# High levels of air pollution reduce team innovation

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**Abstract**

Various studies document that poor air quality can lead to adverse effects on individual worker productivity in routine jobs. Yet, the effect of pollution on team performance in contexts that require individuals to work collaboratively on non-routine problem-solving tasks is not well explored. These settings are particularly conducive to situations that require innovative solutions, including tackling global challenges such as pandemics, poverty, or climate change. Here, we document a sizable adverse effect of air pollution on team performance using data from 7,500 live escape games in London. On high-pollution days, teams take on average 8% more time to solve a sequence of non-routine analytical tasks, which require collaborative skills analogous to those needed in the modern workplace. Negative effects increase exponentially and are heterogeneous depending on the type of air pollutant. As team efforts predominantly drive innovation, high levels of air pollution may significantly hamper economic development.

**Keywords:** Air pollution, Escape games, Innovation, Team performance, WHO air quality guidelines

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Air pollution can have significant effects on human health, behaviour, and cognitive functioning [1, 2]. In the workplace, a sizable literature has documented the adverse effects of air pollution [3] on individual labour productivity [4] in routine manual and analytical jobs (such as fruit pickers [5] and call centre workers [6]) and non-routine analytical jobs in a non-team environment [7–9]. Yet, the effect of pollution on team performance in contexts that require individuals to work collaboratively on non-routine problem-solving tasks is not well explored. The latter is relevant to science and industry where breakthroughs commonly depend on teams confronting complex problems, forcing them to jointly produce and recombine knowledge and apply it to previously unseen problems [10, 11] – a process which we dub 'innovative'. Innovative teams are at the heart of solving complex societal challenges, such as developing Covid-19 vaccines or novel clean energy technologies to combat climate change [12]. Understanding the external environmental barriers to team performance is crucial. In this paper, we are the first to provide evidence on how air pollution impacts team performance on non-routine cognitive tasks conducive to innovative settings.

We leverage unique data from around 7,500 teams participating in escape room games between 2018-2019 in London to study the effect of various airborne pollutants on team performance. In escape games, teams collaborate on a sequence of complex puzzles and tasks which require non-routine problem-solving and interpersonal skills with the objective to complete all tasks and escape within a set time limit, which is typically 60 minutes. As teams in escape games are advised to escape as quickly and efficiently as possible, we make use of time spent until completion as an objective benchmark of innovative team performance. Tasks are designed to take teams at least 45 minutes, but generally not more than one hour, with an average completion time in our sample of 59 minutes. We link outcomes of the escape games to high-frequency pollution and weather data to explore the immediate short-term impacts of pollution exposure within flexible time intervals specific to each pollutant, thereby improving on much of the previous literature which has relied primarily on daily average pollution levels [13]. We also use fixed effects econometric modelling in line with the extant literature to control for possible confounders, such as temporal pollution patterns, room-specific characteristics, and other context-relevant covariates such as the number of clues received.

We find that completion time increased by up to 8% (or 4.5 minutes) between low- and high-pollution days. Disaggregating our results, we show that the effects of air pollution increase exponentially beyond a certain threshold, but effects are highly heterogeneous (see Figure 1). Carbon monoxide and sulphur dioxide exhibit strong effects well below the threshold prescribed by the World Health Organisation (WHO) [14], whereas nitrogen dioxide and PM 2.5 exhibit effects at levels only substantially higher than WHO thresholds. Overall, our results suggest that air pollution can have a sizable and statistically significant adverse impact on team performance, which may be even higher in low- and middle-income countries due to substantially higher levels of pollution than at our study site.

## Results

We study the effect of the four most common air pollutants, namely carbon monoxide (CO), sulphur dioxide ($SO_2$), nitrogen dioxide ($NO_2$) and particulate matter smaller than 2.5$\mu$m (PM 2.5). CO and $NO_2$ are mainly caused by road transport emissions, whereas $SO_2$ is emitted largely by coal and oil burning power plants.

PM 2.5 primarily stems from chemical interactions of different pollutants and can remain suspended in the atmosphere over long periods of time. As a result of varying sources and properties, pollutants impact the human body on different time scales. CO, $SO_2$ and $NO_2$ pose an immediate threat to health, whereas exposure to PM 2.5 over longer periods of time may result in detrimental health outcomes. We therefore use hourly pollution data, averaged across 16 monitoring stations located within Greater London, and define pollutant-specific time intervals to assess the effects of pollution on team performance (see Methods for details).

The effect of pollutants on team performance, proxied by game completion time, increases exponentially beyond specific thresholds. Figure 1 shows the 24-hour average concentration thresholds suggested by the WHO Air Quality Guidelines (AQGs) [14] and the visual threshold beyond which the effect increases exponentially, which we denote EXP. The effects for CO and $SO_2$ show a stronger exponential increase than the effects of $NO_2$ and PM 2.5.

The left panel in Figure 2 shows the individual effects of each pollutant on completion time, and the right panel the change in predicted completion time for high levels (> EXP) of various pollutant combinations. Individually, high levels (>EXP) of $SO_2$ and CO exhibit the strongest increase in completion time, followed by PM 2.5 and $NO_2$. Below the EXP threshold but above the WHO threshold, $NO_2$ and PM 2.5 do not increase completion time. We acknowledge that for CO and $SO_2$ we do not observe any games in our dataset that took place when pollution levels exceeded the WHO thresholds, but it is very likely that for CO and $SO_2$ levels beyond the WHO threshold would strongly increase completion time, as lower levels already exhibit strong effects (see EXP).

We use the econometric model to compute the expected increase in completion time for different combinations of pollutants crossing the EXP threshold (Figure 2 right panel). In more than 19% of observed days, at least one pollutant crosses the EXP threshold, in 3% of days two pollutants are above the threshold, 1% of days across three pollutants, and no days above 4 pollutants. In the presence of high levels of all four pollutants, the expected completion time increases by up to 6% in the full sample (including diverse sets of participants) and up to 8% in a sub-sample that only includes firm groups that participate for team-building purposes. The latter subsample comprises around 2,000 teams and may be more representative of the effect on the work environment than our full sample (which also includes birthday parties and other leisure groups).

## Discussion

Air pollution can have wide-ranging effects on human health and job performance. Here, we show that high levels of air pollution can have a sizable and statistically significant adverse impact on teams' innovation performance. Our results indicate that CO and $SO_2$ lead to significant (exponential) negative effects on team performance at levels which are much lower than current WHO thresholds.

As cognitive functioning is critical to creativity and innovative thinking, it may constitute a potential pathway by which air pollution negatively impacts team performance. For instance, high levels of carbon

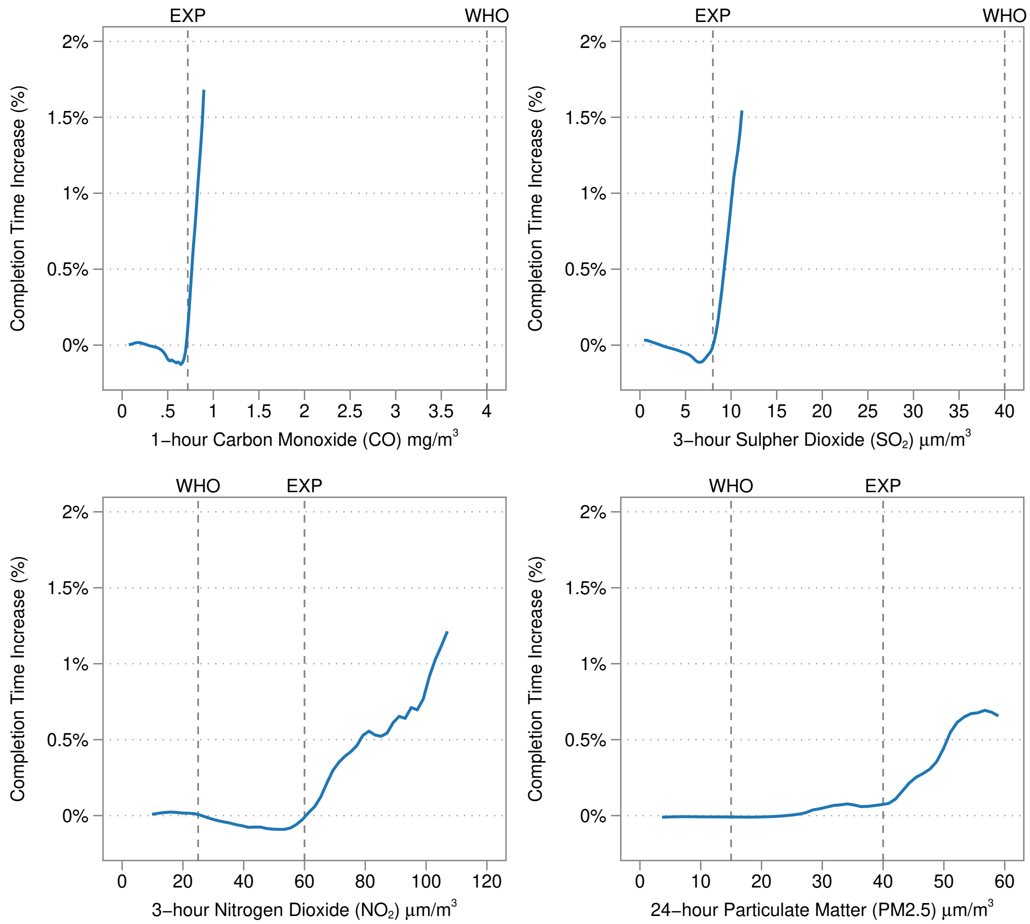


**Figure 1:** Each graph depicts a kernel weighted (Epanechnikov) local polynomial regression of residualized completion time (percentage of average completion time) on ambient pollution concentrations within the specified exposure intervals. Residualized completion time is generated by regressing completion time on a vector of game and team characteristics, a vector of weather controls, room fixed effects and temporal fixed effects for room-month-year, room-day-of-week and room-time-of-day (see Methods). WHO marks the 24-hour AQG level [14] and EXP indicates the threshold after which the effect increases exponentially. Standard errors clustered at the room-month-year level (N=7,477).

monoxide can reduce the oxygen flow to the brain and other organs. This interpretation is in line with other research indicating that air pollution directly impairs cognitive performance [15, 16]. Our findings are also compatible with a pollution-induced negative mood pathway. It is now well established that acute exposure to air pollution can negatively impact people's affective states [17], which in turn may directly stifle creative thinking [18] or inhibit teamwork by increasing risk aversion and lowering pro-sociality [19].

Our results have implications for all settings that require team-based non-routine analytical and interpersonal work, which characterises large parts of the modern work environment. Many low- and middle-income economies face much higher levels of pollution, which could possibly be a drag on economic development and poverty alleviation [20]. As these countries intend to increase the share of service-sector jobs that entail team innovation in their economies, reducing air pollution may be an important contextual factor that can affect innovation capacity, which is critical for economic development

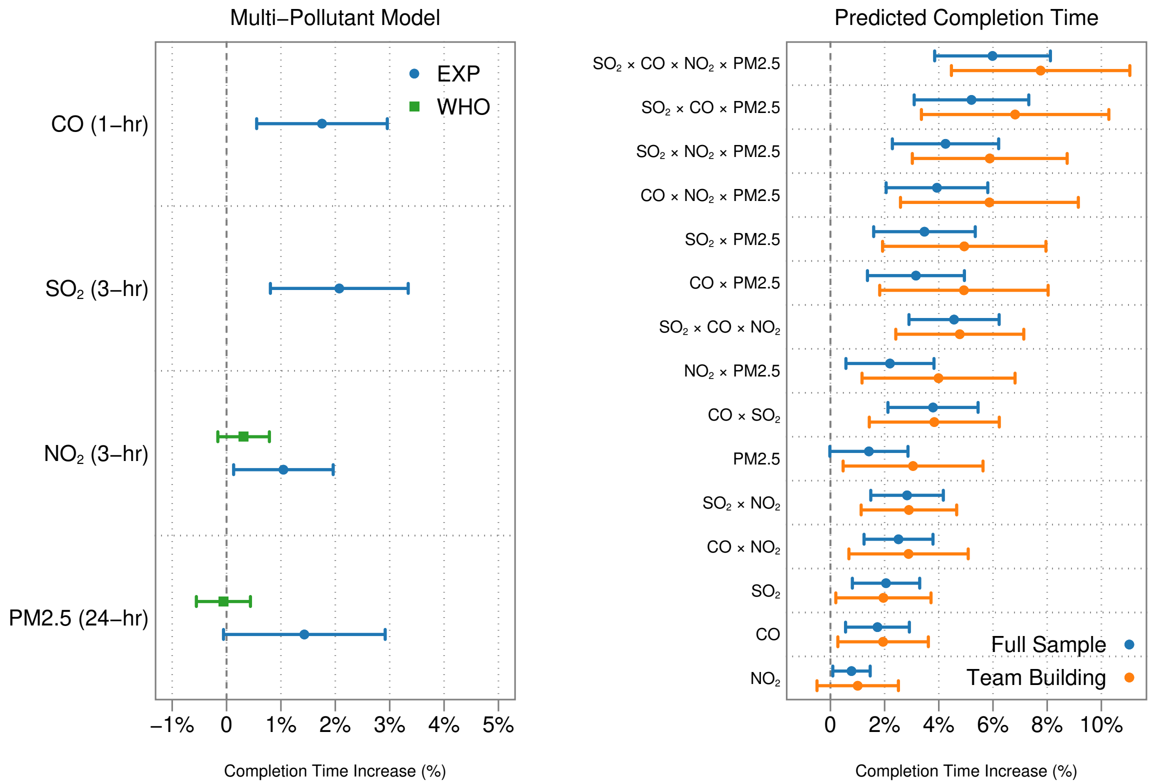


**Figure 2:** Main Results. The left panel presents OLS estimates of equation (1) for each pollutant indicator (see Methods and Supplementary Table 1). The dependent variable is completion time as a percentage of average completion time. The right panel displays the predicted increases in completion time under different combinations of pollution exposure exceeding the EXP threshold for the full sample (N=7,477) and a sub-sample of team-building games (N=2,085). Standard errors are clustered at the room-month-year level. Error bars indicate 95% confidence intervals.

# Methods

## Statistical Analysis

To estimate the causal effect of air pollution on team performance we utilize a fixed effects panel regression approach. We estimate a multi-pollutant model which includes indicator variables for each pollutant identifying observations corresponding to the thresholds shown in Figure 1 (WHO $< \mu g/m^3 \leq$ EXP and $\mu g/m^3 >$ EXP). All models control for game and team characteristics (number of clues, team size, team-building, birthdays, return visits and teams aged under sixteen), weather controls (temperature, pressure, humidity, wind speed, wind speed squared, rainfall, rainfall squared, cloud cover, sunshine hours), room fixed effects and temporal fixed effects for room-month-year, room-day-of-week and room-time-of-day. Standard errors are clustered at the room-month-year level. A detailed description of the data and statistical methods employed is provided below.

## Team performance data

Escape game data were provided by an escape room company based in central London (London borough of Islington). The data span a period of 411 days between 1st November 2018 and 31st December 2019. The provider operates a total of 11 escape rooms at a single location. The average number of games per day during the observation period was 22. According to the provider, the escape games were not altered with respect to design or difficulty during the observation period. A live escape game or escape room is a type of real-life adventure game that consists of a sequence of complex tasks and puzzles which need to be solved within a set amount of time (60 minutes) by a team of up to six players. Escape games require numerous skills analogous to those required in the modern workplace, including teamwork, leadership, attention to detail and communication. Escape rooms thus provide an ideal controlled setting in which to observe team performance.

Summary statistics are presented in Supplementary Table 2. The mean completion time, which serves as our dependent variable, is 58.90 minutes. The average team size is 4.5, ranging between 2 and 6 participants per game. The games are monitored by a game host, who can provide additional clues (on-screen or via radio) if requested by the team when having trouble solving a current puzzle. The number of clues requested (M=10) is strongly positively correlated with completion time and thus serves as a measure of team ability. Importantly, the escape room provider runs an "everyone should win" policy. This implies that if the 60-minute time limit is exceeded, teams are granted additional time to escape until the game has successfully been completed. All teams are made aware of this feature during the pre-game instructions. We exclude three observations in which more than 30 minutes additional time were granted. Escape rooms are popular with people of all ages and are usually booked as a recreational activity with friends or family. The provider also offers sessions for corporate teams, specifically designed for team building and assessment purposes. These sessions are no different to regular sessions, but typically involve additional debriefing and post-game analysis with the teams. The escape game data contains additional information on the booking date and team composition, including whether the game was booked for team building, as a birthday party, if all team members were under the age of 16 and whether the team had previously visited one of the other escape rooms offered by the provider (i.e. return visits).

## Pollution data

Pollution data were obtained from 16 monitoring stations located within Greater London, maintained by the Automatic Urban and Rural Network (AURN). The data are provided by the Department for Environment Food, and Rural Affairs [21]. These sites record high-resolution hourly data for all major pollutants, including $SO_2$ $NO_2$, CO, PM2.5, PM10 and O3. For each pollutant, we average hourly pollution levels across all monitoring stations at which the pollutant is measured. Customers are likely to be dispersed across Greater London prior to visiting the escape rooms and are therefore exposed to different degrees of pollution. Averaging pollution concentrations across all monitoring stations thus provides a more accurate identification of pollution exposure than drawing data from a single monitoring station (e.g. the most proximate), although some measurement error cannot be ruled out.

We take advantage of our high-frequency pollution data to define flexible exposure windows specific to each pollutant, as in Archsmith *et al.* [7]. Particulate matter smaller than 2.5 $\mu$m in diameter (PM2.5) is primarily produced by chemical reactions between different pollutants and can accumulate in the atmosphere over extended periods of time [22]. Therefore, we consider average PM2.5 concentrations over a 24-hour interval prior to the start of the escape game. Regulatory standards for short-term exposure of PM2.5 are also set at 24-hour time frames (e.g. WHO guidelines). $NO_2$ is largely caused by road traffic and $SO_2$ comes from the burning of industrial coal and oil which can have immediate adverse health impacts such as headaches, discomfort, and anxiety. $NO_2$ and $SO_2$ are partly culpable in the formation of haze and smog; we therefore consider a 3-hour exposure interval prior to the start of the escape game. CO is extremely harmful when inhaled, as it deprives the brain and other organs of oxygen, which can lead to dizziness and weakness up to losing consciousness. As carbon monoxide at elevated levels can become dangerous in a matter of minutes, we consider exposure to CO during the hour of the escape game.

For our main analysis, based on our visual assessment of pollution exposure (see Figure 1), we construct binary indicators identifying observations which exceed the EXP threshold (after which completion time increases exponentially) within the pre-specified time interval for each pollutant. For PM2.5 and $NO_2$ we additionally construct indicators equal to one if pollution levels prior to the escape game exceed the WHO threshold but were below the EXP threshold. We do not consider PM10 due to its high correlation with PM2.5 and do not explore O3 as it is negatively correlated with a range of other pollutants, making it challenging to isolate the effects for both of these pollutants.

### Weather data

Weather data were obtained from Met Office Integrated Data Archive System (MIDAS) dataset for three monitoring stations within Greater London [23]. Hourly weather observations for pressure, humidity, rainfall, wind speed, cloud cover and temperature are averaged across stations and over flexible 24-hour intervals prior to the start of each escape game. Additionally, we compute the share of sunshine hours between 7am and the start of the escape game, to control for sunshine induced mood effects on the day of the escape game. We exclude 30 observations (0.4%) for which at least one weather variable is missing.

### Main Regression Model

To estimate the effect of air pollution on team performance we utilize a fixed effects panel regression approach. We follow Archsmith *et al.* [7] by estimating a multi-pollutant model:

$$CT_{grt} = \beta_0 + \beta_1 P_{grt} + \beta_2 W_{grt} + \beta_3 X_{grt} + \delta_r + \lambda_{rt} + \varepsilon_{grt} \tag{1}$$

$CT_{grt}$ is completion time of game $g$ in room $r$ at time $t$, which serves as our measure of team performance. For ease of interpretation, we present completion time (originally recorded in minutes and seconds) as a percentage of average completion time across all games observed in our data ($CT_{grt}/\overline{CT}$). This transformation allows us to interpret our findings as the change in average completion time of a typical game (designed to have a duration of one hour) caused by a given level of pollution. $X_{grt}$ represents a vector of game and team characteristics which may affect completion time. These include continuous variables for the number of clues required by the team during game and the team size, as well as binary indicators identifying teams under the age of sixteen, return visits, birthdays and dedicated team building sessions.

$P_{grt}$ is a vector of pollution variables specific to game $g$, including indicators for CO (1-hr) > 0.72 mg/m$^3$, $SO_2$ (3-hr) > 8 $\mu$g/m$^3$, 25 $\mu$g/m$^3$ < $NO_2$ ≤ 60 $\mu$g/m$^3$, $NO_2$ (3-hr) > 60 $\mu$g/m$^3$, 15 $\mu$g/m$^3$ < PM2.5 (24-hr) ≤ 40 $\mu$g/m$^3$, PM2.5 (24-hr) > 40 $\mu$g/m$^3$. The base category contains all observations which were not subject to elevated pollution levels. Estimating a multi-pollutant model allows us to disentangle the effect of individual pollutants within their respective timeframes.

$W_{grt}$ represents a vector of weather controls for which we define flexible 24-hour rolling averages prior to game $g$ in room $r$ at time $t$. Weather controls include pressure (hPa), humidity (%), wind speed (knots), wind speed squared, rainfall (mm), rainfall squared and cloud cover (octas). Following the literature, we define five equally sized temperature bins to allow for nonlinear temperature effects (<2.5°C, 2.5°C – 10°C, 10°C – 17.5°C, 17.5°C – 25°C, >25°C). Each temperature bin captures the number of hours during the past 24 hours that fell within each respective bin. Finally, we control for the share of sunshine hours between 7am on the day of the escape game and the start of the game. Summary statistics are presented in Supplementary Table 3.

$\delta_r$ are room fixed effects and $\lambda_{rt}$ capture temporal fixed effects specific to each room (room-month-year, room-day-of-week and room-time-of-day) as well as an indicator for bank holidays.

For identification, we exploit the panel structure of the data and estimate panel fixed effects models which control for room-specific idiosyncrasies as well as temporal factors which may be associated with game completion time. For instance, each escape room contains a unique setting comprising different challenges and tasks, resulting in varying degrees of difficulty, which we control for by room-fixed effects. Moreover, pollution levels may be correlated with unobserved short-term temporal factors (such as rush-hours, weekends, and bank holidays) as well as recurring seasonal patterns in pollution which are absorbed by the time fixed effects.

Our identification benefits from the fact that all games in our data are offered by the same provider at the same location and are thus subject to the same contextual factors (e.g., type of customers, game and venue policies, travel to the venue and supporting staff). Moreover, booking data shows that games are booked on average 24 days in advance, thus making pollution-induced avoidance behaviour highly unlikely. After netting out room and time fixed effects, it is reasonable to assume that variation in pollution exposure is plausibly exogenous to game $g$ in room $r$ at time $t$, conditional on local (short-term) weather conditions, thus allowing a causal interpretation of our findings.

To account for potential within-room serial correlation in a given month, standard errors are clustered at the room-month-year level. Residuals for Figure 1 are obtained from a regression of equation (1) excluding indicators for pollution exposure ($P_{grt}$) using all available data (N=7,477). To construct Figure 2, we estimate two variants of equation (1): one for the full sample (N=7,477) and one for a sub-sample of observations which were dedicated team building sessions (N=2,085). The left panel of Figure 2 presents estimates of equation (1) for the full sample (N=7,477) only. The coefficient estimates of equation (1) are used to compute the predicted change in completion time under different combinations of pollutants for the full sample and the team building sample separately (Figure 2, right panel).

### Robustness Checks

The results of our main analysis are robust to a range of alternative weather variables specifications commonly encountered in the literature (e.g., alternative polynomial specifications, temperature and humidity interactions and using daily-average values instead of flexible 24-hour averages). See Supplementary Table 4.

Additionally, we estimate equation (1) for the sub-sample of teams which were composed of members under the age of sixteen (N= 1,270). Younger teams will, on average, take a less structured approach towards solving the escape game tasks and rely less on teamwork and communication. In line with our expectations, we find no statistically significant effects of pollution on team performance for this subgroup (see Supplementary Table 1, column 3). The under 16-year-old subgroup is least representative of the modern working environment, thus reaffirming our finding that pollution is most detrimental for corporate teams which rely heavily on teamwork, communication, and leadership.

### Data Availability

The data and code to replicate the analysis are available from the corresponding author upon reasonable request.

## Supplementary Tables (*for online publication*)

**Table 1: Regression outputs**

| | (1) Full Model | | (2) Team building=1 | | (3) Under 16 = 1 | |
|---|---|---|---|---|---|---|
| CO (1-hr) × (CO > 0.72) | 0.018*** | (0.006) | 0.019** | (0.009) | 0.017 | (0.021) |
| $SO_2$ (3-hr) × ($SO_2$ > 8) | 0.021*** | (0.006) | 0.019** | (0.009) | -0.018 | (0.026) |
| $NO_2$ (3-hr) × (25 < $NO_2$ ≤ 60) | 0.003 | (0.002) | 0.010** | (0.005) | -0.002 | (0.007) |
| $NO_2$ (3-hr) × ($NO_2$ > 60) | 0.010** | (0.005) | 0.018* | (0.010) | -0.006 | (0.019) |
| PM2.5 (24-hr) × (15 < PM2.5 ≤ 40) | -0.001 | (0.003) | 0.000 | (0.005) | 0.001 | (0.007) |
| PM2.5 (24-hr) × (PM2.5 > 40) | 0.014* | (0.008) | 0.030** | (0.013) | 0.003 | (0.019) |
| Total clues | 0.009*** | (0.000) | 0.010*** | (0.000) | 0.008*** | (0.000) |
| Team size | -0.002** | (0.001) | -0.001 | (0.002) | 0.000 | (0.003) |
| Under sixteen | 0.012*** | (0.002) | 0.000 | (.) | 0.000 | (.) |
| Team building | -0.001 | (0.002) | 0.000 | (.) | 0.000 | (.) |
| Birthday | 0.000 | (0.002) | 0.000 | (.) | 0.000 | (0.006) |
| Return visit | -0.001 | (0.002) | 0.001 | (0.005) | 0.008 | (0.006) |
| Humidity (%) | -0.000*** | (0.000) | -0.000 | (0.000) | -0.000 | (0.000) |
| Pressure (hPa) | -0.000 | (0.000) | 0.000 | (0.000) | -0.000 | (0.000) |
| Cloud cover (octas) | 0.000 | (0.001) | 0.000 | (0.001) | 0.001 | (0.002) |
| Wind speed (knots) | 0.001 | (0.001) | 0.000 | (0.003) | 0.006* | (0.004) |
| Wind speed (knots) squared | -0.000 | (0.000) | 0.000 | (0.000) | -0.000* | (0.000) |
| Rain (mm) | -0.014 | (0.011) | -0.019 | (0.017) | -0.017 | (0.049) |
| Rain (mm) squared | 0.016* | (0.009) | 0.022* | (0.012) | -0.024 | (0.062) |
| Sunshine hours (share) | -0.008* | (0.004) | -0.003 | (0.008) | -0.014 | (0.013) |
| Temperature: hours <2.5°C | 0.000 | (0.000) | -0.001 | (0.001) | 0.001 | (0.001) |
| Temperature: hours 2.5°C − 10°C | 0.000** | (0.000) | 0.000 | (0.000) | 0.001 | (0.001) |
| Temperature: hours 17.5°C − 25°C | -0.000 | (0.000) | -0.000 | (0.000) | -0.001 | (0.001) |
| Temperature: hours >25°C | -0.001* | (0.001) | 0.000 | (0.001) | -0.002 | (0.002) |
| Bankholiday | 0.006 | (0.007) | 0.104*** | (0.015) | 0.018 | (0.015) |
| $R^2$ | 0.456 | | 0.519 | | 0.465 | |
| Observations | 7477 | | 2085 | | 1270 | |

*Note:* Multi-pollutant estimates of equation (1) for the full sample (column 1), and sub-samples of team-building games (column 2) and games where all team members were aged under sixteen (column 3). The dependent variable is completion time as a percentage of average completion time. All models control for game and team characteristics (number of clues, team size, team-building, birthdays, return visits and teams aged under sixteen), weather controls (temperature, pressure, humidity, wind speed, wind speed squared, rainfall, rainfall squared, cloud cover, sunshine hours), room fixed effects and temporal fixed effects for room-month-year, room-day-of-week and room-time-of-day. Standard errors are clustered at the room-month-year level.

* p < 0.1, ** p < 0.05, *** p < 0.01.

**Table 2: Game and team characteristics**

| | Mean | S.d. | Min | Max | Count |
|---|---|---|---|---|---|
| Completion time (mins) | 58.90 | 5.41 | 31.48 | 86.05 | 7,477 |
| Total clues | 10.18 | 6.40 | 0.00 | 51.00 | 7,477 |
| Team size | 4.46 | 1.04 | 2.00 | 6.00 | 7,477 |
| Under sixteen | 0.17 | 0.38 | 0.00 | 1.00 | 7,477 |
| Team building | 0.28 | 0.45 | 0.00 | 1.00 | 7,477 |
| Birthday | 0.22 | 0.42 | 0.00 | 1.00 | 7,477 |
| Return visit | 0.21 | 0.41 | 0.00 | 1.00 | 7,477 |

*Note:* Table presents summary statistics for game and team characteristics of the full sample (N=7,477)

**Table 3: Pollution and weather variables**

| | Mean | S.d. | Min | Max | Count |
|---|---|---|---|---|---|
| *Pollution Indicators* | | | | | |
| CO (1-hr) × (CO > 0.72) | 0.011 | 0.105 | 0.0 | 1.0 | 7,477 |
| $SO_2$ (3-hr) × ($SO_2$ > 8) | 0.011 | 0.103 | 0.0 | 1.0 | 7,477 |
| $NO_2$ (3-hr) × (25 < $NO_2$ ≤ 60) | 0.640 | 0.480 | 0.0 | 1.0 | 7,477 |
| $NO_2$ (3-hr) × ($NO_2$ > 60) | 0.065 | 0.247 | 0.0 | 1.0 | 7,477 |
| PM2.5 (24-hr) × (15 < PM2.5 ≤ 40) | 0.184 | 0.388 | 0.0 | 1.0 | 7,477 |
| PM2.5 (24-hr) × (PM2.5 > 40) | 0.015 | 0.122 | 0.0 | 1.0 | 7,477 |
| *Weather Controls* | | | | | |
| Humidity (%) | 76.564 | 10.672 | 46.4 | 96.0 | 7,477 |
| Rain (mm) | 0.089 | 0.168 | 0.0 | 1.7 | 7,477 |
| Pressure (hPa) | 1,010.387 | 12.090 | 973.9 | 1,040.3 | 7,477 |
| Cloud cover (octas) | 5.243 | 2.246 | 0.0 | 8.0 | 7,477 |
| Wind speed (knots) | 8.186 | 3.563 | 2.0 | 19.8 | 7,477 |
| Temperature: hours <2.5°C | 0.904 | 3.224 | 0.0 | 22.0 | 7,477 |
| Temperature: hours 2.5°C − 10°C | 9.555 | 9.293 | 0.0 | 24.0 | 7,477 |
| Temperature: hours 10°C − 17.5°C | 9.441 | 7.810 | 0.0 | 24.0 | 7,477 |
| Temperature: hours 17.5°C − 25°C | 3.747 | 5.961 | 0.0 | 24.0 | 7,477 |
| Temperature: hours >25°C | 0.353 | 1.709 | 0.0 | 15.0 | 7,477 |
| Sunshine hours (share) | 0.314 | 0.297 | 0.0 | 1.0 | 7,477 |

*Note:* Table presents summary statistics for the pollution indicators and weather controls employed in the analysis. Humidity, rainfall, pressure, cloud cover and wind speed are measured in flexible 24-hour intervals prior to the start of each game. The five temperature bins capture the number of hours that fall within in a respective bin during the 24-hour interval prior to the start of each game. Sunshine hours are measured as the share of hours on the day of the game (i.e. between 7am and the start of the game).

**Table 4: Robustness: Alternative weather specifications**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| CO (1-hr) × (CO > 0.72) | 0.018*** | 0.016*** | 0.018*** | 0.017*** | 0.018*** | 0.016*** | 0.018*** | 0.016*** |
| | (0.006) | (0.006) | (0.006) | (0.006) | (0.006) | (0.006) | (0.006) | (0.006) |
| $SO_2$ (3-hr) × ($SO_2$ > 8) | 0.021*** | 0.022*** | 0.021*** | 0.021*** | 0.020*** | 0.019*** | 0.019*** | 0.019*** |
| | (0.006) | (0.006) | (0.006) | (0.006) | (0.006) | (0.006) | (0.006) | (0.006) |
| $NO_2$ (3-hr) × (25 < $NO_2$ ≤ 60) | 0.003 | 0.005* | 0.003 | 0.003 | 0.003 | 0.003 | 0.003 | 0.003 |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| $NO_2$ (3-hr) × ($NO_2$ > 60) | 0.010** | 0.013*** | 0.010** | 0.009** | 0.009** | 0.010** | 0.009** | 0.009** |
| | (0.005) | (0.005) | (0.005) | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) |
| PM2.5 (24-hr) × (15 < PM2.5 ≤ 40) | -0.001 | -0.000 | -0.001 | -0.001 | -0.001 | -0.002 | -0.003 | -0.002 |
| | (0.003) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| PM2.5 (24-hr) × (PM2.5 > 40) | 0.014* | 0.014* | 0.013* | 0.012 | 0.013* | 0.011 | 0.009 | 0.011 |
| | (0.008) | (0.008) | (0.008) | (0.008) | (0.007) | (0.008) | (0.007) | (0.008) |
| $R^2$ | 0.456 | 0.456 | 0.456 | 0.456 | 0.455 | 0.454 | 0.455 | 0.455 |
| Observations | 7477 | 7477 | 7477 | 7477 | 7477 | 7477 | 7477 | 7477 |

*Note:* Multi-pollutant estimates of equation (1) for the main specification (column 1) and alternative weather variable specifications (columns 2-8). Column 2 uses daily averages, instead of flexible 24-hour averages. Column 3 includes 24-hour averages and their polynomials for rainfall, wind speed, temperature and humudity only. Column 4 adds temperature-humidity interactions. Columns 5 to 8 use more simple specifications following recently published literature. Column 5 removes polynomial terms for windspeed and rainfall. Column 6 uses averages of temperature, cloud cover, wind speed and rain fall only. Column 7 uses averages and polynomials of temperature and rainfall only. Column 8 uses averages of temperature, humidity and wind speed only. All models control for game and team characteristics (number of clues, team size, team-building, birthdays, return visits and teams aged under sixteen), room fixed effects and temporal fixed effects for room-month-year, room-day-of-week and room-time-of-day. Standard errors are clustered at the room-month-year level.

* p < 0.1, ** p < 0.05, *** p < 0.01.

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