Journal of Economic Psychology 101 (2024) 102705

Contents lists available at ScienceDirect

Journal of Economic Psychology

journal homepage: www.elsevier.com/locate/joep

Brief Report

High levels of air pollution reduce team performance☆

Paul M. Lohmann[a,b,*], Benedict Probst[c], Elisabeth Gsottbauer[d], Andreas Kontoleon[b]

[a] El-Erian Institute of Behavioural Economics and Policy, Judge Business School, University of Cambridge, UK
[b] Centre for Environment, Energy and Natural Resource Governance, Department of Land Economy, University of Cambridge, UK
[c] Group for Sustainability and Technology, Department of Management, Technology, and Economics, ETH Zurich, Switzerland
[d] Grantham Research Institute for Climate Change and the Environment, The London School of Economics and Political Science, UK

ARTICLE INFO

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

ABSTRACT

Teams play a key role in tackling complex societal challenges, such as developing vaccines or novel clean energy technologies. Yet, the effect of air pollution on team performance in non-routine problem-solving tasks is not well explored. Here, we document a sizable adverse effect of air pollution on team performance using data from 15,000 live escape games in London, United Kingdom. On high-pollution days, teams take on average 5% 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 are non-linear and only occur at high levels of air pollution, which are however commonplace in many developing countries. As team efforts predominantly drive innovation, high levels of air pollution may significantly hamper economic development.

1. Introduction

Teams play a critical role in solving complex societal challenges, such as developing vaccines or novel clean energy technologies to combat climate change (Probst, Touboul, Glachant, & Dechezleprêtre, 2021). To achieve breakthroughs in such settings, teams must work collaboratively to confront intricate problems, jointly produce and recombine knowledge, and apply it to previously unseen problems. However, the external environmental factors that can impact team performance in such settings are not well understood. Previous research has documented the negative effects of air pollution on firm-level innovation (Cavalcanti, Mohaddes, Nian, & Yin, 2023; Chen, Liu, Liu, & Wang, 2023) and more specifically on human capital and individual labour productivity (Cedeño Laurent et al., 2021; Zivin & Neidell, 2018) in routine and manual jobs, such as fruit pickers (Chang, Zivin, Gross, & Neidell, 2016), call centre workers (Chang, Zivin, Gross, & Neidell, 2019) and couriers (Wang, Lin, & Qiu, 2022). This further includes a diverse range of non-routine jobs, such as those found in the public sector (Archsmith, Heyes, & Saberian, 2018; Huang, Xu, & Yu, 2020; Kahn & Li, 2020; Sarmiento, 2022) and in software development (Holub & Thies, 2022).[1] Little, however, is known about the effects of air pollution in

☆ Data and code to replicate the analysis can be accessed from the OSF repository, https://osf.io/n6q7d/.

* Corresponding author at: El-Erian Institute of Behavioural Economics and Policy, University of Cambridge, Judge Business School, Trumpington Street, Cambridge CB2 1AG, UK.

E-mail addresses: p.lohmann@jbs.cam.ac.uk (P.M. Lohmann), bprobst@ethz.ch (B. Probst), e.gsottbauer@lse.ac.uk (E. Gsottbauer), ak219@cam.ac.uk (A. Kontoleon).

[1] Previous studies have also explored non-routine tasks, yet in non-traditional work environments. For instance, research has been conducted on chess players (Künn, Palacios, & Pestel, 2023) and individuals who play brain training games (Krebs & Luechinger, 2022; La Nauze & Severnini, 2021).

https://doi.org/10.1016/j.joep.2024.102705
Received 20 September 2022; Received in revised form 11 October 2023; Accepted 6 February 2024
Available online 9 February 2024
0167-4870/

team work environments (Mo, Wu, & Yuan, 2023).

This paper examines the impact of air pollution on team performance using data from escape room challenges. In an escape game, team members must work together to identify and analyse the cues provided in the room, such as hidden objects and puzzles and use this information to develop a strategy to escape the room before time runs out, which is typically 60 min. Escape rooms provide an ideal setting to study team performance on non-routine, cognitive tasks emblematic of the modern work environment because they require a high level of creativity, collaboration, and communication between team members to complete the game. Additionally, escape games are designed to induce time pressure and create a sense of urgency, which can further challenge a team's ability to perform under pressure.

We leverage unique data from over 15,000 teams participating in escape room games between 2018 and 2022 in London.[2] As teams in escape games are advised to escape as quickly and efficiently as possible, we use time spent until completion as an objective measure of team performance. 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. We thereby improve on much of the previous literature, which has relied primarily on daily average pollution levels (Lichter, Pestel, & Sommer, 2017). To estimate a causal relationship, we utilise 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 5 % (or ~3.2 min) between low- and high-pollution days. Disaggregating our results, we show that the effects of air pollution are highly non-linear and effects are heterogeneous across pollutants. Carbon monoxide and sulphur dioxide exhibit strong effects well below the threshold prescribed by the World Health Organisation (WHO) (World Health Organization, 2021), 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.

2. Background, data and estimation

In this paper, we use data from escape rooms to study the impact of environmental conditions on team performance. Escape rooms are interactive, team-based games in which players solve puzzles and complete challenges to escape a themed room within a set time limit (60-minutes). These games demand creative thinking, complex problem-solving, and the ability to work under pressure. Escape games thus require numerous skills analogous to those required in the modern workplace, and therefore provide an ideal controlled setting in which to observe team performance.[3]

The data for the escape games were sourced from a company located in the central London borough of Islington. The data covers a total of 765 days over two periods, ranging from 1st November 2018 to 31st December 2019 and 1st January 2022 to 31st December 2022. The provider has one location with 11 available escape rooms that can accommodate a maximum of six people per team. When we use the term "room", we refer to a physical room within the escape game facility. The rooms offer different challenges, with some of them being identical duplicates of the same challenge. During the observation period, the average number of games played per day was 19. It is worth noting that each team plays only one game per day. For our analysis, we match all game data with air pollution and weather measures from monitoring stations located within Greater London.

2.1. Escape games: rules and measure of performance

The objective of an escape game is to work together in order to uncover the key to escape the room. The games last for an hour, and players are given a set of instructions and a brief explanation of the rules before beginning the game. The escape room operator has a policy of ensuring that every team can successfully complete the game. Therefore, if the 60-minute time limit is surpassed, extra time will be provided until the team successfully escapes. Prior to the start of the game, all teams are informed of this policy during the pre-game briefing. Overall, we exclude 33 outliers with additional time granted exceeding 30 min.

To assist players in solving the various puzzles and clues within the game, they are permitted to request hints from the game operator. These hints can offer guidance and assistance in progressing through the challenges and ultimately escaping the room within the allotted time frame. The number of hints requested by each team is recorded and incorporated into our dataset. Note that we exclude four games in which over 60 clues were given, as these are likely due to recording errors.

Apart from recreational sessions where escape rooms are booked as a group activity with friends and family, the provider also offers sessions for corporate teams, specifically designed to enhance team building and assess team performance. In our data, we also record whether a session is recreational or corporate. Furthermore, the escape game data contains additional information on the booking date and team composition including team size (2–6) and whether all team members were under the age of 16.

[2] We do not utilise data from 2020 and 2021 which were in part impacted by the COVID-19 pandemic. In 2022, the escape room provider returned to "business as usual" for the entire year.

[3] Data from interactive team-based escape games has also been used by organizational economists and psychologists to analyse behaviour in response to incentives and leadership. For instance, researchers have examined how team leaders can impact overall team performance (Englmaier, Grimm, Grothe, & Schudy, 2021).

We measure the performance of teams in each escape game based on their completion time in minutes, as it reflects how efficiently and effectively the team worked together. The faster the team completes the game, the more successful they are considered to be. Additionally, completion time can also serve as a measure of how well the team communicated and collaborated with each other, as effective communication and teamwork are key factors in completing an escape game quickly.

Summary statistics are presented in Online Appendix Table A1. The mean completion time, which serves as our dependent variable, is 58.89 min. Games are designed to last at least 45 min but typically do not exceed one hour. The average team size is 4.27, 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. In our analysis, we treat the number of clues requested (M = 9.68) as a measure of innate team ability, rather than a measure of team performance, supported by the fact that it is one of the strongest predictors of completion time holding pollution levels constant and thus an important covariate (see coefficient estimate 'Total Clues' in Table A8, Model (1)). Our data show that teams completing the game with few or no clues tend to achieve the best times. Moreover, corporate teams, often composed of experienced professionals, typically require fewer clues on average compared to younger teams (e.g., "under 16″) or casual groups such as birthday parties. This observation underscores the idea that teams with higher innate abilities and problem-solving skills are more self-sufficient and require fewer external clues to navigate the escape game successfully. Finally, regression analysis shows that the number of clues required by a team is not systematically related to air pollution exposure, suggesting that "bad control" bias is unlikely to be a concern in our setting (see Online Appendix Table A8, Model 4).[4]

2.2. Measurement of environmental conditions

Our analysis relies on air pollution and weather data, which we discuss in turn.

2.2.1. Air pollution

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 μm (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.

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 (DEFRA, 2022). 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. (2018). Particulate matter smaller than 2.5 μm in diameter (PM2.5) is primarily produced by chemical reactions between different pollutants and can accumulate in the atmosphere over extended periods of time (20). Therefore, we consider average PM2.5 concentrations over a 24-h interval prior to the start of the escape game. Regulatory standards for short-term exposure of PM2.5 are also set at 24-h 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-h 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, we use both continuous measures of pollution exposure, as well as binary indicators identifying observations which fall into pre-determined pollution bins within the pre-specified time interval for each pollutant. 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.

2.2.2. Weather data

Weather data were obtained from Met Office Integrated Data Archive System (MIDAS) dataset for three monitoring stations within Greater London (Met Office, 2022). Hourly weather observations for pressure, humidity, rainfall, wind speed, cloud cover and temperature are averaged across stations and over flexible 24-h 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 95 observations (0.6 %) for which at least one weather variable is missing.

[4] We recognize that the number of clues may reflect certain aspects of team performance, but may also be influenced by a team's willingness to explore independently or their determination to succeed autonomously, without relying heavily on external assistance, thus making it a less comprehensive measure of team performance than completion time.

2.3. Estimation

To estimate the causal effect of air pollution on team performance, we utilize a fixed effects panel regression approach. We first estimate single pollutant models separately for each pollutant:

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

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 ($CT_{grt}/\underline{CT}$). 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. P_{grt} is a continuous measure of CO, SO_2, NO_2 or PM2.5, respectively, standardised on the mean prior to analysis. 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. Summary statistics of game and team characteristics are provided in the Online Appendix (Table A1). Moreover, we utilise specific team characteristics (corporate and 'under 16′ teams) to explore heterogeneity in pollution effects on team performance.

W_{grt} represents a vector of weather controls for which we define flexible 24-h 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 (oktas). 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 h 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 of weather and pollution variables are presented in Online Appendix Table A2.

δ_r are room fixed effects and λ_{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. To account for potential within-room serial correlation in a given month, standard errors are clustered at the room-month-year level.

To explore non-linear effects of pollution exposure on team performance, we modify Eq. (1) by replacing the continuous measure of pollution with a set of indicators corresponding to four equally sized pollution bins, following the extant literature (see e.g. He, Liu, & Salvo, 2019; Heyes et al., 2019). The bins for each pollutant are presented in Online Appendix Table A3, with the lowest bin serving as the reference category.

Finally, to model the effect of simultaneous exposure to multiple pollutants at high levels we estimate a multi-pollutant model following Archsmith et al. (2018):

$$CT_{grt} = \beta_0 + \beta_1 P_{grt} + \beta_2 W_{grt} + X_{grt} + \delta_r + \lambda_{rt} + \varepsilon_{grt} \tag{2}$$

In Eq. (2), P_{grt} represents a vector of pollution variables specific to game g, including indicators for CO (1-h) > 0.75 mg/m^3, SO_2 (3-h) > 7.5 μg/m^3, NO_2 (3-h) > 75 μg/m^3, PM2.5 (24-h) > 37.5 μg/m^3.[5] The base category contains all observations which were not subject to elevated pollution levels. Estimating a multipollutant model allows us to disentangle the effect of individual pollutants within their respective timeframes.

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.[6] 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.

Our identification strategy thus closely follows previous research exploring the relationship between air pollution and productivity (Chang et al., 2019; Heyes et al., 2019; Huang et al., 2020). To ascertain that our results are not driven by measurement error, we additionally conduct an instrumental variable analysis. We use atmospheric temperature inversion strength to instrument pollution exposure, the prevalent approach in the literature (e.g. Sager, 2019). Details are provided in Section C of the Online Appendix.

[5] The pollution thresholds used in the multipollutant model identify games which were played during high-pollution episodes (i.e. pollution levels that exceed the highest pollution threshold for a given pollutant. See Online Appendix Table A3).

[6] In Online Appendix Table A4, we present game and team characteristics by pollution exposure (based on our definition of extreme pollution thresholds. We find that on high pollution days, teams were slightly larger and less birthdays and more team-building games took place. Importantly, we find no difference in the days between the booking and game dates. Moreover, using the number of clues as a measure of team ability, we find no evidence of systematic avoidance behaviour between low and high-ability teams (see Online Appendix Table A5).

3. Results

Overall, we find a strong and significant adverse effect of air pollution on team performance. though the effects depend on the level and combination of pollutants. We first discuss the effect of varying levels of pollutants on team performance (Fig. 1) and then delve into the effect of high levels of multiple pollutants (Fig. 2).

Fig. 1 shows the change in completion time based on different pollution levels. We find that a one standard deviation increase in pollution levels leads to small but significant increases in completion time. Slightly larger estimates are obtained when instrumenting pollution with atmospheric temperature inversions, indicating that a one standard deviation increase in pollution levels leads to an approximate increase in completion time of 1–1.5 %, significant at the 5 % level (see Online Appendix Table C1).

Next, we follow the extant literature and divide the pollutants into different, evenly-sized thresholds to study non-linear effects (Heyes et al., 2019). For all pollutants, we find a step-change in the effect of pollution on completion times (Fig. 1). High levels of pollution (e.g., >0.75 mg/m^3 for CO) lead to a robust and significant increase of 1–2 % in completion time, significant at the 1 % level. For CO and SO_2 these thresholds are still far below the WHO thresholds (4 mg/m^3 and 40 μg/m^3, respectively), but we already find adverse effects on completion time. For NO_2 and PM2.5 substantial negative effects on pollution exposure occur only at levels which exceed WHO standards (25 μg/m^3 and 15 μg/m^3, respectively), which, however, remain commonplace in many developing countries (World Health Organization, 2021).

Finally, we estimate a multipollutant model with indicators for the four highest pollution thresholds from Fig. 1 (e.g., CO > 0.75 mg/m^3). The left panel in Fig. 2 shows the individual effects of each pollutant on completion time from the multipollutant model, and the right panel the change in completion time for the highest pollution thresholds of various pollutant combinations. Individually, high levels of CO and PM2.5 and exhibit the strongest increase in completion time, followed by SO_2 and NO_2. A similar pattern is obtained from only analysing teams that came for team building exercises, typically from a corporate background. For these teams, only PM2.5 appears to be particularly detrimental for team performance. Finally, we explore the effect of pollution on team performance by group size, using the full sample. Here, we find that the effect observed in the full sample appears to be driven by larger teams (five or six players), while we find no significant effects on teams with four or fewer players (see Table A9). However, as team size is not randomly assigned, these estimates should thus be interpreted cautiously.

We use estimates of Eq. (2) to compute the expected increase in completion time for different combinations of pollutants crossing

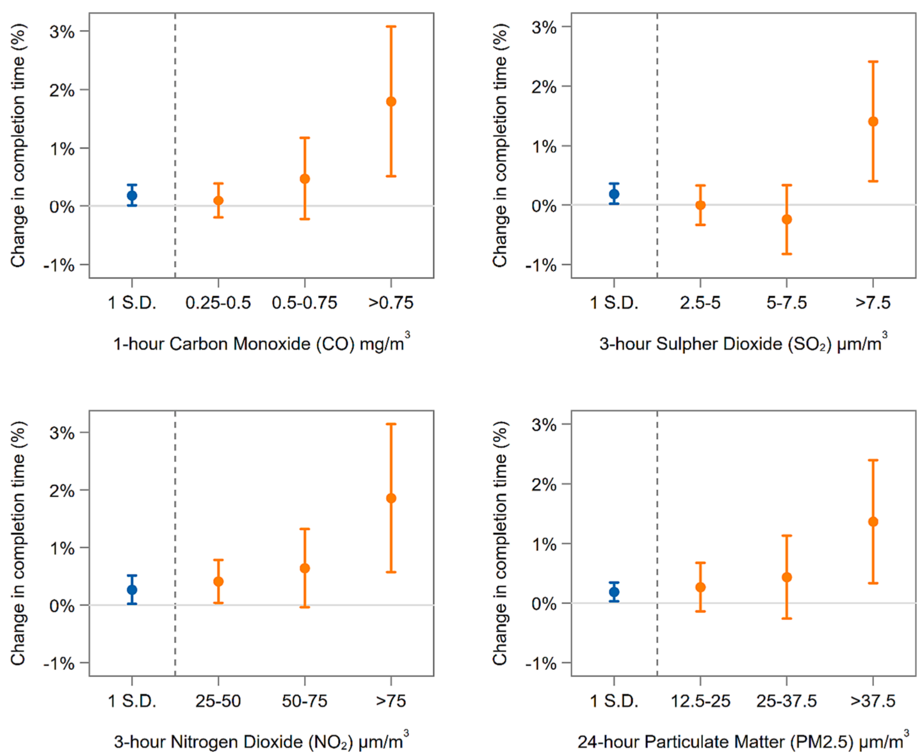

Fig. 1. Main Results – Linear and non-linear effects of pollution on team performance. Note: The left panel of each graph depicts the linear effect of a one standard deviation increase in pollution on team performance (Eq. (1)) for the respective pollutant (N = 15,397). The right panel of each graph depicts the non-linear effect of pollution on team performance for three pollution exposure bins, relative to levels below the lower bound specified for each pollutant. The dependent variable is completion time as a percentage of average completion time. Standard errors are clustered at the room-month-year level. Error bars indicate 95 % confidence intervals. Full regression outputs are provided in Online Appendix Tables A6 and A7.

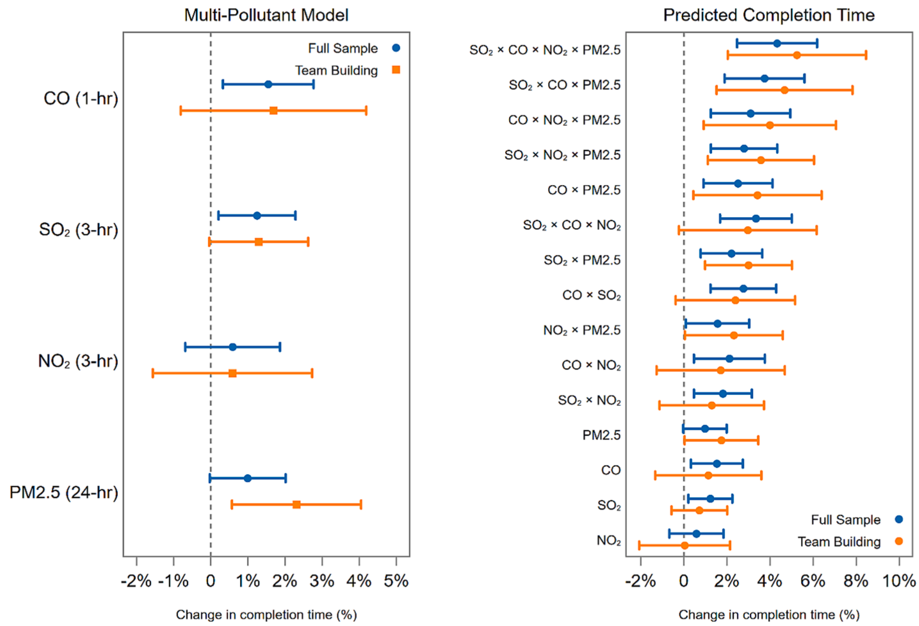

Fig. 2. Multi-pollutant model estimates and predicted pollution burden. Note: The left panel presents OLS estimates of Eq. (2) for each pollutant indicator using the full sample (N = 15,397). The dependent variable is completion time as a percentage of average completion time. The right panel displays the predicted increases in completion time under different combinations of pollution exposure exceeding the highest pollution threshold for the full sample (N = 15,397) and a subsample of team-building games (N = 3,454). Standard errors are clustered at the room-month-year level. Error bars indicate 95 % confidence intervals. Full regression outputs are provided in Online Appendix Table A8.

the highest threshold (Fig. 2, right panel). We find that the highest levels of multiple pollutants leads to a substantial increase in completion time by up to 5 %. The results are robust to only analysing teams that came for team building exercises, typically from a corporate background. In more than 11 % of observed days, at least one pollutant crosses the highest 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 would increase by up to 4 % in the full sample (including diverse sets of participants) and up to 5 % in a subsample that only includes firm groups that participate for team-building purposes. The latter subsample comprises around 3,454 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). In contrast, we find no significant effect of pollution on younger teams (under the age of 16), the sub-group least representative of the modern working environment, thus reaffirming our previous findings (see Online Appendix Table A8).

Section B of the Online Appendix presents additional robustness and falsification checks. Our main results derived from the multipollutant model are robust to a range of alternative weather variables specifications (Table B1), and a series of falsification checks which artificially manipulate pollution exposure along the temporal dimension suggest that our main analysis is accurately capturing the true effects of acute pollution exposure (Table B2).

4. Discussion and conclusion

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 the performance of teams undertaking complex, collaborative, and non-routine problem solving tasks. Our results indicate that all four pollutants lead to significant negative effects on team performance at levels which are much lower than current WHO thresholds for two pollutants studied (CO and SO_2).

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 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 (La Nauze & Severnini, 2021; Shehab & Pope, 2019). 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 (Lohmann, Gsottbauer, You, & Kontoleon, 2023; Zhang, Zhang, & Chen, 2017; Zheng, Wang, Sun, Zhang, & Kahn, 2019), which in turn may directly stifle creative thinking (Davis, 2009) or inhibit teamwork by increasing risk aversion and lowering pro-sociality (Chew, Huang, & Li, 2021). Additionally, other research has revealed that environmental factors such as temperature also play a crucial role in human performance, emphasizing the importance of considering multiple environmental stressors in understanding team dynamics and worker productivity (e.g., Cui, Cao, Park, Ouyang, & Zhu, 2013; Krause, Brandt, Schmidt, & Schunk, 2023; Obradovich, Tingley, & Rahwan, 2018).

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 (World Bank, 2022). 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. Finally, our policy implications align with studies on willingness to pay (WTP) for clean air, which emphasize the potential welfare gains from implementing more stringent air quality regulations (Ito & Zhang, 2020; Zhang & Qin, 2021).

CRediT authorship contribution statement

Paul M. Lohmann: Conceptualization, Methodology, Formal analysis, Visualization, Writing – original draft. **Benedict Probst:** Conceptualization, Methodology, Writing – original draft. **Elisabeth Gsottbauer:** Conceptualization, Methodology, Writing – original draft; **Andreas Kontoleon:** Conceptualization, Methodology, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

We would like to thank Eszter Lantos, Zoltan Papp and the team at clueQuest Ltd. for enabling this research by sharing their data and providing detailed information on the escape room procedures.

Funding information: N.A.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.joep.2024.102705.

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. https://doi.org/10.1086/698728

Cavalcanti, T., Mohaddes, K., Nian, H., & Yin, H. (2023). *Air pollution and firm-level human capital, knowledge and innovation* (Issue January).

Cedeño Laurent, J. G., Macnaughton, P., Jones, E., Young, A. S., Bliss, M., Flanigan, S., Vallarino, J., Chen, L. J., Cao, X., & Allen, J. G. (2021). Associations between acute exposures to PM2.5 and carbon dioxide indoors and cognitive function in office workers: A multicountry longitudinal prospective observational study. *Environmental Research Letters, 16*(9). https://doi.org/10.1088/1748-9326/ac1bd8

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

Chang, T. Y., Zivin, J. G., Gross, T., & Neidell, M. (2019). The effect of pollution on worker productivity: Evidence from call center workers in China. *American Economic Journal: Applied Economics, 11*(1), 151–172. https://doi.org/10.1257/app.20160436

Chen, H., Liu, S., Liu, X., & Wang, J. (2023). Local air pollution and corporate innovation. *Applied Economics Letters, 00*(00), 1–16. https://doi.org/10.1080/13504851.2023.2205084

Chew, S. H., Huang, W., & Li, X. (2021). Does haze cloud decision making? A natural laboratory experiment. *Journal of Economic Behavior and Organization, 182*, 132–161. https://doi.org/10.1016/j.jebo.2020.12.007

Cui, W., Cao, G., Park, J. H., Ouyang, Q., & Zhu, Y. (2013). Influence of indoor air temperature on human thermal comfort, motivation and performance. *Building and Environment, 68*, 114–122. https://doi.org/10.1016/j.buildenv.2013.06.012

Davis, M. A. (2009). Understanding the relationship between mood and creativity: A meta-analysis. *Organizational Behavior and Human Decision Processes, 108*(1), 25–38. https://doi.org/10.1016/j.obhdp.2008.04.001

DEFRA. (2022). *Department for Environment, Food and Rural Affairs, Automatic London Network – DEFRA, UK*. https://uk-air.defra.gov.uk/networks/network-info?view=aln.

Englmaier, F., Grimm, S., Grothe, D., & Schudy, S. (2021). The Value of Leadership: Evidence from a Large- Scale Field Experiment. In *CESIFO Working Paper: Vol. No. 9273* (Issue Center for Economic Studies and ifo Institute (CESifo), Munich). https://doi.org/10.5465/ambpp.2021.12714abstract.

He, J., Liu, H., & Salvo, A. (2019). Severe air pollution and labor productivity: Evidence from industrial towns in China. *American Economic Journal: Applied Economics, 11*(1), 173–201. https://doi.org/10.1257/app.20170286

Heyes, A., Rivers, N., Schaufele, B., Economics, L., Heyes, A., & Sciences, S. (2019). Pollution and politician productivity: The effect of PM on MPs pollution and politician productivity: The effect of PM on MPs S. *Land Economics, 95*(2), 157–173.

Holub, F., & Thies, B. (2022). Air quality and the productivity of high-skilled workers. *Evidence from GitHub.*, 1–84.

Huang, J., Xu, N., & Yu, H. (2020). Pollution and performance: Do investors make worse trades on hazy days? *Management Science, 66*(10), 4455–4476. https://doi.org/10.1287/mnsc.2019.3402

Ito, K., & Zhang, S. (2020). Willingness to pay for clean air: Evidence from air purifier markets in china. *Journal of Political Economy*. https://doi.org/10.1086/705554

Kahn, M. E., & Li, P. (2020). Air pollution lowers high skill public sector worker productivity in China. *Environmental Research Letters, 15*(8). https://doi.org/10.1088/1748-9326/ab8b8c

Krause, J. S., Brandt, G., Schmidt, U., & Schunk, D. (2023). Don't sweat it: Ambient temperature does not affect social behavior and perception. *Journal of Economic Psychology, 99*(June). https://doi.org/10.1016/j.joep.2023.102657

Krebs, B., & Luechinger, S. (2022). *Air Pollution, Cognitive Performance, and the Role of Task Proficiency*. *September 2021*.

Künn, S., Palacios, J., & Pestel, N. (2023). Indoor air quality and strategic decision making. *Management Science*. https://doi.org/10.1287/mnsc.2022.4643

La Nauze, A., & Severnini, E. (2021). Air pollution and adult cognition: evidence from brain training. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3846697
Lichter, A., Pestel, N., & Sommer, E. (2017). Productivity effects of air pollution: Evidence from professional soccer. *Labour Economics, 48*, 54–66. https://doi.org/10.1016/j.labeco.2017.06.002
Lohmann, P. M., Gsottbauer, E., You, J., & Kontoleon, A. (2023). Air pollution and anti-social behaviour: Evidence from a randomised lab-in-the-field experiment. *Social Science and Medicine*, *320*(February 2022), 115617. https://doi.org/10.1016/j.socscimed.2022.115617.
Met Office. (2022). *MIDAS Open: UK hourly weather observation data. NERC EDS Centre for Environmental Data Analysis*.
Mo, J., Wu, Z., & Yuan, Y. (2023). Air pollution kills competition: Evidence from eSports. *Journal of Environmental Economics and Management, 122*(June), Article 102886. https://doi.org/10.1016/j.jeem.2023.102886
Obradovich, N., Tingley, D., & Rahwan, I. (2018). Effects of environmental stressors on daily governance. *Proceedings of the National Academy of Sciences of the United States of America, 115*(35), 8710–8715. https://doi.org/10.1073/pnas.1803765115
Probst, B., Touboul, S., Glachant, M., & Dechezleprêtre, A. (2021). Global trends in the invention and diffusion of climate change mitigation technologies. *Nature Energy, 6*(11), 1077–1086. https://doi.org/10.1038/s41560-021-00931-5
Sager, L. (2019). Estimating the effect of air pollution on road safety using atmospheric temperature inversions. *Journal of Environmental Economics and Management, 98*(251), Article 102250. https://doi.org/10.1016/j.jeem.2019.102250
Sarmiento, L. (2022). Air pollution and the productivity of high-skill labor: Evidence from court hearings*. *Scandinavian Journal of Economics, 124*(1), 301–332. https://doi.org/10.1111/sjoe.12458
Shehab, M. A., & Pope, F. D. (2019). Effects of short-term exposure to particulate matter air pollution on cognitive performance. *Scientific Reports*, *June 2018*, 1–10. https://doi.org/10.1038/s41598-019-44561-0.
Wang, C., Lin, Q., & Qiu, Y. (2022). Productivity loss amid invisible pollution. *Journal of Environmental Economics and Management*, *112*(March 2021), 102638. https://doi.org/10.1016/j.jeem.2022.102638.
World Bank. (2022). *The Global Health Cost of PM2.5 Air Pollution : A Case for Action Beyond 2021. International Development in Focus*. https://openknowledge.worldbank.org/handle/10986/36501.
World Health Organization. (2021). *WHO global air quality guidelines: particulate matter (PM2.5 and PM10), ozone, nitrogen dioxide, sulfur dioxide and carbon monoxide*.
Zhang, N., & Qin, B. (2021). Do buyers and sellers evaluate air pollution reduction differently? Experimental evidence from China. *Journal of Economic Psychology, 87*(November), Article 102460. https://doi.org/10.1016/j.joep.2021.102460
Zhang, X., Zhang, X., & Chen, X. (2017). Happiness in the air: How does a dirty sky affect mental health and subjective well-being? *Journal of Environmental Economics and Management, 85*, 81–94. https://doi.org/10.1016/j.jeem.2017.04.001
Zheng, S., Wang, J., Sun, C., Zhang, X., & Kahn, M. E. (2019). Air pollution lowers Chinese urbanites' expressed happiness on social media. *Nature Human Behaviour, 3*(March). https://doi.org/10.1038/s41562-018-0521-2
Zivin, J. G., & Neidell, M. (2018). Air pollution's hidden impacts. *Science, 359*(6371), 39–40. https://doi.org/10.1126/science.aap7711