distinguish between meteorological variables and air quality measurements. For meteorological variables, we include stations within a 50 km radius around each venue, while for air quality indicators we use a smaller 20 km radius to improve spatial precision of pollution exposure. We then compute inverse-distance weights that assign higher weight to stations closer to the tournament

Figure 2: Construction of environmental exposure measures



Notes: Panel A illustrates spatial matching between tournament venue b and nearby monitoring stations, using inverse-distance normalized weights $w_{jb} = \frac{D_{jb}^{-1}}{\sum_{k=1}^{N} D_{kb}^{-1}}$. Panel B shows the 6-hour averaging window used to construct the sensor-specific measures X_{jbt}.

venue:

$$w_{jb} = \frac{D_{jb}^{-1}}{\sum_{k=1}^{N} D_{kb}^{-1}}, \qquad j \in \{1, \ldots, N\},\ b \in \{1, \ldots, 94\} \tag{1}$$

The weighted average environmental condition at venue b and time t is calculated as:

$$\overline{X}_{bt} = \sum_{j=1}^{N} w_{jb} X_{jbt}. \tag{2}$$

where j indexes monitoring stations within a radius of 20 or 50 km around the tournament venue b. X_{jbt} denotes the 6-hour pre-event average of variable X measured at time t at monitor station j. D_{jb} is the distance between monitor station j and tournament venue b, and $\bar{X}_{bt}$ is the corresponding inverse-distance weighted average across included monitor stations. Panel A in Figure 2 visualizes this matching procedure.

The inverse-distance weighting, giving larger weights to closer stations, provides an approximation of the local outdoor environmental conditions at the tournament location (G. Y. Lu and Wong, 2008). Because the tournaments take place indoors, our approach assumes that outdoor $PM_{2.5}$ measurements are a reliable proxy for $PM_{2.5}$ exposure experienced by players indoors. This assumption is supported by evidence showing a high correlation between indoor and outdoor $PM_{2.5}$ concentrations (Krebs et al., 2021; Künn et al., 2019).

Finally, we restrict the distribution of $\text{PM}_{2.5}$ measurements in India to reduce the influence of extreme outliers. Figure A4 in the appendix shows the full distribution and it can be clearly seen that there are some extreme outliers at the top of the distribution. We exclude observations with $\text{PM}_{2.5}$ above 600 µg/m^3 (corresponding to 1.9% of the distribution), which likely reflect measurement noise or highly localized spikes.

3.3 Estimation sample

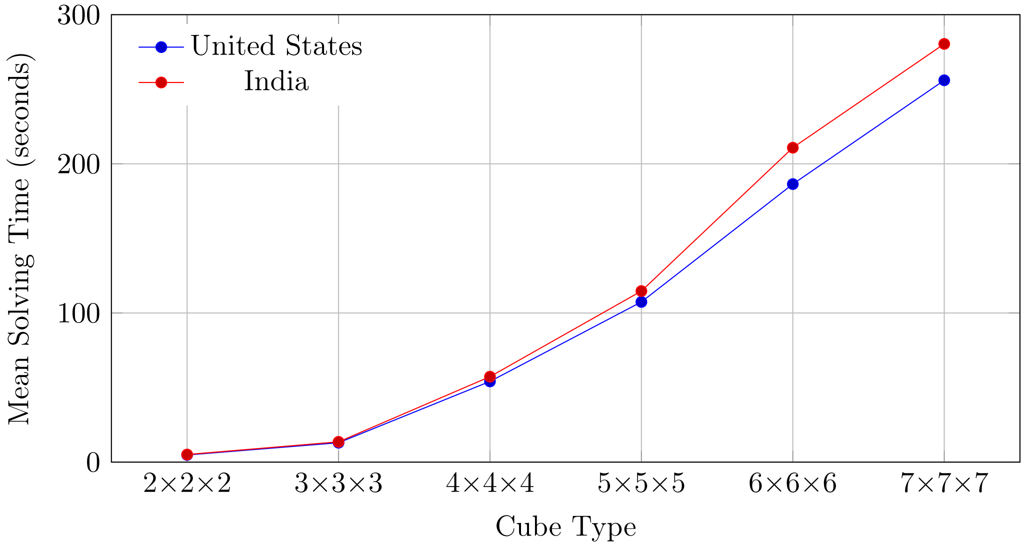
After merging tournament records with environmental data, the final estimation set contains 33,718 observations from 2,734 individuals across 196 tournaments. Each observation represents an individual-by-tournament-by-round-by-cube type tuple (i, c, r, s). Table A2 in the appendix compares the original and the estimation samples. The sample reduction induced by merging weather and pollution variables leads to minor positive selection. Participants in the estimation sample are slightly faster than those in the full tournament data, although the absolute differences in average solving times are small. This positive selection is due to more urban areas with more prestigious tournaments are kept due to higher weather station density.

Table 1 shows that in both the US and India the smallest cube types are played most frequently. Figure 3 displays mean solving times by cube type and shows that, consistent with the sharp rise in combinatorial complexity across cube sizes, average solving times increase steeply from 2×2×2 to 7×7×7. Participants take more than 50 times as long to solve a 7x7x7 cube compared to a 2x2x2 cube, highlighting the higher cognitive demands associated with larger cube types.

Outcome variable: Standardized solving time

We assess performance of players using the average time each individual needs to solve a Rubik's cube. The tournament data contain the average solving time $\overline{Y_{icrs}}$ across all trials for individual i in tournament c playing in round r and cube type s. Figure 4 shows the distribution of the average solving time $\overline{Y_{icrs}}$ which is skewed to the right because the smaller and hence easier cube types (e.g. 2x2x2 and 3x3x3) are overrepresented in tournaments (see Table 1). As Figures A2-A3 in the appendix show, the distributions

Figure 3: Mean solving times by cube type



Notes: Mean solving times are computed using the estimation sample.

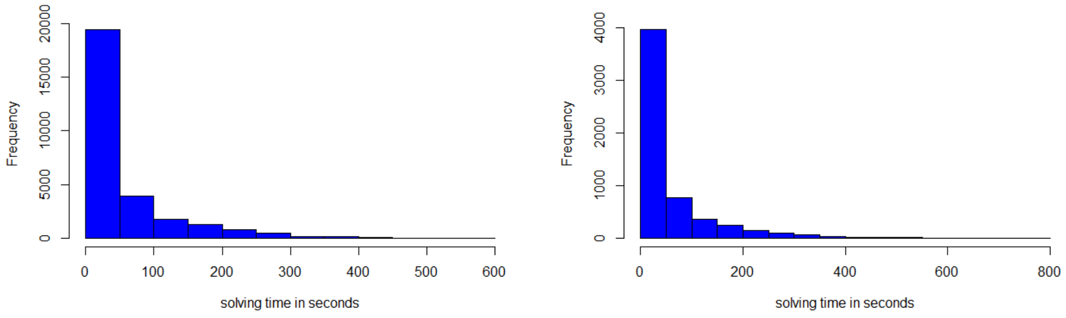
Table 1: Description of the treatment and outcome variables

	United States			India		
	N	Mean	SD	N	Mean	SD
Solving time in seconds, by cube type						
2x2x2	5,319	4.8	2.3	1,383	5.1	2.1
3x3x3	11,398	13.0	5.2	2,028	13.6	5.1
4x4x4	4,820	54.1	23.1	956	57.3	23.8
5x5x5	3,607	107.4	45.8	650	114.7	49.6
6x6x6	1,698	186.4	72.6	352	210.8	93
7x7x7	1,255	256.0	81.2	252	280.4	100.1
Total	28,097	51.9	73.3	5,621	54.9	82.6
$PM_{2.5}$ (in µg/m^3)	28,097	8.320	3.815	5,621	88.125	84.039

Notes: Numbers are based on the estimation sample.

of solving times within each cube type are closer to normal distributions. On average, players in India and the US require about 55 and 52 seconds to solve a cube, respectively.

Figure 4: Solving time by country (non-standardized)



(a) United States

(b) India

Note: This figure shows the full distribution of solving times in seconds in the US and India as observed in the estimation sample.

We standardize solving time to account for large differences in typical solving times across cube types. For example, a one-second increase represents a much larger performance loss for small cubes than for large cubes. Therefore, we standardize solving time $\overline{Y_{icrs}}$ by cube type using the cube type mean $(\overline{Y_s})$ and standard deviation σ_s:

$$Y_{icrs} = \frac{\overline{Y_{icrs}} - \overline{Y_s}}{\sigma_s}. \tag{3}$$

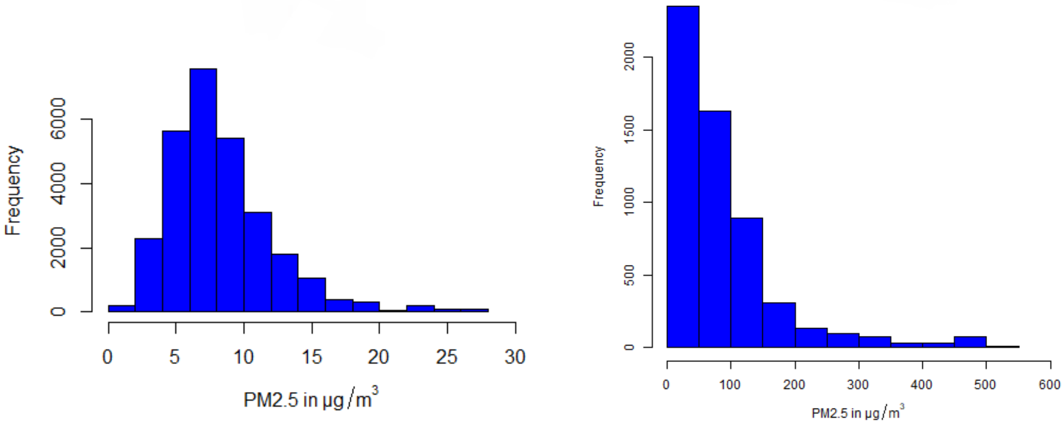
All standardization is performed separately for India and the United States. Cube-type means and standard deviations are computed within each country, ensuring that standardized units reflect country-specific variation in solving times rather than pooled cross-country differences. The resulting standardized variable Y_{icrs} is used to estimate the effect of $\text{PM}_{2.5}$ on solving performance.

Treatment variable: $\text{PM}_{2.5}$

We construct a continuous and a binary measure of short-term $\text{PM}_{2.5}$ exposure. The continuous measure is the average $\text{PM}_{2.5}$ concentration during the six hours prior to tournament round r of cube type s, measured at monitoring stations within a 20km radius around the tournament venue and aggregated using inverse-distance weights. Figure 5b shows a highly skewed distribution of $\text{PM}_{2.5}$ in India. About 70% of observations are below 100 µg/m^3, with a maximum of 542 µg/m^3. In the US, $\text{PM}_{2.5}$ levels are more normally distributed and do not exceed 27 µg/m^3 in our estimation sample. On average, $PM_{2.5}$ levels are about ten times higher during tournaments in India as compared to the US (see Table 1).

In addition, we define a binary indicator for high $PM_{2.5}$ exposure to capture performance effects on unusually polluted days. The indicator equals one if the $PM_{2.5}$ concentration falls in the upper quartile of the country-specific $PM_{2.5}$ distribution during the sample period, and zero otherwise.

Figure 5: $PM_{2.5}$ measurements by country



(a) US (b) India

Note: This figure shows the distribution of local $PM_{2.5}$ levels in µg/m^3 in India and the U.S. within the estimation sample.

4 Empirical Strategy

Our objective is to estimate the causal effect of short-term $PM_{2.5}$ shocks on cognitive performance across tasks of varying complexity. The Rubik's Cube tournament setting allows us to observe the same players solving different cube types at different locations and times, and therefore under varying levels of $PM_{2.5}$ pollution.

4.1 Baseline specification

We begin with the following baseline fixed-effects specification:

$$Y_{icrs} = \alpha + \gamma f(PM2.5_{crs}) + \theta E_{crs} + \beta X_{ic} + \lambda_i + \rho_s + \theta_t + \epsilon_{icrs}, \tag{4}$$

where Y_{icrs} denotes the standardized solving time of individual i in tournament c, round r, and cube type s. The term $f(PM2.5_{crs})$ is the treatment variable measuring the average $\mathrm{PM}_{2.5}$ concentration over the six hours preceding round r at tournament c of cube type s. The vector E_{crs} contains environmental controls, including ozone, barometric pressure, wind direction, relative humidity, wind speed, daily precipitation, and daily outdoor temperature. The vector X_{ic} captures player experiences and includes the total number of previous tournament participations. Finally, λ_i, ρ_s and θ_t denote individual, cube type and time (hour-of-day, weekday, and year) fixed effects, respectively.

The coefficient of interest is γ, which captures the short-term effect of $\mathrm{PM}_{2.5}$ exposure on solving performance. When using the continuous $\mathrm{PM}_{2.5}$ measure, γ represents the change in standardized solving time associated with a 10 µg/m^3 increase in $\mathrm{PM}_{2.5}$. For the binary $\mathrm{PM}_{2.5}$ measure, γ captures the standard deviation change in solving time when a tournament round is played under unusually high $\mathrm{PM}_{2.5}$ levels.

Identification in Equation (4) comes from within-player variation across tournaments and cube types. In other words, we compare the performance of the same player solving cubes of different complexity under different pollution conditions. As discussed in Section 2.2, the tournament environment provides a quasi-experimental setting because competitions take place under standardized rules, participants preregister for events before tournament-day pollution is realized, and competitors have strong incentives to exert effort.

Despite this setup and Equation (4) controlling for a rich set of observable and unobservable factors, two important challenges remain. First, ambient $\mathrm{PM}_{2.5}$ may still be correlated with unobserved local conditions that affect performance. For instance, local traffic may raise $\mathrm{PM}_{2.5}$ levels while also create additional stress for the players when traveling to the tournament venue, which could independently impair cognitive performance

(Heissel et al., 2021; McEwen and Sapolsky, 1995). Second, measurement error in ambient $\mathrm{PM}_{2.5}$ as a proxy for effective exposure may attenuate fixed-effects estimates. We address both concerns using an instrumental-variable strategy.

4.2 Instrumental variable strategy

Following Deryugina et al. (2019), we use exogenous variation in wind direction as an instrument for short-term variations in local $\mathrm{PM}_{2.5}$ levels. Wind direction affects local pollution concentrations because it determines which emission sources are upwind of a given tournament venue at a given point in time. For instance, if a tournament venue is located west of an industrial zone or major road, $\mathrm{PM}_{2.5}$ concentrations at that venue will be higher when the wind blows from the east than when it blows in the opposite direction. Because short-term variation in wind direction is plausibly exogenous to tournament conditions and player behavior, it provides a source of random variation in pollution exposure (Deryugina et al., 2019).

Therefore, our identification strategy assumes that, conditional on fixed effects and environmental controls, variation in wind direction affects solving time only through its effect on local $\mathrm{PM}_{2.5}$ pollution. In particular, controlling for outdoor temperature, humidity, precipitation, barometric pressure, and wind speed helps absorb correlations between wind direction and other environmental factors that may directly influence indoor comfort and performance.

Under this assumption, we estimate the causal effect of $\mathrm{PM}_{2.5}$ on solving time using the following two-stage least squares (2SLS) specification:

$$f(PM2.5_{crs}) = \alpha + \delta(Winddir_{crs} * city_j) + \theta E_{crs} + \beta X_{ic} + \lambda_i + \rho_s + \theta_t + \epsilon_{icrs} \tag{5}$$

$$Y_{icrs} = \alpha + \gamma f(P\hat{M}2.5_{crs}) + \theta E_{crs} + \beta X_{ic} + \lambda_i + \rho_s + \theta_t + \epsilon_{icrs}, \tag{6}$$

where $Winddir_{crs} \times city_j$ denotes the interaction between prevailing wind direction and the city j where tournament c takes place, measured at the time when tournament round r of cube type s is played. This interaction is the IV and allows the effect of wind direction on $\mathrm{PM}_{2.5}$ to vary across local geographies. $\widehat{PM}2.5_{crs}$ denotes the predicted $\mathrm{PM}_{2.5}$

concentration from the first-stage regression in Equation (5). We estimate Equations (5) and (6) separately by country and by $PM_{2.5}$ measure. To assess whether pollution effects increase with task complexity, we also estimate the 2SLS model separately by cube type.

As a validity check, we conduct a falsification test in which we replace $f(PM2.5_{crs})$ ($PM_{2.5}$ concentration during the six hours preceding the tournament round) with the corresponding 6-hour lead mean. Table A4 in the appendix shows that the coefficients on future pollution are close to zero in both countries. Since future pollution cannot affect current performance, this provides strong support for the identification strategy.

Finally, because we observe ambient $PM_{2.5}$ rather than personal exposure, the IV coefficient should be interpreted as the causal effect of wind-driven variation in local pollution concentrations on solving performance. Therefore, it captures the cognitive impact of marginal, short-term changes in $PM_{2.5}$ induced by atmospheric transport, rather than longer-term policy changes or seasonal variation in air quality. As such, our estimates are best interpreted as local average treatment effects of transient, wind-driven pollution shocks.

5 Results

This section presents three sets of findings. We begin with pooled fixed-effects (FE) and instrumental-variables (IV) estimates for the United States and India. We then examine heterogeneity by task complexity and finally investigate nonlinearities in the concentration-response relationship to explain the weaker results for India. Across all analyses, a consistent pattern emerges: short-term $PM_{2.5}$ exposure impairs players' performance, and these effects increase sharply with task complexity.

5.1 Pooled estimation

Table 2 presents estimates of the coefficient γ, capturing the effect of $PM_{2.5}$ exposure on players' solving times using the baseline fixed effects model (Panel A) and instrumental variable model (Panel B), as specified in Equation (4) and (6), respectively. The IV strategy exploits local wind direction as an instrument for $PM_{2.5}$. First-stage F-statistics are high in both countries, indicating strong instrumental relevance.

Table 2: Effects of PM$_{2.5}$ on players' performance - FE and IV model

	US	India
Panel A: Fixed-effects model		
Continuous PM$_{2.5}$ (in 10 µg/m^3)	0.0291***	−0.0000
	(0.0124)	(0.0012)
Adjusted R^2	0.80	0.75
High PM$_{2.5}$ (binary variable)	0.0163	0.0055
	(0.0101)	(0.0219)
Adjusted R^2	0.80	0.75
Panel B: IV model		
Continuous PM$_{2.5}$ (in 10 µg/m^3)	0.0316*	-0.0035
	(0.0192)	(0.0035)
F-test 1st stage	165.07	35.67
Adjusted R^2	0.80	0.75
High PM$_{2.5}$ (binary variable)	0.0202	-0.0641
	(0.0197)	(0.0672)
F-test 1st stage	101.33	24.35
Adjusted R^2	0.80	0.75
Control variables	Yes	Yes
Cube type FE	Yes	Yes
Individual FE	Yes	Yes
Hour of day FE	Yes	Yes
Weekday FE	Yes	Yes
Year FE	Yes	Yes
Observations	28,097	5,621

Notes: The table shows estimates of the coefficient γ, capturing the effect of PM$_{2.5}$ exposure on players' solving times using the baseline fixed effects model (Panel A) and instrumental variable model (Panel B), as specified in Equation (4) and (6), respectively. Standardized solving time is the dependent variable. Control variables include: (i) environmental variables (local 6-hour averages of ozone, barometric pressure, wind direction, relative humidity, wind speed, daily precipitation, and temperature); (ii) experience (number of tournaments participated in). Standard errors are clustered at the tournament–round–cube level and are reported in parentheses. */**/*** indicate statistical significance at the 10%, 5%, and 1% levels.

Focusing on the US results in column 1, the estimated coefficients show that pollution impairs overall performance of players. Using the FE model (Panel A) and focusing on the continuous $PM_{2.5}$ measure, a 10 $\mu g/m^3$ increase in $PM_{2.5}$ is associated with a 0.029 standard deviation (SD) increase in solving time. Relative to the mean solving time in the US sample (see Table 1), this corresponds to an increase of about 4%. The estimate is statistically significant at the 1% level. The corresponding IV estimate is very similar at 0.032 SD (Panel B). The similarity between the FE and IV estimates suggests that omitted variable bias and measurement error are unlikely to be the main drivers of the observed relationship.

In India, where baseline $PM_{2.5}$ concentrations are substantially higher, pooled estimates in column 2 are close to zero and are not statistically significant at conventional levels. As shown below in Section 5.3, this muted pattern is explained by a concave concentration-response relationship, whereby the marginal effects of short-term $PM_{2.5}$ exposure decline as baseline pollution levels increase.

Alternative explanations, such as behavioral adaptations or differences in the selection of players into tournaments, are unlikely to explain the zero effects for India. First, higher baseline $PM_{2.5}$ pollution in India could induce behavioral responses, such as improved protection of indoor environments against outdoor pollution. However, K. Singh et al. (2025) document higher indoor-outdoor infiltration rates in India (0.54-0.73) than in the US (0.42-0.61; Krebs et al., 2021), suggesting that indoor exposure remains closely linked to outdoor pollution. This suggests that reduced indoor exposure is unlikely to be the main explanation for the zero effects in India.

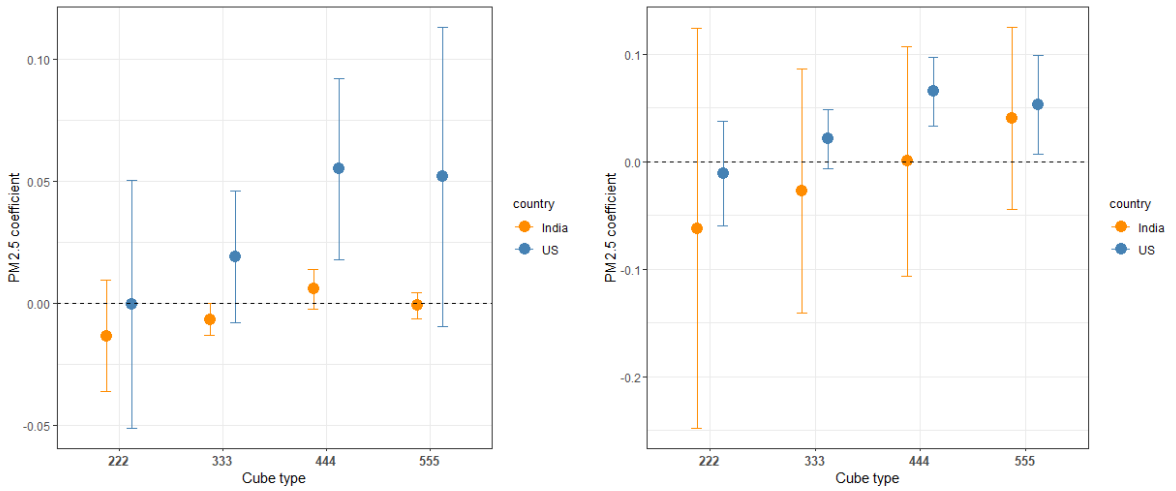
Second, differences in player characteristics are also unlikely to explain the results. Table A5 in the appendix shows that players in India are, on average, slightly less experienced than those in the US. Table A7 shows that the effect of $PM_{2.5}$ on players' performance decreases with experience in our estimation sample. This is consistent with existing evidence showing that individuals with lower skill levels are more affected by pollution exposure (e.g., Künn et al., 2019). Therefore, if anything, one would expect larger effects in India given the slightly less experienced player population, which is contrary to our findings.

5.2 Effect heterogeneity with respect to task complexity

In a next step, we examine whether the effect of $PM_{2.5}$ exposure varies systematically with task complexity. We use cube size as a proxy for task complexity because, as discussed above, larger cubes require substantially greater cognitive processing while the underlying task of solving the Rubik's Cube as quickly as possible remains the same. Therefore, we estimate the parameter of interest γ separately for each cube type (2x2x2, 3x3x3, 4x4x4 and 5x5x5). We do not estimate the separate effect for the largest cube types (6x6x6, 7x7x7) because those categories contain too few observations (see Table 1).

Figure 6 plots the estimated coefficients γ by cube type using the IV model in Equation (6), while Table A3 in the appendix reports the numerical results.

Figure 6: Effect of $PM_{2.5}$ on solving times per cube type



Panel A
$PM_{2.5}$ (in 10 µg/m^3)

Panel B
High $PM_{2.5}$ (dummy variable)

Note: The figure shows the regression estimates of γ based on the IV model as shown in Equation (6) for each cube type separately. Each dot represents the point estimate resulting from a separate regression. The solid lines show the 90% confidence intervals based on clustered standard errors at the tournament-round type level. Panel A (B) show results using the continuous (binary) $PM_{2.5}$ measure. Table A3 in the appendix shows the full estimation results.

Figure 6 shows a clear monotonic pattern in both countries. The effect of $PM_{2.5}$ exposure increases with cube size and hence with task complexity. For the smallest cube type (2×2×2), $PM_{2.5}$ has no measurable effect in either country. The estimated coefficient for the 3×3×3 cube remains close to zero. For the 4×4×4 and 5×5×5 cube types, however, the effects become larger and partially statistically significant in the US.

Using the continuous $PM_{2.5}$ measure, a 10 µg/m^3 increase in $PM_{2.5}$ raises solving time in the US by about 0.05 SD for the 4×4×4 cube, corresponding to roughly 1.2 seconds or about 2.1% of the mean solving time for that event (see Table 1). The effect for the 5x5x5 cube is of similar size but loses statistical significance, most likely due to the smaller sample size. In India, the continuous estimates are smaller and overall statistically insignificant in the baseline specification, suggesting no measurable short-term cognitive effects at prevailing high ambient $PM_{2.5}$ concentrations.

The specification using the high $PM_{2.5}$ exposure dummy reinforces this pattern. In the U.S., exposure to $PM_{2.5}$ levels in the upper quartile of the national distribution increases solving time by about 0.06 SD for the 4×4×4 cube and 0.04 SD for the 5×5×5 cube; both estimates are statistically significant. In line with the results of the continuous measure for India, the coefficients are smaller in magnitude and statistically insignificant.

5.3 Nonlinearities in the concentration–response relationship

While we find a clear and significant effect pattern for tournaments taking place in the US, the results for India are overall insignificant. One explanation might be the drastic difference in ambient $PM_{2.5}$ levels in both countries. In our sample, the mean tournament-time $PM_{2.5}$ concentration in India is 88.1 $\mu g/m^3$, more than ten times the corresponding level in the US. At such high baseline concentrations, marginal sensitivity to short-term variation in $PM_{2.5}$ may be lower, consistent with prior evidence of concave pollution–performance relationships (Li et al., 2019; Vodonos et al., 2018).

To formally test the hypothesis that diminishing marginal sensitivity to $PM_{2.5}$ pollution explains the muted effects in India, we augment the baseline specification by interacting short-term $PM_{2.5}$ exposure with a city-specific measure of baseline $PM_{2.5}$ pollution. We first compute the mean $PM_{2.5}$ concentration across all observations in city j:

$$AvgPM_j = \frac{1}{N_j}\sum_{t=1}^{N_j} PM2.5_{jt}, \qquad t \in \{1,\dots,N_j\},\ j \in \{1,\dots,J\}. \tag{7}$$

We then define city-specific baseline $PM_{2.5}$ as:

$$BaselinePM_j = AvgPM_j - \frac{1}{J}\sum_{k=1}^{J} AvgPM_k. \tag{8}$$

The variable $BaselinePM_j$ measures a city's average $PM_{2.5}$ concentration relative to the sample-wide city mean and therefore captures persistent differences in long-run pollution exposure across locations. The distribution of $BaselinePM_j$ is shown in Figure A5 in the appendix.

We estimate this interaction using both fixed-effects and instrumental-variables versions of our baseline models. Across specifications, the interaction term is negative and statistically significant, indicating that the marginal effect of short-term pollution exposure declines with higher baseline pollution (see Appendix Table A6). The interaction coefficient implies that each additional 10 μg/m^3 in a city's average PM$_{2.5}$ level reduces the marginal effect of a 10 μg/m^3 short-term pollution shock by about 0.001 standard deviations. These results provide direct evidence of a concave dose-response relationship between air pollution and cognitive performance and help reconcile the larger marginal effects observed in the US as compared to India.

6 Conclusion

This study provides novel evidence that the short-term effect of PM$_{2.5}$ exposure on cognitive performance depends critically on task complexity. Using data from official Rubik's Cube tournaments in the United States and India, we show that exposure to fine particulate matter pollution has little to no effect on performance for smaller cube types but significantly affects players' performance when playing more complex cubes. For instance, during tournaments in the US, a 10 µg/m^3 increase in PM$_{2.5}$ raises solving times by roughly 0.05 of a standard deviation for 4x4x4 cubes while there is no effect of PM$_{2.5}$ on solving time for the smaller cube type 2x2x2. In India, the estimated effects are smaller and not statistically significant. We provide evidence suggesting that the smaller and less robust effect pattern for India is explained by fundamentally higher baseline pollution levels. In our sample, average PM$_{2.5}$ levels in India are more than ten times higher as in the US, reducing marginal sensitivity to short-term variations in PM$_{2.5}$ exposure. Alternative mechanisms, such as behavioral adaptations or selection into tournaments, are unlikely to explain the zero effects for India.

Although solving Rubik's Cubes is a specialized activity, several features of the setting make our findings informative for broader labor-market environments. Solving a cube requires multi-step planning, working-memory updating, error monitoring, and sustained attention, which are cognitive processes that are also central to many knowledge-intensive occupations. Rather than claiming broad generalizability, our results help interpret existing evidence from high-skill cognitive settings, such as chess competitions, academic testing, and professional decision-making, by showing that pollution-related performance losses emerge primarily when tasks place greater demands on executive function. Moreover, the indoor competitive setting resembles many office environments in which individuals spend most of their working time.

At the same time, several limitations should temper direct extrapolation. Competitive players are highly trained and perform in environments with minimal distractions, while real-world workers face interruptions, multitasking requirements, and heterogeneous incentives. Moreover, solving a Rubik's Cube reflects high-speed visuo-spatial sequential problem-solving under algorithmic constraints, a form of expert performance under time pressure. This makes the setting particularly informative for cognitively intensive activities such as programming or surgical tasks, where performance relies on rapid planning, working memory, and precise execution.

Taken together, these findings contribute to the literature linking fine particulate matter pollution to productivity by demonstrating that cognitive impacts depend critically on the complexity of the task being performed: they are most likely concentrated in cognitively intensive tasks and attenuated in simpler or more routine tasks.

References

Archsmith, J., Heyes, A., & Saberian, S. (2018). Air quality and error quantity: Pollution and performance in a high-skilled, quality-focused occupation. *Journal of the Association of Environmental and Resource Economists*, *5*(4), 827–863.

Calderón-Garcidueñas, L., Calderón-Garcidueñas, A., Torres-Jardón, R., Avila-Ramírez, J., Kulesza, R. J., & Angiulli, A. D. (2015). Air pollution and your brain: What do you need to know right now. *Primary health care research & development*, *16*(4), 329–345.

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

Deryugina, T., Heutel, G., Miller, N. H., Molitor, D., & Reif, J. (2019). The mortality and medical costs of air pollution: Evidence from changes in wind direction. *American Economic Review*, *109*(12), 4178–4219.

EPA. (2022). *Particulate matter (pm) basics*. Retrieved July 18, 2022, from https://www.epa.gov/pm-pollution/particulate-matter-pm-basics

Feng, S., Gao, D., Liao, F., Zhou, F., & Wang, X. (2016). The health effects of ambient pm2. 5 and potential mechanisms. *Ecotoxicology and environmental safety*, *128*, 67–74.

Gupta, P. (2021). Introduction to minimal thinking technique using an extremely fast implementation of a rubik's cube solver.

He, Q., & Ji, X. (2021). The labor productivity consequences of exposure to particulate matters: Evidence from a chinese national panel survey. *International journal of environmental research and public health*, *18*(23), 12859.

Heissel, J. A., Adam, E. K., Doleac, J. L., Figlio, D. N., & Meer, J. (2021). Testing, stress, and performance: How students respond physiologically to high-stakes testing.

IQAir. (2019). World air quality report 2019: Region and city pm2.5 ranking.

Jonassen, D. H. (2000). Toward a design theory of problem solving. *Educational technology research and development*, *48*(4), 63–85.

Ke, L., Zhang, Y., Fu, Y., Shen, X., Zhang, Y., Ma, X., & Di, Q. (2022). Short-term pm2. 5 exposure and cognitive function: Association and neurophysiological mechanisms. *Environment International*, *170*, 107593.

Krebs, B., Burney, J., Zivin, J. G., & Neidell, M. (2021). Using crowd-sourced data to assess the temporal and spatial relationship between indoor and outdoor particulate matter. *Environmental science & technology*, *55*(9), 6107–6115.

Künn, S., Palacios, J., & Pestel, N. (2019). *Indoor air quality and cognitive performance* (IZA Discussion Paper No. 12632). Institute of Labor Economics (IZA). Bonn. https://doi.org/10.2139/ssrn.3460848

Li, T., Guo, Y., Liu, Y., Wang, J., Wang, Q., Sun, Z., He, M. Z., & Shi, X. (2019). Estimating mortality burden attributable to short-term pm2. 5 exposure: A national observational study in china. *Environment international*, *125*, 245–251.

Liu, J., Liu, R., Zhang, Y., Lao, X., Mandeville, K. L., Ma, X., & Di, Q. (2023). Leisure-time physical activity mitigated the cognitive effect of pm2. 5 and pm2. 5 components exposure: Evidence from a nationwide longitudinal study. *Environment international*, *179*, 108143.

Liu, K., Meng, C., Yang, S., & Zhang, G. (2024). Air pollution and individual risk preference: Evidence from china. *Energy Economics*, *136*, 107738.

Lu, G. Y., & Wong, D. W. (2008). An adaptive inverse-distance weighting spatial interpolation technique. *Computers & geosciences*, *34*(9), 1044–1055.

Lu, X., et al. (2015). Systematic review of the health impacts of outdoor air pollution. *Journal of Environmental Health*, *77*(10), 8–14.

McEwen, B. S., & Sapolsky, R. M. (1995). Stress and cognitive function. *Current opinion in neurobiology*, *5*(2), 205–216.

Meinz, E. J., Hambrick, D. Z., Leach, J. J., & Boschulte, P. J. (2023). Ability and non-ability predictors of real-world skill acquisition: The case of rubik's cube solving. *Journal of Intelligence*, *11*(1), 18.

Pignon, B., Borel, C., Lajnef, M., Richard, J.-R., Szöke, A., Hemery, F., Leboyer, M., Foret, G., & Schürhoff, F. (2022). Pm2. 5 and pm10 air pollution peaks are associated with emergency department visits for psychotic and mood disorders. *Environmental Science and Pollution Research*, *29*(59), 88577–88586.

Rai, P. K. (2016). Impacts of particulate matter pollution on plants: Implications for environmental biomonitoring. *Ecotoxicology and environmental safety*, *129*, 120–136.

Sarmiento, L. (2022). Air pollution and the productivity of high-skill labor: evidence from court hearings. *Scandinavian Journal of Economics*, *124*(1), 301–332.

Singh, K., Baghel, N., Kumari, K. M., & Satsangi, A. (2025). The infiltration, morphology and sources of indoor and outdoor fine particulate matter and metals at the urban residences of agra, india. *Indoor and Built Environment*, *34*(4), 751–775.

Singh, S., Sandhu, K., et al. (2024). Effect of cognitive training on processing speed of school going children: An intervention study with 3x3 rubik cube. *International Journal of Indian Psychology*, *12*(3).

Thiankhaw, K., Chattipakorn, N., & Chattipakorn, S. C. (2022). Pm2. 5 exposure in association with ad-related neuropathology and cognitive outcomes. *Environmental Pollution*, *292*, 118320.

Uttal, D. H., Meadow, N. G., Tipton, E., Hand, L. L., Alden, A. R., Warren, C., & Newcombe, N. S. (2013). The malleability of spatial skills: A meta-analysis of training studies. *Psychological bulletin*, *139*(2), 352.

Vodonos, A., Awad, Y. A., & Schwartz, J. (2018). The concentration-response between long-term pm2. 5 exposure and mortality; a meta-regression approach. *Environmental research*, *166*, 677–689.

Wu, B., Yan, T., & Elahi, E. (2023). The impact of environmental pollution on labor supply: Empirical evidence from china. *Environmental Science and Pollution Research*, *30*(10), 25764–25772.

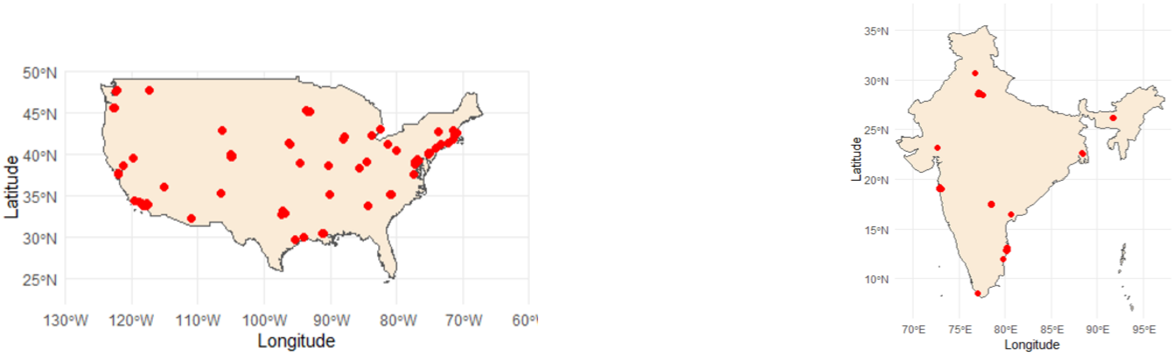
Yin, H., Pizzol, M., Jacobsen, J. B., & Xu, L. (2018). Contingent valuation of health and mood impacts of pm2. 5 in beijing, china. *Science of the Total Environment*, *630*, 1269–1282.

Zhang, X., Chen, X., & Zhang, X. (2018). The impact of exposure to air pollution on cognitive performance. *Proceedings of the National Academy of Sciences*, *115*(37), 9193–9197.

Appendix

Additional Figures

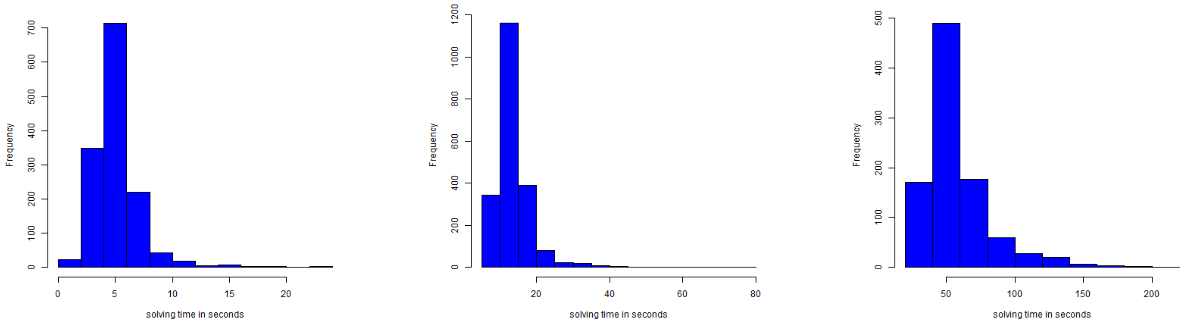
Figure A1: WCA tournaments included in the estimation sample



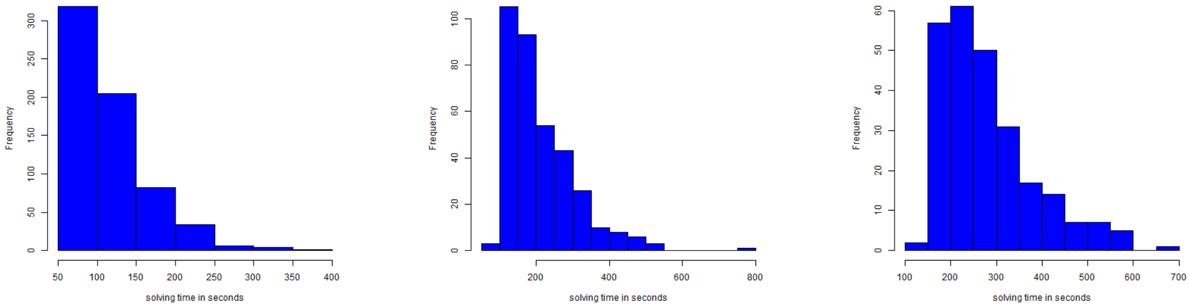
(a) United States (b) India

Notes: The maps illustrate the geographic distribution of competition venues in the United States and India, with each red point marking the location of a WCA tournament in the estimation sample.

Figure A2: Distribution of solving times by cube type: India



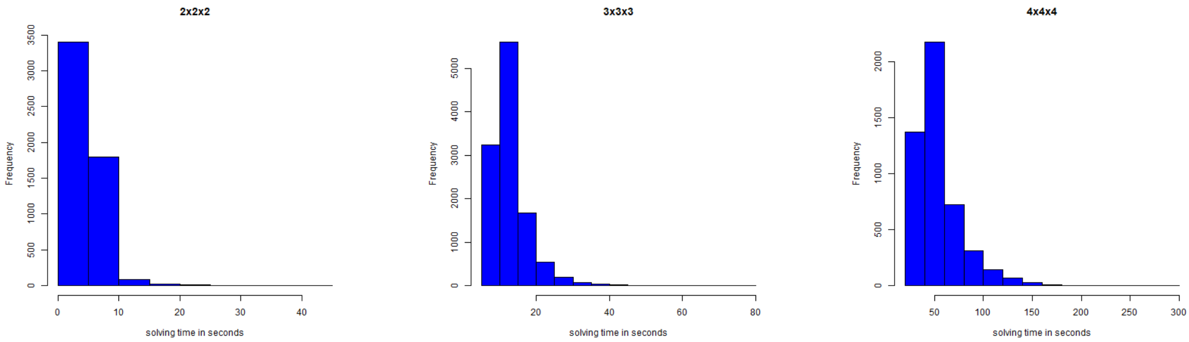
(a) 2×2×2 (b) 3×3×3 (c) 4×4×4



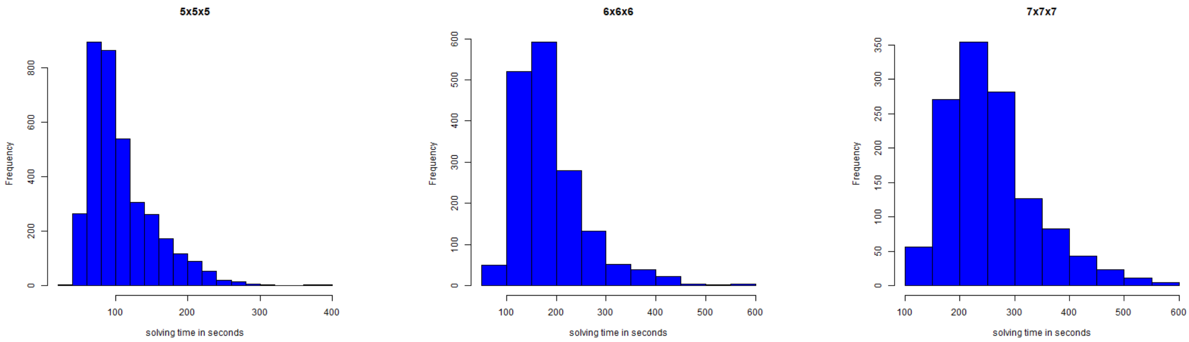
(d) 5×5×5 (e) 6×6×6 (f) 7×7×7

Notes: Each panel shows the distribution of average solving times (in seconds) for a given cube type in India based on the estimation sample.

Figure A3: Distribution of solving times by cube type: United States



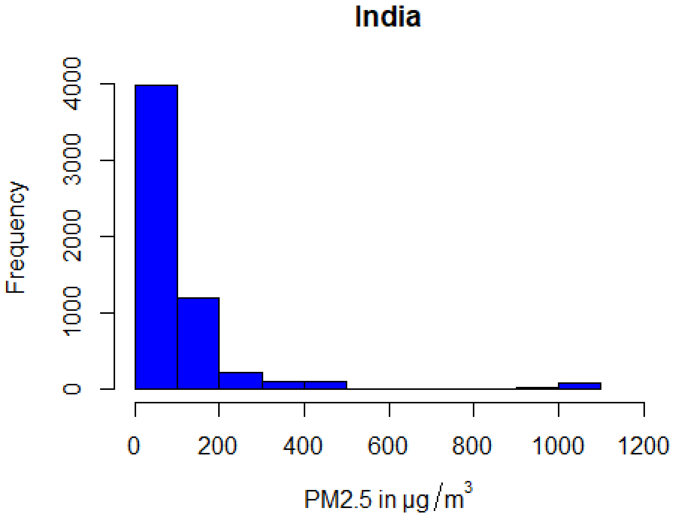
(a) 2×2×2 (b) 3×3×3 (c) 4×4×4



(d) 5×5×5 (e) 6×6×6 (f) 7×7×7

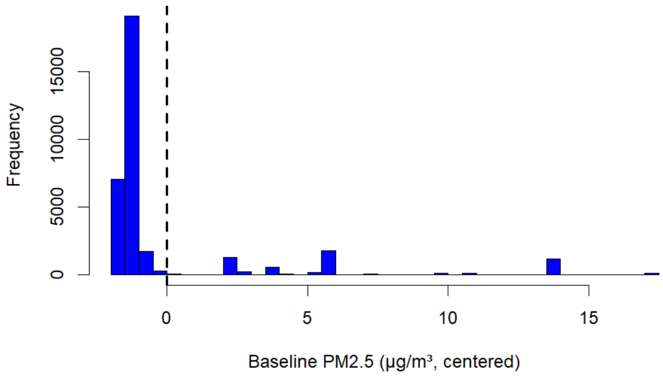
Notes: Each panel shows the distribution of average solving times (in seconds) for a given cube type in the United States based on the estimation sample.

Figure A4: $PM_{2.5}$ distribution in India (full sample)



Notes: The figure displays the full distribution of observed $PM_{2.5}$ levels (μg/m^3) in India. Extreme values above 600 μg/m^3 are included to show the full range of exposure.

Figure A5: Baseline PM2.5 distribution



Notes: The figure displays the distribution of $BaselinePM_j$ which is the mean $\text{PM}_{2.5}$ concentration across all observations in a given city j relative to all other cities in our sample as defined in Equation (8).

Additional Tables

Table A1: Share of failed and non-started attempts by trial

	United States		India	
Trial	DNF	DNS	DNF	DNS
1	0.0147	0.0000	0.0155	0.0000
2	0.0173	0.0002	0.0150	0.0002
3	0.0148	0.0009	0.0168	0.0006
4	0.0152	0.0003	0.0167	0.0002
5	0.0200	0.0008	0.0183	0.0006

Notes: The table reports the share of failed attempts (DNF) and non-started attempts (DNS) by trial for the United States and India. DNF corresponds to unsuccessful completion of a trial, while DNS indicates that a participant did not start the trial.

Table A2: Descriptive statistics: original and estimation samples

	Original sample	**Estimation sample**	**Original sample**	**Estimation sample**
	US	US	India	India
Panel A: Participant characteristics				
Solving times by cube type (seconds)				
2×2×2	4.9 (18%)	4.8 (19%)	5.2 (25%)	5.1 (25%)
3×3×3	13.3 (42%)	13.0 (41%)	14.0 (38%)	13.6 (36%)
4×4×4	55.7 (17%)	54.1 (17%)	59.4 (18%)	57.3 (17%)
5×5×5	111.6 (12%)	107.4 (13%)	124.8 (11%)	114.7 (12%)
6×6×6	192.0 (6%)	186.4 (6%)	218.8 (5%)	210.8 (6%)
7×7×7	270.9 (5%)	256.0 (4%)	297.4 (3%)	280.4 (4%)
Gender (male)	4012 (94%)	2156 (93%)	586 (97%)	415 (98%)
Panel B: Country characteristics				
Observations	100,453	28,097	10,063	5,621
Tournaments	591	137	120	59

Notes: This table compares the original tournament data with the estimation sample after merging with pollution and weather information. Percentages indicate each cube type's share of observations. The estimation sample excludes individuals who never competed in cube types 5×5×5, 6×6×6, or 7×7×7.

Table A3: IV estimates of $\text{PM}_{2.5}$ effects on solving time by cube type

	Continuous $\text{PM}_{2.5}$		**High $\text{PM}_{2.5}$ dummy**	
	US	India	US	India
2×2×2	0.0030	-0.0128	-0.0105	-0.0758
	(0.0250)	(0.0104)	(0.0262)	(0.0966)
F-test (1st stage)	56.50	21.41	45.02	30.96
Adjusted R^2	0.82	0.67	0.82	0.67
Observations	4,573	1,283	4,573	1,283
3×3×3	0.0233	-0.0060	0.0250	-0.0094
	(0.0178)	(0.0037)	(0.0179)	(0.0639)
F-test (1st stage)	61.33	21.72	45.43	16.51
Adjusted R^2	0.90	0.88	0.90	0.88
Observations	10,896	1,927	10,896	1,927
4×4×4	0.0508**	0.0063	0.0601***	0.0073
	(0.0254)	(0.0040)	(0.0199)	(0.0673)
F-test (1st stage)	117.92	53.14	82.33	21.75
Adjusted R^2	0.88	0.88	0.88	0.88
Observations	3,960	806	3,960	806
5×5×5	0.0473	-0.0011	0.0401*	0.0201
	(0.0309)	(0.0025)	(0.0228)	(0.0363)
F-test (1st stage)	128.37	88.94	83.85	442.36
Adjusted R^2	0.88	0.82	0.88	0.82
Observations	2,674	486	2,674	486

Notes: This table presents IV estimates of γ based on the specification in Equation (6) for each cube type in India and the United States, using the full sample. The instrument is wind direction interacted with city fixed effects. All regressions include environmental controls (local 6-hour averages of ozone, barometric pressure, wind direction, relative humidity, wind speed, precipitation, and temperature), tournament experience, and individual, cube-type, hour-of-day, weekday, and year fixed effects. The high $\text{PM}_{2.5}$ dummy equals one for observations in the country-specific top quartile of the $\text{PM}_{2.5}$ distribution. Standard errors are clustered at the tournament–round level; */**/*** indicate statistical significance at the 10%, 5%, and 1% levels.

Table A4: Falsification test using future $PM_{2.5}$ (6-hour lead)

	FE model	IV model
United States		
Lagged $PM_{2.5}$ (6-hour average)	0.0291*** (0.0124)	0.0322** (0.0191)
Future $PM_{2.5}$ (6-hour lead)	0.0182 (0.0141)	0.0077 (0.0201)
India		
Lagged $PM_{2.5}$ (6-hour average)	-0.0001 (0.0012)	-0.0035 (0.0035)
Future $PM_{2.5}$ (6-hour lead)	0.0000 (0.0011)	-0.0013 (0.0036)

Notes: This table reports falsification tests in which a continuous 6-hour *lead* average of $PM_{2.5}$ is used in place of the baseline lagged $PM_{2.5}$ measure. Coefficients on the lagged measure are reproduced from the main specifications for comparison. FE and IV models include individual, cube-type, hour-of-day, weekday, and year fixed effects, as well as the full set of environmental controls as described in Section 4. Standard errors (in parentheses) are clustered at the tournament–round–cube level. */**/*** indicate statistical significance at the 10%, 5%, and 1% levels.

Table A5: Comparison of player's tournament experience across India and the US

Variable	India	US	Difference (India−US)	p-value
Tournament experience	11.76 (14.54)	15.94 (24.83)	-4.17	<0.001
Number of players	425	2309		

Notes: Tournament experience is measured as the maximum observed cumulative number of tournaments played by each individual. Each player is counted once. Standard deviations are reported in parentheses.

Table A6: Interaction between short-term $PM_{2.5}$ exposure and baseline city pollution levels

	FE model	(2) IV model
$PM_{2.5}$ (10 μg/m^3)	0.0079**	0.0109**
	(0.0039)	(0.0049)
BaselinePM (centered)	-0.0033	0.0003
	(0.0033)	(0.0039)
$PM_{2.5}$ × BaselinePM (centered)	-0.0005*	-0.0009**
	(0.0003)	(0.0004)
Marginal effect of $PM_{2.5}$ at specific BaselinePM levels:		
P10 BaselinePM	0.0088**	0.0123**
	(0.0044)	(0.0054)
P50 BaselinePM	0.0085**	0.0120**
	(0.0043)	(0.0053)
P90 BaselinePM	0.0049**	0.0059*
	(0.0024)	(0.0031)
Observations	33,718	33,718
Controls	Yes	Yes
Individual FE	Yes	Yes
Event FE	Yes	Yes
Time FE (hour, weekday, year)	Yes	Yes
Country FE	Yes	Yes
Sanderson–Windmeijer conditional F, $PM_{2.5}$		172.79
Sanderson–Windmeijer conditional F, $PM_{2.5}$ × BaselinePM		105.29

Notes: Dependent variable is standardized solving time. $PM_{2.5}$ is scaled so that one unit equals 10 μg/m^3. *BaselinePM* is the mean $PM_{2.5}$ concentration across all observations in a given city relative to all other cities in our sample (see Equation (8)). Marginal effects are computed as $\partial Y/\partial PM_{2.5} = \beta_1 + \beta_2 \cdot \text{BaselinePM}$ and evaluated at the 10th, 50th, and 90th percentiles of the *BaselinePM* distribution (using the delta-method to calculate standard errors). Standard errors are clustered at the tournament–round–cube level. */**/*** indicate statistical significance at the 10%, 5%, and 1% levels.

Table A7: Heterogeneity by Player Experience

	United States		India	
	FE	IV	FE	IV
$PM_{2.5}$	0.0807***	0.0857***	0.0037**	-0.0047
	(0.0185)	(0.0238)	(0.0016)	(0.0033)
Experience	0.0004	0.0005	-0.0044***	-0.0068***
	(0.0004)	(0.0005)	(0.0014)	(0.0015)
$PM_{2.5}$ × Experience	-0.0019***	-0.0020***	-0.0002***	0.0000
	(0.0004)	(0.0005)	(0.0000)	(0.0001)
Observations	28097	28097	5621	5621
Controls	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Event FE	Yes	Yes	Yes	Yes
Time FE (hour, weekday, year)	Yes	Yes	Yes	Yes
Sanderson–Windmeijer F, $PM_{2.5}$		548.63		43.40
Sanderson–Windmeijer F, $PM_{2.5}$ × Experience		1256.98		92.41

Notes: Dependent variable is standardized solving time. Experience is measured as cumulative prior tournament participation. IV models instrument $PM_{2.5}$ and its interaction with experience using wind direction by city. Standard errors are clustered at the tournament–round–cube level. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.