Information and Practical Experience in the Adoption and Use of Air Purifiers*

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PRELIMINARY AND INCOMPLETE

Abstract

Why don't South Asian households adopt air purifiers, despite extremely high ambient air pollution levels? In our study of middle-class households in Dhaka, Bangladesh, we show that both outdoor and indoor air pollution levels are alarmingly high. However, households are more aware of outdoor pollution and greatly underestimate the severity of indoor pollution. Moreover, there is a notable underestimation of the effectiveness of air purifiers in removing indoor pollution, and households' willingness to pay for air purifiers is less than a tenth of their retail cost. To correct these misconceptions, we conducted a multi-phase field experiment that provided air monitors and purifiers to these households. While air monitors corrected misperceptions about the severity of indoor air pollution, they did not increase willingness to pay for air purifiers. Similarly, providing households with air purifiers corrected misperceptions about their effectiveness, but this did not translate into greater willingness to pay for them, as they were rarely used. However, households that received both monitors and purifiers not only increased their usage but also their valuation of the purifiers. Our results indicate that correcting misperceptions about both the severity of the problem and the effectiveness of the solution is necessary for increasing the adoption and use of certain preventative health technologies.

JEL Codes: D12, I12, I15, O12, O13, Q53

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1 Introduction

High levels of ambient air pollution impose severe economic and welfare costs, especially in low-income countries (Oliva, Alexianu and Nasir, 2019). Over four million people die every year from exposure to ambient air pollution, with South Asia alone accounting for 2.6 million deaths per year (World Health Organisation, 2019; GBD Risk Factors, 2024). The problem has continued to worsen; in the last ten years, deaths attributable to air pollution have increased by 21% in South Asia while decreasing by 25% in high-income countries (IHME, 2020). This persistence of alarming ambient air pollution levels underscores the importance of understanding the economics of *private* defensive investments. Air purifiers, for instance, can dramatically reduce indoor air pollution—which often results from the infiltration of outdoor pollutants—at a relatively low cost (Lu et al., 2024). However, adoption of air purifiers among South Asian households is extremely low; fewer than 1% of middle-class households we contacted in Dhaka, Bangladesh—which is consistently ranked as the city with the worst air pollution in the world (AQLI, 2023)[1]—own an air purifier. We conduct a field experiment to provide evidence that correcting misconceptions about both the severity of indoor air pollution and the effectiveness of air purifiers is necessary for driving their adoption and use.

Our descriptive statistics paint a bleak picture of the state of indoor air pollution (IAP) in Dhaka. First, using IAP monitors we installed in households, we show that IAP is staggeringly high during the winter months with an hourly average of 135 $\mu g/m^3$ or 9 times higher than WHO's 24-hour average guideline of 15 $\mu g/m^3$. However, households are unaware of the extent of the problem with 71% of households reporting that indoor air pollution is not a serious problem. By contrast, a similar percentage of households reported believing that ambient air pollution (AAP) was a serious problem. Second, we find uncertainty about- and underestimation of the effectiveness of air purifiers in removing indoor pollution; fewer than half of the households had formed an opinion on purifier effectiveness, and less than a third believed that purifiers removed more than 25% of air pollution from the room where they were used, contrasting sharply with actual air purifier effectiveness in both controlled conditions and real-world household environments. Relatedly, households' have an extremely low willingness to pay (WTP) for air purifiers; the average household WTP was USD 12.2 or 8.4% of the retail cost of air purifiers.

In this context, we conduct a randomized control trial where in the first phase, we provide a subset of households with air pollution monitors free of cost.[2] In Phase 2 of the experiment, we randomized households to receive a free air purifier. Amongst households who received an air purifier, we randomly assigned one-third to receive no electricity compensation, one-third to

[1] Life expectancy in Dhaka would increase by 8.1 years if ambient air pollution were reduced to the World Health Organization (WHO) recommended maximum level (AQLI, 2023).

[2] All households who received the monitor were given a small incentive to use the monitor to ensure that we received sufficient data on IAP. Households in the control group were randomly matched with households in the monitor group and received matched incentives as part of the study compensation. This was done to ensure that incentives do not complicate the interpretation of our treatment effects (Cefala et al., 2024).

receive electricity compensation paid out daily, and one-third to receive electricity compensation monthly. Finally, in the last phase of the study, we randomized households in the purifier group to receive large incentives for the use of air purifiers.[3] This arm was introduced at the end of the study to provide a monetary incentive equivalent to the effects of the other treatments that induced the use of air purifiers.

We report three important sets of findings. First, providing households with air pollution monitors has a large and significant effect on correcting households' perceptions of indoor air pollution, and its risk to the health of the adults and children in the household. However, it did not affect willingness to pay for an air purifier.

Second, providing households with an air purifier corrected misperceptions about their effectiveness, but this too did not translate into greater willingness to pay for them,[4] as they were rarely used: using smart plugs attached to the purifiers, we collect minute-by-minute data on the use of air purifiers; we show that even when we compensate households for the electricity cost of using them, nearly two out of three households used the air purifier for less than 30 minutes per day.

Third, households that received both monitors and purifiers not only increased their usage but also their valuation of the purifiers. We show that monitors dramatically increase projected, self-reported, and directly measured air purifier use. Smart plugs data on air purifier use show that monitors increased purifier use by 270% equivalent to 74 minutes per day. Using the randomly assigned usage incentives, we show that the effect of the monitor on purifier usage is equivalent to a monetary incentive of BDT 4.2 (USD 0.04) per hour of usage. Over a month, such an incentive is on average equivalent to 0.33% of monthly household income.

Moreover, households that received both monitors and purifiers increased the price they were willing to accept to sell back the air purifiers by 26%, compared to households that received only the purifier. Lastly, households that were provided both a monitor and a purifier increased their WTP for a second purifier by 40%, although this estimate is not statistically significant. In contrast, households that received only a purifier saw a much smaller and statistically insignificant 5% increase in WTP for a second purifier. Similarly, households that received only a monitor exhibited just a noisy 2% increase in WTP for the first air purifier.

Our findings support a model in which both awareness of the underlying health risks and practical experience with the preventative health technology are essential to boost its adoption and use. In such a model there can be two equilibria, one with low information about the underlying health risk and low experience of the technology reducing the health risk, and another with high information and high usage. This could explain why some preventative health technologies, such as air purifiers and improved cook stoves, have seen low adoption rates despite

[3]Households were randomized to receive either BDT 5 (USD 0.05) or BDT 10 (USD 0.10) for each hour they turned on air purifiers. These were approximately 20-40 times the size of the electricity compensation.

[4]Our sample consists of middle-income households for whom the expense of an air purifier is not overwhelmingly large, implying that low WTP is unlikely to be explained by liquidity constraints.

substantial efforts to promote them, while others, such as drinking water purifiers, have disseminated quickly even without public support.

We advance existing work in three important ways. First, we add to an extremely small number of revealed preference estimates for clean air, especially in low- and middle-income countries (LMICs). For example, Ito and Zhang (2020) use scanner data to estimate demand for air purifiers in China. However, other than Baylis et al. (2024), we are aware of no other experimentally-derived revealed preference estimates of demand for clean air.[5] While they study air pollution masks in very low-income settings (in New Delhi, India), we focus on air purifiers in middle-income households (in Dhaka, Bangladesh). We find low willingness to pay for clean air even in households for whom liquidity constraints are unlikely to be binding for purchasing air purifiers. As such other market failures may drive low demand and use (Greenstone and Jack, 2015).[6] Importantly, to the best of our knowledge, we are the first to experimentally demonstrate that air purifiers are experience goods. Kahn, Sun and Zheng (2022) show city-level correlations in China between improvements in air quality during the COVID-19 pandemic and online discussions focused on environmental protection as well as adoption of green subsidies in post-covid stimulus policies. [7]

Second, we contribute to small but growing literature on the economics of air pollution information, particularly about IAP. The literature on the impacts of air pollution awareness on public health and behavior finds mixed results. Barwick et al. (2024) 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. Furthermore, Singh and Thachil (2023) show that sharing indoor air quality information increases air pollution electoral salience and Jha and Nauze (2022) find that monitoring stations at US embassies caused air pollution to drop in the countries where they were set up. Relatedly, Ahmad et al. (2023) show that receiving forecasts of air pollution levels increases demand for air pollution masks as well as reduces time spent outdoors. In contrast, Greenstone, Lee and Sahai (2021) observe that the presence of air monitors in Delhi did not significantly influence the willingness to pay (WTP) for such devices. We advance this literature by not only showing how monitors affect beliefs and use of air purifiers but also

[5] Greenstone, Lee and Sahai (2021) attempts to estimate demand for renting air purifiers by providing a code that could be used to rent a purifier at a discounted rate. However, as none of the households in their survey accepted the offer, it is challenging to estimate the demand for purifiers from their study.

[6] There is an extensive literature examining the health benefits (through reductions in indoor air pollution) from, and low adoption of, improved cookstoves in LMICs. A non-exhaustive set of papers as a starting point to dive into this literature are Hanna, Duflo and Greenstone (2016); Mobarak et al. (2012); Levine et al. (2018); Pattanayak et al. (2019); Berkouwer and Dean (2022).

[7] Dupas (2014) shows that short-run subsidies for malaria nets increase willingness to pay one year later and find no evidence that recipients of the subsidy anchor around subsidized prices. Bergemann and Välimäki (2006) theoretically explore pricing of experience goods in mass and niche markets. Israel (2005) shows that consumers update information about automobile insurers after experiencing their service during claims and that these effects are mitigated when they are locked-in to their current insurer.

by experimentally comparing monitors and incentives to use purifiers to derive experimental estimates of the value of indoor air pollution information. Furthermore, we provide some of the first large-scale longitudinal measurements of indoor air pollution in middle-income homes in urban centers of LMICs.

Third, we contribute to a rich literature on the adoption and use of preventative health technologies (for a review, see Kremer, Rao and Schilbach, 2019).[8] Our study examines 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, 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 role of incorrect beliefs about the extent of the problem and misconceptions about benefits remain relatively unexplored as factors contributing to the observed reluctance in investing in preventative health technologies (Kremer, Rao and Schilbach, 2019). We carefully measure beliefs about the extent of the IAP problem and the effectiveness of purifiers. This allows us to show how monitor information and experience with purifiers affect beliefs about, demand for, and usage of a health-saving technology. Within this literature, measuring use of health-saving technologies often relies on self-reported survey data (Thornton, 2008). By contrast, we use high-frequency independent tracking of air purifiers using smart plugs. Indeed, we find households to dramatically overestimate projected and actual use of air purifiers suggesting that the existing literature may suffer from bias from misreporting and experimenter demand effect (Levine et al., 2018; Jakubowski et al., 2021).

The remainder of the paper is organized as follows. Section 2 describes our research design and data collection. Section 3 presents three stylized facts about perceived and actual indoor air pollution, as well as valuations and usage of air purifiers. Section 4 shows our results for the effects of indoor air pollution information on beliefs and purifier usage. Section 5 discusses our results on households' valuation of air purifiers. Section B shows results for health outcomes and Section 7 concludes.

2 Research Design and Data Collection

We conduct our study in the Mirpur area of Dhaka, Bangladesh, a city notorious for its severe air pollution. Even compared to Los Angeles—the city with the most polluted air in the US—Dhaka's levels stand out as exceedingly high (Figure A.2). During the study months of December through March, PM2.5 levels routinely exceed 10 times the WHO's 24-hour safe limit of 15 $\mu g/m^3$.

[8] An extensive literature in development economics has investigated underinvestment and low adoption of seemingly beneficial technologies in various sectors including seasonal migration (Bryan, Chowdhury and Mobarak, 2014), agriculture (Magruder, 2018) and firms (Verhoogen, 2023).

If Dhaka were to meet WHO air pollution guidelines, life expectancy there could increase by 8.1 years (AQLI, 2023).

We enrolled 1,008 households in Mirpur, housed in apartment blocks managed by three large housing associations that granted permission for our experiment.[9] Appendix Figure A.1 shows a map of our study area. We selected this population for two main reasons. First, middle-income apartment blocks represent a common form of housing in urban South Asia, making this group somewhat representative of a substantial demographic. Moreover, their economic status suggests that purchasing an air purifier would not constitute an overwhelming financial burden.[10]

Second, finer particulate matter such as PM2.5 can penetrate buildings easily (Ozkaynak et al., 1996; Vette et al., 2001), making exposure difficult to avoid. However, middle-class households in apartment settings, unlike many in slum dwellings, can effectively seal windows and doors. This ability may skew their perceptions of indoor versus outdoor air quality, influencing their demand for—and usage of air purifiers.[11]

We restricted the study sample to the 58% of households that answered "yes" to the initial question "Are you interested in an air purifier and/or air monitor for your household?" during the preliminary Phase 1 survey.[12] While screening out households responding "no" makes our sample less representative of the overall population, it allows us to focus on a group that is more likely to adopt and use air purifiers. This group is crucial for policymakers, as they are significantly impacted by measures designed to boost air purifier adoption and use.[13] Lastly, to reduce potential information spillovers between households we only sample one household per floor in each building.

Figure 1 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.

2.1 Phase 1 Survey

After screening households and obtaining consent, we conducted a short survey from November 12 to November 30, 2023. The survey included questions about the age and education of

[9] Approximately 180,000 people reside in the three housing associations, which are all located within a 2 square kilometer area. Each association comprises multiple multi-storey buildings ranging from 3 to 5 storeys, with several apartment units on each floor.

[10] For example, 34% of the households in our sample own an air conditioner. Air conditioners typically cost at least two to three times as much as an air purifier and consume substantially more electricity.

[11] Furthermore, we conducted our experiment during winter, a period when PM2.5 levels are very high but when households are more likely to keep windows closed for comfort; the average daily minimum temperatures in Dhaka are 15°C in December, 14°C in January, and 17°C in February.

[12] We asked two additional screening questions to ensure our sample included only households with a functioning WiFi connection and without an air purifier. These criteria did not significantly limit our sample, as nearly all households in our region already met these conditions.

[13] Examples of such measures include cutting taxes and import duties or government recommendations to use air purifiers, akin to the promotion of hand-washing and other preventive health actions.

the household head, beliefs about health risks from air pollution, and perceptions of indoor and outdoor air quality. After completing the survey, households tossed a digital coin on the survey tablet, and a subset were randomly selected to receive an (indoor) air quality monitor. Amongst these households, we further randomized a subset to receive an attention treatment, where they were incentivized to read the monitor at least once per week. See Appendix D.1 for more information about how the survey data was processed.

Treatment 1: Air quality monitors: We provided 512 randomly selected households with air quality monitors that use optical signatures to measure levels of indoor PM2.5 levels (Figure A.3). These monitors have a small display screen that reports PM2.5 in standard units of micro grams per cubic meter ($\mu g/m^3$). Along with these monitors, households received a chart (in English and Bengali) categorizing PM2.5 levels into six levels: good, moderate, unhealthy for sensitive groups, unhealthy, very unhealthy, and hazardous (Figure A.4). The chart also shows the health risks associated with these air pollution levels in terms of increased likelihood of heart disease, stroke, and lung cancer in adults, and respiratory issues in children under 5.[14] Once randomly selected households received a monitor, the field team helped set up the monitor and connect it to WiFi, ensuring that data was being transmitted before leaving the household.

Each household with an air monitor received a small daily incentive of BDT 15 (USD 0.14) if their monitor transmitted data for at least 16 hours. To mitigate any risk of incentive-driven effects, households without air monitors received the same payment, matched randomly with a household in the treatment group (Cefala et al., 2024). For uniformity in data collection, we suggested placing the air monitors in the bedroom of the household head.

Treatment 2: Air quality attention incentives: Among the 512 households receiving an air pollution monitor, 255 were randomized to receive an attention treatment. In this treatment, they earned a weekly reward of BDT 30 (USD 0.28) for accurately reporting their home's air quality category and the associated increased disease risk via a WhatsApp message. The remaining 257 households received a payment equal to that of a randomly selected household in the attention group. This approach ensures balanced payouts between the treatment and control groups.

2.2 Phase 2 Survey

We conducted the Phase 2 survey from January 5 to February 4, 2024, approximately two months after the phase 1 survey.[15] The Phase 2 survey collected information on household beliefs about air pollution and its health impacts, as well as perceptions of the benefits of air purifiers. We

[14]The hazard ratings were adapted from the US EPA's air quality dial found on www.airnow.gov. The health risks were adapted from Apte et al. (2015).

[15]A small number of surveys were rescheduled and completed by March 12, 2024; however, the average time between the Phase 1 and Phase 2 survey was 61 days.

also employed a modified Becker-DeGroot-Marschak (BDM) mechanism to elicit willingness to pay for air purifiers (Berry, Fischer and Guiteras, 2020; Berkouwer and Dean, 2022). We included questions about sleep, mood, willingness to engage in solving the collective action problem of air pollution, and questions about labor supply. We also collected data on health bio-markers—specifically blood pressure and blood oxygen levels—of household members who slept in the bedroom of the household head.

Attrition: We experienced 17% attrition between Phase 1 and Phase 2; of our Phase 1 sample of 1008 households, 832 households consented to the Phase 2 survey.[16] We regress whether or not a household left the sample in Phase 2 on the monitor and attention treatment to see if treatment is correlated with attrition (Table A.1). Although coefficients on both treatments are statistically insignificant, the magnitude on the monitor treatment is negative and sizable. Attrition in the non-monitor group was 19.6% whereas attrition in the monitor group was 15.2%. There was no differential attrition between households receiving the monitor with or without the attention treatment. We test for balance in the unattrited groups for both monitor (Table A.2) and attention treatments (Table A.3). We find that balance on observables collected during the Phase 1 survey is maintained in the unattrited sample.

Treatment 3: Air purifiers: From our unattrited sample of 832 households, we randomly selected 345 households to receive air purifiers. The model of air purifier used in the experiment is the "Squair Air Purifier" from Smart Air (see Figure A.5 for a picture).[17] At the time of the experiment, the retail price in Bangladesh was BDT 17,000 (approximately USD 150). The randomization was conducted as part of the BDM willingness to pay elicitation.[18] Treatment households were randomly selected to have a 'draw price' set at zero, ensuring that they will receive an air purifier while control households were given a 'draw price' equal to the market price.[19] We encouraged households to place these air purifiers in the bedroom of the household head. We attached smart sockets to each of the air purifiers so we could directly measure air purifier use (Figure A.6).

[16]Of the 176 households who did not consent to the Phase 2 survey, 79 were randomized to receive monitors and 97 were randomized to not receive monitors. Of the 79 who were selected to receive monitors, 34 immediately refused to allow monitor to be installed at the end of the Phase 1 survey. The remaining 45 households allowed monitors to be installed; 22 of them returned the monitor before the Phase 2 survey, 14 stopped using the monitor but did not return it and 9 of them are still using the monitor but did not consent to either the Phase 2 or Phase 3 survey.

[17]For more details on the air purifier, see: https://smartairfilters.com/en/product/sqair-air-purifier/.

[18]In a BDM exercise, households are asked to report the amount they would be willing to pay for an air purifier in decreasing increments of 1000 Taka, starting at the market price of 17,000 Taka. Once a household declares a price they would be willing to pay, a random draw price is selected. If the drawn price is below what the household said they would pay, the household receives the air purifiers at the draw price. Otherwise no transaction takes place.

[19]Only one control household stated a willingness to pay equal to the market price.

Treatment 4: Electricity Compensation: We randomly assigned the 345 households equipped with air purifiers to one of three groups: two groups received compensation for the electricity used by the air purifiers, while one control group did not receive any compensation. Each of the two treatment groups consisted of 106 households, while the control group had 133 households. The compensation for the treatment groups was equal to the electricity cost incurred by the air purifier, tracked via the smart socket.[20] All households received their first payment one week after our visit to build trust. After this initial payment, households in the first treatment group received daily payments, whereas those in the second group received monthly payments.[21]

2.3 Phase 3 Survey

We conducted the Phase 3 survey from February 23 to March 31, 2024, approximately seven weeks after the Phase 2 survey.[22] In the Phase 3 survey, we collected endline data, including households' willingness to pay for an additional air purifier and their willingness to accept cash to sell back purifiers they already had. We repeated many questions from the Phase 2 survey to observe the purifiers' effects on responses. We also collected health bio-markers.

Attrition: Of the 832 households surveyed in Phase 2, 784 consented to participate in the Phase 3 survey representing a low attrition rate of 5.8%. However, we find differential attrition by purifier treatment (Table A.4). Of the 48 households who left our study, 7 were in the purifier group and the rest were in the non-purifier group. The 7 attrited households in the purifier group refused entry during the Phase 3 survey and retained their purifiers after ceasing all contact with the study team. 5 of these 7 households kept their smart plugs connected for a few weeks, allowing us to collect data on purifier usage. Of the 41 attrited households in the non-purifier group, 37 refused consent, while 4 left the area. Importantly, we test for differential attrition and find that the unattrited treatment and control groups are balanced in terms of observables collected during the Phase 2 survey (Table A.5). The differences between non-purifier and purifier households in the unattrited sample are small and statistically insignificant. One exception is household income, where purifier households report having 10% lower monthly income on average but this estimate is very noisy. We also observe no differences in willingness to pay or perceptions of air quality and its effects, suggesting that differential attrition did not undermine the integrity of the random assignment.

[20] To avoid households using different devices in the smart socket we used a small amount of glue, attaching the air purifier plug in the smart socket. Furthermore, we only compensated for electricity usage within the range of wattage used by the air purifier.

[21] There is progressive electricity pricing in Dhaka, with prices being higher for users consuming more electricity. We base our compensation on the highest marginal price of electricity, 13 BDT (0.12 USD) per kwh. This means that no household is under-compensated for their electricity use, but households that used small amounts of electricity overall were slightly over-compensated compared to their true marginal cost of electricity.

[22] A small number of surveys were rescheduled and completed by April 20, 2024; however, the average time between the Phase 2 and Phase 3 survey was 48 days.

Incentives to Use Air Purifiers: In a departure from the pre-analysis plan, we re-randomized the 338 unattrited households in the purifier group, after the endline survey, to receive larger incentives for increasing usage of air purifiers. This was done to assign a monetary value to other treatments aimed at driving increased air purifier usage. We randomized households with purifiers into three groups. The first group received no additional incentives for increasing their usage of air purifiers. A second group was incentivized with 5 BDT per hour of use, and a third group received 10 BDT per hour. These incentives, provided from April 1 to April 30, 2024, were considerably larger than the compensation for electricity costs, which for running the purifier on medium speed are approximately BDT 0.24 per hour. Thus, the incentive treatment payments were 20-40 times greater per hour of use than the electricity compensation. Put another way, households in the two incentivized groups that operated their purifiers continuously throughout the 30-day intervention could earn between 3,600 and 7,200 Taka, amounting to a significant 6% and 12% of the average monthly household income in our sample, respectively.[23]

2.4 Other Data Sources

In addition to data from the three surveys, we collected data from three other sources. First, we collected continuous minute-by-household level indoor air pollution data from households equipped with air monitors. Second, we installed outdoor air pollution monitors in the study regions. Third, we recorded continuous minute-by-household level air purifier usage data, which was collected via the smart sockets connected to the air purifiers.

Indoor Air Pollution: In Phase 1, we installed air pollution monitors in a random subset of our sample. These monitors are designed to record and push to the server minute-by-minute data on PM2.5, PM10, temperature, and humidity.[24] We incentivized households to keep the air monitors on by providing BDT 10 for each day that the device was turned on for more than 16 hours. Despite this incentive, 8% of households refused to install the monitor. Overall, we received data from 61% of the potential hour-by-household observations among those with monitors installed. We winsorize the data at the 1st and 99th percentiles. See Appendix D.2 for more details about attrition in the monitor data.

Outdoor Air Pollution: We installed two outdoor air pollution monitors to cover all three hous-

[23] We included this treatment after receiving additional funding that was not available when we initially wrote and posted the pre-analysis plan.

[24] We used Qingping Lite monitors, a model that has performed well in tests in other highly polluted environments: https://smartairfilters.com/en/blog/how-accurate-are-qingping-qp-pm2-5-air-quality-monitors/.

ing associations, providing us minute-by-minute data on PM2.5 and PM10. [25] We winsorize the data at the 1st and 99th percentiles.

Air Purifier Use: Each air purifier was connected and glued to a smart plug. The smart plugs were connected to WiFi and recorded electricity usage of the connected device, pushing data to the server every minute on how many watts were used. Figure A.7 shows that the smart plugs' recorded electricity usage aligns with the manufacturer's labeling of the air purifier's wattage at various speeds. We classify electricity usage between 3 and 60 watts as indicative of the purifier being in use.

3 Descriptive and Stylized Facts

Our study can shed light on many aspects of indoor air pollution and households' perceptions about it. In this section, we report some important descriptive and stylized facts relevant to our context. It is important to note that our study does not focus on the poorest households in our urban setting. Instead, we concentrate on middle-income households for whom purchasing a monitor and air purifier, while not trivial, is not overwhelmingly expensive either; the retail price of the air purifier used in our experiment is less than 30% of the monthly household income.

3.1 Both outdoor and indoor air pollution levels are alarmingly high

Dhaka is one of the most polluted cities in the world. At our study sites, average ambient PM2.5 levels were 181 $\mu g/m^3$ from November 2023 to March 2024, the period between Phase 1 and Phase 3, roughly 12 times the WHO's 24-hour safe limit of 15 $\mu g/m^3$. Importantly, indoor air pollution levels are also alarmingly high. The average indoor air pollution during our study period was 135 $\mu g/m^3$, or 9 times the WHO's 24-hour recommendation. Figure 2 shows the average indoor air pollution readings in households without air purifiers, alongside outdoor air pollution levels by time of day, clearly showing that indoor air pollution never meets WHO standards at any time of day. We estimate the infiltration coefficient – the ratio of indoor air pollution to ambient air pollution – to be 0.79.

3.2 Households are more attuned to outdoor pollution but underestimate the severity of indoor air pollution

Households are not fully aware of the severity of indoor air pollution. Data collected from the Phase 1 survey at the study's outset suggest that while over 70% of households accurately perceive outdoor air pollution as exceedingly high, rating it 7 or higher on a scale of 10 (Figure

[25] We used AirVisual Outdoor monitors by IQair. For more information, see www.iqair.com/products/air-quality-monitors/airvisual-outdoor-2-pm.

A.8),[26] fewer than 20% similarly assess indoor pollution levels (Figure A.10). A significant 71% of households consider indoor air pollution to be a minor problem, giving it a rating of 5 or lower out 10. In Appendix Figure A.11, we display the distribution of households' perceptions of indoor versus outdoor air pollution. The overwhelming majority of households believe their infiltration coefficient is 0.5 or lower, indicating a dramatic underestimation of indoor air pollution's extent.

3.3 Demand for air purifiers is low likely due to incorrect perceptions about their effectiveness

We find that demand for air purifiers is low. First, in our screening of households to be included in the sample we excluded those who already had an air purifier; only 15 of the 1,841 households – less than 1% – reported having an air purifier. Second, we elicit households' willingness to pay for air purifiers in the Phase 2 survey. In the control (non-monitor) group, we find an average household willingness of BDT 1,431 (USD 12.17) or 8.4% of their retail cost. This is consistent with Greenstone, Lee and Sahai (2021), who found no demand for air purifier rentals among middle-income households in urban Delhi. Third, low adoption rates for air purifiers may stem from incorrect perceptions about their effectiveness. In the control group, fewer than half of the households had formed an opinion on purifier effectiveness, and less than a third believed that purifiers removed more than 25% of air pollution from the room where they were used (Table X). This contrasts sharply with actual air purifier effectiveness, which exceeds 80% in controlled conditions and 40% in real-world household environments (Figure X and X).

3.4 Households claim they would use an air purifier continuously, but in reality, they rarely do

In the preliminary Phase 1 survey, we asked control households (households that did not receive a monitor) how often they would use an air purifier during the winter months if they owned one (Appendix Figure A.12). 58% of households said they would use the air purifiers continuously when at home, nearly 23% indicated they would use them at least once per day, and another 9% would use them a few times a week. In contrast, fewer than 9% of households stated they would never use the air purifiers. These proportions remained more or less consistent through the Phase 2 survey.

However, households' projected use of air purifiers far exceeds their actual usage. Figure 3 shows the number of minutes an air purifier is used at the household-day level among households that were randomly selected to receive air purifiers but were not chosen to receive a monitor or electricity compensation for air purifier use. Most households, on most days, do not use the air

[26] This is even though a majority of households do not regularly check outdoor air pollution levels (Appendix Figure A.9); nearly 83% rarely or never monitor these levels, and only 8% do so daily.

purifier at all, with 80% of household-days seeing no air purifier usage. In Figure 4 household-level data paint an even starker image. More than 3 out of 4 households use an air purifier for less than 30 minutes daily on average, and only 5% of households use the purifier for more than 81 minutes in a day.

While the self-reported usage is lower than the predicted usage of the air purifiers, it is substantially above the actual usage as measured by the smart plugs. In the Phase 3 survey, the average household claim to use the air purifier for at least 30 minutes per day for more than five days in the previous week. However, using the smart plug data we can confirm that on average households used the air purifier for more than 30 minutes only 1 day per week.[27]

4 Effects of Monitor on Beliefs and Air Purifier Use

In this section, we examine the effects of providing air pollution monitors on various outcomes, reporting three principal findings. First, households that randomly received a monitor significantly revised their perception of poor indoor air quality. Second, the presence of air pollution monitors dramatically increased both the predicted, self-reported, and actual use of air purifiers. Third, equipping households with a monitor had a comparable effect on air purifier usage as offering an incentive of BDT 4.2 per hour for using the purifier.

4.1 Air pollution monitors correct household beliefs about indoor air pollution levels

Econometric specification. We begin our experimental analysis by examining how monitors, provided at the end of the Phase 1 survey, influenced households' perceptions of air pollution by the time of the Phase 2 survey. We estimate the following regression specification:

$$\begin{aligned} Belief_i =& \alpha + \beta_1 \times Monitor_i + \beta_2 \times Attention_i + \\ & \gamma_1 BeliefPhase1_i + \varepsilon_i \end{aligned} \tag{1}$$

where $Belief_i$ represents the belief of household i regarding the severity of indoor air pollution levels in the Phase 2 survey. The term $Monitor_i$ indicates whether a household was randomly selected to receive an air quality monitor, while $Attention_i$ denotes whether the household was given both a monitor and an incentive to report their air quality monitor readings, thereby increasing their attention to the indoor air pollution levels.[28] We control for baseline be-

[27] Discrepancies between self-reported and objective measures of health technology usage are quite common. For example, a similar magnitude of discrepancy was found in the usage of face masks during the COVID-19 pandemic in Kenya (Jakubowski et al., 2021). Furthermore, we will demonstrate that this discrepancy is consistent across both treatment and control groups; specifically, the impact of the monitor on air purifier use was similar when assessed through both self-reported and objective measures.

[28] We present and discuss these results in Section XX.

liefs ($BeliefPhase1_i$) elicited in the Phase 1 survey before randomization. Standard errors are clustered at the household level.

We use three questions to capture perceptions of air pollution. First, households were asked to rate indoor air pollution on a scale from 0 to 10, where 10 corresponds to 'extremely polluted' and 0 to 'not polluted at all.' Second, we asked them to rate outdoor air pollution on the same scale. Finally, households rated indoor air quality relative to outdoor air quality on a scale from 0 to 10, where 10 indicates 'Indoor is equally polluted as outdoor' (implying an infiltration coefficient of 1), 5 suggests 'Indoor is half as bad as outdoor' (implying an infiltration coefficient of 0.5), and 0 implies there is almost no indoor air pollution.

Results. We present these results in Table 1. We find that the monitor treatment significantly increases households' perception of the poor quality of indoor air, with the estimate showing an increase of 0.479 points or slightly over 10% (Columns 1-2). In contrast, monitors have no effect on perceptions of outdoor air pollution (Columns 3-4). Furthermore, Columns 5-6 show that the air monitors help reduce the misconception that indoor air quality is substantially better than outdoor air quality, increasing the perceived infiltration coefficient from 0.43 in the control group to 0.47 among households with monitors.[29] Collectively, our results indicate that while monitors effectively update households' beliefs about the severity of indoor air pollution, they do not alter perceptions of outdoor air pollution, given that the typical household already recognizes its high levels.[30]

4.2 Air pollution monitors increase air purifier use

Next, we analyze how air pollution monitors affect different measures of air purifier use—both self-reported in surveys and actual use recorded by smart plugs.

Self-reported use. We asked households in the Phase 2 and 3 surveys how often they would use air purifiers during the months of December through February if they owned one.[31] We convert this question into a binary variable for above and below median projected use. Since over half of

[29] These specifications focus only on Phase 2 data. In Table A.6, we examine the effects of the monitor treatment on households' perception of indoor air quality in Phase 3. These impacts are smaller than those observed in Phase 2, likely because we inquire about perceptions of *current* indoor air quality, and indoor air pollution levels during Phase 2 were XX $\mu g/m^3$ compared to XX $\mu g/m^3$ in Phase 3.

[30] We also examine the effect of air pollution monitors on perceived health risks from indoor air pollution, including lung cancer and stroke in adults, and acute respiratory infections in children, with risk perceptions ranging from 'no effect' to 'more than quadrupling.' We report results in Appendix Table A.7. We find that monitors increase households' perceptions of the health risks from indoor air pollution during the Phase 2 survey for adults and children by 7.3% (Column 1) and 5.6% (Column 2), respectively. In contrast, we fail to find evidence that monitors increase households' perceptions of the health risks from indoor air pollution during the Phase 3 survey (Columns 3 and 4). As before, this is likely because we inquire about perceptions of the health risks from *current* indoor air quality levels, and indoor air pollution levels during Phase 2 were XX $\mu g/m^3$ compared to XX $\mu g/m^3$ in Phase 3.

[31] Response options were (a) all the time when home, (b) at least once per week, (c) a few times per week, (d) once per week, (e) once per month, (f) very rarely, (g) never, (h) don't know or (i) refused.

respondents said they would use the air purifier all the time when home, this effectively creates a binary variable for whether or not the household would use it constantly while at home.

Econometric specification. We estimate following regression specification:

$$\begin{aligned} SelfUse_i =& \alpha + \beta_1 \times Monitor_i + \beta_2 \times Attention_i + \\ & \gamma_1 SelfUsePhase1_i + \varepsilon_i \end{aligned} \tag{2}$$

where $SelfUse_i$ represents the projected self-reported use or actual self-reported use of household i in the Phase 2 and Phase 3 surveys, respectively. We control for projected use reported during the Phase 1 survey ($SelfUsePhase1_i$) before randomization. Standard errors are clustered at the household level.

Results. We report the effects of the monitor treatment on this outcome in Table 2. Column 1 indicates that monitors increase the proportion of households stating they would use air purifiers all the time by 19.5 percentage points, or 35.4%, in the Phase 2 survey. In Phase 3 survey, we asked households how many days in the past week they had used air purifiers. In Column 2, we show that households in the monitor group reported using air purifiers for at least 30 minutes on an extra half day, compared to a control group average of 5 days. Finally, at Phase 3 we asked an ex-post version of the question presented in Column 1 – how often households used air purifiers – using the same options as in Column 1. We show that the monitor treatment increased the likelihood of households self-reporting air purifier usage as "all the time when home" by 14.4 percentage points, or nearly 60% (Column 3).

Use recorded by smart plugs. We also estimate the effect of air pollution monitors on an objective measure of air purifier use, based on continuous minute-by-minute data from the smartplugs that we attached to the air purifiers.

Econometric specification. We estimate the following regression specification:

$$Use_{it} = \alpha + \beta_1 \times Monitor_i + \beta_2 \times Attention_i + \tau_t + \varepsilon_{it} \tag{3}$$

where Use_{it} indicates whether household i used the air purifier during date or week t and τ_t represents date or week fixed effects. Standard errors are clustered at the household level.

Results. We report these results in Table 3.As discussed earlier, unlike the self-reported data, the smart plugs data show extremely low use of air purifiers: the average control household used an air purifier for just over 33 minutes a day. However, providing households with an air monitor

increases the time that the air purifier is running by 74 minutes per day. This is a massive 225% treatment effect.[32]

Next, using data from the smart plugs, we constructed a weekly measure of air purifier usage similar to the self-reported measure: the number of days per week the purifier was used for more than 30 minutes. This metric was generated for all intervention weeks and specifically for the week preceding the Phase 3 survey (Columns 2 and 3). We found that households in the monitor group reported using air purifiers for at least 30 minutes on an additional half-day, compared to an average of 1 day in the control group. The absolute increase is qualitatively and quantitatively consistent with increases estimated using self-reported data. This consistency is reassuring and suggests that, although discrepancies exist between self-reported and objective measures of air purifier use, they are consistent across both treatment and control groups.

Electricity costs do not explain low air purifier use. We also examine whether electricity costs — approximately BDT 0.24 per hour of use — can explain low usage of air purifiers. Households that received an air purifier were randomized into three groups: those receiving no compensation, those receiving daily compensation, and those receiving monthly compensation.

Econometric specification. We estimate the following regression specification:

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

where $Compensation_i$ signifies whether the household receives any compensation (daily or monthly) for the electricity cost, and $DailyCompensation_i$ indicates daily compensation. Our 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, $\beta_2 = 0$.

We included two compensation approaches to explore whether 'present bias' – the tendency to prioritize immediate benefits over future gains – influences air purifier usage. Given that present-biased individuals might be less likely to use the purifiers due to their reluctance to wait for long-term benefits, we hypothesize that air purifier usage will be higher in the daily compensation group compared to the monthly compensation group.

Results. We report these results in Appendix Table A.9. Receiving compensation does increase air purifier use, although the effect is not precisely measured. Incentives increase use by 0.99 percentage points, roughly 31% higher than the mean usage of households that receive no incentive. Providing the incentive on a daily basis further amplifies this effect by 0.66 percentage points, although this estimates is also imprecise. Recall that the first payment to all house-

[32]Of the originally intended 372 households, 309 remained in our sample. Including these households and imputing their air purifier usage as zero yields quantitatively equivalent estimates with similar statistical power (Appendix Table A.8).

holds was made at the end of the first week to establish uniform trust across the two compensation groups. Therefore, the modest additional effect of daily compensation is unlikely to be attributable to households' trust in receiving payments. Overall, while these estimates suggest that electricity costs and present-bias could play some role in explaining the low use of air purifiers, these effects are relatively small compared to the significant impact of receiving air pollution monitors, which dramatically increase air purifier use.

4.3 The value of the information provided by the monitor is equivalent to an hourly incentive of BDT 4.2 to use the air purifier

To assess the value of the information from air pollution monitors in promoting air purifier use, we randomized additional incentives at the conclusion of our planned study, from April 1, 2024 to April 30, 2024. Specifically, we randomized households that had received an air purifier into three groups: (a) a control group, (b) a group that received an incentive of BDT 5 for each hour of air purifier use, and (c) a group that received an incentive of BDT 10 for each hour of air purifier use. These incentives significantly exceed the electricity costs (roughly BDT 0.24 per hour) associated with operating the air purifiers.

Econometric specification. We estimate the following regression specification:

$$Use_{it} = \alpha + \beta_1 \times AnyIncentive_i + \beta_2 \times BDT10Incentive_i + \tau_t + \varepsilon_{it} \tag{5}$$

where $AnyIncentive_i$ indicates whether the household was offered at least a 5 BDT per hour incentive, and $BDT10Incentive_i$ indicates if the household was offered the larger incentive of 10 BDT per hour of air purifier use. Standard errors are clustered at the household level.

Results. We report these results in Table 4. Column 1 shows that providing households with at least 5 BDT per hour increases air purifier usage by 7.83 percentage points (113 minutes per day), compared to a 4.78 percentage point increase (69 minutes per day) from providing a monitor. Column 2 breaks down these estimates further; we find that the BDT 5 per hour incentive increased air purifier use by 5.7 percentage points (82 minutes per day), roughly equal to the effect of providing a monitor. These effects are substantial: the 5 BDT per hour incentive increases usage by over 500% relative to the control mean, while the increase from monitors is just under 500%. This treatment allows us to quantify the value of the indoor air quality information provided by monitors in promoting air purifier use. Figure 6 visually compares the effects of monitors and incentives on air purifier usage. Assuming a linear increase in usage from a zero incentive to a 5 BDT incentive, the effective incentive equivalent to the monitor's impact would be BDT 4.2 per hour. Paying this hourly incentive based on the usage rates observed would amount to 0.3% of the average monthly income each month.

5 Effects of Monitor on Adoption of Air Purifiers

We elicited revealed preference measures for willingness to pay (WTP) for air purifiers at the end of both the Phase 2 and 3 surveys. At the end of Phase 2, we employed a modified BDM mechanism, as previously explained. During the Phase 3 survey, we conducted exercises to gauge willingness to pay for an additional air purifier and willingness to accept (WTA) payments for households considering selling back their existing air purifiers.

We report five main findings: First, despite monitors increasing both perceptions of indoor air pollution levels and air purifier use, they do not affect WTP for air purifiers at the time of the Phase 2 survey. This suggests an additional or different binding constraint on raising WTP for air purifiers. Second, owning an air purifier not only leads to opinion formation among households but also enhances their perception of the purifier's effectiveness. Third, the price at which households are willing to sell back their air purifiers after using them is, on average, ten times higher than their initial WTP, suggesting a substantial valuation increase after usage. Fourth, monitors increase the price that purifier-owning households are willing to accept to sell their purifier. Fifth, monitors increase WTP for an additional, second purifier during the Phase 3 survey among purifier-owning households, but do not increase WTP for a first purifier among non-purifier owning households.

5.1 Monitors do not increase WTP during the Phase 2 survey

Econometric specification. We estimate the following regression specification to examine how air pollution monitors affect WTP for air purifiers during the Phase 2 survey:

$$WTP_i = \alpha + \beta_1 \times Monitor_i + \beta_2 \times Attention_i + \varepsilon_i \tag{6}$$

where WTP_i represents the WTP for household i at the time of the Phase 2 survey, determined through a modified Becker-DeGroot-Marschak (BDM) mechanism (Berry, Fischer and Guiteras, 2020; Berkouwer and Dean, 2022). Standard errors are clustered at the household level.

Results. In the Phase 2 survey data, before households had any practical experience with air purifiers, we observed a low willingness to pay for air purifiers (8.4% of cost), even though the households are within an income segment where such a purchase would not be overwhelming. We did not find a significant treatment effect of monitors on willingness to pay for an air purifier during the Phase 2 survey (Table 5, Column 1).[33]

The null effect of air pollution monitors on WTP for air purifiers during the Phase 2 survey contrasts with our finding that monitors correctly increased households' perceptions of indoor air

[33] Furthermore, after re-estimating the impact on WTP by assigning zero willingness to pay to attrited households, we found no meaningful deviations in our estimates (Appendix Table A.10).

pollution levels and associated risk of illness in adults and children. These seemingly contradictory results suggest that simply providing information from air pollution monitors is not enough to boost adoption of air purifiers among middle-income households. For instance, although the monitor treatment may lead households to update their beliefs about indoor air pollution and its health effects, they might still doubt the effectiveness of air purifiers as a strategy to reduce pollution.

5.2 Experience with air purifiers improves perceptions of their effectiveness

Next, we estimate the impact of receiving an air purifier on opinion formation regarding their effectiveness and on perceptions of their effectiveness. In our Phase 3 survey, we asked households how effective they believe commercially available air purifiers in Dhaka are at removing air pollution from a room. The response options were "remove no air pollution", "remove only a quarter of the air pollution", "remove half of the air pollution", "remove three-quarters of the air pollution" and "remove almost all air pollution". We coded these responses into four binary variables. Each variable takes the value of 1 if a household believes the air purifier removed at least some, more than a quarter, more than half, or more than three-quarters of the air pollution, respectively, and 0 otherwise. Households were also given the option to select 'don't know.' Given the substantial number of households that chose this response, we created a binary variable 'has opinion.' This variable is set to 1 if the household selected any of the specific effectiveness options instead of 'don't know,' and 0 otherwise.

Econometric specification. We estimate the following regression specification:

$$\begin{aligned} Y_i = \alpha + \beta_1 \times Monitor_i + \beta_2 \times Purifier_i + \beta_3 \times Attention_i + \\ \beta_4 \times Monitor_i * Purifier_i \\ + \beta_5 \times Attention_i * Purifier_i + \varepsilon_i \end{aligned} \tag{7}$$

where Y_i represents the binary variables described above for household i at the time of the Phase 3 survey. Standard errors are clustered at the household level.

Results. We report these results in Table 6. In Column 1, we demonstrate that households provided with an air purifier in the Phase 2 survey—and thus having prior experience with one—are 28 percentage points more likely to have an opinion about air purifier effectiveness. This represents a 68% increase in the likelihood of forming an opinion. Interestingly, we also find that households provided with a monitor in the Phase 1 survey are 9 percentage points (22%) more likely to form an opinion about air purifier effectiveness. However, having both the purifier and

monitor does not further influence opinion formation.[34]

In Columns 2-5, we report the effects of providing households with an air purifier during the Phase 2 survey on perceptions of their effectiveness. We find that these households are 28 percentage points (72.90%) more likely to perceive air purifiers as effective, 31 percentage points (97.46%) more likely to believe they are more than 25% effective, 28 percentage points (121.05%) more likely to think they are more than 50% effective, and 13 percentage points (180.82%) more likely to consider them more than 75% effective. Conversely, households provided with a monitor in the Phase 1 survey are 9 percentage points (24.74%) more likely to perceive air purifiers as effective, 10 percentage points (33.02%) more likely to perceive them as more than 25% effective, and 9 percentage points (38.16%) more likely to view them as more than 50% effective. However, there is no significant effect on the perception that air purifiers are more than 75% effective among those provided with a monitor. Again, we find no evidence that having both the purifier and monitor significantly alters households' perceptions of air purifiers' effectiveness, with one exception: households provided with both an air purifier and a monitor are 10 percentage points (132.88%) more likely to perceive that air purifiers are more than 75% effective, although this result is not statistically significant (p-value = 0.14).

5.3 Information about indoor pollution levels and practical experience with purifiers increases their valuation

In this section, we examine: (a) the impact of monitor provision on the willingness to accept (WTA) selling back purifiers among households that received an air purifier in Phase 2, (b) the effect of monitor provision on the willingness to pay (WTP) for an air purifier among households that did not receive one in Phase 2, and (c) the differences between the impact of purifier provision alone and the combined impact of monitor and purifier provision on the willingness to pay for a second purifier among households that received their first purifier in Phase 3.[35]

Before we estimate these effects, it is important to note that the price at which households are willing to sell back their air purifiers after using them is, on average, ten times higher than their initial (Phase 2) WTP, suggesting a substantial valuation increase after usage. This difference may be influenced by an endowment effect from loss aversion, although such effects are typically much lower. Brown et al. (2024) finds that, across numerous studies, the average loss aversion coefficient is 2.0, with coefficients above 5 being extremely rare. Furthermore, Tunçel and Hammitt (2014) observes that the WTP/WTA gap tends to be smaller in studies using incentive-compatible elicitation mechanisms. Therefore, the substantial difference between WTP and WTA

[34]This is despite the fact that receiving an air purifier increases monitor use by 8.8 percentage points, or 16% (Appendix Table A.12).

[35]Recall that we cannot test the effects of air purifiers on WTA since only households that had already received an air purifier from us were eligible for the WTA exercise. Similarly, we cannot capture the willingness to pay for their first air purifier among households that received one in Phase 2. For these households, we can only elicit willingness to pay for a second air purifier.

suggests that experience with an air purifier significantly enhances its valuation by households.

Econometric specifications. To examine the impact of monitor provision on the willingness to accept selling back purifiers among households that received an air purifier in Phase 2, we estimate the following regression specification:

$$WTA_i = \alpha + \beta_1 \times Monitor_i + \beta_2 \times Attention_i + \varepsilon_i \tag{8}$$

where WTA_i represents the WTA for household i at the time of the Phase 3 survey, determined through a modified Becker-DeGroot-Marschak (BDM) mechanism. We restrict the sample to households that were randomly assigned to receive an air purifier in Phase 2. Standard errors are clustered at the household level.

To examine the effect of monitor provision on the willingness to pay (WTP) for an air purifier among households that did not receive one in Phase 2, and the differences between the impact of purifier provision alone and the combined impact of monitor and purifier provision on the willingness to pay for a second purifier among households that received their first purifier in Phase 3, we estimate the following regression specification:

$$\begin{aligned} WTP_{it} = {} & \alpha + \beta_1 \times Monitor_i + \beta_2 \times Purifier_i + \beta_3 \times Attention_i + \beta_4 \times Phase3_t \\ & + \beta_5 \times Monitor_i * Purifier_i + \beta_6 \times Attention_i * Purifier_i \\ & + \beta_7 \times Monitor_i * Phase3_t + \beta_8 \times Purifier_i * Phase3_t + \beta_9 \times Attention_i * Phase3_t \\ & + \beta_{10} \times Monitor_i * Purifier_i * Phase3_t + \beta_{11} \times Attention_i * Purifier_i * Phase3_t + \varepsilon_{it} \end{aligned} \tag{9}$$

where WTP_i represents the WTP for household i at the time of the Phase 2 or Phase 3 survey, determined through a modified Becker-DeGroot-Marschak (BDM) mechanism. Standard errors are clustered at the household level. β_7 captures the change in the willingness to pay for an air purifier between Phase 2 and Phase 3 among households that received a monitor but not an air purifier. β_8 captures the change in the willingness to pay for an air purifier between Phase 2 and Phase 3 among households that received one in Phase 2. β_{10} captures the change in the willingness to pay for an air purifier between Phase 2 and Phase 3 among households that received an air purifier (in Phase 2) and a monitor (in Phase 1).

Results. We report these results in Table 8. First, we estimate Equation 8: we find that possession of a monitor increases the willingness to accept by BDT 3,839.3, which is 26% above the control mean (Column 1) among households that received an air purifier. Specifically, while the control group's mean WTA is approximately BDT 14,500—below the retail price—households that received both a purifier and a monitor placed a higher valuation on the purifiers, exceeding the retail price of BDT 17,000.

In Column 2, we present estimates from Equation 9. While these estimates are statistically insignificant, the magnitude of the point estimates is still informative. We find that households receiving both a monitor and a purifier increased their valuation of the purifier between Phase 2 and Phase 3 by BDT 556.96, which is 40% of the control mean, although the p-value is 0.28. In contrast, households that received only the purifier did not show a similar increase in valuation, with a point estimate of just BDT 72.07. Likewise, households that received only a monitor observed no significant increase in valuation of the air purifier, with a point estimate of BDT 21.06.

Overall, as outlined below, our findings align with a straightforward model where air purifier adoption hinges on beliefs about both indoor air pollution (the problem) and the effectiveness of purifiers (the solution). Practical experience with purifiers, alongside heightened awareness of indoor air pollution levels, are essential factors in boosting air purifier adoption.

6 O-ring Valuation of Preventative Health Technologies

We show that our main results are consistent with a simple model where households value the purifiers according to their beliefs about indoor air pollution as well as their beliefs about purifier effectiveness. While we use indoor air pollution and air purifiers as the examples in our model, We believe that this model can also be useful in explaining the adoption and usage of several other preventative health technologies such as water filters, motorcycle helmets, face masks, and many more.

In our model all households' valuations of purifiers is the product of their belief about their IAP and the purifier's effectiveness. This can be derived from a utility function of the following form:

$$U = Income - Purifier \times p_{purifier} - PrecievedIAP(1 - PrecievedPE \times Purifier) \tag{10}$$

where Purifier is an indicator that is one if the household buys a purifier and zero otherwise. $p_{purifier}$ is the price of the purifier. $PrecievedIAP$ is the household's belief about IAP. In particular, $PrecievedIAP$ is determined by how far above an acceptable level the household thinks IAP is. If IAP is perceived to be below what the household deems acceptable then $PrecievedIAP = 0$. $PrecievedPE$ is equal to what share of $PrecievedIAP$ the household thinks an air purifier can remove.

We denote the price at which a household is indifferent between buying an air purifier and not buying an air purifier $WTP_{purifier}$ and derive that:

$$WTP = PrecievedIAP \times PrecievedPE \tag{11}$$

This creates an "O-ring" valuation function where if any of the factors is zero the total valua-

tion is equal to zero (Kremer, 1993).

In the interest of keeping the model as simple as possible, we will keep the model static and not model the $WTP_{purifier}$ as the net present value of the flow of benefit that the household believes it will bring. However, note that there is an analogous relationship to equation 11 determining if the household uses the purifier or not. Let's assume that the marginal cost of running a purifier at time t is MC_t, this cost would be comprised of the electricity cost, the cost of hearing the slight noise of the air purifier, the psychic cost of remembering to turn the air purifier on, as well as any other marginal cost experienced by the household. The household would use the air purifier during times t when:

$$MC_t \leq PrecievedIAP_t \times PrecievedPE \tag{12}$$

where $PrecievedIAP_t$ is the flow of harm caused by the IAP at time t.

We will assume that if a household i owns an air monitor, it will have a correct view of its IAP, $PrecievedIAP_i = IAP$. However, if it does not own a monitor it will hold the same belief as the average household in the community $PrecievedIAP_i = \frac{1}{N-1}\sum_{j\neq i}^{N} PrecievedIAP_j = \overline{PrecievedIAP}_i$. Similarly for $PrecievedPE$, if the household owns a purifier $PrecievedPE_i = PE$, while if it does not own a purifier $PrecievedPE_i = \frac{1}{N-1}\sum_{j\neq i}^{N} PrecievedPE_j = \overline{PrecievedPE}_i$.

We will assume that for all households:

$$Purifier \times p_{purifier} \leq IAP \times PE$$

and for at least some times:

$$MC_t \leq PrecievedIAP_t \times PrecievedPE$$

such that if households have correct beliefs about IAP and purifier effectiveness, they would buy an air purifier and use the purifier at least some of the time.

6.1 Multiple Equilibria, Successful Preventative Health Technologies, and Experimental results

We can now show that there are two potential equilibria in the model. One where for all households i:

$$Purifier \times p_{purifier} \leq \overline{PrecievedIAP}_i \times \overline{PrecievedPE}_i = \overline{PrecievedIAP}_i \times PE \tag{13}$$

where the equality comes from that all households would buy purifiers and thus $PrecievedPE_i = PE$, for all households. If this was the equilibrium, then if an individual household does not have

experience with a purifier, they would revert to $PrecievedPE_i = \overline{PrecievedPE}_i = PE$, and thus decide to buy a purifier.

This equilibrium may characterize the situation for health technologies that have been successfully adopted by large parts of the population. In the context of middle-class households in Bangladesh, a prominent example is water filters that are ubiquitous in almost all apartments in our sample. There is a widespread correct belief that drinking tap water without filtration carries a substantial health risk and that water filters are effective at reducing this health risk. Thus, almost all households use a water filter that is purchased on the private market and used multiple times per day. As the community as a whole have correct beliefs, anyone without experience of a water filter or who have not tested the quality of their tap water, will default to the correct beliefs and purchase a water filter.

However, our model also shows that there is an equilibrium where:

$$Purifier \times p_{purifier} > \overline{PrecievedIAP}_i \times \overline{PrecievedPE}_i \tag{14}$$

In this equilibrium, no household would buy an air purifier. Furthermore, being in this equilibrium can explain why correcting households' beliefs about air pollution does not increase willingness to pay for the purifiers.

If perceived purifier effectiveness ($\overline{PrecievedPE}_i$) is sufficiently low, correcting $PrecievedIAP_i$ from $\overline{PrecievedIAP}_i$ to IAP would not substantially change WTP_i. In the extreme case where a household's belief is that indoor air quality is already at an acceptable level (i.e. $\overline{PrecievedIAP}_i = 0$), WTP_i would stay at zero regardless of $PrecievedPE_i$. This is consistent with our observations that households substantially underestimate the amount of IAP in their own homes, and that providing a monitor shifts their beliefs about IAP without shifting their willingness to pay for a purifier at the time of the Phase 2 survey.

Similarly, if $\overline{PrecievedIAP}_i$ is sufficiently low, changing $\overline{PrecievedPE}_i$ to PE would not substantially change WTP_i. Furthermore, if $\overline{PrecievedIAP}_i$ is sufficiently low, $MC_t > \overline{PrecievedIAP}_{it} \times PE$. This can explain why even households who have been given an air purifier are not using it, as they already believe that IAP is at an acceptable level.

In the equilibrium of low perceptions of both IAP and purifier effectiveness, if a household receives both an air monitor and a purifier, they would start using the purifier as their beliefs would then be $MC_t \leq IAP_t \times PE$ for at least some times t. Furthermore, among those who own a purifier, the effect of a monitor on households' valuation of the purifier (WTP_i) would be strictly positive. Similarly, among households with monitors, the change in the valuation of a purifier (WTP_i) would be strictly higher after having had the experience of using the purifier and changing $\overline{PrecievedPE}_i$ to PE. However, the equilibrium is stable as a single household has a negligible effect on the community perceptions of IAP and purifier effectiveness. Therefore, to shift the community from the equilibrium with incorrect perceptions to the equilibrium with correct perceptions, a sufficient number of households would have to change their beliefs so that

average community beliefs about IAP and purifier effectiveness simultaneously. This could either be achieved by temporarily lowering costs for purifiers and monitors (or providing both of these for free) until a sufficiently large part of the population is willing to buy one or both of these. However, one could also try to achieve this shift by coordinated information campaigns aimed at changing beliefs both about IAP and purifier effectiveness.

7 Conclusion

In this paper, we present new facts and evidence on IAP and the demand for clean air and air purifiers. We find that IAP is a staggering problem but households have incorrect beliefs about the extent of the problem. We find that IAP monitors correct these beliefs and increase the use of air purifiers but do not affect demand for air purifiers. However, experience with air purifiers improves households' perceptions of their effectiveness. Consequently, amongst households who received an air purifier, monitors do increase revealed valuation of air purifiers.

Our findings have important implications for environmental policy in low- and middle-income countries. First, even when households are aware that ambient air pollution is a significant problem, they may dramatically underestimate the extent of indoor air pollution and the health risk it poses. Information campaigns designed to address this misconception may be an important first step although on their own are unlikely to lead to large increases in demand for private defensive behavior.

Second, we show that clean air and air purifiers can be experience goods. When ambient air pollution levels have been persistently high for years on end, it may be difficult for households to appreciate the returns to clean air. It may also be the case that households don't believe air purifiers are effective in reducing indoor air pollution when they have doors and windows open. We show that experience with purifiers dramatically improves households' perceptions of their effectiveness and amongst households who experience having an air purifier, the monitor treatment increases their willingness to accept to sell back air purifiers. This suggests that a rental market for air purifiers or schemes where households can test air purifiers and have the option of returning them could increase demand through learning. This also presents an opportunity for learning through network effects, that is do households learn from their friends and neighbors who have air purifiers and consequently increase demand? This is an important avenue for future research into the economics of low demand for defensive investments against air pollution.

Finally, we find suggestive evidence that information on indoor air pollution increases demand for public action on air pollution. Importantly, we find that experience with purifiers actually crowds-in demand for government action on ambient air pollution. Unlike the case of clean water where home water purification systems or bottled water are near-complete defensive technologies, air purifiers are incomplete in that they only provide relief from air pollution when one is in the same room where the air purifier is turned on. When stepping out of their homes,

people will invariably experience high ambient air pollution levels. Future work should consider not just how different types of information (e.g., health effects, ambient levels, indoor levels) but also how experience with clean air (e.g., at home or work, or unexpectedly through natural and field experiments) affects demand for governmental and local action on air pollution.

Taken together, our results highlight the extent of the problem of indoor air pollution in urban cities in low- and middle-income countries as well as the barriers to adoption of air purifiers as a health technology.

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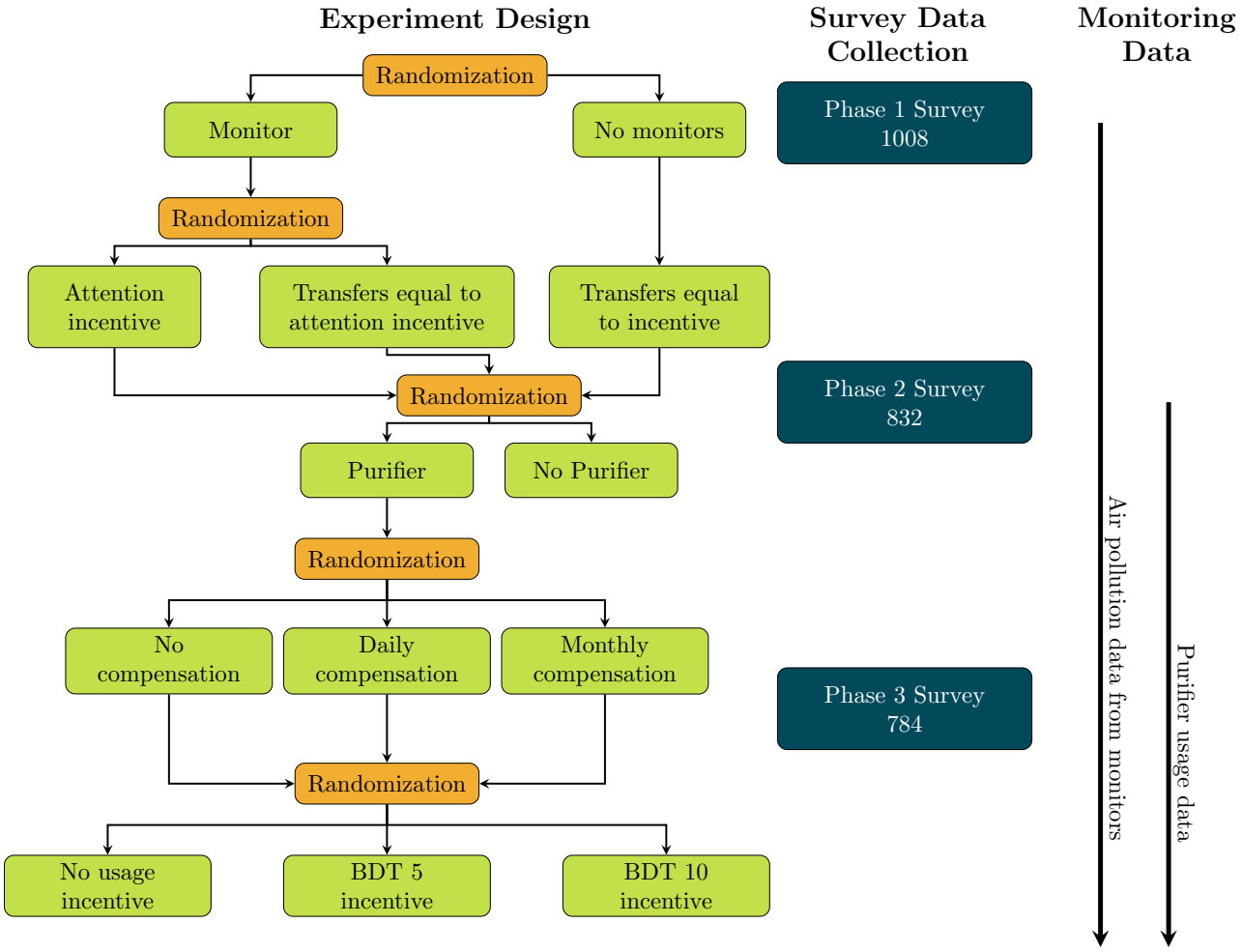
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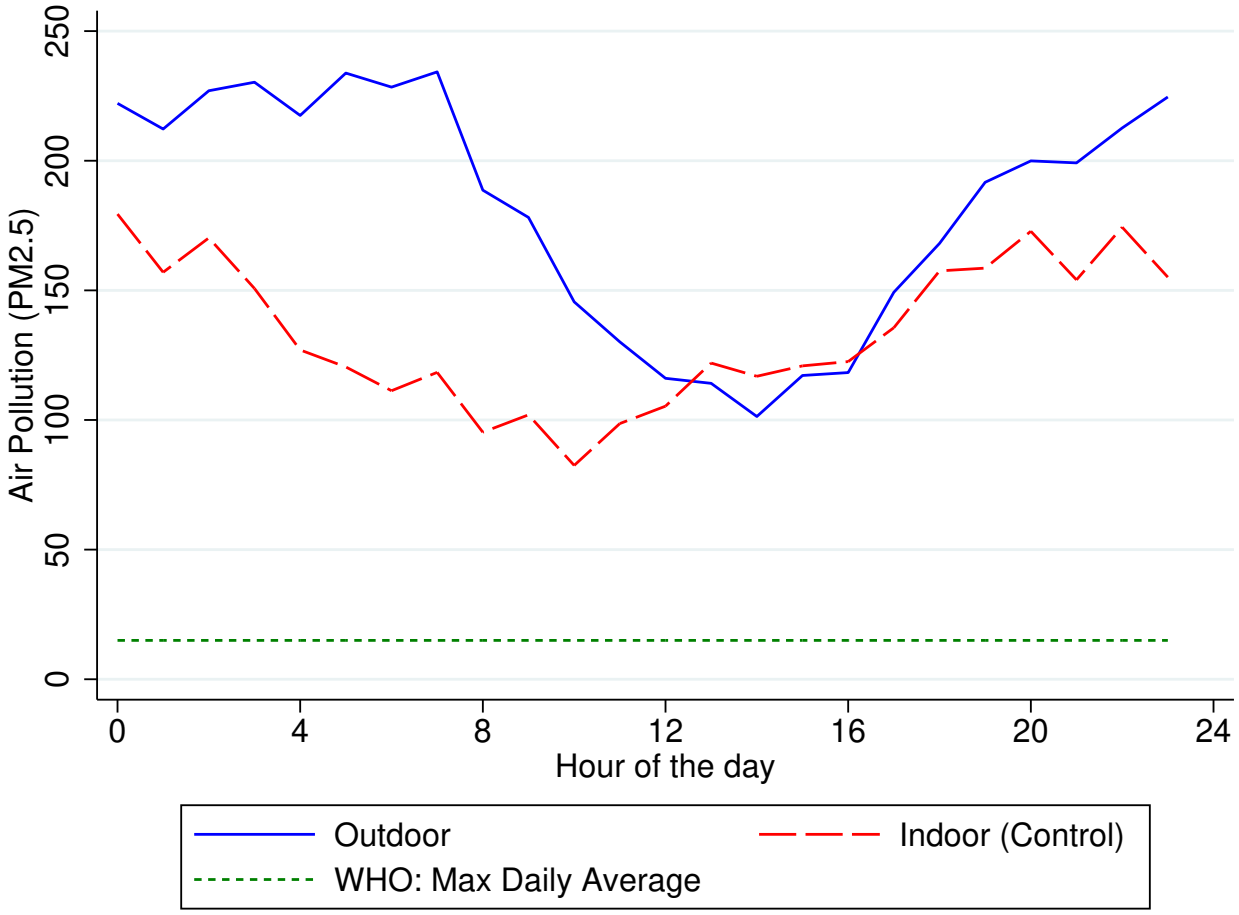
Figures

Figure 1: Overview of Research Design



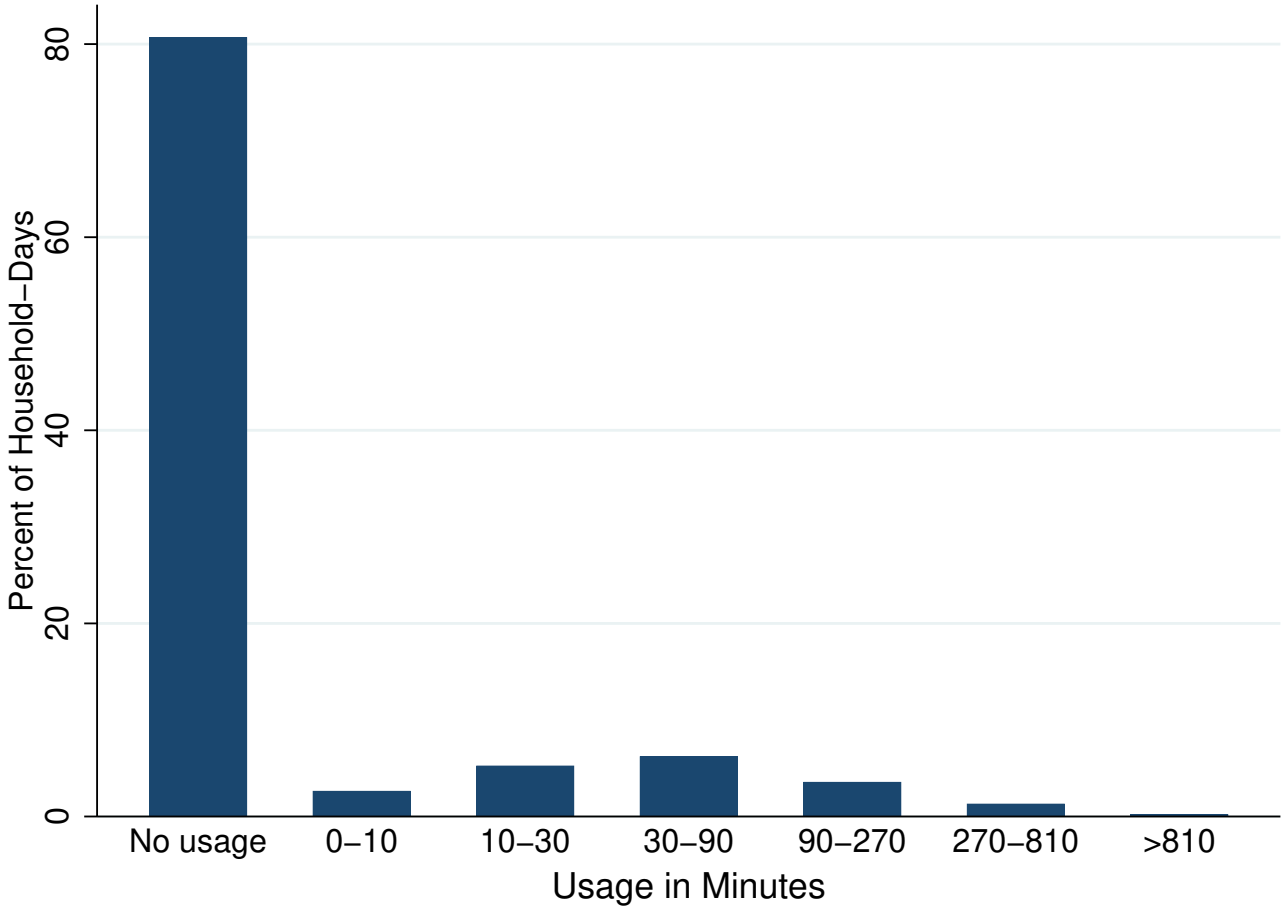
Notes: This figure shows the research design and data collection. We started the Phase 1 survey on 12 November 2023 and concluded it on 30 November 2023. We conducted the Phase 2 survey in December 2023 and January 2024 and the Phase 3 survey in March 2024.

Figure 2: Indoor and Outdoor Air Pollution Levels



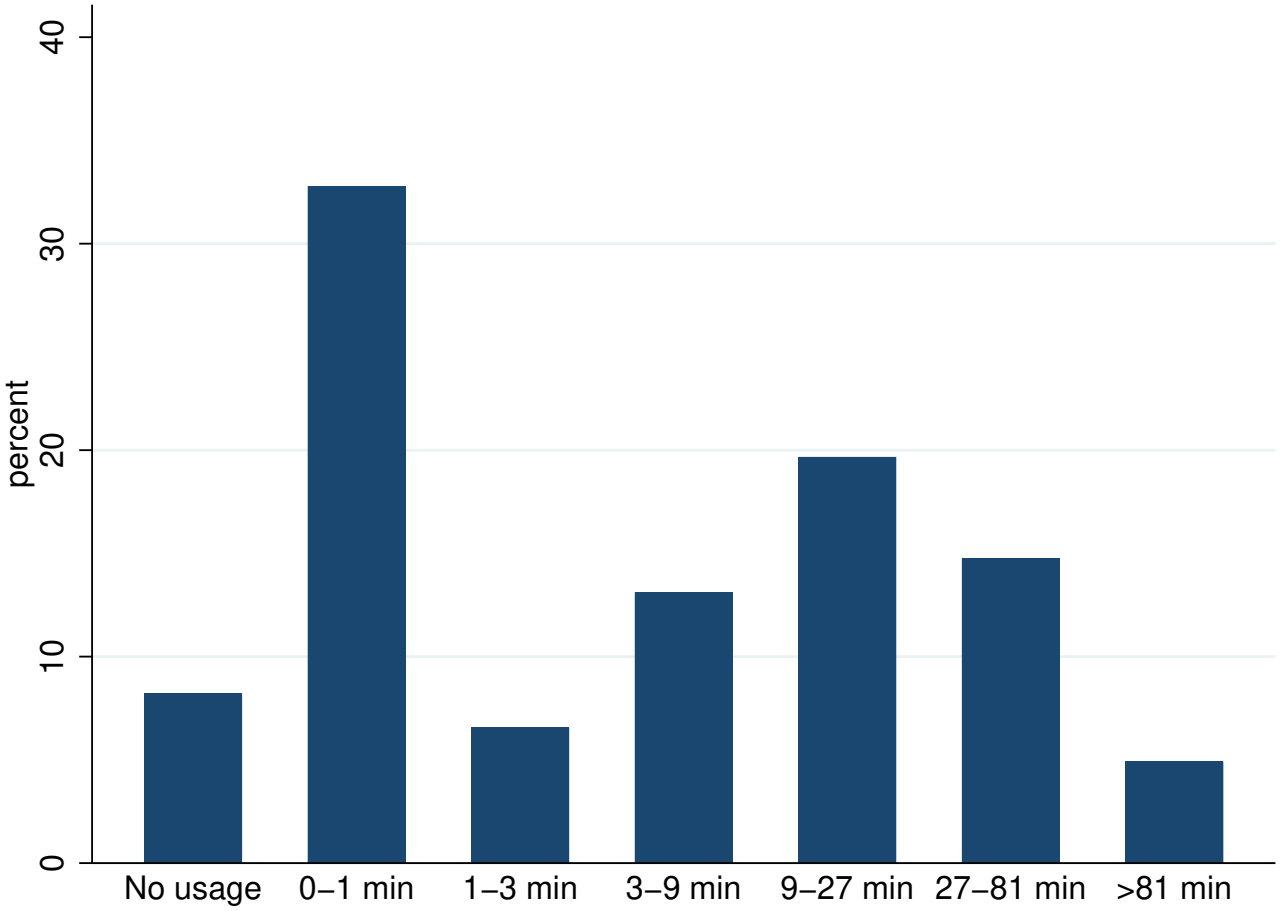
Notes: The figure compares outdoor air pollution levels with indoor air pollution levels for households without the purifier or attention treatments. The comparison is made for each hour of day. Data is at the hour-by-household level from the period between the Phase 2 and 3 surveys for each household. The dotted green line indicates the WHO's recommended daily maximum level of PM2.5.

Figure 3: Minutes of Usage, Household-Day Level



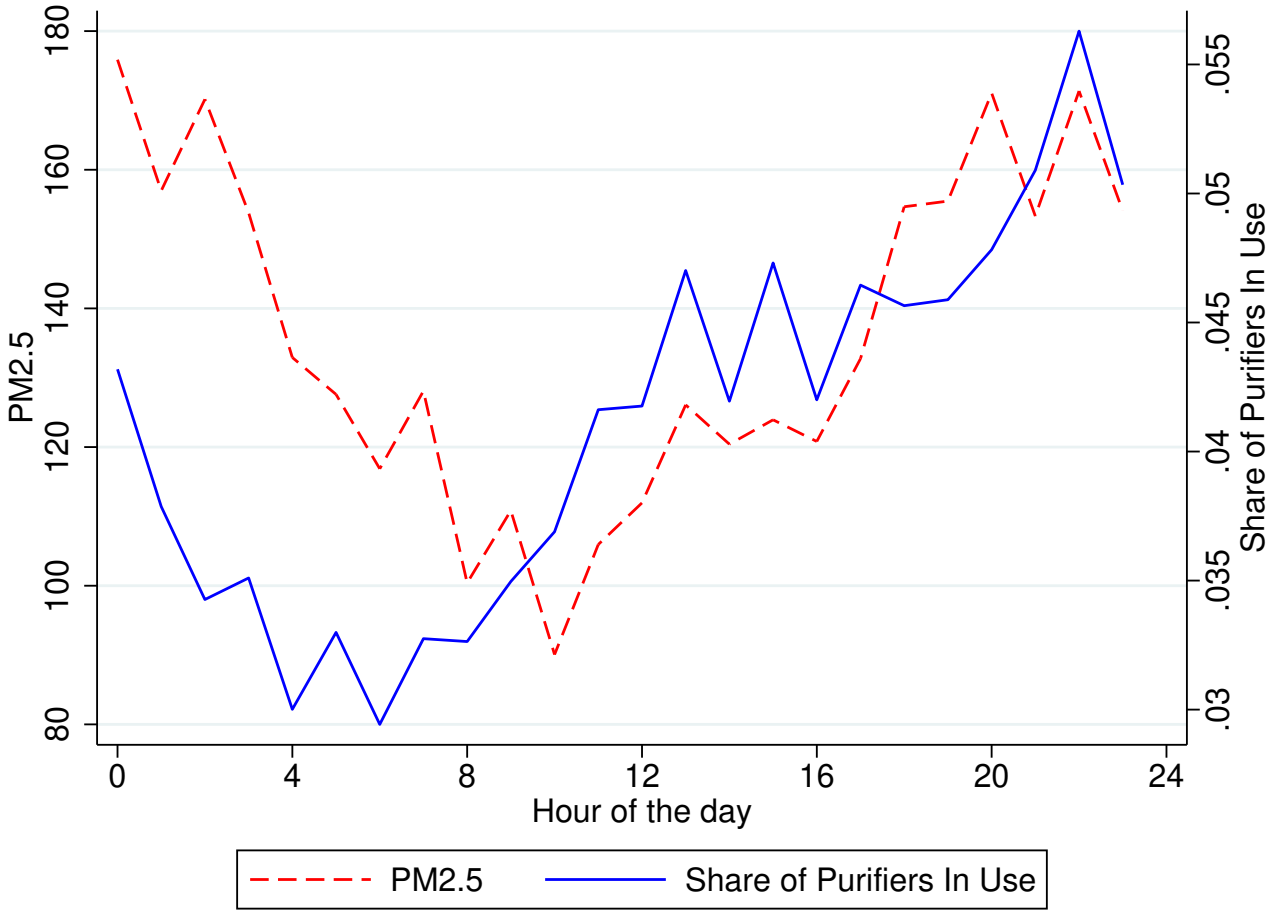
Notes: This figure shows the share of household-days by seven categories of minutes of usage. Except for the first two categories, each category cutoff is 3 times larger than the previous cut-off. Data is for households who participated in the Phase 2 survey and who were assigned the purifier treatment, but who were not assigned the monitor or electricity compensation treatments. The data only includes the period between the Phase 2 and 3 surveys.

Figure 4: Average Minutes of Usage Per Day, Household Level



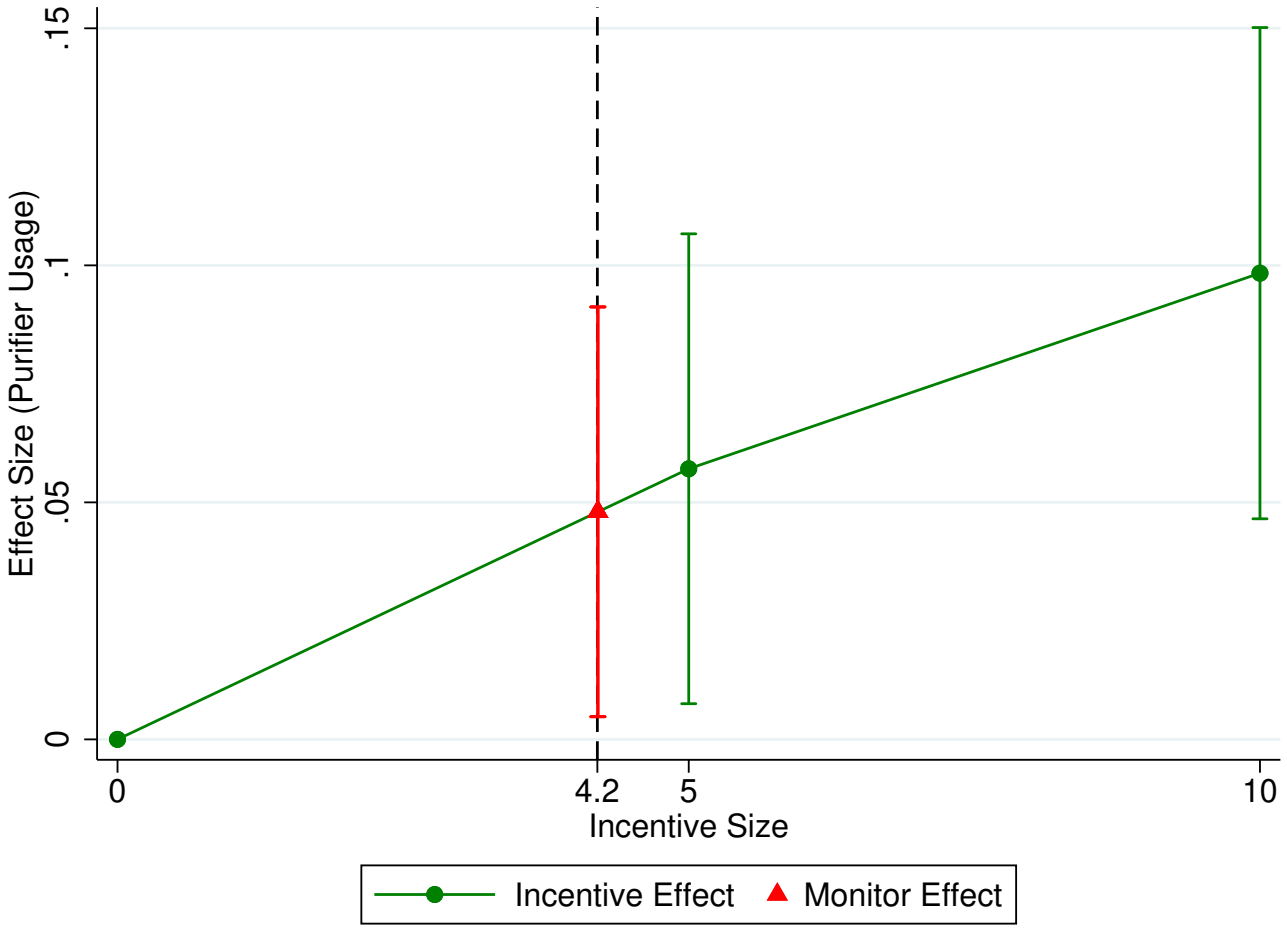
Notes: This figure shows the share of households by seven categories of average minutes of usage. Except for the first two categories, each category cutoff is 3 times larger than the previous cut-off. Data is for households who participated in the Phase 2 survey and who were assigned the purifier treatment, but who were not assigned the monitor or electricity compensation treatments. The data only includes the period between the Phase 2 and Phase 3 surveys.

Figure 5: Air Pollution and Purifier Use Over the Hours of the Day



Notes: The figure shows how air pollution and air purifier use changes over the hours of the day. Data is at the hour-by-household level for the period between the Phase 2 and Phase 3 surveys.

Figure 6: Effect of Monitor vs. Effect of Incentives on Purifier Usage



Notes: This figure compares the effect of the monitor treatment with the effect of the incentives to use the air purifier. We have placed the monitor treatment effect at BDT 4.2 on the x-axis as the monitor effect is equivalent to the linear interpolation of the incentive effect at BDT 4.2. Estimates are based on data from April 1 to April 30, 2024, the period of the incentive payments. 95% confidence intervals are based on standard errors clustered at the household level.

Tables

Table 1: Effect of Monitor and Attention Treatments on Household Perceptions of Air Quality

	(1) Beliefs about Severity of IAP	(2) Beliefs about Severity of AAP	(3) Beliefs about IAP Relative to AAP
Monitor	0.479***	0.0814	0.327*
	(0.149)	(0.162)	(0.175)
Observations	832	832	826
Clusters			
Control mean	4.54	7.05	4.34
Sample			
Phase 1 Controls			

Notes: This table shows the effect of air monitors and the attention treatment on households' perception of indoor air pollution (IAP), ambient air pollution (AIP), and IAP relative to AAP during the Phase 2 survey. In all regressions, we include the respective pre-treatment phase 1 survey response as a control variable to improve precision. $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$.

Table 2: Effect of Monitor and Attention Treatments on Self-Reported Air Purifier Usage

	(1) Use All the Time: Phase 2	(2) Days used 30+ minutes	(3) HH Used All the Time
Monitor	0.195***	0.487	0.144**
	(0.040)	(0.335)	(0.064)
Attention	-0.075	-0.665*	-0.073
	(0.046)	(0.381)	(0.073)
Observations	832	288	292
Control mean	.5513784461152882	5.103703703703704	.2444444444444444
Phase 1 Controls			

Notes: This table presents a regression analysis of air purifier usage and treatment effects. Column 1: question during Phase 2 survey was "If you owned an air purifier, how often would you use it during the winter months (December, January, and February)?" Response options were (a) all the time when home, (b) at least once per week, (c) a few times per week, (d) once per week, (e) once per month, (f) very rarely, (g) never, (h) don't know or (i) refused. We create a binary variable for above and below median self-projected use. Since over half of respondents picked (a), in practice, this creates a binary variable for whether or not the household said they would use it all the time when home. We control for the respondents answer during the Phase 1 survey. Column 2: during the endline survey households who had previously received an air purifier were asked "In the past 7 days, how many days did you use the air purifier for 30 minutes or more? (numerical answer between 0 and 7)?" We control for Phase 1 values of perceived use of air purifers. Column 3: During endline, households who received the air purifier were asked how often they used the air purifier. The response options were the same as Column 1. We follow the same procedure of creating a binary variable. We control for the respondents projected use reported during the Phase 1 survey.

Table 3: Effect of Monitors on Air Purifier Use

	(1) Min per Day	(2) Days Used 30+ min	(3) Days Used 30+ min
Monitor	74.32***	0.600***	0.515*
	(23.50)	(0.230)	(0.274)
Time FE	Yes	Yes	Yes
Sample	All Days	All Weeks	Week Before Survey
Observations	23,205	3,594	308
Clusters	309.000	309.000	308.000
Control mean	33.070	1.178	0.938

Notes: This table shows the effect of providing monitors on purifier use. We control for if the household also receives the attention incentive. In column (1) observations are at the day-by-household level. In columns (2) and (3) observations are at the week-by-household level. Data is only from households with air purifiers. Data in columns (1) and (2) are from the dates between the Phase 2 survey and 1 April 2024. Data in column (3) is from the week before the Phase 3 survey. Standard errors are clustered at the household level. $***p < 0.01; **p < 0.05; *p < 0.1$.

Table 4: Effects of Use Incentives and Air Monitor on Air Purifier Use

	(1) Purifier Used	(2) Purifier Used
Any Incentive	0.0783***	0.0571**
	(0.0204)	(0.0253)
Monitor	0.0478**	0.0480**
	(0.0221)	(0.0221)
BDT 10 Incentive		0.0413
		(0.0321)
Time FE	Yes	Yes
Observations	222,789	222,789
Clusters	309	309
Control mean	0.011	0.011

Notes: This table shows the effect of providing incentives for using the purifier and the effect of owning a monitor on purifier usage. The incentives were either BDT 5 per hour of use, or BDT 10 per hour of use. Each observation is at the hour-by-household level among households with air purifiers. The outcome variable is the share of the hour that the air purifier was turned on. Data is from 1 April 2024 until 30 April 2024, the period during which the incentives were provided. Standard errors are clustered at the household level. $***p < 0.01; **p < 0.05; *p < 0.1$.

Table 5: Effects of Air Monitors on Willingness to Pay for Air Purifiers

	(1) WTP	(2) WTP	(3) WTP	(4) WTP
Monitor	-123.5	-245.2	-9.749	136.1
	(163.6)	(190.3)	(217.4)	(180.6)
Attention		245.5	75.41	-24.50
		(214.8)	(262.6)	(218.4)
Survey FE	N	N	N	Yes
Observations	828	828	778	1,002
Clusters	828	828	778	1,002
Control mean	1,408.65	1,408.65	1,531.70	1,137.13
Sample	Phase 2	Phase 2	Phase 3	Pooled
Imputation	N	N	N	N

Notes: This table shows the effect of air monitors and incentives for attention to air quality information on willingness to pay (WTP) for air purifiers. The outcome variable is the WTP for household h determined through a modified Becker-DeGroot-Marschak (BDM) mechanism. Column 1 restricts the sample to the Phase 2 survey, column 2 to the Phase 3 survey, and column 3 includes the pooled data from both survey rounds (pre-analysis plan specification). Columns 4 and 5 replicate columns 1 and 2, respectively; however, in column 4, households that attrited from the Phase 1 survey to the Phase 2 survey survey were assigned a WTP value of 0, and in column 5, households that attrited from the Phase 1 survey to the Phase 3 survey were assigned a WTP value of 0. Each observation is at the household level. Standard errors are clustered at the household level. $***p < 0.01; **p < 0.05; *p < 0.1$.

Table 6: Effect of Air Purifiers on Perceptions of Purifier Effectiveness

	(1) Has Opinion	(2) $> 0\%$ effective	(3) $> 25\%$ effective	(4) $> 50\%$ effective	(5) $> 75\%$ effective
Monitor	0.090*	0.094*	0.104**	0.087*	-0.011
	(0.054)	(0.054)	(0.052)	(0.048)	(0.029)
Purifier	0.279***	0.277***	0.307***	0.276***	0.132***
	(0.051)	(0.052)	(0.051)	(0.050)	(0.039)
Purifier x Monitor	0.010	0.023	-0.046	-0.066	0.097
	(0.082)	(0.083)	(0.085)	(0.084)	(0.067)
Observations	784	784	784	784	784
Control mean	0.407	0.380	0.315	0.228	0.073

Notes: This table shows the effects of purifier, monitor, and the interaction between the two on perception of air purifier effectiveness. The column 1 shows the effect on if the household has an opinion about air purifiers' effectiveness. Column 2 shows the effect on how effective air purifiers are in terms of the share of air pollution it removes (from 0 to 1), among those who have an opinion. Data from the Phase 3 survey. $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$.

Table 7: Effect of Purifiers and Monitors on Opinions about Government Policy

	(1) Priority(SD)	(2) Priority(SD)
Monitor	0.0737	0.0383
	(0.0691)	(0.112)
Purifier		0.0592
		(0.109)
Purifier x Monitor		0.133
		(0.177)
Observations	1,616	784
Clusters	842	784
Control mean		
Sample		
Phase 2 Controls		

Notes: This table shows the effect of air purifiers and air quality monitors on the standard deviation of air pollution's ranking among a list of government priorities. The outcome variable is the standard deviation of air pollution's ranking among a list of the following government priorities: Education, Healthcare, Reducing air pollution, Job creation, and Elderly care. A higher value of the outcome variable indicates that a household places more importance on air quality. In Columns (1) and (2) data is from the phase 2 and phase 3 surveys. In columns (3) and (4) data is from the phase 3 survey. Observations are at the household by survey level. Standard errors are clustered at the household level. $***p < 0.01; **p < 0.05; *p < 0.1$.

Table 8: Effect of Monitor and Attention Treatment on Willingness to Accept (WTA) to Sell Air Purifiers

	(1)
	WTS
Monitor	3,839.33*
	(2,315.37)
Observations	305
Control mean	14469.00
Clusters	

Notes: This table shows the effect of monitor and attention treatment on households with purifiers' willingness to sell their purifiers (measured in BDT) in the Phase 3 survey. Standard errors are clustered at the household level. Enumerator fixed effects = Y denotes the inclusion of enumerator and supervisor fixed effects who elicited Phase 3 responses. Time fixed effects = Y denotes inclusion of day-of-week and week-of-year fixed effects. $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$.

Appendix

A Air purifiers do not crowd out demand for public action on reducing ambient air pollution

Fourth, we find no evidence of purifiers crowding out demand for public action on reducing ambient air pollution. If anything, we find suggestive evidence that experiencing air purifiers increases demand for public action on reducing ambient air pollution. Finally, we show that at endline, amongst households who already had an air purifier, monitors increased the lowest monetary value they were willing to accept for selling those air purifiers back to us. Taken together, these results are consistent with a model where information is necessary but not sufficient to increase adoption of health savings technology and where experience with the technology is needed to value it fully.

We test whether having purifiers changes households' ratings of air pollution as a governmental priority.[36] In theory, private defensive behavior can reduce prioritizing reducing ambient air pollution since households have a way of protecting themselves from air pollution. On the other hand, experiencing clean air with air purifiers can increase the importance they place on reducing ambient air pollution because air purifiers are an incomplete defensive investment, and owning an air purifier may increase the salience of air pollution as a problem. We construct a measure of the households' rankings of what governmental priorities should be. We asked households to rank five sectors (education, healthcare, air pollution, job creation, and elderly care) in ascending order of what they feel should be the government's priorities with 1 corresponding to "should be lowest priority" and 5 corresponding to "should be highest priority". As specified in the pre-analysis plan, we calculate the standard deviation of air pollution's ranking among these priorities and estimate the effect of the monitor, attention, and purifier treatments on this variable. We collected these data in both the Phase 2 and 3 surveys so we can estimate the effect of monitors in both waves of the data, while for air purifiers we can only estimate the effect in phase 3 as the purifiers were only provided in phase 2.

Table 7 shows that both monitors and purifiers increased the priority given to reducing air pollution when asked about what the government should prioritize, but that the effects are not statistically significant. Column (1) shows that monitors increase the priority placed on reducing air pollution by 0.094 standard deviations. Column (2) shows that the effect is similar between the groups with and without the attention incentive and Appendix Table A.13 shows that the effect is similar across the phase 2 and phase 3 surveys. Column (3) shows that providing an air purifier increases households' prioritization of air pollution by 0.128 standard deviations (p-

[36] 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; Singh and Thachil, 2023).

value = 0.07). At a minimum, this result reveals that air purifiers do not crowd-out demand for public action on ambient air pollution.[37] Column (4) shows that there is a positive but statistically insignificant interaction between having both the monitor and purifier on prioritizing government action on air pollution.

B Effects of Air Purifiers on Health, Well-Being and Labor Supply

In the pre-analysis plan, we listed a number of outcome variables we would consider to measure the effects of providing households with air purifiers. These included self-reported and biomarker health data, sleep and cognition, and labor supply. Although, we were able to experimentally ensure sufficient take-up of air purifiers in our study, air purifier usage was not sufficiently high to expect a sizable average effect on these outcomes. Nearly 2 out of 3 households used an air purifier for less than 30 minutes a day with less than 1 in 5 households using the air purifier for more than 81 minutes per day on average. Even in the monitor treatment group, the mean purifier use was 101 minutes a day or less than 2 hours. This is particularly striking in the backdrop of ambient and indoor air pollution levels that exceed WHO recommended guidelines by as much as 100 times. In fact, at no point during our study period did levels of ambient or indoor air pollution (in non-purifier households) meet WHO guidelines.

Although our air purifiers are factory tested, we tested these in a controlled setting in January 2024. Appendix Figure A.13 reports results from a field test of air purifiers. When turned on, air pollution levels dramatically decline from 150 $\mu g/m^3$ to 25 $\mu g/m^3$. When turned off, air pollution levels start to increase immediately and gradually return to levels observed without air purifiers. However, in the setting of our households, the effects of air purifiers on indoor air pollution levels were muted because of low usage. We also show the patterns of indoor air quality when households turn on air purifiers (Appendix Figure A.14). While this analysis is not causal because the decision to turn on an air purifier is endogenous, we use random matching with households who did not receive an air purifier to create a "matched control" group for those who turned on air their purifiers. The levels of indoor air pollution in households with purifiers on still remain alarmingly high ($\tilde{1}00$ $\mu g/m^3$), but they are significantly lower than those in the matched control.[38]

We also estimate the effect of air purifier treatment on indoor air pollution (Appendix Table A.16). We find that purifiers, on average, reduced air pollution by 11.8% (Column 1). The results

[37] In the pre-analysis plan we had also included an additional outcome variable: donations to an environmental NGO. In both Phase 2 and Phase 3, we gave households a choice of three NGOs that we would donate BDT 100 to on their behalf. They were informed of the core function of each NGO and one of the three was an environmental NGO working to reduce air pollution. We estimate the effect of our treatments on these donations and find small and statistically insignificant effects of monitor, attention, and purifier treatments (Appendix Table A.14).

[38] The smaller effect on air pollution may be because the air purifiers were often used on the lowest setting or because doors or windows to the room were open.

are similar when considering levels, although underpowered (Column 2). When we impute for missing values (e.g., when monitors are turned off) using outdoor air pollution readings and household-specific infiltration coefficients, we get similar results (Columns 3-4). While estimated with more precision, the reductions in PM2.5, on average, are modest. Average indoor PM2.5 levels in treatment households are almost 100 $\mu g/m^3$ which still represents dangerously high levels of air pollution. It's important to reiterate that this is not because purifiers are not effective, but rather because use of air purifiers is low.

Therefore, it is reasonable that we find no discernible effects of providing households with air purifiers on health, labor supply, sleep or cognition. We report results for all pre-specified regressions in the Appendix. We show null effects of purifiers on individual health measures (Appendix Tables A.17 - A.22) as well as on a cumulative health index (Appendix Table A.23. We also report null effects of purifiers on measures of sleep quality index (Appendix Table A.24, Column 1), hours asleep (Column 2) and hours in bed (Column 3)). We also find no effects on a mental health index (Appendix Table A.25). Finally, we also find no effects of purifiers on labor supply (Appendix Table A.26) and income (Appendix Table A.27).

Several explanations, likely together, explain our null effects. First, in our study setting, ambient air pollution levels remain persistently high and air purifier usage is low. As such, reductions in indoor air pollution levels for a short window each day is unlikely to translate into measurable health effects in households. Our findings are consistent with Berkouwer and Dean (2023) who find that reducing air pollution peaks in low-income Kenyan households by encouraging use of improved cook stoves yielded no gains in clinical health outcomes. Second, the two month duration between the Phase 2 survey when we provided air purifiers and the Phase 3 survey when we collected health measurements, may not have been long enough to observe health effects. Health effects from PM2.5 can be cumulative (Bishop, Ketcham and Kuminoff, 2023) and can manifest over different time horizons for different populations (Deryugina et al., 2021). Finally, our research design included health measurements that were easy for survey teams to administer and did not require medical staff. This was done to raise the likelihood of households providing consent and lower field and liability costs associated with the study. It is possible that our measures were not sufficiently accurate to capture modest health effects.

C Effects of Attention Treatment

Compliance with the attention treatment was relatively high with 78% of households sending at least one text message. On average households sent a text message 35% of the weeks that the treatment was active.

Another reason for why households paying more attention to their air monitors may have had a lower valuation of their air purifiers at the time of the Phase 3 survey was the substantial decline in air pollution between the Phase 2 and Phase 3 surveys. The average PM2.5 outdoor

air pollution during the Phase 2 survey was 216 $\mu g/m^3$ while the same number during the Phase 3 survey was 130 $\mu g/m^3$.[39] It is possible that households with attention incentives to a greater degree had realized that air pollution had reached much lower levels compared to when they first received the monitors and purifiers. Thus, they might have felt less strongly about keeping their air purifier.

D Data Collection and Cleaning

D.1 Survey Data

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

D.2 Missing Observations in Monitor Data

We provided a BDT 16 (USD 0.14) incentive for all households with air quality monitors to keep their monitors on for at least 16 hours per day. Appendix Table A.12 shows that between the Phase 2 survey and April 1st monitors were turned on approximately 56% of the time. Column 1 of the table shows that having an air purifier increase the share of time that the air purifier was turned on by 9 percentage points. The attention incentives increased monitor usage by 3 percentage points but the difference is not statistically significant.

The imbalance between the missing monitor data in households with and without purifiers could cause the estimates of the effect of purifiers on air pollution in Appendix Table A.16 to be biased. This would happen if households without purifiers were more likely to turn off their monitors during times when the air in their homes was more polluted than the sample average (causing our estimate of the effect of air purifiers to be biased towards zero) or when it was more polluted than the sample average (causing our estimate of the effect of air purifiers to be more negative than the true causal effect).

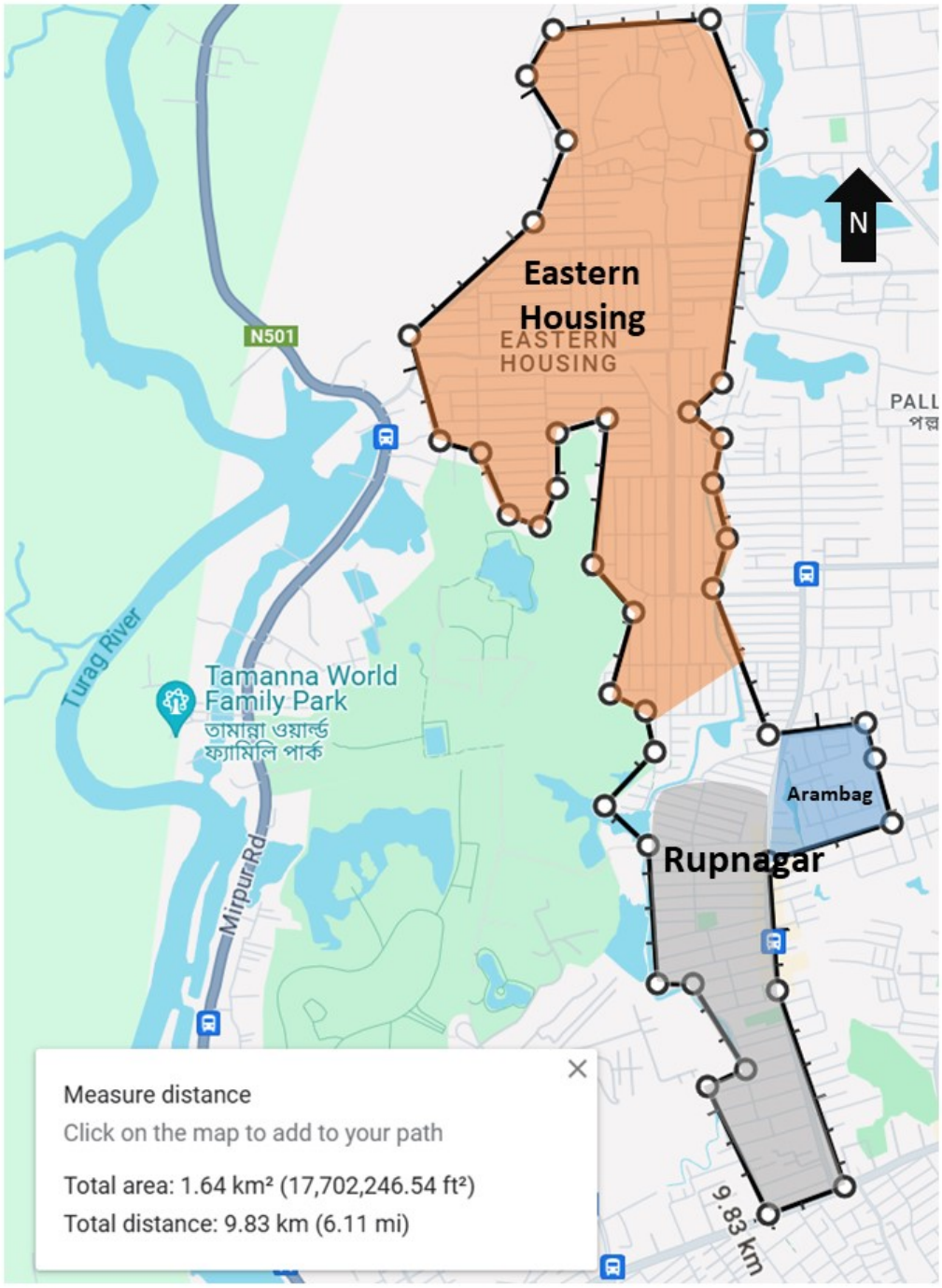
We have three approaches to reduce such a bias. First, we control for time-fixed effects. This means that we are only comparing treatment and control households within a certain hour of the data. If, for example, households without purifiers were more likely to turn off their monitors at times when air pollution is particularly bad across the whole sample, then this would not bias our results since we are controlling for fixed effects for each hour in our sample. However, if households without purifiers with consistently higher (or lower) air pollution are less likely to use the monitors that would still bias our estimate. Therefore, we also control for the average air pollution in the Phase 1 period, before air purifiers were provided. Finally, in columns 3 and 4 of

[39] Averages are weighted by the number of households responding to the survey on each day of the Phase 2 and Phase 3 survey, respectively.

Table A.16 we also impute air pollution levels using the outdoor air pollution and the infiltration coefficient based on households without air purifiers. Reassuringly, this does not substantially change our estimates of the effect of the purifiers.

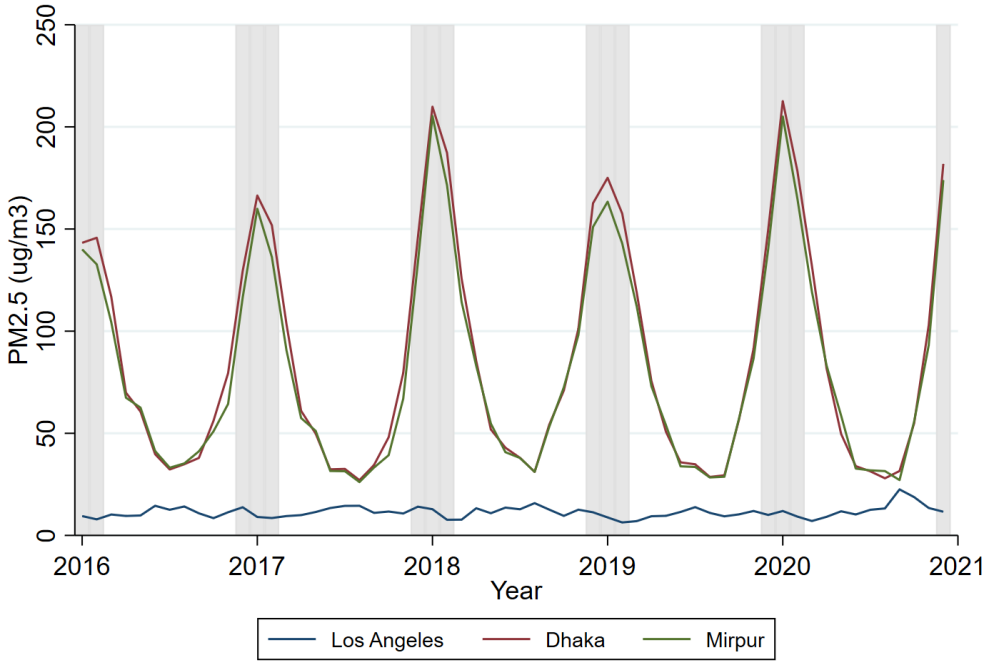
E Additional Figures and Tables

Figure A.1: Map of Study Area



Notes: This is a map of the three housing associations in which the study was conducted. All of the housing associations are located in the Mirpur area of Dhaka, Bangladesh.

Figure A.2: Air Pollution Levels in Dhaka 2016-2021



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

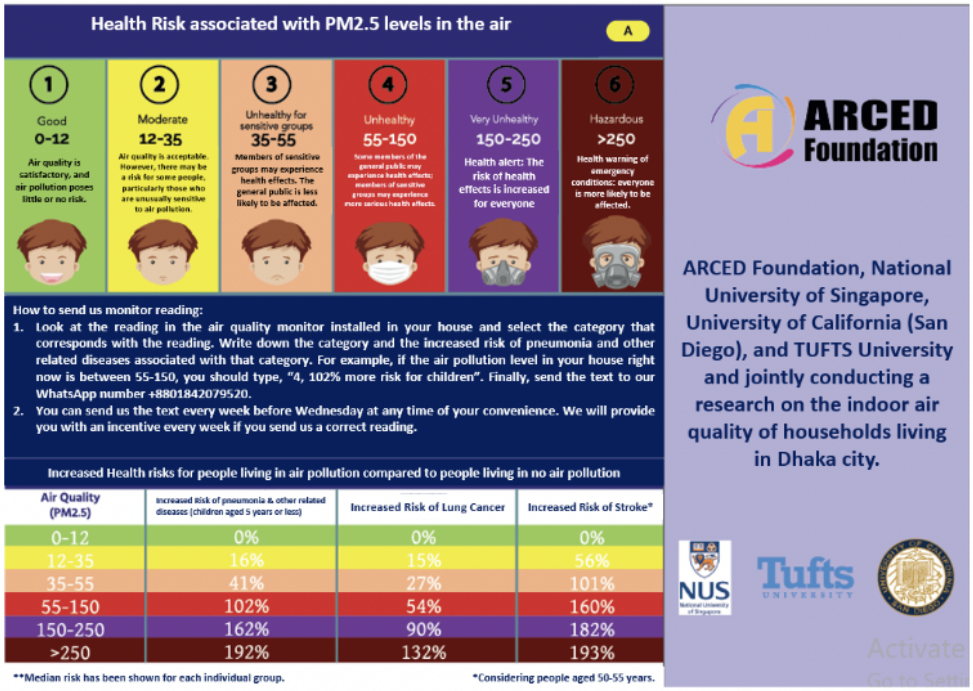
Figure A.3: Air Pollution Monitor



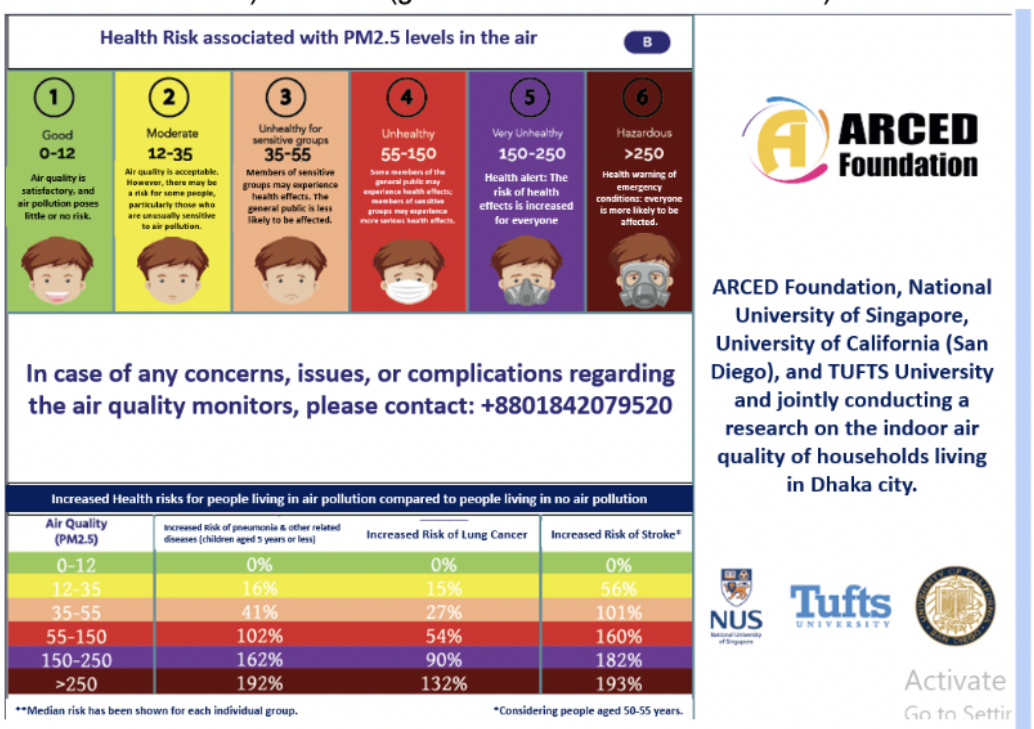
Notes: Image of the air quality monitor provided to the households in the monitor treatment group. For more details, see: https://www.qingping.co/air-monitor-lite/overview

Figure A.4: Air pollution information charts provided to households

A) Chart A (given to attention treatment households)



B) Chart B (given to non-attention households)



Notes: Images of the English translation of the information charts provided to households together with the air quality monitor.

Figure A.5: SQAir Purifer



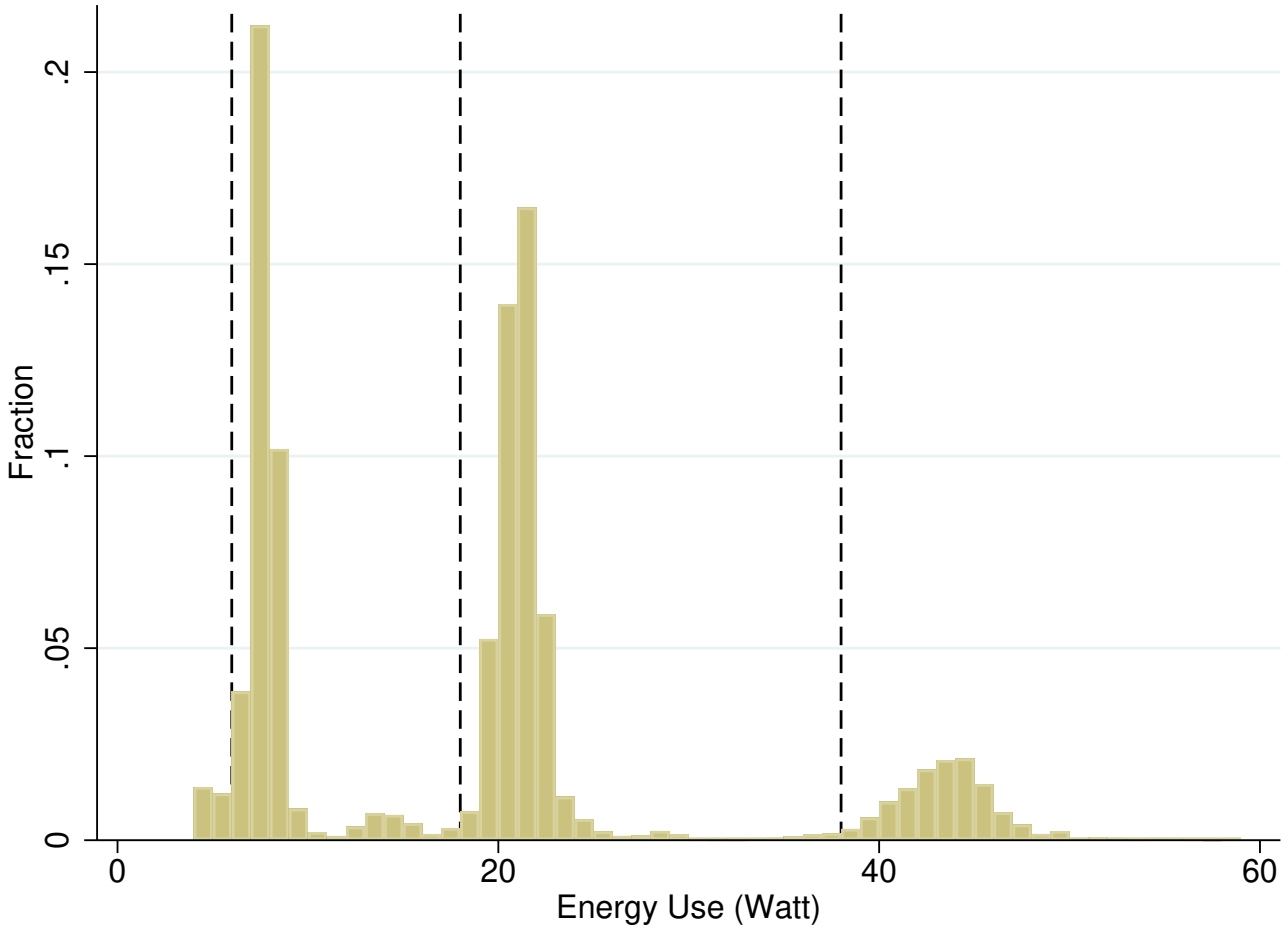
Notes: Image of the air purifier provided to the households in the air purifier treatment group. For more details, see: https://smartairfilters.com/en/product/sqair-air-purifier/

Figure A.6: Smart Plug/Socket



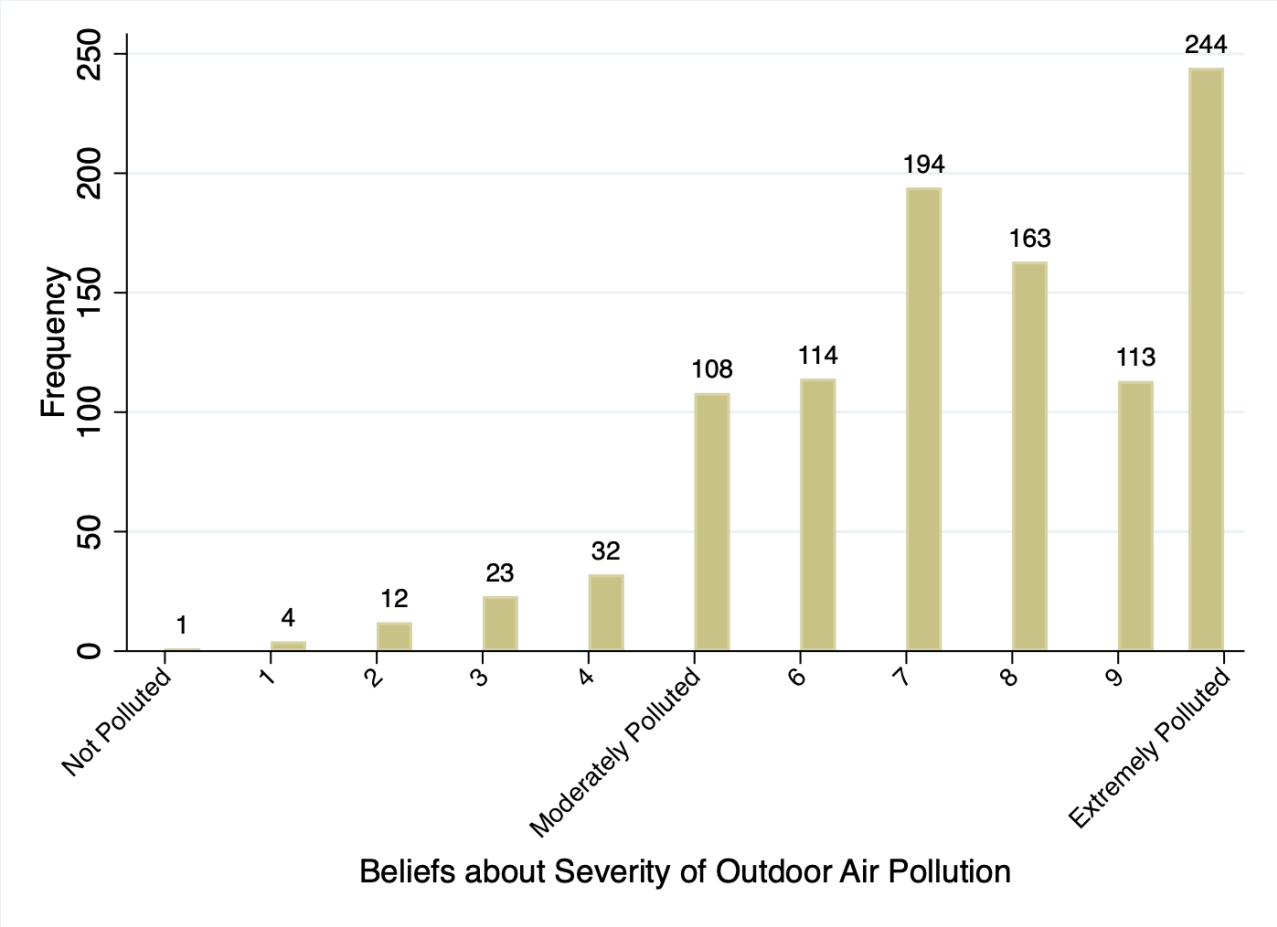
Notes: Image of the smart socket used to measure when the air purifier was used.

Figure A.7: Wattage used by Air Purifiers



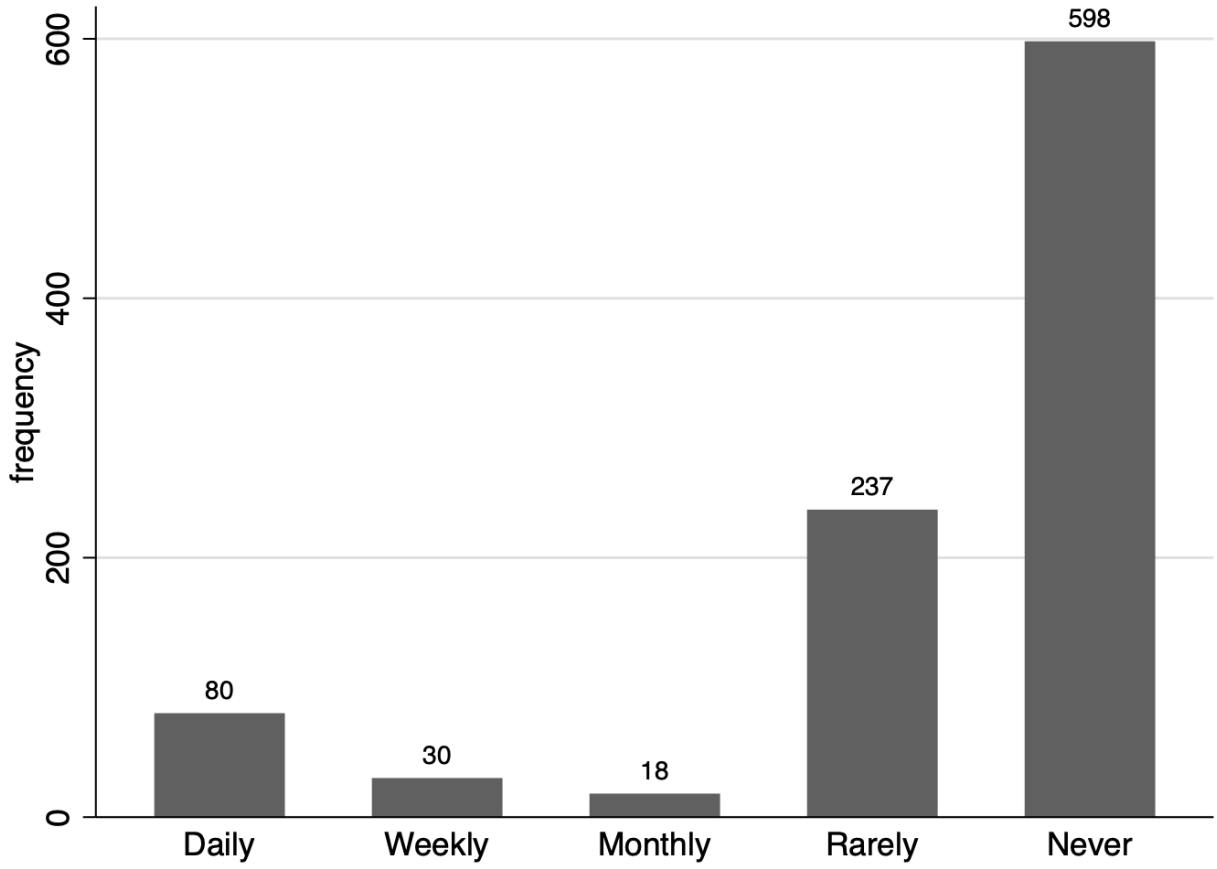
Notes: The figure shows how much electricity each air purifier uses in watts. Each observation is a minute by household smart socket reading. We have only included observations where we classified the air purifier as being used. The three vertical dashed lines represent the manufacturer's description of how much electricity the air purifier uses on the low, medium, and high settings.

Figure A.8: Households' Perceptions of Outdoor Air Pollution in Phase 1 Survey



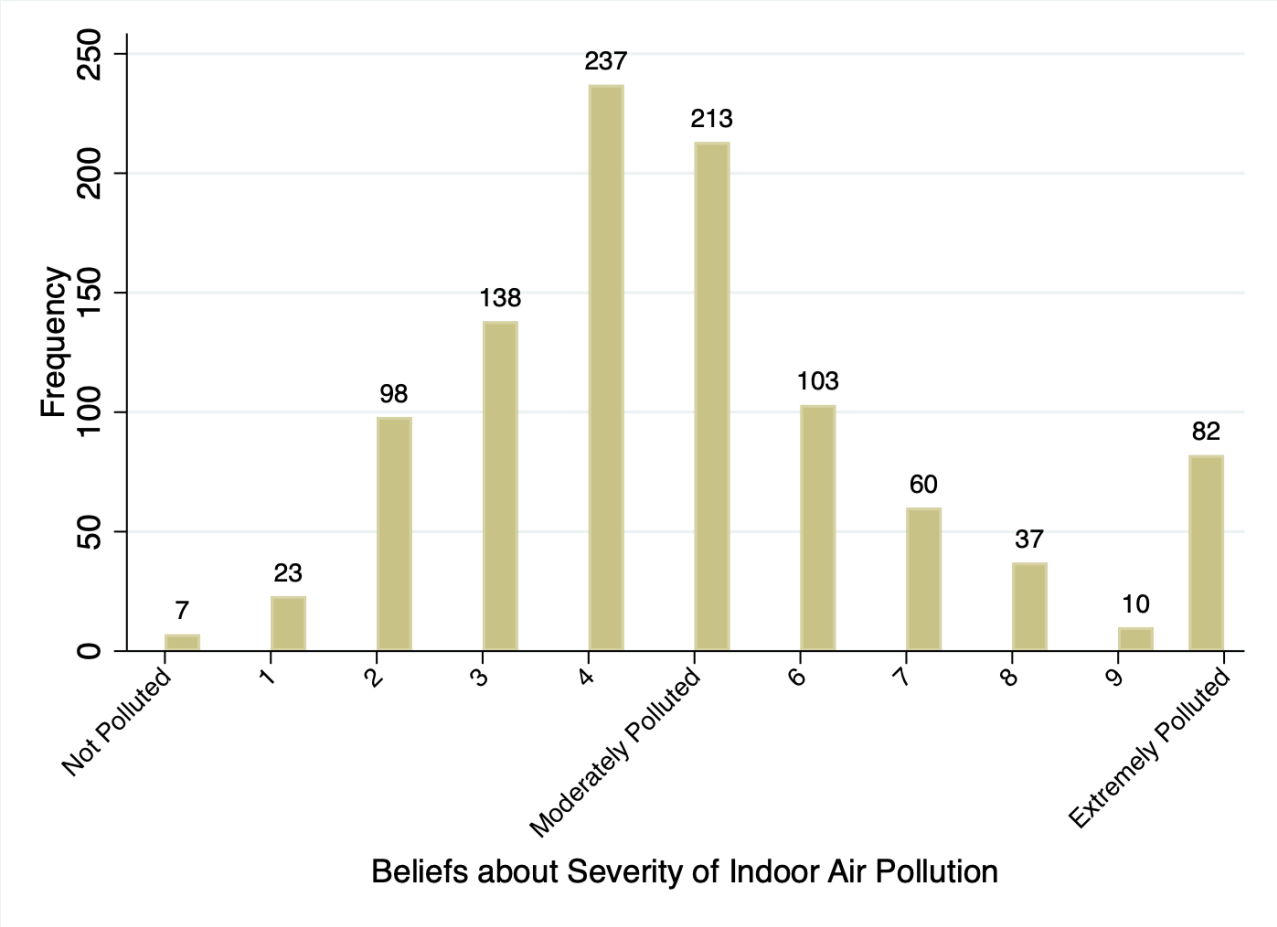
Notes: This figure shows a histogram of households' phase 1 survey responses to the question "How would you rate the current outdoor air quality in your area? On a scale of 1-10, with 0 being not polluted at all and 10 being extremely polluted."

Figure A.9: Distribution of how often households reported checking outdoor air pollution levels (Phase 1 Survey)



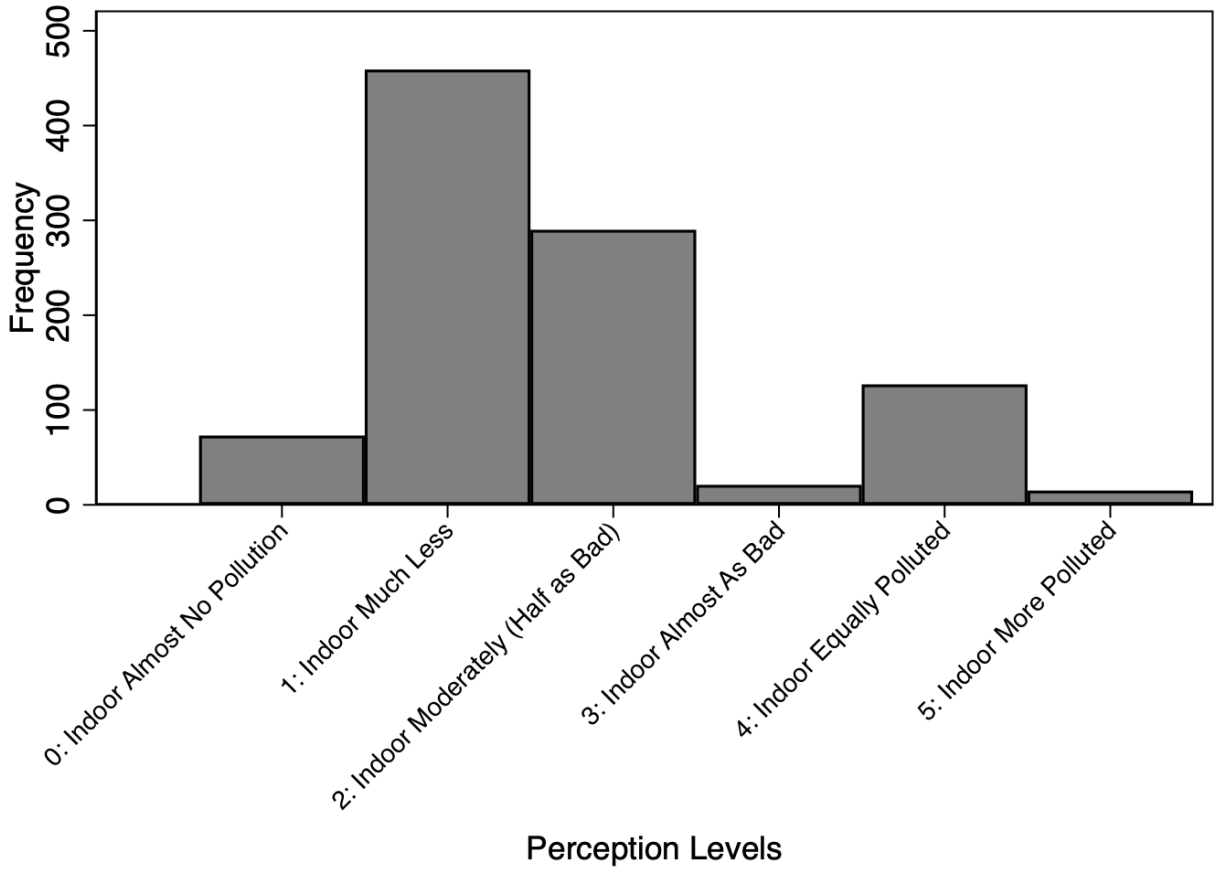
Notes: This histogram shows the distribution of responses in the Phase 1 survey to the the question "How often do you check or monitor outdoor air pollution levels?"

Figure A.10: Households' Perceptions of Indoor Air Pollution in Phase 1 Survey



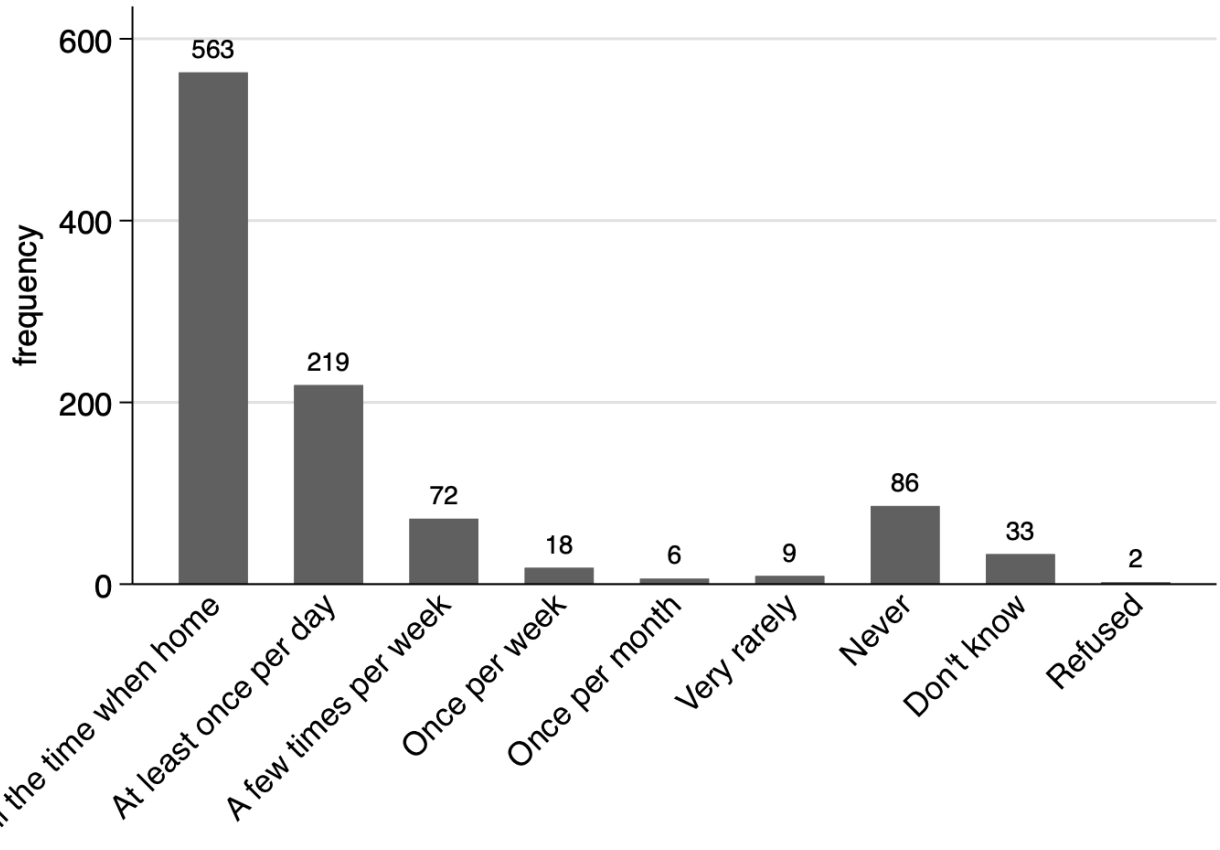
Notes: This figure shows a histogram of households' phase 1 survey responses to the question "How would you rate the indoor air quality of your home? On a scale of 1-10, with 0 being not polluted at all and 10 being extremely polluted."

Figure A.11: Households' Perception of Indoor Air Pollution Relative to Outdoor Pollution in phase 1 survey



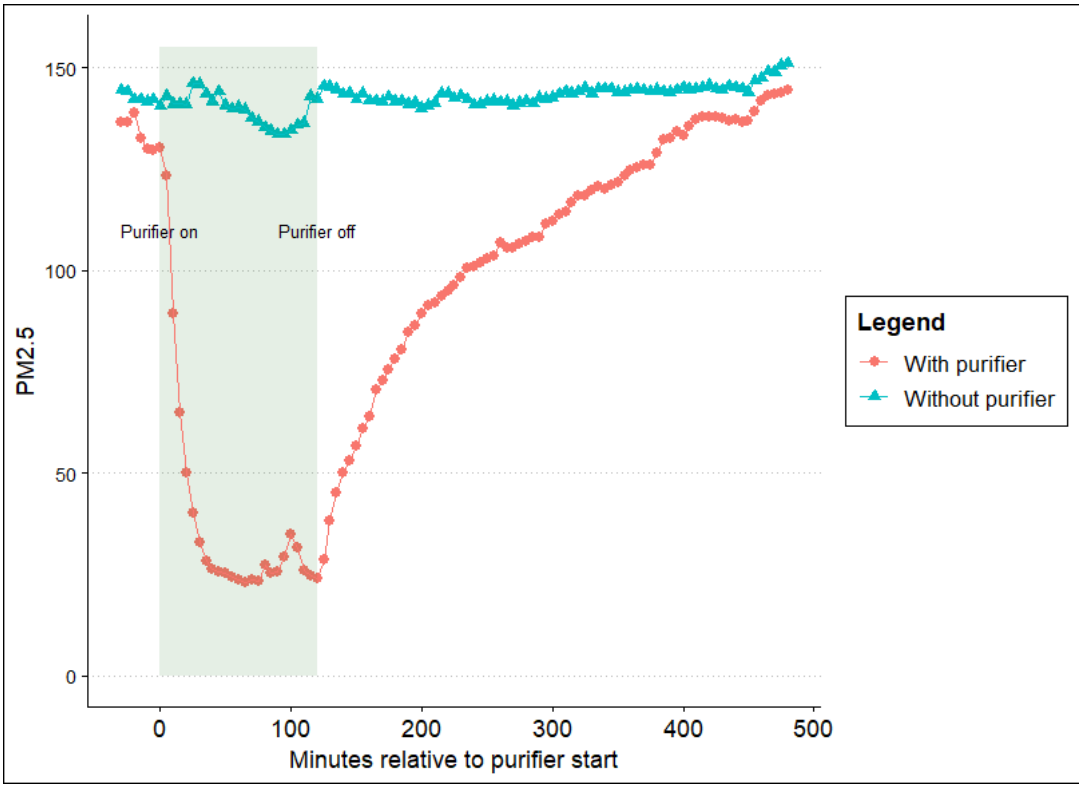
Notes: This figure shows a histogram of households' phase 1 survey responses to the question "How polluted is the air inside your home compared to the outdoor air?"

Figure A.12: Predicted Air Purifier Usage by Households in Phase 1 Survey



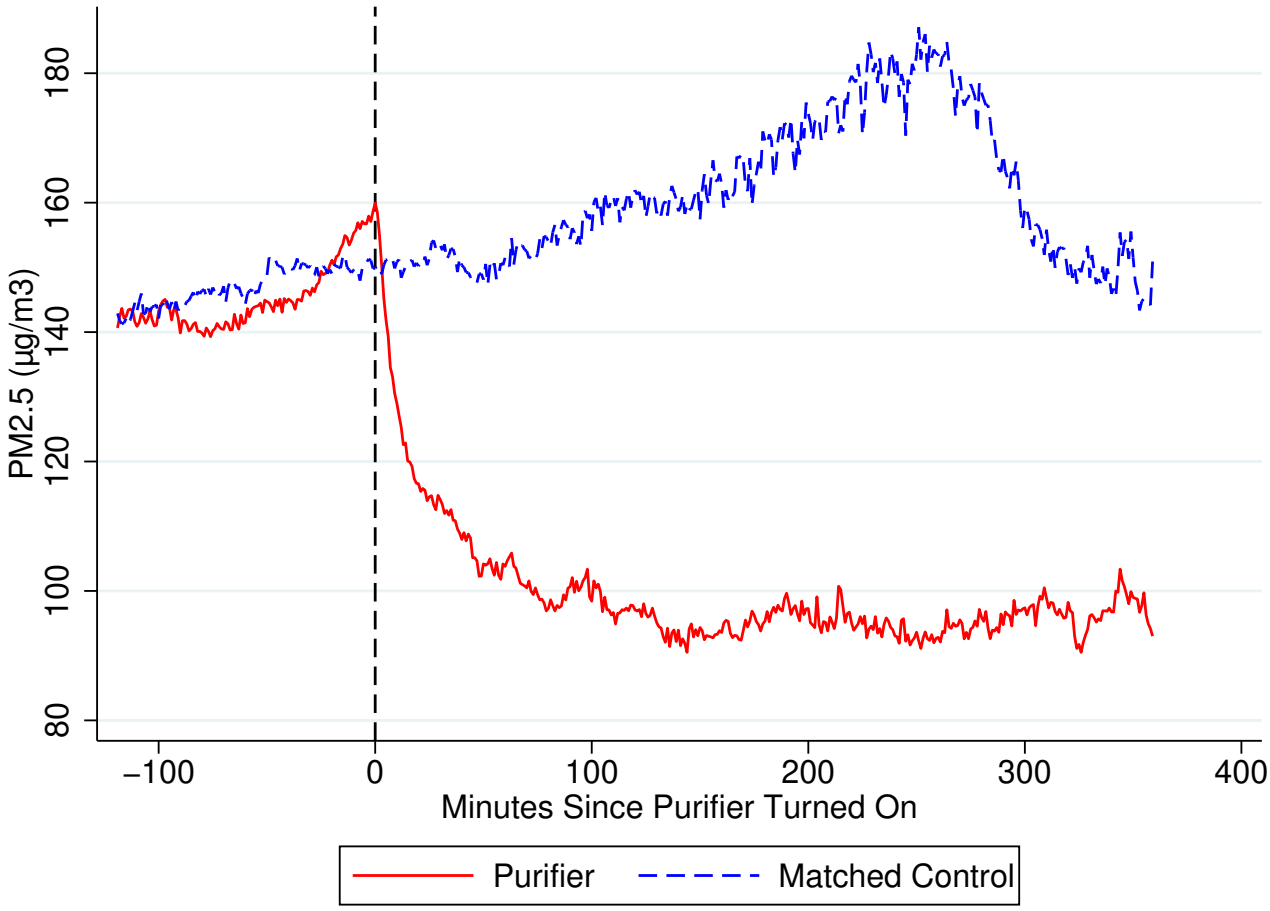
Notes: The question asked was: "If you owned an air purifier, how often would you use it during the winter months?"

Figure A.13: Effect of Air Purifier on Air Pollution Under Controlled Conditions



Notes: The figure shows how air pollution changes after turning on an air purifier at medium power (level 2 out of 3) in three different rooms in an office in Mirpur, Dhaka. The room with the air purifier is compared to a control room without an air purifier. The graph is based on five instances of turning on the air purifier and keeping it on for 120 minutes (the area shaded green). After 120 minutes the air purifier was turned off and kept off for at least 7 hours. Data is from from January 2024.

Figure A.14: Change in Air Pollution When Purifier is Used



Notes: The figure shows the how air pollution changes the minutes after the air purifier was turned on. The data excludes air purifier sessions shorter than 30 minutes and sessions when the air purifier was used in the 30 minutes preceeding the time the air purifier was turned on. We have matched each control household with a household that was given an air purifier. The "matched control" time line shows the average air pollution in the matched control households during the same minutes as the air purifiers were turned on in the households with air purifiers.

Table A.1: Effect of Treatments on Attrition from Phase 1 to Phase 2

	(1)
	Phase 2 Attrition
Monitor	-0.044
	(0.029)
Attention	0.005
	(0.034)
Observations	1,008
Control mean	0.196

Notes: This table shows the effects of treatment on attrition. The outcome variable is attrition at Phase 2, measured by the households who did not consent to or were not available for the Phase 2 survey. This variable is 1 if the household is in the Phase 1 survey but NOT in the Phase 2 survey. Observations are at the household level. $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$.

Table A.2: Monitor Treatment Balance in Unattrited Group: Phase 1 to Phase 2

	Non-Monitor Households	Monitor Households	Diff
College Graduate	0.47	0.48	-0.00
Age	37.55	39.10	-1.55
Beliefs about Risk of Lung Cancer and Stroke from Air Pollution	1.65	1.63	0.02
Beliefs about Risk of ARI for Children from Air Pollution	1.74	1.72	0.02
Beliefs about Severity of AAP	7.38	7.58	-0.20
Beliefs about Severity of IAP	4.79	4.73	0.06
Beliefs about IAP Relative to AAP	3.56	3.50	0.06
Observations	399	433	832

Notes: This table provides a balance test between households who received a monitor and those who did not after accounting for attrition. In the unattrited sample as of phase 2, we test for balance in variables collected during phase 1 survey. Differences are reported in column 3 and statistical significance of differences is denoted as $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$.

Table A.3: Attention Treatment Balance in Unattrited Group: Phase 1 to Phase 2

	Non-Attention Households	Attention Households	Diff
College Graduate	0.47	0.48	-0.02
Age	37.59	40.63	-3.05*
Beliefs about Risk of Lung Cancer and Stroke from Air Pollution	1.65	1.61	0.04
Beliefs about Risk of ARI for Children from Air Pollution	1.75	1.69	0.06
Beliefs about IAP Relative to AAP	3.52	3.48	0.03
Beliefs about Severity of AAP	7.49	7.67	-0.19
Beliefs about Severity of IAP	4.65	4.80	-0.15
Observations	218	215	433

Notes: This table provides a balance test between households who received incentives for attention and those who did not after accounting for attrition. In the unattrited sample as of phase 2, we test for balance in variables collected during phase 1 survey. Differences are reported in column 3 and statistical significance of differences is denoted as $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$.

Table A.4: Effect of Treatments on Attrition from Phase 2 to Phase 3

	(1) Phase 3 Attrition
Purifier	-0.063***
	(0.024)
Pur X Monthly-Incentive	-0.010
	(0.035)
Pur X Daily-Incentive	-0.034
	(0.035)
Observations	832
Control mean	0.088

Notes: This table shows the effects of treatment on attrition. The outcome variable is attrition during Phase 3 survey. This variable is 1 if the household is in the Phase 2 survey but not in the Phase 3 survey. Observations are at the household level, and this sample was restricted to be inclusive of only households that were sampled in the Phase 2 survey (832). For reference, out of 1008 households, 832 households were sampled in the Phase 2 survey, and then 784 were sampled in the Phase 3 survey. In other words, 176 households attritioned between phases 1 and 2, and 48 households attritioned between phases 2 and 3. Statistical significance of differential attrition is denoted by $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$.

Table A.5: Purifier Treatment Balance in Unattrited Group: Phase 2 to Phase 3

	Non-Purifier Households	Purifier Households	Diff
Monthly Income	65216.10	59024.14	6191.96
Education	14.20	14.62	-0.42
Age	43.71	44.37	-0.67
WTP	1379.53	1380.87	-1.33
HH Size	4.18	4.12	0.06
Beliefs about Risk of Lung Cancer and Stroke from Air Pollution	1.93	1.94	-0.01
Beliefs about Risk of ARI for Children from Air Pollution	2.16	2.24	-0.08
Donation	0.25	0.27	-0.03
Priority(SD)	0.00	0.04	-0.03
Beliefs about IAP Relative to AAP	4.48	4.50	-0.02
Beliefs about Severity of IAP	4.73	4.70	0.03
Beliefs about Severity of AAP	7.03	7.19	-0.16
Observations	472	302	774

Notes: This table provides a balance test between households who received a purifier and those who did not after accounting for attrition. In the unattrited sample as of phase 3, we test for balance in variables collected during phase 2 survey. Differences are reported in column 3 and statistical significance of differences is denoted as $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$.

Table A.6: Effect of Having an Air Monitor on Perception of Air Quality

	(1) Beliefs about Severity of AAP	(2) Beliefs about Severity of IAP
Monitor	0.114	0.242**
	(0.108)	(0.0968)
Beliefs about Severity of AAP: Phase 1	0.133***	
	(0.0265)	
Beliefs about Severity of IAP: Phase 1		0.128***
		(0.0231)
Survey FE	Y	Y
Observations	1,616	1,616
Clusters	842.000	842.000
Control mean	7.332	4.609

Notes: This table shows the effect of having an air monitor on the perception of air quality, measured by how polluted households believe their air quality is on a scale from 1 to 10, with 1 being the least polluted and 10 being the most polluted. Column 1 is their outdoor air quality ranking whereas column 2 is their indoor air quality ranking. The coefficients represent the estimated change in perceived pollution levels associated with the presence of an air monitor. Standard errors are reported in parentheses. Observations are at the household level. Standard errors are clustered at the household level. $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$.

Table A.7: Effects of Air Purifiers and Incentives for Attention to Air Quality on Beliefs

	(1) Beliefs about Risk of Lung Cancer and Stroke from Air Pollution	(2) Beliefs about Risk of ARI for Children from Air Pollution	(3) Beliefs about Risk of Lung Cancer and Stroke from Air Pollution	(4) Beliefs about Risk of ARI for Children from Air Pollution	(5) Beliefs about Risk of Lung Cancer and Stroke from Air Pollution	(6) Beliefs about Risk of ARI for Children from Air Pollution
Monitor	0.139**	0.121	-0.0174	-0.0190	0.0620	0.0520
	(0.0683)	(0.0843)	(0.0327)	(0.0518)	(0.0399)	(0.0529)
Attention	-0.0668	-0.0782	0.0275	0.0439	-0.0198	-0.0178
	(0.0806)	(0.0968)	(0.0419)	(0.0606)	(0.0493)	(0.0627)
Survey FE	N	Y	N	Y	Y	Y
Observations	767	795	728	754	1,495	1,549
Clusters	767	795	728	754	801	822
Control mean	1.885	2.160	1.640	1.885	1.767	2.027
Sample	Phase 2	Phase 2	Phase 3	Phase 3	Pooled	Pooled
Phase 1 Control	Y	Y	Y	Y	Y	Y

Notes: This table shows the effect of providing monitors and incentives for attention to air quality on people's beliefs regarding the harmfulness of current air pollution on increasing the risk of (1) lung cancer and stroke in adults and (2) acute respiratory issues for children. Each observation is at the household level. For column 1, the outcome variable is the perceived risk of lung cancer and stroke, categorized into various levels of increased risk ranging from "No effect" to "More than quadrupling". The outcome variable in column 2 is the same categorization but relating to the perceived risk of acute respiratory issues for children. Data is from Phase 1 until Phase 3. Standard errors are clustered at the household level. $***p < 0.01; **p < 0.05; *p < 0.1$.

Table A.8: Effects of Air Monitors on Air Purifier Use (including households not part of the Phase 2 survey)

	(1) Purifier Used	(2) Purifier Used
Monitor	0.0394***	0.0473***
	(0.00934)	(0.0147)
Attention		-0.0156
		(0.0179)
Time FE	Yes	Yes
Observations	649,822	649,822
Clusters	372	372
Control mean	0.016	0.016

Notes: This table shows the effect of providing monitors on purifier use as well as the effect of providing incentives for households to pay attention to the air monitors on a weekly basis. Each observation is at the hour-by-household level among households with air purifiers. The outcome variable is the share of the hour that the air purifier was turned on. Data is from the (scheduled) Phase 2 survey until the (scheduled) Phase 3 survey. Standard errors are clustered at the household level. $***p < 0.01; **p < 0.05; *p < 0.1$.

Table A.9: Effects of Compensation for Electricity Costs on Air Purifier Use

	(1) Purifier Used	(2) Purifier Used
Any Compensation	0.0131	0.00993
	(0.0111)	(0.0127)
Daily Compensation		0.00636
		(0.0167)
Time FE	Yes	Yes
Observations	552,444	552,444
Clusters	309	309
Control mean	0.032	0.032

Notes: This table shows the effect of providing monitors on purifier use as well as the effect of providing incentives for households to pay attention to the air monitors on a weekly basis. Each observation is at the hour-by-household level among households with air purifiers. The outcome variable is the share of the hour that the air purifier was turned on. Data is from the Phase 2 survey until the Phase 3 survey. Standard errors are clustered at the household level. $***p < 0.01; **p < 0.05; *p < 0.1$.

Table A.10: Effects of Air Monitors on Willingness to Pay for Air Purifiers (with imputed values for attrition)

	(1) WTP	(2) WTP	(3) WTP	(4) WT
Monitor	-45.05	-144.6	136.1	-4.22
	(138.3)	(162.0)	(180.6)	(139.
Attention		200.2	-24.50	87.9
		(186.2)	(218.4)	(165.
Survey FE	N	N	N	Y
Observations	1,004	1,004	1,002	2,00
Clusters	1,004	1,004	1,002	1,00
Control mean	1,131.49	1,131.49	1,137.13	1,134
Sample	Phase 2	Phase 2	Phase 3	Poole
Imputation	WTP=0 for AtrPhase2	WTP=0 for AtrPhase2	WTP=0 for AtrPhase1-3	WTP=0 for A
Cont.				WTP=0 for

Notes: This table replicates Table 5 with the imputation of WTP = 0 for attrited households. As in Table 5, this table shows the effect of air monitors and incentives for attention to air quality information on willingness to pay (WTP) for air purifiers. The outcome variable is the WTP for household h determined through a modified Becker-DeGroot-Marschak (BDM) mechanism. Each observation is at the household level. Standard errors are clustered at the household level. $***p < 0.01; **p < 0.05; *p < 0.1$.

Table A.11: Placebo Test: Effect of Air Purifiers on Perceptions of Purifier Effectiveness Outside the Room it is In

	(1) Has Opinion	(2) $> 0\%$ effective	(3) $> 25\%$ effective	(4) $> 50\%$ effective	(5) $> 75\%$ effective
Monitor	0.060	0.074	0.035	0.012	-0.007
	(0.054)	(0.050)	(0.043)	(0.031)	(0.015)
Purifier	0.331***	0.281***	0.154***	0.076**	-0.015
	(0.050)	(0.051)	(0.046)	(0.035)	(0.012)
Purifier x Monitor	-0.005	0.005	0.005	-0.048	0.035
	(0.082)	(0.084)	(0.078)	(0.056)	(0.026)
Observations	784	784	784	784	784
Control mean	0.374	0.273	0.165	0.079	0.019

Notes: This table shows the effects of purifier, monitor, and the interaction between the two on the perception of air purifier effectiveness outside of the room it is in. It is a placebo test for Table 6. Data is from the Phase 3 survey. $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$.

Table A.12: Effect of Purifier on Monitor Usage

	(1) Monitor On	(2) Monitor On	(3) Monitor On
Purifier	0.0880**		0.0880**
	(0.0382)		(0.0381)
Attention		0.0297	0.0297
		(0.0382)	(0.0380)
Time FE	Yes	Yes	Yes
Observations	775,870	775,870	775,870
Clusters	433	433	433
Control mean	0.555	0.571	0.555

Notes: This table shows the effect of having an air purifier on air monitor usage. Each observation is at the hour-by-household level among households with air monitors. Data is from the date of the Phase 2 survey until April 1st. Standard errors are clustered at the household level. $***p < 0.01; **p < 0.05; *p < 0.1$.

Table A.13: Effects on Opinions about Government Policy in Phase 2 and Phase 3 Surveys

	(1) Priority (SD)	(2) Priority(SD)
Monitor	0.0557	0.0906
	(0.0855)	(0.0867)
Attention	0.0498	0.0358
	(0.101)	(0.0990)
Observations	832	784
Clusters	832	784
Control mean	-0.020	0.022
Sample	Phase 2	Phase 3
Controls	N	N

Notes: This table shows the effect of air quality monitors and the attention treatment on the standard deviation of air pollution's ranking among a list of government priorities. The outcome variable is the standard deviation of air pollution's ranking among a list of the following government priorities: Education, Healthcare, Reducing air pollution, Job creation, and Elderly care. A higher value of the outcome variable indicates that a household places more importance on air quality. In column 1 the data is from the phase 2 survey and in Column 2 the data is from the phase 3 survey. Observations are at the household level. $***p < 0.01; **p < 0.05; *p < 0.1$.

Table A.14: Effect of Air Purifier and Monitor on Choosing to donate to environmental NGO

	(1) Donation	(2) Donation	(3) Donation
Monitor	0.0246	0.0121	
	(0.0241)	(0.0293)	
Attention		0.0254	
		(0.0336)	
Purifier			0.0276
			(0.0311)
Donation at Phase 2			0.248***
			(0.0387)
Observations	1,616	1,616	774
Clusters	842	842	774
Control mean	0.240	0.240	0.247
Sample	Pooled	Pooled	Phase 3

Notes: This table shows the effect of air purifiers and air quality monitors on the choice of a household to choose an environmental NGO working on reducing air pollution as the beneficiary of a donation, selected from a list of NGOs with three options. The outcome variable is a dummy variable indicating whether the household's chose the environmental NGO as the beneficiary of their donation. Standard errors are clustered at the household level. $***p < 0.01; **p < 0.05; *p < 0.1$.

Table A.15: The Effect of Monitor and Attention Treatments on Phase 3 WTP (for Non-Purifier Households)

	(1) WTP	(2) WTP
Monitor	75.191	-105.859
	(234.108)	(279.866)
Attention		380.357
		(322.487)
Observations	475	475
Control mean	1503.143	1503.143
Sample	Non-Purifier Households	Non-Purifier Households

Notes: This table shows the effect of monitor and attention treatments on endline WTP for air purifiers, and limits the sample to be the non-purifier group. The outcome variable is WTP for air purifiers at endline. $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$.

Table A.16: Effect of Purifiers on Air Pollution

	(1) PM2.5	(2) ln(PM2.5)	(3) PM2.5 (w. imputed)	(4) ln(PM2.5 (w. imputed))
Purifier	-5.413	-0.118*	-4.553	-0.108**
	(4.710)	(0.0674)	(3.069)	(0.0484)
Baseline PM2.5	0.466***		0.204***	
	(0.0602)		(0.0296)	
ln(Baseline PM2.5)		0.721***		0.168**
		(0.160)		(0.0692)
Time FE	Yes	Yes	Yes	Yes
Observations	475,150	471,085	828,166	828,166
Clusters	378	378	469	469
Control mean	112	112	114	114

Notes: This table shows the effect of providing air purifiers on air pollution, including imputed values for PM2.5 when a household's monitor was turned off. The imputed values are calculated using the average ratio between the indoor and outdoor pollution in households without an air purifier and multiplying that by the outdoor pollution reading during the hour that the household's monitor was turned off. Each observation is at the hour-by-household level among households with air monitors, during the hours for which we have outdoor air pollution data. The outcome variable is the average air pollution in that hour, or the log of the average air pollution. Data is from the date of the Phase 2 survey until April 1st. Standard errors are clustered at the household level. $***p < 0.01; **p < 0.05; *p < 0.1$.

Effect of air purifiers on health outcomes (Pre-analysis plan section 4.3)

Table A.17: Effect of air purifiers on Healthcare spending

	(1) Treatment Cost: Phase 3	(2) Treatment Cost: Phase 3
Purifier	597.6	857.3
	(573.3)	(827.4)
Treatment Cost: Phase 2	0.175***	0.179***
	(0.0601)	(0.0647)
No Phase 2	-1090.9***	-1800.0***
	(333.3)	(320.6)
Observations	2,714	1,868
Clusters	784	766
Control mean	1,306.417	1,875.053
Sample	All	HH Head Bedroom

Notes: This table shows the effect of air purifiers on total healthcare spending in the two months preceding the phase 3 interview. Column 1 shows the results for all household members. Column 2 shows the results for household members sleeping in the same bedroom as the household head, the room where we encouraged the households to place the air purifier. Standard errors are clustered at the household level. $***p < 0.01; **p < 0.05; *p < 0.1$.

Table A.18: Effect of air purifiers on proportion of sick days

	(1) Prop. of Sick Days: Phase 3	(2) Prop. of Sick Days: Phase 3
Purifier	0.000143	0.000298
	(0.00166)	(0.00235)
Prop. of Sick Days: Phase 2	0.0537**	0.0508**
	(0.0229)	(0.0251)
No Phase 2	-0.00668***	-0.00753**
	(0.00128)	(0.00310)
Observations	2,714	1,868
Clusters	784	766
Control mean	0.008	0.012
Sample	All	HH Head Bedroom

Notes: This table shows the effect of air purifiers on the proportion of sick days in the two months before the interview. Sick days are defined as days where illness prevents regular activities like work, school, or household chores. Column 1 shows the results for all household members. Column 2 shows the results for household members sleeping in the same bedroom as the household head, the room where we encouraged the households to place the air purifier. Standard errors are clustered at the household level. $***p < 0.01; **p < 0.05; *p < 0.1$.

Table A.19: Effect of air purifiers on healthcare visits

	(1)	(2)
	Treatment Freq: Phase 3	Treatment Freq: Phase 3
Purifier	-0.345	-0.547
	(0.270)	(0.386)
Treatment Freq: Phase 2	0.0482***	0.0474***
	(0.00903)	(0.00996)
No Phase 2	-1.413***	-1.683***
	(0.171)	(0.450)
Observations	2,705	1,859
Clusters	784	766
Control mean	1.569	2.281
Sample	All	HH Head Bedroom

Notes: This table shows the effect of air purifiers on the number of visits to healthcare providers, including doctors, clinics, and hospitals, in the two months before the interview. Column 1 shows the results for all household members. Column 2 shows the results for household members sleeping in the same bedroom as the household head, the room where we encouraged the households to place the air purifier. Standard errors are clustered at the household level. $***p < 0.01; **p < 0.05; *p < 0.1$.

Table A.20: Effect of air purifiers on blood pressure

	(1) Blood Pressure	(2) Blood Pressure	(3) Blood Pressure	(4) Blood Pressure
Purifier	0.624	0.863	-0.318	-0.255
	(0.883)	(0.886)	(0.575)	(0.580)
BP Systolic: Phase 2	0.590***	0.589***		
	(0.0263)	(0.0263)		
No Phase 2	-1.978	-2.459		
	(1.480)	(1.592)		
BP Diastolic: Phase 2			0.561***	0.560***
			(0.0407)	(0.0409)
No Phase 2			-1.174	-1.714*
			(0.879)	(0.924)
Observations	1,125	1,095	1,125	1,095
Clusters	783	763	783	763
Control mean	121.283	121.233	81.412	81.386
Sample	All	HH Head Bedroom	All	HH Head Bedroom
BP Test	Systolic	Systolic	Diastolic	Diastolic

Notes: This table shows the effect of air purifiers on blood pressure measured in the phase 3 survey. Columns 1 and 2 show the effect on systolic blood pressure while columns 3 and 4 show the effect on diastolic blood pressure. Columns 1 and 3 show the results for all household members. Columns 2 and 4 show the results for household members sleeping in the same bedroom as the household head, the room where we encouraged the households to place the air purifier. Standard errors are clustered at the household level. $***p < 0.01; **p < 0.05; *p < 0.1$.

Table A.21: Effect of air purifiers on lung capacity

	(1) FEV1/FVC	(2) FVC
Purifier	0.0867	-0.0464
	(0.904)	(0.0516)
Observations	1,097	1,067
Clusters	776	756
Control mean	90.287	2.525

Notes: This table shows the effect of air purifiers on lung capacity as measured by a spirometer. FEV1/FVC refers to the FEV1/FVC ratio, a ratio of above 70 is considered normal. Data is from household members sleeping in the same bedroom as the household head, the room where we encouraged the households to place the air purifier. Standard errors are clustered at the household level. $***p < 0.01; **p < 0.05; *p < 0.1$.

Table A.22: Effect of air purifiers on health outcomes: Blood Oxygen Levels

	(1)	(2)
	Blood Oxygen Levels: Phase 3	Blood Oxygen Levels: Phase 3
Purifier	0.0776	0.0841
	(0.0533)	(0.0541)
BO Levels: Phase 2	0.0590	0.0595
	(0.0586)	(0.0586)
No Phase 2	-0.0965	-0.120
	(0.0973)	(0.115)
Observations	1,125	1,095
Clusters	783	763
Control mean	98.739	98.738
Sample	All	HH Head Bedroom

Notes: This table shows the effect of air purifiers on Column 1 shows the results for all household members. Column 2 shows the results for household members sleeping in the same bedroom as the household head, the room where we encouraged the households to place the air purifier. Standard errors are clustered at the household level. $***p < 0.01; **p < 0.05; *p < 0.1$.

Table A.23: Effect of air purifiers on health index.

	(1) Health Index	(2) Health Index
Purifier	0.0371	0.0539
	(0.0334)	(0.0474)
Health Index: Phase 2	0.148***	0.148***
	(0.0356)	(0.0387)
No Phase 2	-0.103***	-0.199***
	(0.0306)	(0.0410)
Observations	2,715	1,868
Clusters	784	766
Control mean	-0.072	0.003
Sample	All	HH Head Bedroom

Notes: This table shows the effect of air purifiers on an inverse covariance weighted index of the six main health outcomes Anderson (2008). Outcome data is from the phase 3 survey. Column 1 shows the results for all household members. Column 2 shows the results for household members sleeping in the same bedroom as the household head, the room where we encouraged the households to place the air purifier. Standard errors are clustered at the household level. $***p < 0.01; **p < 0.05; *p < 0.1$.

Table A.24: Effect on Sleep: "Hours in Bed", "Hours Asleep", and "SleepQuality Index"

	(1) Index	(2) Hours Asleep	(3) Hours in Bed
Purifier	0.0740	3.456	-0.0136
	(0.0707)	(15.56)	(0.115)
Index: Phase 2	0.472***		
	(0.0395)		
Hours Asleep: Phase 2		0.0388	
		(0.0244)	
Hours in Bed: Phase 2			0.341***
			(0.0437)
Observations	3,255	774	3,255
Clusters	774	774	774
Control mean	0.0293	465.2129	5.4212

Notes: Significance levels are denoted by $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$.

Table A.25: Effect of air purifiers on health outcomes: Mental Health Index.

	(1)
	Mental Health Index
Purifier	-0.0386
	(0.0716)
Observations	784
Clusters	784
Control mean	0.020

Notes: This table shows . Mental health index is at the household level and was asked only to the household head of the household, which explains the number of observations matched to the number of clusters. The index was constructed in such a way where the higher the value, the worse the mental state of the respondent. Standard errors are clustered at the household level. $***p < 0.01; **p < 0.05; *p < 0.1$.

Effects of air purifiers on labor supply and income (pre-analysis plan section 4.4)

Table A.26: Effect of air purifiers on labor supply.

	(1) Days Worked	(2) Days Worked
Purifier	-0.00801	0.0194
	(0.0470)	(0.103)
Days Worked: Phase 2	0.900***	
	(0.0102)	
Days Worked: Phase 2		0.718***
		(0.0303)
Observations	3,254	1,073
Clusters	774	769
Control mean	1.783	5.087
Sample	All	Only Working Members of HH

Notes: This table shows the effect of air purifiers on labor supply. For this analysis, 'Labor supply' will be defined as the total number of days worked by each household member in the preceding seven days. Standard errors are clustered at the household level. $***p < 0.01; **p < 0.05; *p < 0.1$.

Table A.27: Effect of air purifiers on income.

	(1) Income
Purifier	824.7
	(2616.2)
Income Phase 2	0.752***
	(0.193)
Observations	1,066
Clusters	765
Control mean	44902.415

Notes: This table shows the effect of air purifiers on income. For this analysis, income refers to the monthly earnings of all individuals in the household who were employed at the time of the Phase 2 survey. Standard errors are clustered at the household level. $***p < 0.01; **p < 0.05; *p < 0.1$.