Helping Under Haze: Evidence from Lost-Letter Field Experiments in Beijing and Delhi

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Abstract

We conduct lost-letter field experiments in Beijing and Delhi to examine whether—and in what direction—ambient air pollution influences helping behavior. Using real-time air quality data and instrumental variables—thermal inversion in Beijing and agricultural burning with wind conditions in Delhi—we find higher levels of air pollution significantly increase the likelihood that individuals post lost letters. The effect is specific to posting, not mere pickup, and most consistent for PM10, the coarser and more perceptually salient pollutant. When PM2.5 and PM10 are jointly included, only PM10 remains significant, consistent with a salience-based psychological mechanism: pollution discomfort prompts helping as a coping response. These patterns are immediate, replicable across cities, and stronger in settings with greater discomfort.

Keywords: air pollution, helping behavior, particulate matter, thermal inversion, China, agricultural burning, India

JEL Codes: D9, Q5

1. Introduction

Air pollution is widely seen as a source of illness, discomfort, and even antisocial behavior (Bondy et al., 2020; Chen and Hoek, 2020; Lu, 2020; Dominski et al., 2021; Aguilar-Gomez et al., 2022). Yet, perhaps counterintuitively, we show that it can also increase helping behavior. In two large-scale lost-letter field experiments in Beijing and Delhi, we find that individuals are significantly more likely to post a lost letter—a small but meaningful prosocial act—when air pollution is high. This behavior occurs despite zero material reward. Our findings reveal that air pollution, beyond its well-known physical effects, can also shape everyday social interactions in subtle and unexpected ways.

While a growing literature links air pollution to a wide range of adverse outcomes—ranging from cognitive impairment and lower productivity to poor mental health and increased crime—much less is known about how pollution affects everyday social interactions.[1] Most existing studies focus on private or performance-related outcomes. The question of whether environmental conditions shape real-world prosocial behavior remains largely unexplored. We address this gap using an unobtrusive field-based measure of helping behavior, avoiding the limitations of survey data and hypothetical scenarios.

We implement lost-letter experiments in Beijing and Delhi—two large urban centers that have faced significant air pollution challenges in recent decades and are located in countries with different cultures, social norms, and institutional environments—across multiple locations, time periods, and pollution levels. In each city, we systematically dropped sealed and stamped letters in public spaces and recorded whether and when they were picked up and subsequently posted by passersby. Each letter-drop event is matched to high-

[1] Recent research reveals that air pollution can harm cognitive performance (Ebenstein et al., 2016; Zhang et al., 2018), decision-making (Burkhardt et al., 2019; Sager, 2019; Huang et al., 2020; Chew et al., 2021; Dong et al., 2021; Herrnstradt et al., 2021), and productivity (Graff Zivin and Neidell, 2012; Chang et al., 2016; Lichter et al., 2017; Guo and Fu, 2019; He et al., 2019; Fu et al., 2021). For recent reviews of non-health effects, refer to Lu (2020) and Aguilar-Gomez et al. (2022).

frequency, location-specific air quality data, enabling precise measurement of air pollution exposure at the moment the behavioral decision was made. In our regressions, we also control for location fixed effects, season fixed effects, and day-of-week fixed effect along with controls for surface-level meteorological conditions.

Our design distinguishes between two observable outcomes: whether a letter is picked up from the ground, and whether it is subsequently posted. Pickup may reflect momentary curiosity or attention, rather than prosocial intent. In contrast, posting—even when logistically simple in our setup—requires a more deliberate decision to help. Unlike prior lost-letter studies, which typically only observe whether the letter is eventually returned, our in-person observation allows us to capture both stages of the behavioral process. This separation enables us to isolate intentional helping from mere responsiveness to one's environment, and to test whether air pollution affects the motivation to help, rather than general attentiveness.

A further innovation of our design is the collection of rich real-time contextual data. Trained observers remained at each drop site to record the number and gender of passersby, time until pickup, and environmental conditions such as ambient temperature and noise using smartphone apps. These additional data allow us to control for foot traffic density, gender composition, and ambient stressors across time and locations. This level of behavioral and environmental detail has not been previously achieved in lost-letter experiments and helps rule out many potential confounders.

Since we are unable to randomize air pollution exposure for ethical and practical reasons, we identify its causal effect on helping behavior by exploiting two sources of plausibly exogenous variation in air pollution levels. In Beijing, we use thermal inversion, a meteorological phenomenon that traps pollutants near the surface, as an instrument for fine and coarse particulate matter. In Delhi, we construct an instrument based on agricultural burning in surrounding regions, interacted with wind speed and the geographic location of monitoring stations. These strategies generate quasi-random variation in local pollution that is arguably orthogonal to unobserved behavioral traits or local crowd composition, enabling us to estimate the causal impact of air pollution exposure on helping behavior.

We examine the effects of both PM2.5 (fine particulate matter) and PM10 (coarse particulate matter) to help distinguish between physiological and psychological channels. PM2.5 particles are smaller than 2.5 micrometers in diameter and are capable of penetrating deep into the lungs, crossing the lung–blood barrier, and circulating through the bloodstream to affect other organs. Because of this, PM2.5 is more likely to trigger biological responses—such as systemic inflammation or hormonal disruption—and has been linked to cardiovascular disease, neurological impacts, and other long-term health risks (Brook et al., 2010; Power et al., 2011; Schraufnagel et al., 2019). In contrast, PM10 particles, though larger and less likely to enter the bloodstream, are more likely to be perceptible in the air and to cause immediate sensory discomfort, such as eye irritation or throat dryness (CDC 2024; UK Department for Environment, Food & Rural Affairs 2025). If helping behavior arises from psychological salience or affective discomfort—rather than from physiological effects—we would expect stronger and more consistent effects for PM10. Our findings are consistent with this interpretation: across cities and specifications, PM10 is more robustly associated with helping behavior.

Our results show that higher levels of air pollution significantly increase the probability that a letter is posted. This effect is consistent across both cities and holds in both ordinary least squares and two-stage least squares specifications. Importantly, the increase in helping is specific to posting behavior—the intentional act of helping—and not to pickup, which may reflect curiosity or attentional engagement. The effect is strongest in the top quartiles of the pollution distribution and most consistent for PM10, the coarser and more perceptually salient pollutant. When both PM2.5 and PM10 are included in the same regressions, only PM10 remains statistically significant. These findings suggest that the behavioral response is triggered by perceptual salience rather than biological harm. Moreover, the response is contemporaneous, occurring within minutes of exposure, which is difficult to reconcile with slower physiological pathways.

These patterns are consistent with psychological coping theories from social psychology, which posit that individuals under stress or discomfort may engage in low-cost helping behavior as a means to restore emotional balance or self-image (Cialdini and Kenrick, 1976; Cialdini et al., 1981; Buchanan and Preston, 2014; Schroeder and Graziano, 2014). Prior experimental studies have found that induced negative affect can influence altruism in lab settings (Vinkers et al., 2013; Pérez-Dueñas et al., 2018). Our findings extend this literature by showing that real-world environmental discomfort—when salient and immediate—can causally increase spontaneous helping in everyday settings without reward, recognition, or feedback. Supporting this interpretation, we show that online search interest in "air pollution" and "stress" is positively correlated over time in both Beijing and Delhi when using local language terms, as well as in six Anglophone countries using English terms. We further show that the helping response to pollution is stronger in crowded settings and varies with the gender composition of passersby, consistent with the idea that stress—and the salience of one's actions—is shaped by local social context. This broader pattern is consistent with the view that public concern about air pollution is often accompanied by elevated psychological strain.

This paper makes four contributions. First, we provide novel causal evidence—based on real-world behavior—that ambient air pollution can increase prosocial action, expanding a literature that has focused primarily on pollution's negative impacts on health, cognition, and aggression. Second, we introduce a redesigned version of the lost-letter technique that captures both pickup and posting behavior and integrates real-time contextual data—including foot traffic, gender composition, ambient noise, and temperature—collected directly at the scene. This allows for more granular measurement of helping behavior and tighter linkage to environmental conditions. Third, we replicate our core finding in two distinct urban contexts—Beijing and Delhi—using separate natural experiments, thereby enhancing external validity. Fourth, we provide novel evidence on the underlying mechanism. The effect is immediate, specific to intentional helping (not mere engagement), and more consistently associated with PM10—the perceptually salient component of pollution—than with PM2.5, which is biologically more harmful but not directly observable. These patterns coupled with supporting evidence from internet search behavior point to a psychological coping response rather than a slower physiological pathway. Together, our findings reveal a previously undocumented behavioral channel through which environmental conditions influence everyday social behavior.

Our findings also raise broader questions about how environmental conditions shape everyday social behavior. While the health and productivity effects of air pollution are well documented, our study suggests that pollution may also influence interpersonal behavior in subtle and counterintuitive ways. This expands the behavioral footprint of pollution to include social interactions, not just individual outcomes. More broadly, our results suggest that spontaneous, low-cost helping may emerge as a psychological coping response under environmental stress. This has potential relevance for how we understand human behavior in high-stress urban environments, and for designing prosocial interventions in contexts of environmental or emotional strain.

The remainder of the paper is organized as follows. Section 2 describes the experimental design and data collection procedures in Beijing and Delhi. Section 3 outlines our identification strategy, including the construction and justification of the instrumental variables used in each city. Section 4 presents the main empirical results, while Section 5 explores the underlying mechanisms, including a discussion of psychological pathways supported by auxiliary evidence. Section 6 concludes.

2. Experiment Design

2.1 The Lost-Letter Field Experiment

The lost-letter technique was originally developed by Stanley Milgram in 1965 and has been widely used in social psychology to study helping behavior (Milgram et al. 1965). In its classic form, the method involves dropping stamped, addressed letters in public places and measuring helping behavior by whether the letters are returned via mail. Most prior studies focus on how observable letter attributes (e.g., the recipient's name or address) affect return rates.

Our design departs from these conventional uses in several important ways. First, rather than varying information on the envelope, our treatment variable is ambient air pollution, which varies across locations and over time. Since pollution is not randomly assigned, we address potential endogeneity using instrumental variable strategies: thermal inversion in Beijing and agricultural burning combined with wind direction in Delhi. Second, unlike prior studies that typically only observe whether a letter is ultimately returned, we distinguish between two stages of behavior: whether a letter is picked up, and whether it is subsequently posted. Pickup may reflect momentary curiosity or attention, rather than prosocial intent. Posting, even when logistically simple in our setup, reflects a more deliberate decision to help. This separation allows us to isolate intentional helping from general responsiveness to one’s environment.

Each envelope displayed a fictional name and post office box number, written in simplified Chinese in Beijing and English in Delhi. Inside was a generic typed letter. A unique code on the back of each envelope allowed us to track the drop time, date, and location. Letters were placed on the footpath directly in front of public letterboxes at nine locations in Beijing and ten in Delhi. At each location, we dropped a total of nine letters per day—three per hour over a three-hour period in the morning. Each letter remained on the ground for up to ten minutes unless picked up earlier. If a letter was not picked up within ten minutes, it was retrieved and replaced. This design increased statistical power by generating multiple observations per hourly pollution reading per location. In our regressions, we cluster standard errors at the location-hour level to account for shared pollution exposure.

We conducted four experimental waves in Beijing and five in Delhi, each representing a distinct season. Each wave lasted five days. In Beijing, the waves occurred on: (1) September 22–25 and 27, 2017 (autumn); (2) May 6–7 and 9–11, 2018 (spring); (3) January 11–15, 2019 (winter); and (4) July 14–18, 2019 (summer). In Delhi, the waves were: (1) September 21–22 and 24–26, 2017 (monsoon); (2) October 26–29 and 31, 2017 (autumn); (3) January 13–17, 2018 (winter); (4) March 3–7, 2018 (spring); and (5) May 19–23, 2018 (summer).

None of these dates overlapped with national holidays or major religious festivals in either country, such as National Day (China), Diwali or Holi (India). A full list of national holidays and public festivals was cross-checked using official calendars to avoid these periods. Since we include full wave fixed effects in all regressions, any month-specific shocks—such as holiday-related behavioral changes or harvest-related variation in agricultural burning—are accounted for in our identification strategy.

In total, we dropped 1,620 letters in Beijing and 2,250 in Delhi. After excluding observations due to unexpected rain, absence of passersby, delays beyond the 10-minute window, or missing pollution data, our final sample included 1,619 observations in Beijing and 2,174 in Delhi.

A key innovation of our design is the systematic collection of rich real-time contextual data. Observers remained at each site after dropping the letters to record the time of drop and removal, as well as whether the letter was picked up and/or posted. We also recorded the number of male and female passersby within a three-meter radius before the letter was removed. Ambient noise and temperature were measured using smartphone apps. This information allows us to control for foot traffic, gender composition, and environmental stressors in our analysis.

2.2 Air Pollution Monitoring

We obtained hourly PM2.5 and PM10 readings from nine monitoring stations in Beijing and ten in Delhi. Station selection was based on coverage and accessibility, ensuring that research assistants could reach each site within logistical constraints. The locations of the stations are shown in Figure A1 in Appendix 1. The nine stations in Beijing span six of the city’s sixteen districts, while the ten Delhi stations cover all districts.

All stations consistently reported PM2.5 throughout the experiment periods. However, not all stations reported PM10, resulting in missing PM10 readings for about 7% of Beijing observations and 49% in Delhi. We conducted robustness checks and found that these missing values do not systematically bias our estimates. Because pollution data are updated hourly, the three letters dropped at each location within the same hour were matched to the same pollution reading.

2.3 Student Recruitment, Training, and Pilot Experiments

We recruited graduate students from the Central University of Finance and Economics in Beijing and Jawaharlal Nehru University in Delhi. Students were first briefed on the goals and procedures of the experiment and later assisted in identifying suitable drop locations near monitoring stations that had nearby street letterboxes. During the experiment, each site was staffed by a trained pair of students responsible for carrying out all tasks.

Participants attended training sessions that covered how to prepare the letters, discreetly drop and collect them, count passersby by gender, measure ambient noise and temperature using mobile apps, and record all observations accurately. They were also instructed on how to behave naturally as bystanders so as not to attract attention or interfere with passersby. Each pair of students submitted their data to a city-specific field coordinator. All students were required to strictly follow the experimental protocol detailed in Appendix 2.

The coordinator was responsible for compiling the observation data and collecting hourly PM2.5 and PM10 readings from the local air pollution monitoring stations. Prior to launching the full study, we conducted pilot experiments to test logistics and train students: March 18–19, 2017 in Beijing and August 23–25, 2017 in Delhi.

3. Instrumental Variable Strategy

3.1 Motivation for Instrumental Variables

Air pollution levels in urban environments are not randomly assigned. They are often influenced by traffic volume, industrial activity, human presence, and other local conditions—factors that may also affect people's mood or behavior in ways unrelated to pollution itself. For instance, a bustling area with heavy traffic may simultaneously exhibit higher pollution and lower helping behavior due to congestion or noise. Moreover, despite the contextual and fixed effects that we control in our regressions, time-varying unobserved factors—such as fluctuations in local traffic congestion, temporary construction, or short-term shifts in public activity—may still confound the relationship between air quality and helping behavior. To isolate the causal impact of pollution, we adopt an instrumental variables (IV) strategy that exploits plausibly exogenous variation in pollution levels generated by natural phenomena.

3.2 Thermal Inversion in Beijing

To address endogeneity in Beijing, we follow prior studies and use thermal inversion as an instrument for air pollution (Arceo et al., 2015; Jans et al., 2018; He et al., 2019; Sager, 2019; Fu et al., 2021; Chen et al., 2023). Under normal atmospheric conditions, air temperature in the troposphere—the lowest layer of the Earth's atmosphere—declines with altitude, allowing air pollutants to disperse vertically. A thermal inversion occurs when a layer of warmer air overlays cooler air near the surface, reversing the normal temperature gradient. This warm layer acts as a lid that traps pollutants near the ground, causing pollution levels to spike.

Beijing is particularly susceptible to thermal inversions due to its geography, with mountains surrounding the city on the west, north, and northeast sides. Inversions that occur closer to the surface tend to have a larger impact on ground-level pollution. Wang et al. (2019) show that not only the occurrence of thermal inversion but also its intensity is positively correlated with PM2.5 concentrations in Beijing during winter. Following Chen et al. (2023), we construct two instruments: a dummy variable indicating whether an inversion occurred at or below 320 meters above ground level, and a continuous measure of inversion intensity, defined as the temperature difference between the base and top of the inversion layer. When multiple inversions occur simultaneously, we use only the lowest one, which is most relevant for trapping pollutants near the surface.

Meteorological data were obtained from NASA's Modern-Era Retrospective Analysis for Research and Applications, Version 2 (MERRA-2). We also control for surface meteorological conditions—including wind speed, humidity, air pressure, and temperature—to isolate the effect of inversion from other weather-related influences on both pollution and behavior. See Appendix 3 for the details of data construction.

This strategy allows us to leverage atmospheric phenomena that are exogenous to local traffic or behavior but strongly predictive of short-term pollution fluctuations. We apply a two-stage least squares (2SLS) estimator to address endogeneity concerns and mitigate potential measurement error in PM2.5 and PM10 concentrations, though the latter is likely minimal given the quality of our monitoring data.

3.3 Agricultural Burning in Delhi

For Delhi, we exploit a second source of plausibly exogenous variation in air pollution: agricultural and vegetation burning in surrounding regions, combined with wind conditions. Large-scale burning of crop residue, deforestation, and peatlands is common in northern India, particularly during the post-harvest season. These fires generate substantial quantities of particulate matter, and depending on wind patterns, some of this pollution can travel long distances and reach Delhi.

To capture this, we construct an instrumental variable based on the interaction between monthly burning intensity and hourly wind speed across a spatial grid surrounding the city. The grid consists of 36 one-degree-by-one-degree cells in latitude and longitude, with Delhi at the center. Each cell covers roughly 10,000 square kilometers.

Let *B* denote the monthly total burning intensity in terms of areas burned divided by 1,000 in cell *c* and month *m*, and let *W* denotes the hourly wind speed in the same cell on day *d*, hour *h*. We compute the instrument as:

$$Burn_{mdh} = \sum_{c \in C} B_{cm} \times W_{cmdh},$$

where *C* includes either the 16 nearest grid cells or all 36. This variable reflects the potential for pollution transport into Delhi, combining exogenous burning events with real-time wind conditions.

Importantly, this variable is not meant to capture the precise amount of pollution carried into the city at any given hour. Rather, it proxies for the likelihood and intensity of exposure to externally generated particulate matter. Because wind directions can shift and pollutants disperse nonlinearly, we omit wind direction in the construction. Conceptually, this instrument represents a stochastic exposure potential that varies across time.

We further interact this variable with fixed indicators for each of the experimental locations to introduce spatial heterogeneity into the first stage. Since agricultural burning tends to produce relatively large particles, this instrument is expected to be more predictive of PM10, the coarser and more perceptible pollutant. Full technical details are provided in Appendix 4.

3.4 Comparing the Two Instruments

The two instrumental variables we use—thermal inversion in Beijing and agricultural burning with wind in Delhi—differ in their underlying atmospheric mechanisms and are valid only within their respective cities due to geographic and meteorological constraints.

Thermal inversion captures the vertical stagnation of locally emitted pollutants, which is particularly relevant in Beijing. The city is geographically enclosed on three sides by mountains, limiting horizontal air movement and making it susceptible to pollution accumulation near the surface during inversion events, especially in winter. This makes thermal inversion a strong predictor of PM2.5 concentrations in Beijing and a widely accepted instrument in previous environmental studies.

In contrast, thermal inversion proves ineffective in Delhi. During our study period, inversions there mostly occurred at very high altitudes, too far above ground to influence surface-level air quality. However, Delhi is uniquely exposed to long-range pollution transport from extensive burning of crop residue and vegetation in surrounding regions. Our burn-based instrument, which interacts monthly burn intensity in each grid cell with hourly wind speed, captures this exogenous source of PM10 variation.

Each instrument therefore leverages a distinct causal channel: local atmospheric trapping versus external pollutant inflow. Moreover, each instrument variable generates plausibly exogenous variation in particulate matter that is orthogonal to behavioral factors in the respective cities. By exploiting two different instruments in two very different urban and institutional settings, we strengthen the credibility of our identification strategy and assess whether the observed behavioral responses to pollution generalize across contexts.

4. Main Results

4.1 Descriptive Patterns

We begin by presenting summary statistics in Table 1. Within 10 minutes, about 72% of letters were picked up in Beijing, compared to 58% in Delhi. The average pickup time was under 6 minutes in Beijing and about 8 minutes in Delhi, patterns consistent with differences in foot traffic. On average, 28 people passed by each letter in Beijing, while only 16 did so in Delhi. A notable difference lies in the gender composition of passersby: in Beijing, the gender ratio was relatively balanced, whereas in Delhi, nearly 70% of the passersby were men. While pickup rates were higher in Beijing, letters were more likely to be posted in Delhi—42% versus 36%. Since only posting constitutes a deliberate act of helping, this distinction is crucial.

PM2.5 and PM10 levels were substantially higher in Delhi than in Beijing. The mean concentrations of PM2.5 and PM10 in Delhi were 171 μg/m³ and 299 μg/m³, respectively, compared to 60 μg/m³ and 110 μg/m³ in Beijing. For all regression analyses and figures presented in this section and thereafter, we standardize PM2.5 and PM10 to have a mean of zero and a standard deviation of one within each city. This allows for a consistent comparison of effect sizes across pollutants and contexts.

We also report three additional meteorological variables—surface wind speed, humidity, and atmospheric pressure—though they are not very different across cities. These variables are included in the analysis as control variables but are not of primary interest.

Figure 2 visually illustrates the raw relationship between pollution and helping behavior. It shows the pickup and posting rates by quartiles of standardized PM2.5 and PM10 in Beijing and Delhi. The posting rate clearly increases with higher PM10 quartiles in both cities, while pickup rates remain relatively flat. In contrast, the patterns for PM2.5 are inconsistent between the two cities, with no clear or common trend. These unadjusted patterns provide suggestive evidence that air pollution—particularly PM10—is positively associated with helping behavior, primarily through increased posting rather than pickup.

4.2 Regression Specification

We estimate the following linear probability model with three-way fixed effects:

$$y_{idwc} = \beta_0 + \beta_1 stdPM_{idwc} + BX_{idwc} + \gamma_d + \delta_w + \tau_c + \varepsilon_{idwc}, \quad (1)$$

where y_{idwc} is a binary indicator for whether letter *i* in day *d* of the week in season *w* and location *c* was picked up or posted; *stdPM* represents the standardized PM2.5 or PM10, each with mean zero and standard deviation one; *X* includes ambient noise, temperature, surface windspeed, specific humidity, air pressure, the number of passersby per minute, the percentage of women among passersby; γ, δ and τ denote day of the week, wave and location fixed effects; and ε is the error term. Robust standard errors are clustered at the location-date-hour level.

We standardized PM2.5 and PM10 by subtracting their respective sample means and dividing by their standard deviations within each city. This ensures that β_1 can be interpreted as the change in the probability of picking up or posting a letter associated with a one standard deviation increase in pollution.

To explore nonlinear effects, we also estimate models in which *stdPM* is replaced by two dummy variables indicating whether the pollution level falls in the third or fourth quartile of the sample distribution.

4.3 OLS Estimates

Table 2 presents the linear effects of standardized PM2.5 and PM10 on both pickup and posting. All estimated coefficients are positive. In Delhi, only the coefficients for posting are statistically significant, suggesting that higher pollution, particularly PM10, is associated with a greater likelihood of mailing a letter. In Beijing, the only statistically significant effect is for PM10 on pickup. Overall, PM10 shows more consistent and stronger associations than PM2.5, especially for the posting outcome.

Table 3 examines nonlinear relationships using dummy variables for the third and fourth quartiles of pollution distributions. These specifications assess potential threshold effects—whether helping behavior increases more markedly at higher levels of pollution. The results are again highly consistent for PM10: in both cities, the probability of posting rises significantly in the third and fourth quartiles of PM10. The estimated effects of the third and fourth quartiles of PM10 on posting (Panel B) are approximately 8 to 9 percentage points higher than the reference group of the bottom two quartiles, representing a sizable behavioral shift. The effect on pickup remains largely flat, except for a positive and statistically significant effect of high PM10 on pickup in Beijing. PM2.5 effects, in contrast, are inconsistent and generally not statistically significant.

One potential concern is that air pollution may change the composition of people on the street if more altruistic individuals are more likely to avoid going outside on high-pollution days—especially during weekends when they have greater flexibility. Such behavioral sorting could bias our estimates of pollution's effect on helping behavior. To assess this possibility, Table 4 presents a robustness check comparing weekday and weekend behavior. Specifically, we include interaction terms between pollution measures and a weekend dummy, allowing us to test whether the pollution effect differs by day type. We find no significant difference in the pollution–posting relationship between weekdays and weekends, alleviating concerns about avoidance-driven sample selection based on air quality.

4.4 2SLS Estimates

Table 5 reports the 2SLS estimates for Beijing. The first-stage results in Panel C show that both the inversion dummy and the temperature difference are positively correlated with air pollution. The Kleibergen-Paap F-statistics indicate that these instruments are strong. The second-stage results for pickup and posting are reported in Panels A and B, respectively. Compared to the OLS estimates in columns (1) and (2) of Table 3, the 2SLS coefficients are not only still positive but also larger in magnitude and more statistically significant.

Table 6 presents the 2SLS results for Delhi. The first-stage results in Panel C reveal that the effects of agricultural burning vary across locations. Columns (1) and (3) use burning data from 16 grid cells, while Columns (2) and (4) use data from all 36 cells. The reference location is the northwesternmost site, which lies closest to the region where agricultural burning is most prevalent and therefore exhibits the strongest predictive effect, as shown by the first row of estimates. The remaining locations generally show weaker effects relative to this reference point. The Kleibergen-Paap F-statistics suggest that the instruments are strong predictors for PM10, but weaker for PM2.5. Given the potential weak instrument issue, we conduct a robustness check using the limited information maximum likelihood (LIML) estimator. The results, reported in Table A1 in Appendix 5, are similar to the 2SLS estimates.

In terms of second-stage results, Panel B shows that air pollution continues to have a strong and consistent positive effect on posting behavior in Delhi. In contrast, the results for pickup behavior are weak and statistically insignificant.

Overall, the 2SLS results reinforce the OLS findings and point to a robust and consistent effect of PM10—rather than PM2.5—on helping behavior as measured by posting a lost letter.

5. Mechanisms

5.1 Psychological and Physiological Mechanisms

Social psychologists have long argued that a central driver of prosocial behavior is the egoistic motive—helping others to experience personal emotional benefits (Cialdini and Kenrick, 1976; Cialdini et al., 1981; Buchanan and Preston, 2014; Schroeder and Graziano, 2014). This idea parallels the theory of warm-glow giving in economics (Andreoni, 1990), in which individuals derive satisfaction simply from the act of helping, regardless of outcomes. In the context of environmental stress, helping behavior may serve as a coping mechanism: individuals exposed to air pollution may be motivated to engage in prosocial behavior if doing so relieves discomfort, enhances self-image, or offers an emotional offset to the negative affect induced by pollution exposure (Midlarsky, 1991).

This framework suggests that psychological salience and discomfort—especially from perceptible or irritating pollutants—may play an important role. Helping may thus function as a self-regulatory strategy that restores emotional equilibrium or affirms moral identity in a stressful setting.

An alternative explanation is physiological: once pollutants enter the body, they may affect the brain and alter the production or regulation of hormones such as oxytocin and dopamine, which influence a range of social behaviors. However, this mechanism remains complex and poorly understood, with much of the supporting evidence drawn from animal studies (Weitekamp and Hofmann, 2021). Crucially, only ultrafine particles, such as PM2.5 and smaller, are capable of penetrating the lung barrier and circulating in the bloodstream to potentially affect neural function (Peters et al., 2006). Coarser particles such as PM10 are less likely to exert such direct physiological effects.

This distinction offers a testable implication: if prosocial behavior responds more strongly to PM10 than to PM2.5, it would lend greater support to the psychological mechanism, whereas a stronger response to PM2.5 would be more consistent with the physiological channel.

In addition to particle size, timing provides another useful lens for distinguishing between psychological and physiological mechanisms. The physiological effects of air pollution—particularly those mediated by hormonal or neurological changes—typically require prolonged or cumulative exposure and may not manifest immediately. In contrast, psychological responses such as discomfort, irritability, or stress can occur contemporaneously with pollution exposure and can prompt immediate behavioral responses.

Since our experiment captures behavior in real time, with pollution measured hourly and helping behavior observed within 10 minutes, the observed effects are more consistent with a short-run psychological response rather than a delayed physiological one. While we cannot rule out all long-term biological influences, the immediacy of the helping behavior—especially the act of posting—suggests that psychological salience may play a more prominent role.

We next turn to empirical evidence that speaks to this distinction by examining whether helping behavior responds more strongly to perceptible pollution (PM10) than to finer particulates (PM2.5).

5.2 Differential Effects of PM2.5 and PM10

To investigate whether immediate perceptual discomfort or slow-acting underlying physiological effects plays a more prominent role in driving helping behavior, Table 7 replicates the posting results from Panel B of Table 2 (linear effect) and Panel B of Table 3 (nonlinear effect) but includes both PM2.5 and PM10 simultaneously in the regressions. This allows us to assess their relative importance when considered jointly. One caveat is that, as shown in Figure 1, the two pollutants are highly correlated—particularly in Delhi—making it difficult to disentangle their effects in a linear specification.

Not surprisingly, none of the linear estimates in Panel A of Table 7 are statistically significant, reflecting this multicollinearity. However, the nonlinear results in Panel B show a consistently positive and statistically significant effect of PM10, while the coefficients on PM2.5 are smaller, statistically insignificant, and vary in sign.

That the effect favors PM10 over PM2.5 lends support to the psychological mechanism. PM10, as a more perceptible pollutant, is more likely to generate immediate discomfort and emotional salience, prompting helping behavior as a coping response. PM2.5, by contrast, may affect health over longer time horizons but lacks the same short-run affective visibility.

As we do not apply 2SLS to this specification due to limitations in identifying separate instruments, the evidence here should be viewed as suggestive rather than definitive. Nonetheless, the results are consistent with the idea that perceived discomfort, rather than biological toxicity, is the more immediate driver of the behavior we observe.

5.3 Heterogeneity by Local Social Context

We next examine whether the effect of pollution on helping behavior varies with features of the local social environment, focusing on two key dimensions: foot traffic density (passersby per minute) and the gender composition of passersby (the ratio of female passersby to all passersby). These contextual factors can shape how salient or stressful a situation feels, thereby influencing the likelihood of prosocial responses to pollution exposure.

Panel A of Table 8 allows the pollution effects to vary by foot traffic density. Across both cities, we find that the interaction coefficients are positive and statistically significant, especially for PM10. This indicates that the effect of pollution on posting becomes stronger in more crowded settings. One interpretation is that dense foot traffic amplifies the discomfort associated with pollution—whether through physical proximity or sensory overload—thereby heightening the psychological salience of the environment and increasing the motivation to engage in helping behavior. An alternative, complementary explanation is that social visibility or reputational concerns are greater in crowded areas, nudging individuals toward low-cost prosocial acts when discomfort is present.

Panel B of Table 8 interacts pollution with the ratio of female passersby and reveals sharply contrasting patterns across the two cities. The interaction terms for PM10 are significantly negative in Delhi but positive in Beijing. That is, in Delhi, the prosocial effect of pollution is stronger in male-dominated environments, whereas in Beijing, it is stronger when more women are present. These opposing signs suggest the influence of city-specific social norms and safety conditions. In Delhi—where public safety concerns for women are prominent and female participation in public space is relatively constrained—pollution-related helping behavior may manifest more strongly in male-dominated settings, potentially reflecting gendered expectations around public responsibility or the reputational salience of being observed helping. In contrast, in Beijing—where gender participation in public spaces is more balanced—the presence of more women may reinforce normative expectations of civility or emotional responsiveness, thereby magnifying the pollution–helping response.

Taken together, the results show that the positive effect of pollution on helping is robust but amplified or dampened by features of the local social context. It interacts not only with perceptual factors like pollutant type, but also with real-time social cues such as crowd size and composition. These findings reinforce a psychological salience mechanism: the likelihood of helping under pollution increases when discomfort is magnified or when social awareness is heightened by the presence of others.

5.4 Co-movement in Online Searches for “Air Pollution” and “Stress”

To further explore the plausibility of the psychological mechanism, we examine whether public concern about air pollution correlates with elevated expressions of stress in online search behavior.[2] Figure 3 presents monthly search data from 2017 to 2023 for Beijing and Delhi.

In Panel A, we use data from Baidu, the largest search engine in China, showing the natural log of the weighted search index for the Simplified Chinese terms "空气污染" (air pollution) and "压力" (stress). In Panel B, we use Google Trends data for Delhi, based on the Hindi terms "वायु प्रदूषण" (air pollution) and "तनाव" (stress). For Delhi, the search values are scaled relative to the highest observed monthly volume during the period, with 100 representing the peak and 50 indicating half that level.

In both cities, the two search terms move together closely: months with more frequent searches for air pollution also tend to see more frequent searches for stress. This positive association suggests that public concern about air pollution tends to coincide with increased concern about stress, even in cities where poor air quality is a persistent feature of daily life. The results are consistent with the hypothesis that air pollution can trigger affective stress, supporting the salience-based psychological mechanism.

To assess whether this association is specific to heavily polluted cities, Figure 4 presents monthly Google Trends data from 2017 to 2023 for six English-speaking countries: Australia, Canada, Ireland, New Zealand, the United Kingdom, and the United States. Each dot in the scatterplot represents the monthly search interest for "stress" and "air pollution" in a given country.

Despite much lower pollution levels in these countries, we again observe a strong positive correlation between the two search terms. This generalizability across countries and

[2] We focus on "stress" because it reflects acute psychological discomfort and is more likely to respond to short-run environmental stimuli such as pollution (Mehta, et al., 2015; Zhang, et al., 2021). In contrast, terms like "anxiety" or "depression" capture more chronic states that are less theoretically aligned with our setting and more prone to unobserved confounders. While stress is not immune to such influences, it is better suited for detecting the immediate psychological salience we aim to test.

languages suggests that air pollution is broadly linked to stress-related cognition, even outside high-exposure environments.

While this evidence is correlational and drawn from population-level behavior, the consistency of patterns across settings supports the view that air pollution awareness is psychologically charged. These search patterns reinforce the plausibility of the mechanism: individuals may experience perceptual stress from pollution, prompting a psychological response that in turn encourages prosocial behavior.

6. Conclusion

Air pollution is commonly viewed as a health hazard—damaging to bodies, minds, and social cohesion. Yet our study shows that pollution may also provoke unexpected forms of human connection. In two large-scale field experiments in Beijing and Delhi, we find that individuals are more likely to engage in a spontaneous act of help—posting a lost letter—when ambient pollution is high. This effect is specific to helping behavior that requires intentional effort and is most consistently associated with PM10, a more perceptible form of pollution. The immediacy of the behavior, the lack of personal gain, and supporting evidence from online search activity all point to a salience-based psychological mechanism: pollution induces stress or discomfort, which in turn prompts individuals to reaffirm their moral identity through a low-cost prosocial act.

This finding complicates the narrative that pollution necessarily erodes social behavior. Instead, it suggests that acute discomfort can catalyze moments of altruism, even in anonymous urban settings. If so, the emotional burden of living in polluted environments may not merely suppress action—it may also activate latent social instincts. Helping, in this case, may function not only as moral expression but as a form of emotional coping in response to environmental strain.

At the same time, our results should not be over-romanticized. The kind of helping we observe is low-cost and situational. It remains an open question whether similar effects would hold for more demanding or sustained forms of prosocial behavior. Nor do our findings diminish the profound long-term harms of pollution. Instead, they point to a more nuanced view: the social consequences of pollution are not linear, and people's behavioral responses may be shaped as much by emotion and perception as by physical exposure.

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References

Aguilar-Gomez, Sandra, Holt Dwyer, Joshua S. Graff Zivin, and Matthew J. Neidell. 2022. “This Is Air: The ‘Non-health’ Effects of Air Pollution.” *NBER Working Paper* No. 29848.

Andreoni, James. 1990. “Impure Altruism and Donations to Public Goods: A Theory of Warm-Glow Giving.” *The Economic Journal* 100 (401): 464–477.

Arceo, Eva, Rema Hanna, and Paulina Oliva. 2015. “Does the Effect of Pollution on Infant Mortality Differ between Developing and Developed Countries? Evidence from Mexico City.” *The Economic Journal* 126: 257–280.

Bondy, Malvina, Sefi Roth, and Lutz Sager. 2020. “Crime Is in the Air: The Contemporaneous Relationship between Air Pollution and Crime.” *Journal of the Association of Environmental and Resource Economists* 7 (3): 555–585.

Brook, Robert D., Sanjay Rajagopalan, C. Arden Pope III, Jeffrey R. Brook, Aruni Bhatnagar, Ana V. Diez-Roux, and Russell V. Luepker. 2010. “Particulate Matter Air Pollution and Cardiovascular Disease: An Update to the Scientific Statement From the American Heart Association.” *Circulation* 121 (21): 2331–2378.

Buchanan, Tony W., and Stephanie D. Preston. 2014. “Stress Leads to Prosocial Action in Immediate Need Situations.” *Frontiers in Behavioral Neuroscience* 8: 5.

Burkhardt, Jesse, Jude Bayham, Ander Wilson, Ellison Carter, Jesse D. Berman, Katelyn O’Dell, Bonne Ford, Emily V. Fischer, and Jeffry R. Pierce. 2019. “The Effect of Pollution on Crime: Evidence from Data on Particulate Matter and Ozone.” *Journal of Environmental Economics and Management* 98: 102267.

Centers for Disease Control and Prevention (CDC). 2024. “Air Pollutants.” https://www.cdc.gov/air-quality/pollutants/index.html.

Chang, Tom, Joshua Graff Zivin, Tal Gross, and Matthew Neidell. 2016. "Particulate Pollution and the Productivity of Pear Packers." *American Economic Journal: Economic Policy* 8 (3): 141–169.

Chen, Jie, and Gerard Hoek. 2020. "Long-Term Exposure to PM and All-Cause and Cause-Specific Mortality: A Systematic Review and Meta-Analysis." *Environment International* 143: 105974.

Chen, Xiaoguang, Luoye Chen, Wei Xie, Nathaniel D. Mueller, and Steven J. Davis. 2023. "Flight Delays Due to Air Pollution in China." *Journal of Environmental Economics and Management* 119: 102810.

Chew, Soo H., Wei Huang, and Xun Li. 2021. "Does Haze Cloud Decision Making? A Natural Laboratory Experiment." *Journal of Economic Behavior and Organization* 182: 132–161.

Cialdini, Robert B., Donald J. Baumann, and Douglas T. Kenrick. 1981. "Insights from Sadness: A Three-Step Model of the Development of Altruism as Hedonism." *Developmental Review* 1: 207–223.

Cialdini, Robert B., and Douglas T. Kenrick. 1976. "Altruism as Hedonism: A Social Development Perspective on the Relationship of Negative Mood State and Helping." *Journal of Personality and Social Psychology* 34 (5): 907–914.

Dominski, Fábio Hech, Joaquim Henrique Lorenzetti Branco, Giorgio Bunanno, Luica Stabile, Manuel Gameiro da Silva, and Alexandro Andrade. 2021. "Effects of Air Pollution on Health: A Mapping Review of Systematic Reviews and Meta-Analyses." *Environmental Research* 201: 111487.

Dong, Rui, Raymond Fisman, Yongxiang Wang, and Nianhang Xu. 2021. "Air Pollution, Affect, and Forecasting Bias: Evidence from Chinese Financial Analysts." *Journal of Financial Economics* 139 (3): 971–984.

Ebenstein, Avraham, Victor Lavy, and Sefi Roth. 2016. “The Long-Run Economic Consequences of High-Stakes Examinations: Evidence from Transitory Variation in Pollution.” *American Economic Journal: Applied Economics* 8 (4): 36–65.

Fu, Shihe, V. Brian Viard, and Peng Zhang. 2021. “Air Pollution and Manufacturing Firm Productivity: Nationwide Estimates for China.” *The Economic Journal* 131: 3241–3273.

Graff Zivin, Joshua, and Matthew Neidell. 2012. “The Impact of Pollution on Worker Productivity.” *American Economic Review* 102 (7): 3652–3673.

Guo, Mengmeng, and Shihe Fu. 2019. “Running with a Mask? The Effect of Air Pollution on Marathon Runners' Performance.” *Journal of Sports Economics* 20 (7): 903–928.

He, Jiaxiu, Haoming Liu, and Alberto Salvo. 2019. “Severe Air Pollution and Labor Productivity: Evidence from Industrial Towns in China.” *American Economic Journal: Applied Economics* 11 (1): 173–201.

Herrnstadt, Evan, Anthony Heyes, Erich Muehlegger, and Soodeh Saberian. 2021. “Air Pollution and Criminal Activity: Microgeographic Evidence from Chicago.” *American Economic Journal: Applied Economics* 13 (4): 70–100.

Huang, Jeikun, Nianhang Xu, and Honghai Yu. 2020. “Pollution and Performance: Do Investors Make Worse Trades on Hazy Days?” *Management Science* 66 (10): 4455–4476.

Jans, Jenny, Per Johansson, and J. Peter Nilsson. 2018. “Economic Status, Air Quality, and Child Health: Evidence from Inversion Episodes.” *Journal of Health Economics* 61: 220–232.

Lichter, Andreas, Nico Pestel, and Eric Sommer. 2017. “Productivity Effects of Air Pollution: Evidence from Professional Soccer.” *Labour Economics* 48: 54–66.

Lu, Jackson G. 2020. “Air Pollution: A Systematic Review of Its Psychological, Economic and Social Effects.” *Current Opinion in Psychology* 32: 52–65.

Mehta, Amar J., Laura D. Kubzansky, Brent A. Coull, Itai Kloog, Petros Koutrakis, David Sparrow, Avron Spiro III, Pantel Vokonas, and Joel Schwartz. 2015. “Associations between Air Pollution and Perceived Stress: The Veterans Administrative Normative Aging Study.” *Environmental Health* 14 (10). https://doi.org/10.1186/1476-069X-14-10.

Midlarsky, Elizabeth. 1991. “Helping as Coping.” In *Prosocial Behavior*, edited by Margaret S. Clark, 238–264. Sage Publications, Inc.

Milgram, Stanley, Leon Mann, and Susan Harter. 1965. “The Lost-Letter Technique: A Tool of Social Research.” *Public Opinion Quarterly* 29: 437–438.

Pérez-Dueñas, Carolina, M. Fernanda Rivas, Olusegun A. Oyediran, and Francisco Garcia-Torres. 2018. “Induced Negative Mood Increases Dictator Game Giving.” *Frontiers in Psychology* 9: 1542.

Peters, Annette, Bellina Veronesi, Lilian Calderón-Garcidueñas, Peter Gehr, Lung Chi Chen, Marianne Geiser, William Reed, Barbara Rothen-Rutishauser, Samuel Schürch, and Holger Schulz. 2006. “Translocation and Potential Neurological Effects of Fine and Ultrafine Particles: A Critical Update.” *Particle and Fibre Toxicology* 3: 13.

Power, Melinda C., Jennifer Weuve, Kimberly A. G. Jimenez, David C. Grodstein, Joel D. Schwartz, and Francine Laden. 2011. “Exposure to Air Pollution and Cognitive Function, with an Emphasis on Exposure to Fine Particulate Matter.” *Environmental Health Perspectives* 119 (5): 682–687.

Sager, Lutz. 2019. “Estimating the Effect of Air Pollution on Road Safety Using Atmospheric Temperature Inversions.” *Journal of Environmental Economics and Management* 98: 102250.

Schraufnagel, Dean E., Sarath Raju, Susan G. Koenig, Christina M. Alamo Rojas, Dean T. Nardell, and Barbara Hoffmann. 2019. “Air Pollution and Noncommunicable

Diseases: A Review by the Forum of International Respiratory Societies' Environmental Committee." *Chest* 155 (2): 409–416.

Schroeder, David A., and William G. Graziano. 2014. "The Field of Prosocial Behavior: An Introduction and Overview." In *The Oxford Handbook of Prosocial Behavior*, edited by D. A. Schroeder and W. G. Graziano, 3–34. New York: Oxford University Press.

UK Department for Environment, Food & Rural Affairs. 2025. "Particulate Matter (PM10) – Check Air Quality." https://check-air-quality.service.gov.uk/pollutants/particulate-matter-10.

Vinkers, Christian H., Jelle V. Zorn, Sandra Cornelisse, Susanne Koot, Lotte C. Houtepen, Berend Olivier, Joris C. Verster, Rene S. Kahn, Marco P. M. Boks, Tobias Kalenscher, and Marian Joëls. 2013. "Time-Dependent Changes in Altruistic Punishment Following Stress." *Psychoneuroendocrinology* 38: 1467–1475.

Wang, Linlin, Hong Wang, Junkai Li, Zhiqiu Gao, Yuanjian Yang, Xiaoye Zhang, Yubin Li, and Meng Huang. 2019. "Impacts of the Near-Surface Urban Boundary Layer Structure on PM2.5 Concentrations in Beijing during Winter." *Science of the Total Environment* 669: 493–504.

Weitekamp, Chelsea A., and Hans A. Hoffmann. 2021. "Effects of Air Pollution Exposure on Social Behavior: A Synthesis and Call for Research." *Environmental Health* 20 (72). https://doi.org/10.1186/s12940-021-00761-8.

Zhang, Weifang, Sihui Peng, Jialu Fu, Ke Xu, Huihui Wang, Yu Jin, Tingzhong Yang, and Randall R. Cottrell. 2021. "Urban Air Pollution and Mental Stress: A Nationwide Study of University Students in China." *Frontiers in Public Health* 9. https://doi.org/10.3389/fpubh.2021.685431.

Zhang, Xin, Xi Chen, and Xiaobo Zhang. 2018. "The Impact of Exposure to Air Pollution on Cognitive Performance." *Proceedings of the National Academy of Sciences* 115 (37): 9193–9197.

Table 1. Summary Statistics

	Beijing (N=1,619)		Delhi (N=2,174)	
	Mean (1)	S.D. (2)	Mean (3)	S.D. (4)
Letter picked up (%)	0.716	0.451	0.583	0.493
Letter posted (%)	0.362	0.481	0.417	0.493
Time (minutes)	5.594	3.493	7.759	2.596
Passersby (person)	28.145	23.773	15.973	11.534
Male	13.959	11.694	11.126	8.281
Female	14.186	12.664	4.847	4.531
PM2.5 (μg/m^3)	59.912	32.252	170.888	106.447
PM10 (μg/m^3)	109.792	56.541	298.586	174.928
Ambient noise (decibel)	67.692	10.124	78.015	15.774
Ambient temperature (°C)	18.321	11.392	24.105	8.138
Surface wind speed (m/s)	4.310	2.377	3.761	1.841
Surface specific humidity	0.006	0.005	0.006	0.004
Surface pressure (Pa)	98931	820	98707	526

Notes: Time refers to the time interval between the moment the letter was dropped on the ground and the moment it was picked up, or the end of 10 minutes if it was not yet picked up. Passersby include all people who passed by the letter during this period and the person who picked up the letter. Due to nonreporting, the number of observations of PM10 is 1,508 in Beijing and 1,119 in Delhi.

Sources: Data on surface specific humidity, surface wind speed, surface pressure are acquired from the Modern-Era Retrospective Analysis for Research and Applications, Version 2 (MERRA-2) from the Global Model and Assimilation Office (GMAO) at National Aeronautics and Space Administration (NASA). PM2.5 and PM10 data are from the air pollution monitoring stations in Beijing and Delhi. All other variables are authors' own collection in the experiment.

Table 2. OLS Estimates of the Linear Particulate Matters Effects

	Beijing (1)	Beijing (2)	Delhi (3)	Delhi (4)
	Panel A: Pickup			
Std. PM2.5	0.016		0.007	
	(0.015)		(0.011)	
Std. PM10		0.055***		0.015
		(0.016)		(0.021)
Observations	1,619	1,508	2,174	1,119
Cluster	539	502	738	377
	Panel B: Post			
Std. PM2.5	0.006		0.031***	
	(0.015)		(0.011)	
Std. PM10		0.029		0.038*
		(0.018)		(0.020)
Observations	1,619	1,508	2,174	1,119
Cluster	539	502	738	377

Notes: The dependent variable is a dummy variable indicating whether the letter was picked up in Panel A or posted in Panel B. The particulate matter variables are the standardized PM2.5 and PM10. All regressions additionally control for ambient noise, ambient temperature, surface wind speed, surface specific humidity, surface pressure, passersby per minute, the ratio of female passersby, a full set of day of week fixed effect, wave fixed effect and location fixed effect. Robust standard errors clustered at location-date-hour level are in parentheses. ***, ** and * indicate statistically significant at 1%, 5%, and 10%, respectively.

Table 3. OLS Estimates of the Nonlinear Particulate Matters Effects

	Beijing (1)	Beijing (2)	Delhi (3)	Delhi (4)
	Panel A: Pickup			
Std. PM2.5				
3rd Quartile	0.037		0.026	
	(0.030)		(0.026)	
4th Quartile	0.022		0.032	
	(0.030)		(0.030)	
Std. PM10				
3rd Quartile		0.068*		0.020
		(0.035)		(0.039)
4th Quartile		0.143***		0.049
		(0.041)		(0.047)
Observations	1,619	1,508	2,174	1,119
Cluster	539	502	738	377
	Panel B: Post			
Std. PM2.5				
3rd Quartile	0.002		-0.004	
	(0.033)		(0.023)	
4th Quartile	0.002		0.065**	
	(0.034)		(0.029)	
Std. PM10				
3rd Quartile		0.096**		0.083**
		(0.037)		(0.038)
4th Quartile		0.090**		0.087**
		(0.044)		(0.043)
Observations	1,619	1,508	2,174	1,119
Cluster	539	502	738	377

Notes: The dependent variable is a dummy variable indicating whether the letter was picked up in Panel A or posted in Panel B. The particulate matter variables are dummy variables indicating the third and fourth quartile of the standardized PM2.5 and PM10 distribution respectively. The reference group is the bottom two quartiles. All regressions additionally control for ambient noise, ambient temperature, surface wind speed, surface specific humidity, surface pressure, passersby per minute, the ratio of female passersby, a full set of day of week fixed effect, wave fixed effect and location fixed effect. Robust standard errors clustered at location-date-hour level are in parentheses. ***, ** and * indicate statistically significant at 1%, 5%, and 10%, respectively.

Table 4. Comparison of the Linear Effects of Particulate Matters between Weekdays and Weekends

	Beijing (1)	Beijing (2)	Delhi (3)	Delhi (4)
	Panel A: Pickup			
Std. PM2.5	0.031		0.006	
	(0.020)		(0.013)	
Std. PM2.5 × Weekend	-0.035		0.005	
	(0.028)		(0.019)	
Std. PM10		0.058**		-0.000
		(0.024)		(0.022)
Std. PM10 × Weekend		-0.005		0.055**
		(0.024)		(0.027)
Observations	1,619	1,508	2,174	1,119
Cluster	539	502	738	377
	Panel B: Post			
Std. PM2.5	0.009		0.028**	
	(0.020)		(0.012)	
Std. PM2.5 × Weekend	-0.009		0.009	
	(0.028)		(0.017)	
Std. PM10		0.023		0.032
		(0.024)		(0.021)
Std. PM10 × Weekend		0.010		0.021
		(0.027)		(0.027)
Observations	1,619	1,508	2,174	1,119
Cluster	539	502	738	377

Notes: The dependent variable is a dummy variable indicating whether the letter was picked up in Panel A or posted in Panel B. The particulate matter variables are the standardized PM2.5 and PM10. Weekend is a dummy variable indicating either Saturday or Sunday. All regressions additionally control for ambient noise, ambient temperature, surface wind speed, surface specific humidity, surface pressure, passersby per minute, the ratio of female passersby, a full set of day of week fixed effect, wave fixed effect and location fixed effect. Robust standard errors clustered at location-date-hour level are in parentheses. ***, ** and * indicate statistically significant at 1%, 5%, and 10%, respectively.

Table 5. 2SLS Estimates of the Linear Effect of Particulate Matters in Beijing

	(1)	(2)	(3)	(4)
	Panel A: Second Stage Results-Pickup			
Std. PM2.5	0.098*	0.091**		
	(0.059)	(0.042)		
Std. PM10			0.072	0.075*
			(0.049)	(0.039)
	Panel B: Second Stage Results-Post			
Std. PM2.5	0.207**	0.171**		
	(0.092)	(0.067)		
Std. PM10			0.162**	0.159**
			(0.076)	(0.062)
	Panel C: First Stage Results			
Inversion	0.788***	1.866***	0.902***	1.826***
	(0.153)	(0.256)	(0.180)	(0.296)
Temperature difference		0.732***		0.633***
		(0.132)		(0.146)
Mean of Inversion	0.069	0.069	0.074	0.074
Mean of Temperature Difference		-0.108		-0.116
Kleibergen-Paap *F* stat	26.58	27.21	24.98	19.99
Cluster	539	539	502	502
Observations	1,619	1,619	1,508	1,508

Notes: The dependent variable is a dummy variable indicating whether the letter was picked up in Panel A or posted in Panel B. In Panel C, the dependent variable is Std. PM2.5 in column (1) and (2) and Std. PM10 in column (3) and (4). Thermal inversion in Panel C is a dummy variable indicating whether thermal inversion occurred at the altitude of 320 meter or below; the change in temperature is the difference between the temperature at the top and bottom of the inversion layer. All regressions additionally control for ambient noise, ambient temperature, surface wind speed, surface specific humidity, surface pressure, passersby per minute, the ratio of female passersby, a full set of day of week fixed effect, wave fixed effect and location fixed effect. Robust standard errors clustered at location-date-hour level are in parentheses. ***, ** and * indicate statistically significant at 1%, 5%, and 10%, respectively.

Table 6. 2SLS Estimates of the Linear Effect of Particulate Matters in Delhi				
	(1)	(2)	(3)	(4)
	Panel A: Second Stage Results-Pickup			
Std. PM2.5	0.021	0.021		
	(0.044)	(0.045)		
Std. PM10			0.032	0.026
			(0.045)	(0.047)
	Panel B: Second Stage Results-Post			
Std. PM2.5	0.119***	0.123***		
	(0.045)	(0.047)		
Std. PM10			0.127***	0.139***
			(0.044)	(0.046)
	Panel C: First Stage Results			
	16 cells	36 cells	16 cells	36 cells
Burn	0.077***	0.023***	0.101***	0.031***
	(0.025)	(0.007)	(0.024)	(0.007)
Burn × Anand Vihar	-0.084***	-0.025***	-0.014	-0.013
	(0.025)	(0.008)	(0.054)	(0.021)
Burn × Dwarka	-0.087***	-0.026***	-2.644***	-0.875***
	(0.025)	(0.007)	(0.266)	(0.098)
Burn × IHBAS	-0.054**	-0.017**	0.386	0.106
	(0.024)	(0.007)	(0.252)	(0.086)
Burn × ITO	-0.070***	-0.021***	-0.042***	-0.014***
	(0.026)	(0.008)	(0.016)	(0.005)
Burn × Mandir Marg	-0.082***	-0.025***	-0.091***	-0.028***
	(0.024)	(0.007)	(0.015)	(0.005)
Burn × Punjabi Bagh	-0.060**	-0.017**	-0.054***	-0.017***
	(0.026)	(0.008)	(0.016)	(0.005)
Burn × RKP	-0.041*	-0.013*	-0.047***	-0.014***
	(0.024)	(0.007)	(0.016)	(0.005)
Burn × Shadipur	-0.064***	-0.019***		
	(0.024)	(0.007)		
Burn × Siri Fort	-0.083***	-0.024***	-0.015	-0.011
	(0.025)	(0.007)	(0.028)	(0.013)
Mean of Burn	6.495	21.42	6.495	21.42
Kleibergen-Paap *F* stat	3.716	3.543	18.15	14.98
Cluster	738	738	377	377
Observations	2,174	2,174	1,119	1,119

Notes: The dependent variable is a dummy variable indicating whether the letter was picked up in Panel A or posted in Panel B. In Panel C, the dependent variable is Std. PM2.5 in column (1) and (2) and Std. PM10 in column (3) and (4). The instrumental variables contain two crops burning indices (16 cells and all cells) interacted with location dummies. Shadipur did not report PM10. All regressions additionally control for ambient noise, ambient temperature, surface wind speed, surface specific humidity, surface pressure, passersby per minute, the ratio of female passersby, a full set of day of week fixed effect, wave fixed effect and location fixed effect. Robust standard errors clustered at location-date-hour level are in parentheses. ***, ** and * indicate statistically significant at 1%, 5%, and 10%, respectively.

Table 7. OLS Estimates of the Linear and Nonlinear Particulate Matters Effects on Posting by Including Both PM2.5 and PM10

	Beijing	Delhi
	(1)	(2)
	Panel A: Linear Effect	
Std. PM2.5	-0.009	0.007
	(0.023)	(0.013)
Std. PM10	0.035	0.011
	(0.024)	(0.021)
Observations	1,508	1,119
Cluster	502	377
	Panel B: Nonlinear Effect	
Std. PM2.5		
3rd Quartile	0.007	-0.019
	(0.034)	(0.040)
4th Quartile	-0.029	0.002
	(0.038)	(0.046)
Std. PM10		
3rd Quartile	0.108***	0.086**
	(0.040)	(0.042)
4th Quartile	0.105**	0.083
	(0.048)	(0.053)
Observations	1,508	1,119
Cluster	502	377

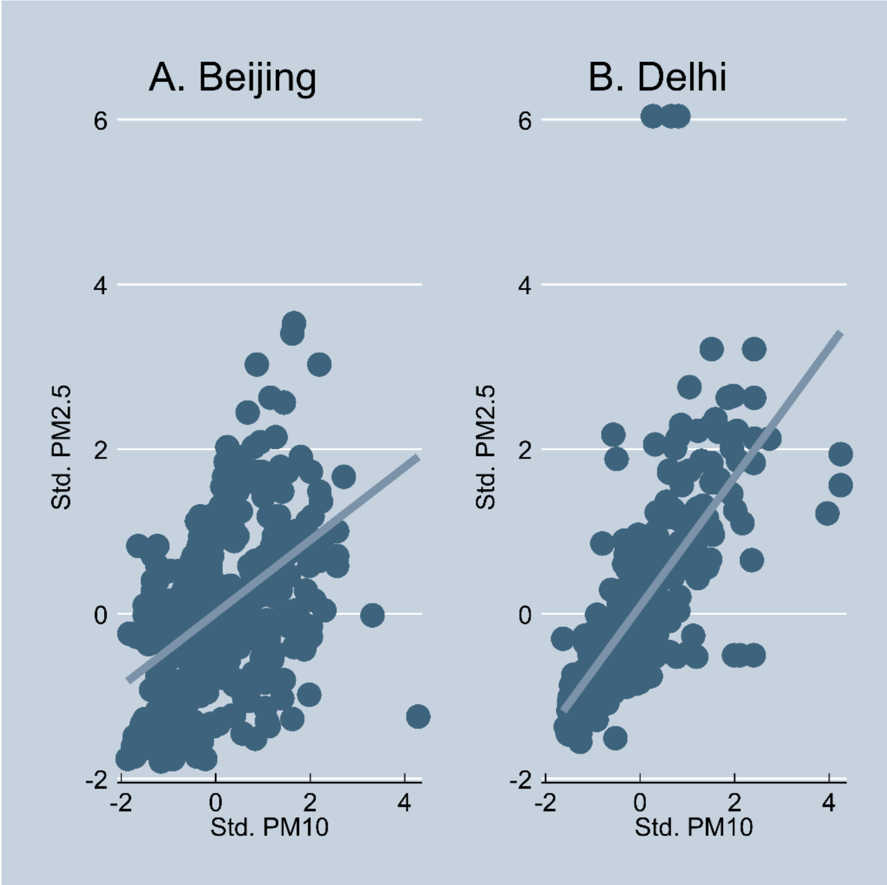
Notes: The dependent variable is a dummy variable indicating whether the letter was posted. The particulate matter variables in Panel B are dummy variables indicating the third and fourth quartile of the standardized PM2.5 and PM10 distribution respectively. The reference group is the bottom two quartiles. All regressions additionally control for ambient noise, ambient temperature, surface wind speed, surface specific humidity, surface pressure, passersby per minute, the ratio of female passersby, a full set of day of week fixed effect, wave fixed effect and location fixed effect. Robust standard errors clustered at location-date-hour level are in parentheses. ***, ** and * indicate statistically significant at 1%, 5%, and 10%, respectively.

Table 8. Heterogeneous Linear Effects of Particulate Matters on Posting by Local Social Context

	Beijing (1)	Beijing (2)	Delhi (3)	Delhi (4)
	Panel A: Passersby per Minute			
Std. PM2.5	-0.035		0.002	
	(0.024)		(0.020)	
Passersby per minute	0.012**		0.077***	
	(0.005)		(0.011)	
Std. PM2.5 × Passersby per minute	0.007**		0.013*	
	(0.003)		(0.007)	
Std. PM10		-0.023		-0.016
		(0.026)		(0.027)
Passersby per minute		0.017***		0.132***
		(0.004)		(0.013)
Std. PM10 × Passersby per minute		0.010***		0.026***
		(0.004)		(0.009)
Observations	1,619	1,508	2,174	1,119
Cluster	539	502	738	377
	Panel B: The Ratio of Female Passersby			
Std. PM2.5	-0.024		0.058***	
	(0.039)		(0.021)	
Female Ratio	0.001		-0.002***	
	(0.001)		(0.001)	
Std. PM2.5 × Female Ratio	0.001		-0.001*	
	(0.001)		(0.001)	
Std. PM10		-0.063		0.083***
		(0.039)		(0.024)
Female Ratio		0.001		-0.003***
		(0.001)		(0.001)
Std. PM10 × Female Ratio		0.002***		-0.002***
		(0.001)		(0.001)
Observations	1,619	1,508	2,174	1,119
Cluster	539	502	738	377

Notes: The dependent variable is a dummy variable indicating whether the letter was posted. The particulate matter variables are the standardized PM2.5 and PM10. The particulate matter variables are further interacted with passersby per minute in Panel A and the ratio of female passersby in Panel B. All regressions additionally control for ambient noise, ambient temperature, surface wind speed, surface specific humidity, surface pressure, the ratio of female passerby (Panel A), passersby per minute (Panel B) and a full set of day of the week fixed effect, wave fixed effect and location fixed effect. Robust standard errors clustered at location-date-hour level are in parentheses. ***, ** and * indicate statistically significant at 1%, 5%, and 10%, respectively.

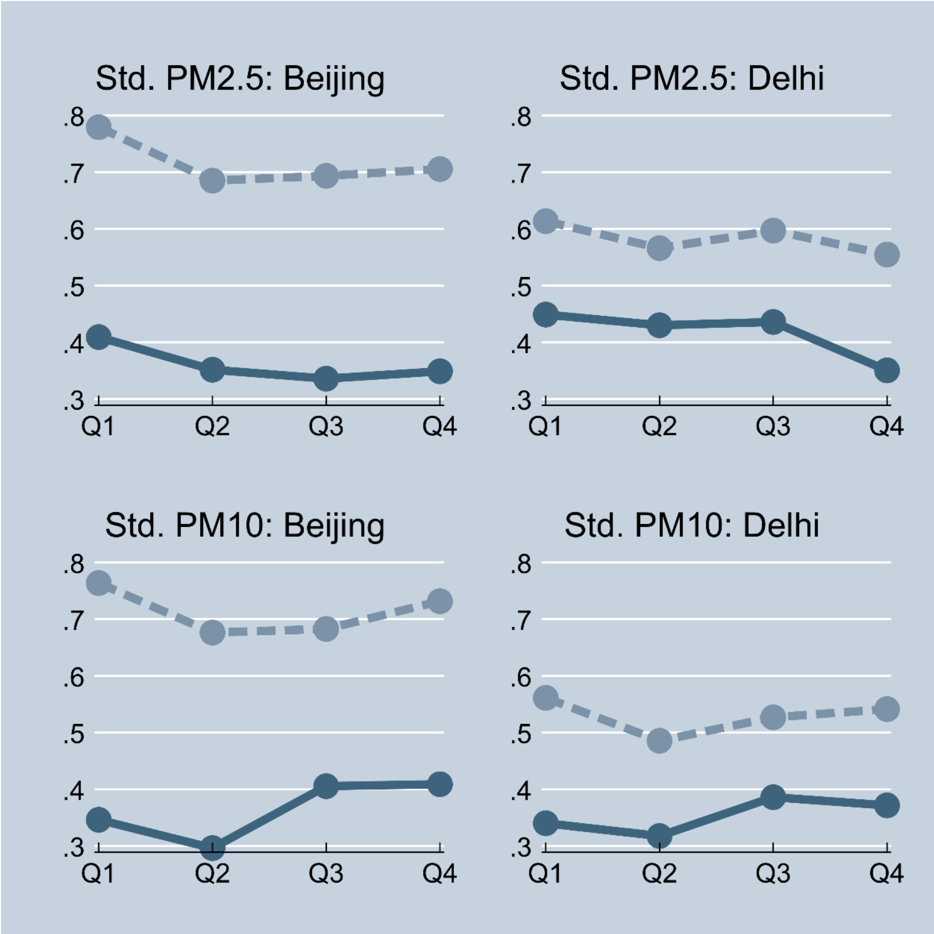
Figure 1. Correlation Between Standardized PM2.5 and PM10 in Beijing and Delhi



Notes: Each dot represents a letter-drop event.

Sources: Authors' own collection.

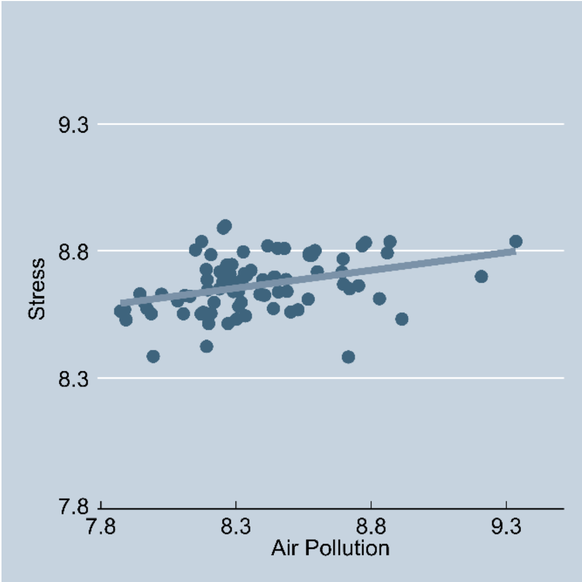
Figure 2. Pickup and Posting Rates by Quartiles of Standardized PM2.5 and PM10 in Beijing and Delhi



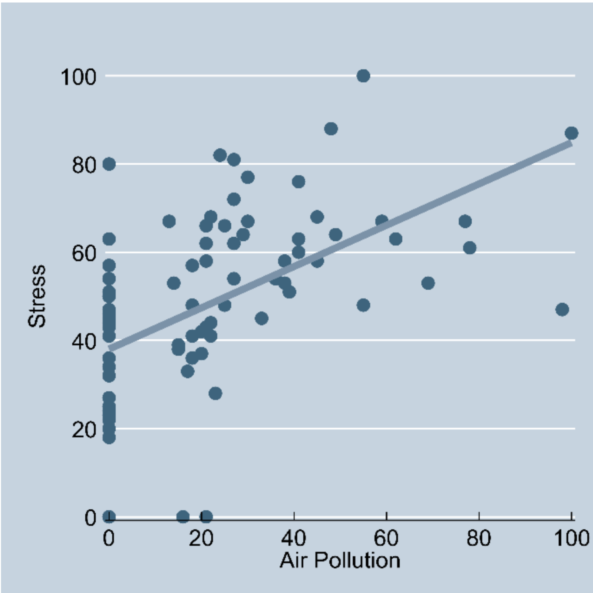
Notes: The dashed line is the pickup rate, and the solid line is the posting rate. Each dot shows the proportion of letters picked up or posted within each quartile of standardized PM2.5 or PM10.

Figure 3. Internet Searches for "Air Pollution" and "Stress" in Beijing and Delhi

Panel A. Beijing



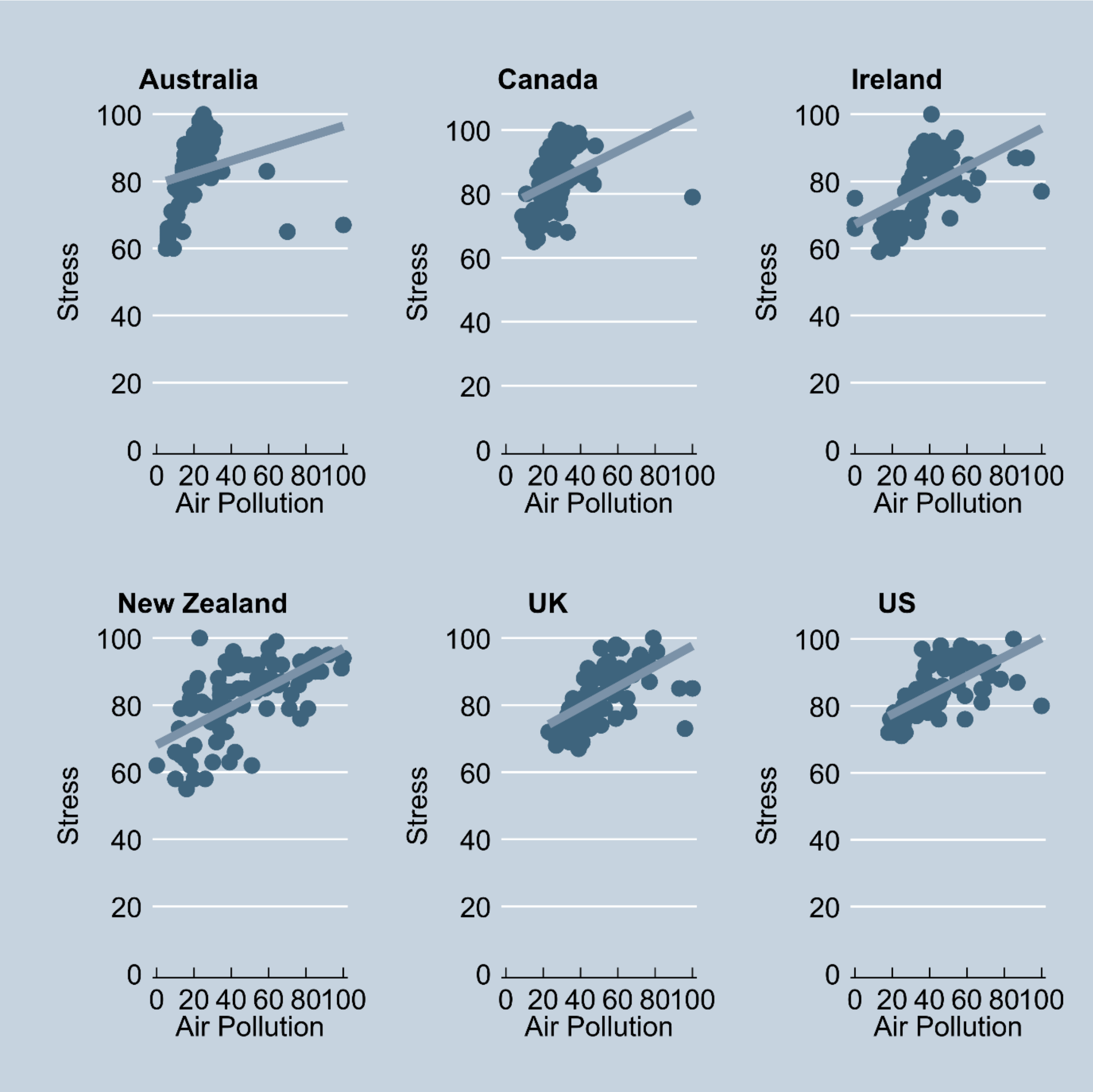
Panel B. Delhi



Notes: For Beijing in Panel A, the searches data are obtained from Baidu, the largest search engine in China. Each axis represents the natural log of weighted index of monthly search interest of each Chinese term during 2017-2023. The corresponding simplified Chinese characters are as follows: stress 压力 and air pollution 空气污染. For Delhi in Panel B, the searches data are obtained from Google. Numbers on each axis represent search interest relative to the highest point during 2017−2023 in each country. A value of 100 is the peak popularity for the term of interest, while 50 means the term is half as popular. The corresponding Hindi characters are as follows: stress तनाव and air pollution वायु प्रदूषण.

Sources: Baidu Index https://index.baidu.com/v2/index.html#/. Baidu Index data were accessed on April 28, 2024. Google Trends https://trends.google.com/home?geo=AU&hl=en-US. Google Trends data were accessed on July 4, 2025.

Figure4. Google Searches for "Air Pollution" and "Stress" in Six Anglophone Countries

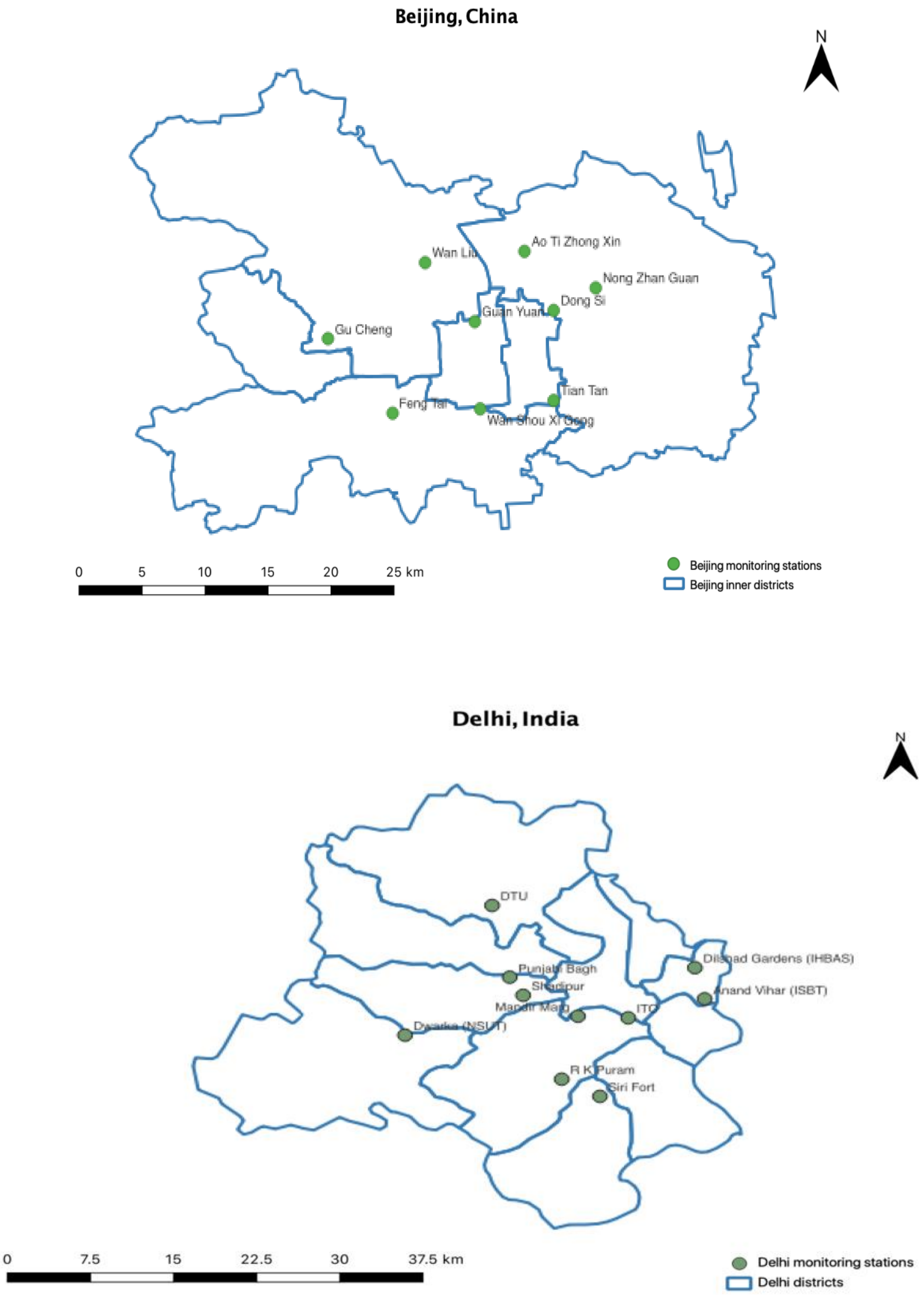


Notes: Numbers on each axis represent search interest relative to the highest point during 2017–2023 in each country. A value of 100 is the peak popularity for the term of interest, while 50 means the term is half as popular. Each dot indicates the search interest for "stress" and "air pollution" in each month.

Source: Google Trends https://trends.google.com/home?geo=AU&hl=en-US. Data were accessed on July 15, 2025.

Appendix 1

Figure A1. Air pollution monitoring stations in Beijing and Delhi



Notes: The dots indicate the locations of the air pollution monitoring stations. The top map only plots the 6 districts in the inner city of Beijing where we conducted the experiment.

Appendix 2 Experiment Protocol

1. Experiment Preparation

Prepare the letters by 1) writing the name and address on each envelope, 2) inserting the letter into the envelope, and 3) stamping and sealing the letter.

It is important to mark a code on the back of each envelope to clearly indicate the date, location and sequence of letters.

Before you set out to drop the letters, make sure you have the letters and the apps installed on your smart phones.

2. Experiment Procedure

The experiment will be carried out by multiple field teams. The observation period for each letter has a maximum of 10 minutes after it is dropped on the ground. A total of 9 letters should be dropped in each location with 3 letters in each hour.

A field team consists of two research assistants, who are referred as A and B below.

<u>Task Assignments</u>

A's tasks include: 1) count the male and female passersby using the counter app (Kountr Free for iPhone or Multi Counter by akibonn or t.s. for Android phones); 2) record the dropping time and outcome of each letter in the worksheet (see worksheet example).

B's tasks include: 1) drop the letter; 2) record the ambient temperature and noise using the apps; 3) collect the letter if it has not been removed in 10 minutes.

<u>Procedure</u>

Step 1: Seek for a spot for observation. Note that this is where you stay and observe, instead of where you drop the letter. A good location for observation would be a spot where you can clearly see the letter and passersby without raising any suspicion.

Step 2: Seek for a spot to drop the letter. Choose a spot, if possible, 3-5 meters away from the street letter box. Make it easy for people to find the letter box after picking up the letter.

Step 3: Turn on your devices (Smart phones) and apps. Make sure they work properly.

Step 4: B walks to the spot to drop the letter, while A stays in the observation location. B needs to drop the letter when no one else is watching and then walk back to the observation location. It is important NOT to raise suspicions. After B drops the letter, B immediately writes down the dropping time (hour and minute) on the worksheet.

Step 5: Count male and female passersby separately using the counter app. The passerby is defined as any person who walks roughly within the circle with a 3-meter radius that centers at the letter.

Step 6: Record the results of the experiment termination on the worksheet. An experiment terminates when the letter is removed from its dropping spot or has not been removed at the end of the 10-minute observation period. If it has not been removed at the end of the observation period, B walks to collect it. The results include 1) the time of termination, 2) whether the letter is removed by a passerby or for other reasons, e.g. wind or car, 3) the gender of the person who picks up the letter, 4) whether the letter is put into the letter box and 5) the average of the noise during observation.

Step 7: Repeat Step 3-6 for another two times.

Step 8: Walk to the fixed-point people to conduct mood survey.

3. Data Feedback

Every field team should report all collected data to the coordinator each day. In addition, the coordinator should record the data on hourly air pollution measures (PM2.5 and PM10) from all the air pollution monitoring stations. The coordinator should compile all data into an appropriate format and keep them in proper storage.

Appendix 3. Thermal Inversion and Meteorological Data in Beijing

We obtained thermal inversion and surface meteorological data for Beijing from NASA's Modern-Era Retrospective Analysis for Research and Applications, Version 2 (MERRA-2), produced by the Global Modeling and Assimilation Office (GMAO). MERRA-2 covers the entire globe on a fixed grid of 576 longitudinal by 361 latitudinal points, with each cell approximately 50 km × 50 km. All of our Beijing experiment sites fall within a single MERRA-2 grid cell, so we rely exclusively on temporal variation in inversion and weather conditions.

We use two MERRA-2 data products: 1) inst3_3d_asm_Np, which provides vertical air temperature profiles at 42 pressure levels every three hours; 2) inst1_2d_1fo_Nx, which includes hourly surface-level meteorological data such as wind speed, specific humidity, air pressure, and surface temperature.

To construct our inversion variables, we aligned the MERRA-2 timestamps with the hours during which we dropped letters (9 AM, 10 AM, and 11 AM Beijing time). Specifically, we matched the 9–10 AM letters to the 00:00 UTC temperature profile (08:00 Beijing time) and the 11 AM letters to the 03:00 UTC profile (11:00 Beijing time). We also tried matching the 9AM letters to the 00:00UTC readings and 10-11AM letter to the 03:00UTC readings. The results are similar and available upon request.

We calculated the corresponding altitudes for each pressure level and identified whether an inversion occurred by locating any reversal in the temperature gradient (i.e., where temperature increases with altitude). Following Chen et al. (2023), we constructed a dummy variable equal to one if a thermal inversion occurred at or below 320 meters above ground level. We also computed a continuous measure of inversion intensity, defined as the temperature difference between the base and the top of the lowest inversion layer. If multiple inversions were detected at different altitudes during the same time, we retained only the lowest inversion, which is most relevant for trapping surface-level pollutants.

The surface meteorological controls used in our regressions—wind speed, specific humidity, and air pressure—were drawn from the inst1_2d_1fo_Nx product. Wind speed is measured in meters per second, specific humidity as the mass of water vapor per unit mass of air, and air pressure in Pascals. While this product also includes surface temperature, we instead used temperature data collected directly during our fieldwork, which offers both geographic and temporal variation across locations and time.

All MERRA-2 data used in this study were accessed on December 2, 2023, via NASA's GES DISC data portal: https://disc.gsfc.nasa.gov/. The specific grid cell used corresponds to latitude 40°N and longitude 116.25°E, which covers the central area of Beijing where all our experimental locations are situated.

Reference

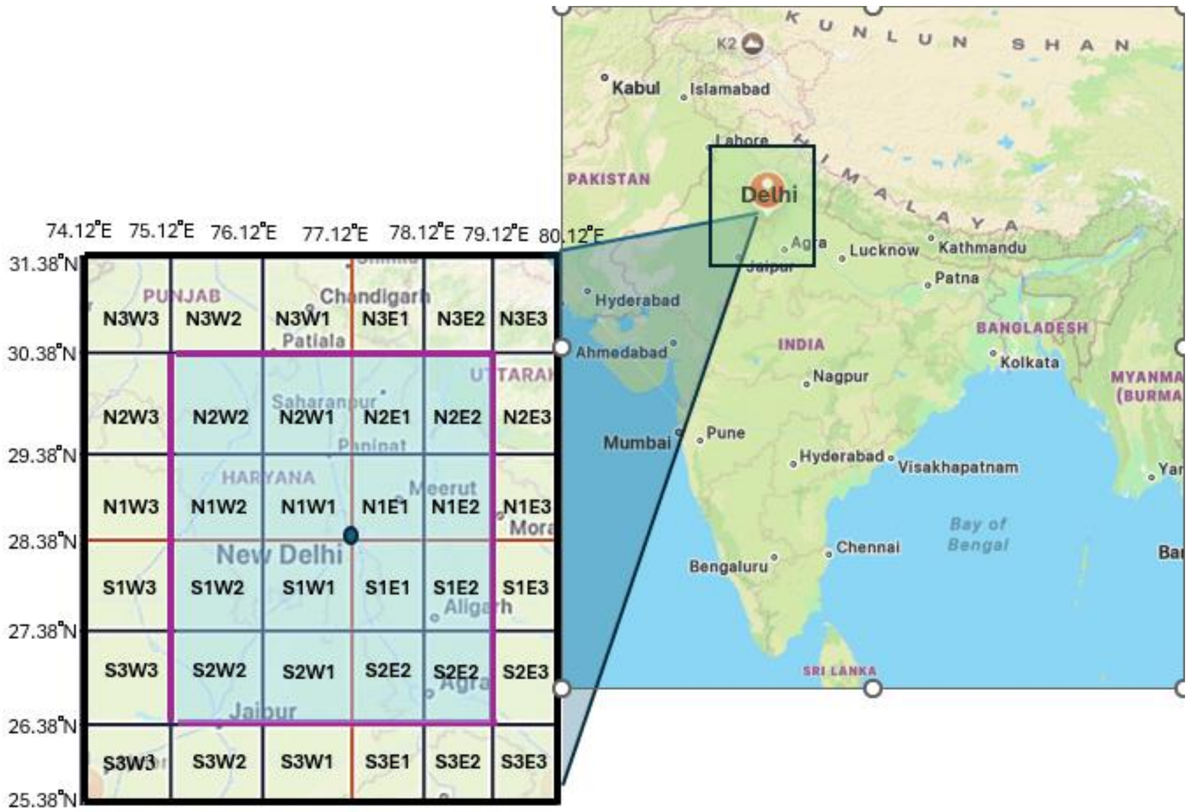
Chen, Xiaoguang, Luoye Chen, Wei Xie, Nathaniel D. Mueller, and Steven J. Davis. 2023. "Flight Delays Due to Air Pollution in China." *Journal of Environmental Economics and Management* 119: 102810.

Appendix 4. Agricultural Burning and Wind Instrument in Delhi

To instrument for variation in air pollution in Delhi, we use a measure that combines satellite-based data on agricultural and vegetation burning with local wind conditions. The underlying idea is that pollutants produced from crop residue burning, deforestation, and peatland fires in surrounding regions can be transported into Delhi by prevailing winds, thereby increasing ambient particulate matter concentrations (Lan et al., 2022).

We construct a 6×6 grid of 1°×1° latitude–longitude cells centered around Delhi's coordinates (28.38°N, 77.12°E), extending up to 3 degrees in each direction (north, south, east, and west). Each cell covers approximately 10,000 square kilometers, and the grid allows us to identify spatially where burning occurs in the region relative to Delhi. Each cell is uniquely labeled (e.g., N1W1, S2E3), with Delhi positioned at the center of the grid (Figure A4.1).

Figure A4.1 The Grid of Regions Surrounding Delhi



Grid: author's construct. Map Source: https://www.gps-coordinates.net/map/country/IN

Monthly burn data come from the Global Fire Emissions Database version 5 (GFED5) (Chen et al., 2023a, 2023b), which reports the area burned (in square kilometers) for cropland, deforestation, and peatland fires at 0.25°×0.25° resolution. For each cell, we aggregate the total burn area for the month in which our field experiment was conducted.

Hourly wind data are drawn from NASA's Modern-Era Retrospective Analysis for Research and Applications, Version 2 (MERRA-2), specifically from the M2T1NXSLV product, which provides hourly wind diagnostics at 0.5°×0.625° resolution. We extract both easterly (u) and northerly (v) wind components measured at 10 meters above ground level—the standard height used in meteorology for capturing surface-level wind speeds and fire spread conditions (Royal Meteorological Society, n.d.). The overall wind speed at each cell and hour is computed as $\sqrt{u^2 + v^2}$.

References

Burn Data

Chen, Y., Hall, J., van Wees, D., Andela, N., Hantson, S., Giglio, L., van der Werf, G. R., Morton, D. C., & Randerson, J. T. (2023a). Global Fire Emissions Database (GFED5) Burned Area (0.1) [Data set]. Zenodo. https://doi.org/10.5281/zenodo.7668424

Chen, Y., Hall, J., van Wees, D., Andela, N., Hantson, S., Giglio, L., van der Werf, G. R., Morton, D. C., & Randerson, J. T. (2023b). Multi-decadal trends and variability in burned area from the fifth version of the Global Fire Emissions Database (GFED5). Earth System Science Data, 15, 5227–5259. https://doi.org/10.5194/essd-15-5227-2023

Wind Data

Global Modeling and Assimilation Office (GMAO). (2015a). M2T1NXSLV dataset, MERRA-2 tavg1_2d_slv_Nx: 2d,1-Hourly, Time-Averaged, Single-Level, Assimilation, Single-Level Diagnostics V5.12.4, Goddard Earth Sciences Data and

Information Services Center (GES DISC). Accessed: 25 December 2023. https://doi.org/10.5067/VJAFPLI1CSIV

Surface Meteorological Data

Global Modeling and Assimilation Office (GMAO). (2015b). M2I1NXLFO dataset, MERRA-2 inst1_2d_lfo_Nx: 2d,1-Hourly, Instantaneous, Single-Level, Assimilation, Land Surface Forcings V5.12.4, Goddard Earth Sciences Data and Information Services Center (GES DISC). Accessed: 25 May 2025. https://doi.org/10.5067/RCMZA6TL70BG

Supporting Literature

Lan, R., Eastham, S. D., Liu, T., et al. (2022). Air quality impacts of crop residue burning in India and mitigation alternatives. Nature Communications, 13, 6537. https://doi.org/10.1038/s41467-022-34093-z

Royal Meteorological Society. (n.d.). The Beaufort Wind Scale. Accessed 16 June 2025. https://www.rmets.org/metmatters/beaufort-wind-scale

Appendix 5. Robustness Check: LIML Estimates for Delhi

Table A1. LIML Estimates of the Linear Effect of Particulate Matters in Delhi

	(1)	(2)	(3)	(4)
	Panel A: Second Stage Results-Pickup			
Std. PM2.5	0.023	0.024		
	(0.050)	(0.053)		
Std. PM10			0.033	0.027
			(0.047)	(0.049)
	Panel B: Second Stage Results-Post			
Std. PM2.5	0.124**	0.130**		
	(0.049)	(0.050)		
Std. PM10			0.134***	0.146***
			(0.047)	(0.049)
Cluster	738	738	377	377
Observations	2,174	2,174	1,119	1,119

Notes: The dependent variable is a dummy variable indicating whether the letter was picked up in Panel A or posted in Panel B. The instrumental variables contain two crops burning indices (16 cells and all cells) interacted with location dummies. All regressions additionally control for ambient noise, ambient temperature, surface wind speed, surface specific humidity, surface pressure, passersby per minute, the ratio of female passersby, a full set of day of week fixed effect, wave fixed effect and location fixed effect. Robust standard errors clustered at location-date-hour level are in parentheses. ***, ** and * indicate statistically significant at 1%, 5%, and 10%, respectively.