Residential Air Purifiers and the Value of Clean Air*

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Abstract

In this paper, we show that standard approaches for valuing non-market amenities like clean air through defensive expenditures are methodologically fragile. Estimates are highly sensitive to assumptions about household use of defensive technologies, and survey data on usage is unreliable. Moreover, because researchers convert a one-time purchase or willingness-to-pay elicitation into a flow value by dividing by assumed hours of use, lower assumed usage can mechanically imply higher valuations. To address this fragility, we develop a revealed-preference approach that estimates the flow value of clean air using high-frequency data on residential air purifier usage in Dhaka, Bangladesh. Leveraging randomized variation in the marginal cost of operation, we recover the households' trade-off between money and clean air without relying on purchase decisions or stated usage intentions. We find that the marginal willingness to pay (MWTP) for clean air is lower and much more tightly bounded than previous estimates. This low valuation is not driven by traditional market frictions like liquidity constraints or misperceptions about pollution severity and technology effectiveness, suggesting limits to environmental policies that rely on sustained complementary household action.

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1 Introduction

Many important policy questions require valuing improvements in well-being that are not directly bought and sold, and researchers often infer these values from one-time purchases of defensive technologies such as air purifiers, water filters, and mosquito nets. In this paper, we show that standard approaches for valuing non-market amenities through defensive expenditures are methodologically fragile. They rely on assumptions about expected usage, and varying these assumptions changes estimates by an order of magnitude. Because researchers convert a one-time purchase or willingness-to-pay elicitation into a flow value by dividing by assumed hours of use, lower assumed usage can mechanically imply higher valuations. Moreover, we show that survey-reported usage is an unreliable basis for assumptions about expected usage.

We address this fragility by proposing a new revealed-preference approach that directly values the flow utility of clean air. Our approach requires no assumptions about expected usage because we observe actual usage at high frequency. We leverage randomized variation in the marginal cost of operation to trace out households' demand for clean air. Our approach yields a marginal willingness to pay (MWTP) estimate that is lower and much more tightly bounded than previous estimates that rely on usage assumptions. Moreover, this low valuation is not driven by traditional market frictions such as liquidity constraints or information gaps, suggesting limits to environmental policies that rely on sustained complementary household action.

Ambient air pollution represents one of the world's most significant environmental health challenges (Figure 1). Over 7.3 billion people breathe unsafe air, resulting in more than 4 million annual deaths (Rentschler and Leonova, 2023; Health Effects Institute, 2024). Bangladesh is at the epicenter of this crisis: average exposure to fine particulate matter is more than 12 times the WHO annual guideline (IQAir, 2024). Reducing ambient air pollution to recommended levels in Bangladesh is estimated to increase life expectancy by 5.5 years (Figure 2).

Air purifiers provide an effective private defense against this exposure (EPA, 2024). Multiple experimental studies in controlled residential settings find that air purifiers decrease PM2.5 levels by roughly 50% and improve a range of health outcomes including reduced allergy and asthma symptoms as well as decreased cardiovascular morbidity (for a review, see EPA, 2018). Yet, despite these potential benefits, fewer than 1% of the middle-class households we surveyed in Dhaka own one. To understand this low adoption, we conducted two field experiments examining household perceptions, barriers to adoption and use, and health impacts. This setting, high exposure, effective purification, and low adoption, provides a clear test of purchase-based valuation, motivates our use-based valuation approach, and helps isolate whether standard market frictions explain the gap between purifier benefits and household adoption.

In our first experiment (Experiment 1, November 2023-April 2024), we provided free air monitors and purifiers to households. In November 2023, we recruited 1,008 households from three large housing associations that are emblematic of middle-income households in Dhaka. Imme-

diately following recruitment, we conducted a short Phase 1 survey on perceptions of indoor and outdoor air pollution. Then, 512 randomly selected households received a free indoor air pollution monitor displaying real-time PM2.5 levels along with a chart that categorized these levels from "good" to "hazardous" and informed them of the health risks associated with higher levels of air pollution. These monitors also recorded and transmitted minute-by-minute data on indoor PM2.5 levels to the research team. Among households receiving a monitor, half were randomly assigned to an attention treatment, receiving a small incentive to correctly report monitor readings and corresponding hazard levels.

In January 2024, two months later, we conducted a Phase 2 survey, again gathering information on household beliefs about indoor and outdoor air pollution. We used a Becker-DeGroot-Marschak (BDM) mechanism to elicit households' willingness to pay (WTP) for air purifiers. Subsequently, we randomly provided 306 households with a free air purifier with a retail price of BDT 16,500 (USD 150). Each purifier was connected to a Wi-Fi-enabled smart socket that relayed minute-by-minute usage data. This allows us to capture air purifier usage with unusually high precision and frequency. We further randomly assigned some purifier-receiving households to receive compensation for the electricity used by the purifier, with either a daily or monthly frequency.

In March 2024, we conducted a Phase 3 survey, collecting data on perceptions of air purifier benefits, and households' willingness to accept (WTA) to sell back the purifiers that were provided to them more than two months ago. In Phase 3, like in Phase 2, we collected household member data on physical and mental health, sleep, labor supply, and income. Finally, in April, we randomized households to whom we had previously provided a free air purifier to receive significant incentives for using air purifiers: either BDT 5 (USD 0.045) or BDT 10 (USD 0.09) per hour of operation, or 6-12% of household monthly income if the purifier is used continuously.

In our second experiment (Experiment 2, November 2024-January 2025), we recruited 2,400 new households from four other housing associations in the same neighborhood. Unlike the multi-phase first experiment, we visited each household only once. During this single visit, enumerators first collected baseline beliefs about indoor and outdoor air pollution, as well as perceived air purifier effectiveness. Households were then randomly assigned to one of six treatment arms: a control group with no intervention; a group offered to pay for the purifier through a 12-month interest-free payment plan; and four demonstration treatments: purifier demonstration only, monitor demonstration only, sequential demonstration of both purifier and monitor, and combined demonstration showing the real-time PM2.5 reduction when using the purifier. Immediately after the treatment, we again elicited beliefs about air quality and purifier effectiveness to capture how each intervention shifted perceptions. Finally, we used the BDM mechanism to elicit WTP for air purifiers.

Our descriptive statistics paint a bleak picture of the state of indoor air pollution in Dhaka and reveal significant misconceptions among households. First, using the monitor data, we show that

during the winter months, indoor pollution is staggeringly high, with an average of 150 $\mu g/m^3$, 10 times higher than the WHO 24-hour recommendation. Importantly, indoor air is nearly as polluted as outdoor air, with an average indoor to outdoor ratio of 0.88. However, while over 70% of households believe that outdoor pollution is a serious problem, they greatly underestimate the severity of indoor pollution, with the same percentage reporting that indoor air pollution is not a serious issue.

Second, households are uncertain about and underestimate 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 rooms where they were used, which contrasts sharply with the actual effectiveness of air purifiers: 80% in controlled conditions in the field and over 40% in real-world household environments. Finally, we find that households have a low WTP for air purifiers; the average household WTP was USD 13, or 8.4% of the retail cost of air purifiers.

We report six sets of results from our experiments. First, 12-month interest-free payment plans had no impact on households' WTP for air purifiers. Second, households provided with a free monitor for two months in Experiment 1 believed that the air in their homes is more polluted (a 10% increase, p-value < 0.01) and more likely to pose health risks compared to households without monitors. However, importantly, the monitors did not increase households' WTP for an air purifier, even though they were informed about its purpose in removing indoor air pollution before elicitation. This pattern held even with brief exposures to this information in Experiment 2: households given a five-minute demonstration of an air quality monitor immediately recognized their indoor air was more polluted (a 20% increase, p-value < 0.01), but this did not increase their WTP for purifiers.

Third, households provided with a free air purifier for three months in Experiment 1 were less uncertain about its effectiveness compared to households without purifiers; they were 73% (p-value < 0.01) more likely to perceive air purifiers as effective. However, households did not seem to value the devices, as they rarely used them, even when we compensated them for the (low) electricity costs of operating them. Specifically, even with compensation, the average household used the air purifier for less than 40 minutes per day. Five-minute demonstrations in Experiment 2 yielded the same result: households became more certain about purifier effectiveness (25% increase, p-value < 0.01) but showed no increase in WTP.

Fourth, households shown both devices separately (monitor first, then purifier) recognized both indoor pollution severity and purifier effectiveness, yet still showed no increase in WTP. Most strikingly, households shown both devices simultaneously, who directly observed PM2.5 levels drop 44% from 159 $\mu g/m^3$, recognized both pollution severity and purifier effectiveness but still showed no increase in WTP. Furthermore, compared to households given only purifiers, households given both monitors and purifiers increased their average purifier use over the next three months by about 75 minutes per day (p-value < 0.01), but only to an average of 105 minutes

per day. This increased usage was reflected in their willingness to accept for selling back the purifiers, which rose by 26% (p-value < 0.1), still far from bridging the gap between their baseline valuation (8.4% of retail price) and actual retail cost.

Fifth, although purifier ownership reduced average indoor PM2.5 levels by 5.8 $\mu g/m^3$ over the intervention period, driven by a statistically significant 6-11 $\mu g/m^3$ decrease between 4 pm and 4 am, we detect no improvements in objective or self-reported health outcomes, sleep, mental health, labor income, or labor supply, suggesting use was too modest to generate substantial health benefits within a roughly two-month period.

Sixth, we show that deriving MWTP for clean air from device purchase decisions yields fragile results. Plausible choices regarding expected usage, perceived effectiveness, and valuation metrics (WTP vs. WTA) can shift the estimate by orders of magnitude. The results are especially sensitive to the expected usage assumption: substituting the conventional assumption of continuous usage with our observed usage rate (<5%) leads to a 20-fold increase in implied MWTP (USD 0.27 to 6 per $\mu g/m^3$ per season). Furthermore, survey-based measures of usage are unreliable, exacerbating this fragility. Before receiving purifiers, most households stated they expected to use the device all the time when home. Post-receipt, 30% still claimed to do so, and over 50% claimed use at least once per day. Yet, our objective data reveals that almost no households actually met either frequency.

To bypass the reliance on expected usage assumptions inherent in purchase-based estimates, we propose a method to derive the flow value of clean air from high-frequency usage decisions. We combine objective usage data with randomized variation in the marginal cost of operation (via electricity reimbursements and incentives) and exogenous variation in potential pollution reduction (driven by outdoor air quality fluctuations). This allows us to directly recover the clean-air–money tradeoff revealed by household usage decisions. Across reasonable purifier effectiveness assumptions,[1] the resulting MWTP band (assuming MWTP ≥ 0) is tight: 0 to USD 0.30 per $\mu g/m^3$ per year (p-value = 0.23). This range is far narrower than purchase-based estimates and indicates that the typical household's valuation of clean air is very small. When we restrict the analysis to periods when household members are typically home and awake (6 PM to midnight), the estimates remain low, 0 to USD 0.68 per $\mu g/m^3$ per year, and are statistically significant (p-value < 0.05).

We can compare our estimates (0 to USD 0.30 per $\mu g/m^3$ per year) to purchase-based estimates from other lower-income settings after adjusting for PPP, inflation, household size, and technology effectiveness. The upper bound of our baseline estimate is \$1.07 per $\mu g/m^3$ per year (2023 PPP-adjusted USD), compared to \$7.43 in China (Ito and Zhang, 2020) and \$3.11 in India (Baylis et al., 2023).[2] However, these comparisons are misleading because the purchase-based es-

[1] Purchase-based approaches also require assumptions about the effectiveness of defensive technologies.

[2] Our sample households earn at least \$24,122 annually (PPP-adjusted USD), over double the average in the China (\$11,804) and India (\$9,454) samples, so income differences cannot explain our lower estimate.

timates rely on strong expected usage assumptions, either near-complete usage or self-reported usage taken at face value. Applying our observed usage rates to the Ito and Zhang (2020) framework would inflate their estimate to $148.68; adjusting Baylis et al. (2023) for the self-reporting bias we document would push theirs to $18.64. The key distinction is not that our estimate is lower, which it is, but that it is tightly bounded, whereas purchase-based estimates can vary by more than an order of magnitude depending on usage assumptions.

Contributions. These findings contribute to three literatures. First, we contribute to the growing environmental economics literature examining the MWTP for clean air (Ito and Zhang, 2020; Baylis et al., 2023; Tarduno and Walker, 2025; for a review, see Greenstone and Jack, 2015).[3] We advance this literature by demonstrating that standard approaches for deriving MWTP for environmental quality, based on the decision to buy a defensive technology, are fragile. Embedded in the denominator of these estimates are strong assumptions about expected usage, where, paradoxically, the lower the assumed usage, the higher the implied MWTP estimate. Furthermore, we show that survey data is an unreliable basis for calibrating these assumptions. To address this fragility, we develop a novel approach that prices the flow value of clean air directly, leveraging objectively measured high-frequency device use and potential indoor exposure reductions, identified through randomized price variation rather than purchase decisions or stated intentions. Moreover, due to the falling cost of smart sockets and sensors, this use-based method can now be easily adapted to other contexts, such as water purifiers, cold storage units, and electric cookstoves.

More broadly, this critique extends to revealed-preference studies that infer the value of a statistical life (VSL) from WTP for life-saving technologies while assuming the acquired technology will be used continuously or as reported (Berry, Fischer and Guiteras, 2020; Killeen, 2025). Among existing approaches, ours is methodologically closest to Kremer et al. (2011), who derive VSL from water source choice decisions in Kenya using a travel cost framework. Their setting highlights the same wedge we emphasize: health benefits depend not just on acquisition but on consumption behavior. We build on this insight by observing consumption behavior directly and identifying demand through randomized variation in the marginal cost of use, allowing us to price the flow value of the amenity without assumptions about usage.

Second, we are the first to experimentally test air purifier effectiveness in real-world residential settings.[4] Our finding that households provided with purifiers barely used them echoes empirical evidence from Hanna, Duflo and Greenstone (2016) and theoretical insights from Chassang, Padró i Miquel and Snowberg (2012). Following these papers, we caution against extrapolat-

[3] Our study also relates to literature on air quality information interventions, including research on public air quality alerts (e.g. Neidell, 2009; Anderson, Hyun and Lee, 2022; Barwick et al., 2024; Ahmad et al., 2025), and household-level air quality information (Metcalfe and Roth, 2025; Sater et al., 2021; Baquié et al., 2024).

[4] Concurrent work by Sun, Sorin and Resosudarmo (2025) examines air purifiers in residential settings in Indonesia.

ing from lab or controlled field experiments to real-world settings where use depends on complementary household action. As Chassang, Padró i Miquel and Snowberg (2012) note, such studies cannot distinguish whether low effectiveness stems from "true returns [being] low or because most agents believe they are low and therefore expend no effort using the technology." Our experimental design resolves this ambiguity. We show that correcting household beliefs significantly increased purifier usage (by >200%); however, absolute usage remained low (roughly 100 minutes per day), generating an 6–11 $\mu g/m^3$ decrease in PM2.5 between 4 pm and 4 am. Importantly, we detect no short-run health or socioeconomic improvements, contrasting sharply with the experimental public health literature (for a review, see EPA, 2018). These studies are efficacy rather than effectiveness trials: they ensure high compliance (e.g., mandating or incentivizing use).[5] The discrepancy suggests that real-world usage in our context is insufficient to generate health improvements, potentially due to extremely high baseline pollution and non-linearities in the dose-response relationship (Apte et al., 2015; Miller, Molitor and Zou, 2025).

Third, we contribute to the development economics literature on credit, beliefs, and experience in technology adoption (for reviews, see Dupas, 2011; Magruder, 2018; Kremer, Rao and Schilbach, 2019; Verhoogen, 2023). We are among the first studies to examine barriers to residential air purifier adoption.[6] We show that the removal of traditional adoption barriers, specifically credit constraints, misperceptions about the problem (indoor air severity), and uncertainty about the solution (air purifier effectiveness), does not increase adoption. In fact, we find that even a 100% capital subsidy with electricity compensation fails to generate significant usage, a result directly relevant to the active policy debate on price subsidies for health products in lower-income countries (Kremer and Miguel, 2007; Ashraf, Berry and Shapiro, 2010; Cohen and Dupas, 2010; Adhvaryu, 2014; Dupas, 2014*a*,*b*).

2 Context, Research Design, and Data Collection

2.1 Context

We conduct our study in the Mirpur area of Dhaka, Bangladesh, a city notorious for its severe air pollution. Annual average PM2.5 levels in Dhaka have risen since the late 1990s; between 1998 and 2023, they increased by 62% from 50.7 to 82.3 $\mu g/m^3$ (Figure A.1a). Indeed, reducing Dhaka's

[5]The EPA review includes two controlled trials from urban China, the setting most comparable to ours, with intervention periods of 2 days to 2 weeks and baseline PM2.5 levels of 95 and 60 $\mu g/m^3$, respectively. Notably, Chen et al. (2015) found that just 48 hours of air purifier exposure produced measurable cardiopulmonary benefits in healthy young adults living in severely polluted Chinese dormitories, including improvements in inflammatory, thrombogenic, and vasoconstriction biomarkers, lung function, blood pressure, and fractional exhaled nitric oxide. However, these trials ensured continuous purifier operation, unlike the low usage we observe.

[6]Greenstone, Lee and Sahai (2021) deployed indoor pollution monitors in Delhi households across the SES spectrum during peak winter air pollution and, consistent with our findings, found no impact on demand for air purifier rentals. However, they caution that due to nonresponse and attrition, their results should be interpreted as suggestive.

current ambient air pollution to WHO-recommended levels would increase life expectancy by 7 years (AQLI, 2025). Even compared to Los Angeles—the most polluted of the large cities in the US—Dhaka's levels are exceedingly high (Figure A.1b). Air pollution in Dhaka follows a seasonal pattern, reaching its highest levels during the dry winter months of December, January, and February, the period when we conducted most of our experiments. During these months, PM2.5 levels routinely exceed 150 $\mu g/m^3$, 10 times the WHO's 24-hour guideline of 15 $\mu g/m^3$ (Figure A.2).

Across the two experiments, we enrolled 3,400 households in Mirpur, housed in apartment blocks managed by seven large housing associations that granted permission for our experiment.[7] We enrolled 1,008 households across three housing associations for Experiment 1 and 2,400 households across four housing associations for Experiment 2. Each association comprises multiple multi-story buildings ranging from 3 to 8 floors, with several apartment units on each floor. Appendix Figure A.3 shows a map of our study area.

We selected this population for three 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. Second, their economic status suggests that purchasing an air purifier would not constitute an overwhelming financial burden; their average annual household labor income is above USD 6,000 (USD 24,000 PPP-adjusted or roughly 2.3 times the per-capita income in Bangladesh).[8] Although the retail price of the air purifier used in our experiment would still constitute about 30% of monthly household income, 34% of the households in our sample own an air conditioner, which typically costs at least two to three times as much as an air purifier and consumes substantially more electricity. Finally, unlike many slum dwellers, middle-class apartments are better insulated from outside air, increasing the effectiveness of air purifiers. Furthermore, we conducted both our experiments during the months with milder (less hot) temperatures, a period when PM2.5 levels are very high but when households are more likely to keep windows closed for comfort, particularly during the night.[9]

2.2 Research Design and Data Collection

This section describes the design and implementation of our two field experiments. Across both experiments, we collect detailed survey and device-based data from more than 3,400 middle-income households in Dhaka to examine how beliefs, credit access, and experience affect the adoption and use of air purifiers. Experiment 1 (November 2023 – April 2024, $N = 1,008$) is a multi-phase longitudinal design that examines how free allocation of monitors and purifiers influences beliefs about indoor air pollution and purifier effectiveness, purifier usage, and health

[7] All seven housing associations are located within a 2 square kilometer area.

[8] We did not collect data on other forms of income such as pensions or income from investments, this is therefore an underestimate of the households' total income.

[9] The average daily minimum temperatures in Dhaka are 19°C in November, 15°C in December, 14°C in January, 17°C in February, 21°C in March, and 24°C in April.

outcomes. Experiment 2 (November 2024 – January 2025, $N = 2400$) is a single-visit cross-sectional experiment that isolates mechanisms through which experience changes beliefs, and tests a credit offer for purifier purchase.

Figure 3 offers a visual representation of the research design. Figure A.4 presents the timelines for the different phases and interventions of the experiments. Figure A.5 presents the distributions of survey dates.

2.2.1 Experiment 1

We sampled households by visiting each building within each of the three housing associations. To minimize spillovers between households, we then sampled one household per floor in each building. We asked three screening questions to determine whether the household was eligible for the study. Specifically, we inquired whether the household had a Wi-Fi connection, whether they owned an air purifier, and whether they were interested in acquiring an air purifier and/or air monitor for their household. Only 0.8% of the households we contacted owned an air purifier, while 73% had a Wi-Fi connection, and 58% of households expressed interest in an air purifier and/or air monitor. We included households that had a Wi-Fi connection (to allow real-time data collection), were interested in obtaining either an air purifier and/or air monitor, and did not already own an air purifier. Although excluding households that were not interested makes our sample less representative of the overall population, it allows us to focus on a group more likely to adopt and use air purifiers. This group is crucial for policymakers, as they are the target population for measures designed to boost air purifier adoption.[10]

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 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 half were randomly selected to receive an indoor air quality monitor. Amongst these households, we further randomized half to receive an attention treatment, where they were incentivized to read the monitor once per week and send a text message with the mapping between the reading and interpreted air quality category and health risk to the research team. See Appendix A.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.6). 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

[10]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.

English and Bengali) categorizing PM2.5 levels into six levels: good, moderate, unhealthy for sensitive groups, unhealthy, very unhealthy, and hazardous (Figure A.7). 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.[11] Once randomly selected households received a monitor, the field team helped set up the monitor and connect it to Wi-Fi, ensuring that data was being transmitted before leaving the household. For uniformity in data collection, we recommended to households that they place the air monitors in the bedroom of the household head.

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.[12] To mitigate any risk of income effects driven by this incentive, households without air monitors received the same payment as a randomly matched household in the monitor group (Cefala et al., 2024).

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 0.27) 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 monitor group, the monitor and attention incentive group, and the group without monitors.

Phase 2 survey We conducted the Phase 2 survey from January 5 to February 4, 2024, approximately two months after the Phase 1 survey.[13] The Phase 2 survey collected information on household beliefs about air pollution and its health impacts.[14] We also employed a BDM mechanism to elicit WTP for air purifiers (Berry, Fischer and Guiteras, 2020). See Appendix A.2 for more information about the WTP elicitation. We included questions about physical and mental health, sleep, labor income, and labor supply. We also collected data on health bio-markers—specifically blood pressure, vital capacity, and blood oxygen levels—of household members who slept in the bedroom of the household head.

Treatment 3: Air purifiers. Of the 1,008 households, we randomly assigned 372 households to

[11] 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).

[12] Throughout the paper we use a USD/BDT exchange rate of 110 during Experiment 1 and 120 for Experiment 2, these corresponds to the exchange rates on January 1, 2024 and 2025, respectively.

[13] 97% of surveys were conducted during this period. The remaining surveys were rescheduled and completed by March 12, 2024. The average time between the Phase 1 and Phase 2 survey was 61 days.

[14] To measure how much the household prioritized air pollution as a societal issue, we asked households to choose a charity organization out of three, to which we donated BDT 100. One of the organizations worked directly on reducing air pollution.

receive air purifiers during the Phase 2 survey without stratifying on any prior treatments.[15] The model of air purifier used in the experiment is the "Sqair Air Purifier" from Smart Air (see Figure A.8 for a picture).[16] At the time of the experiment, the retail price in Bangladesh was BDT 16,500 (USD 150). The randomization was conducted as part of the WTP elicitation. Treatment households were randomly selected to have a draw price set to zero, ensuring that they will receive an air purifier, while control households were given a draw price equal to the market price.[17] 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.9).

Treatment 4: Electricity compensation. We randomly assigned the 372 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 group that did not receive compensation had 160 households. The compensation for the treatment groups was equal to the electricity cost incurred by the air purifier, tracked via the smart socket.[18] 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.[19]

Phase 3 survey We conducted the Phase 3 survey from February 23 to March 31, 2024.[20] In the Phase 3 survey, we collected endline data, including beliefs about purifier effectiveness, and via a BDM mechanism, households' willingness to accept cash to sell back purifiers they already had.[21] We repeated many questions from the Phase 2 survey to observe the purifiers' effects on responses. We also collected health bio-markers.

Incentives to use air purifiers. Once all our incentives ended on March 31, we re-randomized

[15]Since randomization was done for the initial sample, and not conditional on attrition, this includes households that attrited between Phase 1 and Phase 2 surveys.

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

[17]No control household stated a WTP above the market price. Thus, none of the control households received a purifier.

[18]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.

[19]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.

[20]99% of surveys were completed during this period. The remaining surveys were rescheduled and completed by April 20, 2024. The average time between the Phase 2 and Phase 3 survey was 63 days.

[21]Due to budget constraints, we randomized the lottery prices drawn in the BDM exercise such that we would purchase only one air purifier for BDT 16,000.

the households in the purifier group, to receive larger incentives using the purifiers. 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 electricity cost, which for running the purifier on medium speed is approximately BDT 0.24 per hour. Treatment households that operated their purifiers continuously throughout the 30-day intervention could earn 3,600 or 7,200 Taka, amounting to 6% and 12% of the average monthly household labor income in our sample, respectively.

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.

Indoor air pollution. The air pollution monitors record minute-by-minute data on PM2.5, PM10, temperature, and humidity.[22] 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. Overall, we received data from 67% of the potential hour-by-household observations among those with monitors installed. We winsorize the data at the 1st and 99th percentiles.

Outdoor air pollution. On December 1, 2023, we installed outdoor air pollution monitors in two of the three housing associations where Experiment 1 was conducted. These monitors provide us with minute-by-minute data on outdoor PM2.5 and PM10.[23] We winsorize the data at the 1st and 99th percentiles. Appendix A.3 shows that the indoor and outdoor monitors do not substantially differ in their pollution measurements when placed in the same room. We impute outdoor air pollution data for the period between November 1 and 30 from the air quality monitors of the US Embassy.[24]

Air purifier use. Each air purifier was connected and glued to a smart socket. The smart sockets were connected to Wi-Fi and recorded electricity usage of the connected device, pushing data to the server every minute on how many watts were used. Figure A.10 shows that the smart sockets' recorded electricity usage aligns with the manufacturer's labeling of the air purifier's wattage at

[22]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/.

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

[24]The correlation between our outdoor monitors and the US embassy monitor is 0.96 (Appendix A.3).

various speeds. We classify electricity usage between 3 and 60 watts as indicative of the purifier being in use.

Attrition and balance. We discuss attrition and balance in Appendix B. We find some differential attrition by treatment status, but balance tests confirm that attrited and unattrited groups remain comparable on observables, and our main results are robust because they rely either on real-time sensor data (which has minimal attrition) or are replicated in Experiment 2 where no differential attrition occurred.

2.2.2 Experiment 2

The second experiment was conducted between November 2024 and January 2025. In this experiment, we visited households only once. Before implementing any treatments, enumerators collected baseline information including household demographics, beliefs about health risks from air pollution, perceptions of indoor and outdoor air quality, and views on air purifier effectiveness. We then randomly assigned households to one of six experimental arms:

1. Control: A control group receiving no intervention
2. Credit Only: A group offered a 12-month interest-free equal monthly installments payment plan to purchase a purifier. The enumerators carried an official contract of the payment plan from our implementation agency
3. Purifier Only: A 5-minute demonstration of the air purifier, which included a tutorial on how it worked
4. Monitor Only: A 5-minute demonstration of the air quality monitor. Similar to Experiment 1, along with the monitors, households received the chart shown in Appendix Figure A.7 to help them interpret the monitor reading
5. Both (Separately): The monitor was demonstrated for 5 minutes together with the interpretation chart and then the purifier was demonstrated for 5 minutes, as distinct demonstrations
6. Both (Together): The monitor was demonstrated for 5 minutes together with the interpretation chart, followed by a demonstration of the air purifier for 5 minutes while the monitor remained on, allowing households to observe pollution levels drop on the monitor screen in real-time

We recorded the pollution levels for each household, either as part of the monitor demonstration or after the survey was completed. For the 'Both (Together)' group, enumerators recorded air quality levels both before and after the purifier was activated to precisely measure the change in

pollution levels each household observed. Figure A.11 shows the variation in air purifier effectiveness. Households in the 'Both (Together)' group observed a 44% average decline in PM2.5 levels from an average reading of 159 $\mu g/m^3$ before the purifier was turned on.[25]

After administering these treatments, we repeated our questions about air quality perceptions, health risk beliefs, and views on purifier effectiveness to measure how each intervention affected these outcomes. We then employed a BDM mechanism to elicit households' WTP for air purifiers, using the same methodology as in our first experiment to ensure comparability of results.[26] Table A.12 confirms our successful randomization, demonstrating balance across all but one pre-treatment variable.

3 Descriptive and Stylized Facts

Our descriptive statistics reveal an alarming picture of the state of indoor air pollution in Dhaka and reveal significant misconceptions among households regarding its severity and the effectiveness of air purifiers. Indoor air is nearly as polluted as outdoor air, yet most households believe it to be far cleaner and vastly underestimate how well purifiers work. Consequently, fewer than 1% of households own a purifier, and the average WTP is 8.4% of the retail price.

3.1 Both outdoor and indoor air pollution levels are alarmingly high, but households believe indoor air is much less polluted than outdoor air

Between the Phase 1 and Phase 2 surveys in Experiment 1, at our study sites, average outdoor PM2.5 levels were 185 $\mu g/m^3$, 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 this time was 162 $\mu g/m^3$, or 11 times the WHO's 24-hour recommendation. Figure 4a shows the average indoor air pollution readings in households, alongside outdoor air pollution. The average ratio of indoor air pollution to outdoor air pollution is 0.95.[27] Similarly, during the Experiment 2 surveys, the average outdoor PM2.5 level was 130 $\mu g/m^3$ and average indoor air pollution was 138 $\mu g/m^3$, with the average ratio of indoor to outdoor air pollution being 1.08 (Figure 4b). Overall, this is consistent with the ability of finer particulate matter such as PM2.5

[25] This variation in air purifier effectiveness is not experimental and depends on numerous factors during the demonstration: structural elements (room size, ceiling height, number of windows and doors, whether they're open or closed, air circulation patterns); placement factors (purifier position, distance from monitor); and circumstantial variables (protocol adherence by enumerators, time of day, date, number of people present, ongoing activities like cooking or smoking).

[26] We set up the random price draw to sell no more than one purifier for either BDT 500 or 1,000 in each treatment group. Among these low-price opportunities, only one household stated a valuation above the drawn price (BDT 1,000), and we successfully sold the purifier to this household.

[27] This is similar to the finding of Saha et al. (2025) who estimate an indoor to outdoor ratio of 0.97 during the winter season, using data from 17 households in Dhaka.

to easily penetrate buildings (Ozkaynak et al., 1996; Vette et al., 2001), making exposure difficult to avoid unless the air inside the building is continuously purified.

Data collected from the Phase 1 survey in Experiment 1 shows that while the modal household accurately perceived outdoor air pollution as exceedingly high, rating it 10 on a scale of 10 (Figure 4c), they perceived indoor air quality as better than moderately polluted, rating it 4 on a scale of 10. In Figure 4e, we display the distribution of households' perceptions of indoor versus outdoor air pollution. The overwhelming majority of households believe their indoor to outdoor ratio is 0.5 or lower, indicating a significant underestimation of indoor air pollution's extent. In Figures 4d and 4f, we observe a very similar pattern for households in Experiment 2: far more households accurately perceived outdoor air pollution as exceedingly high (rating it 10 out of 10), with the overwhelmingly majority estimating indoor pollution at half or less of outdoor levels.

3.2 Air purifiers are very effective, but households are uncertain about their effectiveness and demand for air purifiers is low

Although our air purifiers are factory-tested,[28] we conducted our own controlled tests in January 2024 by closing the doors and windows in two rooms, slightly larger than typical bedrooms, at our field office in Dhaka. We randomly assigned an air purifier to one room and turned it on for two hours. We recorded PM2.5 levels in both rooms and repeated this procedure six times. Figure 5a presents the results from these tests. When the air purifier is turned on, air pollution levels start to decrease almost immediately, with an overall decrease from 134$\mu g/m^3$ to 26 $\mu g/m^3$ within 30 minutes—an 81% decline in PM2.5 levels. Importantly, when the purifiers were turned off, air pollution levels began to increase immediately, even with doors and windows closed, gradually returning to baseline levels.

We also analyzed real-world pre-post patterns of indoor air quality when Experiment 1 households that received free purifiers in Phase 2 turned them on between Phase 2 and Phase 3 (Figure 5b). The levels of indoor air pollution before households turned on their purifiers were alarmingly high (131 $\mu g/m^3$),[29] but decreased significantly once the purifier was turned on (75 $\mu g/m^3$)—a 43% decrease in PM2.5 levels.[30] Finally, as we discussed earlier, in Experiment 2's 'Both (Together)' group, we recorded air quality before and after purifier activation to measure the pollution change each household observed. Figure A.11 shows the variation in purifier effectiveness:

[28] The manufacturer's own test found the purifier to remove 98% of PM2.5 pollution (compared to outdoor levels) when used on the highest setting in a 15m^2 bedroom and outdoor PM2.5 levels at 40 $\mu g/m^3$ (Vanzo, 2021). However, in a separate test, they show that for most types of purifiers, the percentage of PM2.5 removed compared to outdoor levels decreases at higher levels of outdoor pollution and is around 85% at the outdoor pollution levels present in our study (Talhelm, 2017).

[29] The spike in PM2.5 levels immediately before the purifier was turned on may be driven by household behaviors such as opening doors when entering a room and then turning on the purifier.

[30] The smaller effect on air pollution, compared to effects observed in our controlled setting, may be due to the air purifiers often being used on the lowest setting, in larger rooms, or because doors or windows in the room were open.

households observed an average 44% PM2.5 decline from a baseline of 159 $\mu g/m^3$ over a short demonstration when the purifier was on for only five minutes.

However, in the non-purifier group in Experiment 1 and pre-intervention in Experiment 2, only half of the households had formed an opinion on purifier effectiveness, and about a third believed that purifiers removed more than 25% of air pollution from the room where they were used (Figures 5c and 5e).

We also find that demand for air purifiers is low. When we elicit households' WTP for air purifiers in the Phase 2 survey of Experiment 1. In the non-monitor group, we find an average household willingness of BDT 1,431 (USD 13.0) or 8.4% of their retail cost. In fact, no household in our sample was willing to pay the retail price (Figure 5d). This is consistent with non-ownership; hardly anyone in our listing survey owned an air purifier similar to Greenstone, Lee and Sahai (2021), who found no demand for air purifier rentals among middle-income households in urban Delhi. Similarly, in Experiment 2, the WTP for air purifiers in the control group was BDT 2,700 (USD 22.5) or 16% of their retail cost, and no household in our sample was willing to pay the retail price (Figure 5f).

4 Credit Constraints Do Not Explain Low Purifier Adoption

We first test whether financial constraints explain the low WTP for air purifiers by offering 12-month interest-free equal monthly installments payment plan in Experiment 2. This addresses a fundamental question: is low adoption driven by inability to pay upfront costs, despite long-term benefits?

Econometric specification. We estimate the following regression specification:

$$\begin{aligned} Y_i = \alpha + &\beta_1 \times \text{Credit Only}_i + \beta_2 \times \text{Monitor Only}_i + \\ &\beta_3 \times \text{Purifier Only}_i + \beta_4 \times \text{Both (Separately)}_i + \\ &\beta_5 \times \text{Both (Together)}_i + \varepsilon_i \end{aligned} \tag{1}$$

where Y_i represents household i's WTP elicited through the BDM mechanism. β_1 captures the effect of access to free credit. We report heteroskedasticity-robust standard errors.

Results. Table 1, Panel B, presents our results. Access to 12-month interest-free loans had no impact on WTP for air purifiers—households offered credit showed virtually identical valuations to the control group. This null effect is perhaps not surprising given our sample characteristics. They are relatively affluent by Bangladeshi standards with an average annual household labor income exceeding US$24,122 (2023 PPP-adjusted). They also demonstrate capacity for similar purchases with 34% owning air conditioners, which typically cost two to three time more than

air purifiers and consume substantially more electricity.

Our finding contrasts with that of Berkouwer and Dean (2022), who find that credit access dramatically increases willingness-to-pay for energy-efficient cookstoves. It is likely that differences in household characteristics are an important factor in explaining these differences. Their sample consists of Kenyan households earning US$6,835 (2023 PPP-adjusted), roughly one-fourth our sample's income. Our null result, despite offering generous loan terms (zero interest, 12-month duration), suggests that financial barriers alone cannot explain the air purifier adoption puzzle in middle-income urban South Asian contexts.

5 Improving Misperceptions about Indoor Air Pollution Severity Fails to Increase Purifier WTP

In this section, we examine the effects of providing air pollution monitors and monitor demonstrations on beliefs about indoor air quality and WTP for an air purifier. We find that despite monitors correcting perceptions of indoor air pollution levels, they do not affect WTP for air purifiers.

Econometric specification. We examine how monitors, provided at the end of the Phase 1 survey in Experiment 1, influenced households' perceptions of air pollution and WTP for air purifiers by the time of the Phase 2 survey. We estimate the following regression specification:

$$Y_i = \alpha + \beta_1 \times Monitor_i + \beta_2 \times \mathbf{X}_i + \varepsilon_i \tag{2}$$

where Y_i represents either the belief of household i regarding the severity of indoor air pollution levels, the health risks associated with this air pollution, or the WTP for household i, determined through a BDM mechanism. The term $Monitor_i$ indicates whether a household was randomly selected to receive an air quality monitor two months earlier, while $\mathbf{X}_i$ includes $MonitorXAttention_i$, which denotes whether the household was given both a monitor and an incentive to report their air quality monitor readings. We use heteroskedasticity robust standard errors.

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 indoor to outdoor ratio of 1), 5 suggests 'Indoor is half as bad as outdoor' (implying an indoor to outdoor ratio of

0.5), and 0 implies there is almost no indoor air pollution.[31]

Results. We present these results in Panel A of Table 1 and the the corresponding shifts in the underlying distribution in Figure A.12. We find that the monitor treatment significantly increases households' perception of the extent of indoor air pollution, with the estimate showing an increase of 0.45 points or 10% (Column 1). Monitors only have a small positive and statistically insignificant, effect on perceptions of outdoor air pollution (Column 2), likely because, unlike for indoor air, the typical household already recognizes the poor quality of outdoor air. Furthermore, Column 3 shows that monitors help reduce the misconception that indoor air quality is substantially better than outdoor air quality, increasing the perceived indoor to outdoor air pollution ratio by 3.1 percentage points (a 7% increase).

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. We report results in Table A.13. We find that monitors increase households' perceptions of the health risks from indoor air pollution during the Phase 2 survey. In particular, the perception of the effect of air pollution on adults increased by 0.18 standard deviations (Column 1) and the perception of the effect on children increased by 0.12 standard deviations (Column 2), although this latter coefficient is not statistically significant.

Interestingly, we find no evidence that our attention incentives affected beliefs about indoor air pollution (Table A.14). This suggests that the monitor's impact on beliefs operates through providing new information about pollution levels rather than merely increasing the salience of existing information.

However, we did not find a significant positive effect of monitors on WTP for an air purifier during the Phase 2 survey, as shown in Column 4 of Table 1. The lack of a positive effect of air pollution monitors on WTP for air purifiers contrasts with our finding that monitors correctly increased households' perceptions of indoor air pollution levels and associated risk of illness in adults and children.

Experiment 2 replicates findings, but with larger effects. In Panel B of Table 1 we show the results from Experiment 2, estimated using Equation 1. We find that brief five-minute monitor demonstrations generated even stronger belief corrections than two months of monitor ownership in Experiment 1. Households exposed to monitors increased their perception of indoor air pollution severity by 0.790 points (approximately 20%)—nearly double the increase observed in Experiment 1. Unlike Experiment 1, these households also significantly updated their beliefs about outdoor air pollution, suggesting that the immediate visual feedback from monitors made pollution more salient across contexts. Most importantly, the perceived indoor-to-outdoor pollu-

[31] We removed the option "Indoor is more polluted than outdoor" in the Phase 2 survey as virtually no households chose this response in the Phase 1 survey.

tion ratio increased from 0.43 in the control group to 0.50 in the treatment group (a 16% increase), correcting the substantial underestimation of indoor pollution infiltration. Households also updated their health risk perceptions, becoming more likely to believe indoor air pollution poses health risks, though these estimates were not always statistically significant (Table A.15).

Despite these substantial belief corrections, we again find no effect on purifier WTP. Overall, even when information provision generates substantial belief updating about both pollution severity and health risks, it fails to translate into increased valuation of the solution. Importantly, as we discuss in Section 7, these belief shifts are unlikely to be driven by experimenter demand effects; indeed, once we shift beliefs about both pollution severity and purifier effectiveness, we observe a corresponding increase in objective measures of purifier use. This consistency across both experiments, despite different delivery methods and effect magnitudes, strongly suggests that correcting misperceptions about indoor air pollution and its health harms is insufficient to drive air purifier adoption.

6 Improving Beliefs about Purifier Effectiveness Does Not Increase Usage or WTP

Next, we estimate the impact of receiving an air purifier on opinion formation and perceptions of its effectiveness. We find that households that were provided with an air purifier are less uncertain about its effectiveness compared to households that were not provided with an air purifier. However, households rarely used them, even when we compensated them for the electricity costs of operating them.

Econometric specification. To assess the impact of receiving an air purifier, we estimate the following regression specification:

$$Y_i = \alpha + \beta_1 \times Monitor_i + \beta_2 \times Purifier_i + \beta_3 \times Monitor_i * Purifier_i + \beta_4 \times \mathbf{X}_i + \varepsilon_i \quad (3)$$

where Y_i represents the binary variables described below for household i at the time of the Phase 3 survey. The term $Purifier_i$ indicates whether a household was randomly selected to receive an air purifier about three months earlier during the Phase 2 survey, while $\mathbf{X}_i$ includes $MonitorXAttention_i$ and the interaction term between $MonitorXAttention_i$ and $Purifier_i$. We use heteroskedasticity robust standard errors.

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.

Results. We report these results in Panel A of Table 2. Figure A.13 presents the corresponding shift in the distribution of air purifier perceptions. We find that households provided with an air purifier in the Phase 2 survey are 28 percentage points more likely to have an opinion about air purifier effectiveness (Column 1). This represents a 74% increase in the likelihood of forming an opinion. Interestingly, we also find that households provided with a monitor in the Phase 1 survey are 11 percentage points (29%) more likely to form an opinion about air purifier effectiveness. However, having both the purifier and monitor does not further influence opinion formation.

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 (78%) more likely to perceive air purifiers as at least somewhat effective, 30 percentage points (107%) more likely to believe they are more than 25% effective, 27 percentage points (135%) more likely to think they are more than 50% effective, and 13 percentage points (162%) more likely to consider them more than 75% effective. Households provided with a monitor in the Phase 1 survey are also more likely to perceive air purifiers as effective, but the magnitude of the effect is substantially smaller than the effect of the purifier and there is no effect on the perception that air purifiers are more than 75% effective.[32] We find no evidence that having both the purifier and monitor significantly alters households' perceptions of air purifiers' effectiveness compared to households that only received an air purifier, with one exception: households provided with both an air purifier and a monitor are 10 percentage points (125%) more likely to perceive that air purifiers are more than 75% effective, although this result is not statistically significant at conventional levels (p-value = 0.16).

These findings raise the question of how purifier ownership alone is sufficient to improve effectiveness perceptions. Several mechanisms might explain this effect. Seeing the physical device and understanding how it works after interacting with it could build familiarity and trust. Households may also perceive a noticeable difference in air quality, experiencing reduced odors or easier breathing after running the purifier. Finally, examining the filter and observing accumulated dirt after the purifier has been used provides visible evidence of pollutant capture.

[32]It may be that because air monitors let households observe daily PM2.5 fluctuations from cooking, traffic, weather, and other sources, they somewhat shifted beliefs about how effective air purifiers can be. Or, because monitors corrected households' beliefs about the severity of indoor air pollution, households may have discussed with others or explored the effectiveness of air purifiers.

6.1 Experiment 2 provides complementary evidence using brief demonstrations

In Panel B of Table 2 we show the results from Experiment 2. The results are estimated using Equation 1 where Y_i represents household i's purifier effectiveness beliefs, we find that five-minute purifier demonstrations also increased certainty about effectiveness, though with weaker effects than prolonged ownership. Households observing demonstrations were 12 percentage points more likely to form an opinion about purifier effectiveness (a 22% increase), but less than half the 28 percentage point effect from three months of ownership in Experiment 1. This pattern persisted across the entire distribution of perceived effectiveness: all coefficients were roughly half those observed when households actually received free purifiers.

Our demonstrations showed selective updating that validates our research design. Purifier demonstrations altered beliefs about purifier effectiveness but not indoor pollution severity, while monitor demonstrations changed beliefs about pollution severity but not purifier effectiveness. This selective updating—where each device changed only its directly relevant beliefs—confirms that households processed distinct information about the problem (pollution severity) versus the solution (purifier effectiveness), rather than being primed on the importance of air quality.

This contrasts with the results from Experiment 1, where monitor ownership did increase beliefs about purifier effectiveness. Households in Experiment 2 only updated beliefs directly related to what they observed, providing cleaner identification of each device's informational effect.[33]

Importantly, despite successfully shifting effectiveness beliefs, we find no impact on WTP, as shown in Panel B of Table 1. Even when households understand that purifiers work, they do not value them enough to purchase. This null result parallels Experiment 1, where even households that owned purifiers for three months and updated their effectiveness beliefs rarely used the device. The consistency across both experiments—whether through extended ownership or brief demonstrations—reinforces that improving beliefs about purifier effectiveness alone is unlikely to overcome adoption barriers.

6.2 Households rarely use their air purifier

In Figure 6, the gray bars and line show purifier usage 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. The average usage in this group was 20 minutes per day (Figures 6a and 6b). Most households, on most days, do not use the air purifier at all, with 82% of household-days

[33]The difference likely stems from the longer exposure period in Experiment 1: over several months of owning air monitors, households could observe daily PM2.5 fluctuations from cooking, traffic, and weather patterns, and shifted beliefs about how effective air purifiers can be. This extended observation period may also have led them to discuss air quality solutions with others or research purifiers online.

seeing no air purifier usage (Figure 6c). At the household level, only 23% of households have an average usage of more than 27 minutes per day (Figure 6d).

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:

$$Use_{it} = \alpha + \beta_1 \times AnyCompensation_i + \beta_2 \times DailyCompensation_i + \tau_t + \varepsilon_{it} \quad (4)$$

where Use_{it} is the number of minutes household i used the purifier on date t, $Compensation_i$ signifies whether the household receives any compensation for the electricity cost, $DailyCompensation_i$ indicates daily compensation, and τ_t indicates date fixed effects. Standard errors are clustered at the household level.

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 Figure 6 and Table A.16. Electricity cost compensation does increase air purifier use, although the effects are not statistically significant (Columns 1 and 2). Monthly compensation increases purifier use by approximately 13 minutes per day, roughly 24% higher than households receiving no incentive (Column 2). Daily incentives further increase usage by 9 minutes compared to monthly payments, though the difference is not statistically significant.

When restricting our sample to households without monitors, we find a statistically significant 20-minute increase in daily purifier use for compensated households compared to uncompensated ones (Column 3). However, Figure 6b reveals that this increase is mostly concentrated in the first few weeks of purifier ownership.

Overall, while these results indicate that electricity costs and present-bias may contribute somewhat to low air purifier usage, the magnitude of the effect is small in absolute terms and not sustained over time.

7 Improving Beliefs about Both Indoor Air Quality and Purifier Effectiveness Generates Modest Usage and No Increase in Purifier WTP

In this section, we analyze how air pollution monitors affect air purifier use and purifier valuation. We find even when households understand both the problem (indoor air pollution) and the solution (purifier effectiveness), both usage and purifier valuation increase, but remains low.

Econometric specification. We estimate the following regression specification:

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

where Use_{it} indicates how many minutes household i used their air purifier during date t. τ_t indicates date fixed effects, while X_i includes $MonitorXAttention_i$. Standard errors are clustered at the household level.

Results. Table 3 and Figure 7a show that households with both monitors and purifiers used purifiers only 105 minutes daily on average, less than two hours in a 24-hour period (Column 1). While the 74-minute increase relative to households without monitors represents a large percentage change (234%), it remains small in absolute terms;[34] households breathe polluted indoor air for over 22 hours daily despite owning both monitoring and purification technology.[35] This minimal usage becomes even more striking when examined through a practical lens. Households with monitors used purifiers for at least 30 minutes on only 1.8 days per week, compared to just 1.1 days for those without monitors (Columns 2-3). Put differently, even households informed about both pollution levels and purifier effectiveness left their purifiers off for more than 5 days out of every 7.

Even the sustained usage patterns shown in Figure 7b represent households using purifiers just 7% of the time. 68% of days see zero purifier usage even among monitor households, rising to 78% for non-monitor households (Figure 7c). Figure 7d confirms this is not driven by a small subset of non-users; the household-level distribution shows that most households across both treatment arms average less than 81 minutes of daily usage throughout the study period.

These results reveal a fundamental challenge: even when households possess updated information about indoor pollution severity and purifier effectiveness, and own an air purifier, they choose breathe polluted air 93% of the time.

[34] Nonetheless, these effects on objective measures of purifier use suggest that the effects of monitor and purifier distribution on beliefs are not driven by experimenter demand effects.

[35] Although self-reported usage vastly overstates actual usage (Section 9.1), exceeding it by more than five-fold in the control group, the monitor's absolute effect remains consistent across both measures (Appendix D).

7.1 Small effects on purifier valuation despite information and experience

Even when households update their beliefs correctly about both the problem and solution, or directly experience the purifier and monitor together for almost three months, their WTP remains far below market prices.

Information fails to increase WTP. Using the data from Experiment 2 to estimate Equation 1 where Y_i represents household i's beliefs and WTP, we find households exposed to both devices separately (monitor first, then purifier) recognized both indoor pollution severity and purifier effectiveness, yet still showed no increase in WTP (Table 1, Panel B; Table 2, Panel B). The size of the effect for perceived purifier effectiveness was similar to that observed in households exposed only to a purifier. Similarly, the magnitude of the effects for indoor air pollution severity is largely similar to that observed in households exposed only to the monitor. The consistency of these magnitudes is reassuring, as these three groups of households didn't fundamentally observe anything different when exposed to either or both devices. However, despite recognizing both the problem (indoor pollution) and the solution (purifier effectiveness), these households did not demonstrate an increased WTP for air purifiers.

Moreover, as mentioned above, households exposed to a simultaneous demonstration of both devices observed a 44% average decline in PM2.5 levels from an average reading of 159 $\mu g/m^3$ before the purifier was turned on. Here, the size of the effect for perceived purifier effectiveness is larger than that observed in households exposed only to a purifier or than that for households exposed to both devices separately, but still smaller than that observed in Experiment 1. The magnitude of the effect for indoor pollution severity is largely similar to that observed in households exposed only to a monitor or for households exposed to both devices separately. However, despite the clear demonstration of effectiveness and their resulting recognition of both indoor pollution severity and purifier effectiveness, this group also showed no increase in WTP.

Extended ownership generates small valuation increases. We next examine whether three months of purifier and monitor ownership meaningfully impact purifier valuation using willingness to accept (WTA) data from Experiment 1's Phase 3 survey.

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 of Experiment 1, we estimate the regression Equation 2. We use the WTA to sell back the purifier—determined through a BDM mechanism—as the outcome variable.

Results. Table 3, Column 4 shows that monitors increase WTA by BDT 3,983, a 26% increase over the control mean of BDT 14,333, suggesting that experience with air purifiers increases their valuation. While this pushes the average valuation for households with both devices just above

the retail price of BDT 16,500, it would be misleading to conclude that experience alone would lead to adoption for two reasons.[36]

First, the endowment effect severely inflates these WTA figures. The baseline WTA of BDT 14,333 is ten times higher than the initial WTP of BDT 1,409, a gap consistent with well-documented loss aversion (Tunçel and Hammitt, 2014; Brown et al., 2024). This suggests the WTA increase at least partly reflects reluctance to give up an owned item.

Second, if we assumed the 26% increase applied to WTP, these households, who owned both monitors and purifiers for three months and used them most intensively (105 minutes daily), would still only pay BDT 1,764 (1,409 × 1.26), barely 11% of the retail price.

8 Purifier Households Observe Lower PM2.5 Levels But No Improvements In Health Outcomes

In this section we show that while air purifiers meaningfully reduce indoor pollution, these reductions do not translate into measurable health improvements. Households with purifiers experienced roughly 5.8 $\mu g/m^3$ lower indoor $PM_{2.5}$ levels, driven by evening and nighttime reductions of 8–11 $\mu g/m^3$, yet showed no detectable gains in respiratory or cardiovascular health, sleep quality, mental well-being, or labor outcomes.

8.1 Households with purifiers experienced PM2.5 reductions

Econometric specification. To test whether households provided a free purifier experienced lower indoor PM2.5, we use indoor PM2.5 readings from Experiment 1, collected by the randomly assigned monitors between the Phase 2 survey and April 1 (end of Phase 3). Because monitor and purifier use are complements; receiving a monitor increases purifier use, while receiving a purifier increases monitor use (Table A.17); monitor readings could be endogenously missing. To address this, we impute indoor PM2.5 when monitors are off by multiplying outdoor PM2.5 by the average indoor-outdoor ratio (1) observed in households without purifiers during this period.[37] This assumes purifiers are off whenever monitors are off, yielding conservative treatment effect estimates. We estimate the following regression specification:

$$Y_{ijt} = \alpha + \beta_1 \times Purifier_i + \tau_t + \varepsilon_{ijt} \tag{6}$$

where Y_{ijt} indicates either PM2.5 levels or the logarithm of PM2.5 values for household i on hour j of date t. τ_t indicates date fixed effects. Standard errors are clustered at the household

[36] Figure A.14 shows the WTA distributions between households with purifiers alone versus those with both devices.

[37] Restricting the sample to hours with observed indoor-monitor readings produces coefficients that closely match the main results in both level and log models, though with wider confidence intervals (Table A.18, Figure A.16).

level.

Results. We find that air purifiers lower daily-average PM2.5 by 5.8 $\mu g/m^3$ (5.2%) from a baseline of 112 $\mu g/m^3$ (Table 4). In the log specification, the same data imply a 14% reduction. Purifier efficiency declines on the dirtiest days (Talhelm, 2017); therefore the level regression, driven by high-pollution observations and divided by a large sample mean, delivers a muted 5.2% change. The log regression, which weights each day's proportional change equally, captures the larger percentage gains seen on cleaner days.

When we split the day into six four-hour windows, the biggest absolute gains appear in the late afternoon and evening—about 9–11 $\mu g/m^3$ between 4 p.m. and midnight—while midday effects are smaller. The log results echo this pattern, showing fairly uniform 10–16% drops across the day but peaking after 4 p.m. The larger evening gains may stem from behavior. After work, the household may switch the purifier on and keep it running while everyone is indoors, then power it down before sleep. Furthermore, windows tend to be closed in the cooler evening hours during winter, so less outdoor pollution leaks in, letting the purifier clean the air more effectively.

Reductions in PM2.5 become evident two weeks after the purifier's installation and remain sustained through the end of the study (week 12) (Figure A.15). The absolute (level) effects are stable over this period, whereas the log effects increase over time, consistent with improving ambient air quality as winter ends.

8.2 Households with purifiers did not observe any health benefits

Lastly, we examine health impacts after three months of purifier ownership. We estimate equation 3 where Y_i represents both objective health measures (e.g., blood pressure, blood oxygen) and self-reported outcomes (e.g., physical health, sleep quality, mental health, labor income, and labor supply) for household i at the time of the Phase 3 survey.

We detect no improvements in biomarkers related to respiratory health (lung capacity, breathing capacity, blood oxygen levels) or cardiovascular health (blood pressure) among households assigned a monitor, a purifier, or both (Table A.19). Furthermore, we find no evidence of reduced self-reported sick days, medical costs, or improvements in an aggregate health index combining all of the health indicators. Similarly, we observe no improvements across a broad set of self-reported illness symptoms, including cough, asthma, breathing problems, high blood pressure, and migraines (Table A.20). Finally, we also find no evidence of improvements in sleep, mental health, labor income, or labor supply (Tables A.21 and A.22).

This result contrasts with prior experimental work in public health and epidemiology (for a review, see EPA, 2018). Previous studies show that residential air purifiers typically decrease PM2.5 levels by around 50% and improve health outcomes, including reduced allergy and asthma symptoms (measured via peak expiratory flow, bronchial inflammation markers, self-reported

medication use and symptoms) and decreased cardiovascular morbidity (assessed via lung function, blood pressure, heart rate, and markers of inflammation and oxidative stress).

Several explanations may account for these differences. First, the length of time of exposure to cleaner air (less than three months) may be too short for health effects to manifest. However, this seems unlikely given that most prior studies use even shorter intervention periods (e.g., 1-2 days) and the non-experimental literature on the health effects of air pollution also finds effects after shorter exposures (e.g. Deryugina et al., 2019).

Second, health effects may concentrate among participants with pre-existing respiratory or cardiovascular conditions. Unlike most prior experimental studies with small samples (fewer than 30 participants) or participants selected based on pre-existing conditions, our sample is larger and drawn from the general population.

Third, the purifier use and the resulting average PM2.5 reductions may be insufficient to generate measurable health improvements for two complementary reasons. One, given extremely high baseline levels and potential non-linear dose-response effect (Apte et al., 2015; Miller, Molitor and Zou, 2025), our 5-14% average reduction in PM2.5 may not be large enough to improve health outcomes. Two, health improvements may require consistently large reductions in PM2.5 throughout the day, rather than uneven patterns with large decreases at certain times and smaller effects at others (Berkouwer and Dean, 2025).[38]

9 Estimating the Marginal Willingness To Pay for Clean Air

A recent experimental literature estimates marginal willingness to pay for clean air from purchase decisions or stated WTP for defensive technologies, inferring valuations from how demand responds to variation in pollution reduction. We show this "purchase-based" approach is fragile: it either assumes households will fully utilize the technology or utilize it as reported in surveys, and violations of these assumptions can change estimated MWTP by more than an order of magnitude. We propose an alternative "use-based" approach that combines high-frequency utilization data with randomized variation in operating costs to estimate MWTP directly from revealed usage behavior.

9.1 Purchase-based MWTP estimates

Simple conversions of device WTP into MWTP. The simplest purchase-based approach characterized MWTP for clean air as the ratio of WTP for a purifier and the marginal reduction in air

[38] EPA (2018) lists nine experimental studies with sample sizes above 30 and no selection based on pre-existing conditions, four are in developed countries with PM2.5 levels below 15 $\mu g/m^3$ (the WHO recommended 24-hour maximum), three are in developed countries with PM2.5 levels between 15 and 45 $\mu g/m^3$ and observed average reductions of 20–70%. The remaining two studies from urban China examined intervention periods of 2 days to 2 weeks and found average reductions of 60% in PM2.5 levels from baselines of 95 and 60 $\mu g/m^3$, respectively.

pollution:

$$\text{MWTP}^{\text{clean air}} = \frac{WTP^{\text{air purifier}}}{\Delta PM2.5^{\text{air purifier}}} \tag{7}$$

Table 5 demonstrates how different assumptions about $\text{WTP}^{\text{air purifier}}$ and $\Delta\text{PM2.5}^{\text{air purifier}}$ can alter this calculation by more than an order of magnitude. We measure $\text{WTP}^{\text{air purifier}}$ using the BDM procedure, while $\Delta\text{PM2.5}^{\text{air purifier}}$ is calculated as:

$$\Delta\text{PM2.5}^{\text{air purifier}} = \text{PM2.5} \times \text{Purifier Effectiveness} \times \text{Purifier Usage} \tag{8}$$

In row (1), we base our assumptions on those made in the seminal paper by Ito and Zhang (2020) when possible. First, households are fully aware of indoor air pollution levels. Second, households expect to use the purifier continuously and remain in the same room as the device. Third, the HEPA purifier removes virtually all particulate matter.[39] Together, these assumptions yield an expected 110 $\mu\text{g}/\text{m}^3$ reduction in PM2.5 exposure. Throughout our calculations, we assume that air purifiers can only be used during the winter season and that the purifier lasts one season (3 months).[40] This assumption is realistic if few households purchase replacement filters, likely because their WTP for the purifier is typically below the cost of a replacement filter. Using the average WTP from Phase 2 of Experiment 1, this yields an MWTP for a 1 $\mu\text{g}/\text{m}^3$ reduction in PM2.5 air pollution of USD 0.11 per season.[41]

These conversions are very sensitive to assumptions about use. In Row (2), we show the estimated MWTP using the stated indoor pollution beliefs and purifier effectiveness beliefs from Experiment 1. These beliefs are theoretically the most relevant for MWTP estimation, as they reflect household beliefs at the time of the BDM exercise when revealing their WTP. For indoor pollution beliefs, we multiply actual outdoor pollution levels by the average belief about the indoor-outdoor pollution ratio. For purifier effectiveness beliefs, we use the average response from Phase 3 survey participants who were not given a purifier regarding how effectively they believe the purifier removes air pollution from the room where it is placed.[42] However, we continue to assume that households expect to use the purifier continuously and remain in the same room as the device. These assumptions yield an MWTP for clean air of USD 0.27 per winter season, almost three times higher than the estimate generated by the previous set of assumptions.

[39] This is based on the manufacturer's classification of the filtration for the air that passes through the filter. However, as shown by our results, this is not a reasonable expectation even for the air in the room in which the purifier is used, as the room is not perfectly sealed and air pollution continuously enters the room.

[40] Ito and Zhang (2020) assumes that the purifier lasts for five years; if such an assumption were applied to our calculations, corresponding to 5 seasons of relevant use, it would reduce our MWTP estimates by 80%.

[41] Following Ito and Zhang (2020), we do not include the cost of electricity, but given the very low electricity costs, this would not make a significant difference if included.

[42] This question was not asked in the Phase 2 survey, but the average answer was similar in the Experiment 2 survey, suggesting that the Phase 3 perceptions in the control group are similar to the Phase 2 perceptions among all Experiment 1 participants.

In Row (3), we make only one change: for expected use, we take the average response from the Phase 2 survey regarding how often households believe they would use a purifier, converting categorical responses to time percentages (as described below). This yields an MWTP for clean air of USD 0.7 per winter season, more than two times higher than the previous estimate. In Row (4), we maintain all assumptions from Row (3) but replace the expected usage from the Phase 2 survey with stated ex-post usage from the Phase 3 survey. Since this usage is lower than the Phase 2 expected usage, it produces a higher estimated MWTP (USD 0.9 per winter season). However, the substantial difference emerges when we substitute actual usage for stated usage in the formula. Given that households used the purifier only 5% of the time on average, Row (5) shows this increases the MWTP to USD 6 per winter season, six- to eightfold more than when using the stated expected or historical usage. This suggests that, paradoxically, if households purchase technology but rarely use it, standard models will yield a much higher value of clean air, and consequently, the welfare loss of pollution. This exercise highlights a fundamental problem with estimating MWTP for environmental amenities using WTP for defensive technologies: it relies on strong, often unverified assumptions about utilization.

Self-reported vs. actual use. To measure self-reported purifier use, we asked households how often they used an air purifier, with response options ranging from "all the time when home" to "never".[43] For the MWTP calculations discussed above, we convert these seven response options into percentages of time that the purifier was used.[44] Figure 8 shows the distributions of ex-ante predicted use, ex-post self-reported use, and actual use (as measured by the smart sockets). Panel (a) shows that before receiving the purifier, the modal household in the Phase 2 survey stated that they expected to use the purifier "all the time when home." Panel (b) shows that after having owned a purifier for 2 to 3 months, self-reported use is lower than the ex-ante predicted use, but still relatively high. 30% of households state that they use the purifier "all the time when home" and 50% state they use the purifier "at least once per day." However, Panel (c) shows that actual use is much lower than self-reported use when compared using the percentage conversion described above. Almost no household used the purifier "all the time when home" or "at least once per day." If this discrepancy stems from experimenter demand effects, it also undermines the reliability of stated future use expectations provided in Phase 2. That is, households may not have actually expected to use the purifier as much as they claimed. As Rows (2)-(5) demonstrate, the choice of usage expectation has substantial consequences for MWTP estimates.

[43] The response options were (a) all the time when home, (b) at least once per day, (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.

[44] "All the time when home" is assumed to mean 50% of the time; "At least once per day," 25% of the time; "A few times per week," 10% of the time; "Once per week," 5% of the time; "Once per month," 1% of the time; "Very rarely," 0.5% of the time; and "Never," 0% of the time.

Conversions based on actual decrease in pollution. In Row (6), we move away from stated or assumed expectations of $\Delta \text{PM2.5}^{\text{air purifier}}$ and instead use the actual decrease in PM2.5 exposure as measured by air pollution monitors in households with both purifiers and monitors. The estimate comes from Column (1) of Table 4, Panel A. Using the actual decrease in PM2.5 is advantageous because, assuming households only run the purifier when present in the room, it provides a direct estimate of the reduction in air pollution exposure for the household decision maker.[45] This approach eliminates the need to make assumptions about the share of time household members spend in the room with the air purifier. This yields an MWTP for a 1 $\mu\text{g}/\text{m}^3$ improvement of USD 1.9 per winter season.

WTA-based MWTP estimate. The policy-relevant figure for understanding air purifier adoption is clearly WTP, as opposed to the WTA to sell back the purifier, since households must first purchase a purifier before they can own it and potentially sell it back. However, households may have had difficulty estimating the purifier's effectiveness before using it. By the Phase 3 survey, those with both purifiers and monitors should have been best positioned to form well-founded beliefs about $\Delta \text{PM2.5}^{\text{air purifier}}$ by the Phase 3 survey.[46] It is therefore natural to use the actual effect of the purifier on PM2.5 together with the WTA to sell back the purifier at the time of the Phase 3 survey to calculate the implied MWTP for clean air. In Row (7), we show the estimated MWTP using the average WTA valuation together with the actual decrease in air pollution exposure. As noted in Section 7.1, the WTA to sell among households already owning a purifier is approximately 10 times higher than the WTP among households not owning one, yielding an estimated MWTP for a 1 $\mu\text{g}/\text{m}^3$ improvement of USD 26 per winter season.

WTP-based MWTP estimates. In Appendix E, we also estimate MWTP from Experiment 2 WTP data by instrumenting perceived pollution reduction with randomized treatment assignment. Although these estimates are imprecise, the more fundamental point is that they vary far more widely than the use-based estimates presented below, from negligible under full usage to substantially higher under observed 5% usage (USD 0.02 to 0.55 per $\mu\text{g}/\text{m}^3$ per season), reinforcing that purchase-based approaches produce fragile MWTP estimates.

[45] To keep the calculation as parsimonious as possible, we consider the household to be a unitary decision maker, and abstract away from any intrahousehold bargaining concerns.

[46] Hanemann (1991) shows that WTP and WTA can differ substantially, even among households without behavioral biases and with full information. However, such differences are only realistic for goods without close substitutes. While clean air itself is a public good without substitutes, an air purifier is a private good with many available alternatives. In fact, households in our experiments could easily purchase the identical model we offered from stores in Dhaka. Therefore, it is likely that the difference between WTP and WTA is driven by behavioral biases or changes in beliefs.

9.2 Usage-based MWTP estimates

In this section, we use an ordinary least squares (OLS) model to estimate the sensitivity of households' purifier use to both the potential air pollution reduction from running the purifier and its monetary cost. We estimate the following OLS specification:

$$\text{Use}_{it} = \beta_0 + \beta_{PM} \cdot \text{Potential PM2.5 Improvement}_{it} + \beta_c \cdot \text{Cost}_{it} + \alpha_i + \delta_t + \gamma_h + \epsilon_{it} \tag{9}$$

where Use_{it} is the share of hour t that household i operated the purifier; Potential PM2.5 Improvement$_{it}$ is the expected reduction in indoor PM2.5 from running the purifier during hour t; Cost_{it} is the net hourly cost of operating the purifier (in BDT); α_i denotes household fixed effects (to capture household-specific time-invariant unobservables); δ_t denotes date fixed effects (to capture date-specific shocks); and γ_h denotes hour-of-day fixed effects (to capture routine or convenience by clock time). Standard errors are clustered at the household level.

By taking the ratio of the coefficient on potential air pollution reduction (marginal utility of clean air) to the negative coefficient on cost of use (marginal utility of money), we obtain the estimated MWTP for a 1 $\mu\text{g}/\text{m}^3$ reduction in air pollution per hour in BDT:

$$\widehat{\text{MWTP}} = -\frac{\hat{\beta}_{PM}}{\hat{\beta}_c} \tag{10}$$

We then convert this hourly MWTP to seasonal and annual estimates by multiplying by the number of hours in a winter season and year, respectively, and applying the USD/BDT exchange rate.

This approach prices the *flow* value of clean air directly: randomized price shifts combined with exogenous variation in potential indoor PM2.5 reductions identify a MWTP that avoids assumptions about households' expectations regarding future use and does not rely on WTP/WTA values elicited through BDM procedures.

We leverage experimental variation in Cost_{it} from two sources. Before April 1, every household was randomly assigned to one of two groups for the entire pre–April 1 period: (i) a non-reimbursed group that paid the electricity cost to run the purifier (BDT 0.24 per hour), or (ii) a reimbursed group whose electricity cost was covered, allowing households to run the purifier at no monetary cost. After April 1, the same households were re-randomized into one of three per-hour use-incentive arms for all days after April 1: BDT 0, BDT 5, or BDT 10 per hour of purifier use. These incentives directly reduce the out-of-pocket cost of running the device by the incentive amount, making the net cost negative for households receiving incentives.[47]

This timing creates within-household changes in the hourly cost of use, even though each household's assignment is fixed within each phase. Concretely, for a given household i, the price it faces in hour t is the baseline electricity cost (BDT 0.24/hr) minus any electricity reimbursement

[47] In Appendix F we show that the BDT 5 incentive increased usage by 82 minutes per day, comparable to providing a pollution monitor. Doubling the payment to BDT 10 per hour increased use by an additional 60 minutes.

it was assigned before April 1, and minus any per-hour incentive it was assigned after April 1. Because the study switches from the "reimbursement/no-reimbursement" regime to the "0/5/10 incentive" regime on a fixed date for everyone, the same household experiences a clear change in the marginal price of running the purifier at April 1.

Because the reimbursement regime ends and the per-hour incentive regime begins on the same date for all households, one might worry that seasonality around April 1 could contaminate the estimated cost sensitivity. Our specification includes date fixed effects, so any shocks common to all households on a given day, including seasonal changes and aggregate time trends in usage, are absorbed. Identification therefore comes from within-household changes in the net hourly price induced by randomized assignment (reimbursement vs. no reimbursement before April 1; 0/5/10 incentives after April 1), net of common day shocks captured by date fixed effects.

To calculate hour-by-hour changes in potential PM2.5 reductions, we must make assumptions about purifier effectiveness. Our baseline effectiveness assumption is that the purifier reduces PM2.5 by 80% (based on controlled experimental conditions). We calculate the potential PM2.5 improvement by multiplying this 80% effectiveness rate by outdoor air pollution levels adjusted for the average indoor-outdoor pollution ratio.[48] Thus, hour-to-hour variation in outdoor air pollution generates variation in the potential PM2.5 improvement from purifier use.

Variation in outdoor air pollution is driven by meteorological factors and regional emissions patterns that are exogenous to individual household decisions. Households cannot anticipate hour-to-hour fluctuations in outdoor PM2.5, nor can they influence ambient pollution levels through their own behavior. Consistent with this, 87% of households reported during the Phase 1 survey that they never or rarely check outdoor air pollution levels. The identifying variation for our baseline estimates thus comes from comparing how the same household responds to high- versus low-pollution hours, conditional on time-of-day routines and common daily shocks. Estimates are essentially unchanged when we remove date fixed effects, suggesting households do not anticipate daily pollution levels and adjust usage accordingly.

A separate interpretive concern is that our Potential PM2.5 Improvement measure varies with ambient PM2.5, while most households report rarely checking outdoor pollution levels. Two points mitigate this concern. First, ambient PM2.5 is used as a high-frequency proxy for the underlying indoor pollution state that households experience (through infiltration), so higher ambient pollution corresponds to hours in which running the purifier would deliver larger indoor exposure reductions. Second, our valuation sample consists of monitor-equipped households, and we show that receiving a monitor increases perceived indoor air pollution relative to households without monitors. Moreover, an additional attention-to-monitor treatment does not further increase perceived indoor air pollution beyond the effect of monitor provision itself, suggesting that the monitor treatment already shifts beliefs as much as incremental attention interventions

[48] We assume linear effects of outdoor air pollution on purifier effectiveness, consistent with real-world patterns observed in Table A.25 and Figure A.17.

do. Taken together, these results support interpreting Potential PM2.5 Improvement as capturing meaningful variation in the perceived (and experienced) pollution state in our monitor sample. Consistent with this proxy interpretation, and as discussed before, indoor PM2.5 measured by the monitors closely tracks ambient PM2.5 in our setting.

A related concern is that outdoor pollution may correlate with other determinants of purifier use, such as weather or occupancy. The experiment was conducted during dry winter months, when weather conditions in Dhaka to not tend to change drastically from one hour to the next as there is very little rain. Moreover, hour-of-day and date fixed effects absorb routine occupancy patterns and daily weather variation. The remaining identifying variation, within-day deviations from typical pollution levels, is unlikely to systematically associated with unobserved behavioral changes that may be correlated with air purifier use. Importantly, when we estimate MWTP for periods when household members are most likely home and awake (6 PM to midnight), the results closely match our main estimates, suggesting occupancy is not driving our findings.

Results. Assuming the purifier reduces air pollution by 80%, the estimated MWTP is USD 0.07 per season and USD 0.30 per year for households with monitors (Column (1) of Table 6). However, the MWTP estimate is not statistically distinguishable from zero (p-value = 0.23). Moreover, we can rule out MWTP values larger than USD 0.78 per year with 95% confidence.

In Column (1) we assume air pollution returns to baseline immediately when the purifier is turned off. While this assumption provides transparency and simplicity, it contradicts the actual dynamics of purifier operation shown in Figure 5a, where pollution levels adjust gradually rather than instantaneously. After activation, air pollution declines linearly for 30 minutes, then stabilizes at approximately 20% of counterfactual levels until the purifier is turned off. Following deactivation, pollution gradually returns to baseline over four hours along a roughly linear trajectory. Consequently, the total effect of running the purifier depends on usage duration.

Figure A.18a simulates the effect for a 108-minute session (the average duration in our data), yielding an effectiveness of 158% per minute of operation. This exceeds 100% because the purifier continues reducing pollution even after being turned off. Figure A.18b presents the simulation for a 23-minute session (the median duration), resulting in 276% effectiveness. We use these duration-specific effectiveness measures to estimate MWTP in Columns (2) and (3) of Table 6.

The resulting annual MWTP estimates in Columns (2)-(3) of Table 6 are USD 0.12 and 0.07, respectively, and are not statistically significant. We can reject with 95% confidence that the annual MWTP exceeds USD 0.32 and 0.18 for these specifications, respectively.

Finally, Column (4) uses each household's stated belief about purifier effectiveness from the Phase 3 survey.[49] This specification yields a tiny negative association between perceived potential PM2.5 improvement and usage, resulting in a negative MWTP estimate that is not statistically different from zero, with an upper bound of the 95% confidence level at USD 1.40 per year.

[49] For households responding "I don't know," we impute the average belief among households with a purifier.

Robustness. Appendix Table A.26 shows that point estimates are very similar with or without fixed effects. This is consistent with our design: price is randomized within households and hour-to-hour variation in PM2.5 exposure is plausibly orthogonal to time-invariant household burdens (e.g., a home's constant disutility from running the purifier), so in a linear model omitting those burdens only shifts the intercept, not the slopes. Indeed, sequentially adding hour-of-day, household, and date fixed effects does not materially change the MWTP point estimates; it primarily tightens standard errors and improves precision.

We also show that the estimated MWTP is wrong-signed, small, and statistically indistinguishable from zero for households without monitors. This is unsurprising: without real-time pollution information, these households cannot respond to hour-to-hour variation in air quality, making it impossible to identify their valuation of clean air from usage patterns.

Importantly, when we estimate MWTP for periods when household members are most likely home and awake, 6 PM to midnight, the results closely match our main estimates: 0 to USD 0.68 per $\mu g/m^3$ per year (p-value < 0.05) (Table 7). This pattern is reassuring: it suggests that our low MWTP is not primarily driven by households being away from home during the day and thus unable to respond to within-day variation in PM2.5.

While daily usage is often zero, our MWTP is identified from randomized variation in the hourly net cost of running the purifier and plausibly exogenous variation in potential pollution reduction, and thus speaks to the marginal value of additional runtime among households at the margin of adjusting use. To address the corner-solution nature of usage directly, we also re-estimate MWTP using an extensive-margin specification for whether the purifier is on in a given hour; the implied MWTP is similar (Table A.27). Finally, we estimate a fractional logit model (described in Appendix G). These estimates are quantitatively similar to our OLS estimates.

External validity. A potential concern is that, because households received the purifier for free, the usage-based MWTP we recover from operating decisions may differ from what we would estimate in a market setting. In particular, if households had to purchase the purifier, owners/users would likely be positively selected on underlying demand, and their marginal willingness to pay for cleaner air could exceed what we estimate in a sample where everyone receives a purifier. We address this concern in three ways. First, our sample already consists of households with ex ante interest in acquiring an air purifier: during recruitment, 58% of households expressed interest in an air purifier. Second, if the goal is to characterize a representative MWTP, conditioning on market purchase would yield an even more selected sample than ours and would therefore move further away from population-representative valuation. Third, prior work in development economics finds that prices primarily affect take-up through selection, with limited evidence that paying more increases subsequent usage through sunk-cost motives (e.g., Ashraf, Berry and Shapiro (2010) on chlorine; Cohen and Dupas (2010) on bed nets).

To directly assess the selection channel in our setting, we estimate MWTP separately by pre-treatment stated demand for a purifier (Phase 2 WTP), which was elicited before any household

had used the purifier (Table A.28 and A.29). In a market setting, Phase 2 WTP is a natural proxy for households more likely to purchase absent free provision. We find that households with above-median baseline WTP exhibit a higher usage-based MWTP, consistent with meaningful heterogeneity and suggesting that stated demand is a valid proxy for market selection. Importantly, however, even in this higher-demand subgroup, the estimated MWTP remains very low in absolute terms (USD 0.62 per $\mu g/m^3$ per year with p-value $= 0.21$), suggesting that valuation of clean air is low even among higher-demand households.[50]

Overall, this approach analyzes hour-to-hour usage decisions by households with extended purifier experience who can directly observe indoor air quality and purifier effectiveness through monitors. Unlike purchase-based estimates, which require assumptions about perceived air quality, perceived effectiveness, expected usage, and whether to measure WTP or WTA, our approach yields much more stable estimates. When we vary purifier effectiveness assumptions over reasonable values, our usage-based estimates range narrowly from 0 to 0.07 per $\mu g/m^3$ per season, compared to 0.11 to 26 per $\mu g/m^3$ per season using simple purchase-based conversions (or 0.27 to 6 per $\mu g/m^3$ per season when only varying assumptions about use) and 0.02 to 0.55 per $\mu g/m^3$ per season using the estimates derived from WTP sensitivity to beliefs. Overall, our evidence indicates that MWTP for clean air is close to zero.

Comparison of our MWTP estimates to the literature. While our MWTP estimate is lower than previous studies, the key distinction is that it is tightly bounded, whereas purchase-based estimates can vary by more than an order of magnitude depending on usage assumptions (Table 8). After adjusting our baseline estimate (USD 0.3 per $\mu g/m^3$ per year) for PPP, inflation, and household size for comparability, we find MWTP of \$1.1 per $\mu g/m^3$ per year (2023 PPP-adjusted USD), compared to \$5.9 from Ito and Zhang (2020) (China) and \$3.1 from Baylis et al. (2023) (India). This gap cannot be explained by income: if anything, our households earn at least \$24,122 annually, over double the \$11,804 in the China sample and \$9,454 in the India sample.

The discrepancy grows slightly when we assume similar technology effectiveness for comparability. Ito and Zhang (2020) assume 100% purifier effectiveness; assuming our effectiveness rate (80%) would inflate their MWTP to \$7.4.[51] Importantly, the discrepancy grows significantly with different usage assumptions. Ito and Zhang (2020) assume 100% usage; applying our reported expected usage rates would inflate their MWTP to \$19. If we were to apply our actual usage rates, it would further inflate their MWTP to \$149. Baylis et al. (2023) rely on self-reported usage as a proxy for expected usage; correcting for the overreporting we document for self-reported usage in our context would push their estimate to \$19.

[50] Our usage-based MWTP is identified from randomized variation in the hourly net cost of running the purifier and plausibly exogenous variation in potential pollution reduction, rather than from the one-time purchase decision. Low average usage therefore does not mechanically imply low MWTP.

[51] Baylis et al. (2023) assume 90% effectiveness for face masks based on empirical studies, so no adjustment is needed.

Our MWTP estimates are also smaller than those from a high-income U.S. context. Tarduno and Walker (2025) report an MWTP of \$2.7 per $\mu g/m^3$ per year (household income \$65,000) under an implicit 100% runtime assumption. If we rescale their figure using our sample's stated expected runtime, the implied MWTP rises to \$6.7; using our observed actual runtime, it rises further to \$54.

Overall, these adjustments further underscore how purchase-based estimates hinge on usage assumptions, and lower expected usage assumptions paradoxically inflate MWTP estimates.

10 Conclusion

In this paper, we demonstrate that standard approaches for valuing non-market amenities like clean air through defensive expenditures are methodologically fragile. These approaches infer the value of clean air from purchase decisions for durable goods like air purifiers and face masks, relying on unverified assumptions about expected usage. We show that varying these assumptions changes MWTP estimates by an order of magnitude, that self-reported usage is an unreliable proxy for actual use, and that, counterintuitively, lower assumed usage yields higher implied MWTP estimates.

To address this fragility, we develop a novel approach that prices the flow value of clean air directly. By leveraging objective, high-frequency data on device use, identified through randomized price variation rather than binary purchase decisions or willingness to pay elicitation, we avoid the need for assumptions about expected usage. Given the falling cost of smart sockets and sensors, this approach can be readily adapted to value other non-market amenities through observed use of defensive technologies such as water purifiers, cold storage units, air conditioners, and electric cookstoves (Simons et al., 2018).

Applying this use-based revealed-preference method in Dhaka, Bangladesh, yields a MWTP estimate for clean air that is lower and much more tightly bounded than previous estimates that rely on usage assumptions. This result is not driven by liquidity constraints, misperceptions about pollution severity or technology effectiveness, or disutility of device operation.

Why is private valuation of a critical health amenity so low? One explanation is that the primary benefits of cleaner air, mortality reductions, are realized only in the distant future and are therefore heavily discounted. This hypothesis is supported by contrasting our results with recent evidence from Bangladeshi manufacturing firms, where cleaner air translates into immediate, high-value productivity gains (Garg, Jagnani and Lozano-Gracia, 2025). In that context, the estimated MWTP is USD 15 per $\mu g/m^3$ per year (2023 PPP-adjusted), more than an order of magnitude higher than the residential valuation we find in this paper. Future research should rigorously test the disconnect between immediate and delayed returns to better understand the determinants of environmental demand in developing countries.

A second possibility involves households' perceptions of the dose-response relationship be-

tween air pollution and health. Households may believe that purifying air in only one setting (the home) is insufficient to improve overall health outcomes, given the toxicity of the outdoor and work environments. This skepticism that a partial defense yields meaningful returns effectively lowers the expected benefit of adoption. Future research should rigorously map this dose-response relationship, especially at the extreme levels found in cities such as Dhaka, and evaluate the health benefits of temporary but regular reductions in exposure. Once a clear scientific consensus on these relationships emerges, future work can test whether updating households' beliefs to reflect this consensus generates higher adoption.

A third possibility involves rational inattention and the cognitive tax required to consistently use a defensive technology. Sustained usage requires overriding deeply ingrained energy-saving heuristics in South Asia, where historical grid instability and price sensitivity have conditioned households to turn off appliances immediately upon vacating a room (Wilhite, 2008). In contexts where cognitive bandwidth is a strictly constrained resource (Mullainathan and Shafir, 2013), households may exercise rational inattention, efficiently choosing not to allocate their limited mental bandwidth to overriding standard appliance norms for the sake of pollution monitoring. The fact that usage remains modest even under electricity compensation and physically optimal winter conditions isolates the pure behavioral cost of adherence. Future research should quantify the magnitude of this cognitive tax.

Finally, our results imply that standard policy tools, such as subsidies or information campaigns, are unlikely to drive widespread household adoption of defensive technologies. Instead, our results point toward interventions that reduce exposure without requiring sustained household action: filtration in public settings like schools, childcare centers, health clinics, and buildings with centralized ventilation, as well as upstream regulatory measures that address pollution at the source.

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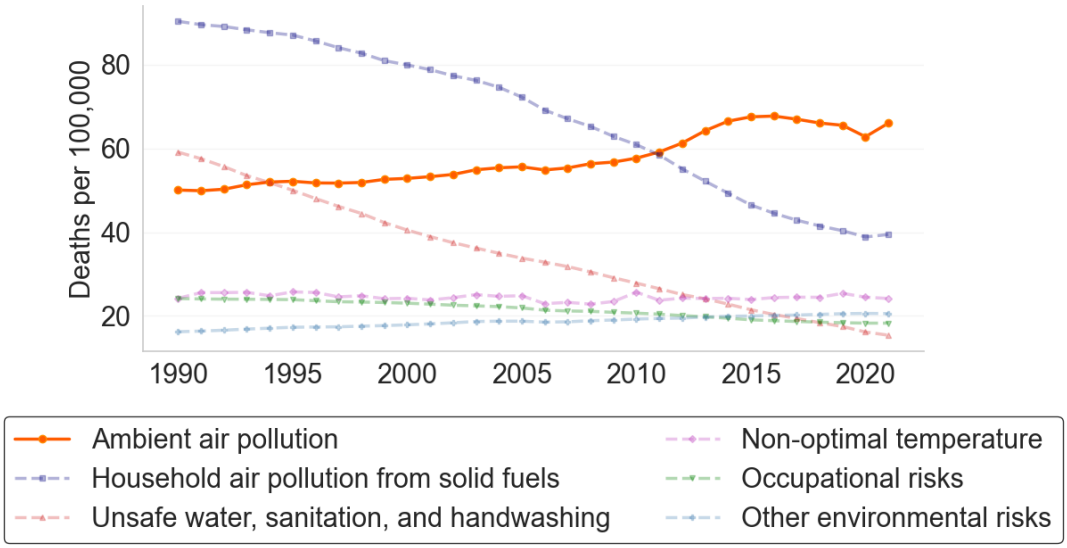
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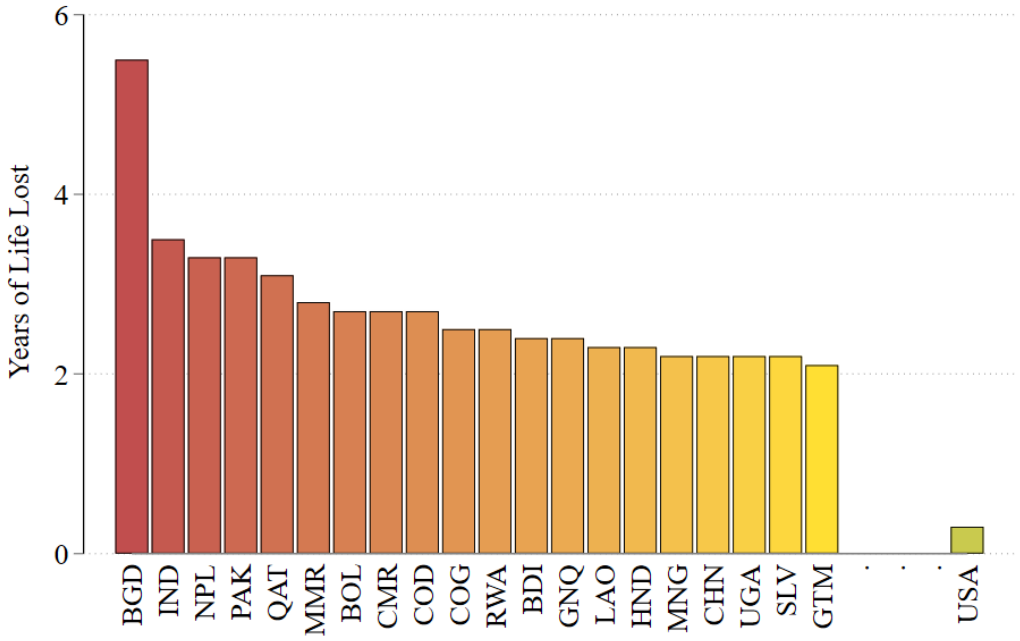
Figures

Figure 1: Mortality Impacts of Different Environmental Stressors



Notes: This figure shows estimates from GBD (2026) of the deaths caused by air pollution globally, compared to other environmental factors. See discussion in Section 1.

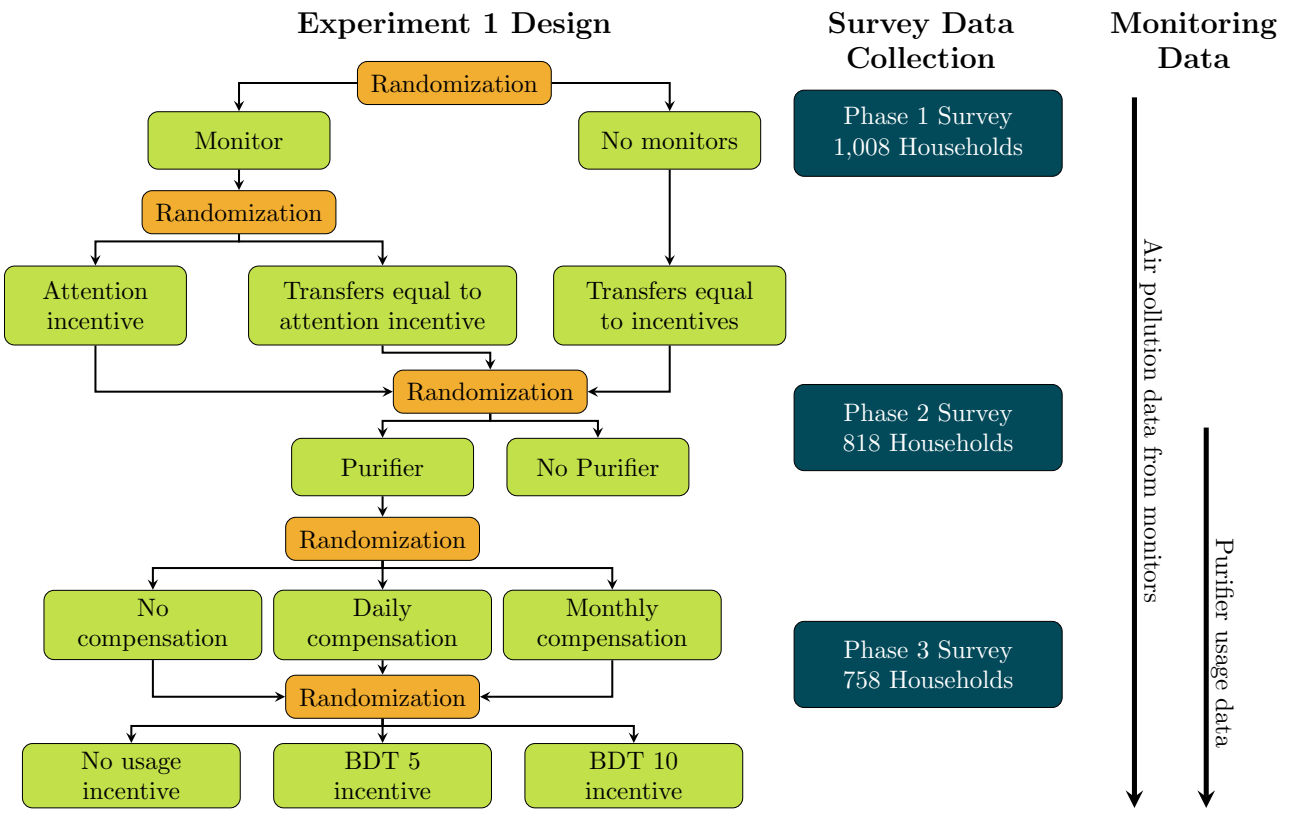
Figure 2: Years of Life Lost in Bangladesh



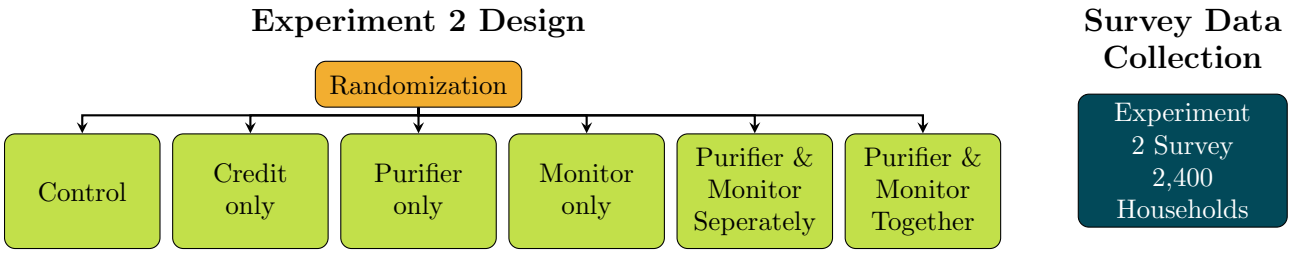
Notes: This figure shows estimates from AQLI (2025) of the life years lost due to air pollution across the top 20 countries and the USA. See discussion in Section 1.

Figure 3: Flowchart of Research Design

(a) Experiment 1



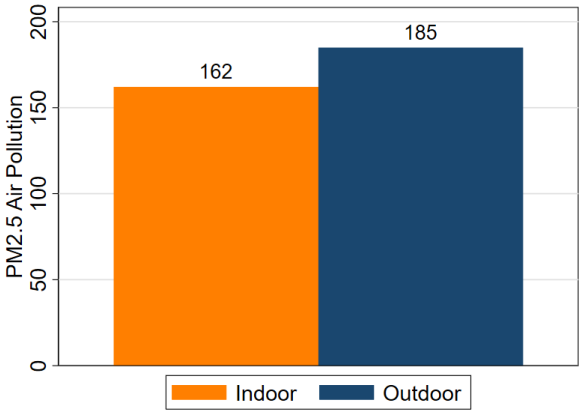
(b) Experiment 2



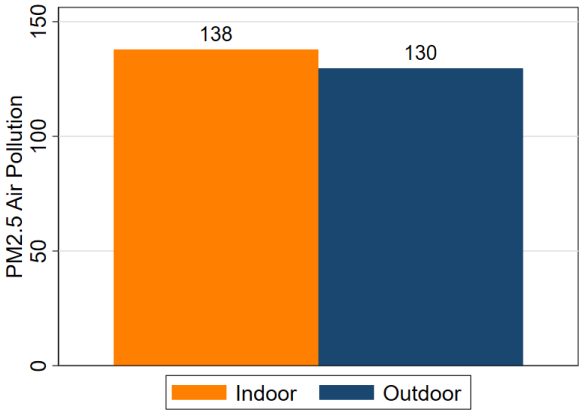
Notes: This figure shows the research design and data collection for Experiment 1 and Experiment 2. The Experiment 1 Phase 1 survey started on 12 November 2023 and concluded on 30 November 2023. The Experiment 1 Phase 2 survey started on 5 January 2024 and concluded on 12 March 2024. The Experiment 1 Phase 3 survey started on 23 February 2024 and concluded on 20 April 2024. Experiment 2 started on 19 November 2024 and concluded on 22 January 2025. See discussion in Section 2.2.

Figure 4: Indoor vs. Outdoor Air Pollution: Reality and Perceptions in Experiments 1 and 2

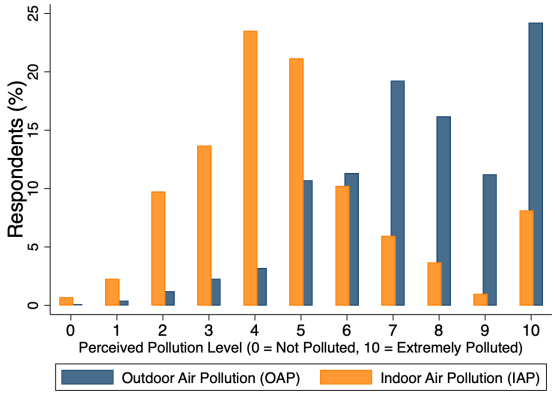
(a) Indoor vs. outdoor pollution (Exp. 1)



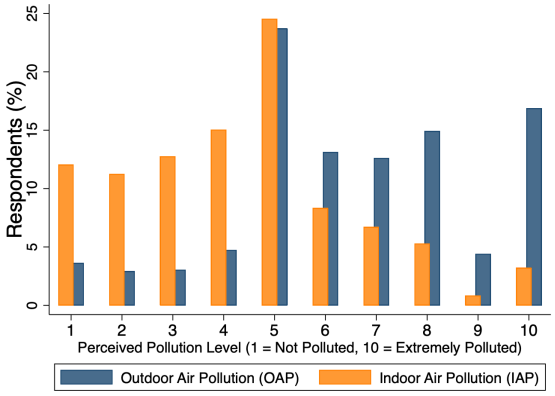
(b) Indoor vs. outdoor pollution (Exp. 2)



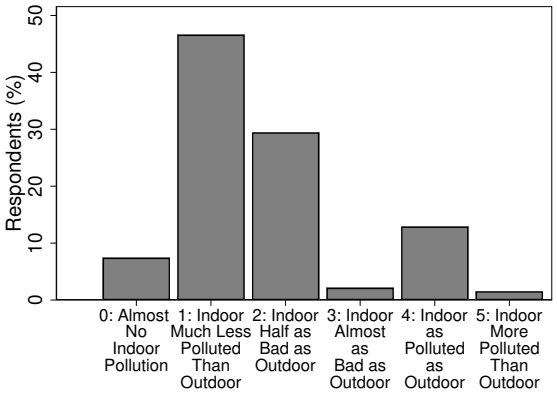
(c) Air pollution beliefs (Exp. 1)



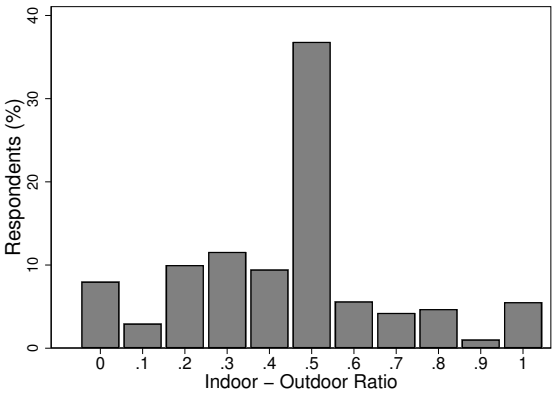
(d) Air pollution beliefs (Exp. 2)



(e) Indoor-outdoor ratio beliefs (Exp. 1)



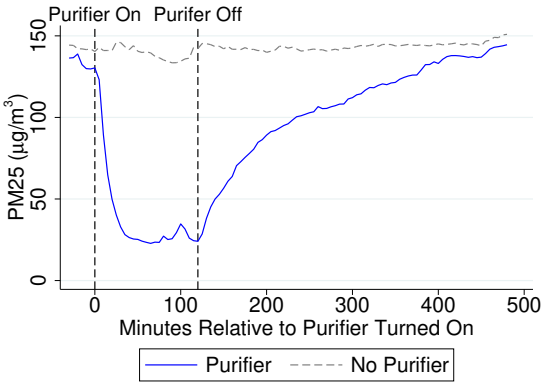
(f) Indoor-outdoor ratio beliefs (Exp. 2)



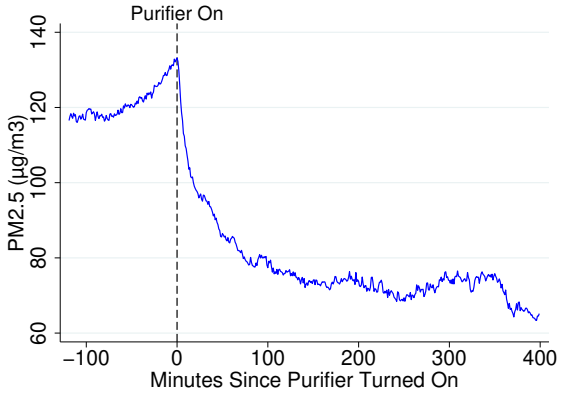
Notes: Panels (a)–(b) show average indoor and outdoor $PM_{2.5}$ concentrations (in $\mu g/m^3$) measured by monitors. Panels (c)–(d) display household beliefs about the severity of indoor and outdoor pollution. Panels (e)–(f) show household beliefs about the relative severity of indoor versus outdoor pollution (the indoor–outdoor ratio). Left column (a, c, e) corresponds to Experiment 1 (Phase 1 survey); right column (b, d, f) corresponds to Experiment 2. For Experiment 1, air quality averages are between Phase 1 and Phase 2 surveys; for Experiment 2, indoor and outdoor monitor data were matched to the survey hour. See discussion in Section 3.1.

Figure 5: Air Purifier Effectiveness: Actual Effects vs. Perceptions

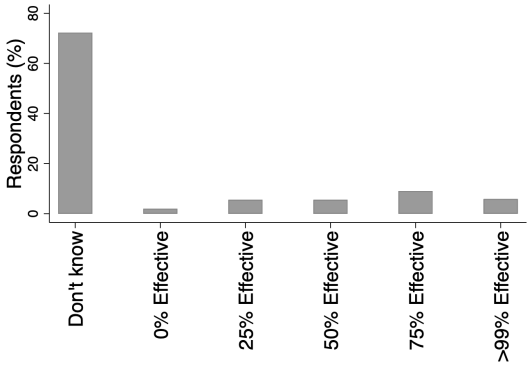
(a) Purifier Effectiveness: Controlled Conditions



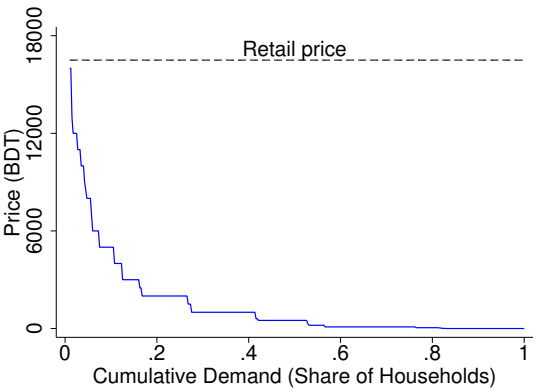
(b) Purifier Effectiveness: Households Provided Free Purifier



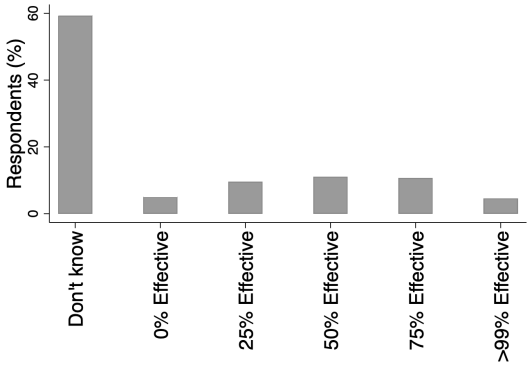
(c) Purifier Effectiveness Perceptions (Experiment 1, Phase 3, Control Only)



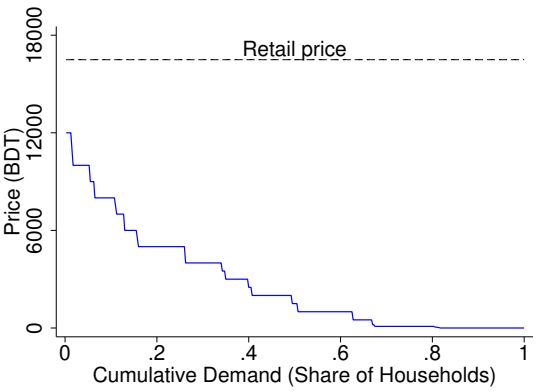
(d) Demand for Purifiers (Experiment 1, Phase 2, No Monitor)



(e) Purifier Effectiveness Perceptions (Experiment 2, Baseline)

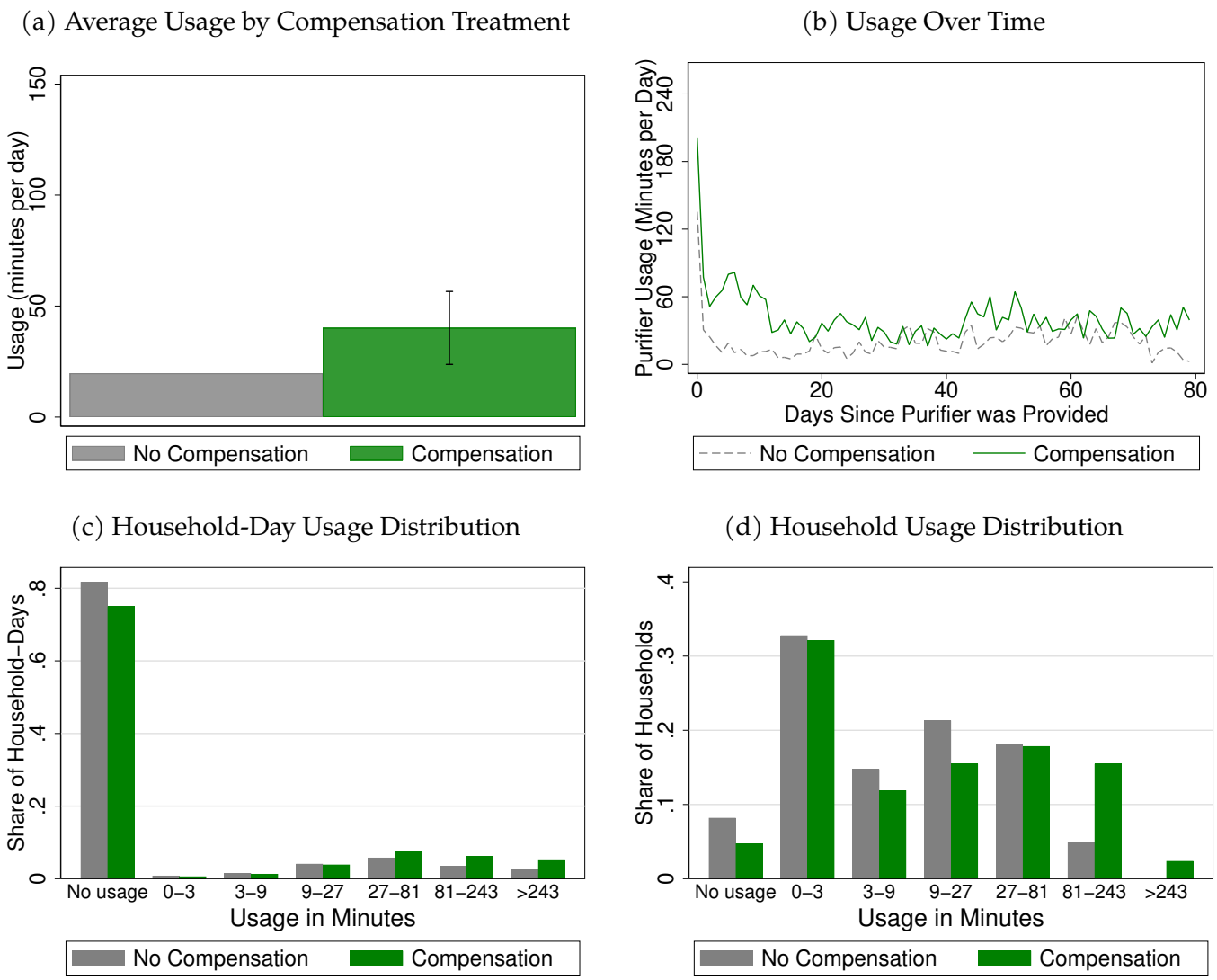


(f) Demand for Purifiers (Experiment 2, Control Only)



Notes: This figure describes the effectiveness of air purifiers, households' perception of their effectiveness, and households' WTP for purifiers during Experiments 1 and 2. Panel (a) shows how air pollution changes after an air purifier is turned on. This experiment was carried out six times in a setting similar to the apartments of the subjects in the main experiments. The air purifier was used on the medium setting and doors and windows were closed. Panel (b) shows how air pollution changes after an air purifier is turned on by the households in the experiment. Data is from the monitors and smart sockets and includes each time a purifier was turned on between the Phase 2 survey until 1 April 2024. Panel (c) shows beliefs about purifier effectiveness at the time of the Phase 3 survey among households that had not received an air purifier. Panel (d) shows households' WTP for a purifier at the time of the Phase 2 survey among households that did not receive a monitor. Panel (e) shows purifier effectiveness perceptions elicited during Experiment 2 before any demonstrations (N=2400). Panel (f) shows WTP for a purifier among households in the control group (N=400). See discussion in Section 3.2.

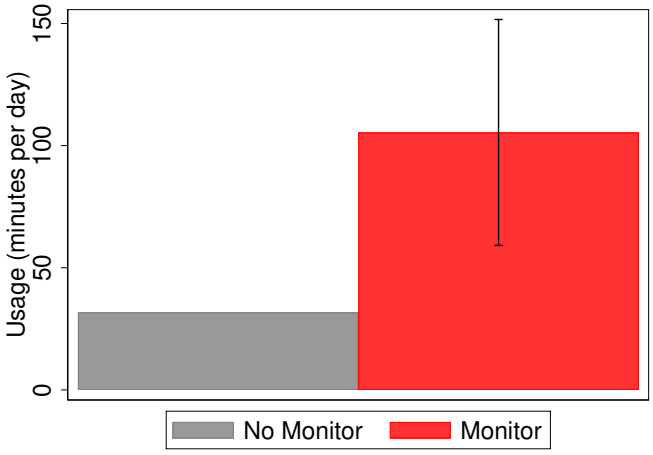
Figure 6: Air Purifier Usage: Effect of Electricity Compensation Treatment (without Monitor)



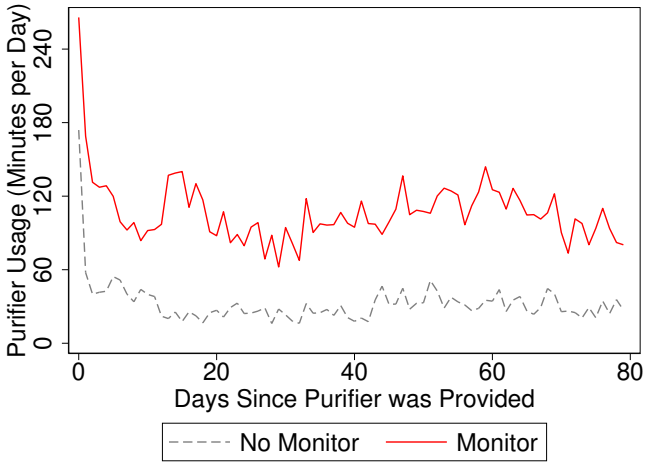
Notes: This figure use smart socket data to show the difference in purifier usage among households receiving electricity compensation, compared to households not receiving compensation during Experiment 1. Only households without a monitor are included in the figure. Panel (a) compares the average minutes of purifier usage per day. The confidence interval is constructed using standard errors of the difference between the two means. Panel (b) shows the minutes of purifier usage over time. Appendix C shows the share of households represented in this analysis of air purifier use over time. Panel (c) shows the distribution of minutes of purifier usage in a household on a particular day (i.e. each observation is a household on a specific day). Panel (d) shows the distribution of average minutes the purifier was used in a household per day (i.e. each observation is a household). In panels (c) and (d), each bin is three times wider than the previous bin. Data is from the Phase 2 survey until 1 April 2024. See discussion in Section 6.2.

Figure 7: Air Purifier Usage: Effect of Monitor

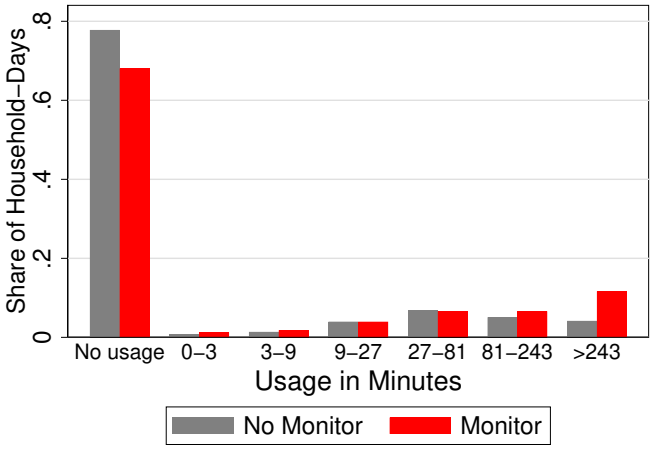
(a) Average Usage by Monitor Treatment



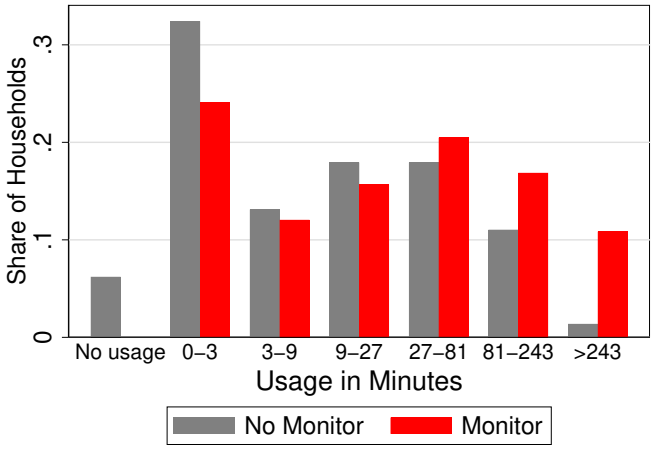
(b) Usage Over Time



(c) Household-Day Usage Distribution



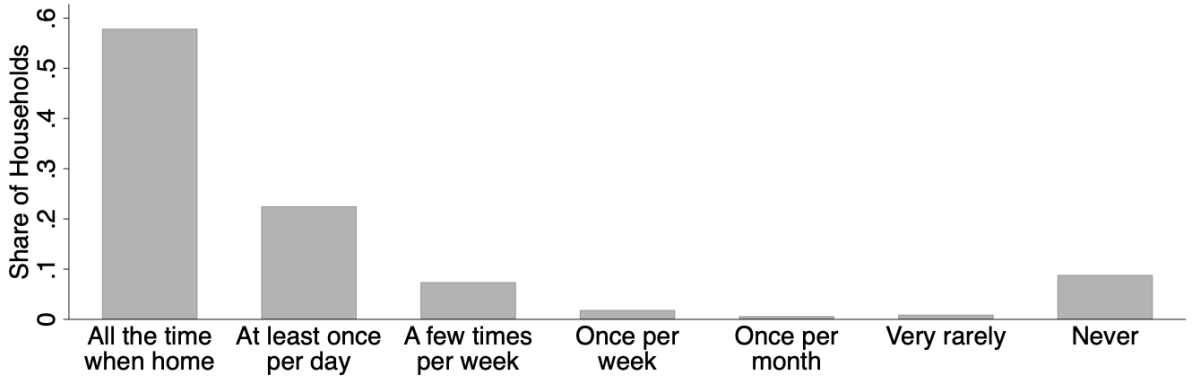
(d) Household Usage Distribution



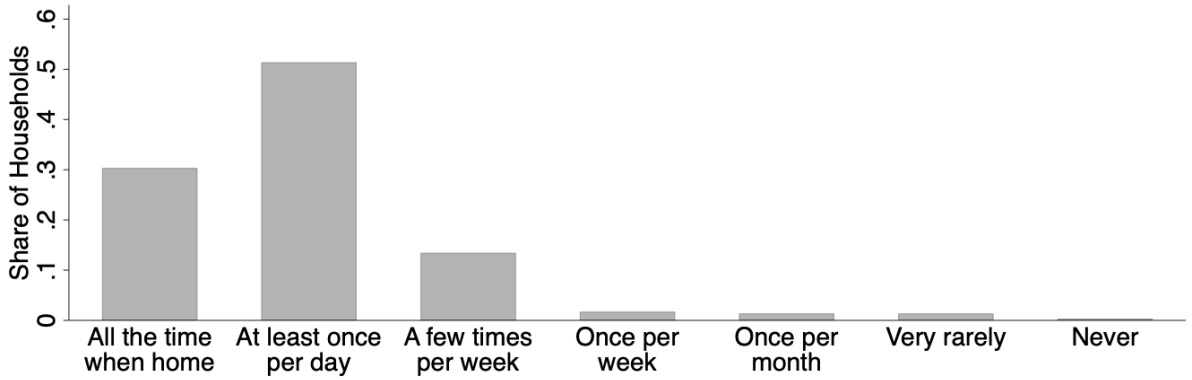
Notes: This figure uses smart socket data show the difference in purifier usage among households in the monitor treatment (without the attention treatment), compared to those households not receiving the monitor treatment during Experiment 1. Only households with purifiers are included in the data. Panel (a) compares the average minutes of purifier usage. The confidence interval is constructed using standard errors of the difference between the two means. Panel (b) shows the minutes of purifier usage over time. Appendix C shows the share of households represented in this analysis of air purifier use over time. Panel (c) shows the distribution of minutes of purifier usage in a household on a particular day (i.e. each observation is a household on a specific day). Panel (d) shows the distribution of average minutes the purifier was used in a household per day (i.e. each observation is a household). In panels (c) and (d), each bin is three times wider than the previous bin. Data is from the Phase 2 survey until 1 April 2024. See discussion in Section 7.

Figure 8: Ex-ante Predicted, Ex-post Reported, and Actual Purifier Usage (Experiment 1)

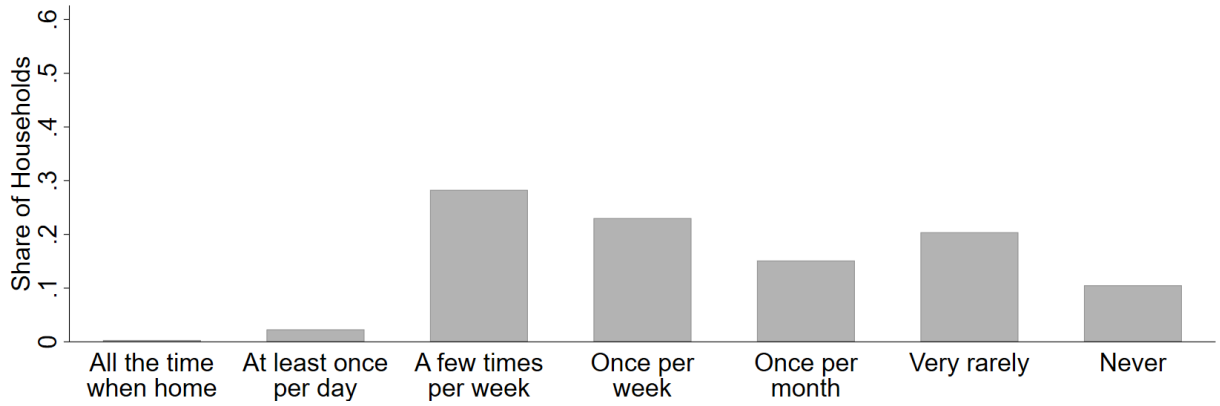
(a) Ex-ante Predicted Use



(b) Ex-post Self-Reported Use



(c) Actual Use



Notes: This figure compares the predicted purifier usage in the phase 2 survey, the reported usage in the phase 3 survey, and actual purifier usage measured by the smart sockets between the phase 2 and phase 3 surveys. Sub-figure (a) shows the distribution of responses during the Phase 1 survey to the question: "If you owned an air purifier, how often would you use it during the winter months?" This figure excludes the 3% of respondents who replied "Don't Know." Sub-figure (b) shows the distribution of responses during the Phase 3 survey to the question: "How often did you use the air purifier since it was provided to you?" Sub-figure (c) shows the distribution of actual usage, as measured by the smart sockets. A household is classified as using the purifier "all the time when home" if it uses it at least a third of the time at least 95% of days, "at least once a day" if it uses it for 5 minutes at least 95% of days, "a few times per week" if it uses it for 5 minutes at least three days a week on average, "once per week" if it uses it for 5 minutes at least one day a week on average, "once per month" if it uses it for 5 minutes at least one day per month on average, "very rarely" if it for 5 minutes any day, and "never" if it never used the purifier for more than 5 minutes in a day. See discussion in Section 9.1.

Tables

Table 1: Effects on Households' Perceptions of Indoor and Outdoor Air Quality and WTP for Air Purifiers

	(1) Beliefs about Severity of Indoor Air Pollution	(2) Beliefs about Severity of Outdoor Air Pollution	(3) Beliefs about Indoor v. Outdoor Air Pollution	(4) Willingness To Pay (In BDT)
Panel A: Experiment 1				
Monitor	0.447***	0.161	0.0305*	-242.7
	(0.151)	(0.161)	(0.0176)	(191.8)
Observations	818	818	818	814
Control mean	4.54	7.05	0.43	1408.65
Panel B: Experiment 2				
	(1)	(2)	(3)	(4)
Credit Only	0.115	-0.110	-0.00950	-213.9
	(0.161)	(0.169)	(0.0163)	(218.9)
Monitor Only	0.790***	0.492***	0.0663***	-250.4
	(0.153)	(0.163)	(0.0157)	(210.2)
Purifier Only	0.180	-0.142	0.00450	199.3
	(0.153)	(0.169)	(0.0156)	(220.3)
Both (Separately)	0.665***	0.245	0.0375**	-168.9
	(0.155)	(0.168)	(0.0159)	(208.4)
Both (Together)	0.695***	0.563***	0.0630***	-47.89
	(0.157)	(0.163)	(0.0159)	(205.3)
Observations	2400	2400	2400	2400
Control Mean	4.21	6.66	0.43	2699.55

Notes: Column 1: "Beliefs about Severity of Indoor Air Pollution" is households' response to: "How would you rate the current indoor air quality in your area? [On a scale of 1-10, with 1 being "not polluted at all" and 10 being "extremely polluted.]" Column 2: "Beliefs about Severity of Outdoor Air Pollution" is households' response to: "How would you rate the current outdoor air quality in your area? [On a scale of 1-10, with 1 being "not polluted at all" and 10 being "extremely polluted.]" Column 3: "Beliefs about Indoor v. Outdoor Air Pollution" is households' response to: "How polluted do you believe the air in your home is compared to the air outdoors?" Column 4: "Willingness to Pay for Air Purifier" is the revealed valuation of an air purifier by the household during a BDM game measured in Bangladeshi Takas. WTP is winsorized at the 99% level. Observations are at the household level. . Panel A shows effects of monitor provision in experiment 1 (Phase 2 survey). Panel B shows the effects of five different treatments in experiment 2. Credit only: the household is offered a zero-interest option for financing the purifier purchase. Monitor only: household is shown that the monitor works and allowed to see the reading. Purifier only: household is shown the purifier and that it works. Both (separately): first the household is shown the monitor works and the reading on the monitor. The monitor is then put away the household is shown the purifier and that it works. Both (together): the household is first shown the monitor and it's reading. Then while the monitor is still on and visible, the purifier is turned on for five minutes and the household is allowed to see the changes in the reading. Each of the five treatment arms are measured against a control group. . Significance levels are denoted by $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$. See discussion in Section 5.

Table 2: Effects on Perceptions of Purifier Effectiveness

Panel A: Experiment 1

	(1) Has Opinion on Purifier Effectiveness	(2) Perceived Reduction: $> 0\%$	(3) Perceived Reduction: $> 25\%$	(4) Perceived Reduction: $> 50\%$	(5) Perceived Reduction: $> 75\%$
Monitor	0.112**	0.114**	0.125**	0.104**	-0.007
	(0.056)	(0.055)	(0.054)	(0.050)	(0.030)
Purifier	0.280***	0.279***	0.304***	0.273***	0.134***
	(0.052)	(0.052)	(0.052)	(0.050)	(0.039)
Purifier x Monitor	0.004	0.018	-0.052	-0.070	0.098
	(0.083)	(0.083)	(0.086)	(0.086)	(0.069)
Observations	758	758	758	758	758
Control mean	0.384	0.357	0.281	0.205	0.080

Panel B: Experiment 2

	(1)	(2)	(3)	(4)	(5)
Credit Only	-0.0200	-0.0250	-0.0375	-0.00500	0.0300*
	(0.0354)	(0.0351)	(0.0330)	(0.0269)	(0.0161)
Monitor Only	0.00750	0.0150	0.0125	0.0325	0.0200
	(0.0354)	(0.0352)	(0.0337)	(0.0280)	(0.0154)
Purifier Only	0.117***	0.130***	0.120***	0.1000***	0.0675***
	(0.0350)	(0.0351)	(0.0344)	(0.0295)	(0.0183)
Both (Separately)	0.137***	0.135***	0.140***	0.0925***	0.0400**
	(0.0348)	(0.0351)	(0.0345)	(0.0293)	(0.0168)
Both (Together)	0.153***	0.183***	0.200***	0.158***	0.0600***
	(0.0347)	(0.0347)	(0.0344)	(0.0304)	(0.0179)
Observations	2400	2400	2400	2400	2400
Control Mean	0.49	0.45	0.34	0.18	0.04

Notes: The outcome is the response to a question asking how effective the household thinks regular air purifiers that can be bought in shops in Dhaka are at removing air pollution from the room in which they are being run. This variable ranges from 0 being completely ineffective to 1 being (almost) completely effective. Column 1 is a binary variable equal to 1 if the household selected any option other than "Don't know/unsure". Columns (2) - (5) are binary variables equal to 1 if the household said the purifier was more than 0%, 25%, 50% or 75% effective. Observations are at the household level. . Panel A shows effects of monitor provision, purifier provision and the interaction of the two in experiment 1 (Phase 3 survey). Panel B shows the effects of five different treatments in experiment 2. Credit only: the household is offered a zero-interest option for financing the purifier purchase. Monitor only: household is shown that the monitor works and allowed to see the reading. Purifier only: household is shown the purifier and that it works. Both (separately): first the household is shown the monitor works and the reading on the monitor. The monitor is then put away the household is shown the purifier and that it works. Both (together): the household is first shown the monitor and it's reading. Then while the monitor is still on and visible, the purifier is turned on for five minutes and the household is allowed to see the changes in the reading. Each of the five treatment arms are measured against a control group. Significance levels are denoted by $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$. See discussion in Section 6.

Table 3: Effect of Monitors on Air Purifier Use (Experiment 1)

	(1) Min per Day	(2) Days Used (30+ min)	(3) Days Used (60+ min)	(4) WTA (BDT)
Monitor	74.09***	0.651***	0.671***	3983.0*
	(23.57)	(0.233)	(0.215)	(2365.2)
Time FE	Yes	Yes	Yes	No
Sample	All Days	All Weeks	All Weeks	Households
Observations	22,840	3,539	3,539	298
Clusters	304	304	304	298
Control mean	31.72	1.13	0.81	14,332.84

Notes: This table shows the effect of providing monitors on purifier use during Experiment 1. 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. In column (4) data is at the household level. Data is only from households that participated in the Phase 2 survey and were assigned a purifier. Data is from the smart sockets are for the dates between the Phase 2 survey and 1 April 2024. Standard errors clustered at the household level, except in column 4, which uses heteroskedasticity robust stadard errors. $***p < 0.01; **p < 0.05; *p < 0.1$. See discussion in Section 7.

Table 4: Effect of Purifiers on Pollution (Experiment 1)

Panel A:	PM2.5 ($\mu g/m^3$, with imputed values)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Purifier	-5.80*	-7.78*	-3.97	-1.25	-1.15	-9.56**	-11.04**
	(3.13)	(4.27)	(4.24)	(2.74)	(4.65)	(4.30)	(4.51)
Baseline PM2.5 (w. imputed)	0.42***	0.51***	0.33***	0.25***	0.33***	0.52***	0.58***
	(0.05)	(0.08)	(0.08)	(0.05)	(0.09)	(0.08)	(0.08)
Panel B:	ln(PM2.5, with imputed values)						
Purifier	-0.143***	-0.158***	-0.148**	-0.120**	-0.104*	-0.162***	-0.166***
	(0.054)	(0.058)	(0.064)	(0.057)	(0.056)	(0.053)	(0.056)
ln(Baseline PM2.5, w. imputed)	1.189***	1.274***	1.245***	1.118***	0.999***	1.193***	1.306***
	(0.172)	(0.187)	(0.202)	(0.177)	(0.171)	(0.163)	(0.179)
Hours	All	0-4	4-8	8-12	12-16	16-20	20-24
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	744,861	123,200	123,582	123,322	124,461	125,038	125,258
Clusters	416	416	416	416	416	416	416
Control mean	112	138	117	86	87	111	132

Notes: This table shows the effect of providing air purifiers on air pollution during Experiment 1, using imputed values for pollution when monitors are turned off. The imputed values are calculated by multiplying the average ratio between the indoor and outdoor pollution in households without a purifier and the outdoor pollution 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 who remained in the survey until the Phase 2 survey (when the purifiers were provided). Note that all days are included, regardless of whether the purifier was turned on or not. The outcome variable in Panel A is the average air pollution in that hour. In Panel B, the outcome variable is the log of the average air pollution. Column (1) shows results for all hours of the day. Columns (2)-(7) show results for specific times of the day, divided into 4-hour periods. Data is from the date of the Phase 2 survey until 1 April 2024. Standard errors are clustered at the household level. $***p < 0.01; **p < 0.05; *p < 0.1$. See discussion in Section 8.1.

Table 5: Potential assumptions about beliefs and expectations and the resulting MWTP values

Row	Data Source	Pollution beliefs		Purifier use		Purifier effectiveness belief		Expected decrease PM exposure		WTP measure (USD)		MWTP for 1 μg/m^3 reduction per season (USD)
		Assumption (1)	Value (2)	Assumption (3)	Value (4)	Assumption (5)	Value (6)	Assumption (7)	Value (8)	Assumption (9)	Value (10)	(11)
(1)	Experiment 1: All	Full information	111	All the time	100%	HEPA filter	99%	Calculated	110	WTP	12.4	0.11
(2)	Experiment 1: All	Stated	69	All the time	100%	Stated	66%	Calculated	45	WTP	12.4	0.27
(3)	Experiment 1: All	Stated	69	Stated Ex-Ante	40%	Stated	66%	Calculated	18	WTP	12.4	0.7
(4)	Experiment 1: All	Stated	69	Stated Ex-Post	29%	Stated	66%	Calculated	13	WTP	12.4	0.9
(5)	Experiment 1: All	Stated	69	Actual	5%	Stated	66%	Calculated	2	WTP	12.4	6.0
(6)	Experiment 1: Both	N/A	N/A	N/A	N/A	N/A	N/A	Actual	6	WTP	10.9	1.9
(7)	Experiment 1: Both	N/A	N/A	N/A	N/A	N/A	N/A	Actual	6	WTA	146	26

Notes: This table shows the results of calculating Equations 7 and 8 under different assumptions about indoor air pollution beliefs, expectations of purifier use, and purifier effectiveness beliefs. The data source "Experiment 1: All" refers to all households in Experiment 1, "Experiment 1: Both" refers to households that received both a purifier and a monitor. See discussion in Section 9.1.

Table 6: Usage Based MWTP Estimates Under Different Purifier Effectiveness Assumptions

	Use Purifier			
	(1)	(2)	(3)	(4)
Potential PM2.5 Improvement	0.00005	0.00002	0.00001	-0.00009
	(0.00003)	(0.00001)	(0.00001)	(0.00015)
Cost of Use	-0.01207***	-0.01207***	-0.01207***	-0.01203***
	(0.00345)	(0.00345)	(0.00345)	(0.00345)
Hour of Day FE	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
Sample	Monitor	Monitor	Monitor	Monitor
PM2.5 Improvement Assumption	80%	Simulated: 108 min	Simulated: 23 min	Household Belief
-beta/alpha	0.0037	0.0015	0.0009	-0.0076
MWTP per season (USD)	0.07	0.03	0.02	-0.15
MWTP per year (USD)	0.30	0.12	0.07	-0.60
P-value: MWTP	0.23	0.23	0.23	0.56
Upper bound 95% CI: MWTP/year	0.78	0.32	0.18	1.40
Observations	399,864	399,864	399,864	399,864
Clusters	159	159	159	159
Outcome Variable Mean	0.0815	0.0815	0.0815	0.0815

Notes: This table shows the results of a regression estimating the sensitivity of purifier use to the potential reduction in PM2.5 air pollution and the marginal monetary cost of using the purifier. Potential PM2.5 improvement is the effect of turning on an air purifier on indoor air pollution, it is calculated as the purifier's assumed effectiveness multiplied by outdoor air pollution, multiplied by the average indoor-outdoor air pollution ratio. Each column shows results for a different purifier effectiveness assumption. Before the incentive period, the cost of using the purifier is equal to the electricity cost per hour (BDT 0.24) for households without electricity cost compensation and zero for households with electricity compensation. During the incentive period, the cost of using the purifier is 0.24 per hour for those in the control group and the difference between the incentive and electricity cost (-4.76 or -9.76) for those in the incentive group. Standard errors clustered at the household level. $***p < 0.01; **p < 0.05; *p < 0.1$. See discussion in Section 9.2.

Table 7: Usage Based MWTP Estimates Under Different Purifier Effectiveness Assumptions (Between 6pm and midnight)

	Use Purifier			
	(1)	(2)	(3)	(4)
Potential PM2.5 Improvement	0.00010**	0.00004**	0.00002**	-0.00021
	(0.00005)	(0.00002)	(0.00001)	(0.00021)
Cost of Use	-0.01216***	-0.01216***	-0.01216***	-0.01205***
	(0.00350)	(0.00350)	(0.00350)	(0.00350)
Hour of Day FE	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
Sample	Monitor	Monitor	Monitor	Monitor
PM2.5 Improvement Assumption	80%	Simulated: 108 min	Simulated: 23 min	Household Belief
-beta/alpha	0.0085	0.0034	0.0020	-0.0176
MWTP per season (USD)	0.17	0.07	0.04	-0.34
MWTP per year (USD)	0.68	0.27	0.16	-1.40
P-value: MWTP	0.05	0.05	0.05	0.35
Upper bound 95% CI: MWTP/year	1.35	0.55	0.31	1.56
Observations	100,307	100,307	100,307	100,307
Clusters	159	159	159	159
Outcome Variable Mean	0.0865	0.0865	0.0865	0.0865

Notes: This table shows the results of a regression estimating the sensitivity of purifier use to the potential reduction in PM2.5 air pollution and the marginal monetary cost of using the purifier, using only data from between 6pm and midnight. Potential PM2.5 improvement is the effect of turning on an air purifier on indoor air pollution, it is calculated as the purifier's assumed effectiveness multiplied by outdoor air pollution, multiplied by the average indoor-outdoor air pollution ratio. Each column shows results for a different purifier effectiveness assumption. Before the incentive period, the cost of using the purifier is equal to the electricity cost per hour (BDT 0.24) for households without electricity cost compensation and zero for households with electricity compensation. During the incentive period, the cost of using the purifier is 0.24 per hour for those in the control group and the difference between the incentive and electricity cost (-4.76 or -9.76) for those in the incentive group. Standard errors clustered at the household level. $***p < 0.01; **p < 0.05; *p < 0.1$. See discussion in Section 9.2.

Table 8: Comparison of MWTP Estimates Across Contexts and Methodologies

Study Context	**Household Income** (2023 PPP USD)	**Methodology**	**Adjustment Scenarios**	**MWTP** (USD/$\mu g/m^3$/yr)
Bangladesh				
Chowdhury et al. (2025)	24,122	Use-based	Baseline (Observed Use)	1.07
China				
Ito and Zhang (2020)	11,804	Purchase-based	Baseline	5.95
			Effectiveness correction ($\times 1.25$)	7.43
			Expected usage correction ($\times 2.5$)	18.59
			Actual usage correction ($\times 8$)	148.68
India				
Baylis et al. (2023)	9,454	WTP-based	Baseline	3.11
			Actual usage correction ($\times 6$)	18.64
USA				
Tarduno and Walker (2025)	65,000	WTP-based	Baseline	2.68
			Expected usage correction ($\times 2.5$)	6.69
			Actual usage correction ($\times 8$)	53.54

Notes: This table compares the annualized Marginal Willingness to Pay (MWTP) for a 1 $\mu g/m^3$ reduction in PM2.5 estimated in this paper (Bangladesh) with estimates from recent literature in China, India, and the USA. All monetary values are reported in 2023 PPP-adjusted USD. The "Adjustment Scenarios" illustrate the structural fragility of purchase-based models discussed in the text. Standard estimates (labeled "Baseline") typically assume high or full utilization of the defensive technology. We show how these estimates scale when re-calculated using more realistic purifier effectiveness and usage assumptions derived from our high-frequency data. The multiplication factors are relative to the estimate on the row above. For example, applying the "Actual usage" multiplier observed in our setting to the Ito and Zhang (2020) or Tarduno and Walker (2025) estimates increases the implied MWTP by a factor of 20 ($2.5 \times 8 = 20$), rendering the valuations implausibly high. This highlights that low apparent valuations in standard models often rely on strong assumptions about utilization intensity.

Online Appendix

A Data Collection, Cleaning, and Validation

A.1 Data Preprocessing: Winsorization

To improve the reliability of the data and mitigate outliers from misreporting or measurement errors, we winsorize continuous variables in our data at the 1st and 99th percentiles. This procedure replaces values below the 1st percentile with the 1st percentile value, and values above the 99th percentile with the 99th percentile value for each variable.

A.2 WTP Elicitation

To elicit WTP, we implemented a Becker-DeGroot-Marschak (BDM) mechanism following the approach of Berry, Fischer and Guiteras (2020). In this procedure, households first reported their WTP, after which a random price was drawn. If the household's stated WTP exceeded the random price, they were offered the opportunity to complete the transaction by paying the random price (not their stated WTP). This mechanism creates incentive compatibility, encouraging households to truthfully reveal their actual WTP.

Households were informed that the random price would fall somewhere between zero and the market price of the air purifier, which was disclosed to them, but they were not shown the full distribution of possible random prices. To familiarize participants with this elicitation method before the main task, we conducted a real-stakes practice round using the same protocol to elicit WTP for a food storage container with a market price of BDT 60.

A.3 Air Quality Monitoring Devices

A.3.1 Comparing readings from indoor and outdoor monitors

We deployed two distinct models of air quality monitors in our data collection efforts. For indoor monitoring, households used Qingping Lite monitors, while outdoor measurements were conducted using IQAir AirVisual Outdoor monitors. To validate the equipment and ensure that observed differences between indoor and outdoor air pollution measurements were not artifacts of different monitoring technologies, we conducted a calibration test. We placed one outdoor monitor alongside three indoor monitors in the same room for a one-week period and analyzed their hourly average readings. The difference in average $PM_{2.5}$ readings between the indoor and outdoor monitors was 1.3 $\mu g/m^3$ or 2.2%. The correlation coefficient between the indoor and outdoor monitor readings was 0.96. These results confirm that systematic measurement differences between the two monitor types are minimal, particularly when compared to the natural

hour-to-hour variations in air pollution levels.

A.3.2 Comparing readings from our outdoor monitors and the US embassy monitor

We can also measure the differences between our outdoor monitors and the reference-grade monitor of the US embassy in Dhaka. These differences could be driven by both differences in measurement as well as actual differences in air pollution between our research site and the US embassy, which are approximately 6km apart from each other. The average difference between our monitors and the US embassy monitor is -0.80 $\mu g/m^3$ or -2.99%. The correlation between our monitors and the US embassy monitor is 0.96. Again, we conclude that when compared to the natural variations in air pollution levels the differences in measurement error are small even when amplified by geographical differences in air pollution levels.

B Experiment 1: Attrition and Balance

Phase 1 to Phase 2 attrition. We experienced 18.8% attrition between Phase 1 and Phase 2; of our Phase 1 sample of 1,008 households, 818 households consented to the Phase 2 survey. 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). We fail to find evidence for differential attrition between monitor and non-monitor households. There was also no differential attrition between households receiving the monitor with or without the attention treatment. Finally, we test for balance in the unattrited groups for both monitor (Table A.2) and attention treatments (Table A.3). Balance on observables from the Phase 1 survey is maintained in the unattrited sample. Joint test p-values of 0.39 and 0.35 confirm no significant differences in Phase 1 attributes between monitor vs. non-monitor households and attention vs. non-attention households that consented to Phase 2, respectively.

Phase 2 to Phase 3 attrition. Of the 818 households surveyed in Phase 2, 758 consented to participate in the Phase 3 survey, representing an attrition rate of 7.3%. We find differential attrition by purifier assignment (Table A.4): households receiving purifiers were less likely to drop out than non-purifier households by 5.6 percentage points. However, balance tests show the unattrited purifier and non-purifier groups remain comparable (Table A.5). Differences between purifier and non-purifier households in the unattrited sample are small and statistically insignificant for all Phase 2 observables (joint test p-value = 0.92).

Table A.4 also shows that households receiving daily electricity compensation were less likely to attrit than those receiving monthly or no compensation. However, again, balance tests confirm the three unattrited compensation groups remain comparable (Table A.6). Differences are small and statistically insignificant.

Next, we examine differential attrition within the purifier group by monitor assignment, and within the monitor group by purifier assignment. We find differential attrition by purifier assignment within the monitor group (Table A.7): households receiving purifiers were less likely to drop out than non-purifier households. However, balance tests show the unattrited purifier and non-purifier households remain comparable (Table A.8). Differences between these groups in the unattrited monitor sample are small and statistically insignificant for all Phase 2 observables (joint test p-value = 0.78).

Importantly, we find no differential attrition by monitor treatment amongst purifier households (Table A.9). Moreover, differences between monitor and non-monitor households in the unattrited purifier sample are small and always statistically insignificant for the vast majority of Phase 2 observables (Table A.10), with a joint test p-value of 0.57.

Even if we ignore the balance tests for unattrited samples across our various comparison groups and simply take the differential attrition rates for some comparison groups as evidence of bias, this would only possibly affect four of our main results: (i) impact of purifier and/or monitor assignment on beliefs and WTP for purifiers, (ii) impact of electricity compensation on purifier use, (iii) impact of purifier assignment on indoor PM2.5 levels, and (iv) impact of purifier and/or monitor assignment on health and other socioeconomic outcomes.

However, these concerns are mitigated for several reasons. First, we replicate the belief and WTP results from Experiment 1 in Experiment 2, where no differential attrition occurred. Therefore, result (i) from Experiment 1 is unlikely to be due to attrition bias. Second, concerns about attrition bias in results (ii) and (iii) are addressed because we rely on real-time data from smart plugs and air monitors rather than Phase 3 survey data. Attrition here, defined as households explicitly returning equipment or indicating their withdrawal from the study, is only 0.5%. That is, households withdrew from sharing monitor readings or purifier use data on 0.5% of the days between Phase 2 and April 1. Moreover, we find no differential attrition in purifier withdrawal based on electricity compensation nor in monitor withdrawal based on purifier assignment (Table A.11). Finally, differential attrition on unobservables is unlikely to explain our null findings on health and socioeconomic outcomes. Purifier households were indeed more likely to remain in the sample than non-purifier households, a pattern that could theoretically bias estimates toward zero by retaining a broader mix of households in the treatment arm (than the positively selected or healthier mix of households in the control arm). However, we find balance on baseline variables between purifier and non-purifier households in the unattrited sample, including health outcomes, suggesting that differential attrition did not systematically select households on characteristics correlated with our outcomes.

C Share of Households Represented in Analysis of Air Purifier Use Over Time

In Figures 6b and 7b, we present the purifier usage per household over time, relative to the Phase 2 survey when the air purifier was provided to the household. The sample ends on April 1, 2024, as we then started the usage incentive treatments, which substantially altered purifier usage. However, as households received their purifiers on different dates, the number of days between provision of the purifier and April 1, 2024, differs from household to household. Figure A.19 shows how the share of households in the sample decreases over time as more households reach April 1, 2024. The vertical dashed line indicates where the timelines in Figures 6b and 7b end as the sample becomes very small.

D Effect of Monitor on Self-Reported Purifier Use

Econometric specification. To examine the impact of monitor provision on self-reported purifier use, we estimate the regression Equation 2, with the self-reported use as the outcome variable. To measure self-reported purifier use, we asked households in the Phase 3 survey how many days they used the air purifier for 30 minutes or more in the past 7 days. We also asked households how often they used an air purifier, with response options ranging from "all the time when home" to "never". The response options were (a) all the time when home, (b) at least once per day, (c) a few times per week, (d) once per week, (e) once per month, (f) very rarely, or (g) never.

Results. In Table A.30, Column 1, we show that households in the monitor group reported using air purifiers for at least 30 minutes on an extra half day in the past 7 days, compared to the only-purifier group's average of 5 days, a 10% increase (p-value = 0.11).

In Column 2, we use the number of days in the 7 days preceding the survey that the household actually used the purifier.[52] Although self-reported usage vastly overstates actual usage, exceeding it by more than five-fold in the control group, the monitor's absolute effect remains consistent across both measures. This similarity suggests that monitors modestly increase actual usage without altering reporting bias.

In Column 3, we show that the monitor treatment increased the likelihood of households self-reporting air purifier usage as "all the time when home" by a statistically significant 14 percentage points, or 58%, compared to households who did not receive a monitor.

[52] To assess whether overreporting differs between monitor and non-monitor groups, we constructed an objective weekly usage measure from smart socket data comparable to the self-reported measure: the number of days in the week preceding the Phase 3 survey that the purifier operated for at least 30 minutes.

E WTP-based MWTP Estimates

We can also estimate MWTP for clean air using the sensitivity of the WTP for the purifier to beliefs about the reduction in pollution exposure the purifier would provide. We do this by estimating a two-stage least squares linear probability model using the data from Experiment 2. We exploit the randomized treatment assignment (monitor and/or purifier demonstrations) to instrument for the household's perceived reduction in PM2.5 exposure:

$$\textbf{First Stage:} \quad \text{Perceived Reduction}_i = \pi_0 + \pi_1 \text{Treatment}_i + \gamma \text{Price}_i + \mathbf{X}_i + \nu_i \tag{11}$$

$$\textbf{Second Stage:} \quad \text{Bid}_{ip} = \alpha + \beta_{red} \widehat{\text{Perceived Reduction}}_i + \beta_{price} \text{Price}_{ip} + \mathbf{X}_i + \epsilon_{ip} \tag{12}$$

where Bid_{ip} is a binary indicator equal to 1 if household i's bid exceeded price p (BDT 0 to BDT 17,000 in BDT 1,000 increments), Price_{ip}; $\text{Perceived Reduction}_i$ is the household's expected reduction in PM2.5 exposure in $\mu\text{g}/\text{m}^3$, instrumented by Treatment_i in Equation 11. $\mathbf{X}_i$ denotes baseline perception controls. Standard errors are clustered at the household level. The MWTP for a 1 $\mu\text{g}/\text{m}^3$ reduction in $\text{PM}_{2.5}$ is the ratio of the marginal utility of air quality to the marginal utility of income:

$$\widehat{\text{MWTP}} = -\frac{\hat{\beta}_{red}}{\hat{\beta}_{price}}$$

Table A.23 presents the first stage estimates, while Table A.24 presents the second stage estimates. The implied MWTP is sensitive to usage assumptions used to construct $\text{Perceived Reduction}_i$, for the same reasons as highlighted in the discussion about Table 5. We show results for four usage assumptions: full usage (Column 1), stated household expectations (Column 2), average ex-post self-reports from Experiment 1 at 29% (Column 3), and average actual usage from Experiment 1 at 5% (Column 4). Assuming full usage (Column 1), the model implies a negligible MWTP of USD 0.02 per $\mu\text{g}/\text{m}^3$ per season (USD 0.10 annualized). Applying the empirically observed usage rate of 5% (Column 4), the implied MWTP rises to USD 0.55 per season (USD 2.21 annualized).

Although these estimates are imprecise, with wide 95% confidence intervals, the more fundamental point is that MWTP estimates vary widely depending on usage assumptions, making them difficult to pin down even in principle. More generally, using any purchase decisions for defensive technologies to infer environmental amenity values produces estimates that vary widely depending on assumptions about usage. This methodological limitation highlights the need for alternative approaches to valuing environmental amenities.

F Effect of Monetary Incentives on Purifier Use

At the conclusion of Experiment 1 on March 31, we implemented substantial monetary incentives that should have made purifier use immediately profitable. From April 1, 2024 to April 30, 2024, 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 payments dwarf electricity costs (approximately BDT 0.24 per hour) by a factor of 20-40 times, and if a household used the purifier continuously, they would have been paid 6-12% of the average household labor income.

Econometric specification. We estimate the following regression specification:

$$Use_{it} = \alpha + \beta_1 \times AnyIncentive_i + \beta_2 \times BDT10Incentive_i + \beta_3 \times Monitor_i + \tau_t + \varepsilon_{it} \quad (13)$$

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. As before, $Monitor_i$ indicates whether a household was randomly selected to receive an air quality monitor two months earlier. τ_t indicates date fixed effects. Standard errors are clustered at the household level.

Results. Table A.31 documents remarkably modest responses to these substantial payments. The BDT 5 incentive increased usage by only 82 minutes daily, comparable to simply providing a pollution monitor (Column 2). Figure A.20 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 4.4 per hour. Doubling the payment to BDT 10 per hour added just 60 additional minutes. Put differently, households offered 12% of their income for running the purifier continuously still chose to breathe polluted air for more than 21 hours per day on average.

This behavior defies standard economic logic. A rational household should run purifiers continuously to maximize payments. Instead, we observe households leaving substantial money on the table, over BDT 7,000 if they had run purifiers continuously, equivalent to close to 12% of average monthly income, suggesting that financial barriers cannot explain low adoption.

This behavior suggests either significant (perceived) disutility associated with purifier use or behavioral constraints that prevent optimization. Potential perceived disutility could include

noise pollution,[53] and concerns about accelerating filter degradation or device wear that would necessitate costly replacements. Alternatively, behavioral explanations may dominate: cognitive load from remembering to operate the device and track usage may prove burdensome. Social norms around appliance use (e.g., turning off electronic devices before going to bed) or satisficing behavior, where households aim for "adequate" rather than optimal air quality, could also limit usage.

G Using Fractional Logit to Estimate MWTP from Usage Data

In this Appendix we test the robustness of the linear probability model using a fractional logit model. As in Section 9, we use our hour-by-hour data on purifier usage decisions, leveraging randomized time-varying incentives (price variation) and potential indoor exposure reductions (benefit variation).

G.1 Random-Utility Framework

At hour t, household i chooses $d_{it} \in \{0, 1\}$ (OFF/ON). The utility difference is

$$\Delta V_{it} \;=\; \underbrace{\beta\,\Delta PM_{it}}_{\text{benefit of cleaner air}} \;-\; \underbrace{\alpha\,p_{it}}_{\text{monetary price of use}} \;+\; \underbrace{\kappa_i + \phi_{h(t)} + \tau_t}_{\text{fixed effects}} \;+\; \varepsilon_{it}, \tag{14}$$

where ΔPM_{it} is the *potential* indoor $PM_{2.5}$ reduction if ON at (i, t), p_{it} is the per-hour monetary price (electricity minus reimbursement minus incentive), $\beta > 0$ and $\alpha > 0$ scale the marginal utility of clean air and money, and ε_{it} is an idiosyncratic shock. The household fixed effect κ_i absorbs time-invariant household-specific burdens of running (e.g., noise, placement, effort). The hour-of-day fixed effect $\phi_{h(t)}$ absorbs time-of-day factors common across households (e.g., typical sleep hours, general occupancy patterns). The date fixed effect τ_t absorbs day-specific factors common across households (e.g., weekends and public holidays).

G.2 How the Logit Identifies MWTP

Assuming Type-I Extreme Value errors, the ON probability is

$$\Pr(d_{it} = 1) \;=\; \Lambda\big(\beta\,\Delta PM_{it} - \alpha\,p_{it} + \kappa_i + \phi_{h(t)} + \tau_t\big), \tag{15}$$

[53] Noise is unlikely to explain low purifier usage (Figure A.21). To test whether purifier noise deters use, we conducted a controlled experiment on February 18-19, 2025, in two bedrooms in Mirpur apartments similar to our study households. We placed a purifier running at medium speed in one room for 24 hours, then switched it to the other room for comparison. We found virtually no difference in noise levels between rooms with and without the purifier (45.5 dB versus 46.2 dB). This null effect likely reflects Dhaka's high ambient noise environment; the marginal noise from a purifier is imperceptible against the existing soundscape.

Equation (15) links the *ON* probability to two observed, hour-level drivers: a *cost* shifter (p_{it}) and a *benefit* shifter (ΔPM_{it}).

- Randomized incentives change p_{it} exogenously within household. The sensitivity of ON to p_{it} pins down the *marginal utility of money* $-\alpha$.
- Hour-to-hour changes in potential pollution removal (via ambient conditions and effectiveness rules) move ΔPM_{it}. The sensitivity of ON to ΔPM_{it} pins down the *marginal utility of cleaner air* β.

The *gross, flow* marginal willingness to pay (currency per $\mu g/m^3$ *this hour*) is the taste ratio

$$\text{MWTP}^{\text{gross}} = \frac{\beta}{\alpha}. \tag{16}$$

Intuition: the per-hour incentive $\mathrm{d}s$ that just offsets a given per-hour benefit $\beta\,\Delta PM_{it}$ satisfies $\beta\,\Delta PM_{it} = \alpha\,\mathrm{d}s$, so $\beta/\alpha = \mathrm{d}s/\Delta PM_{it}$.

G.3 Link to Our Data and Identification

We construct ΔPM_{it} as the *potential* indoor reduction if ON using monitor data and an effectiveness rule (constant, duration dynamics, and household-specific beliefs). The monetary price is

$$p_{it} = c^{\text{elec}} - r_{it} - s_{it},$$

where r_{it} is electricity reimbursement (pre–Apr 1 assignment) and $s_{it} \in \{0, 5, 10\}$ BDT/hr are randomized use incentives (post–Apr 1 assignment). Because the *same* household transitions from one pricing regime to another at a common cutoff date, p_{it} varies within household over time, providing clean within-household price variation. We estimate (15) via fractional logit for the share-of-hour ON. We cluster standard errors at the household level.

G.4 Flow vs. Seasonal/Annual Units

$\text{MWTP}^{\text{gross}}$ in (16) is an hourly *flow* value. To express seasonal or annual units, we multiply by the relevant hours:

$$\text{MWTP}^{\text{season}} = \text{MWTP}^{\text{gross}} \times H_{\text{season}}, \qquad \text{MWTP}^{\text{year}} = \text{MWTP}^{\text{gross}} \times H_{\text{year}}.$$

where $H_{\text{season}} = 90 \times 24$ and $H_{\text{year}} = 365 \times 24$.

G.5 Why Household Fixed Effects Matter for Identifying the *Gross* Trade-off

For expositional clarity, rewrite (14) by suppressing hour-of-day and date fixed effects and collecting the time-invariant household burden of running into a term h_i:

$$\Delta V_{it} = \underbrace{\beta\,\Delta PM_{it}}_{\text{benefit of cleaner air}} - \underbrace{\alpha\,p_{it}}_{\text{monetary price of use}} - \underbrace{h_i}_{\text{household's time-invariant nuisance}} + \varepsilon_{it}, \tag{17}$$

Key identity at the margin. At a "just-indifferent" hour for household i (index ≈ 0),

$$0 \;=\; \beta\,\Delta PM_{it} \;-\; \alpha\,p_{it} \;-\; h_i \quad\Longrightarrow\quad \frac{\beta}{\alpha} \;=\; \frac{p_{it} + h_i/\alpha}{\Delta PM_{it}}.$$

This shows why h_i matters *across* households: it shifts the apparent price needed to induce use.

With household fixed effects (within-household comparison ⇒ gross MWTP). Take two marginal hours t and s for the *same* household i:

$$0 = \beta\,\Delta PM_{it} - \alpha\,p_{it} - h_i,$$
$$0 = \beta\,\Delta PM_{is} - \alpha\,p_{is} - h_i.$$

Subtract:

$$0 \;=\; \beta(\Delta PM_{it} - \Delta PM_{is}) \;-\; \alpha(p_{it} - p_{is}) \quad\Longrightarrow\quad \boxed{\frac{\beta}{\alpha} \;=\; \frac{p_{it} - p_{is}}{\Delta PM_{it} - \Delta PM_{is}}}.$$

The fixed hassle h_i *cancels*. Estimating from within-household changes (what household fixed effects force) recovers the *gross* trade-off β/α.

Without household fixed effects (cross-household mix ⇒ contaminated by net). Take one marginal hour for household A and another for B:

$$0 = \beta\,\Delta PM_{At} - \alpha\,p_{At} - h_A,$$
$$0 = \beta\,\Delta PM_{Bs} - \alpha\,p_{Bs} - h_B.$$

Subtract:

$$0 \;=\; \beta(\Delta PM_{At} - \Delta PM_{Bs}) \;-\; \alpha(p_{At} - p_{Bs}) \;-\; (h_A - h_B),$$

so

$$\boxed{\frac{\beta}{\alpha} \;=\; \frac{p_{At} - p_{Bs}}{\Delta PM_{At} - \Delta PM_{Bs}} \;+\; \frac{h_A - h_B}{\alpha(\Delta PM_{At} - \Delta PM_{Bs})}}.$$

Differences in hassles $(h_A - h_B)$ contaminate the ratio: cross-household comparisons bake in "annoyance taxes," yielding a *netted* object rather than the pure taste ratio.

Why this especially matters in logit/fractional logit. With

$$\Pr(\text{ON}_{it} = 1) = \Lambda\big(\beta\,\Delta PM_{it} - \alpha\,p_{it} - h_i\big),$$

the derivative $\Lambda(1-\Lambda)$ depends on the intercept $(-h_i)$. Pooling households without fixed effects reweights slopes toward households near mid-probabilities (non-collapsibility), mixing tastes and hassles. Household fixed effects condition out h_i, so β and α come from *within-household* movements, delivering the clean *gross* ratio β/α.

Put differently, logit gives more weight to observations near the middle (about 50% ON), and little weight to observations that are almost always OFF or ON. If some households sit in the middle *only* because their baseline annoyance is low, their reactions dominate the pooled estimate. Household fixed effects fix this by comparing each household only to itself over time, removing each home's baseline annoyance, so the estimated money-for-clean-air trade-off reflects the *gross* value, not a blend of value and annoyance.

The same logic extends to time fixed effects. Hour–of–day fixed effects absorb clock–time factors common to all homes that shift the baseline propensity to run without changing the money–for–clean-air trade-off. Date fixed effects absorb day-level shocks that likewise tilt the intercept. In logit, leaving these out lets baseline shifts reweight the slopes; including them forces identification off *within* hour-of-day and *within* date variation, keeping the estimate of the benefit–price ratio focused on the *gross* trade-off rather than a blend of preferences and time-specific propensities to run.

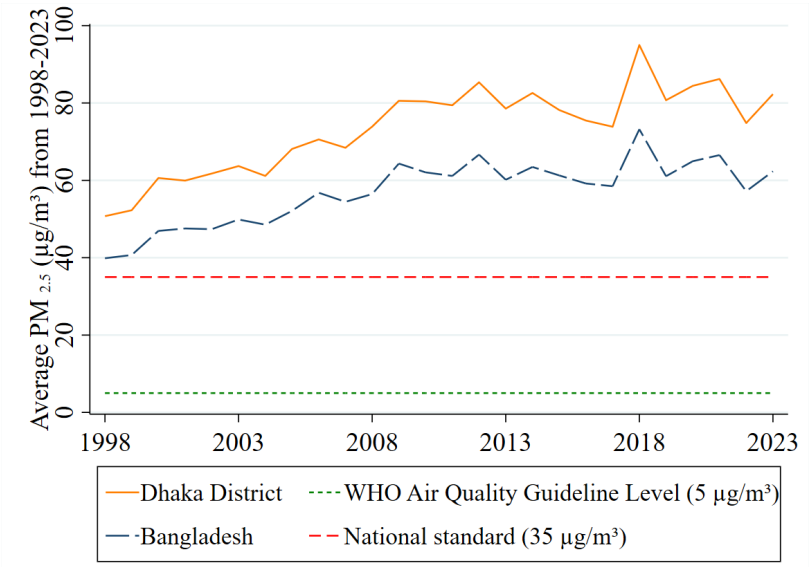
G.6 Results

Table A.32 and A.33 shows the logit estimates are quantitatively similar to our OLS estimates. Assuming the purifier reduces air pollution by 80%, the estimated MWTP is USD 0.09 per season and USD 0.38 per year for households with monitors (Column (1) of Table A.32). However, the estimate is not statistically significant (p-value = 0.29). We use duration-specific effectiveness measures to estimate MWTP in Columns (2) and (3) of Table A.32. The resulting annual MWTP estimates are USD 0.15 and 0.09, respectively, and not statistically significant. Finally, Column (4) uses each household's stated belief about purifier effectiveness from the Phase 3 survey. This specification yields a tiny negative association between perceived potential PM2.5 improvement and usage, resulting in a negative MWTP estimate that is not statistically different from zero. Importantly, when we estimate MWTP for periods when household members are most likely home and awake, 6 PM to midnight, the results closely match the above fractional logit estimates. Assuming that the MWTP cannot be below zero, our estimates are 0 to USD 0.26 per $\mu g/m^3$ per season (0 to USD 1.07 per $\mu g/m^3$ per year), which is statistically significantly different from zero in our main specification ($p < 0.05$) (Table A.33).

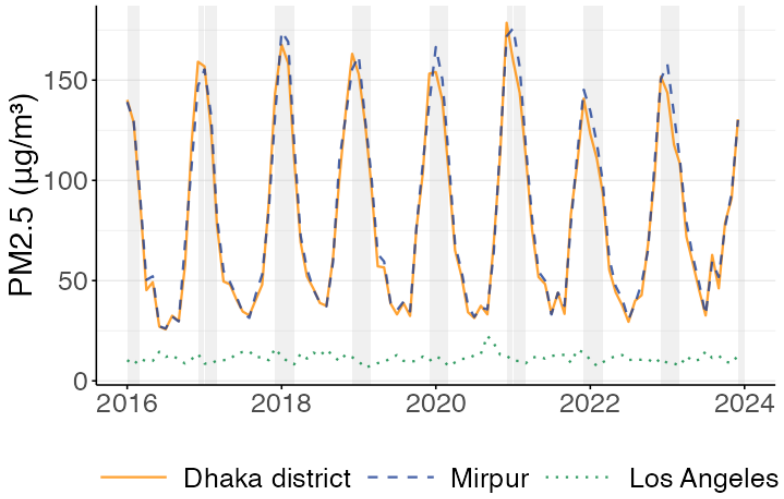
H Figures

Figure A.1: Air Pollution in Bangladesh

(a) Bangladesh Over Time



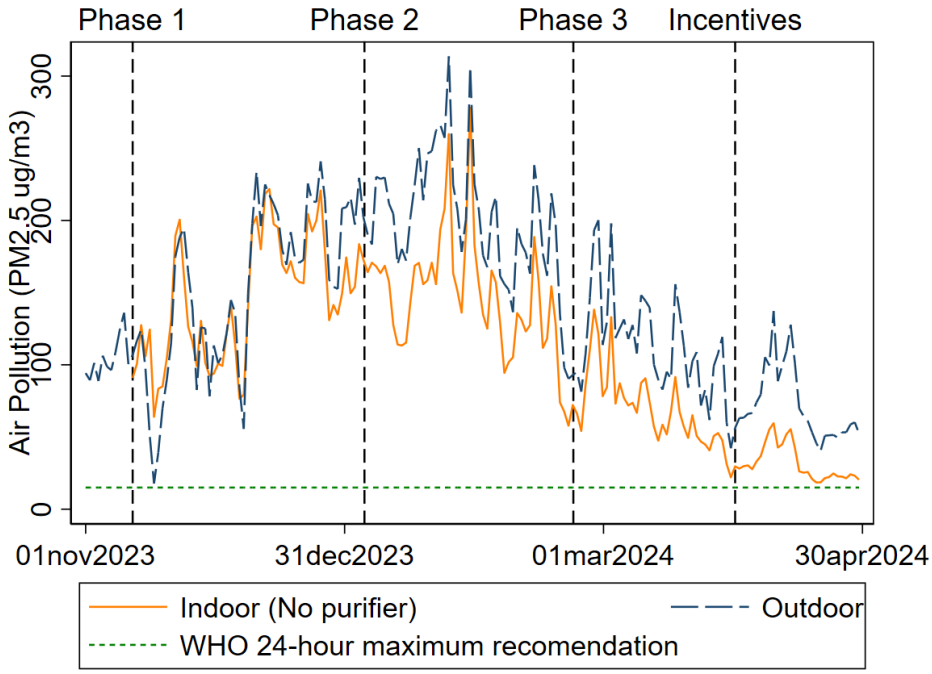
(b) Seasonality in Bangladesh



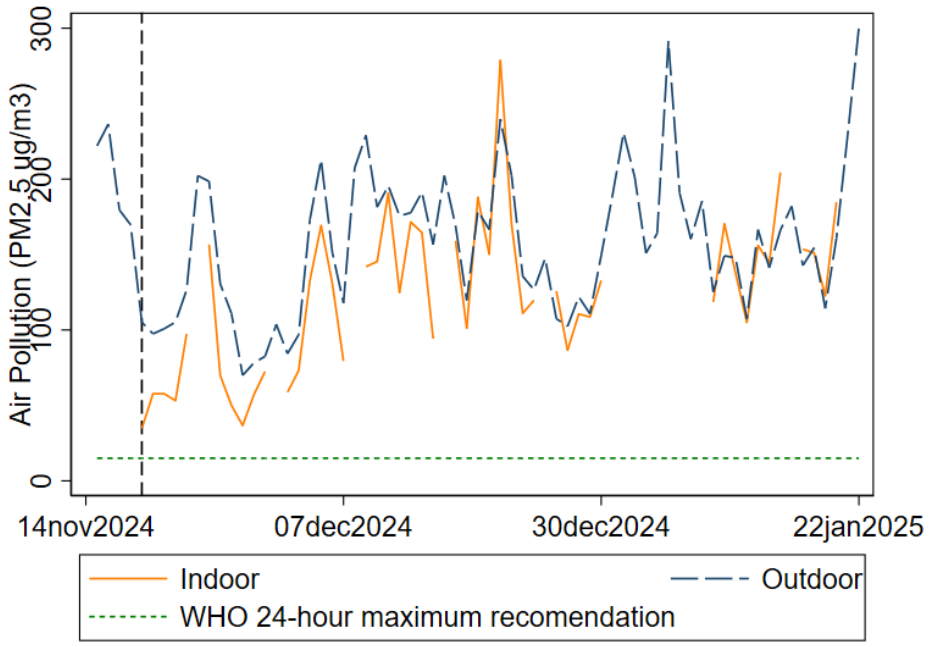
Notes: This figure provides an overview of air pollution in Bangladesh. Panel (a) shows annual satellite-derived air pollution levels across Bangladesh and in Dhaka district, compared to the WHO annual guideline and Bangladesh's National Standard. Panel (b) shows monthly satellite-derived air pollution levels in Dhaka, Mirpur (the locality in Dhaka where the experiments are 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). See discussion in Section 2.1.

Figure A.2: Indoor vs. Outdoor Air Pollution

(a) Indoor vs. outdoor air pollution: Experiment 1

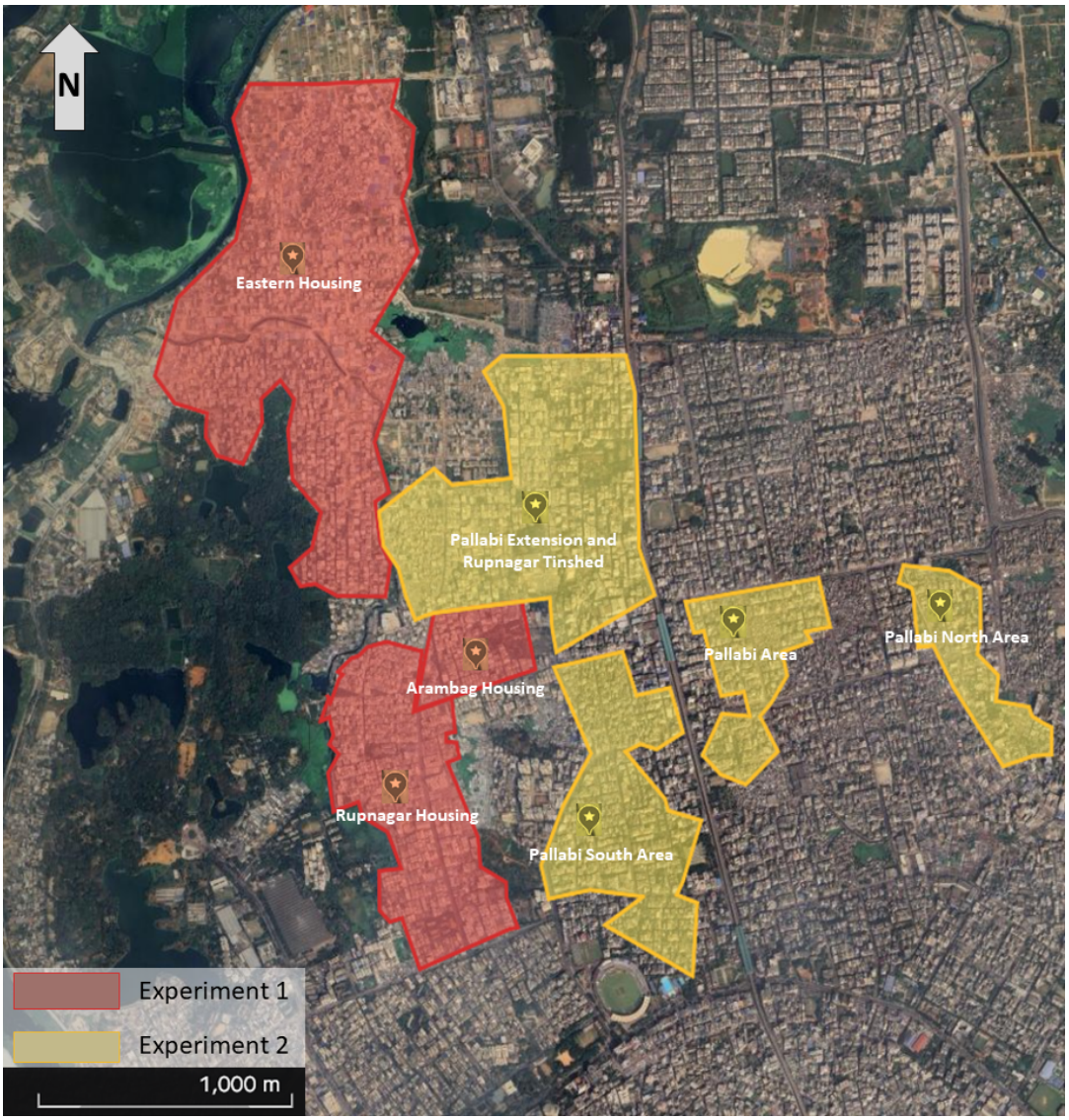


(b) Outdoor air pollution: Experiment 2



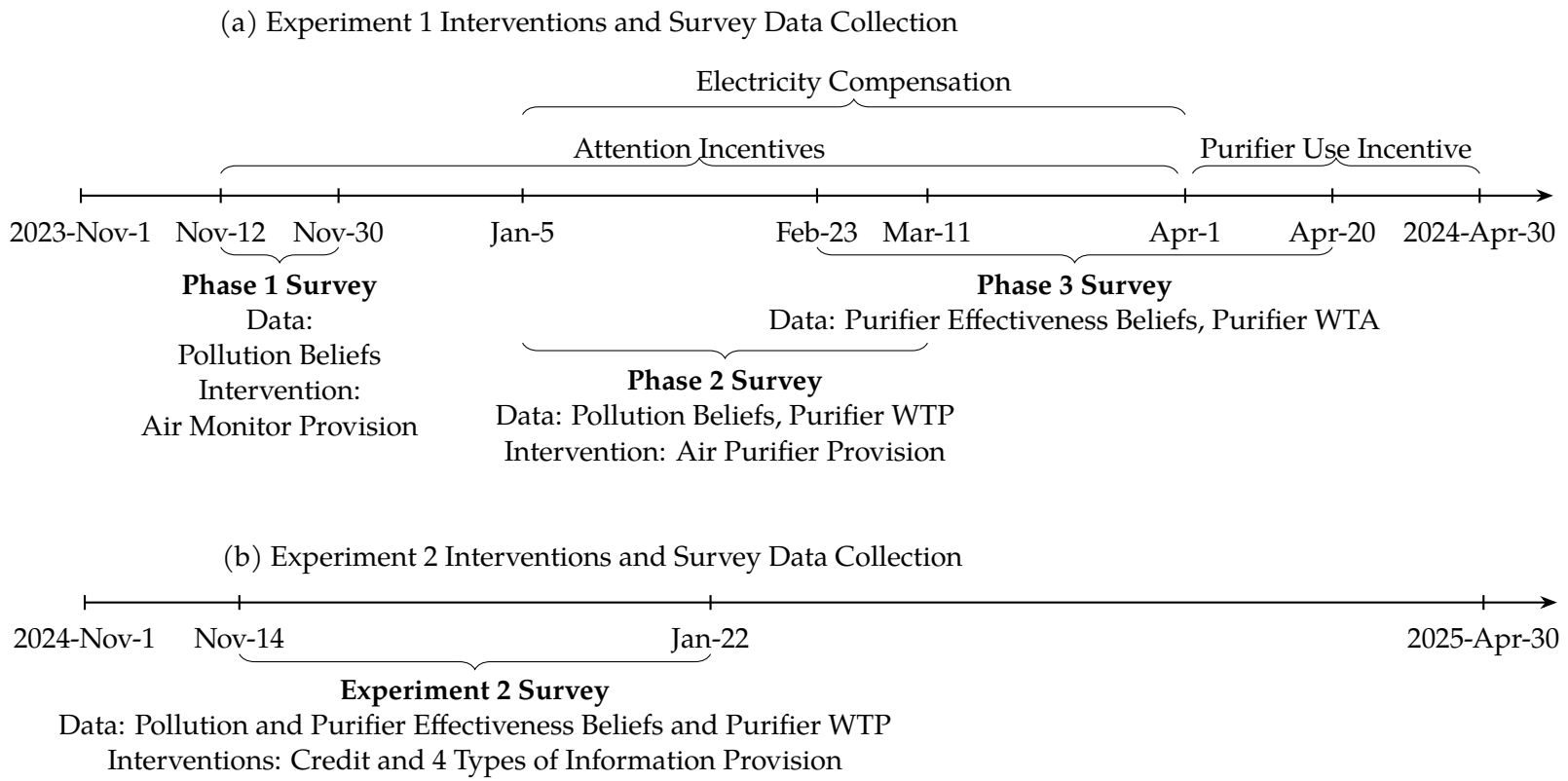
Notes: This figure compares indoor and outdoor air pollution using data from our monitors. The levels are compared to the WHO 24-hour guideline. Panel (a) shows the average daily air pollution outdoors and indoors for households without air purifiers during Experiment 1. The four vertical dashed lines indicate the start of the Phase 1, 2, and 3 surveys as well as the start of the incentive experiment. Outdoor air pollution data from November 1, 2023 until November 30, 2023 is imputed using US Embassy monitor readings. Panel (b) shows the average daily air pollution outdoors compared to the indoor measurements of air pollution during Experiment 2. As we did not conduct surveys on all days, there are gaps in the measurements of indoor air pollution. See discussion in Section 2.1.

Figure A.3: Map of Study Area



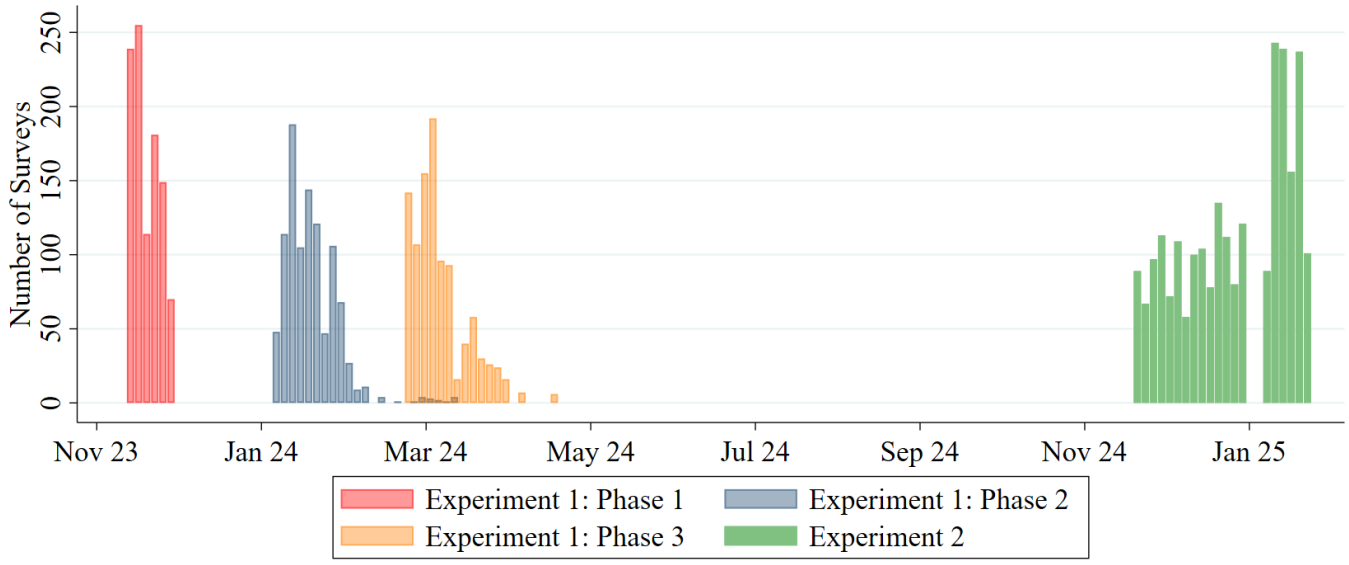
Notes: This is a map of the seven housing associations in which the two experiments were conducted. All of the housing associations are located in the Mirpur area of Dhaka, Bangladesh. See discussion in Section 2.1.

Figure A.4: Timelines of Interventions and Survey Data Collection



Notes: This figure shows the timeline of the interventions and data collection for Experiments 1 and 2. Sub-Figure (a) shows the timeline for Experiment 1. Figure (b) shows the timeline for Experiment 2. See discussion in Section 2.2.

Figure A.5: Distribution of Survey Dates for Experiments 1 and 2



Notes: This figure shows the distributions of the individual survey dates for each survey. In Experiment 1, the surveys were carried out in the same sequence so that the households first surveyed in Phase 1 were contacted first in Phase 2 and so on. See discussion in Section 2.2.

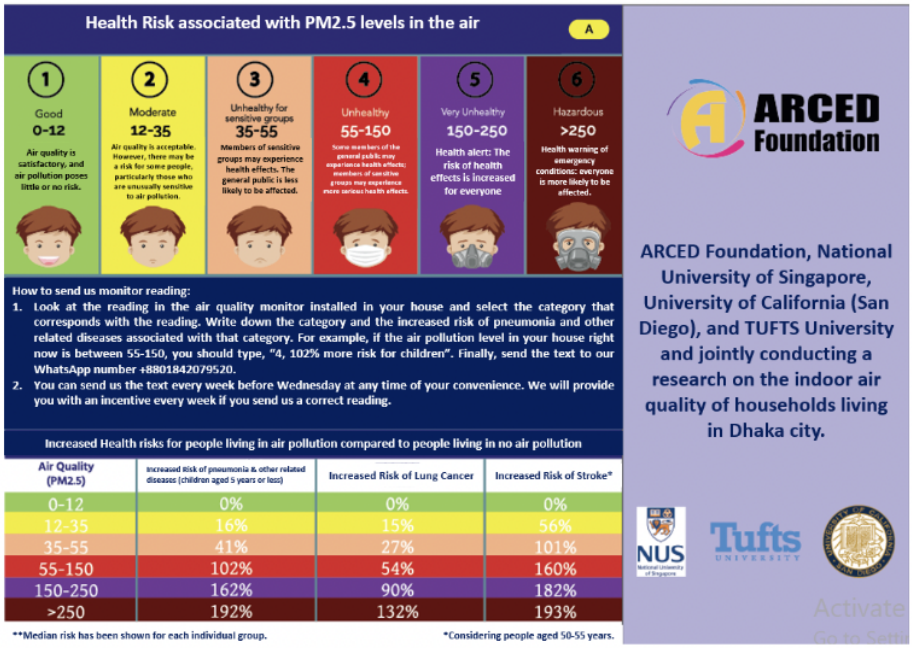
Figure A.6: Air Pollution Monitor



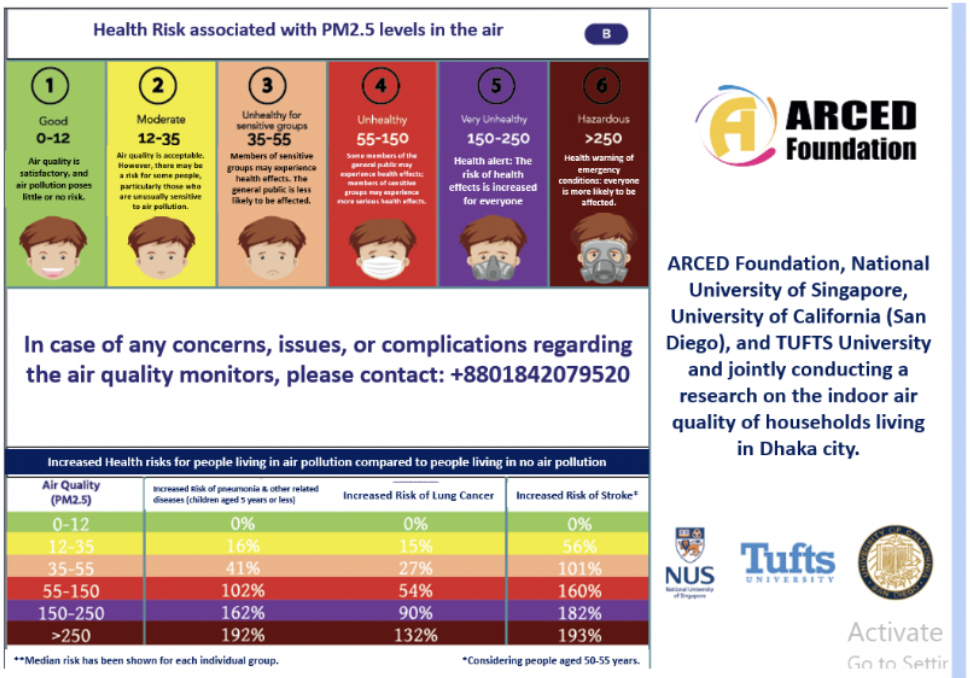
Notes: Image of the air quality monitor provided to the households in the monitor treatment group. For more details, see: https://www.qingping.co/air-monitor-lite/overview. See discussion in Section 2.2.1.

Figure A.7: 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. See discussion in Section 2.2.1.

Figure A.8: Sqair Purifer



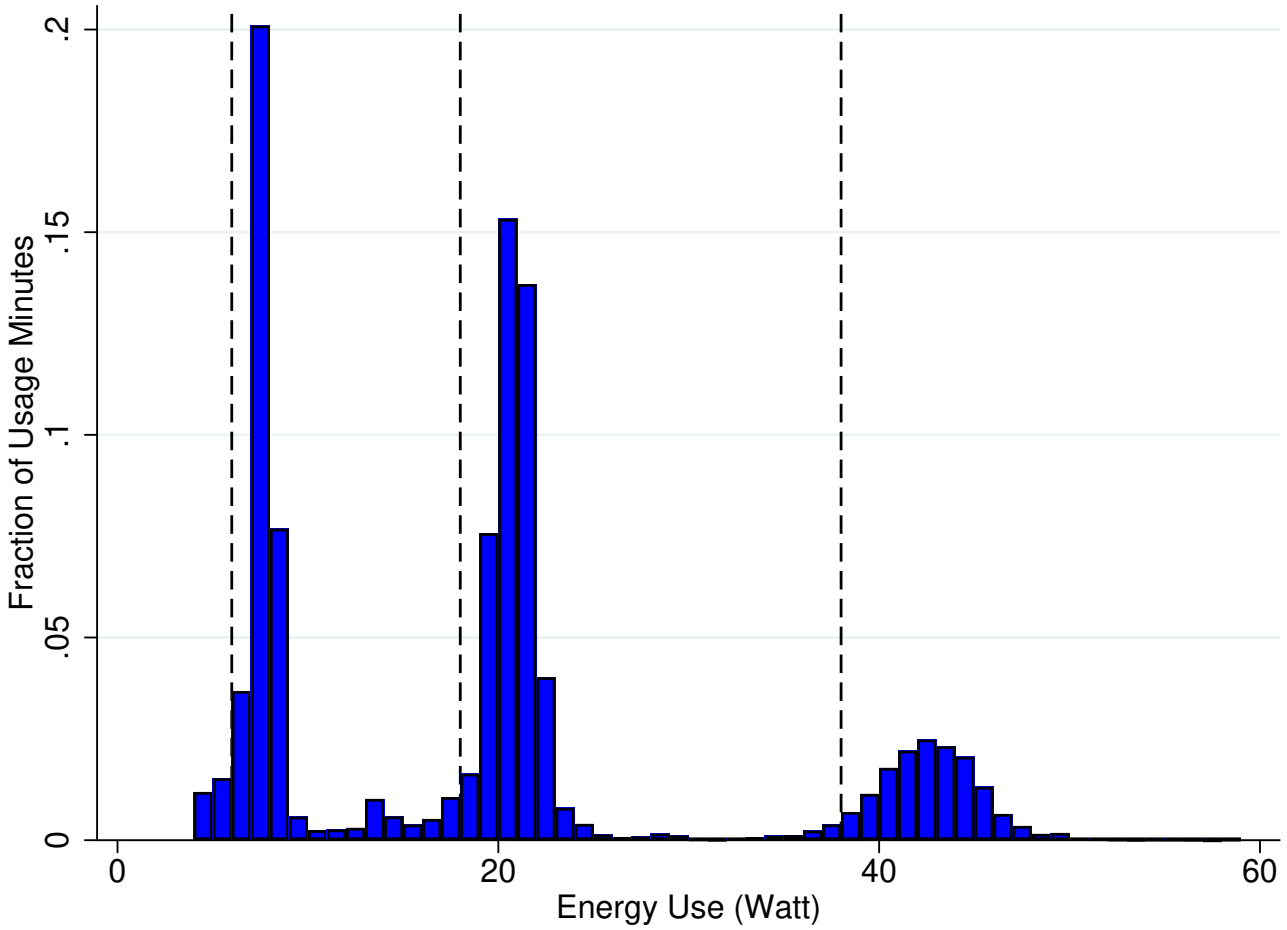
Notes: Image of the air purifier model provided to the households in the air purifier treatment group. For more details, see: https://smartairfilters.com/en/product/sqair-air-purifier/. See discussion in Section 2.2.1.

Figure A.9: Smart Socket



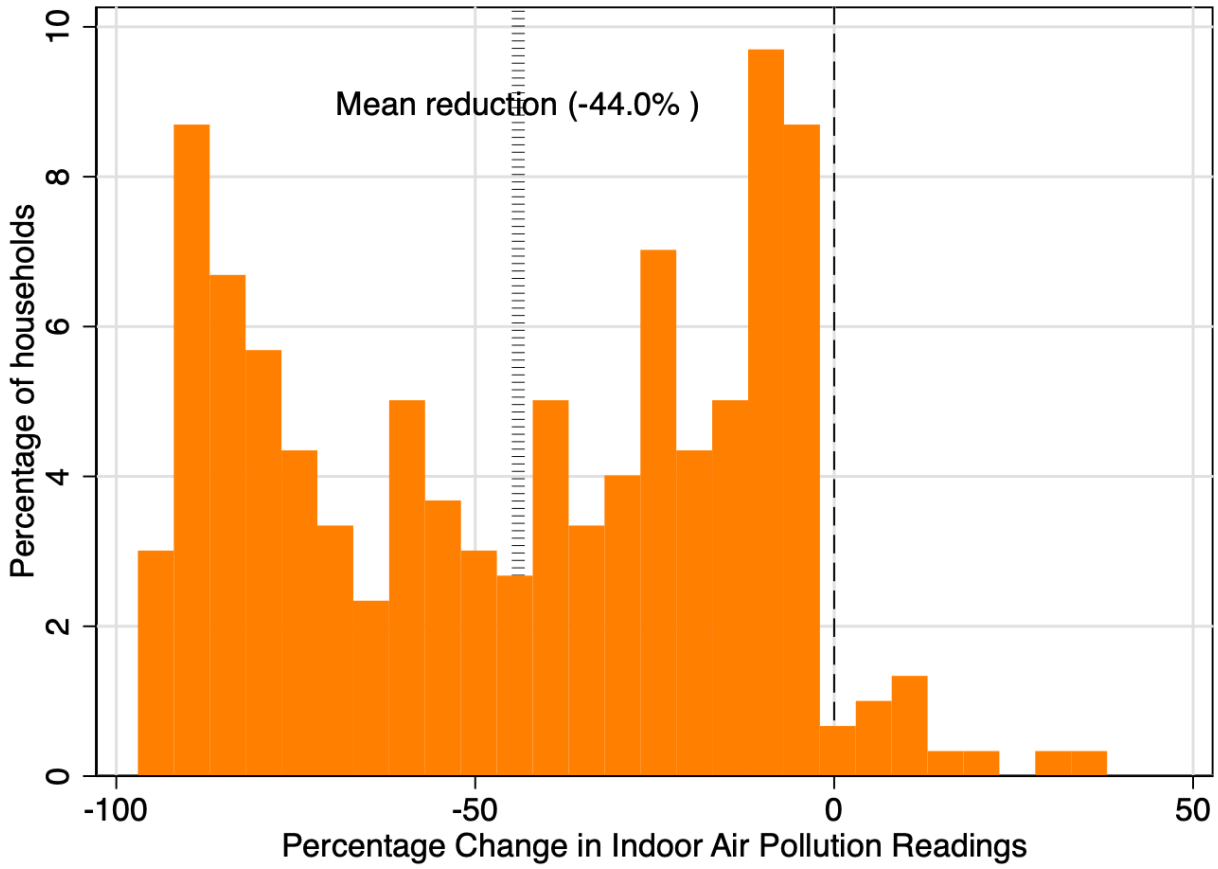
Notes: Image of the smart socket used to measure air purifier usage. Each purifiers' electricity chord was glued into a smart socket. The smart socket transmits minute-by-minute usage data to the research team via Wi-Fi. See discussion in Section 2.2.1.

Figure A.10: Wattage Used by Air Purifiers (Experiment 1, Smart Socket Data)



Notes: The figure shows how much electricity each air purifier uses in watts. Each observation is a minute by household smart socket reading between the Phase 2 survey and 1 April 2024. We have only included observations where the air purifier is in use. 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. See discussion in Section 2.2.1.

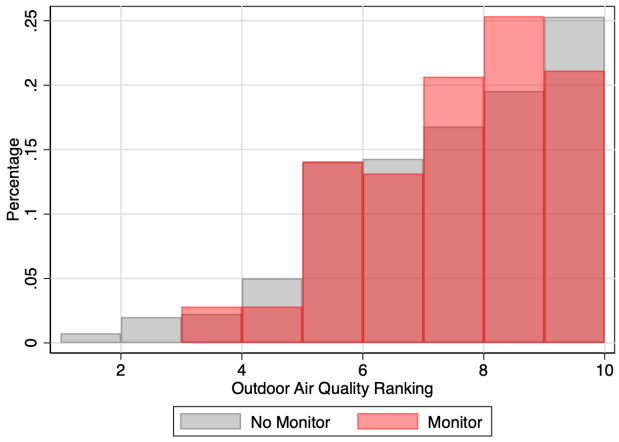
Figure A.11: Experiment 2: Change in Air Pollution During Demonstration for the "Both (Together)" Group



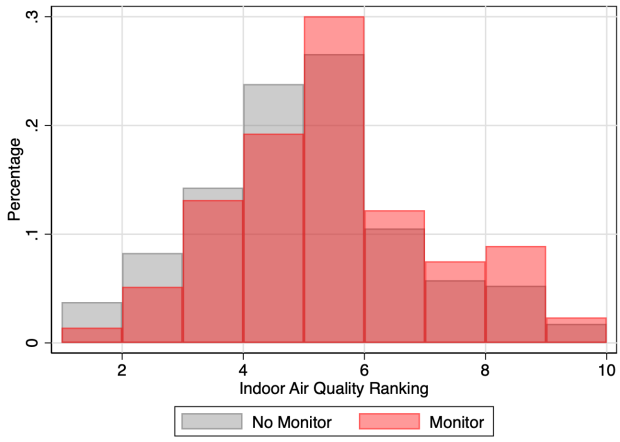
Notes: The figure shows the distribution of percentage changes in indoor pollution during the demonstration for both (together) treatment arm in Experiment 2. The second recordings in this group were initiated only after December 7, 2024 and therefore the graph is based on 299 observations (as opposed to 400 observations). See discussion in sections 2.2.2 and 3.2.

Figure A.12: Effect of Monitor on Perceptions and WTP for Purifier (Experiment 1, Phase 2 Survey)

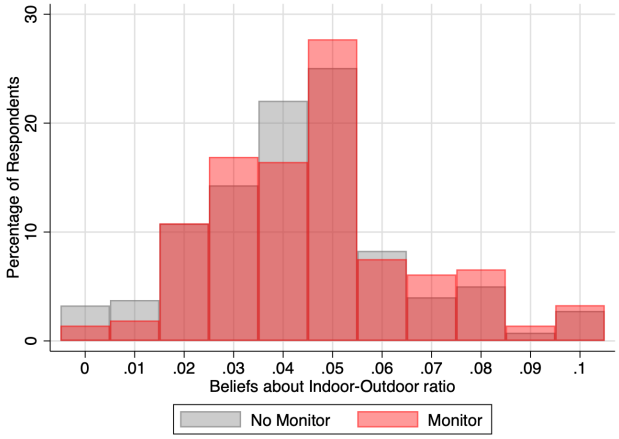
(a) Shift in Outdoor Air Pollution Perceptions



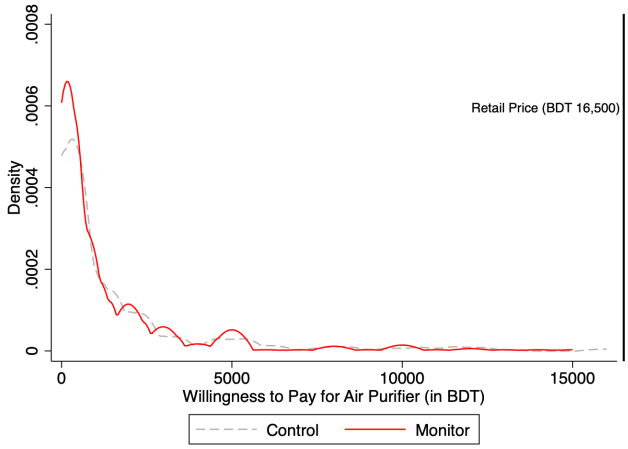
(b) Shift in Indoor Air Pollution Perceptions



(c) Shift in Perceptions of Indoor-Outdoor Ratio

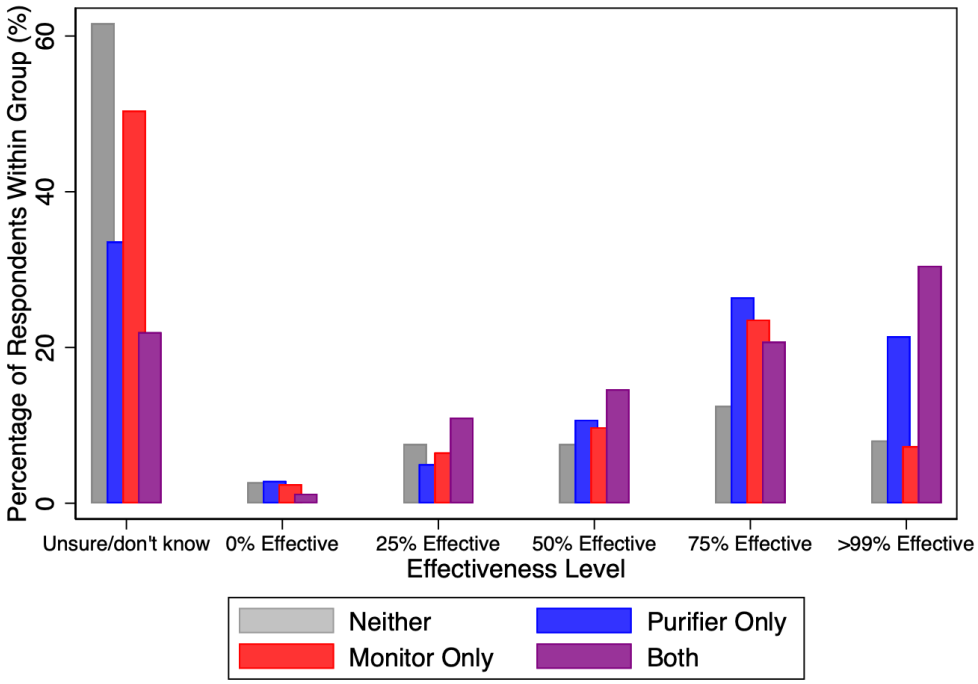


(d) No shift in WTP for purifier in Phase 2



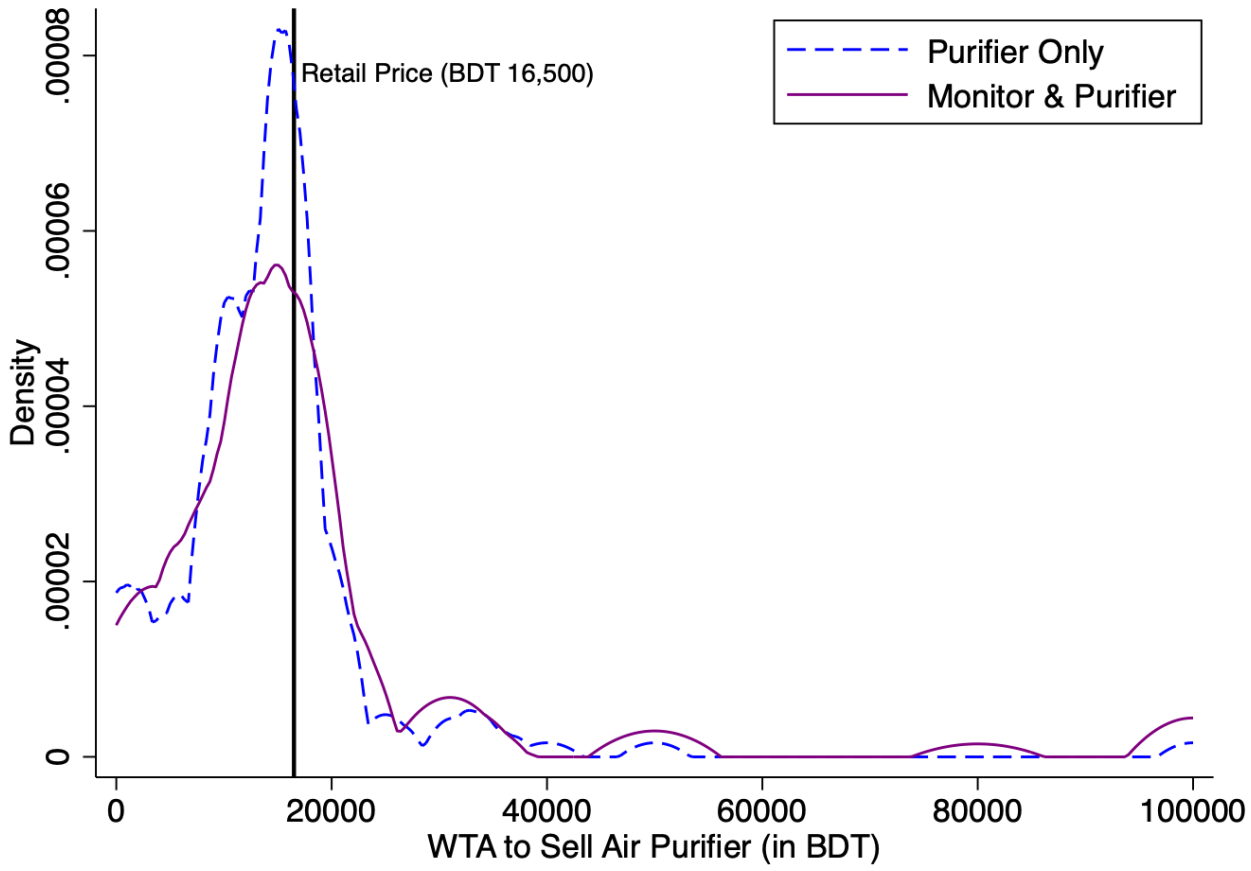
Notes: This figure describes the shifts in household beliefs during phase 2 survey of Experiment 1 with monitor treatment. Panel (a) shows the shift in beliefs about the severity of outdoor air pollution with monitor treatment. Panel (b) shows the shift in beliefs about the severity of indoor air pollution with monitor treatment. Panel (c) shows the shift in beliefs about the ratio of indoor to outdoor air pollution with monitor treatment. Panel (d) shows the density of a revealed preference measure for WTP for air purifiers during phase 2 for households in the control group and monitor treatment group. See discussion in Section 5.

Figure A.13: Distribution of Air Purifier Effectiveness Perceptions by Monitor and Purifier Treatment (Experiment 1, Phase 3 Survey)



This figure shows the differences in beliefs during the Phase 3 survey of Experiment 1 about effectiveness of air purifiers for the following groups: neither monitor nor purifier, monitor only, purifier only, and both monitor and purifier. The outcome is the response to a question asking how effective the household thinks regular air purifiers that can be bought in shops in Dhaka are at removing air pollution from the room in which they are being run. This variable ranges from 0 being completely ineffective to 1 being (almost) completely effective. Unsure/don't know: is a binary variable equal to 1 if the household selected the option "Don't know/unsure". 0% effective, 25% effective, 50% effective, 75% effective and >99% effective are binary variables equal to 1 if the household said the purifier was 0%, 25%, 50%, 75% and >99% effective respectively. Observations are at the household level. See discussion in Section 6.

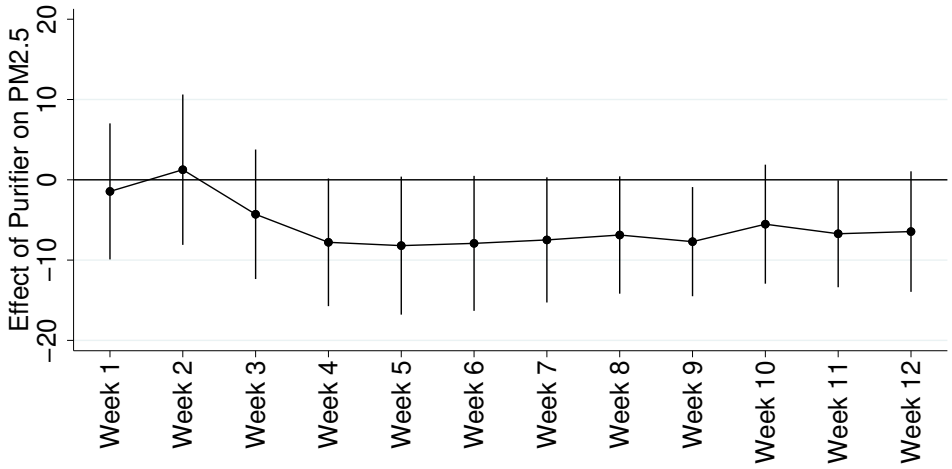
Figure A.14: Distribution of WTA in Phase 3 by Monitor + Purifier vs. Purifier Group



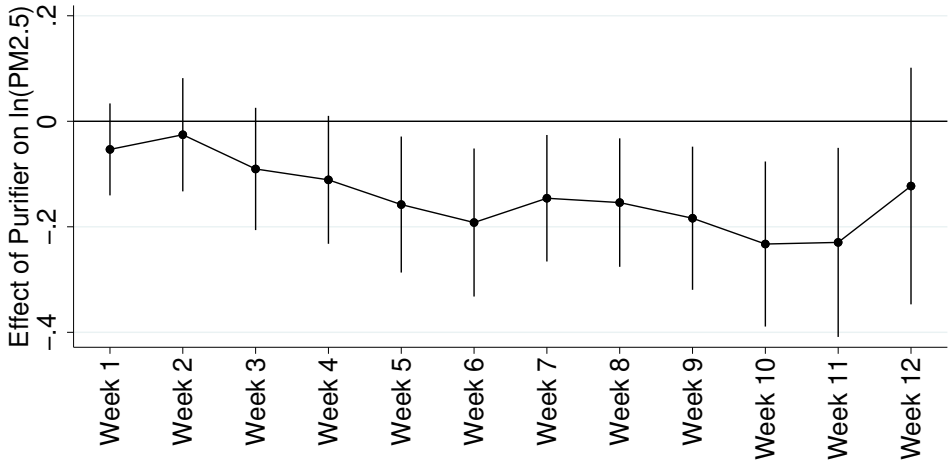
Notes: This figure describes the density of a revealed preference measure for willingness to accept (WTA) to sell an air purifier during phase 3 survey of Experiment 1 for households in the purifier group by whether or not they also received a monitor. The solid black vertical line denotes the retail price of air purifiers. See discussion in Section 7.1.

Figure A.15: Effect of Purifiers on Air Pollution Over Time

(a) Effect on Levels of PM2.5, with imputed values



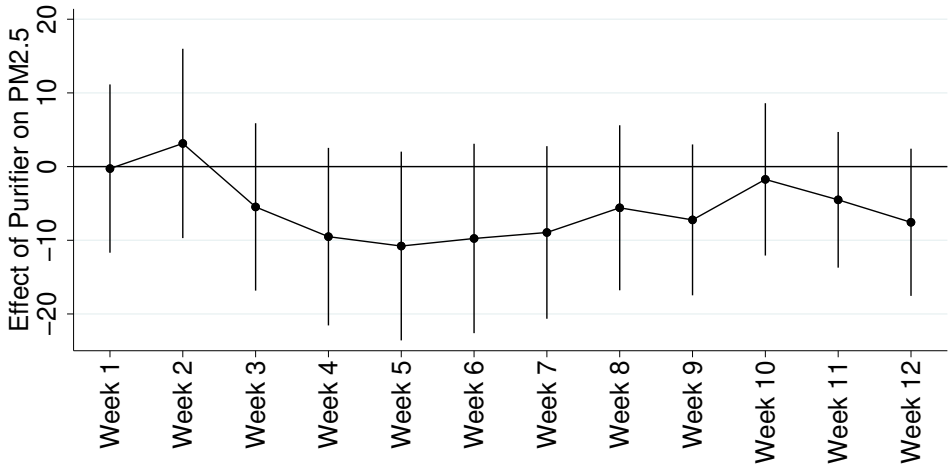
(b) Effect on ln(PM2.5, with imputed values)



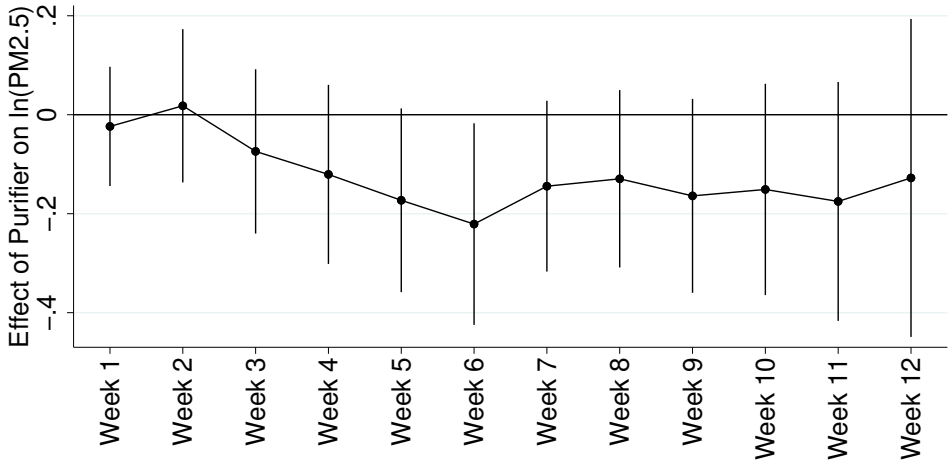
Notes: This figure shows the effect of air purifiers on pollution, using imputed values for pollution when monitors are turned off. The imputed values are calculated using the average ratio between the indoor and outdoor pollution in households without an air purifier and multiplying that by the outdoor pollution reading during the hour that the household's monitor was turned off. All coefficients come from one regression where each observation is at the hour-by-household level and we have include time fixed effects. The coefficients are on the purifier variable interacted with an indicator for the observation being from a specific week since the phase 2 survey, when the purifiers were provided. The outcome variable in Panel A is the air pollution in that hour. In Panel B, the outcome variable is the log of pollution. Data is from the Phase 2 survey until 1 April 2024. 95% Confidence intervals are constructed with standard errors clustered at the household level. See discussion in Section 8.1.

Figure A.16: Effect of Purifiers on Air Pollution Over Time, Without Imputed Values

(a) Effect on Levels of PM2.5

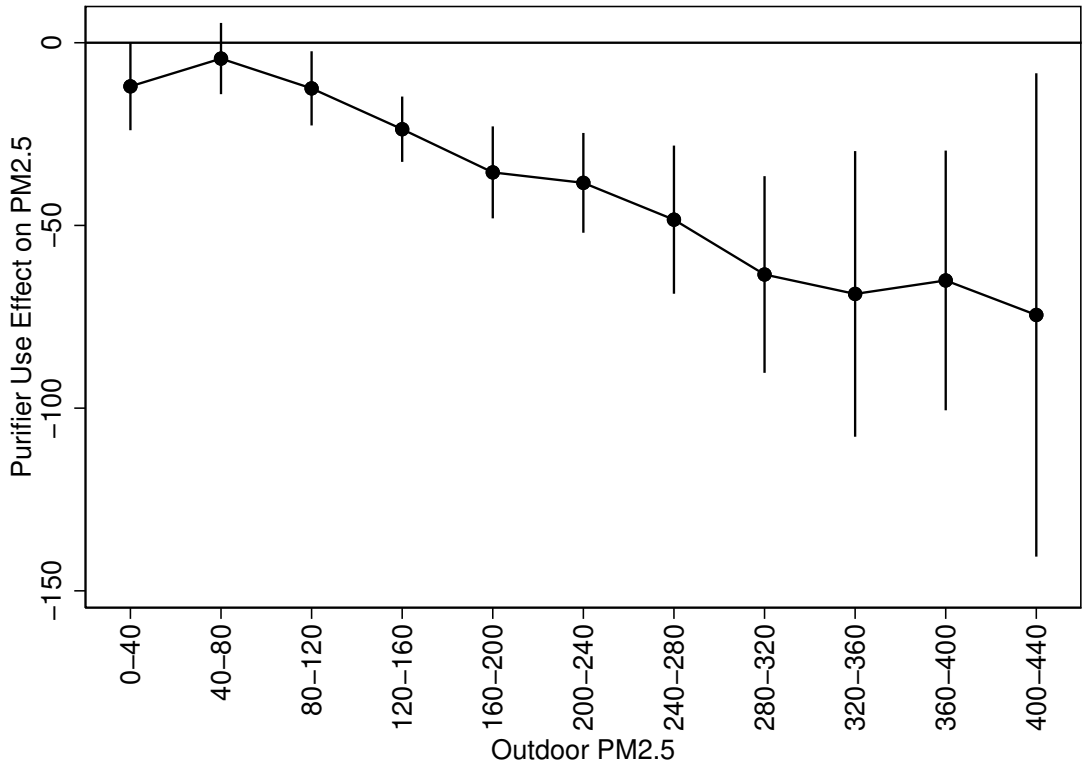


(b) Effect on ln(PM2.5)



Notes: This figure shows the effect of providing air purifiers on air pollution, when not imputing air pollution values. All coefficients come from one regression where each observation is at the hour-by-household level and we have included time fixed effects. The coefficients are on the purifier variable interacted with an indicator for the observation being from a specific week since the phase 2 survey, when the purifiers were provided. The outcome variable in Panel A is the air pollution in that hour. In Panel B, the outcome variable is the log of pollution. Data is from the Phase 2 survey until 1 April 2024. 95% Confidence intervals are constructed with standard errors clustered at the household level. See discussion in Section 8.1.

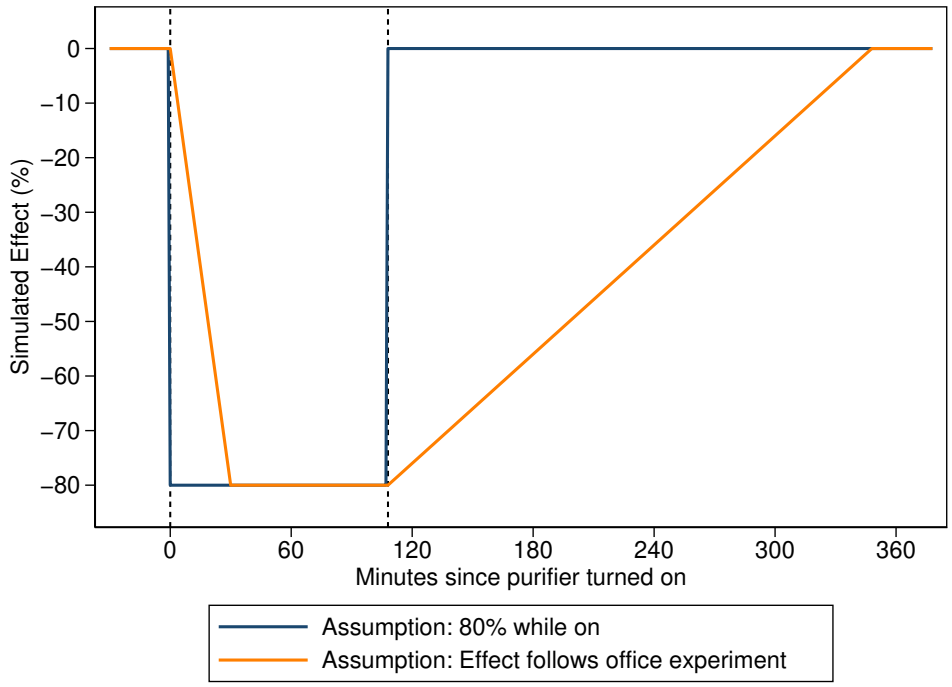
Figure A.17: Effect of Purifier Use On Indoor Pollution by Outdoor Pollution Level



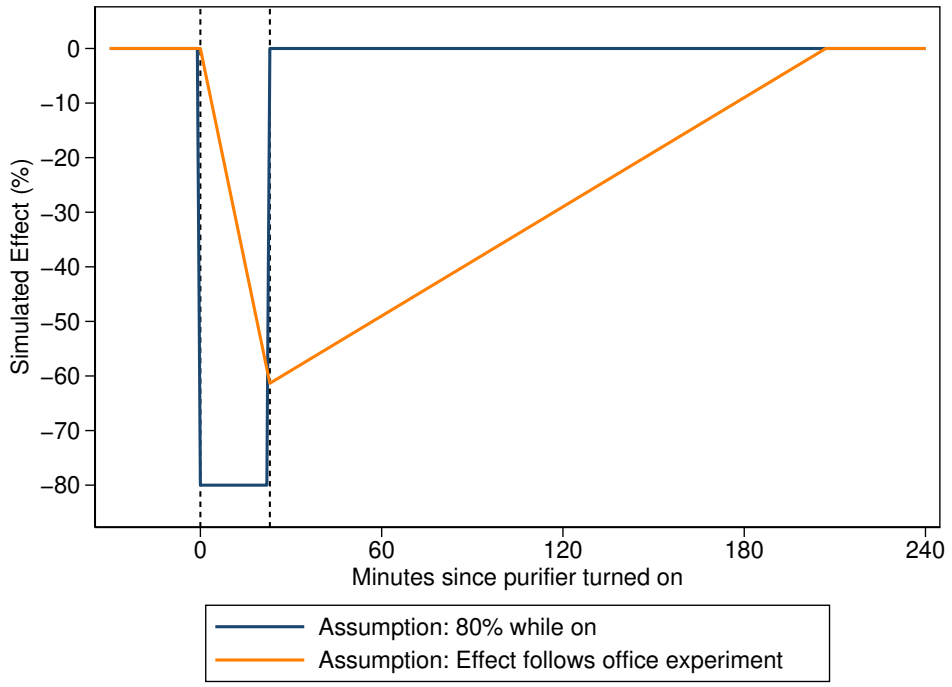
Notes: This table shows the estimated effect of households turning on their air purifiers on indoor PM2.5 air pollution for different levels of outdoor air pollution. The coefficients shown come from Column (2) of Appendix Table A.25. Data is from the Phase 2 survey of Experiment 1 until April 30, 2024. Standard errors clustered at the household level. See discussion in Section 9.2.

Figure A.18: Simulated Effect of Purifier Use

(a) Simulated Effect of 108 min Purifier Use



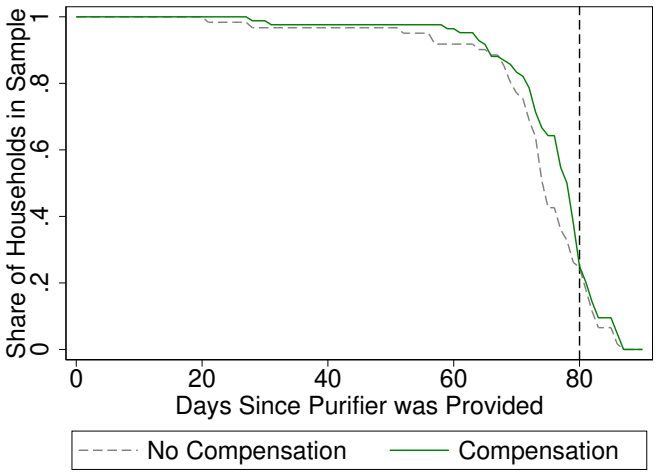
(b) Simulated Effect of 23 min Purifier Use



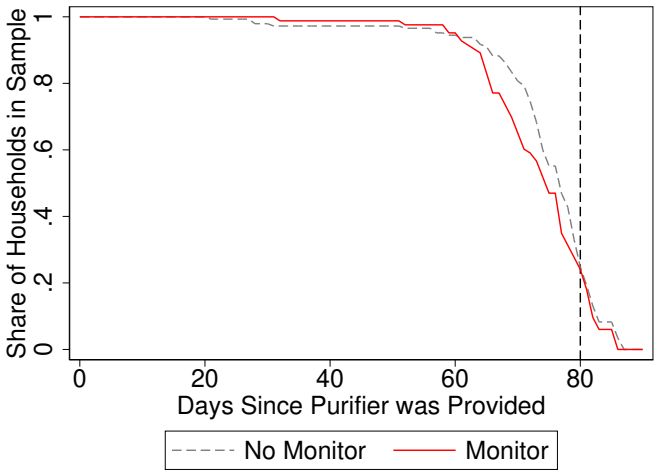
Notes: This figure shows the simulated effect on air pollution of turning a purifier on for a limited amount of time. For the "80% whole on assumption" we assume that the air purifier immediately reduces air pollution by 80% and that the effect disappears immediately when the purifier is turned off. We assume that the air pollution decreases linearly for 30 minutes after the purifier is turned on until it has reduced air pollution by 80%. When the purifier is turned off, we assume that air pollution increases linearly at a rate so that an 80% reduction completely disappears after 4 hours. Sub-figure (a) shows the simulated reduction when turning the purifier on for 108 minutes, the average length of a purifier session in our data. Sub-figure (b) shows the simulated reduction when turning the purifier on for 23 minutes, the median length of a purifier session in our data. See discussion in Section 9.2.

Figure A.19: Share of Households Represented in Analysis of Air Purifier Use Over Time

(a) Compensation vs. No compensation (Figure 6b)

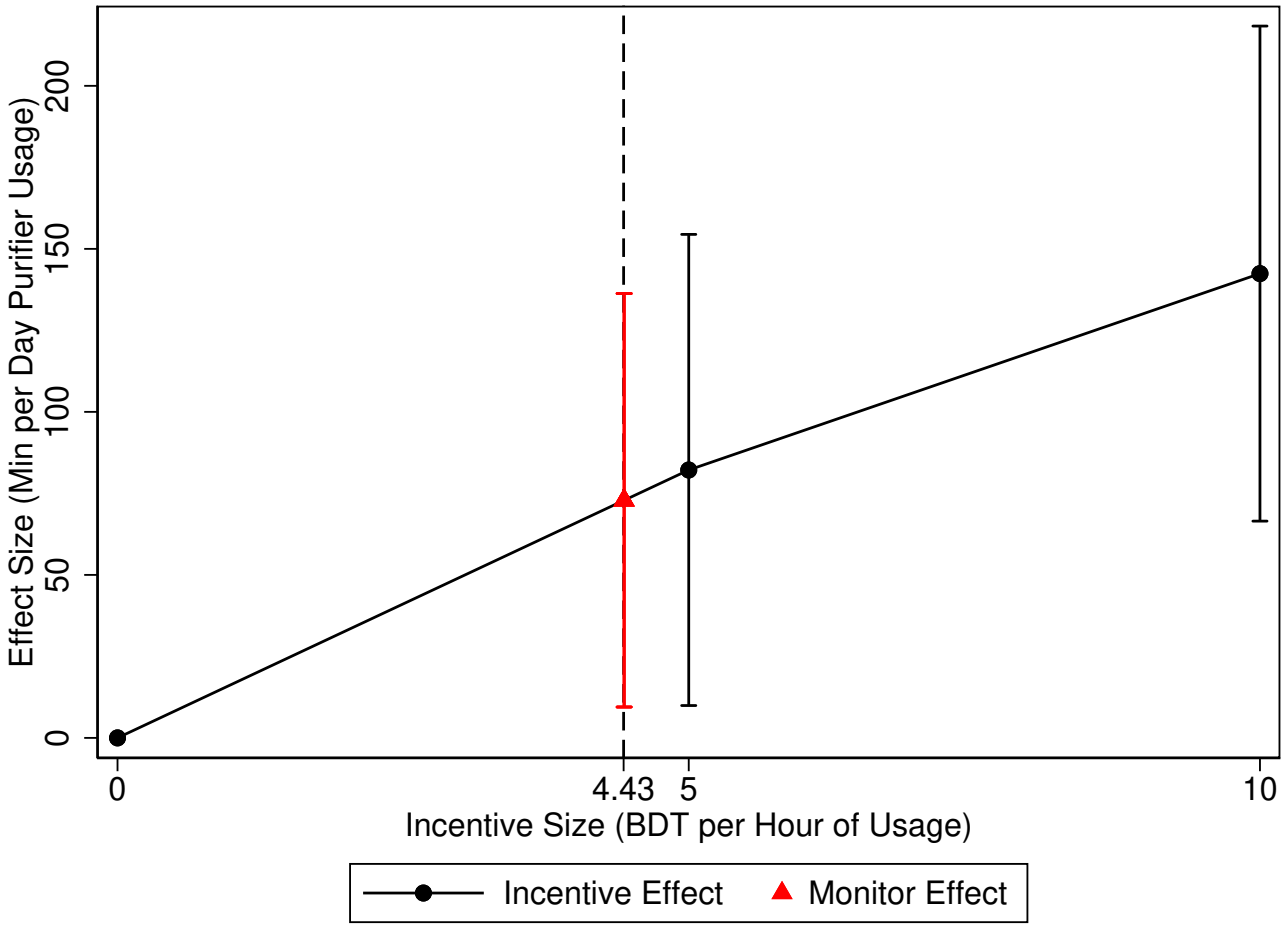


(b) Monitor vs. No Monitor (Figure 7b)



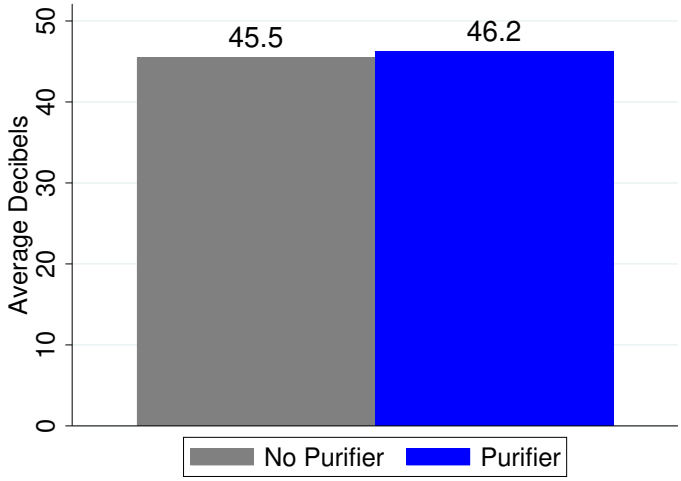
Notes: The figure shows the share of households that have not yet reached 1 April 2024 (when they are dropped from the sample), at each relative time since the Phase 2 survey. The vertical dashed line indicates where the data in Figures 6b and 7b end. See discussion in Appendix C.

Figure A.20: Comparison of the Effect of Monitors and the Effect of Incentives on Purifier Usage (Experiment 1, Smart Socket Data)



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 4.4 on the x-axis as the monitor effect is equivalent to the linear interpolation of the incentive effect at BDT 4.4. 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. See discussion in Section F.

Figure A.21: Effect of Purifier on Noise



Notes: This figure shows how running a purifier affects noise levels. The experiment was carried out over two days, February 18 and 19, 2025, in two bedrooms in apartments in Mirpur, similar to those where the main experiments took place. We placed a purifier running at the medium speed in one room and then switched the room in which the purifier was placed after 24 hours. The "Purifier" bar shows the average decibel level in the rooms when the purifier was placed there, and the "No Purifier" bar shows the average decibel level in the rooms when the purifier was not placed there. See discussion in Section F.

I Tables

Table A.1: Effect of Treatments on Attrition: Phase 1 to Phase 2 (Experiment 1)

	(1) Phase 2 Attrition
Monitor	-0.024
	(0.030)
Monitor x Attention	0.021
	(0.035)
Observations	1,008
Control mean	0.196

Notes: This table shows the effects of the monitor and attention treatment on attrition from phase 1 survey to phase 2 survey during Experiment 1. The outcome variable is attrition during phase 2 survey, measured by the households who participated in phase 1 survey but not 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. Significance levels are denoted by $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$. See discussion in Section B.

Table A.2: Balance Among Unattrited Households in Phase 2: Monitor Treatment

	(1) No-Monitor Group		(2) Monitor Group		(2)-(1) Pairwise t-test	
Variable	N	Mean/(SE)	N	Mean/(SE)	N	Mean difference
College Graduate	399	0.474 (0.025)	419	0.480 (0.024)	818	0.006
Age	399	37.554 (0.696)	419	38.969 (0.700)	818	1.415
Beliefs about Risk of Lung Cancer and Stroke from Air Pollution	380	1.648 (0.024)	401	1.627 (0.023)	781	-0.021
Beliefs about Risk of ARI for Children from Air Pollution	390	1.740 (0.029)	410	1.723 (0.029)	800	-0.017
Beliefs about Severity of Outdoor Air Pollution	399	7.376 (0.102)	419	7.566 (0.101)	818	0.190
Beliefs about Severity of Indoor Air Pollution	399	4.789 (0.105)	419	4.692 (0.105)	818	-0.097
Beliefs about Indoor v. Outdoor Air Pollution	395	3.557 (0.062)	418	3.507 (0.061)	813	-0.050
F-test of joint significance (P-value)						0.392
F-test, number of observations						773

Notes: This table provides balance test on Phase 1 survey data for households unattrited by Phase 2 survey in Experiment 1 for the monitor and non-monitor groups. For each variable, we report the difference and the statistical significance of the t-test. We also report the joint F-test with p-value. Statistical significance thresholds are reported conventionally using $***p < 0.01; **p < 0.05; *p < 0.1$. See discussion in Section B.

Table A.3: Balance Among Unattrited Households in Phase 2: Attention Treatment

	(1) No-Attention Group		(2) Attention Group		(2)-(1) Pairwise t-test	
Variable	N	Mean/(SE)	N	Mean/(SE)	N	Mean difference
College Graduate	213	0.479 (0.034)	206	0.481 (0.035)	419	0.002
Age	213	37.568 (0.943)	206	40.417 (1.031)	419	2.849**
Beliefs about Risk of Lung Cancer and Stroke from Air Pollution	204	1.651 (0.032)	197	1.602 (0.032)	401	-0.050
Beliefs about Risk of ARI for Children from Air Pollution	209	1.756 (0.042)	201	1.689 (0.039)	410	-0.066
Beliefs about Severity of Outdoor Air Pollution	213	7.460 (0.138)	206	7.675 (0.147)	419	0.215
Beliefs about Severity of Indoor Air Pollution	213	4.629 (0.143)	206	4.757 (0.154)	419	0.128
Beliefs about Indoor v. Outdoor Air Pollution	213	3.512 (0.084)	205	3.502 (0.090)	418	-0.009
F-test of joint significance (P-value)						0.352
F-test, number of observations						400

Notes: This table provides balance test on Phase 1 survey data for households unattrited by Phase 2 survey of Experiment 1 for the attention and non-attention groups (monitor households only). We also report the joint F-test with p-value. Statistical significance thresholds are reported conventionally using $***p < 0.01; **p < 0.05; *p < 0.1$. See discussion in Section B.

Table A.4: Effect of Purifier Treatment on Attrition: Phase 2 to Phase 3

	(1) Phase 3 Attrition
Purifier	-0.056**
	(0.022)
Pur X Monthly-Incentive	-0.022
	(0.024)
Pur X Daily-Incentive	-0.045**
	(0.018)
Observations	818
Control Mean	0.102

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table shows the effects of the purifier treatment as well as the purifier treatment interacted with monthly and daily electricity incentives on attrition between phase 2 and phase 3 survey during Experiment 1. The outcome variable is attrition during phase 3 survey. This variable is 1 if the household participated in phase 2 survey but not 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 (818). For reference, out of 1,008 households, 818 households were sampled in the Phase 2 survey, and then 758 were sampled in the Phase 3 survey. In other words, 190 households attritioned at between Phase 1 and Phase 2, and 60 households attritioned between Phase 2 and Phase 3. Significance levels are denoted by $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$. See discussion in Section B.

Table A.5: Balance Among Unattrited Households in Phase 3: Purifier Treatment

	(1) No Purifier		(2) Purifier		(2)-(1) Pairwise t-test	
Variable	N	Mean/(SE)	N	Mean/(SE)	N	Mean difference
Monthly Income	460	61813.478 (2490.459)	298	58235.872 (2676.912)	758	-3577.606
Education	460	14.228 (0.273)	298	14.587 (0.325)	758	0.359
Age	460	43.593 (0.628)	298	44.466 (0.780)	758	0.873
WTP	459	1399.041 (111.519)	296	1362.365 (148.880)	755	-36.677
HH Size	460	4.183 (0.068)	298	4.111 (0.073)	758	-0.072
Beliefs about Risk of Lung Cancer and Stroke from Air Pollution	440	1.924 (0.035)	290	1.943 (0.043)	730	0.020
Beliefs about Risk of ARI for Children from Air Pollution	449	2.169 (0.043)	291	2.251 (0.056)	740	0.081
Donate to Clean Air NGO (0/1)	460	0.246 (0.020)	298	0.268 (0.026)	758	0.023
Clean Air Priority (Z-score)	460	-0.002 (0.046)	298	0.034 (0.061)	758	0.035
Beliefs about Indoor v. Outdoor Air Pollution	460	0.446 (0.010)	298	0.448 (0.012)	758	0.002
Beliefs about Severity of Indoor Air Pollution	460	4.713 (0.084)	298	4.691 (0.103)	758	-0.022
Beliefs about Severity of Outdoor Air Pollution	460	7.041 (0.088)	298	7.171 (0.117)	758	0.130
Health Index (ICW)	460	0.056 (0.028)	298	0.080 (0.030)	758	0.023
F-test of joint significance (P-value)						0.924
F-test, number of observations						725

Notes: This table provides balance test on Phase 2 survey data for households unattrited by Phase 3 survey of Experiment 1 for the purifier and non-purifier groups. For each variable, we report the difference and the statistical significance of the t-test. We also report the joint F-test with p-value. Statistical significance thresholds are reported conventionally using $***p < 0.01; **p < 0.05; *p < 0.1$. See discussion in Section B.

Table A.6: Balance Among Unattrited Households in Phase 3: Purifier Treatment By Incentive

Variable	(1) No Incentive N	(1) Mean/(SE)	(2) Daily Incentive N	(2) Mean/(SE)	(3) Monthly Incentive N	(3) Mean/(SE)	F-test for balance across all groups N	F-test for balance across all groups F-stat/P-value
Monthly Income	127	58200.000	86	57029.070	85	59510.471	298	0.061
		(4413.947)		(4403.505)		(5027.168)		0.941
Education	127	14.732	86	14.512	85	14.447	298	0.076
		(0.524)		(0.585)		(0.588)		0.927
Age	127	44.945	86	46.163	85	42.035	298	2.166
		(1.150)		(1.522)		(1.448)		0.117
WTP	126	1663.016	85	1044.235	85	1234.824	296	1.636
		(268.384)		(186.408)		(272.842)		0.197
HH Size	127	4.197	86	4.128	85	3.965	298	0.875
		(0.116)		(0.133)		(0.132)		0.418
Beliefs about Risk of Lung Cancer and Stroke from Air Pollution	122	1.958	85	2.010	83	1.854	290	0.980
		(0.067)		(0.093)		(0.066)		0.377
Beliefs about Risk of ARI for Children from Air Pollution	123	2.218	85	2.394	83	2.152	291	1.483
		(0.087)		(0.117)		(0.084)		0.229
Donate to Clean Air NGO (0/1)	127	0.213	86	0.314	85	0.306	298	1.768
		(0.036)		(0.050)		(0.050)		0.172
Clean Air Priority (Z-score)	127	0.029	86	0.022	85	0.052	298	0.020
		(0.100)		(0.109)		(0.108)		0.980
Beliefs about Indoor v. Outdoor Air Pollution	127	0.450	86	0.467	85	0.426	298	0.808
		(0.020)		(0.022)		(0.023)		0.447
Beliefs about Severity of Indoor Air Pollution	127	4.583	86	4.942	85	4.600	298	1.204
		(0.159)		(0.186)		(0.197)		0.302
Beliefs about Severity of Outdoor Air Pollution	127	7.087	86	7.547	85	6.918	298	2.284
		(0.180)		(0.183)		(0.245)		0.104
Health Index (ICW)	127	0.032	86	0.131	85	0.099	298	0.999
		(0.050)		(0.050)		(0.056)		0.370

Omnibus F-test $F(13, 274) = 1.22$ $p = 0.263$

Notes: This table provides balance test on Phase 2 survey data for households unattrited by Phase 3 survey of Experiment 1 within the purifier group by type of incentive (none, daily, monthly). For each variable, we report the difference and the statistical significance of the t-test. We also report the joint F-test with p-value. Statistical significance thresholds are reported conventionally using $***p < 0.01; **p < 0.05; *p < 0.1$. See discussion in Section B.

Table A.7: Effect of Purifier Treatment on Attrition in Monitor Households: Phase 2 to Phase 3

	(1) Phase 3 Attrition
Purifier	-0.044
	(0.029)
Pur X Monthly-Incentive	-0.042*
	(0.024)
Pur X Daily-Incentive	-0.042*
	(0.024)
Observations	419
Control Mean	0.089

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table shows the effects of the purifier and incentive treatments on attrition between phase 2 and phase 3 survey during Experiment 1 for the subset of households who received a monitor after Phase 1 survey. The outcome variable is attrition during phase 3 survey. This variable is 1 if the household participated in phase 2 survey but not 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 and received an air monitor. For reference, out of 1,008 households, 818 households were sampled in the Phase 2 survey, and then 758 were sampled in the Phase 3 survey. In other words, 190 households attritioned at between Phase 1 and Phase 2, and 60 households attritioned between Phase 2 and Phase 3. Significance levels are denoted by $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$. See discussion in Section B.

Table A.8: Balance Among Unattrited Households with Monitors in Phase 3: Purifier Treatment

	(1) No Purifier		(2) Purifier		(2)-(1) Pairwise t-test	
Variable	N	Mean/(SE)	N	Mean/(SE)	N	Mean difference
Monthly Income	236	63087.288 (3589.395)	158	61337.911 (3874.768)	394	-1749.377
Education	236	14.708 (0.376)	158	14.829 (0.421)	394	0.121
Age	236	44.627 (0.879)	158	43.829 (1.055)	394	-0.798
WTP	236	1392.182 (157.451)	158	1176.899 (165.799)	394	-215.283
HH Size	236	4.068 (0.089)	158	4.095 (0.103)	394	0.027
Beliefs about Risk of Lung Cancer and Stroke from Air Pollution	225	2.000 (0.055)	156	1.965 (0.065)	381	-0.035
Beliefs about Risk of ARI for Children from Air Pollution	228	2.208 (0.063)	156	2.301 (0.082)	384	0.093
Donate to Clean Air NGO (0/1)	236	0.271 (0.029)	158	0.253 (0.035)	394	-0.018
Clean Air Priority (Z-score)	236	0.029 (0.068)	158	0.079 (0.084)	394	0.050
Beliefs about Indoor v. Outdoor Air Pollution	236	0.470 (0.014)	158	0.449 (0.017)	394	-0.022
Beliefs about Severity of Indoor Air Pollution	236	5.000 (0.116)	158	4.747 (0.145)	394	-0.253
Beliefs about Severity of Outdoor Air Pollution	236	7.161 (0.116)	158	7.120 (0.153)	394	-0.041
Health Index (ICW)	236	0.009 (0.044)	158	0.044 (0.043)	394	0.035
F-test of joint significance (P-value)						0.835
F-test, number of observations						379

Notes: This table provides balance test on Phase 2 survey data for monitor households unattrited by Phase 3 survey of Experiment 1 for purifier and non-purifier households. For each variable, we report the difference and the statistical significance of the t-test. We also report the joint F-test with p-value. Statistical significance thresholds are reported conventionally using $***p < 0.01; **p < 0.05; *p < 0.1$. See discussion in Section B.

Table A.9: Effect of Monitor Treatment on Attrition in Purifier Households: Phase 2 to Phase 3

	(1) Phase 3 Attrition
Monitor	-0.011
	(0.023)
Monitor x Attention	-0.011
	(0.021)
Observations	306
Control Mean	0.034

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table shows the effects of the monitor and attention treatment on attrition between phase 2 and phase 3 survey during Experiment 1 for the subset of households who received an air purifier after Phase 2 survey. The outcome variable is attrition during phase 3 survey. This variable is 1 if the household participated in phase 2 survey but not 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 and received an air purifier. For reference, out of 1,008 households, 818 households were sampled in the Phase 2 survey, and then 758 were sampled in the Phase 3 survey. In other words, 190 households attritioned at between Phase 1 and Phase 2, and 60 households attritioned between Phase 2 and Phase 3. Significance levels are denoted by $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$. See discussion in Section B.

Table A.10: Balance Among Unattrited Purifier Households in Phase 3: Monitor Treatment

	(1) No-Monitor Group		(2) Monitor Group		(2)-(1) Pairwise t-test	
Variable	N	Mean/(SE)	N	Mean/(SE)	N	Mean difference
Monthly Income	140	54735.000 (3645.044)	158	61337.911 (3874.768)	298	6602.911
Education	140	14.314 (0.504)	158	14.829 (0.421)	298	0.515
Age	140	45.186 (1.158)	158	43.829 (1.055)	298	-1.357
WTP	138	1574.710 (256.299)	158	1176.899 (165.799)	296	-397.811
HH Size	140	4.129 (0.103)	158	4.095 (0.103)	298	-0.034
Beliefs about Risk of Lung Cancer and Stroke from Air Pollution	134	1.918 (0.056)	156	1.965 (0.065)	290	0.047
Beliefs about Risk of ARI for Children from Air Pollution	135	2.193 (0.073)	156	2.301 (0.082)	291	0.109
Donate to Clean Air NGO (0/1)	140	0.286 (0.038)	158	0.253 (0.035)	298	-0.033
Clean Air Priority (Z-score)	140	-0.017 (0.090)	158	0.079 (0.084)	298	0.096
Beliefs about Indoor v. Outdoor Air Pollution	140	0.448 (0.019)	158	0.449 (0.017)	298	0.001
Beliefs about Severity of Indoor Air Pollution	140	4.629 (0.146)	158	4.747 (0.145)	298	0.118
Beliefs about Severity of Outdoor Air Pollution	140	7.229 (0.180)	158	7.120 (0.153)	298	-0.108
Health Index (ICW)	140	0.120 (0.043)	158	0.044 (0.043)	298	-0.076
F-test of joint significance (P-value)						0.432
F-test, number of observations						288

Notes: This table provides balance test on Phase 2 survey data for purifier households unattrited by Phase 3 survey of Experiment 1 for monitor and non-monitor households. For each variable, we report the difference and the statistical significance of the t-test. We also report the joint F-test with p-value. Statistical significance thresholds are reported conventionally using $***p < 0.01; **p < 0.05; *p < 0.1$. See discussion in Section B.

Table A.11: Effect of Treatments on Withdrawals from Study

	(1) Purifier Status: Withdrawn	(2) Purifier Status: Withdrawn	(3) Monitor Status: Withdrawn
Monitor	0.0113		
	(0.0113)		
Monitor x Attention	0.00101		
	(0.0167)		
Purifier x Any Compensation		-0.0143	-0.0134
		(0.0101)	(0.0133)
Purifier x Daily Compensation		-0.0000315	0.0000182
		(0.0000547)	(0.0000296)
Purifier			0.00910
			(0.0140)
Time FE	Yes	Yes	Yes
Observations	22,983	22,983	31,501
Control mean	0.000	0.014	0.004

Notes: This table reports the effects of the monitor treatment, purifier treatments, and their interaction, on participants withdrawing from the study. We define withdrawal from the study as a participant contacting us to return the equipment or to communicate that they no longer want to be part of the study. Each observation is a day by household. The outcome variable is an indicator of whether the household had withdrawn on that day. Column (1) shows the effect of the monitor and attention treatments on withdrawing from the purifier treatment, among households assigned to the purifier treatment. Column (2) shows the effect of the electricity compensation treatments on withdrawing from the purifier treatment, among households assigned to the purifier treatment. Column (3) shows the effect of the purifier and electricity compensation treatments on withdrawal from the monitor treatment, among households assigned to the monitor treatment. Standard errors are clustered at the household level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. See discussion in Section B.

Table A.12: Experiment 2: Balance Table

Variable	(1) Control Mean/(SE)	(2) Credit Only Mean/(SE)	(3) Monitor Only Mean/(SE)	(4) Purifier Only Mean/(SE)	(5) Both (Separately) Mean/(SE)	(6) Both (Together) Mean/(SE)	F-test for balance across all groups F-stat/P-value
Male (0/1)	0.873	0.897	0.875	0.882	0.885	0.875	0.316
	(0.017)	(0.015)	(0.017)	(0.016)	(0.016)	(0.017)	0.904
Age (Years)	47.960	47.458	47.040	48.127	46.627	46.528	0.863
	(0.741)	(0.748)	(0.693)	(0.764)	(0.688)	(0.750)	0.505
Highest Education Level	13.473	13.180	13.643	13.287	13.670	13.040	0.582
	(0.290)	(0.402)	(0.290)	(0.299)	(0.268)	(0.293)	0.714
HH Members (#)	4.430	4.367	4.370	4.505	4.272	4.370	0.888
	(0.089)	(0.084)	(0.078)	(0.088)	(0.083)	(0.081)	0.488
Beliefs about Severity of Outdoor Air Pollution	6.650	6.520	6.560	6.372	6.348	6.615	1.037
	(0.120)	(0.119)	(0.114)	(0.120)	(0.118)	(0.120)	0.394
Beliefs about Severity of Indoor Air Pollution	4.322	4.287	4.482	4.447	4.185	4.348	1.010
	(0.115)	(0.116)	(0.106)	(0.110)	(0.105)	(0.114)	0.410
Beliefs about Indoor v. Outdoor Air Pollution	4.482	4.420	4.543	4.450	4.143	4.702	2.233**
	(0.122)	(0.125)	(0.116)	(0.118)	(0.119)	(0.123)	0.049
Indoor PM2.5 (50 ug/m3)	2.608	2.775	2.776	2.690	2.853	2.755	1.314
	(0.084)	(0.086)	(0.086)	(0.087)	(0.090)	(0.086)	0.255
Has Opinion: Lung Cancer Risk	0.907	0.877	0.905	0.885	0.887	0.887	0.580
	(0.015)	(0.016)	(0.015)	(0.016)	(0.016)	(0.016)	0.715
Has Opinion: ARI Risk	0.930	0.912	0.915	0.912	0.925	0.907	0.339
	(0.013)	(0.014)	(0.014)	(0.014)	(0.013)	(0.015)	0.889
Has Opinion: Purifier Effectiveness	0.420	0.385	0.403	0.438	0.443	0.357	1.714
	(0.025)	(0.024)	(0.025)	(0.025)	(0.025)	(0.024)	0.128
WTP (Practice Round)	12.873	13.482	11.912	11.578	12.610	13.488	1.613
	(0.640)	(0.676)	(0.585)	(0.580)	(0.621)	(0.624)	0.153
Do you own an air conditioner?	0.335	0.328	0.390	0.370	0.352	0.365	0.952
	(0.024)	(0.023)	(0.024)	(0.024)	(0.024)	(0.024)	0.446
Number of observations	400	400	400	400	400	400	2400

Omnibus F-test $F(13, 2386) = 1.24$ $p = 0.242$

Notes: This table provides balance test on the baseline variables in Experiment 2. Balance variables were collected before households received any of the treatment conditions which were Control, Purifier Only, Monitor Only, Both (Separately), Both (Together) and Credit Only. For each variable, we report the joint F-test with p-values. Statistical significance thresholds are reported conventionally using $***p < 0.01; **p < 0.05; *p < 0.1$. See discussion in Section 2.2.2.

Table A.13: Effects of Monitor on Beliefs of Health Risk (Z-scores)

	(1) Beliefs about Risk of Lung Cancer and Stroke from Air Pollution	(2) Beliefs about Risk of ARI for Children from Air Pollution
Monitor	0.184**	0.121
	(0.0926)	(0.0897)
Observations	789	799

Notes: This table shows the effect of providing monitors on people's beliefs (measured in standard deviations) 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 measured during phase 2 survey of Experiment 1. 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 columns 2 has the same categorization but relating to the perceived risk of acute respiratory issues for children. We use heteroskedasticity robust standard errors. $***p < 0.01; **p < 0.05; *p < 0.1$. See discussion in Section 5.

Table A.14: Effect of Monitor and Attention Incentives on Household Perception of Indoor and Outdoor Air Quality and WTP for Air Purifiers (Experiment 1, Phase 2 Survey)

	(1) Beliefs about Severity of Indoor Air Pollution	(2) Beliefs about Severity of Outdoor Air Pollution	(3) Beliefs about Indoor v. Outdoor Air Pollution
Monitor	0.447***	0.161	0.0305*
	(0.151)	(0.161)	(0.0176)
Monitor X Attention	-0.161	-0.0705	-0.00558
	(0.176)	(0.181)	(0.0207)
Observations	818	818	818
Control mean	4.54	7.05	0.43

Notes: This table shows the effect of air quality monitor and incentives for attention to air quality monitor on households' perception of indoor and outdoor air pollution (IAP and OAP). All outcome variables are measured during Phase 2 survey of Experiment 1. Observations are at the household level. Column 1: "Beliefs about Severity of IAP" is households' response to: "How would you rate the current indoor air quality in your area? [On a scale of 1-10, with 1 being "not polluted at all" and 10 being "extremely polluted.]" Column 2: "Beliefs about Severity of OAP" is households' response to: "How would you rate the current outdoor air quality in your area? [On a scale of 1-10, with 1 being "not polluted at all" and 10 being "extremely polluted.]" Column 3: "Beliefs about IAP v. OAP" is households' response to: "How polluted do you believe the air in your home is compared to the air outdoors?" Column 4: Revealed preference WTP for an air purifier elicited using a BDM mechanism. WTP values are winsorized at the 99% level. Significance levels are denoted by $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$. See discussion in Section 5.

Table A.15: Treatment Effects - ARI and Lung Risk (Experiment 2)

	(1) Opinion on ARI Risk (0/1)	(2) Perceived ARI Risk Increase (0/1)	(3) Opinion on Lung Risk (0/1)	(4) Perceived Lung Risk Increase (0/1)
Purifier Only	-0.0877	-0.0284	-0.0900	-0.0113
	(0.0673)	(0.0732)	(0.0710)	(0.0725)
Monitor Only	-0.0779	0.136*	-0.0360	0.163**
	(0.0667)	(0.0701)	(0.0682)	(0.0691)
Both (Separately)	-0.0682	0.119*	-0.0360	0.0844
	(0.0661)	(0.0705)	(0.0682)	(0.0708)
Both (Together)	-0.0585	0.108	-0.0180	0.0732
	(0.0655)	(0.0708)	(0.0671)	(0.0710)
Credit Only	-0.136*	3.17e-15	-0.0720	-0.0394
	(0.0702)	(0.0728)	(0.0701)	(0.0730)
Observations	2400	2400	2400	2400

Notes: This table shows the effect on treatments in experiment 2 on perceived risks of acute respiratory infections (ARI) and lung cancer risk from exposure to air pollution. Credit only: the household is offered a zero-interest option for financing the purifier purchase. Monitor only: household is shown that the monitor works and allowed to see the reading. Purifier only: household is shown the purifier and that it works. Both (separately): first the household is shown the monitor works and the reading on the monitor. The monitor is then put away the household is shown the purifier and that it works. Both (together): the household is first shown the monitor and it's reading. Then while the monitor is still on and visible, the purifier is turned on for five minutes and the household is allowed to see the changes in the reading. Each of the five treatment arms are measured against a control group. . The outcome is the response to a question asking how much do households believe exposure to air pollution increases their risk of lung cancer. This variable ranges from no increase in risk to an increase in risk by 400%. Column 1 and 3 reports the effects on a binary variable equal to 1 if the household selected any option other than "Don't know/unsure". Columns 2 and 4 are binary variables equal to 1 if the household said the risk increased. Observations are at the household level. Significance levels are denoted by $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$. See discussion in Section 5.

Table A.16: Effect of Compensation for Electricity Costs on Purifier Use (Experiment 1, Smart Socket Data)

	Minutes of Usage per Day		
	(1)	(2)	(3)
Purifier x Any Compensation	17.37	12.98	19.93**
	(16.05)	(18.34)	(8.318)
Purifier x Daily Compensation		8.949	
		(23.89)	
Time FE	Yes	Yes	Yes
Sample	Full	Full	Without monitor
Observations	22,840	22,840	10,853
Clusters	304	304	145
Control mean	55.2	55.2	19.7

Notes: This table shows the effect of providing compensation for the cost of electricity used by the purifier. Each observation is at the day-by-household level. Column (1) and (2) includes all households with purifiers. Column (3) excludes households with monitors. The outcome variable is the minutes of the day that the air purifier was turned on. Data is from the Phase 2 survey until 1 April 2024. Standard errors are clustered at the household level. $***p < 0.01; **p < 0.05; *p < 0.1$. See discussion in Section 6.2.

Table A.17: Effect of Purifier on Monitor Usage

	(1) Usage per Day (Minutes)
Purifier	107.2**
	(54.17)
Time FE	Yes
Observations	31,501
Clusters	419
Control mean	825

Notes: This table shows the effect of having an air purifier on the minutes of air monitor usage per day. Each observation is at the day-by-household level among households with air monitors. We control for if the household received the attention treatment. Data is from between the Phase 2 survey and 1 April, 2024. Standard errors are clustered at the household level. $***p < 0.01; **p < 0.05; *p < 0.1$. See discussion in Section 8.1.

Table A.18: Effect of Purifier Treatment on Air Pollution (Experiment 1)

Panel A:	PM2.5 ($\mu g/m^3$)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Purifier	-5.66	-6.23	2.30	1.73	-3.42	-14.12**	-13.81**
	(4.54)	(6.14)	(5.26)	(3.77)	(6.71)	(6.39)	(6.70)
Baseline PM2.5	0.48***	0.54***	0.38***	0.29***	0.40***	0.61***	0.67***
	(0.06)	(0.11)	(0.10)	(0.05)	(0.09)	(0.09)	(0.10)
Panel B:	ln(PM2.5)						
Purifier	-0.124	-0.125	-0.079	-0.076	-0.120	-0.183**	-0.160**
	(0.076)	(0.080)	(0.082)	(0.077)	(0.084)	(0.078)	(0.080)
ln(Baseline PM2.5)	0.903***	0.921***	0.837***	0.799***	0.886***	0.986***	0.985***
	(0.186)	(0.210)	(0.214)	(0.190)	(0.174)	(0.177)	(0.205)
Hours	All	0-4	4-8	8-12	12-16	16-20	20-24
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	473,475	77,351	77,418	78,330	80,117	80,450	79,809
Clusters	376	370	372	372	375	373	371
Control mean	111	132	97	79	100	121	135

Notes: This table shows the effect of providing air purifiers on average air pollution during Experiment 1. Each observation is at the hour-by-household level among households with air monitors who remained in the survey until the Phase 2 survey (when the purifiers were provided). Note that all days are included, regardless of whether the purifier was turned on or not. The outcome variable in Panel A is the average air pollution in that hour. In Panel B, the outcome variable is the log of the average air pollution. Column (1) shows results for all hours of the day. Columns (2)-(7) show results for specific times of the day, divided into 4-hour periods. Data is from the date of the Phase 2 survey until 1 April 2024. Standard errors are clustered at the household level. $***p < 0.01; **p < 0.05; *p < 0.1$. See discussion in Section 8.1.

Table A.19: Effect of Monitor and Purifier on Health Outcomes

	(1) Systolic BP	(2) Diastolic BP	(3) Lung Capacity (FVC)	(4) FEV1/ FVC Ratio	(5) Blood Oxygen Level	(6) Healthcare Provider Visits	(7) Treatment Cost	(8) Sick Days	(9) Health Index (ICW)
Monitor	-0.19	-0.44	-0.03	-1.65	-0.02	0.23	318.04	0.26	-0.09
	(1.59)	(1.02)	(0.08)	(1.51)	(0.07)	(0.65)	(218.29)	(0.18)	(0.09)
Purifier	1.22	-0.10	-0.10	-0.58	0.11**	-0.81	495.57**	-0.04	0.06
	(1.76)	(1.00)	(0.08)	(1.36)	(0.05)	(0.57)	(236.09)	(0.18)	(0.09)
Purifier x Monitor	-0.97	-0.52	0.12	1.79	-0.08	-0.26	-163.89	-0.21	0.10
	(2.59)	(1.55)	(0.13)	(2.28)	(0.10)	(0.91)	(411.84)	(0.29)	(0.14)
Observations	1,073	1,073	1,046	1,046	1,073	1,842	1,842	1,842	1,842
Clusters	747	747	740	740	747	756	756	756	756
Control Mean	120.98	81.62	2.53	90.52	98.77	2.34	997.92	0.62	-0.00

Notes: This table reports the effects of the monitor and purifier treatments, as well as their interaction, on various health outcomes. We control for if the household also receives the attention incentive and the interaction between the purifier and the attention incentive. Each observation is a household member sleeping in the bedroom of the household head at the time of the phase 2 survey. The data is from the Phase 3 survey of Experiment 1. Forced Vital Capacity (FVC), is the total amount air exhaled after a deep breath and a low FVC is an indicator of restrictive lung disease. The FEV1/FVC ratio is the ratio of the Forced Expiratory Volume in 1 second and the FVC, a low ratio is an indicator of Chronic Obstructive Pulmonary Disease (COPD) or asthma. The health index is an inverse-covariance weighted index of all listed components where variables have been flipped so that a higher value represents a better outcome. Standard errors clustered at the household level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. See discussion in Section 8.2.

Table A.20: Effect of Monitor and Purifier on Specific Symptoms

	(1) Cough	(2) Asthma	(3) Other lung or breathing problem	(4) Blood pressure or heart problem	(5) Pain (Back, Abdomen, Migraine, etc.)	(6) Eye or skin problem	(7) Diarrhea or Constipation	(8) Fever, Nausea, Dizzyness, or Vomiting	(9) Symptom free
Monitor	0.052	-0.000	0.000	0.001	-0.015	-0.002	0.012	0.010	-0.014
	(0.037)	(0.006)	(0.013)	(0.013)	(0.021)	(0.014)	(0.010)	(0.039)	(0.042)
Purifier	-0.002	0.002	-0.008	-0.005	0.020	-0.004	-0.005	-0.025	-0.004
	(0.034)	(0.006)	(0.009)	(0.013)	(0.024)	(0.011)	(0.007)	(0.036)	(0.041)
Purifier x Monitor	-0.022	0.002	0.003	-0.013	0.028	0.006	0.014	0.012	-0.051
	(0.059)	(0.011)	(0.017)	(0.018)	(0.038)	(0.019)	(0.017)	(0.061)	(0.069)
Observations	1,849	1,849	1,849	1,849	1,849	1,849	1,849	1,849	1,849
Clusters	757	757	757	757	757	757	757	757	757
Control Mean	0.207	0.007	0.020	0.032	0.095	0.025	0.014	0.263	0.529

This table reports the effects of the monitor and purifier treatments, as well as their interaction, on if a household member experienced a specific symptom in the past 30 days. We control for if the household also receives the attention incentive and the interaction between the purifier and the attention incentive. Each observation is a household member sleeping in the bedroom of the household head at the time of the phase 2 survey. The data is from the Phase 3 survey of Experiment 1. Standard errors clustered at the household level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. See discussion in Section 8.2.

Table A.21: Effect of Monitor and Purifier on Labor Supply and Labor Income

	(1) Days worked past 7 days	(2) Income past month
Monitor	-0.07	1920.58
	(0.26)	(7332.22)
Purifier	-0.14	2800.37
	(0.26)	(5223.58)
Purifier x Monitor	-0.19	789.91
	(0.46)	(10204.47)
Observations	830	829
Clusters	721	720
Control Mean	5.07	43,251.10

Notes: This table reports the effects of the monitor and purifier treatments, as well as their interaction, on various labor supply and labor income. We control for if the household also receives the attention incentive and the interaction between the purifier and the attention incentive. Each observation is a household member sleeping in the bedroom of the household head and who held a job at the time of the phase 2 survey. The data is from the Phase 3 survey of Experiment 1. The dependent variables are the number of days worked in the past 7 days and labor income in the past month. Standard errors clustered at the household level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. See discussion in Section 8.2.

Table A.22: Effect of Monitor and Purifier on Mental Heath and Sleep

	(1) Sleep Index	(2) Mental Health Index
Monitor	-0.13	0.19
	(0.12)	(0.14)
Purifier	-0.01	0.00
	(0.11)	(0.11)
Purifier x Monitor	0.12	-0.26
	(0.18)	(0.20)
Observations	1,852	1,852
Clusters	758	758
Control Mean	-0.00	-0.00

Notes: This table reports the effects of the monitor and purifier treatments, as well as their interaction, on mental health and sleep. We control for if the household also receives the attention incentive and the interaction between the purifier and the attention incentive. Each observation is a household member sleeping in the bedroom of the household head at the time of the phase 2 survey. The data is from the Phase 3 survey of Experiment 1. The dependent variables are the sum of 10 questions about sleep (Column 1) and 10 questions about mental health (Column 2). The underlying variables have been flipped so that a higher value represents a better outcome. The sums have been normalized to have a mean of zero and standard deviation of one in the control group. Standard errors clustered at the household level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. See discussion in Section 8.2.

Table A.23: Decision-To-Buy Based Estimates of MWTP for Cleaner Air: First Stage of 2SLS (Experiment 2)

	Perceived PM Reduction			
	(1)	(2)	(3)	(4)
Baseline Perceived PM Reduction	0.66407***	0.73777***	0.66407***	0.66407***
	(0.03079)	(0.03209)	(0.03079)	(0.03079)
Purifier Only	4.11413***	1.59706***	1.21113***	0.18693***
	(1.17823)	(0.49461)	(0.34685)	(0.05353)
Monitor Only	3.47672***	1.05121**	1.02349***	0.15797***
	(1.19384)	(0.49894)	(0.35145)	(0.05424)
Both (Separately)	9.30645***	3.02804***	2.73967***	0.42284***
	(1.46928)	(0.62364)	(0.43253)	(0.06676)
Both (Together)	11.31935***	4.10935***	3.33223***	0.51430***
	(1.48203)	(0.61783)	(0.43629)	(0.06734)
Credit Only	-0.81835	-0.56790	-0.24091	-0.03718
	(1.07839)	(0.45445)	(0.31746)	(0.04900)
Usage Assumption	All the time	Stated Household Expectation	Ex-post Reported (Ex. 1)	Actual (Ex. 1)
Observations	43,200	43,200	43,200	43,200
Clusters	2,400	2,400	2,400	2,400
F-stat	21.9	17.2	21.9	21.9

Notes: This table shows the first stage for the purchased-based two-stage least squares esimates of the MWTP for cleaner air. The first stage uses the household×price grid (with 43,200 bid-level rows and 2,400 household clusters, and a dependent variable that is constant within each cluster). The second stage is shown in Table A.24. The F-stat is for the null hypothesis that the coefficient on all treatment groups is zero, but it does not include the coefficient on the baseline perceived PM reduction. $***p < 0.01; **p < 0.05; *p < 0.1$. See discussion in Section 9.1.

Table A.24: Decision-To-Buy Based Estimates of MWTP for Cleaner Air: Second Stage of 2SLS (Experiment 2)

	Buy Purifier			
	(1)	(2)	(3)	(4)
Perceived PM Reduction	0.00012	0.00081	0.00040	0.00262
	(0.00081)	(0.00223)	(0.00275)	(0.01783)
Price	-0.00004***	-0.00004***	-0.00004***	-0.00004***
	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Sample	All Experiment 2	All Experiment 2	All Experiment 2	All Experiment 2
Usage Assumption	All the time	Stated Household Expectation	Ex-post Reported (Ex. 1)	Actual (Ex. 1)
Baseline perception control	Yes	Yes	Yes	Yes
Kleibergen-Paap Stat	21.9	17.2	21.9	21.9
-beta/alpha	3.0	20.3	10.1	65.5
MWTP per season (USD)	0.02	0.17	0.08	0.55
MWTP per year (USD)	0.10	0.69	0.34	2.21
P-value: MWTP	0.88	0.72	0.88	0.88
Upper bound 95% CI: MWTP/year	1.4	4.4	4.9	31.8
Observations	43,200	43,200	43,200	43,200
Clusters	2,400	2,400	2,400	2,400

Notes: This table shows the second stage results of the decision-to-buy based two-stage least squares estimates of the MWTP for cleaner air. The regression is estimating the sensitivity of the decision to buy a purifier to the household's perceived reduction in PM2.5 air pollution (Actual average outdoor pollution * Perception of indoor-outdoor pollution ratio * Perceived purifier effectiveness * Expected/assumed usage) and the price of the purifier. The perceived reduction in PM2.5 air pollution is instrumented for using all Experiment 2 treatment indicators. The first stage is shown in Appendix Table A.23. If a household did not know or did not answer the question about a belief/perception we assumed that they are in the lowest category, e.g., if a household said they don't know how effective the purifier was we group them together with households stating they did not think the purifier was effective at all. Column (1) assumes that the household expects to use the purifier all the time. Column (2) uses the households stated usage expectation. Column (3) assumes that the household expects to use the purifier as much as the households in Experiment 1 reported to use the purifier (29% of the time). Column (4) assumes that the household expects to use the purifier as much as the households in Experiment 1 actually used the purifier (5% of the time). Standard errors clustered at the household level. $***p < 0.01; **p < 0.05; *p < 0.1$. See discussion in Section 9.1.

Table A.25: Effect of Purifier Use on Indoor Air Pollution

	PM2.5	ln(PM2.5)
	(1)	(2)
Purifier in Use x Outdoor PM 0-40	-11.93*	-0.18*
	(6.08)	(0.09)
Purifier in Use x Outdoor PM 40-80	-4.33	-0.11
	(4.93)	(0.07)
Purifier in Use x Outdoor PM 80-120	-12.49**	-0.24***
	(5.14)	(0.07)
Purifier in Use x Outdoor PM 120-160	-23.67***	-0.35***
	(4.52)	(0.07)
Purifier in Use x Outdoor PM 160-200	-35.48***	-0.48***
	(6.37)	(0.12)
Purifier in Use x Outdoor PM 200-240	-38.34***	-0.52***
	(6.91)	(0.12)
Purifier in Use x Outdoor PM 240-280	-48.42***	-0.55***
	(10.26)	(0.16)
Purifier in Use x Outdoor PM 280-320	-63.43***	-0.61***
	(13.62)	(0.17)
Purifier in Use x Outdoor PM 320-360	-68.74***	-0.62***
	(19.78)	(0.19)
Purifier in Use x Outdoor PM 360-400	-65.05***	-0.43***
	(17.99)	(0.15)
Purifier in Use x Outdoor PM 400-440	-74.50**	-0.58**
	(33.48)	(0.22)
Time FE	Yes	Yes
Household FE	Yes	Yes
Observations	196,206	196,206
Clusters	152	152
Outcome Variable Mean	106	106

Notes: This table shows the estimated effect of households turning on their air purifiers on indoor PM2.5 air pollution each level of outdoor air PM2.5 air pollution. Each observation is at the hour-by-household level among households with both a purifier and a monitor. The "Purifier Used" variable indicates what share of the hour the purifier was used. Pollution levels are the average pollution level within the hour. Outdoor PM is the average reading of our two outdoor monitoring stations. Data is from the Phase 2 survey of Experiment 1 until April 1, 2024. Standard errors clustered at the household level. $***p < 0.01; **p < 0.05; *p < 0.1$. See discussion in Section 9.2.

Table A.26: Estimating MWTP using alternative fixed effects and for households with and without monitors

	Use Purifier					
	(1)	(2)	(3)	(4)	(5)	(6)
Potential PM2.5 Improvement	0.00002	0.00004	0.00004	0.00005	0.00001	-0.00003
	(0.00009)	(0.00010)	(0.00008)	(0.00003)	(0.00002)	(0.00002)
Cost of Use	-0.01093***	-0.01104***	-0.01149***	-0.01207***	-0.00977***	-0.00722**
	(0.00322)	(0.00323)	(0.00279)	(0.00345)	(0.00226)	(0.00285)
Hour of Day FE	No	Yes	Yes	Yes	Yes	Yes
Household FE	No	No	Yes	Yes	Yes	Yes
Date FE	No	No	No	Yes	Yes	Yes
Sample	Monitor	Monitor	Monitor	Monitor	All	No Monitor
PM2.5 Improvement Assumption	80%	80%	80%	80%	80%	80%
-beta/alpha	0.0016	0.0035	0.0031	0.0037	0.0009	-0.0045
MWTP per season (USD)	0.03	0.07	0.06	0.07	0.02	-0.09
MWTP per year (USD)	0.13	0.28	0.24	0.30	0.07	-0.35
P-value: MWTP	0.84	0.69	0.68	0.23	0.68	0.19
Upper bound 95% CI: MWTP/year	1.35	1.64	1.39	0.78	0.40	0.18
Observations	399,864	399,864	399,864	399,864	762,638	362,774
Clusters	159	159	159	159	304	145
Outcome Variable Mean	0.0815	0.0815	0.0815	0.0815	0.0587	0.0335

Notes: This table shows the results of a regression estimating the sensitivity of purifier use to the potential reduction in PM2.5 air pollution and the marginal monetary cost of using the purifier. Columns (1)-(4) shows results using alternative fixed effects for the households with monitors. Column (5) and (6) show the results for all households and households without monitors, respectively. Potential PM2.5 improvement is the effect of turning on an air purifier on indoor air pollution (80%), multiplied by outdoor air pollution, multiplied by the average indoor-outdoor pollution ratio. Before the incentive period, the cost of using the purifier is equal to the electricity cost per hour (BDT 0.24) for households without electricity cost compensation and zero for households with electricity compensation. During the incentive period, the cost of using the purifier is 0.24 per hour for those in the control group and the difference between the incentive and electricity cost (-4.76 or -9.76) for those in the incentive group. Standard errors clustered at the household level. $***p < 0.01; **p < 0.05; *p < 0.1$. See discussion in Section 9.2.

Table A.27: Usage Based MWTP Estimates Under Different Purifier Effectiveness Assumptions (Binary Use Variable)

	Use Purifier (Binary)			
	(1)	(2)	(3)	(4)
Potential PM2.5 Improvement	0.00006*	0.00003*	0.00001*	-0.00010
	(0.00004)	(0.00002)	(0.00001)	(0.00016)
Cost of Use	-0.01268***	-0.01268***	-0.01268***	-0.01264***
	(0.00360)	(0.00360)	(0.00360)	(0.00361)
Hour of Day FE	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
Sample	Monitor	Monitor	Monitor	Monitor
PM2.5 Improvement Assumption	80%	Simulated: 108 min	Simulated: 23 min	Household Belief
-beta/alpha	0.0050	0.0020	0.0012	-0.0080
MWTP per season (USD)	0.10	0.04	0.02	-0.16
MWTP per year (USD)	0.40	0.16	0.09	-0.64
P-value: MWTP	0.13	0.13	0.13	0.55
Upper bound 95% CI: MWTP/year	0.92	0.37	0.21	1.43
Observations	399,864	399,864	399,864	399,864
Clusters	159	159	159	159
Outcome Variable Mean	0.1006	0.1006	0.1006	0.1006

Notes: This table shows the results of a regression estimating the sensitivity of purifier use to the potential reduction in PM2.5 air pollution and the marginal monetary cost of using the purifier. The use variable is binary variable indicating if there was any use in that hour. Potential PM2.5 improvement is the effect of turning on an air purifier on indoor air pollution, it is calculated as the purifier's assumed effectiveness multiplied by outdoor air pollution, multiplied by the average indoor-outdoor air pollution ratio. Each column shows results for a different purifier effectiveness assumption. Before the incentive period, the cost of using the purifier is equal to the electricity cost per hour (BDT 0.24) for households without electricity cost compensation and zero for households with electricity compensation. During the incentive period, the cost of using the purifier is 0.24 per hour for those in the control group and the difference between the incentive and electricity cost (-4.76 or -9.76) for those in the incentive group. Standard errors clustered at the household level. $***p < 0.01; **p < 0.05; *p < 0.1$. See discussion in Section 9.2.

Table A.28: Usage Based MWTP Estimates Under Different Purifier Effectiveness Assumptions (Above Median WTP for Purifier in Phase 2)

	Use Purifier			
	(1)	(2)	(3)	(4)
Potential PM2.5 Improvement	0.00008*	0.00003*	0.00002*	-0.00014
	(0.00004)	(0.00002)	(0.00001)	(0.00018)
Cost of Use	-0.00971**	-0.00971**	-0.00971**	-0.00964**
	(0.00437)	(0.00437)	(0.00437)	(0.00435)
Hour of Day FE	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
Sample	Monitor	Monitor	Monitor	Monitor
PM2.5 Improvement Assumption	80%	Simulated: 108 min	Simulated: 23 min	Household Belief
-beta/alpha	0.0077	0.0031	0.0018	-0.0148
MWTP per season (USD)	0.15	0.06	0.04	-0.29
MWTP per year (USD)	0.62	0.25	0.14	-1.18
P-value: MWTP	0.21	0.21	0.21	0.43
Upper bound 95% CI: MWTP/year	1.59	0.64	0.37	1.73
Observations	221,847	221,847	221,847	221,847
Clusters	88	88	88	88
Outcome Variable Mean	0.0823	0.0823	0.0823	0.0823

Notes: This table shows the results of a regression estimating the sensitivity of purifier use to the potential reduction in PM2.5 air pollution and the marginal monetary cost of using the purifier, using only data from households with WTP for the purifier in Phase 2 that is above or equal to the median (BDT 500). Potential PM2.5 improvement is the effect of turning on an air purifier on indoor air pollution, it is calculated as the purifier's assumed effectiveness multiplied by outdoor air pollution, multiplied by the average indoor-outdoor air pollution ratio. Each column shows results for a different purifier effectiveness assumption. Before the incentive period, the cost of using the purifier is equal to the electricity cost per hour (BDT 0.24) for households without electricity cost compensation and zero for households with electricity compensation. During the incentive period, the cost of using the purifier is 0.24 per hour for those in the control group and the difference between the incentive and electricity cost (-4.76 or -9.76) for those in the incentive group. Standard errors clustered at the household level. $***p < 0.01; **p < 0.05; *p < 0.1$. See discussion in Section 9.2.

Table A.29: Usage Based MWTP Estimates Under Different Purifier Effectiveness Assumptions (Below Median WTP for Purifier in Phase 2)

	Use Purifier			
	(1)	(2)	(3)	(4)
Potential PM2.5 Improvement	0.00001	0.00000	0.00000	-0.00003
	(0.00006)	(0.00002)	(0.00001)	(0.00026)
Cost of Use	-0.01560***	-0.01560***	-0.01560***	-0.01559***
	(0.00557)	(0.00557)	(0.00557)	(0.00560)
Hour of Day FE	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
Sample	Monitor	Monitor	Monitor	Monitor
PM2.5 Improvement Assumption	80%	Simulated: 108 min	Simulated: 23 min	Household Belief
-beta/alpha	0.0005	0.0002	0.0001	-0.0019
MWTP per season (USD)	0.01	0.00	0.00	-0.04
MWTP per year (USD)	0.04	0.02	0.01	-0.15
P-value: MWTP	0.89	0.89	0.89	0.91
Upper bound 95% CI: MWTP/year	0.59	0.24	0.14	2.46
Observations	178,017	178,017	178,017	178,017
Clusters	71	71	71	71
Outcome Variable Mean	0.0804	0.0804	0.0804	0.0804

Notes: This table shows the results of a regression estimating the sensitivity of purifier use to the potential reduction in PM2.5 air pollution and the marginal monetary cost of using the purifier, using only data from households with WTP for the purifier in Phase 2 that is strictly below the median (BDT 500). Potential PM2.5 improvement is the effect of turning on an air purifier on indoor air pollution, it is calculated as the purifier's assumed effectiveness multiplied by outdoor air pollution, multiplied by the average indoor-outdoor air pollution ratio. Each column shows results for a different purifier effectiveness assumption. Before the incentive period, the cost of using the purifier is equal to the electricity cost per hour (BDT 0.24) for households without electricity cost compensation and zero for households with electricity compensation. During the incentive period, the cost of using the purifier is 0.24 per hour for those in the control group and the difference between the incentive and electricity cost (-4.76 or -9.76) for those in the incentive group. Standard errors clustered at the household level. $***p < 0.01; **p < 0.05; *p < 0.1$. See discussion in Section 9.2.

Table A.30: Effect of Monitor on Self-Reported and Actual Air Purifier Usage

	(1) Days used 30+ minutes	(2) Days used 30+ minutes	(3) HH Used All the Time
Monitor	0.521	0.492*	0.143**
	(0.326)	(0.281)	(0.065)
Data	Self-reported	Actual	Self-reported
Observations	292	297	292
Control mean	5.104	0.96	.244

Notes: This table shows the effect of monitors on self-reported and actual air purifier use during phase 3 survey of Experiment 1. Column 1: during the phase 3 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)?" Column 2: Actual usage as measured by smart sockets in the 7 days before the phase 3 survey. Column 3: During Phase 3 survey, households who received the air purifier were asked how often they used the air purifier. The options provided were "All the time when home", "At least once per day", "A few times per week", "Once per week", "Once per month", "Very rarely", "Never", "Don't know" or "Refused". We create a binary variable for whether or not they said they would use the air purifier "all the time when home" or not. Significance levels are denoted by $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$. See discussion in Section D.

Table A.31: Effects of Use Incentives and Air Monitor on Air Purifier Use

	(1) Minutes per Day	(2) Minutes per Day
Any Incentive	113.0***	82.18**
	(29.75)	(36.87)
Monitor	72.40**	72.89**
	(32.39)	(32.36)
BDT 10 Incentive		60.23
		(46.91)
Time FE	Yes	Yes
Observations	9,120	9,120
Clusters	304	304
Control mean	15.5	15.5

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 day-by-household level among households with air purifiers. The outcome variable is the number of minutes that the air purifier was used on that day. 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. $***p < 0.01; **p < 0.05; *p < 0.1$. See discussion in Section F.

Table A.32: Usage Based MWTP Estimates Under Different Purifier Effectiveness Assumptions (Fractional Logit)

	Use Purifier			
	(1)	(2)	(3)	(4)
Potential PM2.5 Improvement	0.0008	0.0003	0.0002	-0.0031
	(0.0007)	(0.0003)	(0.0002)	(0.0029)
Cost of Use	-0.1694***	-0.1694***	-0.1694***	-0.1661***
	(0.0503)	(0.0503)	(0.0503)	(0.0508)
Hour of Day FE	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
Sample	Monitor	Monitor	Monitor	Monitor
PM2.5 Improvement Assumption	80%	Simulated: 108 min	Simulated: 23 min	Household Belief
-beta/alpha	0.0047	0.0019	0.0011	-0.0186
MWTP per season (USD)	0.09	0.04	0.02	-0.36
MWTP per year (USD)	0.38	0.15	0.09	-1.48
P-value: MWTP	0.29	0.29	0.29	0.36
Upper bound 95% CI: MWTP/year	1.08	0.44	0.25	1.67
Observations	399,864	399,864	399,864	399,864
Clusters	159	159	159	159
Outcome Variable Mean	0.0815	0.0815	0.0815	0.0815

Notes: This table shows the results of a fractional logit regression estimating the sensitivity of purifier use to the potential reduction in PM2.5 air pollution and the marginal monetary cost of using the purifier. Potential PM2.5 improvement is the effect of turning on an air purifier on indoor air pollution multiplied by outdoor air pollution, multiplied by the average indoor-outdoor pollution ratio. In each column, we show results for a different purifier effectiveness assumption. Before the incentive period, the cost of using the purifier is equal to the electricity cost per hour (BDT 0.24) for households without electricity cost compensation and zero for households with electricity compensation. During the incentive period, the cost of using the purifier is 0.24 per hour for those in the control group and the difference between the incentive and electricity cost (-4.76 or -9.76) for those in the incentive group. Standard errors clustered at the household level. $***p < 0.01; **p < 0.05; *p < 0.1$. See discussion in Section 9.2.

Table A.33: Usage Based MWTP Estimates Under Different Purifier Effectiveness Assumptions (Fractional Logit between 6pm and midnight)

	Use Purifier			
	(1)	(2)	(3)	(4)
Potential PM2.5 Improvement	0.0023**	0.0009**	0.0005**	-0.0048
	(0.0009)	(0.0004)	(0.0002)	(0.0035)
Cost of Use	-0.1692***	-0.1692***	-0.1692***	-0.1644***
	(0.0481)	(0.0481)	(0.0481)	(0.0486)
Hour of Day FE	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
Sample	Monitor	Monitor	Monitor	Monitor
PM2.5 Improvement Assumption	80%	Simulated: 108 min	Simulated: 23 min	Household Belief
-beta/alpha	0.0134	0.0055	0.0031	-0.0295
MWTP per season (USD)	0.26	0.11	0.06	-0.58
MWTP per year (USD)	1.07	0.43	0.25	-2.35
P-value: MWTP	0.03	0.03	0.03	0.25
Upper bound 95% CI: MWTP/year	2.04	0.83	0.47	1.61
Observations	89,131	89,131	89,131	89,131
Clusters	141	141	141	141
Outcome Variable Mean	0.0974	0.0974	0.0974	0.0974

Notes: This table shows the results of a fractional logit regression estimating the sensitivity of purifier use to the potential reduction in PM2.5 air pollution and the marginal monetary cost of using the purifier, using only data from between 6pm and midnight. Households that never used their purifier between 6pm and midnight are excluded from the sample. Potential PM2.5 improvement is the effect of turning on an air purifier on indoor air pollution multiplied by outdoor air pollution, multiplied by the average indoor-outdoor pollution ratio. In each column, we show results for a different purifier effectiveness assumption. Before the incentive period, the cost of using the purifier is equal to the electricity cost per hour (BDT 0.24) for households without electricity cost compensation and zero for households with electricity compensation. During the incentive period, the cost of using the purifier is 0.24 per hour for those in the control group and the difference between the incentive and electricity cost (-4.76 or -9.76) for those in the incentive group. Standard errors clustered at the household level. $***p < 0.01; **p < 0.05; *p < 0.1$. See discussion in Section 9.2.