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Adoption, use, and effects of air purifiers in households

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Registered Report: Adoption, Use, and Effects of Air Purifiers in Households

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Abstract

Poor air quality is a pressing environmental health concern in many low-income countries, especially in South Asia, where stringent environmental laws coexist with weak regulatory institutions and inconsistent enforcement. In such a context, understanding the role of private defensive investments like air purifiers in households and workplaces is paramount. However, we know extremely little about the adoption, use, and impact of air purifiers. To fill this void, we will conduct a randomized control trial with households in Dhaka, Bangladesh. The project will answer four research questions: (i) What are the benefits of air purifier use? (ii) Does correcting misperceptions about air pollution severity increase the demand for and use of air purifiers? (iii) Does subsidizing electricity costs or altering the frequency of electricity compensation increase air purifier use? (iv) Do investments in air purifiers diminish households' engagement in efforts to reduce ambient air pollution?

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1 Introduction

Poor air quality has become a pressing environmental health concern in many low-income countries. In South Asia, an estimated 2 million deaths per year are caused by air pollution and the deaths caused by air pollution per capita have increased by 21% in the last 10 years, while it has decreased by 25% in high-income countries (IHME, 2020; The World Bank, 2023). This escalating crisis is further exacerbated by the region's paradoxical situation, where stringent environmental laws coexist with weak regulatory institutions and inconsistent enforcement. In such a context, understanding the role of *private* defensive investments like air purifiers in households and workplaces is paramount. However, we know extremely little about the adoption, use, and impact of air purifiers in any context.

To fill this void, we will conduct a randomized control trial with households in Dhaka, Bangladesh. The project will answer four research questions:

First, we will evaluate the causal benefits of air purifiers in households. In our pilot we provided all participants with pollution monitors and randomized an offer of a free air purifier. We find that on average providing an air purifier reduced indoor air pollution levels by 27%. This translated into a PM2.5 reduction of 74 $\mu g/m^3$ off a control mean of 279 $\mu g/m^3$. Therefore, even with air purifiers, PM2.5 levels remain well-above WHO standards begging the question if these improvements in indoor air quality are meaningful from a health standpoint. Moreover, air purifiers provide only temporary respite from air pollution – for example, when air purifiers are installed at home, individuals may still be exposed to ambient air pollution levels at work. This is important since we have only a partial understanding of the dose-response function of air pollution – that is, we do not know what health effects to expect from reducing air pollution at this margin during a limited amount of time. Our upcoming, large-scale field experiment will focus on measuring the direct impact of air purifiers on various critical aspects, including health (measured by both survey questions and bio-markers), labor supply, cognitive function, income, and sleep quality. These areas have been previously identified as adversely affected by air pollution, according to existing research which primarily examines the effects of outdoor air pollution (e.g., Currie and Walker, 2011; Hanna and Oliva, 2015; Cao et al., 2021; Künn et al., 2023).

Second, we aim to investigate whether misperceptions about air pollution contribute to the low demand for air purifiers. Despite the fact that air pollution levels are 17 times above the WHO's recommended annual average, air purifier ownership is surprisingly rare. In a pilot, none of the 41 households we contacted had an air purifier.[1] Our study will explore whether correcting misunderstandings about air pollution's severity can boost households' willingness to invest in air purifiers. We plan to correct these misconceptions by providing households with air monitors and informational charts detailing the health impacts associated with various pollution levels. Additionally, we will offer incentives to a subset of households to encourage engagement with the air monitor data. This approach will also help us determine if a deeper comprehension of air pollution's risks increases people's readiness to contribute to addressing the broader issue of air pollution as a collective action problem.

Third, we will examine the barriers to air purifier use. Ownership does not guarantee regular use. Despite staggeringly high pollution levels in Dhaka, air purifier usage (as measured by smart sockets) in our pilot was far from universal. Among households receiving an air purifier, only about half used the air purifiers for more than 2 hours a day on average. Electricity usage costs of air purifiers are small (approximately half the cost of running a ceiling fan) implying monetary factors are unlikely to drive low use of air purifiers. This indicates that non-monetary aspects also play a role in usage patterns. Such issues are common with preventive health technologies (Kremer et al., 2019; Bai et al., 2021; John and Orkin, 2022). We aim to test three hypotheses to understand the low engagement with air purifiers and similar health technologies. Our first hypothesis questions whether even minimal direct costs significantly deter usage; we'll address this by subsidizing the electricity costs for a group of households. Secondly, we'll assess if incorrect beliefs about indoor air pollution levels or misconceptions about the health harms of this pollution are a major barrier, using insights from our monitor experiment to inform this. Lastly, by altering the frequency of electricity compensation, we'll explore whether 'present bias' – a tendency to prioritize immediate benefits over future gains – influences air

[1] This trend aligns with observations in Delhi, as noted by Greenstone et al. (2021).

purifier usage.

Fourth, we will investigate whether private defensive investments, like air purifiers, impact the collective drive to address broader environmental issues. A possible downside to adopting such technologies is the potential decrease in community motivation to tackle the underlying causes of the problem. Specifically, the use of air purifiers could diminish households' willingness to actively engage in efforts to reduce ambient air pollution, such as advocating for stricter enforcement or holding political leaders and public officials accountable.

This project will contribute to three stands of literature. The first is to assess the health benefits of household air purifiers. While there is extensive research on the adverse health effects of air pollution, studies on effective countermeasures, especially at the household level, are not as comprehensive. In fact, household interventions have shown varying results. For instance, literature on improved cook stoves indicates that temporarily reducing air pollution during cooking hours does not significantly alter health markers like blood pressure, oxygen saturation, or birth weight in children exposed in utero (Clasen et al., 2022; Ye et al., 2022; Berkouwer and Dean, 2023). On the other hand, research employing quasi-experimental methods to examine air pollution reveals significant impacts on general mortality, child mortality, and birth weight (Currie and Walker, 2011; Deryugina et al., 2019; Heft-Neal et al., 2020). There are also well-documented correlations between air pollution and factors like blood pressure, oxygen saturation, and lung function (e.g., Pope et al., 1999; Brook and Rajagopalan, 2009; Cakmak et al., 2011).

The second is the literature on the adoption and use of preventative health technologies. Our study will specifically examine three hypotheses that could explain the low uptake and usage of these technologies. These include the impact of minimal direct costs associated with technology use, incorrect beliefs about indoor air pollution and underestimation of the technology's health benefits, and present bias. While the role of small costs, along with the effectiveness of subsidies and conditional cash transfers to mitigate this barrier, has been well researched (e.g., Gertler, 2004; Barham and Maluccio, 2009; Cohen and Dupas, 2010; Banerjee et al., 2010), the concepts of misconceptions about benefits and present bias remain relatively unexplored as factors contributing to the observed reluctance in investing in preventative health technologies (Kremer et al., 2019). Furthermore, the literature on the impacts of ambient air pollution awareness on public health and behavior finds mixed results. Barwick et al. (2019) finds that increased awareness, achieved through the establishment of monitoring stations in China, led to a notable reduction in health risks associated with air pollution. This was largely due to a heightened use of preventative measures like masks and air purifiers. In contrast, Greenstone et al. (2021) observe that the presence of air monitors in Delhi did not significantly influence the willingness to pay for such devices.[2]

The third is the literature on collective action problems (e.g., Olson, 1971; Ostrom, 1990; Bursztyn et al., 2021). We aim to test the hypothesis that private defensive investments, such as air purifiers, may diminish the willingness to collectively address broader environmental issues. This concept ties into the broader debate on the choice between 'exit' and 'voice' strategies as outlined by Hirschman (1972). We hypothesize that as private solutions to public issues become more accessible and affordable, it could potentially weaken public engagement in political processes necessary for policy change. Conversely, making such defensive measures prohibitively expensive would only exacerbate the problem by excluding a significant portion of the population. Understanding the extent of this 'exit' effect is crucial for policymaking. Specifically, we will explore whether owning an air purifier lessens the household's demand for government action on air pollution and reduces their likelihood of supporting NGOs working towards this cause.

The remainder of this registered report is structured as follows. Section 2 describes the context in which the experiment will be carried out. Section 3 describes the research design and the randomized interventions we will introduce. Section 4 describes the data we will collect. Section 5 provides a pre-analysis plan for how the data will be analyzed. Section 6 shows the results from the pilot we carried out in Dhaka from November, 2022 to March, 2023. Section 7 shows power calculations for our main planned analyses. Section 8 provides the proposed timeline of the project

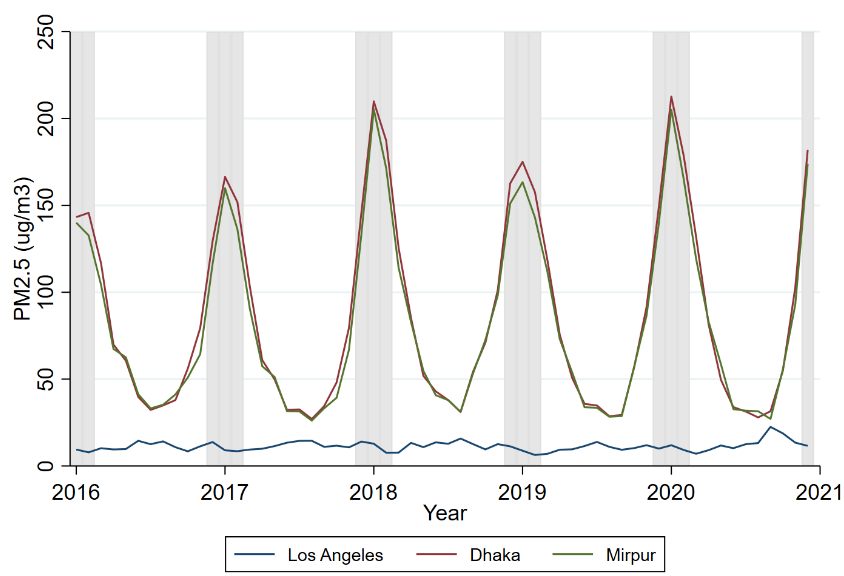
[2]This lack of effect may be attributed to the already low willingness to pay in both the experimental and control groups, hovering close to zero.

and Section 9 provides administrative information.

2 Context of the Experiment

Dhaka is one of the cities with the worst air pollution in the world. Figure 1 shows the monthly air pollution levels in Dhaka estimated from satellite data for the time-period 2016-2021 (van Donkelaar et al., 2021). It is estimated that the average reduction in life expectancy due to air pollution levels being above the WHO guidelines in Dhaka is 8.1 years (AQLI, 2023).

Figure 1: Air Pollution Levels in Dhaka 2016-2021



Notes: The figure shows the monthly air pollution levels in Dhaka, Mirpur (the locality in Dhaka where the experiment is carried out), and Los Angeles (for reference). The months when the experiment will take place (December, January, and February) are shaded in gray. Data is from van Donkelaar et al. (2021).

We will carry out our experiment in a middle-income neighborhood in the Mirpur area of Dhaka. The households will be in apartment blocks belonging to three large housing associations that have given us permission to conduct the experiment in their buildings. There are two main reasons why we chose to carry out the experiment with this population. First, middle-class apartment buildings have sealed windows and doors that insulate the rooms from outdoor air pollution when closed. Thus, these apartments are the type of households where using air purifiers will be effective. Second, middle-income apartment blocks are a common form of housing in urban South Asia making this population somewhat representative of a large number of people. At the same time, they are wealthy enough that purchasing an air purifier would not be a major expense for them. Therefore, this is the most policy-relevant population for the understanding of the adoption and use of air purifiers.

The experiment will be carried out in the winter months of December, January, February, and partially in March. These are the months with the highest levels of air pollution, as shown in Figure 1. Furthermore, the temperature is lower in these months, especially during the night[3], making it comfortable to sleep with windows closed. This will further reduce the risk of air purifiers being ineffective due to windows being open.

3 Research Design

Figure 2 offers a visual representation of our research methodology. This diagram illustrates the structure of our study, which includes four distinct randomized interventions, each designed to investigate different parts of our research questions.

1. Air quality monitors: We plan to visit 1,000 households for a short preliminary survey. During this visit, 500 households, chosen randomly, will be given an air monitor. Along with these monitors, they will receive a chart categorizing PM2.5 levels into six levels: good, moderate, unhealthy for sensitive groups, unhealthy, very unhealthy, and hazardous. This chart will also show the estimated health risks associated with these air pollution levels. In particular, it will show the increased likelihood of heart disease, stroke, and lung cancer in adults, and respiratory issues in

[3] Average daily minimum temperatures in Dhaka during December, January, and February are 15°C, 14°C, and 17°C, respectively.

children under 5. Each household with an air monitor will get a small daily payment of BDT 15 (USD 0.14), but only on days when the monitor sends us data for at least 16 hours. The households not receiving air monitors will be given a similar payment, randomly matched to a household in the treatment group, to ensure income levels are comparable between the two groups. To maintain uniformity in data collection, we will suggest placing the air monitors in the bedroom of the household head.

2. Air quality attention incentives: We will divide the 500 households who are given an air monitor into two groups through an additional randomization. 250 households will be chosen to receive a BDT 30 (USD 0.28) reward each week for accurately reporting their home's air quality category and the associated increased risk of at least one disease. The households in the control group will be given a payment equal to that received by a randomly selected household in the treatment group. This approach is to ensure that income levels are balanced between the treatment and control groups.

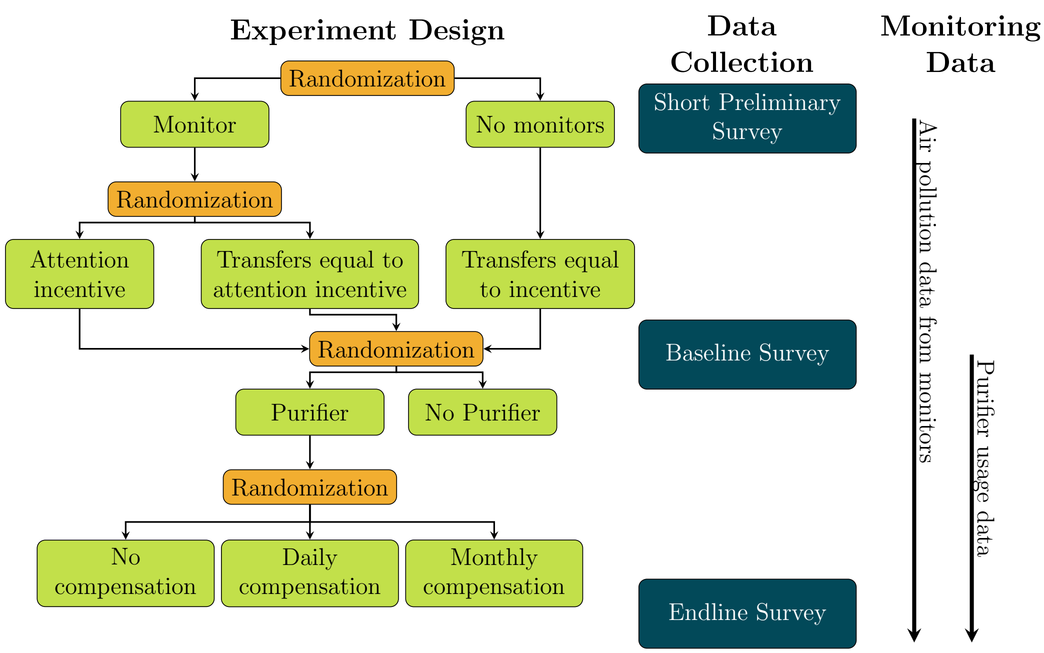
3. Air purifiers: About a month after distributing the monitors, we will revisit all households to conduct the baseline survey. This survey will gather information on household beliefs about air pollution and its health impacts, as well as perceptions of the benefits of air purifiers. We will employ a modified Becker-DeGroot-Marschak (BDM) mechanism, as referenced in (Berry et al., 2020; Berkouwer and Dean, 2022), to determine the baseline willingness to pay for air purifiers. In this exercise, 350 households will be randomly selected to have a 'draw price' set at zero, ensuring a sufficient number of households will adopt air purifiers for us to assess their direct effects. We will also encourage households to place these air purifiers in the bedroom of the household head.[4]

4. Air purifier electricity usage compensation: We will proceed to assign households equipped with air purifiers to one of three groups: two groups will receive compensation for the electricity used by the air purifiers, and one control group will not receive any compensation. Each of the two treatment groups will consist of 100

[4]At the endline survey, we will again employ the BDM mechanism to measure willingness to pay for air purifiers but with a low share of households randomly selected to have a low 'draw price'. Thus, we do not expect many households to purchase an air purifier in the endline survey.

households, while the control group will have 150 households. The compensation for the treatment groups will be equal to the electricity cost incurred by the air purifier, tracked via a smart socket. All households will receive their first payment one week after our visit to build trust. After this initial payment, households in the first treatment group will receive daily payments, whereas those in the second group will receive monthly payments.

Figure 2: Overview of Research Design



Notes: This figure shows the planned research design and data collection. We started the Short Preliminary Survey on 12 November 2023 and concluded it on 30 November 2023. We plan to conduct the baseline survey in December 2023 and January 2024 and the endline survey in March 2023.

4 Data

Our study will utilize five key data sources:

1. Continuous indoor air pollution data from households equipped with air mon-

itors.

2. Continuous usage data of air purifiers, collected via smart sockets to which the air purifiers are connected.

3. Data from three household surveys to gather information on willingness to pay for air purifiers, self-reported health, views on air pollution severity, labor supply, and other self-reported factors. These surveys include a brief initial survey at the time of air quality monitor distribution, a more detailed baseline survey during air purifier distribution, and a final endline survey. Our primary focus will be on individuals sleeping in the bedroom of the household head, but we will collect data on all household members via interviews with the household head.

4. Health bio-markers (blood pressure, lung capacity, and blood oxygen levels) of household members sleeping in the bedroom of the household head, recorded during the baseline and endline surveys.

5. Readings from two outdoor air monitors placed in the neighborhoods where the study is conducted.

To ensure the reliability of our data and minimize the impact of outliers caused by misreporting or measurement errors, we will 'winsorize' our data at the 1st and 99th percentiles. This means we will adjust the most extreme values to the value at the 1st and 99th percentile values of that variable.

5 Analysis Plan

Our analysis plan for each research question is detailed below. For every analysis conducted, we will cluster the standard errors at the same level at which the treatment was administered.

5.1 Effect of air quality monitors and attention incentives on air pollution beliefs and air purifier adoption

Our first research question investigates whether providing information about air pollution, and the associated health impacts, and encouraging attention to this information alters beliefs about air pollution's health risks and increases the willingness to invest in air purifiers. We will assess the impact of air monitors and incentives for attention to air quality information on people's beliefs using the following regression:

$$\begin{aligned} Belief_{is} = \alpha + \beta_1 \times Monitor_i + \beta_2 \times Attention_i + \\ \gamma_1 BeliefShortSurvey_i + \gamma_2 \times SurveyRound_s + \varepsilon_{is} \end{aligned} \tag{1}$$

where $Belief_{is}$ represents the belief of household i regarding the harmfulness of current air pollution levels in survey round s, specifically its impact on increasing the risk of stroke, heart disease, lung cancer in adults, and respiratory issues in children under 5. These beliefs are measured against the backdrop of information provided with the air monitors, which includes small cards detailing how various levels of air pollution are estimated to increase the likelihood of these diseases, based on Apte et al. (2015). The term $Monitor_i$ indicates whether a household received an air quality monitor. $Attention_i$ represents whether the household was given an incentive to report their air quality monitor readings, which aims to increase their attention to the data provided by the air quality monitor. $BeliefShortSurvey_i$ is the belief in the short preliminary survey before the randomized air monitor provision. $SurveyRound_s$ is a survey round fixed effect for the endline survey.

We will use the following regression to estimate the effect of air monitors and incentives for attention to air quality information on willingness to pay for air purifiers:

$$WTP_{is} = \alpha + \beta_1 \times Monitor_i + \beta_2 \times Attention_i + \gamma_1 \times SurveyRound_s + \varepsilon_{is} \tag{2}$$

where WTP_{is} represents the willingness-to-pay for household i in survey round s, determined through a modified Becker-DeGroot-Marschak (BDM) mechanism (Berry et al., 2020; Berkouwer and Dean, 2022).

The willingness-to-pay for an air purifier will be recorded in the baseline survey and then again in the endline survey. In the endline survey, the group who will have received air purifiers will be asked about their willingness to pay for a second air purifier. Although the question is somewhat different between those who received air purifiers and those who did not, the $Monitor_i$ and $Attention_i$ treatments will be uncorrelated with receiving an air purifier, thus not biasing our estimate.

Our null hypothesis is that air quality monitors, with or without reporting incentives, has no effect on the outcomes measured, meaning that $\beta_1 = 0$ and $\beta_2 = 0$.

We will also test the hypothesis that having used an air purifier increases the willingness-to-pay for another air purifier by running the following regression on the endline data:

$$WTP_i = \alpha + \beta_1 \times Purifier_i + \gamma_1 \times BaselineWTP_i + \varepsilon_{is} \tag{3}$$

where WTP_i is the willingness to pay at endline, $Purifier_i$ indicates that the household received an air purifier at baseline, and $BaselineWTP_i$ is the household's willingness to pay before the purifier randomization. Here the willingness to pay for households who already received an air purifier is the willingness to pay for a second air purifier. Thus, if $\beta_1 \leq 0$ we will not be able to distinguish decreasing marginal utility from additional air purifiers from a potential negative effect on willingness to pay from having used an air purifier. However, if $\beta_1 > 0$ we will interpret this as evidence in favor of using an air purifier increases the willingness to pay for air purifiers.

5.2 Effect of air quality monitors, cost, and attention incentives on air purifiers use and air quality

5.2.1 Air purifier use

Our subsequent key research question focuses on understanding the factors influencing air purifier use in households that already own them. We aim to test three hypotheses: 1) Incorrect beliefs about indoor air pollution levels or misconceptions about the health effects of air pollution lead to lower usage, 2) The electricity cost is a deterrent to using air purifiers, and 3) Present bias causes people to underuse air purifiers due to a preference for immediate benefits over future ones.

To examine whether incorrect beliefs about indoor air pollution levels or misconceptions about the health effects of air pollution are significant barriers to air purifier use, we will evaluate the impact of providing households with air monitors and information cards. The effect on usage will be assessed with the following OLS regression:

$$Use_{it} = \alpha + \beta_1 \times Monitor_i + \beta_2 \times Attention_i + \tau_t + \varepsilon_{it} \tag{4}$$

where Use_{it} indicates whether household i used the air purifier during hour-date t and τ_t represents time fixed effects.

The null hypothesis posits that air quality monitors have no impact on usage, regardless of the attention incentives, $\beta_1 = \beta_2 = 0$.

To determine if the electricity cost is a barrier, we will offer small monetary payments to offset these costs. The impact of these compensations on usage will be analyzed with this regression:

$$Use_{it} = \alpha + \beta_1 \times Compensation_i + \beta_2 \times DailyCompensation_i + \tau_t + \varepsilon_{it} \tag{5}$$

where $Compensation_i$ signifies whether the household receives compensation for the electricity cost, and $DailyCompensation_i$ indicates daily compensation.

The null hypothesis is that compensating for electricity costs has no effect, $\beta_1 = 0$, and the frequency of compensation (daily or otherwise) does not matter, $\beta_2 = 0$. This will help us explore whether present bias affects air purifier usage, as present-biased individuals might not use the purifiers due to their impatience to wait for long-term benefits.

5.2.2 Air quality

We will next explore the extent to which owning an air purifier impacts indoor air pollution. This will be assessed by analyzing the hourly data from air monitors in households that received them, using the following regression:

$$PM2.5_{it} = \alpha + \beta_1 \times Purifier_i + \gamma_1 \times OutdoorPM2.5_{it} + \gamma_2 \times BaselinePM2.5_i + \tau_t + \varepsilon_{it} \tag{6}$$

where $PM2.5_{it}$ is the average indoor air pollution level for household i during hour t, $OutdoorPM2.5_{it}$ is the corresponding outdoor air pollution reading from the outdoor monitor closest to the household, and $BaselinePM2.5_{it}$ is the average PM2.5 reading for the period before the baseline survey. We aim to test the null hypothesis that air purifiers have no effect on reducing indoor air pollution, indicated by $\beta_1 = 0$.

To further dissect the influence of air purifiers on air quality, we will also examine the impact of incentives for using the air purifiers and for paying attention to the air monitor readings. This will be done with the following expanded regression:

$$\begin{aligned} PM2.5_{it} = &\alpha + \beta_1 \times Purifier_i + \beta_2 \times Compensation_i \\ &\beta_3 \times Attention_i + \beta_4 \times Attention_i \times Purifier_i \\ &+ \gamma_1 \times OutdoorPM2.5_{it} + \tau_t + \varepsilon_{it} \end{aligned} \tag{7}$$

In this model, we will test several null hypotheses: firstly, that providing an air purifier without additional incentives doesn't reduce air pollution ($\beta_1 = 0$), secondly, that compensating for electricity costs doesn't affect air pollution levels ($\beta_2 = 0$), thirdly, that attention incentives don't reduce pollution in households without an air purifier ($\beta_3 = 0$), and finally, that the impact of attention incentives on air pollution doesn't differ between households with and without air purifiers ($\beta_4 = 0$).

5.3 Effect of air purifiers on health outcomes

We plan to assess the impact of air purifiers on health outcomes for individuals sleeping the the bedroom of the household head through the following OLS regression:

$$\begin{aligned} Health_{ji} = &\alpha + \beta_1 \times AirPurifier_i + \\ &\gamma_1 \times HealthBaseline_{ji} + \gamma_2 \times NoBaseline_{ji} + \varepsilon_i \end{aligned} \tag{8}$$

where $Health_{ji}$ represents a variety of health outcomes and bio-markers for individual j in household i. $HealthBaseline_{ji}$ is the initial measurement of these health outcomes. If there are cases where $HealthBaseline_{ji}$ is missing (i.e. a specific health measure was not successfully collected for individual j at baseline) we will employ the 'missingness-indicator method' (Zhao and Ding, 2022). For missing observations we will impute $HealthBaseline_{ji}$ to the mean of the variable and control for $NoBaseline_{ji}$ which is an indicator variable for if there is missing baseline data.[5]

The primary health outcomes we will evaluate are:

- Proportion of sick days in the two months before the interview, defined as days where illness prevents regular activities like work, school, or household chores.
- Number of visits to healthcare providers, including doctors, clinics, and hospitals, in the two months before the interview.
- Total healthcare spending in the two months before the interview.
- Blood pressure.
- Lung capacity (as measured by spirometer).

[5] We will employ the 'missingness-indicator method' if baseline data is missing for other non-health variables as well. However, we expect that this will mostly be the case for individual health measures as some household members may not be home for the measurement of bio-markers at baseline.

- Blood oxygen levels.
- An inverse covariance weighted index compiled from the six aforementioned outcomes, as per (Anderson, 2008).

5.3.1 Effects of air purifiers on cognition and sleep

We aim to evaluate the impact of air purifiers on various aspects of sleep and cognitive function. This will be done using the same regression model as outlined in Equation 8. Specifically, we'll assess changes in sleep quality, time spent in bed, overall sleep duration, and cognitive abilities.

Sleep quality. Our sleep questionnaire will incorporate 10 items from the Patient Reported Outcomes Measurement Information System (PROMIS), for the past 7 days for all household members over 15 years of age: 5 items each from the sleep disturbance and sleep-related impairment item banks, respectively. The PROMIS sleep items have been carefully developed and evaluated against other well-known sleep indices such as the Pittsburgh Sleep Quality Index and the Epworth Sleepiness Scale, as well as by comparing sleep disturbance and sleep-related impairment scores from subjects with and without sleep disorders (Yu et al., 2012; Buysse et al., 2010; Cella et al., 2010). Importantly, they have also been validated against objective actigraphy sleep measures like sleep latency and sleep efficiency (Giordano et al., 2022; Hanish et al., 2017; Sletten et al., 2018). We will use all ten items to construct an aggregate sleep quality index (SQI). In our analysis, we examine impacts on this aggregate index, as well as on its component parts.

Time in bed. We will also include questions on bedtime and wake-up time for the day prior to the survey for every member of the household, which allows us to infer time spent in bed.

Sleep quantity. Lastly, we will include a question on sleep quantity for the day prior to the survey for every member of the household.

Cognition. To capture effects on cognition, we will test all household members over 15 years of age via the Montreal Cognitive Assessment (MoCA) questionnaire. The MoCA was designed as a rapid screening instrument for mild cognitive dysfunction. It assesses several different cognitive domains: attention and concentration, executive functions, memory, language, visuoconstructional skills, conceptual thinking, calculations, and orientation. Our outcomes here will include an aggregate index, as well as domain-specific indices.

5.4 Effects of air purifiers on labor supply and income

We plan to assess the impact of air purifiers on labor supply and income using the same regression model as specified in Equation 8. For this analysis, 'Labor supply' will be defined as the total number of days worked by each household member in the preceding seven days. 'Income' will refer to the monthly earnings of all individuals in the household who were employed at baseline.

5.5 Effect of air purifiers and air quality monitors on willingness to address collective action problem

Our study also aims to understand how owning an air purifier and air influences a household's willingness to engage in solving the broader issue of air pollution as a collective action problem. Additionally, we will investigate the impact of possessing an air monitor and receiving incentives to monitor air quality on this willingness.[6]

To estimate these effects, we will use the following OLS regression:

$$\begin{aligned} Priority_i = & \alpha + \beta_1 \times Purifier_i \\ & + \beta_2 \times Monitor_i + \beta_3 \times Attention_i \\ & \gamma_1 \times PriorityBaseline_i + \varepsilon_i \end{aligned} \tag{9}$$

Where $Priority_i$ represents one of the following measures:

[6] Previous research has shown that public air monitors can affect air pollution levels in other contexts by raising awareness and shifting public opinion (Jha and Nauze, 2022; Liu et al., 2021).

- The standard deviation of air pollution's ranking among a list of government priorities (like Education, Healthcare, Air pollution, Job creation, Elderly care).[7]
- The choice of an environmental NGO focused on air pollution as the beneficiary of a donation, selected from a list of NGOs with various priorities.

Our null hypothesis tests whether air purifiers (β_1), air quality monitors (β_2), and incentives for monitoring air quality (β_3) have no effect on the importance households assign to air pollution as a social issue.

5.6 Secondary outcomes and heterogeneity

5.6.1 Differential effects based on bedroom used

We will advise households to install both the air quality monitors and air purifiers in the bedroom of the household head. Consequently, our analysis at the individual level will primarily concentrate on the effects experienced by those who regularly use this bedroom, as recorded at baseline. Additionally, we will carry out a comprehensive analysis encompassing all household members to determine the average impact of the devices across the entire household.

5.6.2 Effects of air quality monitors on health outcomes

We plan to examine the impact of air monitors on health outcomes and explore whether there is an interactive effect between owning an air monitor and an air purifier. The air quality monitors may have a direct effect if they change how households behave. For example, air quality monitors may cause individuals to take defensive actions (other than using an air purifier) such as wearing masks. They may also cause household members to stay indoors on particularly high air pollution days, or, by revealing to households that staying indoors does not help much, cause them not to stay indoors. This will be assessed using the following regression analysis:

[7] Respondents will be asked, "Which of the following areas should the government focus on improving first?"

$$
\begin{aligned}
Health_{ij} =& \alpha + \beta_1 \times Purifier_i + \beta_2 \times Monitor_i \\
&+ \beta_3 \times Purifier_i \times Monitor_i \\
&+ \gamma_1 \times HealthBaseline_{ij} + \gamma_2 \times NoBaseline_{ij} + \varepsilon_{ij}
\end{aligned} \tag{10}
$$

This analysis will be applied to each of the health outcomes detailed in Section 5.3.

Additionally, we will use two more regressions to analyze the relationship between outdoor air pollution and the usage of air purifiers. First, we will estimate the association between outdoor air pollution and air purifier usage:

$$
Use_{it} = \alpha + \beta_1 \times OutdoorPM2.5_{it} + \varepsilon_{it} \tag{11}
$$

Second, we will test the difference in the association between households owning air monitors and those that do not:

$$
\begin{aligned}
Use_{it} = \alpha + \beta_1 \times Monitor_i \times OutdoorPM2.5_{it} + \\
\beta_2 \times Monitor_i + \beta_3 \times OutdoorPM2.5_{it} + \varepsilon_{it}
\end{aligned} \tag{12}
$$

5.6.3 Average treatment effect on the treated (ATT)

To specifically evaluate the health benefits of actually using air purifiers, as distinct from merely owning them, we will use randomized ownership as an instrumental variable for air purifier usage. This approach will enable us to ascertain the average treatment effect on those who use the air purifiers, rather than the intent-to-treat effect, which considers the impact of merely having access to the purifiers.

5.7 Adjusting for multiple hypothesis testing

In Section 5, our pre-analysis plan is structured based on the specific types of questions we aim to address. Each subsection is dedicated to answering a distinct overarching question. Following the approach of Finkelstein et al. (2012), we will not modify p-values for multiple hypothesis testing across these separate, conceptually different analyses.

Within each thematic area, we will consolidate outcomes into a single index or a few indices, wherever possible. This strategy aims to minimize the number of hypotheses tested, thereby reducing the necessity for adjustments due to multiple hypotheses. Additionally, we will employ F-tests to collectively assess the null hypothesis that none of the treatment arms have any effect, which further limits the number of hypotheses. Lastly, to control the False Discovery Rate (FDR) at 5%, we will apply the sharpened FDR q-values method as described by Anderson (2008).

6 Pilot Results

A pilot study was conducted in 41 households in Mirpur, Dhaka starting in November 2022. In the pilot study, only the provision of air purifiers was randomized and all participating households received an air quality monitor. There were no incentives to use the air purifiers or pay attention to the air quality monitors. The main purpose of the pilot was to test the logistics of our study design and test to what extent air purifiers decreased air pollution. While we did conduct a baseline and an endline survey, this data was mainly collected for the purpose of testing the survey instruments as the pilot was under-powered to detect any health or labor supply effects.

41 households participated in the pilot, half of whom received air purifiers. However, problems with the automatic submission of data from the air quality monitors were common, with only 44% of household-date observations having at least 4 hours of air monitor data. This was due to the air monitors being unplugged by the households and because when the specific air monitor model used lost internet connection, it was often unable to reconnect to the internet automatically. However, in Appendix Table A.1 we show that there was no effect of the treatment on air monitor data availability. For the full-scale experiment, we have addressed this issue in two ways. First, we have changed the air monitor model to a model that reconnects to the internet automatically and has performed in a more stable manner in our tests. Second, we will pay households a daily incentive of BDT 15 (input 0.14) for each day

that the air monitor submits data for at least 16 hours.

Table 1 shows the effect of the air purifiers on daily particulate matter air pollution levels, using data from November 25 2022 to March 31 2023. Our preferred specification in Column (2) shows that providing households with an air purifier decreased PM2.5 air pollution by 74 µg/m^3 on average. Note that the average air pollution levels in the control group are 279 PM2.5 µg/m^3 (56 times above the WHO recommended annual average) so while providing air purifiers reduced air pollution by 27%, it did not bring air pollution levels down to levels considered healthy by international standard.

Table 1: Effects of Air Purifier Treatment on Air Pollution

	(1)	(2)	(3)	(4)
	PM2.5	PM2.5	PM10	PM10
Air Purifier	-79.6**	-73.7**	-85.1**	-78.4**
	(37.5)	(33.9)	(39.1)	(34.9)
Observations	2,332	2,332	2,332	2,332
Clusters	41	41	41	41
Date FE	No	Yes	No	Yes
Control mean	279	279	306	306

Notes: This table shows the effect of providing air purifiers on air pollution as measured by the air quality monitors. Each observation is a daily average for a household during the pilot period from November 25 2022 to March 31 2023. Standard errors are clustered at the household level. $***p < 0.01; **p < 0.05; *p < 0.1$.

While the effect in Table 1 is substantial, it is an Intent-To-Treat (ITT) effect as not all of the households used the air purifiers at all times. To measure the direct effect of an air purifier we turned an air purifier on at medium power (level 2 out of 3) three times in a room in our office in Dhaka. The room is approximately twice as large as a typical bedroom in our sample. Appendix Figure A.1 shows that air pollution decreased by 71% within 45 minutes of turning the air purifier on and that the air pollution level remained lower than at baseline for approximately two and a half hours after turning the air purifier off again.

Table 2 shows the effect of the air purifiers on the relative importance placed on government action to reduce air pollution, compared to four other policy areas. The average importance placed on each policy area is shown in Appendix Figure A.2. We find no evidence in favor of the hypothesis that providing air purifiers to households reduces the willingness to overcome the collective action problem of addressing emissions of air pollution. While our estimate has large standard errors it is positive.

Table 2: Effect of Treatment on Opinions about Importance of Government Action

	(1) Importance (SD)	(2) Importance (SD)
Air Purifier Treatment	0.32	0.33
	(0.34)	(0.34)
Baseline control	No	Yes
Observations	32	32
Control mean	-0.00	-0.00

Notes: This table shows the effect of providing air purifiers on the importance that respondents placed on air pollution when asked to rank 5 issues in terms of "Which of the following areas should the Government focus on improving first?". The issues were Education, Healthcare, Reducing Air Pollution, Creating Good Jobs, and Caring for the elderly, shown in a random default order. $***p < 0.01; **p < 0.05; *p < 0.1$.

The pilot shows that some households were willing to use the air purifiers on a consistent basis and that households used the air purifier in a way that actually reduced indoor air pollution. In the endline survey 81% of households reported using the air purifier six or seven days per week, while 19% of households reported that they did not use the air purifier. However, we did not ask how many hours per day they used the air purifier and there might be a degree of over-reporting of the usage.[8] This was despite the lack of any incentives or monetary compensation for electricity costs to use the air purifiers. We believe that for the groups receiving monetary compensation for the electricity cost of using the air purifiers, the usage rates and thus effects on air pollution will be even higher.

The pilot also showed that a sufficient number of households were interested in participating in the research and that households were willing to install air monitors and purifiers in their households. The pilot had a 22% attrition rate, (20% in the treatment group and 24% in the control group) which is higher than most studies in rural contexts, but similar to other studies in urban contexts (Greenstone et al., 2021). For the full-scale experiment, we will attempt to reduce attrition by better screening households before they enter the study. We will only consider households showing an interest in having an air purifier and air monitor. Furthermore, we will introduce and increase the payments to households as incentives for using the air monitor, air purifier, and for taking the surveys. As described above, the incentives are designed so that they are equal between treatment and control groups, avoiding any potential income effects to influence our results. We believe these payments will further reduce attrition.

7 Power Calculations

In Table 3, we provide power calculations for five outcome variables: PM2.5 as measured by indoor air monitors, air purifier usage as measured by the smart sockets, self-reported number of days sick in the past 3 months, days worked in the past 7

[8]We also attempted to use smart sockets to monitor the electricity consumption of the air purifiers. However, the particular model of smart socket used did not distinguish if the smart socket was offline or if the air purifier was not being used. Hence, we cannot use this data to measure air purifier usage. If we restrict the smart socket data to the beginning of the intervention when the smart sockets were less likely to have gone offline, we find that 41% of households used the air purifier more than 2 hours per day. This is a lower bound of the usage during that period. For the full-scale experiment, we have addressed this issue by changing the smart socket model to one that can distinguish between the smart socket being offline and there being no electricity running through the smart socket.

days, and relative importance placed on air pollution by the households, compared to other societal issues. All of these variables were measured in the pilot and our assumptions are therefore based on the pilot data. Minimum Detectable Effects (MDE) are calculated for a statistical significance level of 5% and power of 80%.[9] The table also provides the assumptions needed to calculate the MDEs. All of the assumptions, except for the sample size and percentage of households treated, are taken directly from the pilot data.

In Column (1) of Table 3, the sample size for the PM2.5 variable is determined by the number of households with air monitors, it is therefore just half of the total number 1,000 of households participating in the experiment. The effect of the incentives can only be measured among the 350 households with air purifiers. Furthermore, there will be two treatment arms (daily incentive and monthly incentive) with 100 households in each, compared with a control group with 150 households. Therefore, Column (2) of Table 3, has a sample size of 250 households.

The MDEs for the air pollution, labor supply, and the importance placed on air pollution are smaller or similar to the effects we found in the pilot. The MDE for the number of days household members reported being sick in the past three months is larger than the effect we found in the pilot. However, given the small sample size in the pilot the real effect on these variables may be substantially larger or smaller than the effects estimated by the pilot. As we did not have any incentives or variation in air monitor access in the pilot, we do not have an estimated effect of these variables on air purifier usage from the pilot.

[9] We display all MDEs as positive numbers, although the expected effects on PM2.5 and the number of days household members are sick are negative.

Table 3: Power Calculations: Assumptions and Results

	(1)	(2)	(3)	(4)	(5)
Variable	PM2.5 (µg/m^3)	% Days Air Purifier Used	Days Sick	Days Worked	Air Pollution Importance (St. Dev.)
Treatment	Air purifier	Usage incentive	Air purifier	Air purifier	Air purifier
Level of Observation	Household	Household	Individual	Individual	Household
Observations per Household	1	1	4.10	1.13	1
Coefficient of Variation, Household Size	NA	NA	0.298	0.305	NA
Control Group Mean	257	41	4.5	3.9	-0.00
St. Dev at Endline	130	30	6.2	2.6	1.00
Correlation with Baseline Measure	NA	NA	0.14	0.43	-0.05
Intraclass Correlation	NA	NA	0.21	0.78	NA
Percent Treated	35%	40%	35%	35%	35%
Number of Households	500	250	1,000	1,000	1,000
MDE	33	11	0.75	0.45	0.19
MDE (%) of control mean	13	27	17	11	NA
Effect in Pilot	-74	NA	-0.35	0.47	0.33

Notes: We display all MDEs as positive numbers, although the expected effects on PM2.5 and the number of days household members are sick are negative. Sick days are measured over the past 3 months. Days worked are measured over the past 7 days.

8 Proposed Timeline

We started the Short Preliminary Survey on 12 November 2023 and concluded it on 30 November 2023. We plan to conduct the baseline survey in December 2023 and

January 2024 and the endline survey in March 2023. We will submit our pre-analysis plan to the AEA RCT registry before the start of the baseline survey.

9 Administrative Information

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Institutional Review Board (ethics approval): This project was approved by IRB committees at the Institute for Health Economics, University of Dhaka (IHE/IRB/DU/23/2023), the National University of Singapore (NUS-IRB-2022-578), and the University of California - San Diego (#805749).
Pre-registration: The pre-analysis plan will be registered at the AEA RCT registry before outcome data collection begins.
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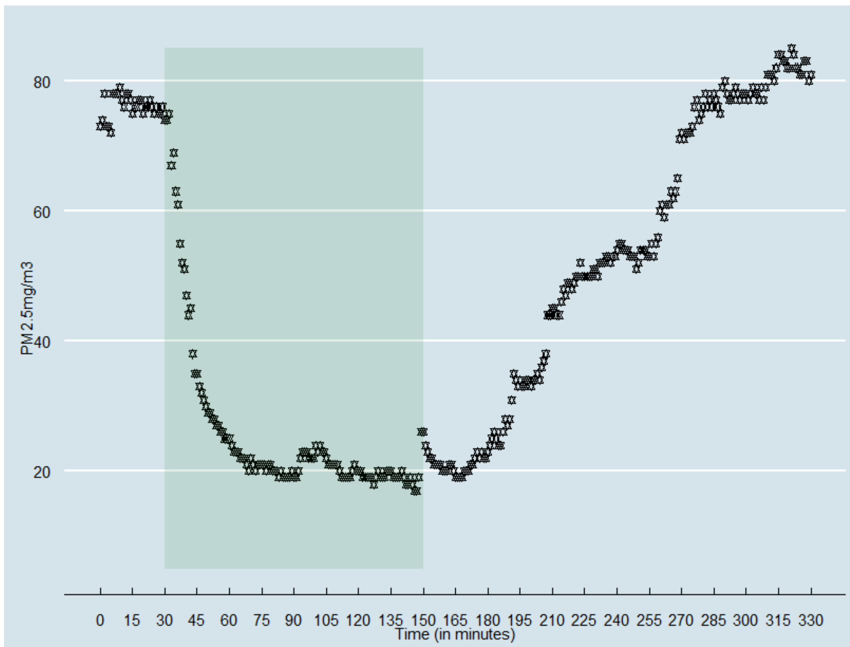
Appendix

Table A.1: Effects of Air Purifier Treatment on Air Monitor Usage

	(1) Monitor on $\geq$ 4h	(2) Monitor on $\geq$ 16h	(3) Monitor on $\geq$ 4h	(4) Monitor on $\geq$ 16h
Air Purifier	-0.011	-0.020	-0.011	-0.020
	(0.101)	(0.101)	(0.103)	(0.102)
Observations	5,248	5,248	5,248	5,248
Clusters	41	41	41	41
Date FE	No	No	Yes	Yes
Control mean	0.44	0.39	0.44	0.39

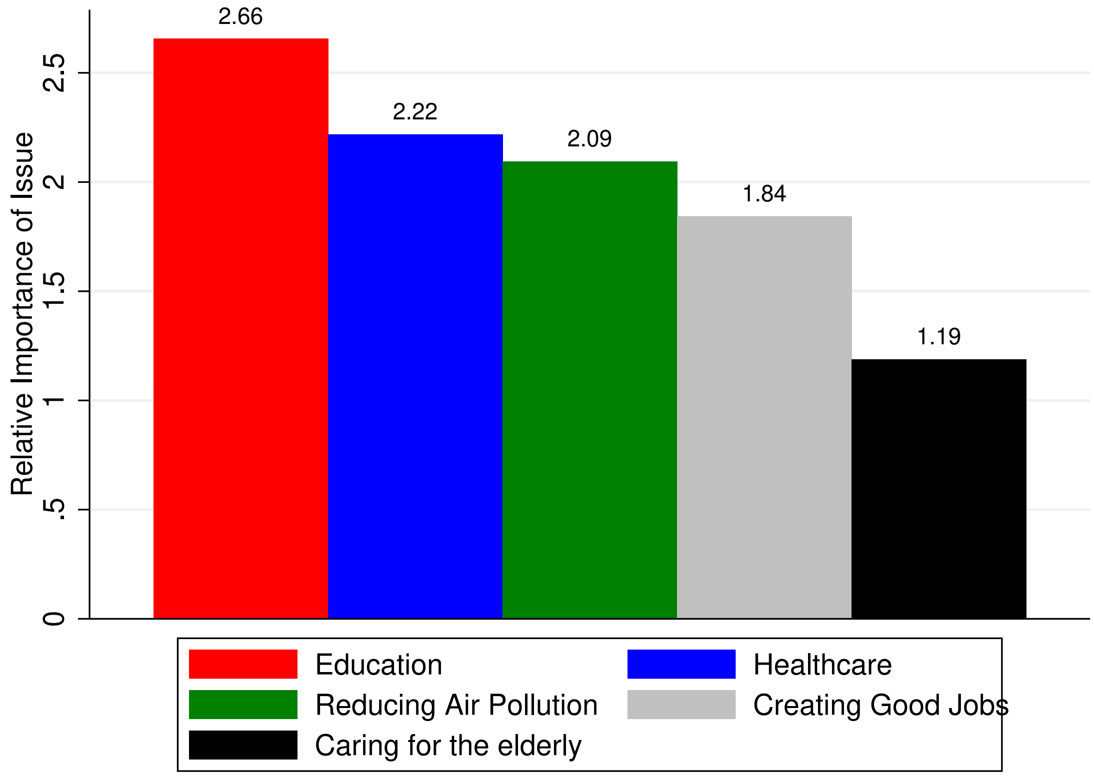
Notes: This table shows the effect of providing air purifiers on air monitor usage. Each observation is a household day during the pilot period from November 25, 2022 to March 31, 2023. Standard errors are clustered at the household level. $***p < 0.01; **p < 0.05; *p < 0.1$.

Figure A.1: Change in Air Pollution After Turning on Air Purifier



Notes: The figure shows how air pollution changes after turning on an air purifier at medium power (level 2 out of 3) in a room in our office in Dhaka. The graph is based on three instances of turning on the air purifier at minute 30 and keeping it on for 120 minutes (the area shaded green) until minute 150. After minute 150 the air purifier was turned off and kept off for five hours. Data from November 2023.

Figure A.2: Average Importance Placed on Societal Issues



Notes: This figure shows the average importance placed on five societal issues at endline. The question asked was "Which of the following areas should the Government focus on improving first?". Placing an issue first is equivalent to putting an importance of 4 on that issue. Placing an issue last is equivalent to placing an importance of 0 on that issue.

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