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Air pollution and anti-social behaviour: Evidence from a randomised lab-in-the-field experiment ☆

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ABSTRACT

We conducted a pre-registered randomised lab-in-the-field online experiment in Beijing, China, to explore the relationship between acute air pollution and anti-social behaviour. Our novel experimental design exploits naturally occurring discontinuities in pollution episodes to mimic an experimental setting in which pollution exposure is exogenously manipulated, thus allowing us to identify a causal relationship. Participants were randomly assigned to be surveyed on either high pollution or low pollution days, thereby exogenously varying the degree of pollution exposure. In addition, a subset of individuals surveyed on the high-pollution days received an additional 'pollution alert' to explore whether providing air pollution warnings influences (protective) behaviour. We used a set of well-established incentivised economic games to obtain clean measures of anti-social behaviour, as well as a range of secondary outcomes which may drive the proposed pollution-behaviour relationship. Our results indicate that exposure to acute air pollution had no statistically significant effect on anti-social behaviour, but significantly reduced both psychological and physiological well-being. However, these effects do not remain statistically significant after adjusting for multiple hypothesis testing. We find no evidence that pollution affects cognitive ability, present bias, discounting, or risk aversion, four potential pathways which may explain the relationship between pollution and anti-social behaviour. Our study adds to the growing calls for purposefully designed and pre-registered experiments that strengthen experimental (as opposed to correlational or quasi-experimental) identification and thus allow causal insights into the relationship between pollution and anti-social behaviour.

1. Introduction

Air pollution is a growing global health concern and its adverse and, in many instances, lethal effects are widely documented (Arceo et al., 2016; Currie and Neidell, 2005; Kampa and Castanas, 2008; Lelieveld et al., 2015; Pope et al., 1995, 2020; Schlenker and Walker, 2016). In addition to acute harm, usually manifested by respiratory or cardiac symptoms, air pollution potentially harms every organ in the body, including the brain (Schraufnagel et al., 2019). An emerging literature in economics shows that air pollution is associated with a range of economic and behavioural outcomes (Lu, 2020; Zivin and Neidell, 2018). For instance, air pollution has been found to adversely impact human capital formation, including worker and firm productivity and educational outcomes (Chang et al., 2019, 2016; Currie et al., 2009; Ebenstein et al., 2019; He et al., 2019; Heyes et al., 2019; Lohmann et al., 2022; Zivin and Neidell, 2012, 2018). Studies have also shown that higher daily air pollution levels are positively associated with observed criminal activity, suggesting a direct link between pollution exposure

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and unethical behaviour (Bondy et al., 2020; Burkhardt et al., 2019; Chalfin et al., 2019; Gong et al., 2020; Herrnstadt et al., 2021; Lu et al., 2020, 2018; Zou, 2021). Identifying this causal relationship and its mechanisms is the central focus of this paper, whereby we address two challenges encountered in the existing literature.

The first challenge in the existing literature exploring the impact of pollution on social behaviour is the identification of a causal effect. Most of the previous literature has thus relied on ex-post analyses employing quasi-experimental research designs (Baryshnikova et al., 2019; Lu et al., 2020, 2018; Mapou et al., 2017; Singh and Visaria, 2021). Quasi-experimental studies have many advantages and strengths when compared to experimental or randomized control trials, including their ability to control for a battery of explanatory variables and fixed effects. Further, they often exploit large high-quality administrative datasets instead of relying only on data from smaller experimental trials on non-representative samples, which may suffer from low generalizability issues. However, quasi-experimental designs cannot adequately purge important (and often unobserved) confounders such as the surrounding policy and policing environment and how air pollution is subjectively perceived by individuals. It is also worth noting that quasi-experimental studies typically prohibit the investigation into specific (psychological) mechanisms underlying observed relationships between pollution and certain behavioural outcomes and can, thus, be thought of as complementary to experimental trials that are able to focus on such mechanisms.

In contrast to the quasi-experimental setting, lab experiments allow exogenous manipulation of the degree of air pollution to which participants are exposed. While similar studies have been conducted with respect to other environmental stressors, including thermal stress (Almås et al., 2019) and noise pollution (Dean, 2019), exposing individuals to high levels of air pollution would entail serious ethical concerns and potential health impacts. Nonetheless, attempts have been made to experimentally manipulate the level of air pollution exposure, for instance by burning candles in the study space (Shehab and Pope, 2019), priming participants with vivid imagery of clean versus polluted cities (Lu et al., 2018), by providing mock air purifiers for student dorm rooms (Li et al., 2017) or by exposing individuals to diesel exhaust (Crüts et al., 2008). However, these methods cannot guarantee sufficiently large variation in exposure (or perceived exposure) to air pollution or are ethically questionable.

More recently, research has linked air pollution measurements with behavioural outcomes obtained from "natural laboratory settings" matching the individuals' experimental data from the lab (or similar controlled settings) to the air quality of the survey day (Bedi et al., 2021; Chew et al., 2021). This allows for both stronger identification of exogenous changes of pollution to individual behaviour – without the aforementioned ethical concerns – and direct investigation into transmission channels. The study most comparable to ours is Chew et al. (2021) who use data from a set of incentivised laboratory experiments which were conducted during and after an extreme pollution episode in 2012. The authors explore a series of economic and social decision-making outcomes, including risk and ambiguity aversion, pro-social behaviour and cooperation. However, the study is not based on a pre-registered protocol designed for the specific purpose of assessing the impact of air pollution on (anti-)social behaviour and has two main limitations. Firstly, the allocation of subjects into the various experimental sessions is not randomised and subject to possible (pollution induced) endogenous sorting, as some participants might have avoided travelling to the experimental laboratory on polluted days. This brings into question the robustness of their identification strategy, leading to potentially biased treatment effect estimates. Further, the experiments used to measure social behaviour in Chew et al. (2021) are standard ultimatum and public goods games. While their findings add to our understanding of preferential and behavioural responses to different levels of air pollution, the study does not directly measure unethical or antisocial behaviour, nor does it allow an exploration of potential psychological mechanisms.

The second main challenge in the relevant literature, that we address in this paper, is to isolate potential mechanisms behind the relationship between air pollution and anti-social behaviour. Both physiological and psychological pathways may be at play. With respect to physiological channels, research suggests that due to their small size, ultrafine particulate matter smaller than 2.5 μm (PM2.5) can directly enter the brain (Boda et al., 2020; Kilian and Kitazawa, 2018; Power et al., 2016; Thomson, 2019) where they can trigger oxidative stress and systemic inflammation which consequently raises stress hormone levels (Costa et al., 2014; Li et al., 2017). From a physiological perspective, elevated stress hormone levels may be associated with a range of detrimental behavioural outcomes, which in turn might influence social behaviour. For instance, air pollution might affect decision-making via its negative impact on emotional well-being, state anxiety and mental health (Chen et al., 2018b; Khan et al., 2019; Li et al., 2019; Lu et al., 2020; Sass et al., 2017; Zeng et al., 2019; Zhang et al., 2017) and/or cognitive ability (Archsmith et al., 2018; Chen, 2019; Lai et al., 2022; Shehab and Pope, 2019; Steffen et al., 2019; Zhang et al., 2018). Others have suggested that air pollution induced elevated stress hormone levels (Li et al., 2017) may temporarily change people's discount rate (Bondy et al., 2020) and risk aversion (Chew et al., 2021; Heyes et al., 2016; Klingen and van Ommeren, 2022), which in turn may lead to changes in criminal activity (Bondy et al., 2020).

From a psychological perspective, the subjective perception of air pollution may be sufficient to induce anxiety and concern about one's health, well-being and future, which may lead to similar detrimental behavioural outcomes and ultimately affect social behaviour (Gong et al., 2020; Li and Zhou, 2020; Lu et al., 2018).

In this study, our goal is to advance economic experimental research on the effects of air pollution on anti-social behaviour by introducing a novel experimental design that addresses both aforementioned challenges. First, our pre-registered study was specifically designed to exploit naturally occurring discontinuity in pollution on both high and low-pollution days in Beijing, China, where we administered the experimental (online) survey to a sample of university students. Second, we utilise a set of well-established incentive-compatible economic games to obtain measures for (anti)-social behaviour as our primary outcomes. The games used in our study are specifically designed to rule out alternative motives for anti-social behaviour and thus allow us to study fundamental aspects of decision-making, independent of contextual factors (as is the case in studies that rely for example on crime data). In addition, we also collect a range of secondary outcomes, which may constitute potential mechanisms. Here we employed incentivised tasks to measure cognitive ability, risk and time preferences. We also assessed self-reported depressive symptoms, momentary emotions, and self-control. Finally, we explore whether providing air-pollution warnings or alerts can change behaviour to assess the efficacy of providing such information as a potential remedy to mitigate the negative impact of air pollution exposure.

Our study makes multiple contributions to several strands of economic literature. From a methodological standpoint, we contribute to an emerging literature which utilises controlled experimental settings to explore the impact of environmental stressors on economic behavioural measures (Almås et al., 2019; Bedi et al., 2021; Chew et al., 2021; Dean, 2019). In contrast to previous studies, we are not limited to conducting our research within an experimental laboratory type of environment, but introduce an experimental design that combines elements of a lab-in-the-field experiment with data collection done via social media channels (Gneezy and Imas, 2017). This provides us with the needed flexibility to survey participants on specific days when pollution episodes are occurring without requiring participants to travel to a certain location and thereby potentially introducing endogenous attrition. Additionally, in our experiment, individuals are randomly assigned to either take part in our online study during low or high-pollution exposure, which provides clean experimental variation and hence allows us to identify a causal effect.

In addition to methodological advancements, the findings from this study contribute to the broader literature on how anti-social behaviour is impacted by environmental stressors such as extreme weather events, temperature or air pollution (Bondy et al., 2020; Burkhardt et al., 2019; Cane et al., 2014; Goin et al., 2017; Gong et al., 2020; Heilmann et al., 2021; Herrnstadt et al., 2021; Lu et al., 2020, 2018). Furthermore, our findings contribute to our understanding of mechanisms, i.e. whether the effects of air pollution on economic and behavioural outcomes are of psychological or physiological nature (Fehr et al., 2017; Gong et al., 2020). Finally, we also study the provision of air quality information and thus link to the literature on air pollution communication campaigns and their effects on avoidance and protective behaviour (Saberian et al., 2017; Sexton Ward and Beatty, 2016).

We find that while subjects exposed to high-pollution levels display slightly more anti-social behaviour on average, the differences are not statistically distinguishable from the control group which was surveyed on a low-pollution day. Moreover, we find no significant effect of pollution exposure on cognitive ability, present bias, temporal discounting and risk aversion, which may constitute potential mechanisms through which pollution impacts social behaviour. Nonetheless, we find some heterogeneity with respect to effects on anti-social behaviour. In an exploratory analysis we provide indicative evidence that anti-social behaviour increases, and altruism decreases for individuals who perceived the pollution episode to be extremely severe. These findings contribute to our understanding of whether the effect of pollution on behaviour is more psychological rather than physiological.

With respect to health and well-being outcomes, we find that acute exposure to air pollution significantly decreases self-reported positive affect and increases the likelihood of reporting physical health symptoms. These findings highlight the immediate short-term detrimental health effects of pollution exposure for both psychological and physiological well-being. However, they must be interpreted with caution, as the effects are no longer significant after adjusting for multiple hypothesis testing. Finally, we find that providing a pollution alert via direct message had no significant effect on protective behaviour.

2. Research hypotheses

In this section, we briefly summarize findings from prior literature and use these to formulate a set of testable hypotheses for our analysis.

Previous research has linked pollution with aggressive and criminal behaviour (Herrnstadt et al., 2021) using quasi-experimental research designs. This is in line with research that shows that, besides pollution, other environmental stressors such as heat can also increase aggressive behaviour and violence (for an overview, see Anderson (2001)). Almås et al. (2019) is the only experimental trial, which experimentally manipulates heat exposure (i.e., thermal stress) to study the effect of heat on social behaviour and economic preferences. They find mixed results. While heat significantly affects individuals' willingness to destroy other participants assets in a standardized task, the authors do not find any other dimensions of economic decision-making or cognition to be significantly affected by thermal stress. Based on these results, we formulate the following hypothesis:

Hypothesis 1. Air pollution increases anti-social behaviour.

As criminal or anti-social acts are frequently linked to more risky action, we also assess the relationship between pollution and risk taking. Prior quasi-experimental studies provide mixed results: while Heyes et al. (2016), Chew et al. (2021) and Klingen and van Ommeren (2022) find higher levels of risk aversion on more polluted days, Bondy et al. (2020) find no evidence of air pollution impacting lottery sales (as proxy for risk taking behaviour) yet indicate that discount rates might be affected. Experimental trials on the effect of other stressors such as heat exposure (Almås et al., 2019) and scarcity (Carvalho et al., 2016) on risk and time preferences find no evidence of these stressors on the willingness to take risk and on discounting (i.e., time preferences). We thus proceed to test the following hypothesis:

Hypothesis 2. Air pollution increases risk aversion, present bias and temporal discounting.

Furthermore, there exists a large body of quasi-experimental work on the negative impact of air pollution on well-being and mental health (for a recent evidence from China, see Chen et al. (2018a)) as well as cognitive performance (for recent evidence from China, see Zhang et al. (2018)). This extensive body of work suggests the following hypothesis:

Hypothesis 3. Air pollution has a negative effect on well-being and cognitive performance.

The provision of pollution related information in the form of pollution alerts is a common policy instrument, which aims to increase behaviours to avoid pollution exposure and help protect people from its harmful effects. Previous research indicates that people do respond to such alerts in the intended manner (e.g. Graff Zivin and Neidell, 2009; Neidell, 2009). For instance, Sun et al. (2017) find that Chinese households respond to pollution alerts by increasing the purchase of protective items such as masks and filters. Hanna et al. (2021) is the only experimental trial evaluating the impact of air quality information provided via SMS on avoidance behaviour and show that while alerts do increase avoidance behaviour, participant's perception of high pollution is a more reliable predictor of behaviour change than alerts.

Hypothesis 4. Pollution alerts increase protective and avoidance behaviours, thereby mitigating its harmful effects.

3. Research design

We conducted a novel lab-in-the-field experiment where we randomly assigned participants to be surveyed on high and low-pollution days in a between-subject design, exploiting rapidly occurring natural discontinuities in air pollution episodes. While a longitudinal design would have had the benefit of controlling for time-invariant unobserved individual-level factors, the between-subject design employed in our study minimises the potential threat of bias arising from unobserved time-varying contextual factors and learning effects (i.e. participants becoming accustomed to the games). The study was pre-registered at the AEA RCT Registry under the reference number 0004856: Gsottbauer, Elisabeth et al. 2021. "The Causal Effect of Air Pollution on Anti-social Behaviour." AEA RCT Registry. https://doi.org/10.1257/rct.4856. See SI Appendix Section 1.5 for more information on the pre-registration.

3.1. Recruitment

Recruitment took place in October 2019 on the campus of Renmin University in Beijing and through online social-media channels, targeting university students from any discipline currently enrolled in either undergraduate or postgraduate degrees at any university located in Beijing. The study was advertised as a generic 'Decision-Making-Study' and no link to the topic of 'air pollution' was made. After providing informed consent, participants completed an initial baseline survey, for which they were rewarded 10 Yuan. The primary objective of the baseline survey was to build a subject pool for our experiment and capture basic socio-demographic information and specific baseline preferences. Participants were notified that they would be contacted again later in the semester to complete a further survey. Moreover, to incentivise participation, participants were informed that if they completed all surveys, they would be eligible to participate in a prize draw of 100 Yuan to be awarded a selected number of students.

Table 1
Experimental treatments.

Alert	Air Pollution	
	Low	High
No	Low-P (Control Group)	High-P (Treatment 1)
Yes	-	High-P-Alert (Treatment 2)

3.2. Sample and randomisation

In total, 793 participants completed the baseline survey. Of these, 45 respondents were excluded as their university was not located in Beijing, or they were currently not in Beijing (e.g., on exchange) or they could not be re-contacted via WeChat by our research assistants. The main experiment relies therefore on a sample of 748 students. Treatment assignment was conducted using a stratified sample and re-randomisation procedure. Participants were stratified by gender, university cluster, year of study, Hukou status and perceived air pollution health tolerance across treatments groups in a between-subject design. Universities were clustered by geographic location within Beijing into North, Central and South. Hukou status refers to whether the participant's household origin is registered as rural or urban in accordance with China's family residence registration system. Perceived air pollution health tolerance was based on the question "Do you think air pollution affects your health?", measured on a five-point scale ('Not at all' to 'Very much'). Within each stratum, every third student was assigned to a given treatment or control group. Randomisation was re-run until balance was achieved for a pre-specified set of control variables deemed important for the study. These included basic demographic and health measures, baseline social preferences following Fehr et al. (2002), cooperation (hypothetical investment in a public goods game), perceptions specific to air pollution in Beijing, the participant's hometown and their current place of residence. A detailed overview of all variables used for balance checks can be found in SI Appendix, Section 3, Table 6.

As specified in our pre-registration, subjects were randomly assigned to one of three experimental conditions: (1) a low pollution [Low-P] control group, (2) a high pollution [High-P] group and (3) a high pollution alert [High-P-Alert] group which received a pollution warning 24-hours prior to the survey. The latter treatment was introduced to experimentally assess the efficacy of providing pollution alerts via direct message on days with objectively high levels of air pollution (see SI Appendix, Section 5 for the exact message content). Specifically, we sought to understand whether alerts significantly influence how pollution is perceived, which in turn could encourage protective behaviours against exposure or directly impact social and economic decision-making. Table 1 provides a summary of the experimental treatments.

3.3. Exposure to air pollution and timeline

Our study exploits naturally occurring variation in air pollution by carefully selecting high-pollution and low-pollution episodes for data collection purposes. Natural variation in air pollution is common in Beijing, especially during the winter-heating period from mid-November to mid-March (Xiao et al., 2015). Pollution episodes generally occur over a series of consecutive days with light southerly winds which transport pollution emitted from industrial compounds into the city and are often amplified by thermal inversions, which are meteorological phenomena where abnormal temperature profiles in the atmosphere trap air pollution near to the ground (Sager, 2019). Such episodes generally come to an abrupt end with the onset of strong winds from north-westerly direction, clearing out the air pollution.

Data were collected on three carefully selected days in December 2019 guided by pre-defined criteria for objective pollution concentrations, weather conditions and the day of the week (see SI Appendix Section 1.1 for details). The primary criterion was the predicted level of air pollution, guided by the categorisation of the official Air Quality Index (AQI) which classifies pollution into one of six categories increasing in severity and health impact (see Figure 1 in the SI Appendix). A forecasted AQI exceeding 'Very Unhealthy' levels of pollution (AQI $>$ 200) was selected to trigger the survey for participants in the 'High-P' groups, whereas an AQI forecast in the 'Good' range (AQI $<$ 50) would be used to determine days to survey the 'Low-P' control group.

Fig. 1 shows the experimental timeline and objective pollution levels. High-pollution groups were surveyed during two pollution episodes, for which forecasts predicted 'very unhealthy' pollution concentrations. In practice, only the first pollution episode reached 'very unhealthy' levels (mean AQI of 245), while the second pollution episode was less severe and classified as 'Unhealthy for sensitive groups', during the 7-hour sampling window (mean AQI of 105). However, we feel confident to also classify the second pollution episode as 'high pollution' given that an AQI of 100 is considered an important public health threshold in many legislations (e.g. the EPA in the USA or the EEA in the EU). Participants in the low-pollution group were subsequently surveyed when pollution levels were objectively "good" (mean AQI of 23). Official pollution levels were verified with measurements from our own indoor pollution monitor located on the campus of Renmin University, which produced slightly higher average values. Tables 2 and 3 in the SI Appendix provides an overview of the number of participants and pollution exposure by treatment group. In addition, we refer to section 1.2 in the Appendix for further details on the timeline.

3.4. Survey procedures and outcome measures

Participants were invited to complete the survey via an online messenger (WeChat) during a pre-specified window (5pm to 1am) and were additionally notified 24-hours in advance about the upcoming survey (alongside a pollution warning for the alert group).

Our experimental survey consisted of three experimental modules, a health and well-being questionnaire and a debriefing questionnaire. To encourage truthfulness and effort, all decision-making tasks were incentivised so that payoff depended on the participants choices. On average, participants took 30 minutes to complete the experimental survey (SD = 19 min).

Module I included three well-established experimental games to assess (anti)social behaviour: a joy of destruction game, which provides a measure of nasty behaviour (Abbink and Herrmann, 2011). In this two-player game, participants are anonymously matched in pairs and then face the binary decision whether to destroy their assigned partner's endowment by half at an own cost or maintain the status quo. The main outcome variable obtained from this game is the binary decision of whether to destroy half of the other player's endowment a take game with and without deterrence (Schildberg-Hörisch and Strassmair, 2012) which provides a measure of covert anti-social behaviour in the form of stealing or theft. In this two-player game, participants are anonymously matched and provided unequal endowment. Participants then decide whether to take from the other player's initial endowment; and a third-party punishment game, which included a dictator game donation decision as a measure for pro-social behaviour and a third-party sanction decision as a measure for the willingness to enforce for distribution norm via punishment (Fehr and Fischbacher, 2004). From this game, we obtained two primary outcomes: an incentivised measure of giving from the dictator game, as a measure of pro-social behaviour under observability, and the amount punished if the assigned dictator transfers zero. Note that those games are commonly used in the experimental literature to measure dimensions of (anti)-social or criminal behaviour and enforcement of inappropriate behaviour (Almås et al., 2019; Friehe and Schildberg-Hörisch, 2017; Prediger et al., 2014). In all three decision tasks, respondents' choices have an impact on their own payoff as well as their matched player's payoff, who would be determined after the completion of the survey. Participants were informed that their behaviour would have real financial consequences for their matched

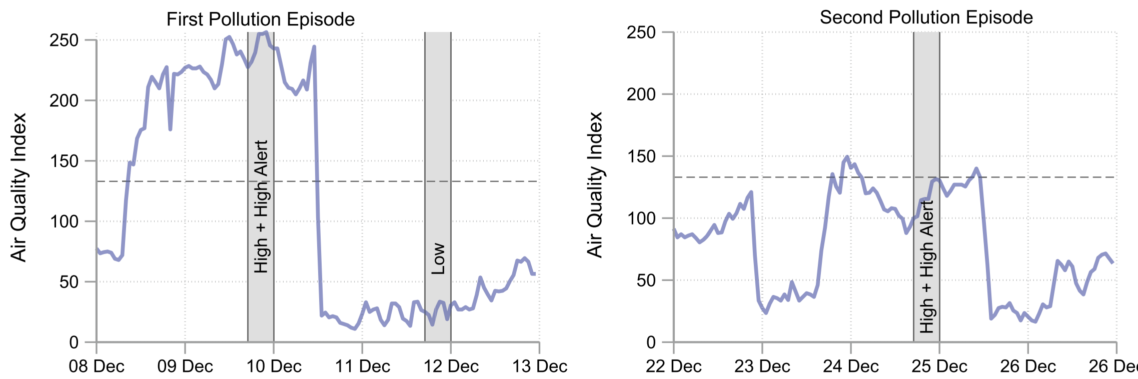

Fig. 1. Pollution Episodes – Sampling Periods. *Note:* Dashed line shows annual average $AQI = 133$.

player, and payoffs were adjusted corresponding to one randomly selected decision made in this module.

Module II was designed to elicit standard risk and time preferences using a lottery choice task (Eckel and Grossman, 2002) and a convex time budget (CTB) task (Andreoni et al., 2015). Participants made one decision in the lottery choice task and 24 decisions in the CTB task. To increase the stakes, but remain within our budget, participants were informed that 30 respondents would be selected at random and one of their choices from Module II would be selected at random to determine the pay-off for that part of the survey.

Module III assessed participant's cognitive functioning and psychological well-being. Participants first completed a set of Raven's Matrices (or puzzles) and a Numerical Stroop Task to assess cognitive ability and self-control. In both tasks, correct answers were financially rewarded to incentivise effort. The remaining questions in Module III were non-incentivised self-report measures of physiological and psychological well-being. We utilised clinically verified multi-item scales which are commonly used in the psychological literature including momentary ego-depletion, positive and negative affect, depressive symptoms, sleep quality and physical health symptoms.

An overview of all modules, tasks and how outcome measures were constructed can be found in SI Appendix Section 1.4 and SI Appendix Table 9. Translated instructions are provided in the online SI Experimental Protocol. Screenshots of all incentivised experimental decision tasks in original language are provided in the online SI (Decision Tasks).

3.5. Incentives

Every participant received a "show up fee" of 10 Yuan (= £1.10) for completing the study. In addition, a bonus payment was determined by one randomly selected decision from Module I, one randomly selected decision from Module II (risk or time) and the number of correct choices made in the cognitive ability tasks. Moreover, once all data collection was completed, 10 participants were selected at random to receive a bonus of 100 (£11.13) Yuan for completing both the baseline and experimental surveys. Once the final payoff had been calculated, participants received the money via WeChat's built-in money transfer tool (WeChat Transfer) on the following day. Time preferences payments from Module II were delivered according to the time schedule indicated in the selected decision task. Participants received an average bonus payment of 32 Yuan (=£3.70) and the maximum amount paid out was 131 Yuan (=£15.20).

3.6. Estimation

The main specification estimates the treatment effect of air pollution on the outcome of interest as follows:

$$Y_i = \beta_0 + \beta_1 High_i + \beta_2 High_i \times Alert_i + \beta_3 EP2_i + \beta_4 H_i + S_i' + \varepsilon_i \tag{1}$$

where i references individual and Y_i is the outcome of interest. $High_i$ is the treatment indicator equal to one for individuals in the High Pollution treatment group; $Alert_i$ is an indicator for individuals that received an additional pollution alert message. The coefficient β_2 on the interaction term $High \times Alert_i$ thus identifies the difference between individuals in the high-pollution group that received a pollution alert and those that did not. The coefficient β_1 is the estimated difference between the low-pollution group and the high-pollution group (that did not receive an alert message). $EP2_i$ is an indicator identifying individuals that were surveyed during the less severe second pollution episode; H_i controls for baseline general health status, the only socio-demographic variable that is unbalanced across groups (see SI Appendix Section 3.7). Since the randomisation took place after stratifying on gender, university cluster, year of study, Hukou status and perceived air pollution health tolerance, we additionally control for these variables (S_i') to increases statistical precision, as recommended by Bruhn and Mckenzie (2009). Heteroscedasticity robust (Eicker-Huber-White) standard errors are computed and displayed throughout the analysis.

Finally, we address the threat of multiple hypothesis testing (MHT) and the possibility of false positives controlling for the familywise error rate (FWER) using the step-down procedure outlined in Romano and Wolf (2016), implemented in Stata using the rwolf2 command (Clarke, 2021). We group outcomes corresponding to hypotheses 1 — 3 (see Section 1.1) and compute FWER adjusted p-values for our main coefficients of interest (β_1 and β_2), respectively. We report both conventional p-values and FDR adjusted q-values in all regression output tables. The figures visualising the main results show conventional p-values and results are discussed considering both conventional and FWER-corrected p-values.

We refer the reader to SI Appendix Section 2 for more information on the estimation strategy, including further details on risk and time-preference estimation, as well as the exploratory analysis of perceived pollution (Section 4.3). In SI Appendix Section 3 (Balance) we show that our randomisation procedure was successful in achieving balance across experimental conditions and provide additional robustness checks for differential non-response.

4. Summary statistics

Table 2 presents summary statistics for all outcome variables employed in the analysis, as well as the socio-demographic characteristics of our analysis sample. In total, 632 participants completed the experimental survey within the pre-specified time frame, which serves as our analysis sample. The section on 'Social & Economic Preferences' (including Module 1 and Module 2 tasks) comprises our primary outcomes on social behaviour and secondary outcomes for risk and time preferences. With respect to anti-social behaviour, 16% of participants chose to destroy their matched player's payoff, which is slightly lower than

Table 2
Summary Statistics.

	Mean	SD	Min	Max	N
Social & Economic Preferences					
Joy of Destruction (Destroy = 1)	0.16	0.36	0.00	1.00	632
Taking (¥)	10.12	6.30	0.00	18.00	632
Taking with Detterence (¥)	9.56	6.83	0.00	18.00	632
Dictator Giving (¥)	3.94	3.45	0.00	10.00	632
Punish (Punish = 1)	0.59	0.49	0.00	1.00	632
Punishment (¥)	2.12	2.39	0.00	10.00	632
Risk Aversion (CRRA midpoint)	2.96	2.83	-0.50	6.73	632
Present Bias (β parameter)	0.92	0.20	0.00	1.00	622
Patience (δ parameter)	0.98	0.09	0.00	1.00	622
Cognition and Health					
Cognitive Ability (correct puzzles)	6.48	1.49	1.00	9.00	632
Depletion (score)	0.43	0.73	-1.40	2.40	632
Depressive Symptomns (Yes = 1)	0.67	0.47	0.00	1.00	632
Negative Affect (score)	10.36	4.27	5.00	25.00	632
Positive Affect (score)	13.21	3.41	5.00	24.00	632
Physical Health (index)	0.00	0.68	-0.37	2.73	632
General Health (scale)	3.70	0.83	1.00	5.00	632
Sleep Quality Last Night (scale)	7.48	1.81	1.00	10.00	632
Socio-demographic Characteristics					
Age	19.90	1.54	17.00	29.00	632
Female	0.78	0.42	0.00	1.00	632
Only Child	0.65	0.48	0.00	1.00	632
Rural Hukou	0.20	0.40	0.00	1.00	632
Economics/Finance Major	0.45	0.50	0.00	1.00	632
Year of Study	2.58	1.16	1.00	6.00	632
Airpollution impacts my health	3.89	0.92	1.00	5.00	632
Years living in Beijing	6.24	6.88	1.00	22.50	632

Note: Table displays the summary statistics for the analysis sample ($N = 632$). *Score* refers to variables constructed from multi-item survey measures; *scale* refers to variables constructed from single-item survey measures; *index* refers to variables combining (averaging) multiple standardised single-item variables.

the destruction rate (25.8%) of the original experiment conducted with students in Ukraine (Abbink and Herrmann, 2011). Participants took, on average, 10.12 Yuan from their counterpart and only slightly less (9.56 Yuan) if there was a risk of being detected. The average amount transferred to an anonymous partner in a dictator game decision (with observability) was 3.94 Yuan. Participants chose to spend on average 2.12 Yuan to enact punishment (multiplied by a factor of three) if the dictator transferred zero in the preceding dictator game decision, thus showing a significant willingness to enact costly punishment to enforce a pro-social norm. With respect to time preferences, the sample mean of the individual-level beta and delta parameters are 0.92 and 0.98, respectively, which are in line with previous estimates (Imai et al., 2021) and indicate a slight degree of present bias in our sample population.

The section on 'Cognition & Health' presents additional secondary outcomes in the health and cognition domain including (i) cognitive ability and depletion, (ii) emotional affect and depressive symptoms and (iii) health variables (general health, sleep quality). The majority of health outcomes were measured as scores constructed from multi-item screening questionnaires or single-item Likert scale survey instruments, and thus must be viewed within their respective response range (Min and Max). A noteworthy observation is that 67% of participants scored above the 10-point threshold on the CESD Scale, thus showing presence of depressive symptoms.

The section on 'Socio-demographic Characteristics' summarises a selection of indicators obtained from the baseline survey conducted in October 2019. We find that our final sample consists primarily of younger undergraduate students (mean age of 20 and mean year of study 2.5), was primarily from an urban household background (Hukou) and the majority of participants were female (78%). Most students were not local to Beijing, but had spent on average 6.24 years living in the city at the time of the baseline survey. Finally, we explored whether participants believed that air pollution had an impact on their health, with the majority stating that air pollution had a stronger impact (mean = 3.89).

5. Results

5.1. The effect of acute pollution exposure

We start our empirical analysis by testing whether our experimental design was successful in exposing individuals to varying degrees of air pollution while completing the survey, using a series of manipulation checks (details in SI Appendix Section 4). Fig. 2 shows that differences in pollution exposure between the low-pollution day and the two pollution episodes were substantial, based on objective AQI measurements and subjective perception of pollution.

Next, we estimate the effect of acute air pollution on social behaviour and economic decision-making. We compare the high pollution to the low pollution group, and additionally explore whether receiving a pollution alert changes behaviour of those surveyed during the pollution episodes. Fig. 3 summarises the main results. The left panel visualises the standardised treatment effect of acute exposure to high pollution levels whilst completing the survey. The right panel visualises the difference between the high pollution and the high-pollution alert groups, thus capturing the effect of receiving a pollution warning prior to completing the survey on a polluted day. We utilise all available data by pooling both pollution episodes. Estimates are obtained from equation (1) using standardised dependent variables to allow for a comparison of treatment effects in units of standard deviations across different outcomes (see SI Appendix, Section 2).

While our study design was successful in exogenously exposing individuals to varying degrees of air pollution, we find that social behaviour and economic preferences are unaffected by acute pollution exposure. We find some indication that being exposed to high pollution slightly increases anti-social behaviour in the form of increased destructive behaviour (0.09 SD or 3.4%-points) and taking (0.11 SD or 0.7 Yuan), however, the differences are not statistically distinguishable from zero. Moreover, providing an additional pollution alert appears to slightly attenuate the effect of high-pollution exposure on anti-social behaviour and leads to a statistically significant reduction in taking behaviour when there is no risk of being detected (0.22 SD or 1.4 Yuan). Yet, the effect is no longer statistically different from zero after correcting for the FWER. With respect to risk and time preferences, we observe that all estimates are close to zero and statistically insignificant, suggesting that air pollution has no effect on standard economic preferences in the risk and time dimension for individuals in our sample. For risk aversion, we find comparable null effects when using the CRRA interval (upper and lower bounds) as dependent variables in an interval regression (see SI Appendix, Table 16). For present bias and patience, our analysis of aggregate beta and delta parameter estimates suggests that there are no statistically significant differences between treatment conditions (see SI Appendix, Table 16).

Fig. 4 visualises the standardised treatment effects of air pollution exposure and receiving an alert message on cognition and health outcomes (pre-registered as secondary outcomes). We measure cognitive ability using an incentivised task and primarily rely on clinically verified multi-item screening questionnaires to assess participants' health status. Both changes in cognition and health have often been thought to explain the relationship between air pollution and economic decision-making (Chew et al., 2021). Effects are presented in standard deviation units to allow direct comparison between outcomes.

We find that acute pollution exposure had no effect on cognitive ability or self-reported depletion levels, with both estimates precisely estimated and close to zero. Turning to psychological health, we show that acute exposure to pollution reduced positive affect (0.15 SD, significant at the 5% level) and increased the likelihood of reporting depressive symptoms, yet the latter is not statistically different from zero. Moreover, pollution exposure had a detrimental effect on physical health, measured by three types of symptoms potentially related to pollution exposure (cough, sore throat and stuffy nose). Interestingly, this negative effect is reversed by approximately the same magnitude

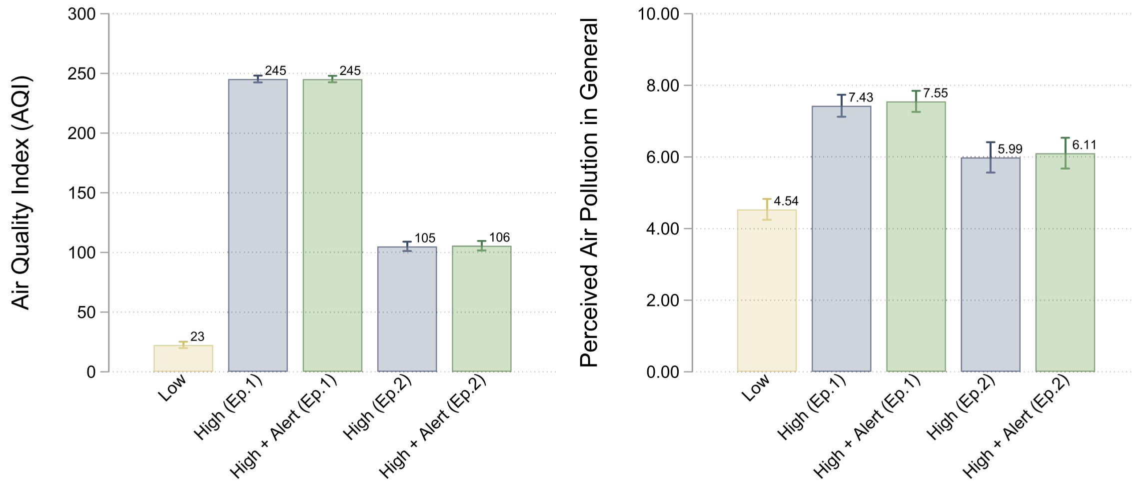

Fig. 2. Manipulation Checks. *Note:* The left panel displays the average AQI (from the closest official monitoring station) during the sampling period of each experimental condition. AQI ranges from 0 to 500. 0 to 50: Good; 51 to 100: Moderate; 101 to 150: Unhealthy for sensitive groups; 151 to 200: Unhealthy; 201 to 300: Very Unhealthy; 301 and higher: Hazardous. The right panel shows average perceived pollution for each experimental condition measured on an 11-point scale ranging from very low (0) to very high (10). Error bars indicate 95% confidence intervals (based on heteroskedasticity-robust standard errors).

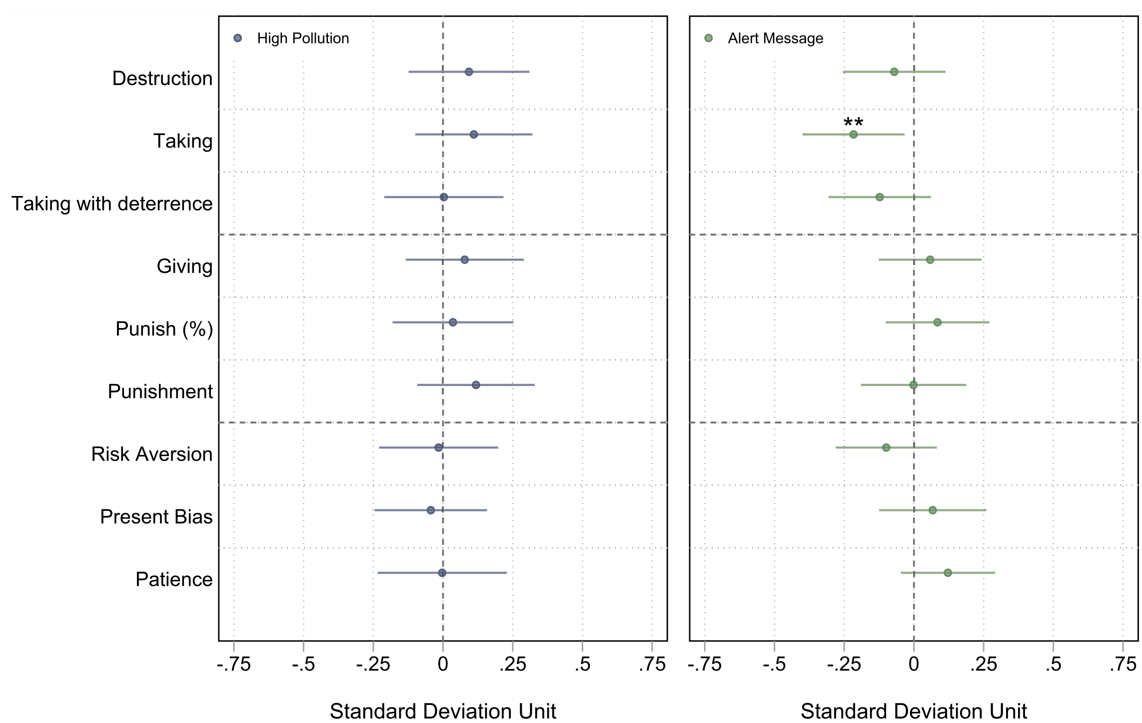

Fig. 3. Results summary: Social behaviour and economic preferences. *Note:* OLS estimates of equation (1). The left panel displays the difference between the 'high-pollution' treatment group and the 'low-pollution' control group. The right panel shows the difference between 'high-pollution group' and 'high-pollution alert' group. All dependent variables were standardized (z-scored) on the mean prior to analysis. All regressions control for baseline health status, pollution episode two responses and stratification variables used for randomisation (gender, university cluster, year of study, Hukou status and perceived air pollution health tolerance). Estimates for Present Bias and Patience are based on the individual-level beta and delta parameters estimated by non-linear least squares following Andreoni et al. (2015). The treatment effect for present bias was inverted so that a positive treatment effect indicates greater present bias. Unstandardised coefficient estimates are presented in SI Appendix, Tables 10-12. Error bars indicate 95% confidence intervals (based on heteroskedasticity-robust standard errors) and significance stars are based on conventional p-values prior to FWER-corrections; N = 632.

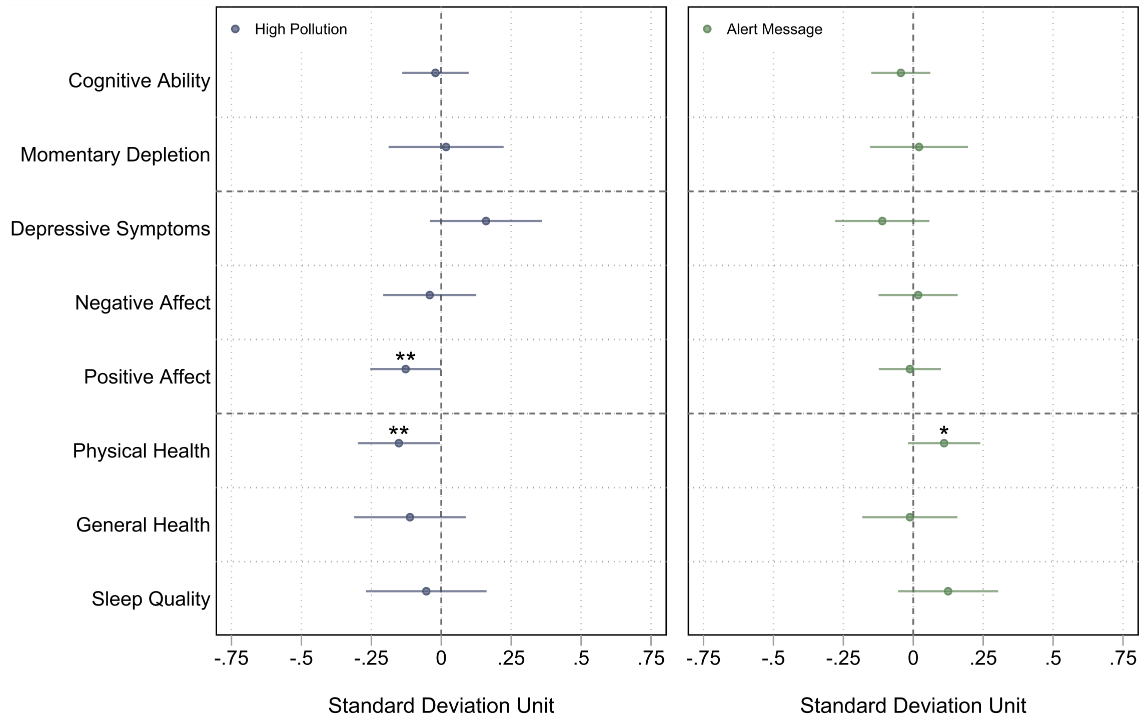

Fig. 4. Results summary: Cognition and health outcomes. *Note:* OLS estimates of equation (1). The left panel displays the difference between the 'high-pollution' treatment group and the 'low-pollution' control group. The right panel shows the difference between 'high-pollution group' and 'high-pollution alert' group. All dependent variables were standardized (z-scored) on the mean prior to analysis. All regressions control for baseline health status, pollution episode two responses and stratification variables used for randomisation (gender, university cluster, year of study, Hukou status and perceived air pollution health tolerance). Unstandardised coefficient estimates are presented in SI Appendix, Tables 13-15. Error bars indicate 95% confidence intervals (based on heteroskedasticity-robust standard errors) and significance stars are based on conventional p-values prior to FWER-corrections; N = 632.

if subjects received a pollution alert message (significant at the 10% level).

Taken together, the findings suggest that exposure to high levels of pollution has the expected negative impact on self-reported psychological well-being and physical health. In addition to the existing literature, which has often established a long-term affect, our findings suggest that the effect is also observable when people are subject to acute exposure. However, these findings must be interpreted with caution, as none of the previously discussed effects remain statistically significant after multiple hypothesis testing corrections.

5.2. The effect of pollution alert messages

Our additional treatment manipulation allows us to explore whether providing pollution warnings via direct message on WeChat influenced how pollution was perceived and whether it had an impact on protective behaviours. To assess protective behaviour, we asked participants to self-report whether they had checked pollution levels online, worn a mask, limited time outdoors or stayed indoors entirely on the day of the survey. For our analysis, we construct binary indicators identifying individuals that reported that they had engaged in the respective protective behaviour and utilise them as dependent variables in equation (1) (see SI Appendix, Section 2). We additionally control for individual-specific characteristics relevant to pollution tolerance (subjects' general perception of pollution in Beijing, years lived in Beijing and whether there is an air purifier in their student dorm). In this case, we are particularly interested in the coefficient on the interaction term (High Pollution × Alert) which indicates whether those individuals that received an alert message behaved differently from those that did not.

Our results suggest that all participants surveyed during high pollution episodes were significantly more likely to engage in protective behaviour (i.e., wear a mask, limit time outdoors and stay indoors), relative to individuals in the low-pollution group. However, we find no statistically significant differences between individuals that received a pollution alert and those that did not (see SI Appendix, Table 17). The findings may be explained by the fact that providing a pollution alert message had no impact on the perceived level of air pollution (Column 5). As discussed in SI Appendix Section 4, participants had a relatively accurate perception of air pollution and may take protective behaviour accordingly, regardless of having received an alert message or not. This explanation is further supported by the significant differences in protective behaviour between the first and the second pollution episode across all four behaviours. Participants surveyed during the second pollution episode perceived pollution to be significantly lower, and thus were less likely to engage in protective behaviours. Our findings contribute to a growing literature exploring the efficacy of pollution alerts in encouraging protective behaviours (e.g. Delmas and Kohli, 2020).

5.3. The effect of perceived pollution

Lastly, we conducted an additional exploratory analysis, as previous research has suggested that perceived pollution mediates the effect of actual air pollution levels on unethical behaviour (Fehr et al., 2017; Gong et al., 2020; Lu et al., 2018). To further explore the role of perceived pollution in shaping social behaviour and economic decision-making, we classify individuals surveyed during the high pollution episodes into two groups: those that perceived pollution to be extremely high (i.e., above the 75th percentile of the response distribution, corresponding to those that reported air pollution to be equal to 9 or 10 on a scale of 1 to 10.) and those that perceived pollution to be less extreme (i.e., below the 75th percentile. Moreover, we exclude individuals who received a pollution alert to focus on those subjects that were in no way influenced by the experimental pollution warning. We estimate differences between the low-pollution group and the high-pollution group that did not perceive pollution to be extremely high, and differences

Table 3
Perceived Pollution - Primary Outcomes.

	(1) JOD	(2) Taking	(3) Taking (Det.)	(4) Giving	(5) Punish (Binary)	(6) Punish (Extent)
High	0.032	0.292	-0.292	0.582	0.031	0.434
	(0.046)	(0.776)	(0.856)	(0.436)	(0.061)	(0.304)
High × High Perceived	-0.006	1.491	2.408**	-1.561***	0.019	-0.458
	(0.062)	(1.023)	(1.204)	(0.544)	(0.081)	(0.374)
Constant	0.008	10.530***	9.933***	4.195***	0.247	0.696
	(0.166)	(2.522)	(2.730)	(1.359)	(0.200)	(0.914)
R^2	0.015	0.039	0.033	0.046	0.033	0.035
Observations	393	393	393	393	393	393

Note: OLS estimates of equation (2) (see SI Appendix, Section 2). The dependent variables are primary outcomes for social behaviour. All regressions control for baseline health status, pollution episode two responses and stratification variables used for randomisation (gender, university cluster, year of study, Hukou status and perceived air pollution health tolerance). The sample used to estimate all models excludes subjects that received a pollution alert warning. *High* is an indicator identifying individuals randomly assigned to complete the survey during a pollution episode. *High Perceived* is an indicator identifying individuals who subjectively perceived pollution to be very high (≥9 on a scale of 1-10). The interaction of both coefficients thus shows the difference between subjects who were in the high-pollution group and those who also perceived pollution to be extremely high. The coefficient for *High* indicates the difference between the low-pollution group and the subjects in the high-pollution group that did not perceive pollution to be extremely high. Robust standard errors in brackets.
* p < 0.1, ** p < 0.05, *** p < 0.01.

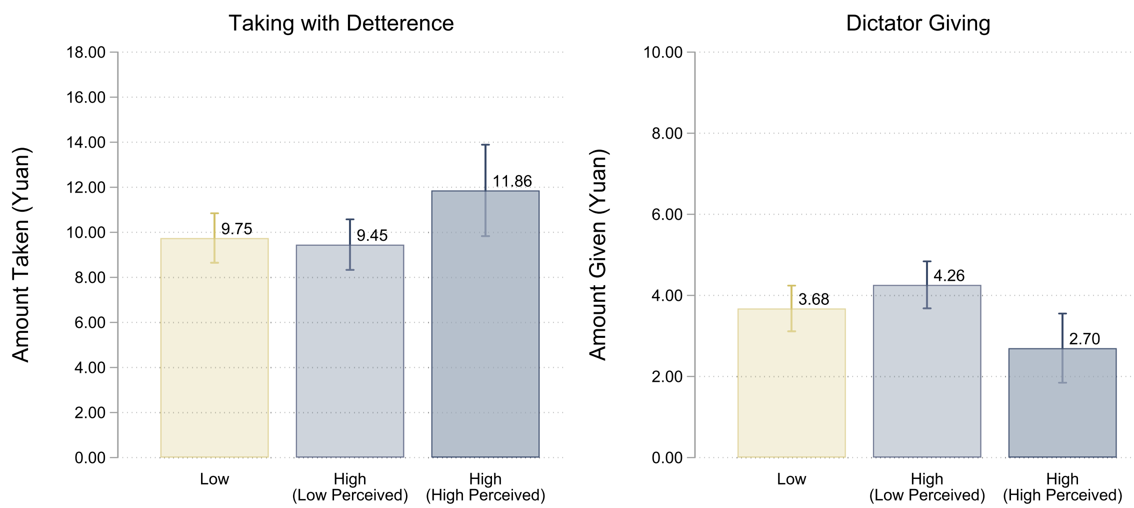

Fig. 5. Taking and giving behaviour (¥) by pollution perceptions in the high-pollution group. *Note:* Error bars indicate 95% confidence intervals (based on heteroskedasticity-robust standard errors); N = 393.

between the latter group and the high-pollution group that did perceive pollution to be extremely high (see SI Appendix Section 2 for details).

Table 3 presents the results from this analysis for our primary outcomes for social behaviour. We find significant differences in decision-making between the two groups for two of our six primary outcomes. Subjects that perceived pollution to be extremely high on the day of the survey took on average 2.4 Yuan more from their counterpart in the variation of the Take Game with deterrence incentives and gave 1.57 Yuan less in the dictator transfer decision, compared to subjects who perceived air pollution to be less extreme, significant at the 5% and 1% level respectively.

Fig. 5 visualises the mean taking and giving behaviour across the three groups. The average amount taken in the 'high-perceived' group is 11.86 Yuan, which is significantly higher than the amount taken in the 'low-pollution' (9.75 Yuan) and 'low-perceived' (9.45 Yuan) groups, at the 95% confidence level. Similarly, we observe that altruistic behaviour in the form of giving is substantially lower amongst individuals who perceived the pollution to be extremely high. Dictators in this group gave, on average, only approximately half the amount given by subjects who did not perceive pollution to be high (2.70 Yuan vs. 4.26 Yuan) and also significantly less than the control group, with both differences statistically significant at the 1% and 10% level, respectively.

We repeat this analysis for all secondary outcomes which were obtained from incentivised tasks (SI Appendix, Table 18). We find no statistically significant differences in risk aversion, present bias or cognitive ability with respect to how the pollution levels were perceived. However, somewhat unexpectedly, we observe higher levels of patience amongst those participants who perceive pollution to be extremely high (SI Appendix, Table 18, column 3). This finding stands in contrast to some of the recent evidence, which argues that temporary increases in intertemporal discounting (i.e., decreased patience) may explain the relationship between pollution and criminal behaviour (Bondy et al., 2020).

It is important to note a limitation of this exploratory analysis, which implies that results must be interpreted with caution. In the absence of an external manipulation of perceived pollution, we cannot rule out that differences in behaviour between subjects that perceived pollution to be high and those that did not, is due to some unobserved factors (such as personality traits). Nonetheless, the estimated differences in social behaviour are striking and display a consistent pattern.

6. Discussion and conclusion

This paper sets out a novel experimental design which exploits naturally occurring discontinuities in air pollution to experimentally examine the causal effect of acute air pollution on social behaviour, standard economic preferences and psychological well-being. The experiment combines elements of a lab-in-the-field design with online data collection procedures to imitate a setting in which respondents are randomly assigned to pollution exposure. This was achieved by using targeted surveys on both high and low-pollution days, which were carefully selected to differ only with respect to pollution levels.

Our results do not support the hypothesis that short-term exposure to elevated levels of air pollution affects anti-social behaviour, on average. While we observe a slight increase in anti-social behaviour under acute air pollution exposure, none of the differences are statistically significant at meaningful levels. Our findings, thus, do not align with Chew et al. (2021), the only other study exploring social behaviour in a controlled experimental setting using incentivised tasks. The authors find that exposure to "haze" (i.e., elevated levels of PM2.5) had a negative impact on student's other-regarding behaviour, making them less prosocial across several games. Our results also stand in contrast to significant increases in risk aversion reported in Chew et al. (2021). We find a precisely estimated null effect of pollution exposure on risk aversion using a lottery-choice task with comparable incentivisation. Moreover, we find no significant effect of acute pollution on incentivised measures of present bias, patience and cognitive ability or self-control depletion, several plausible pathways through which pollution may affect anti-social behaviour.

Within the context of the broader quasi-experimental literature exploring the pollution-behaviour link, our results suggest that previous significant findings on the association between air pollution and (violent) crime rates (e.g. Bondy et al., 2020; Burkhardt et al., 2019) may be due to contextual factors which do not apply to our sample population of university students. For instance, social and contextual factors such as poverty or financial hardship might be more predominant in a population likely to commit crimes than in our sample of students. Individual factors such as a predisposition for risk taking may influence behaviour, as (baseline) risk seeking is one explanation of higher levels of criminal activity. Nevertheless, focusing on the subgroup of individuals who actually perceived air pollution to be extremely severe on days with objectively high levels of air pollution, we find evidence that pollution increases anti-social behaviour in the form of 'taking behaviour' and simultaneously reduces altruism in a Dictator Game. Interestingly, these subjects take more Yuan from their counterparts in the variant of the Take Game in which there is a risk of being detected, which more accurately represents real-world criminal behaviour which contains an element of risk. This finding, thus, aligns with the recent literature on pollution and criminal behaviour (Bondy et al., 2020; Burkhardt et al., 2019; Lu et al., 2020). However, our findings fail to support the hypothesis that increased discounting underlies changes in criminal behaviour brought about by pollution.

Nonetheless, these findings indicate that the impact of air pollution may be underestimated if measurement relies solely on objective metrics (Fehr et al., 2017). Recent research suggests that individuals' psychological experience of air pollution appears to influence real-world decision-making (Fehr et al., 2017; Gong et al., 2020; Lu et al., 2018). For instance, Fehr et al. (2017) find that perceived air pollution (i.e., air pollution appraisals) negatively impacts social behaviour in an organisational work context. Similarly, Lu et al. (2018) find that perceived pollution significantly increases unethical behaviour in the form of cheating. Gong et al. (2020) replicate and extend this research and conclude that "the effect of air pollution on unethical behaviour is driven more by the subjective perception of increased air pollution rather than by actual increases in air pollution" (Gong et al., 2020, p. 1045). Our results support these earlier findings by showing that social behaviour is impacted only for those participants who perceive pollution to be more extreme. However, unlike the previously discussed studies, we find no evidence that self-control depletion or other psychological health indicators vary based on how pollution levels were perceived.

Moreover, our results indicate that acute exposure to extreme levels of air pollution negatively impacts psychological and physiological well-being, although these findings must be interpreted with caution. Participants surveyed during a pollution episode were, on average, significantly more likely to report lower levels of physical health (measured by common illness symptoms) and positive affect (or mood). Our findings are thus in close accordance with Zhang et al. (2017) who find that air pollution reduces hedonic happiness and increases the rate of depressive symptoms. Moreover, our findings are consistent with the broader economic and epidemiological literature on the adverse consequences of air pollution on mental well-being, happiness and depression, most of which has studied long-term exposure to air pollutants (e.g. Khan et al., 2019; Power et al., 2015; Pun et al., 2017; Xue et al., 2019; Zeng et al., 2019; Zhang et al., 2017). Our findings complement this literature by exploring the immediate short-term dimension of pollution exposure and provide evidence that even acute exposure to air pollution can have a direct negative impact on mental health. Our findings thus provide support for Zheng et al. (2019) who find that pollution increases negative emotions (such as bad) mood expressed on Chinese social media, and Li et al. (2019) who show that negative emotions occur when pollution levels surpass an AQI of 150 using psychophysical visual experiments.

Finally, our findings contribute to an emerging literature exploring the efficacy of pollution warnings and alerts (Delmas and Kohli, 2020; Graff Zivin and Neidell, 2009; Saberian et al., 2017; Sexton Ward and Beatty, 2016). First, we show that issuing pollution alerts via direct message on the day prior to a severe pollution episode were unsuccessful in encouraging additional self-reported protective behaviour (mask-wearing, checking pollution levels online, limiting time outdoors or staying indoors). However, we nonetheless document significant behavioural effects associated with providing alert messages. Specifically, we find that subjects in the high-pollution alert group were less likely to take from their counterparts and report improved physical health, compared to the high-pollution group that received no alert. Interestingly, these findings suggest that some of the detrimental impacts of air pollution exposure are offset by receiving an alert message. Future research should explore this somewhat unexpected finding in more detail.

While our novel study design was successful in experimentally manipulating the level of air pollution that subjects were exposed to while completing the survey, it is important to discuss certain limitations. First, it remains unclear how cumulative pollution exposure prior to the survey date may confound our results. Participants in the high pollution groups were exposed to two days of increasing pollution prior to the day of the survey, whilst participants in the low-pollution group were exposed to the entire pollution episode as well as one day of low-pollution prior to the survey. If we assume that pollution has a more pro-longed (cumulative) physiological impact on the body and brain, participants in the low pollution group may not have fully "recovered" from the pollution episode, despite having had one day of clean air prior to completing the survey. Future research should employ larger samples to explore potential effects of short-term cumulative exposure and whether people behave differently after longer periods of "recovery".

Second, we acknowledge that our analysis is based on a relatively small sample size, which thus may be underpowered to detect an effect on behaviour even if an effect is present. We may however argue that small effect sizes, as observed in our data (such as a 3-percentage point increase in destructive behaviour), are not of particular economic significance, even if they were found to be statistically significant with a larger sample size. We thus believe that Type II error is not a significant cause of concern in our study.

Third, we must caution with respect to the external validity of our findings, which relies on a sample of students who permanently live in Beijing. Students in Beijing may be familiar with extreme levels of air pollution and therefore habituation may attenuate the effects. For example, if we were to conduct the same experiment with tourists visiting

Beijing from rural (low-polluted) regions, we may come to very different conclusions. For instance, Li et al. (2019) found that people living in the UK showed a stronger negative response to viewing images of extreme pollution than Chinese observers. Moreover, our student sample is clearly not representative of the general population, a common drawback of experimental research that utilises student subjects. However, there is increasing evidence that student samples are appropriate for studying human social behaviour (Exadaktylos et al., 2013; Falk et al., 2013). Moreover, if air pollution were to affect fundamental aspects of decision-making, independent of contextual factors, this should also be detectable in a student sample. In this regard, our findings point to the importance of contextual factors which may interact with air pollution to bring about changes in social behaviour and economic preferences.

In sum, our results suggest that people's mood is negatively affected on polluted days, however, not enough to significantly impact decision-making in our sample. Nonetheless, we present suggestive evidence that pollution exposure raises anti-social behaviour and decreases altruistic behaviour on polluted days amongst individuals who perceived pollution levels to be extremely high. Future research should attempt to experimentally manipulate perceived pollution to further probe the robustness of our findings. Moreover, future research should utilise larger non-student samples to further explore the link between pollution and human decision-making. We hope that our experimental design provides a methodological foundation for future work and will stimulate further innovations in research design to strengthen experimental identification and causal inference.

Ethical approval

Ethical approval for the experiment was granted by the Department of Land Economy Ethical Research Committee (University of Cambridge).

CRediT authorship contribution statement

Paul M. Lohmann: Conceptualization, Research Design, Formal analysis, Funding acquisition, Writing - original draft;
Elisabeth Gsottbauer: Conceptualization, Research Design, Funding acquisition, Writing - original draft;
Jing You: Conceptualization, Research Design, Data collection & processing, Writing - review & editing;
Andreas Kontoleon: Conceptualization, Research Design, Writing - review & editing.

Declaration of competing interest

None.

Data availability

Data will be made available on request.

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Appendix A. Supplementary material

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.socscimed.2022.115617.

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