Residential Air Purifiers and the Value of Clean Air*

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Abstract

Valuing non-market amenities from purchases of durables that deliver them, like clean air from purifiers, requires an assumption about use intensity. Anticipated use is private; where operating costs suppress it below the assumed intensity, the inferred value is understated. Our use-based estimator prices clean air from how metered purifier use responds to randomized operating costs, uncorrelated with the disutility of operation. In field experiments among middle-income households in Dhaka, where PM2.5 is ten times WHO guidelines and under 1% own a purifier, neither credit nor information raises demand, free purifiers are barely used, and most decline to run one even when paid forty times the operating cost. Even with the bias removed, marginal willingness to pay for the partial, in-home exposure reduction a purifier provides is near zero, its 95% upper bound below prior estimates. Operating one is costly: private defense fails at the operating margin, invisible to purchase data.

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1 Introduction

Nearly 2.8 billion people in low- and middle-income countries are exposed to hazardous levels of ambient air pollution (Rentschler and Leonova, 2023). Defensive technologies such as air purifiers are widely available in these settings and, when operated, highly effective (EPA, 2024). Yet adoption is strikingly low. In our survey of middle-income households in Dhaka, a city with PM2.5 levels routinely ten times above WHO guidelines, fewer than 1% own a purifier, while 34% own an air conditioner, a device that costs two to three times more than a purifier. Why do so few households invest in clean air?

Valuing non-market amenities such as clean air and clean water is a central concern of environmental and welfare economics (Hanemann, 1994; Freeman et al., 2014; Greenstone and Jack, 2015); a leading empirical approach infers valuation from demand for private defensive technologies such as air purifiers, water filters, and masks, and the revealed willingness to pay (WTP) it recovers is consistently low, often far below the value implied by epidemiological evidence on the underlying health damage (Greenstone and Jack, 2015; Jack and Ryan, 2026). The gap matters because these valuations underpin estimates of the welfare cost of pollution, the value of statistical life (VSL), and the social returns to environmental regulation (Courant and Porter, 1981; Bartik, 1988; Viscusi and Aldy, 2003; Greenstone and Hanna, 2014). The pattern is not unique to environmental amenities: the energy efficiency gap is an analogous wedge, between the value of energy savings revealed by purchases of efficient durables and the engineering-projected value of those savings (Allcott and Greenstone, 2012).

There are four candidate explanations. First, the marginal WTP (MWTP) for clean air may be low at low income: because the marginal utility of money is high when consumption is low, a poor household converts a given underlying valuation into a smaller MWTP than a rich household with the same valuation would. Second, market failures such as credit constraints or misinformation about pollution and defensive technologies may depress demand below true valuation. Third, the low values may be an artifact of how they are inferred. Valuing clean air from the purchase of a device requires an assumption about how intensively the buyer expects to use the device, and if monetary or non-monetary costs of operation suppress anticipated use below the assumed level, the inferred value is understated;

because anticipated use is private, the shortfall can neither be detected nor corrected from purchase data. The problem is general: it arises whenever the value of an amenity is inferred from the purchase of a durable good whose benefit depends on how much it is used. Fourth, the low MWTP may be accurate, and the underlying value of the amenity genuinely low. Distinguishing these requires removing the first two forces and, to address the third, measuring the value of the amenity directly: without assumptions about anticipated use. This paper does so, with two field experiments among middle-income households in Dhaka and a use-based estimator that prices the flow value of clean air from directly measured device use, uncontaminated by any disutility of operation and without assumptions about anticipated use. We find that the first three explanations do not explain the gap and that households place little value on the partial, in-home pollution exposure reduction the device provides.

The first explanation, that the MWTP for clean air is low at low incomes, is unlikely to apply in our setting by construction: our sample is middle-income, with average annual labor income of roughly PPP USD 24,000. The two field experiments test the second explanation, that market failures depress MWTP, using interventions designed to alleviate the most commonly hypothesized market failures. We offer interest-free credit, provide information about indoor pollution severity, and about purifier effectiveness. None of these interventions significantly increased the WTP for purifiers, although they successfully changed households' beliefs about indoor pollution severity, perceived health risks, and purifier effectiveness. The third explanation, that MWTP is underestimated because the assumed anticipated purifier use is overestimated, is a problem that is common to any approach based on the WTP for owning the device itself, and cannot be addressed using purchase data alone. Instead, we measure use directly, with smart plugs that record actual operation. Even households provided free purifiers with electricity costs reimbursed used them for less than 40 minutes per day on average over the following two to three months. Pairing the purifier with a real-time air quality monitor raises usage to 105 minutes per day on average ($\text{p-value} < 0.01$), still under two hours in twenty-four, and incentivizing attention to monitor readings adds nothing further. Hourly payments to operate the device, worth 12 percent of monthly income at continuous use, also fail to generate consistent use; households run it for three and a half hours per day on average. This low average usage is broadly similar across baseline vul-

nerability (age, chronic conditions), awareness (education, knowledge of pollution and its harms), and household income.

We then develop a use-based estimator of the MWTP for clean air that exploits randomized variation in operating costs and within-day variation in the absolute level of potential pollution reduction. Because it is built on realized use rather than on a purchase, the estimator requires no assumption about anticipated use. Household self-reported usage seems exaggerated: before they received purifiers, most expected to use the device "all the time when home," and after months of ownership 82% report at least daily use, yet smart-plug data show almost none use it that often. Moreover, because operating costs are assigned at random and uncorrelated with how much households dislike running the device, the estimator is uncontaminated by the disutility of operation: households that find the device more bothersome are no more likely to face a high monetary operating cost than a low one, so this reluctance does not contaminate the estimated response to price. Our MWTP estimate is close to zero and statistically insignificant; we can rule out values above PPP USD 1.50 per $\mu g/m^3$ per year with 95% confidence, an upper bound that lies below prior experimental and quasi-experimental estimates in the literature. The broader pattern of results points in the same direction: even when credit is offered, information is provided, attention is incentivized, and operation itself is rewarded, households decline to operate purifiers in their own homes. Households' low marginal valuation is best understood as what they will pay for the partial, in-home exposure reduction a private device delivers, rather than for comprehensive ambient air quality, though we cannot fully exclude that residual frictions, such as underweighting of long-run harm, also depress it.

Contributions. This paper makes two main contributions: to the literature on the valuation of non-market environmental amenities, and to the literature on technology adoption in low- and middle-income countries.

Valuing non-market environmental amenities. We contribute to the literature that values non-market environmental amenities, such as clean air, from demand for defensive technologies (Ito and Zhang, 2020; Baylis et al., 2023; Tarduno and Walker, 2025, for a review, see Greenstone and Jack, 2015). These approaches face two challenges that our design addresses. First, when valuation is inferred from the purchase of a defensive technology, the decision conflates the value of the amenity

with market failures that depress demand: e.g., credit constraints, imperfect information about the severity of the problem or the effectiveness of the technology, and uncertainty about whether the device performs in the household's own setting. A low estimate may therefore reflect these frictions rather than a low underlying valuation. Existing studies address imperfect information: Ito and Zhang (2020) find higher MWTP after the 2013 surge in media coverage of air pollution in China, and Tarduno and Walker (2025) and Baylis et al. (2023) experimentally manipulate beliefs to isolate the role of misperceptions, but no study jointly relaxes credit constraints and corrects beliefs about air pollution, its health impacts, and the effectiveness of the defensive technology.[1] Second, purchase-based estimates require dividing WTP for the device by the implied reduction in exposure, a denominator that rests on untestable assumptions about how intensively the buyer expects to use the device. This means that the value of clean air inferred from demand for air purifiers will be understated if monetary or non-monetary costs of operation suppress anticipated use below the level the inference assumes. This persists in more sophisticated designs that recover MWTP from how WTP varies across devices of differing effectiveness, because the implied change in exposure reduction still scales with usage, anticipated on the household's side and assumed on the researcher's. While the first challenge, contamination from market failures, can be addressed within a purchase-based design, the second is structural to inferring valuation from a purchase, which prices the household's private forecast of its own usage.[2]

The MWTP estimate is right only if the divisor matches that forecast, and no available usage figure can stand in for it. Assuming full utilization as in Ito and Zhang (2020) and Tarduno and Walker (2025) risks ignoring monetary or non-monetary costs of operation, likely overstating anticipated usage. Substituting realized use, whether self-reported as in Baylis et al. (2023) or directly measured, does

[1] Tarduno and Walker (2025) and Baylis et al. (2023) state the effectiveness of the device to every respondent rather than varying beliefs about it experimentally; their randomized information treatments concern pollution exposure or its health effects, not the technology.

[2] Modeling purchase and use jointly in the discrete/continuous tradition (Dubin and McFadden, 1984; Hanemann, 1984) does not remove the problem. That approach recovers the realized use of owners from observational price variation under a parametric selection correction, whereas the purchase-based divisor requires the forecast that priced the device, which realized use need not equal for the reasons given below. Our estimator does not need that forecast: it prices the amenity on the use margin among owners whose operating cost is experimentally assigned.

not resolve the problem either: directly measured use may fall short of the forecast that priced the device, because households underpredict the inconvenience of operation until they experience it, consistent with projection bias (Loewenstein et al., 2003), and self-reported use is likely inflated by experimenter demand (de Quidt et al., 2018). Nor can the forecast simply be elicited: stated expectations are subject to the same reporting bias, and although households asked before acquisition report near-continuous expected use that their subsequent behavior contradicts, the divergence cannot tell us whether the report or the behavior is closer to the forecast, since an honest but mistaken forecast and an inflated report of an accurate one produce the same gap. Nor is this structure particular to defensive technologies. It arises wherever a valuation is inferred from the purchase of a durable whose benefit is a flow that depends on use. Implied valuations of energy efficiency divide the purchase premium by savings projected under an assumed utilization profile (Allcott and Greenstone, 2012; Busse et al., 2013; Allcott and Wozny, 2014); in the one setting where realized use has been compared with the projection that served as divisor, projected savings were more than three times realized savings, the direction the divisor problem predicts (Fowlie et al., 2018). Consumer-market estimates of the value of statistical life divide expenditure on safety devices by a risk reduction that presumes the device is used as designed (Dardis, 1980; Jenkins et al., 2001), and estimates of the value of electricity access from connection demand require a consumption path that, where measured after randomized connection, has been very low (Lee et al., 2020). In each case the divisor is the researcher's stand-in for a forecast that only the buyer holds.

We address both problems. We experimentally remove the leading market failures, providing interest-free credit and correcting beliefs about both the problem and the solution, and we estimate MWTP for households who already own the device, which strips out the liquidity constraints and product-performance uncertainty that contaminate purchase decisions. We then develop a use-based estimator that prices the flow value of the amenity from directly measured, high-frequency device use, identifying demand through randomized variation in the marginal cost of operation and plausibly exogenous variation in absolute levels of potential exposure reductions. The logic that an amenity can be priced from the use of a market good it is consumed with is the weak complementarity tradition behind travel cost and related methods (Mäler, 1974; Bockstael and McConnell, 1983), and behind the

pricing of risk reduction from the decision to use a seat belt (Blomquist, 1979). In that tradition the quantity of use is observed but its price must be imputed, typically from an assumed value of time, and the imputation drives the estimate (Cesario, 1976; Fezzi et al., 2014), including in the development application closest to ours (Kremer et al., 2011). Our design randomizes the price of use. The estimator therefore requires neither an assumed quantity of use, as purchase-based methods do, nor an imputed price of use, as existing use-based methods do; and because operating costs are assigned at random, they are uncorrelated with how much households dislike running the device, so the estimate is not contaminated by the disutility of operation. It generalizes to any durable that delivers a non-market amenity as a flow, for which one observes or can generate (i) high-frequency usage, (ii) exogenous variation in operating cost, and (iii) exogenous variation in the benefit delivered, with natural applications to clean water (filters), malaria protection (bednets), and thermal comfort (air conditioners). The condition that matters is that the value of the flow is the unknown. Where the flow is market-priced, as with energy savings, the divisor problem concerns the buyer's forecast of use rather than the value of the flow, and use data cannot recover that forecast.

Technology adoption in LMICs. We contribute to the literature on the roles of price, credit, beliefs, and experience in technology adoption (for reviews, see Dupas, 2011; Magruder, 2018; Kremer et al., 2019; Verhoogen, 2023). A central finding of this literature is that free or subsidized distribution raises demand for some preventive technologies, such as insecticide-treated bednets (Cohen and Dupas, 2010; Dupas, 2014), but not others, such as point-of-use chlorine (Ashraf et al., 2010); the difference appears to hinge on whether beneficiaries actually use the product, which may depend on beliefs and on the non-monetary costs of regular use. Our setting is one where the standard explanations for low adoption are least likely to bind. Our households are middle-income (PPP USD 24,000, 34% owning air conditioners), so high marginal utility of consumption is a less plausible explanation; and use elsewhere is mediated by concrete recurring costs: a bednet must be hung and slept under every night in the heat, chlorine dosed into every container of drinking water and its aftertaste tolerated, an improved stove tended through every meal and the preferred taste of food cooked over the wood fire forgone; the purifier asks none of this, since the household plugs it in once, each use is the press of a button, and the benefit accrues passively to everyone in the room. If adoption fails even

here, it points to a low marginal valuation of the amenity itself, or to non-standard frictions. We are among the first to study residential air purifier adoption experimentally; Greenstone et al. (2021) is closest, finding no demand for purifier rentals in Delhi,[3] and ongoing work by Sun et al. (2026) studies Indonesia.

2 Context, Research Design, and Data

2.1 Existing Evidence on Air Purifiers and Human Health

Portable air purifiers are a widely available private defense against fine particulate pollution. High-efficiency (HEPA) filters are rated to capture upwards of 99.9% of microscopic particles, including PM2.5, on a single pass through the device (EPA, 2024). Realized reductions in indoor concentrations are necessarily smaller than this engineering efficiency, since they depend on airflow, room size, and how the device is used, but they remain substantial: intervention studies of purifiers operating in homes consistently find statistically significant reductions in indoor PM2.5, typically on the order of 50% or more (EPA, 2018). A body of experimental, observational, and meta-analytic evidence further links residential purifier use to improved health, including reduced allergy and asthma symptoms and improvements in markers of cardiovascular function (Allen et al., 2011; Lanphear et al., 2011; Walzer et al., 2020; Xia et al., 2021; Sublett, 2011; Park et al., 2020; Li et al., 2018; for a review, see EPA, 2018).

The evidence most relevant to a high-pollution context like ours comes from short, intensive-use trials. Chen et al. (2015) find that 48 hours of continuous, enforced purifier use, with participants kept in sealed dormitory rooms, reduced indoor PM2.5 by 57% (from 96 to 41 $\mu g/m^3$) and produced measurable cardiopulmonary benefits in healthy young adults, including improvements in inflammatory and thrombogenic biomarkers, lung function, and blood pressure. Complementary evidence comes from workplace settings: Garg et al. (2026) show that providing air purifiers to manufacturing firms in Dhaka, where they were operated with windows and doors open for ventilation, led to extensive use (40% of firms ran them

[3] Greenstone et al. (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.

more than six hours per day over the one-year intervention) and raised worker productivity by roughly 10%. Together, this evidence establishes that purifiers, *when operated*, can deliver meaningful health and productivity benefits even where outdoor pollution is extreme.

2.2 Context

We conduct our study in Mirpur, Dhaka, a city with some of the world's highest levels of ambient air pollution. Between 1998 and 2023, annual average PM2.5 levels in Dhaka rose by 62% to 82.3 $\mu g/m^3$ (Figure A.1a), and reducing them to WHO-recommended levels would increase life expectancy by 7 years (AQLI, 2025). Pollution peaks during the dry winter months (December–February), when PM2.5 routinely exceeds 150 $\mu g/m^3$, ten times the WHO 24-hour guideline, and when we conducted the bulk of our experiments (Figures A.1b and A.1c).

We enrolled 3,408 households across seven housing associations in Mirpur: 1,008 in three associations for the Longitudinal Experiment, and 2,400 in four associations for the Single-Visit Experiment.[4] Each association comprises multiple multi-story apartment buildings. We selected this population for three reasons. First, middle-income apartments represent a common urban housing form in South Asia. Second, average annual household labor income exceeds PPP USD 24,000,[5] and 34% of sample households own an air conditioner, a device that costs two to three times more than a purifier, suggesting that purifier prices are not prohibitive. Third, apartments are better insulated than typical low-income dwellings, and households in our study period (cooler months) tend to keep windows closed, both of which increase purifier effectiveness.

2.3 Research Design

We conducted two complementary field experiments. The Longitudinal Experiment (November 2023-April 2024; $N = 1{,}008$) is a multi-phase longitudinal design examining how free allocation of monitors and purifiers affects beliefs, usage, and health. The Single-Visit Experiment (November 2024-January 2025; $N = 2{,}400$) is a cross-sectional experiment that isolates the mechanisms through which experience

[4] Figure A.2 shows the study area.

[5] Throughout, USD values are expressed in 2023 purchasing-power-parity-adjusted USD.

shifts beliefs, and tests whether credit access affects purifier demand. Figures 1 and A.3 summarize the design, timing, and survey dates.

2.3.1 Longitudinal Experiment

We sampled one household per floor across buildings in three housing associations, screening for (i) Wi-Fi access, (ii) not already owning a purifier, and (iii) interest in acquiring a monitor or purifier.[6]

Across three survey phases spaced roughly two months apart (Phase 1: Nov 12-30, 2023; Phase 2: Jan 5-Feb 4, 2024; Phase 3: Feb 23-Mar 31, 2024), we randomized four treatments. After the Phase 1 survey, half of households (512) received an **air quality monitor** with an interpretation chart mapping PM2.5 readings to six AQI categories and associated health risks (Figures A.4a, A.4b); among these, half (255) additionally received **weekly attention incentives** for reporting their readings. During the Phase 2 survey, we used a BDM mechanism to randomize 372 households into receiving a **free air purifier** (Smart Air "Sqair"; retail price BDT 16,500 / PPP USD 537; Figure A.4c), with assignment orthogonal to monitor status. Each purifier was attached to a smart socket recording minute-level usage. Within the purifier group, we randomized three **electricity-compensation** arms (no compensation, daily compensation, monthly compensation) to test whether electricity costs or present bias deter use. After all compensation payments ended on March 31, we re-randomized purifier households into three **usage-incentive** arms for April 2024, offering BDT 0, 5, or 10 per hour of purifier use, payments that far exceed the BDT 0.24 hourly electricity cost and, at full use, would amount to 6% or 12% of average monthly household labor income. Together with the electricity-compensation arms, these usage incentives generate randomized, within-household variation in the marginal cost of operating the purifier, ranging from a positive electricity cost to a large negative cost when households are paid to run the device; this variation identifies the use-based WTP estimates in Section 7. Appendix A.1 details the payments and incentives.

The three surveys collected baseline beliefs about air pollution and health risks (Phase 1); updated beliefs, BDM-elicited WTP for purifiers, health biomarkers, and

[6]Only 0.8% of contacted households owned a purifier, 73% had Wi-Fi, and 58% expressed interest. Focusing on interested households makes the sample less representative of the general population but more policy-relevant, as these are the households most likely to adopt.

self-reported outcomes (Phase 2); and endline beliefs, BDM-elicited willingness-to-accept (WTA) to sell back owned purifiers, and repeated health measures (Phase 3). Appendix A.3 describes the WTP elicitation. Attrition and balance are discussed in Appendix B; our main results are robust because they rely either on real-time sensor data (minimal attrition) or are replicated in the Single-Visit Experiment, where no differential attrition occurred.

2.3.2 Single-Visit Experiment

The Single-Visit Experiment randomizes 2,400 households across six arms: (1) *Control*, (2) *Credit Only*: an offer of a 12-month interest-free installment plan to purchase a purifier, (3) *Purifier Only*: a 5-minute purifier demonstration, (4) *Monitor Only*: a 5-minute monitor demonstration with the interpretation chart, (5) *Both* (*Separately*): sequential demonstrations of each device, and (6) *Both* (*Together*): a simultaneous demonstration in which households observed real-time PM2.5 reductions on the monitor as the purifier ran. Households in arm (6) observed an average 44% decline in PM2.5 from a pre-demonstration baseline of 138 $\mu g/m^3$. Before treatment, enumerators collected baseline data on demographics, beliefs, and perceptions; after treatment, they re-administered belief questions and elicited WTP via the same BDM mechanism used in the Longitudinal Experiment. Table A.1 confirms balance across all but one pre-treatment variable.

2.4 Data

We combine data from four sources. Survey data from both experiments capture beliefs, perceptions, WTP/WTA, health biomarkers, and self-reported outcomes. Indoor PM2.5 is measured at the household-minute level by the air monitors distributed in the Longitudinal Experiment, which record PM2.5, PM10, temperature, and humidity; we obtain data for 67% of potential observations.[7] Outdoor PM2.5 is measured at two of the three Longitudinal Experiment housing associations via monitors installed on December 1, 2023, with earlier periods imputed from the US Embassy monitor (correlation 0.96). Air purifier use is recorded at the household-minute level by smart sockets; we classify 3-60 watts as indicative of active use.

[7] All pollution data are winsorized at the 1st and 99th percentiles. Appendix A.4 reports monitor validation tests.

3 Descriptive and Stylized Facts

Our descriptive statistics reveal several new insights: indoor air in Dhaka is nearly as polluted as outdoor air, purifiers sharply reduce indoor PM2.5 when operated, yet households underestimate indoor pollution, are uncertain about purifier effectiveness, and almost never own purifiers.

Indoor pollution is nearly as high as outdoor pollution. During the Longitudinal Experiment study period, average outdoor PM2.5 at our study sites was 185 $\mu g/m^3$, roughly 12 times the WHO 24-hour guideline. Average indoor PM2.5 was 162 $\mu g/m^3$, and the hourly indoor-to-outdoor ratio averaged 0.95 (Figure 2a).[8] Data from the Single-Visit Experiment show the same pattern: outdoor PM2.5 of 130 $\mu g/m^3$, indoor PM2.5 of 138 $\mu g/m^3$, and an indoor-to-outdoor ratio of 1.08 (Figure 2b).

Households dramatically underestimate indoor pollution. In the Longitudinal Experiment, the modal household accurately rates outdoor pollution as extremely high (10 on a 10-point scale) but rates indoor pollution as only moderately polluted (4 on the same scale). The overwhelming majority of households believe their indoor-to-outdoor pollution ratio is 0.5 or lower, even though the true ratio exceeds 0.8 (Figures 2c–2f).

Purifiers sharply reduce PM2.5 when operated. We conducted controlled tests in January 2024 by randomly assigning a purifier to one of two closed rooms at our field office and running it for two hours, repeated six times. PM2.5 fell from 134 $\mu g/m^3$ to 26 $\mu g/m^3$ within 30 minutes, an 80% decline, and rebounded to baseline once the purifier was switched off, underscoring that the benefit accrues only while the device is running continuously (Figure 3a). Real-world pre-post patterns among Longitudinal Experiment households that turned on newly received purifiers show a similar, if smaller, decline: from 131 $\mu g/m^3$ to 75 $\mu g/m^3$, a 43% reduction (Figure 3b). In the Single-Visit Experiment's "Both (Together)" arm, a 5-minute demonstration produced an average 44% decline from a baseline of 138 $\mu g/m^3$.

[8] This is consistent with Saha et al. (2025), who estimate an indoor-to-outdoor ratio of 0.97 during winter using data from 17 Dhaka households, and with evidence that fine particulates penetrate buildings easily (Ozkaynak et al., 1996; Vette et al., 2001).

Households are uncertain about effectiveness and rarely own purifiers. Despite the clear efficacy of purifiers, only about half of Longitudinal Experiment non-purifier households and Single-Visit Experiment pre-intervention households had formed any opinion on effectiveness, and only a third believed purifiers removed more than 25% of indoor pollution (Figures 3c, 3e). Consistent with this uncertainty, BDM-elicited WTP is low: BDT 1,409 (PPP USD 46) on average among Longitudinal Experiment households without a monitor, 8.5% of retail, and BDT 2,700 (PPP USD 88) in the Single-Visit Experiment, 16% of retail. No household in either experiment was willing to pay the retail price (Figures 3d, 3f). Consistent with this, purifier ownership in our screening survey was under 1%, mirroring Greenstone et al. (2021)'s finding of zero rental demand among middle-income Delhi households.

4 The Adoption Puzzle: Standard Explanations Fail

A natural first hypothesis is that low adoption reflects the market failures most often invoked to explain low take-up of technologies in low- and middle-income countries: liquidity constraints, mistaken beliefs about the problem, or mistaken beliefs about the solution. We test these explanations using the Single-Visit Experiment, a cross-sectional design in which credit access and beliefs are manipulated cleanly and without the attrition that accompanies longitudinal designs. We then turn to the Longitudinal Experiment, which lets us follow households from belief formation through purchase, ownership, and, critically, directly measured use.

Econometric approach. For Single-Visit Experiment outcomes, we regress the outcome Y_i on indicators for each of the five treatment arms (Credit Only, Monitor Only, Purifier Only, Both Separately, Both Together), with Control as the omitted category. For Longitudinal Experiment outcomes, we regress Y_i on indicators for random monitor assignment (Phase 1), random purifier assignment (Phase 2), their interaction, and an indicator for the monitor-plus-attention-incentive arm. All specifications use heteroskedasticity-robust standard errors. Table 1 reports the Single-Visit Experiment results; Table 2 reports the Longitudinal Experiment results.

4.1 Single-Visit Experiment: Neither credit nor information moves WTP

Credit access does not increase WTP. We first rule out the most obvious explanation for low adoption: that households cannot afford the upfront cost. In the Single-Visit Experiment, we randomized offers of a 12-month interest-free installment plan, with enumerators carrying an official contract from our implementation agency. The effect on WTP is wrong-signed and close to zero (Table 1); households offered credit valued purifiers essentially identically to the control group. This null is consistent with our sample's financial profile: average annual household labor income exceeds PPP USD 24,000, and 34% own an air conditioner, a device that costs two to three times more than a purifier. The contrast with Berkouwer and Dean (2022), who find large credit effects on energy-efficient cookstove demand among Kenyan households earning roughly one-fourth our sample's income, suggests that credit constraints bind for low-income populations but not for the middle-income urban South Asian households who form the natural market for purifier adoption.

Correcting beliefs about pollution severity does not increase WTP. Brief five-minute monitor demonstrations, combined with a chart translating monitor readings into health risks, produced large shifts in beliefs about the air pollution problem.[9] Perceived indoor pollution rose by 0.79 points on a 10-point scale (19%), the perceived indoor-to-outdoor ratio rose from 0.43 to 0.50, and the perceived health risk of the household's own air pollution exposure increased by 0.16 standard deviations (Table 1).[10] Despite these corrections, WTP did not move.

Correcting beliefs about purifier effectiveness does not increase WTP. Brief five-minute purifier demonstrations shifted beliefs about the solution, raising the probability that households rated purifiers effective at every threshold (Table 1; Table A.2). Yet even in the Purifier-Only arm, where demonstrations generated the clearest updates about effectiveness, WTP remained statistically indistinguishable

[9] That showing households air-quality monitor data shifts their views on air pollution is consistent with Singh and Thachil (2026), who find that in Delhi such an intervention raised citizens' political prioritization of the issue.

[10] The Health Risk Beliefs Index combines two indicators of whether the household believes that air pollution increases the risk of acute respiratory issues for children and of lung cancer and stroke for adults, with "don't know" coded as no perceived increase.

from control (Table 1).

Combined information and direct experience also fail. In the "Both (Separately)" arm, households received sequential demonstrations of both devices and updated beliefs about both pollution severity and purifier effectiveness. In the "Both (Together)" arm, households watched PM2.5 on the monitor fall in real time as the purifier ran (44% on average), the most direct possible demonstration, and the arm that produced the largest effectiveness updates in the Single-Visit Experiment. Neither arm produced a detectable increase in WTP (Table 1).

A validation of the design. The Single-Visit Experiment also validates that households process distinct information about the problem and the solution rather than being primed on the general importance of air quality: purifier demonstrations shifted beliefs about purifier effectiveness but not about pollution severity, while monitor demonstrations did the reverse. This selective updating indicates genuine, content-specific belief revision.

4.2 Longitudinal Experiment: Ownership and extended experience tell the same story

The Longitudinal Experiment follows the same households across three survey waves spaced roughly two months apart, allowing us to ask whether sustained ownership, rather than a brief demonstration, changes the picture. It does not.

Table 2 shows that while beliefs move, WTP does not. Two months of monitor ownership raised perceived indoor pollution by 0.45 points on a 10-point scale (10%) and the perceived indoor-to-outdoor ratio by 3.0 percentage points (7%), with smaller effects on outdoor perceptions (Table A.2), and raised perceived health risks by 0.04 standard deviations (Table 2, Panel A), although the effect on perceived health risks is not statistically significant. Attention incentives produced no additional belief movement, indicating that monitors operate through information rather than salience (Table A.3). Households that received a free purifier became markedly more likely to form, and to raise, beliefs about purifier effectiveness: 28 percentage points (73%) more likely to have formed any opinion by Phase 3, and more likely to rate purifiers effective at every threshold, up to 167% more likely

at the highest (Table 2, Panel B; Table A.2). Despite belief corrections larger than, or comparable to, those in the Single-Visit Experiment, WTP did not rise (Table 2, Panel A).

The Longitudinal Experiment lets us observe WTA to sell back purifiers among households that had owned them for 47 days on average. Monitor assignment raised WTA by BDT 3,983, a 28% increase over the purifier-only mean of BDT 14,333 (Table 3, Column 4), pushing average WTA just above the BDT 16,500 retail price. Two features argue against reading this as genuine valuation. First, the purifier-only group's average WTA is more than nine times the same households' Phase 2 WTP of BDT 1,517, a gap consistent with well-documented endowment effects (Tunçel and Hammitt, 2014; Brown et al., 2024);[11] the increase more plausibly reflects reluctance to surrender an owned object than valuation of its services.[12] Second, even applying the 28% monitor effect to WTP rather than WTA yields BDT 1,938, just 12% of retail—barely distinguishable from the baseline that prompted the puzzle.

Taken together, both experiments establish the paper's central puzzle. Among middle-income urban households breathing air ten times above WHO guidelines, in a setting where purifiers cut PM2.5 sharply when operated and credit is not a binding constraint, no combination of information or demonstration produces WTP approaching retail prices.

5 Even When Purifiers Are Free, Households Barely Use Them

The puzzle extends beyond the purchase decision. Even among households given purifiers for free, usage is strikingly low, and neither compensating electricity costs nor offering payments that dwarf those costs generates sustained use. Throughout, usage is measured directly at the household-minute level by smart sockets, so these patterns are not merely artifacts of self-reporting.

[11] This is also consistent with lack of usage that we document in Section 5.

[12] Hanemann (1991) shows that WTP and WTA can diverge substantially even without behavioral biases, but only for goods that lack close substitutes; clean water, for instance, where Burlig et al. (2026) document such a gap. The air purifier is a private good with many market substitutes; households could buy the identical model in a Dhaka store; so the WTP–WTA gap here most plausibly reflects an endowment effect rather than a fundamental valuation wedge.

5.1 Baseline usage is very low

Among Longitudinal Experiment households that received free purifiers but neither a monitor nor electricity compensation, average use was only 20 minutes per day (Figure 4, gray bars). Most household-days saw no use at all: 82% of household-days had zero purifier activity, and only 23% of households averaged more than 27 minutes per day. These are households facing indoor PM2.5 ten times the WHO guideline, with a working purifier already installed in the home. This low average usage is broadly similar across baseline vulnerability (age, children or elderly members, asthma), awareness (education, beliefs about indoor pollution), and household income; the main exception is that households reporting no baseline defensive actions against pollution use the purifier somewhat less (Figure A.5).

5.2 Electricity cost does not explain low use

To test whether electricity costs (approximately BDT 0.24 per hour) deter use, we randomized households into no-compensation, daily-compensation, and monthly-compensation arms. Compensation increased use only modestly, by roughly 17 minutes per day (31%), and the effect is not statistically significant; differences between daily and monthly schedules, which might reveal present bias, were also null (Table A.4). What effect there was concentrated in the first few weeks of ownership and did not persist (Figure 4b).

5.3 Monitors raise usage, but the level remains low

Households that received both a monitor and a purifier used purifiers 105 minutes per day on average, 74 minutes (234%) more than purifier-only households (Table 3, Column 1; Figure 5a). The proportional change is large; the absolute level is not, amounting to under two hours out of every twenty-four. Monitor households still saw zero purifier activity on 68% of days and ran purifiers for at least 30 minutes on only 1.7 days per week (Column 2), and most households averaged under 81 minutes daily throughout the study (Figure 5d). Even with accurate information about both the severity of the problem, the effectiveness of the solution, and a working purifier already at hand, households left the device off, and breathed polluted air, for 93% of the time.

5.4 Large monetary incentives also fail to generate sustained use

The sharpest test pays households to run the device. After all other Longitudinal Experiment interventions ended on March 31, we re-randomized purifier households into three arms for April 2024, offering BDT 0, 5, or 10 per hour of purifier use, payments that exceed the BDT 0.24 hourly electricity cost by a factor of 20–40 and that, at continuous use, would pay 6–12% of average monthly household labor income.

The central fact is not that average use rose modestly but that, even at the largest payment, most households declined to run the device at all. Among the 98 households offered BDT 10 per hour, roughly forty times the electricity cost, 68% ran the purifier less than 10% of the time, and the median household in this arm ran it for about 1% of paid hours. Only 10% ran it at least half the time. Average use in the arm masks this near-complete refusal because it is pulled up by a small, strongly responsive minority: mean use when paid was 14% of hours, even as the median sat near zero (Table A.5). Put differently, offered 12% of monthly income to operate a device already installed in their homes, a clear majority of households still chose to breathe polluted air, leaving thousands of taka per month unclaimed.[13]

This refusal-when-paid is the central fact of the paper, and it constrains the explanations sharply. Because the payment more than offsets every monetary cost of operation, electricity included, and yet most households still do not run the device, the binding obstacle cannot be financial. What remains is a large *non-financial* cost of operating the device itself: a disutility of use that, for the majority of households, exceeds both the value they place on the resulting clean air and the substantial sum offered to overcome it. In Section 7, we estimate the value of clean air directly, in a way that does not confound it with this disutility of operation.

[13] The BDT 5 arm raised average use by about as much as providing a monitor did, and doubling the payment to BDT 10 raised it further by a similar amount again, though that increment is not statistically significant (Table A.5).

6 Small Pollution Reductions Without Health Improvements

We finally examine whether the modest use that does occur delivers measurable health benefits. It does not, but, as we explain, this reflects how little the devices are run rather than any failure of clean air to matter for health.

Purifiers reduce indoor PM2.5, but far less than under continuous operation. Using continuous monitor data from the Longitudinal Experiment between the Phase 2 and Phase 3 surveys, we estimate that households with purifiers experienced roughly 6.2 $\mu g/m^3$ lower average PM2.5 than those without, a 5.5% reduction off a baseline of 112 $\mu g/m^3$ (Table A.6; Figure A.6).[14] This realized reduction is a small fraction of what the same device achieves under continuous operation: in our controlled office tests, running a purifier in a closed room cut PM2.5 by 80% within thirty minutes. The gap between that efficacy and the reduction realized in households is precisely the operating problem: the device works when it is on, and households rarely turn it on.

No detectable health improvements. Across a broad set of biomarkers (blood pressure, blood oxygen, lung capacity, breathing capacity) and self-reported outcomes (sick days, medical costs, and symptom indices covering cough, asthma, breathing problems, hypertension, and migraines), we find no evidence of improvement for households receiving monitors, purifiers, or both (Table A.8). Nor do we detect effects on sleep, mental health, labor income, or labor supply (Table A.9).

Interpretation: the health null follows from low usage, not from a low value of clean air. These nulls differ from much of the prior experimental literature, which documents measurable benefits from residential purifiers (EPA, 2018). However, the difference is what one would expect given how little the devices are run, and it does not imply that clean air is unimportant for health. Prior studies reviewed in

[14] Because monitor and purifier use are complements (Table A.7), we impute indoor PM2.5 when monitors are off by multiplying outdoor PM2.5 by the average indoor-outdoor ratio (0.76) observed in non-purifier households. Restricting to observed readings yields similar coefficients with wider confidence intervals (Column (2) of Table A.6).

Section 2.1, typically achieve average PM2.5 reductions of 50% or more, comparable to our own controlled tests under continuous operation, whereas intermittent household use achieves only 5.5%.

7 Estimating the Marginal WTP for Clean Air

A recent literature estimates marginal willingness to pay (MWTP) for clean air from demand for defensive technologies, inferring valuations from how demand responds to variation in pollution reduction, and finds values that are consistently low (Jack and Ryan, 2026; Greenstone and Jack, 2015). Converting WTP for a device into MWTP for clean air requires dividing by the exposure reduction the device will deliver, and that reduction scales with how intensively the household anticipates using it. Studies that assume full utilization likely overstate anticipated use when operation carries monetary or non-monetary costs, and so understate MWTP; at use levels like those we observe, their estimates would be more than an order of magnitude higher. The use assumption is therefore one candidate explanation for the low values the literature has found. It cannot be checked from purchase data, because the divisor must match the household's private forecast of its own use, and neither realized nor stated use can stand in for it, for reasons we develop below. We therefore build a use-based estimator that prices the flow value of clean air directly from high-frequency utilization data and randomized operating costs, requires no assumption about anticipated use, and is uncontaminated by any disutility of operation. Applied in our context, it recovers estimates close to zero, with an upper bound below prior estimates.

7.1 Purchase-based estimates rest on unverifiable use assumption

The simplest purchase-based approach expresses MWTP for clean air as the ratio of WTP for a purifier to the marginal reduction in PM2.5 exposure it delivers:

$$\text{MWTP}^{\text{clean air}} = \frac{WTP^{\text{air purifier}}}{\Delta PM2.5^{\text{air purifier}}} \tag{1}$$

where

$$\Delta PM2.5^{\text{air purifier}} = PM2.5 \times e \times u, \tag{2}$$

e is the share of PM2.5 the purifier removes while running, and u is the fraction of hours it runs. The numerator and denominator of equation (1) refer to different usage rates. WTP is priced on the use the household anticipates, $\tilde{u}$; the divisor uses the rate the researcher assumes, $\hat{u}$. Writing $WTP = \text{MWTP} \times PM2.5 \times e \times \tilde{u}$, the estimate is

$$\widehat{\text{MWTP}} = \frac{\text{MWTP} \times PM2.5 \times e \times \tilde{u}}{PM2.5 \times e \times \hat{u}} = \text{MWTP} \times \frac{\tilde{u}}{\hat{u}}, \tag{3}$$

correct only when the two rates coincide, and understated in proportion to the shortfall of anticipated from assumed use. Any operating cost the household nets out of its WTP lowers the numerator further and pushes the estimate the same way. Throughout our calculations we assume that purifiers are used only during the winter season and last for one season (3 months); each row of Table A.10 then varies the assumed usage rate $\hat{u}$.[15]

Row (1) applies the assumption of continuous use from Ito and Zhang (2020) to determine $\Delta PM2.5$. This yields an MWTP of PPP USD 0.40 per $\mu\text{g}/\text{m}^3$ per season. Rows (3) and (4) substitute stated expected and ex-post reported usage, respectively, for the continuous use assumption in Row (1); estimates rise to PPP USD 2.4 and PPP USD 3.3 per $\mu\text{g}/\text{m}^3$ per season. Row (5) uses actual measured usage (just 5% of hours) in place of stated usage, raising the MWTP to PPP USD 21 per $\mu\text{g}/\text{m}^3$ per season.

Two features of Table A.10 matter for the literature's estimates. First, Row (1), the continuous-use assumption, is the floor: every divisor below continuous operation raises the estimate, so if households anticipate anything less than continuous use, estimates built on this assumption are too low. Second, the interval is wide. Measured use yields an estimate more than fifty times Row (1) (PPP USD 0.40 to PPP USD 21), and it is a ceiling on the correct estimate if, as we argue below, households anticipated more use than they delivered. The purchase-based MWTP consistent with households' own anticipations lies somewhere in this interval, and purchase data cannot locate it. Importantly, this problem is not resolved by more sophisticated designs that recover MWTP from how WTP varies across devices of differing effectiveness, as in Tarduno and Walker (2025), who elicit WTP for two

[15] Ito and Zhang (2020) assumes purifiers last five years; applying that assumption to our calculations would reduce our MWTP estimates by 80%, in the same direction as the use assumption. A one-season lifetime is realistic in our setting given the low WTP for the purifier itself, which is typically below the cost of a replacement filter.

purifiers that differ only in cleaning capacity, because the implied differential in exposure reduction still scales with usage:

$$\text{MWTP}^{\text{clean air}} = \frac{WTP^A - WTP^B}{\Delta PM2.5^A - \Delta PM2.5^B} = \frac{WTP^A - WTP^B}{PM2.5 \times (e_A - e_B) \times u}, \tag{4}$$

where the last equality assumes the two devices are run the same fraction of the time u. The usage term does not cancel: it factors out of the difference in exposure reduction and reappears as a divisor, so the estimate is again $\text{MWTP} \times \tilde{u}/\hat{u}$. Any purchase-based estimate therefore hinges on a use assumption the researcher cannot verify, and under the full-utilization assumption common in the literature it is a lower bound.

Our data speak to where in the interval of Table A.10 the truth lies, and to why purchase data cannot locate it, through a gap between stated and actual usage that opens at two distinct stages, which we observe separately because we elicited expected use before households received the purifier (Phase 2) and recalled use after 47 days of ownership on average (Phase 3). Before acquisition, households' stated expectations far exceeded their eventual use: in Phase 2, 64% expected to run the device "all the time when home" (Figure 6), a forecast consistent with projection bias, in which households extrapolate from their initial, newly informed enthusiasm and underweight how the ongoing inconvenience of operation will erode use (Loewenstein et al., 2003). After acquisition, they over-reported realized use: in Phase 3, 30% reported using the device "all the time when home" and 82% reported use at least once per day, yet smart-plug data show that almost no household used it that much, a discrepancy consistent with experimenter demand (de Quidt et al., 2018). To the extent projection bias drives a wedge between the usage households anticipate at purchase and the usage they realize, estimates corrected with *measured* realized use over-correct, dividing a willingness to pay priced on optimistic anticipations by the far smaller reality (Row (5) of Table A.10). Stated expected use might seem to escape this, since dividing by the household's own anticipation would recover the valuation; but the statement can be trusted only if it faithfully transmits the private anticipation, and our Phase 3 evidence shows self-reports are inflated well beyond behavior, consistent with experimenter demand. Whether ex-ante statements are similarly inflated beyond genuine anticipations cannot be verified, because the anticipation itself is never observed. Every candidate divisor

thus fails for its own reason: assumed full use overstates any plausible anticipation, measured use falls short of the anticipation that priced the device, and stated use is reliable only under an untestable assumption about survey honesty. Estimates built on the first, as in Ito and Zhang (2020) and Tarduno and Walker (2025), sit at the floor of the interval in Table A.10.[16]

7.2 A use-based MWTP estimator

We develop an alternative that identifies MWTP from hour-to-hour operating decisions, exploiting randomized variation in operating costs together with plausibly exogenous variation in the potential pollution reduction from running the purifier. The approach prices the flow value of clean air directly and requires no assumption about expected future use.

7.2.1 Deriving our empirical specification

In each hour t, household i chooses whether to run the purifier. Running it delivers a reduction in exposure worth $v_i \cdot \Delta_{it}$, where Δ_{it} is the potential PM2.5 improvement available that hour and v_i is the household's marginal valuation of clean air, the object we wish to recover. It also imposes a monetary cost c_{it} (the net hourly cost of operation, which our design randomizes) and a non-monetary disutility of operation d_{it} (noise[17], dryness, a cognitive cost of paying attention, the inconvenience of switching the device on and tending it). The household runs the purifier when the benefit exceeds the total cost:

$$v_i \, \Delta_{it} \; - \; c_{it} \; - \; d_{it} \; + \; \varepsilon_{it} \; > \; 0, \tag{5}$$

[16] Because experimenter demand threatens not only these usage figures but any self-reported outcome, in Appendix C we verify that the gap between reported and measured use is not differential by treatment status. This protects our belief and WTP estimates: were the over-reporting differential across arms, if, say, households that received a monitor felt more accountable and inflated their reports more, it could manufacture or mask apparent treatment effects on self-reported outcomes. We find no such differential, so our estimated treatment effects on beliefs and WTP are unlikely to be driven by treatment-varying misreporting.

[17] In a controlled comparison across two Mirpur bedrooms on February 18–19, 2025, ambient noise with and without a running purifier differed negligibly (46.2 vs. 45.5 dB), because Dhaka's baseline soundscape dominates the purifier's marginal acoustic contribution. Noise is therefore unlikely to explain much of the low usage we document.

where ε_{it} is an idiosyncratic shock. Let F denote the distribution function of $-\varepsilon_{it}$, so household i runs the purifier in hour t with probability $F(v_i\,\Delta_{it} - c_{it} - d_{it})$. Suppose first that the valuation is common across households, $v_i = v$. Linearizing F around the mean of its argument, with λ the density at that point, and decomposing the disutility of operation as $d_{it} = d_i + d_{h(t)} + \tilde{d}_{it}$, yields the specification below, with $\beta_{PM} = \lambda v$, $\beta_c = -\lambda$, and household and hour-of-day fixed effects absorbing d_i and $d_{h(t)}$. The density λ, which measures how many households are at the margin of use in a given hour, cancels in the ratio, so $\mathrm{MWTP} = -\beta_{PM}/\beta_c = v$, the flow value of a one-$\mu\mathrm{g}/\mathrm{m}^3$ reduction in indoor PM2.5 in the current hour; seasonal and annual values multiply this flow by the hours in the 90-day winter season and in the year. When valuations differ across households, the ratio recovers a weighted average of the v_i with weights proportional to each household's mass at the margin of use, so the estimator prices clean air from the households whose operating decisions respond to prices and pollution. Appendix D restates the derivation without the linearization: when the taste shock in (5) is the difference of two Type-I extreme value shocks, the decision rule implies a logit whose coefficient ratio $-\beta_{PM}/\beta_c$ equals v exactly, which we estimate in Column (4) of Table 4.

Specification. We estimate:

$$\text{Use}_{it} = \beta_0 + \beta_{PM}\,\text{Potential PM2.5 Improvement}_t + \beta_c\,\text{Cost}_{it} + \alpha_i + \delta_{d(t)} + \gamma_{h(t)} + \epsilon_{it}, \quad (6)$$

where Use_{it} is the share of hour t for which household i operates the purifier; $\text{Potential PM2.5 Improvement}_t$ is the expected reduction from running the purifier that hour (outdoor PM2.5 scaled by the indoor-outdoor ratio and purifier effectiveness); Cost_{it} is the net hourly cost of operation in BDT; and α_i, $\delta_{d(t)}$, $\gamma_{h(t)}$ are household, date, and hour-of-day fixed effects. Applied at each instant of the hour, the threshold rule (5) implies that the share of the hour the device runs is the fraction of instants at which it holds, so the same linearization applies to the share outcome. The error ϵ_{it} collects the idiosyncratic disutility $\tilde{d}_{it}$, the taste shock, and linearization error. Standard errors are clustered at the household level.

Why disutility does not contaminate the estimate. The disutility of operation d_{it} also shapes how much households run the device and could in principle distort

the recovered valuation. Randomization of the operating cost addresses this. Because c_{it} is assigned at random, it is uncorrelated with v_i, with d_{it}, and with any household characteristic: a household that finds the device especially bothersome is no more likely to face a high operating cost than a low one. The estimated response of use to price, β_c, therefore measures how use responds to money, not how households' reluctance to operate the device happens to line up with the prices they face. Clean air enters through β_{PM}, and the trade-off between the two is the ratio $-\beta_{PM}/\beta_c$, in which the density of households at the margin, which the disutility of operation shapes, cancels. Decomposing d_{it} into a household-fixed component, an hour-of-day component, and an idiosyncratic remainder, the first two are absorbed by the household and hour-of-day fixed effects; estimates are essentially unchanged whether or not these fixed effects are included (Table A.11, Columns 1–3), confirming that the randomized design leaves the price variation orthogonal to this structured disutility. The estimator thus recovers the average marginal valuation of clean air, uncontaminated by the time-invariant and hour-of-day disutility of operating the device. The same argument covers benefits of running the device other than PM2.5 reduction, such as creating air circulation or removing odors. These may raise the level of use, but not its response to potential PM2.5 improvement, as long as they do not vary from hour to hour with outdoor PM2.5. Controlling for hourly temperature and humidity, the conditions in which air circulation is most valuable, leaves the estimate close to zero, with 95% upper bounds of PPP USD 1.65 per year when both are measured outdoors and PPP USD 1.24 when both are measured by the household's own monitor (Table A.11, Columns 10 and 11).

Identification. Variation in Cost_{it} comes from two randomized regimes. Before April 1, households were randomly assigned to pay the BDT 0.24/hour electricity cost or to have it reimbursed; on April 1 they were re-randomized into per-hour usage-incentive arms (BDT 0, 5, or 10 of payment for use), making the net cost of operation negative for households receiving an incentive. Because the regime switches on a common date, the same household experiences a sharp, randomized change in the marginal price of running the purifier; date fixed effects absorb any seasonality or aggregate trend common to all households around that transition.[18]

[18] Estimates are essentially unchanged when date fixed effects are omitted, indicating that the April 1 regime change, rather than coincident seasonality, drives the price variation.

Variation in Potential PM2.5 Improvement$_t$ comes from hour-to-hour fluctuations in outdoor PM2.5, which we scale by the average indoor-outdoor ratio and assumed purifier effectiveness. These fluctuations are driven by meteorology and regional emissions, are exogenous to individual households, and cannot be anticipated or influenced by household behavior; consistent with this, 87% of households report never or rarely checking outdoor air quality. Hour-of-day fixed effects absorb routine occupancy and convenience patterns. Identification therefore comes from comparing how the same household responds to higher- versus lower-pollution hours, conditional on time-of-day routines and common daily shocks.

Purifier effectiveness assumption. The purifier's effect on indoor pollution is not instantaneous: the dynamics (Figure 3a) are gradual; pollution declines roughly linearly for 30 minutes after the device is switched on, stabilizes at about 20% of counterfactual levels, and returns to baseline only over the following four hours. The total reduction delivered by a session therefore depends on its duration, so our main specification uses the effectiveness implied by the *average* purifier session in our data, which lasts 108 minutes (Figure A.7a); the resulting per-minute effectiveness is 158%, exceeding 100% because pollution stays low even after the purifier is switched off.

Do households perceive the variation they are scored on responding to? A natural concern is that the low estimated MWTP could reflect inattention rather than low valuation: if households do not perceive the hour-to-hour variation in potential pollution reduction, a muted response would be uninformative about how they value clean air. Indeed, the same statistic that establishes exogeneity (that households rarely track *outdoor* air quality) might seem to imply they cannot perceive this variation at all. Three features of our design address this directly.

First, and most importantly, our valuation sample consists of households equipped with a real-time indoor air-quality monitor. These households do not need to track outdoor pollution to perceive the variation our estimator exploits: the monitor displays the indoor PM2.5 state in their own home, continuously, at the moment they decide whether to run the device. The 87% who rarely check *outdoor* conditions are nonetheless able to observe *indoor* pollution directly, so the inattention that makes ambient PM2.5 exogenous does not imply inattention to the pollution state the esti-

mator uses. Consistent with this, receiving a monitor raises perceived indoor pollution relative to households without one, and an additional attention-to-monitor incentive does not raise it further, indicating that monitor provision alone shifts beliefs about the indoor pollution state about as much as incremental attention interventions do.

Second, ambient PM2.5 is a high-frequency proxy for the indoor pollution state households experience through infiltration (indoor PM2.5 measured by the monitors closely tracks ambient PM2.5 in our setting; Figures A.1c and A.1d) so high-ambient hours are precisely the hours in which running the purifier would deliver larger indoor exposure reductions, and in which an attentive, clean-air-valuing household would be most inclined to run it.

Third, the null does not strengthen in the hours when households are most present and most able to respond. Re-estimating separately by time of day (Figure A.8), MWTP is statistically indistinguishable from zero in every four-hour block, including the 4 PM–midnight windows when household members are most likely to be home and awake. If inattention were muting the effect, the response should be most detectable precisely when households are present and engaged; instead it is uniformly near zero. Occupancy and attention, in other words, do not appear to be masking a latent valuation.

Inattention to the operating price. A parallel concern applies to the cost side. Consumers often under-respond to the marginal price of operating a durable when that price is small and buried in a periodic bill: residential electricity customers respond to average rather than marginal prices (Ito, 2014), and their price elasticity rises sharply when they receive real-time feedback on usage and prices (Jessoe and Rapson, 2014). Two features of our setting limit this concern. First, the identifying price variation comes mainly from the usage incentives, which are explicit, announced to the household, and twenty to forty times the electricity tariff, rather than from a tariff embedded in a monthly bill. Second, inattention to price would attenuate β_c toward zero and thereby inflate the ratio $-\beta_{PM}/\beta_c$. Inattention to the operating price therefore cannot produce a spuriously low MWTP.

7.2.2 Results

Main estimate. Column (1) of Table 4 yields an MWTP of PPP USD 0.15 per $\mu g/m^3$ per season, or PPP USD 0.59 per year. The estimate is close to zero and not statistically distinguishable from it ($p = 0.20$); we can reject with 95% confidence annual values above PPP USD 1.50. The result is robust to how we model the operating decision: a binary "any use" specification (Column 2), a fractional logit (Column 3), and the fixed-effects logit implied by the discrete-choice model of Appendix D (Column 4) yield annual MWTP of PPP USD 0.81, 0.75, and 0.86, with 95% upper bounds of PPP USD 1.79, 2.05, and 2.14; every upper bound remains below the lowest prior estimate in Table A.12.

Robustness. Table A.11 shows the estimate is stable across modeling choices. Point estimates are very similar with and without fixed effects and weather controls. They are also similar under alternative effectiveness assumptions: a constant 80% reduction while the purifier is on yields PPP USD 1.17 per year (95% upper bound PPP USD 2.95), and the effectiveness of the *median* 23-minute session (Figure A.7b) yields PPP USD 0.34 per year; both remain indistinguishable from zero. For households *without* monitors the estimate is small, wrong-signed, and indistinguishable from zero; as expected, since these households cannot observe hour-to-hour pollution and so cannot respond to it. The estimate is also stable across the day: re-estimated separately for each four-hour block, use-based MWTP is statistically indistinguishable from zero throughout (Figure A.8).

7.3 External validity

Because households received purifiers for free, the use-based MWTP we recover may differ from the valuation of households who would buy purifiers in a market. If market purchasers were positively selected on demand for clean air, their MWTP could exceed ours. However, if the goal is a population-representative MWTP, conditioning on market purchase would yield a *more* selected sample than ours, not less.[19]

We also assess selection directly, re-estimating MWTP separately for households

[19] Furthermore, our sample is weakly selected on demand: 58% of households expressed ex ante interest during recruitment, and we excluded those who were not interested.

with above- and below-median baseline (Phase 2) WTP, a proxy for who would self-select into purchase (Table A.11). Above-median households do show higher use-based MWTP, consistent with meaningful selection on demand, but even there it remains very low: PPP USD 1.14 per $\mu g/m^3$ per year ($p = 0.21$).

7.4 Comparison to the literature

Table A.12 compares our estimate to prior MWTP estimates from Ito and Zhang (2020) (China), Baylis et al. (2023) (India), and Tarduno and Walker (2025) (U.S.), adjusted for PPP, inflation, and household size. Our baseline of PPP USD 0.59 per $\mu g/m^3$ per year compares to PPP USD 6.4 in China, PPP USD 3.1 in India, and PPP USD 2.7 in the U.S. Even the upper bound of our 95% confidence interval, PPP USD 1.50, lies below the lowest of these estimates as published after adjustment for PPP, inflation, and household size: the entire range we cannot reject sits beneath the valuations the existing literature reports. The gap cannot be explained by income, which runs the wrong way: our households earn PPP USD 24,122 annually, more than double the comparable figures in the China and India samples, and a richer household converts a given valuation into a larger WTP, not a smaller one.

We cannot observe how intensively the subjects of these studies anticipated using their devices at the moment their WTP was determined; that anticipation is private, which is the argument of Section 7.1. What each published number does embed is a divisor: full utilization in Ito and Zhang (2020) and Tarduno and Walker (2025), self-reported use in Baylis et al. (2023). By equation (3), if their subjects anticipated less use than these divisors assume, the published numbers understate MWTP. Substituting lower use levels shows by how much: dividing the WTP in Ito and Zhang (2020) by our stated expected usage in place of continuous use raises the estimate to PPP USD 16, and our measured usage raises it to PPP USD 141. Comparable substitutions in Baylis et al. (2023) and Tarduno and Walker (2025) produce similar inflation (Table A.12). Usage in Dhaka need not transfer to their settings, and these magnitudes are illustrative; the direction requires no transfer, only that operation was costly enough that their subjects anticipated something less than the assumed use. The comparison above is therefore conservative. It sets the ceiling of our confidence interval against estimates that are, for the full-utilization studies, floors; for Baylis et al. (2023), whose divisor is reported rather than assumed,

the same direction holds if reports exceeded private anticipations, as experimenter demand would produce.

8 Conclusion

This paper asks why households in one of the world's most polluted cities do so little to defend themselves against air pollution, and answers by taking the standard explanations apart one at a time. Among middle-income households in Dhaka, purifier ownership is below 1%. Neither interest-free credit, nor correcting beliefs about the severity of indoor pollution, nor correcting beliefs about purifier effectiveness, nor watching the device cut pollution in real time moves willingness to pay beyond a small fraction of the retail price. Ownership itself does not change the picture: households given free purifiers run them for under an hour a day, and a clear majority declines to run the device even when paid an hourly amount roughly forty times the operating cost.

We estimate that the marginal value households place on the clean air a purifier delivers is close to zero; we can rule out annual values above PPP USD 1.50 per $\mu g/m^3$ with 95% confidence, below prior experimental and quasi-experimental estimates. And the non-financial cost of operating the device is large; for most households it exceeds the value of the clean air produced plus the substantial payment offered. Low valuation and high operating disutility coexist and are distinct, and neither is an artifact of the other: because operating costs were assigned at random, the value estimate is uncontaminated by the disutility of operation.

The use-based estimator is complementary to purchase-based approaches, and it carries requirements of its own. It prices the amenity through the operating margin, and so requires that households can perceive and act on variation in the benefits and costs of running the device, that use be observed at high frequency, and that the price of use vary exogenously. Where those conditions hold or can be created, the estimator needs neither an assumed quantity of use, as purchase-based methods do, nor an imputed price of use, as travel-cost methods do, and it applies to any durable that delivers a non-market amenity as a flow. It is also, by construction, the value of the partial, in-home pollution exposure reduction a private device delivers, not of comprehensive ambient air quality, and we cannot fully exclude that residual frictions, such as underweighting of long-run harm, also depress it.

Residential purifiers are unlikely to become a large part of the answer to South Asia's air pollution crisis, and not because they fail to work. In controlled operations the device cuts indoor PM2.5 by 80%, enforced continuous use improves measured health in comparably polluted settings (Chen et al., 2015), and firms in Dhaka that run purifiers through the workday realize sizable productivity and profit gains (Garg et al., 2026). The constraint is not efficacy, price, credit, or information; it is that households will not operate the device in their own homes. For the adoption literature, the lesson is that the operating demands that block use need not be onerous: here they amount to a switch, and they still bind. This gives little reason to expect that the standard levers, subsidies or information campaigns, can raise residential adoption and use to a level with meaningful public health consequences. Two directions look more promising. The first is institutional settings, schools (e.g., Kremer et al., 2025), clinics, offices, and factories, where operation can be made a default; the firm evidence suggests utilization and benefits are both attainable there. The second is ambient air quality itself. Publicly provided improvements in ambient air arrive, in effect, as a finished good: there is nothing for the household to switch on, so the operating wedge that blocks private defense does not apply.

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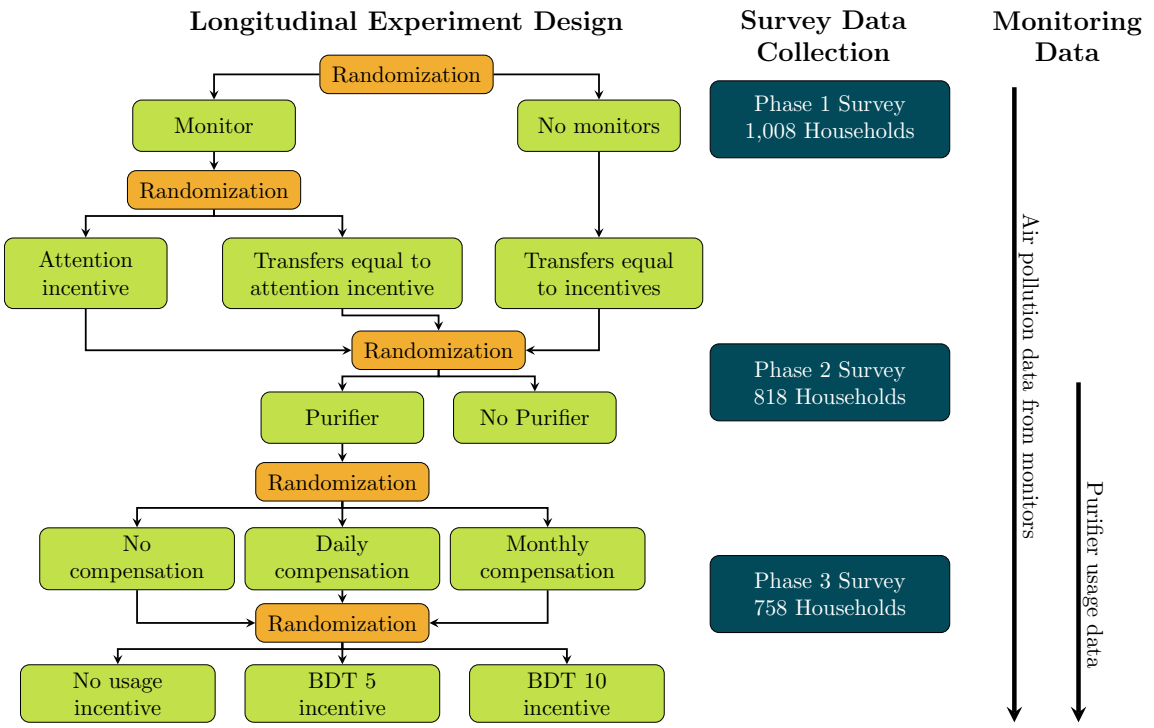
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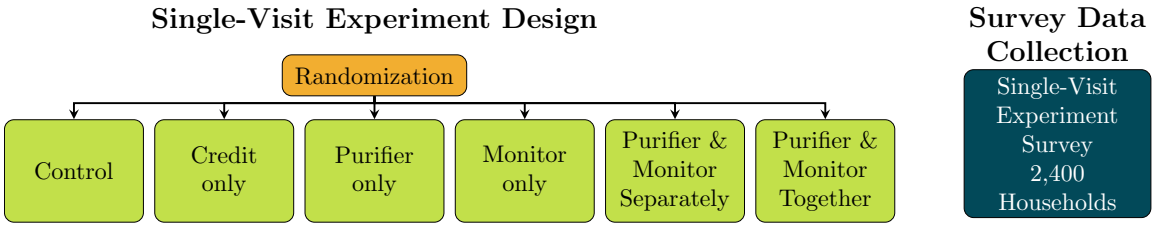
Figures

Figure 1: Flowchart of Research Design

(a) Longitudinal Experiment



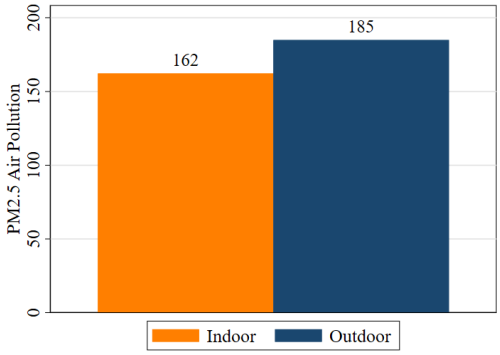
(b) Single-Visit Experiment



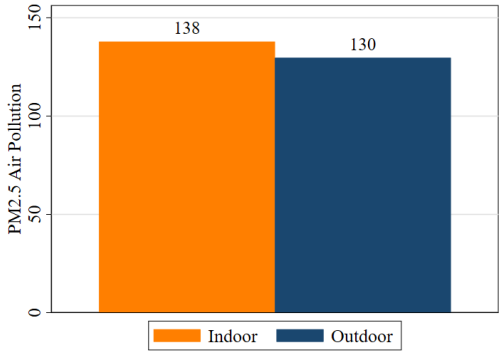
Notes: This figure shows the research design and data collection for the Longitudinal and Single-Visit Experiments. The Longitudinal Experiment's Phase 1 survey ran from 12 to 30 November 2023, Phase 2 from 5 January to 12 March 2024, and Phase 3 from 23 February to 20 April 2024. The Single-Visit Experiment started on 19 November 2024 and concluded on 22 January 2025. See discussion in Section 2.

Figure 2: Indoor vs. Outdoor Air Pollution: Reality and Perceptions

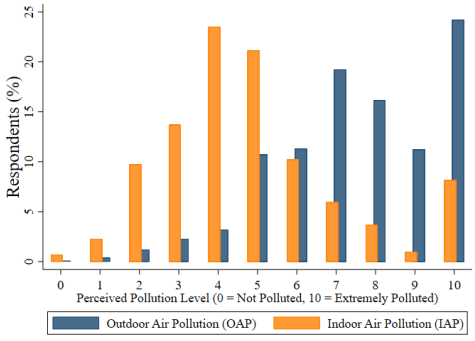
(a) Indoor vs. outdoor pollution (Longitudinal Experiment)



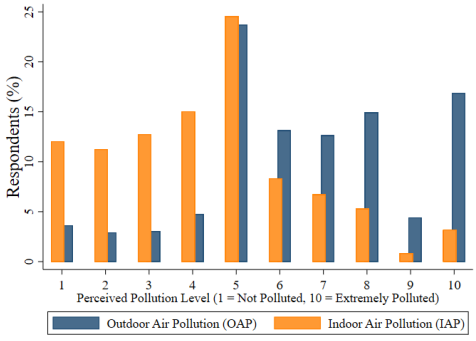
(b) Indoor vs. outdoor pollution (Single-Visit Experiment)



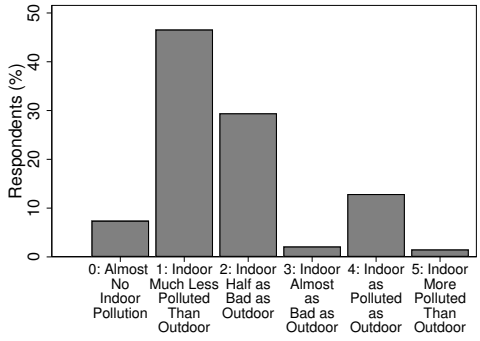
(c) Air pollution beliefs (Longitudinal Experiment)



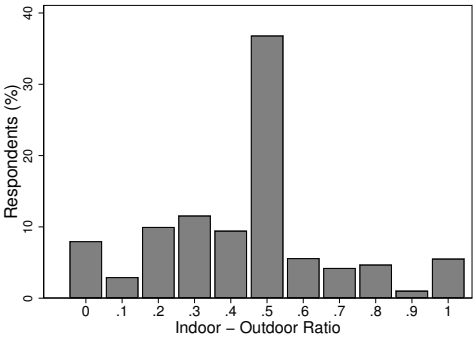
(d) Air pollution beliefs (Single-Visit Experiment)



(e) Indoor-outdoor ratio beliefs (Longitudinal Experiment)



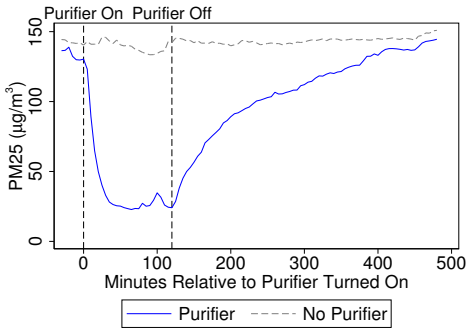
(f) Indoor-outdoor ratio beliefs (Single-Visit Experiment)



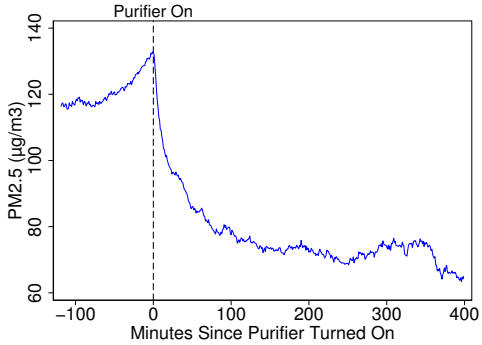
Notes: Panels (a)–(b) show indoor and outdoor $PM_{2.5}$ concentrations (in $\mu g/m^3$). Panels (c)–(d) display household beliefs about the severity of indoor and outdoor pollution. Panels (e)–(f) show household beliefs about the relative severity of indoor versus outdoor pollution. Left column (a, c, e) corresponds to the Longitudinal Experiment (Phase 1 survey); right column (b, d, f) corresponds to the Single-Visit Experiment. For the Longitudinal Experiment, air quality averages are between Phase 1 and Phase 2 surveys. See discussion in Section 3.

Figure 3: Air Purifier Effectiveness: Actual Effects vs. Perceptions

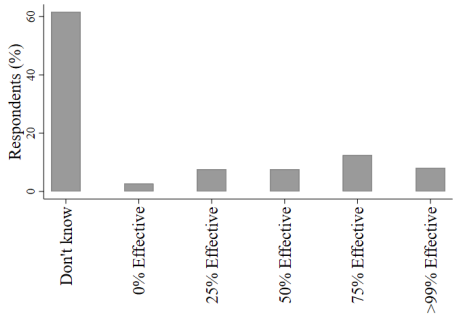
(a) Purifier Effectiveness: Controlled Conditions



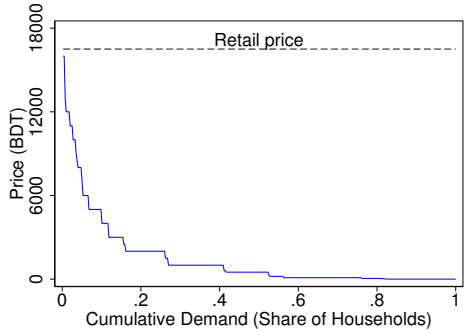
(b) Purifier Effectiveness: Households Provided Free Purifier



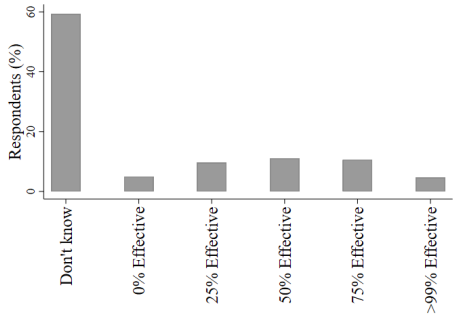
(c) Purifier Effectiveness Perceptions (Longitudinal Experiment, Phase 3, Control Only)



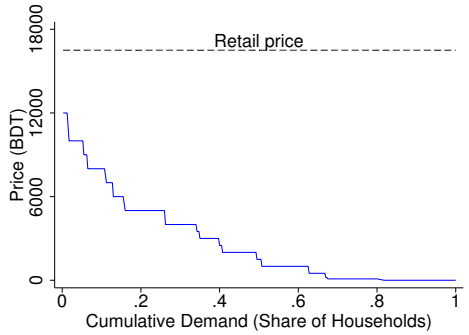
(d) Demand for Purifiers (Longitudinal Experiment, Phase 2, No Monitor)



(e) Purifier Effectiveness Perceptions (Single-Visit Experiment, Baseline)

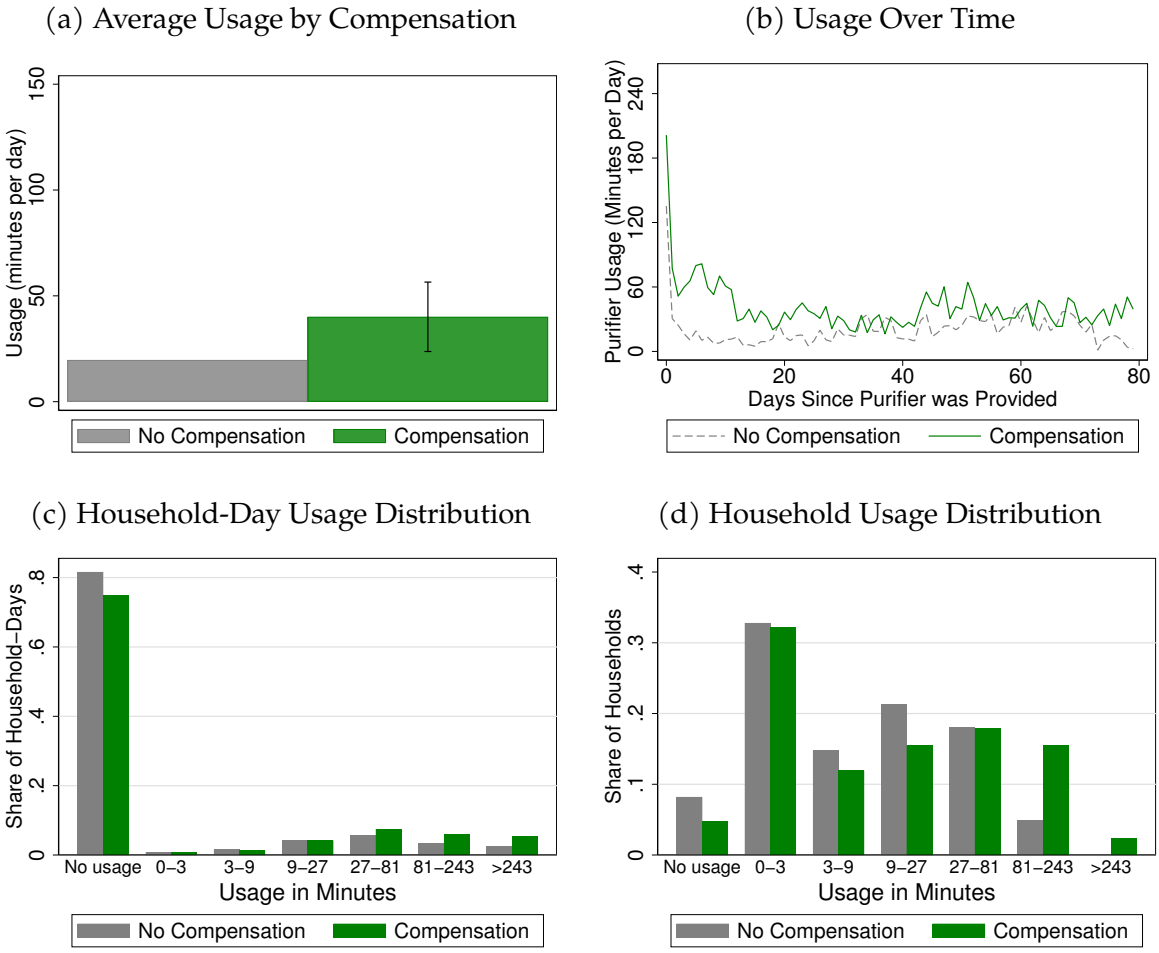


(f) Demand for Purifiers (Single-Visit Experiment, Control Only)



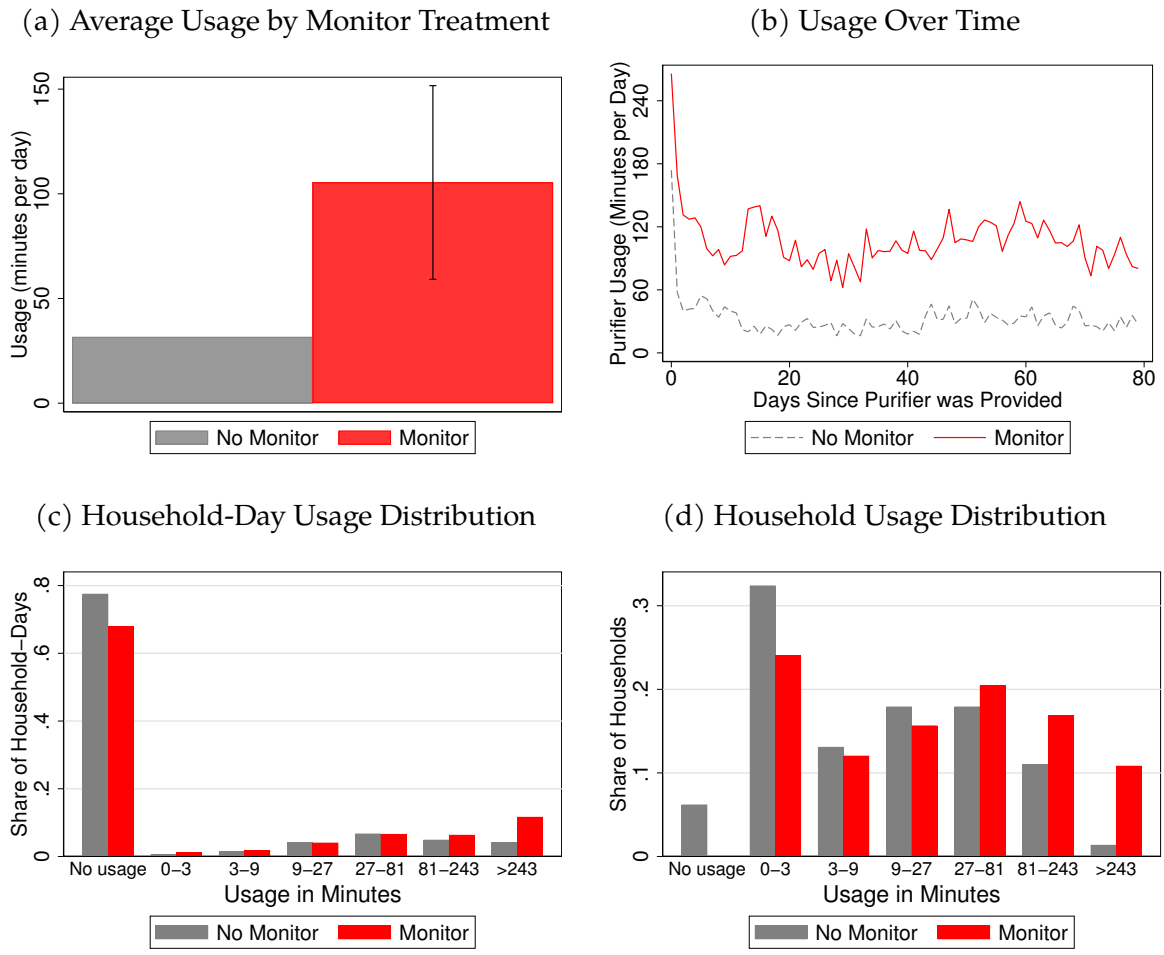
Notes: This figure describes the effectiveness of air purifiers, households' perception of their effectiveness, and households' WTP. Panel (a) shows how air pollution changes after an air purifier is turned on in a controlled setting similar to the apartments of the subjects in the main experiments. Panel (b) shows how air pollution changes after a purifier is turned on by households in the longitudinal experiment. Panel (c) shows beliefs about purifier effectiveness in 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 the Single-Visit Experiment before any demonstrations. Panel (f) shows WTP for a purifier among households in the single-visit experiment control group. See discussion in Section 3.

Figure 4: Air Purifier Usage: Effect of Electricity Compensation Treatment (without Monitor)



Notes: This figure uses smart socket data to show the difference in purifier usage among households receiving electricity compensation, compared to households not receiving compensation during the Longitudinal Experiment. 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. 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 5.2.

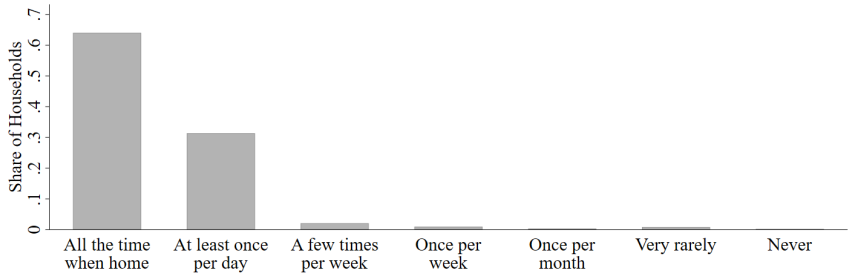
Figure 5: Air Purifier Usage: Effect of Monitor



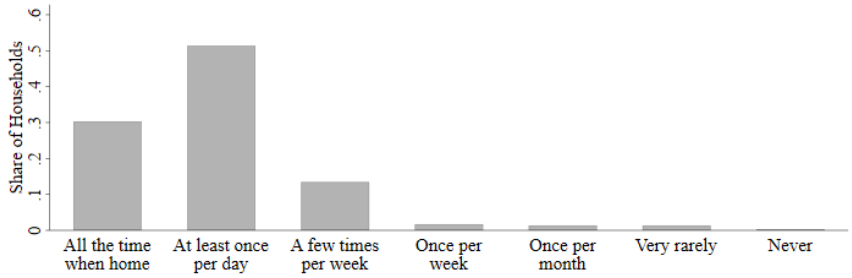
Notes: This figure uses smart socket data to show the difference in purifier usage among households in the monitor treatment (without the attention treatment), compared to those households not receiving the monitor treatment during the Longitudinal Experiment. Only households with purifiers are included 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. 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 5.3.

Figure 6: Ex-ante Predicted, Ex-post Reported, and Actual Purifier Usage (Longitudinal Experiment)

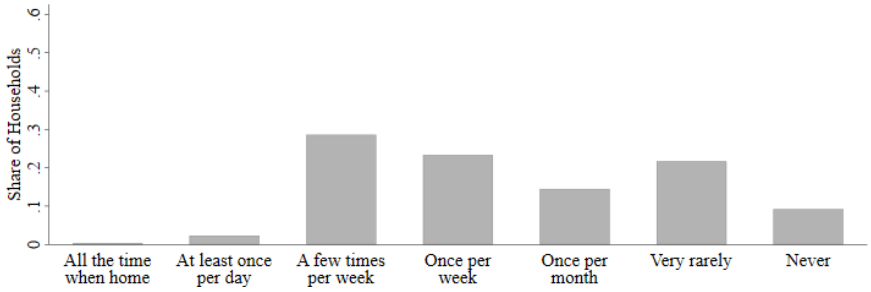
(a) Ex-ante Predicted Use



(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 2 survey, the round in which WTP was elicited, to the question: "If you owned an air purifier, how often would you use it during the winter months?" This figure excludes 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 uses 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 7.1.

Table 1: Single-Visit Experiment: Effects on Beliefs, WTP, and Perceived Purifier Effectiveness

	(1)	(2)	(3)	(4)	(5)	(6)
	Beliefs about Severity of IAP	Beliefs about IAP v. OAP	Health Risk Beliefs Index	Has Opinion on Purifier Effectiveness	Perceived Reduction: $> 50\%$	WTP (In BDT)
Credit Only	0.115	-0.0095	-0.021	-0.020	-0.0050	-214
	(0.161)	(0.016)	(0.071)	(0.035)	(0.027)	(219)
Monitor Only	0.790***	0.066***	0.159**	0.0075	0.033	-250
	(0.153)	(0.016)	(0.068)	(0.035)	(0.028)	(210)
Purifier Only	0.180	0.0045	-0.021	0.117***	0.100***	199
	(0.153)	(0.016)	(0.072)	(0.035)	(0.029)	(220)
Both (Separately)	0.665***	0.037**	0.109	0.138***	0.092***	-169
	(0.155)	(0.016)	(0.070)	(0.035)	(0.029)	(208)
Both (Together)	0.695***	0.063***	0.097	0.153***	0.158***	-47.9
	(0.157)	(0.016)	(0.069)	(0.035)	(0.030)	(205)
Observations	2,400	2,400	2,400	2,400	2,400	2,400
Control Mean	4.21	0.43	0.00	0.49	0.18	2,700

Notes: This table reports the effects of the five Single-Visit Experiment treatment arms on beliefs, perceived purifier effectiveness, and willingness to pay, all measured after the demonstration in the same visit; the control group is the omitted category. The arms differ in what the household is offered or shown: a 12-month interest-free installment plan for the purifier (Credit Only); a working monitor and its reading (Monitor Only); the purifier running (Purifier Only); both in sequence, with the monitor put away before the purifier is demonstrated (Both Separately); and both at once (Both Together). Column (1) is the household's rating of indoor air pollution in its area, from 1 ("not polluted at all") to 10 ("extremely polluted"); Column (2) is its perceived ratio of indoor to outdoor pollution, from 0 to 1; Column (3) is an inverse-covariance weighted index of two indicators for believing that air pollution raises the risk of acute respiratory issues in children and of lung cancer and stroke in adults, with don't know coded as no perceived increase; Column (4) equals one if the household stated any opinion on purifier effectiveness rather than answering don't know; Column (5) equals one if it said purifiers remove more than half of indoor air pollution; and Column (6) is willingness to pay for the purifier in BDT, elicited with a BDM mechanism and winsorized at the 99th percentile. Standard errors are clustered at the household level. $***p < 0.01; **p < 0.05; *p < 0.1$. See discussion in Section 4.1.

Table 2: Longitudinal Experiment: Effects on Beliefs, WTP, and Perceived Purifier Effectiveness

Panel A: Beliefs and WTP (Phase 2 Survey)				
	(1) Beliefs about Severity of Indoor Air Pollution	(2) Beliefs about Indoor v. Outdoor Air Pollution	(3) Health Risk Beliefs Index	(4) Willingness To Pay (In BDT)
Monitor	0.447***	0.030*	0.037	-243
	(0.151)	(0.018)	(0.083)	(192)
Observations	818	818	818	814
Control mean	4.54	0.43	0.00	1,409
Panel B: Perceived Purifier Effectiveness (Phase 3 Survey)				
	(1) Has Opinion on Purifier Effectiveness	(2) Perceived Reduction: $> 50\%$		
Monitor	0.112**	0.104**		
	(0.056)	(0.050)		
Purifier	0.280***	0.273***		
	(0.052)	(0.050)		
Purifier x Monitor	0.004	-0.070		
	(0.083)	(0.086)		
Observations	758	758		
Control mean	0.384	0.205		

Notes: Panel A shows the effect of monitor provision on Phase 2 outcomes; regressions control for the attention-incentive arm. The Health Risk Beliefs Index is constructed as in Table 1, normalized in the no-monitor group. Panel B shows the effects of purifier provision, monitor provision, and their interaction on Phase 3 perceptions of purifier effectiveness, with outcome definitions as in Table 1; regressions control for the attention arm and its purifier interaction. Standard errors clustered at the household level. $***p < 0.01; **p < 0.05; *p < 0.1$. See discussion in Section 4.2.

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

	(1)	(2)	(3)	(4)
	Min per Day	Days Used (30+ min)	Days Used (60+ min)	WTA (BDT)
Monitor	74.1***	0.643***	0.669***	3,983*
	(23.6)	(0.231)	(0.213)	(2,365)
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	31.7	1.12	0.80	14,333

Notes: This table shows the effect of providing monitors on purifier use and willingness to accept to sell back the purifier during the Longitudinal Experiment. 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. Column (4) reports the effect on households' willingness to accept to sell back the purifier, in BDT, elicited with a BDM mechanism in the Phase 3 survey; observations are at the household level. Data is only from households that participated in the Phase 2 survey and were assigned a purifier. Data 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 standard errors. $***p < 0.01; **p < 0.05; *p < 0.1$. See discussion in Sections 5.3 and 4.2.

Table 4: Usage Based MWTP Estimates

	Purifier Use			
	(1)	(2)	(3)	(4)
Potential PM2.5 Improvement	0.0025	0.0036*	0.0004	0.0005
	(0.0018)	(0.0019)	(0.0003)	(0.0003)
Cost of Use	-1.21***	-1.27***	-0.169***	-0.156***
	(0.345)	(0.360)	(0.050)	(0.045)
Estimator	OLS	OLS, binary	Fractional logit	Logit, binary
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	Sim.: 108 min	Sim.: 108 min	Sim.: 108 min	Sim.: 108 min
$-\beta_{PM}/\beta_c$ (BDT per μg/m^3-hour)	0.0021	0.0028	0.0026	0.0030
MWTP per season (PPP USD)	0.15	0.20	0.18	0.21
MWTP per year (PPP USD)	0.59	0.81	0.75	0.86
P-value: MWTP	0.20	0.11	0.26	0.19
Upper bound 95% CI: MWTP/year	1.50	1.79	2.05	2.14
Observations	399,864	399,864	399,864	399,847
Clusters	159	159	159	159
Outcome Variable Mean	8.15	10.1	8.15	10.1

Notes: This table reports our main use-based MWTP estimate, which prices the flow value of clean air from hour-to-hour purifier use (Equation 6). All four columns use the simulated effectiveness of the average (108-minute) purifier session in our data and differ only in how the use decision is modeled: Column (1) is OLS on the share of the hour the purifier is on, Column (2) is a linear probability model for any use in the hour, Column (3) is a fractional logit on the share, and Column (4) is a logit for any use in the hour with household, date, and hour-of-day fixed effects entered as indicators (Appendix D). Potential PM2.5 improvement is the purifier's assumed effectiveness multiplied by outdoor air pollution and the average indoor-outdoor air pollution ratio. Before the incentive period, the cost of using the purifier equals 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 the control group and the difference between the electricity cost and the incentive (-4.76 or -9.76) for the incentive group. Standard errors clustered at the household level. $***p < 0.01; **p < 0.05; *p < 0.1$. See discussion in Section 7.2.

Online Appendix

A Data Collection, Cleaning, and Validation

A.1 Payments and Incentives

Households with an air quality monitor received BDT 15 on each day the monitor transmitted data for at least 16 hours, and the 255 households in the attention arm could earn a further BDT 30 per week for correctly reporting their air-quality category and the associated disease risk by WhatsApp. To keep payments comparable across arms, households without a monitor, and monitor households outside the attention arm, were paid what a randomly matched household in the corresponding arm had earned (Cefala et al., 2024). Electricity compensation equalled the purifier's metered consumption valued at the highest marginal tariff in Dhaka, BDT 13 per kWh, so that no household was under-compensated. Compensated households received a first payment one week after the Phase 2 visit and daily or monthly payments thereafter, by arm. The usage incentives paid BDT 5 or BDT 10 per hour of measured operation throughout April 2024.

A.2 Data Processing: 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 1^{st} and 99^{th} percentiles. This procedure replaces values below the 1^{st} percentile with the 1^{st} percentile value, and values above the 99^{th} percentile with the 99^{th} percentile value for each variable.

A.3 WTP Elicitation

To elicit WTP, we implemented a Becker-DeGroot-Marschak (BDM) mechanism following the approach of Berry et al. (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. In the Single-Visit Experiment, the drawn price was BDT 17,000 except for one randomly selected household in each arm, which drew BDT 1,000; one of these six households had bid more than BDT 1,000 and bought the purifier at that price.

A.4 Air Quality Monitoring Devices

A.4.1 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.4.2 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 -0.73 $\mu g/m^3$ or -2.90%. 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 Longitudinal Experiment: 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.13, Column (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.14) and attention treatments (Table A.15). Balance on observables from the Phase 1 survey is maintained in the unattrited sample. Joint test p-values of 0.32 and 0.38 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.13, Column (2)): 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.16). 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).

Column (2) of Table A.13 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.17). Differences are small and statistically in-

significant.

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.13, Column (3)): 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.18). Differences between these groups in the unattrited monitor sample are small and statistically insignificant for all Phase 2 observables (joint test p-value = 0.83).

Importantly, we find no differential attrition by monitor treatment amongst purifier households (Table A.13, Column (4)). 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.19), with a joint test p-value of 0.43.

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 the Longitudinal Experiment in the Single-Visit Experiment, where no differential attrition occurred. Therefore, result (i) from the Longitudinal Experiment 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.20). 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 Effect of Monitor on Self-Reported Purifier Use

In this section, we examine the impact of monitor provision on self-reported purifier use. 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.21, 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 = 0.09).

In Column 2, we use the number of days in the 7 days preceding the survey that the household actually used the purifier.[20] 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 59%, compared to households who did

[20]To assess whether overreporting differs between monitor and non-monitor groups, we constructed a 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.

not receive a monitor.

D Deriving the Use-Based MWTP Estimator

This appendix derives the fixed-effects logit reported in Column (4) of Table 4 from the hourly decision rule (5). The linear specification (6) follows from the linearization in Section 7.2.1, and the fractional logit of Column (3) applies the same index function to the share of the hour the device runs, so neither requires a separate derivation.

Suppose first that the valuation is common across households, $v_i = v$, and decompose the disutility of operation as in the main text, $d_{it} = d_i + d_{h(t)} + \tilde{d}_{it}$. Suppose the taste shock in (5) is the difference of independent Type-I extreme value shocks attached to running and to not running the device; this difference follows a logistic distribution with scale σ, and we fold the idiosyncratic disutility $\tilde{d}_{it}$ into it. The probability of use in hour t is then

$$\Pr(\text{Use}_{it} = 1) \;=\; \Lambda\!\left(\frac{v\,\Delta_{it} - c_{it} - d_i - d_{h(t)}}{\sigma}\right),$$

where Λ is the logistic distribution function: a logit with coefficient $\beta_{PM} = v/\sigma$ on the potential PM2.5 improvement and $\beta_c = -1/\sigma$ on the cost of use, with household and hour-of-day fixed effects absorbing d_i/σ and $d_{h(t)}/\sigma$. The error scale cancels in the coefficient ratio, so $-\beta_{PM}/\beta_c = v$ exactly, with no linearization step. When valuations differ across households, the logit, like the linear model, recovers a valuation weighted toward households near the margin of use.

We estimate the logit by maximum likelihood with household, date, and hour-of-day indicators, mirroring the fixed effects of Equation (6). With roughly 2,500 hourly observations per household, the incidental-parameters bias of dummy-variable logit is negligible. A household whose purifier use never varies would be dropped because its indicator would perfectly predict the outcome; every household in the estimation sample records both use and non-use hours, so no household is dropped, and the small difference in observation counts between Columns (1) and (4) reflects hours in which an indicator perfectly predicts non-use. Because logit coefficients are identified only up to the error scale, their magnitudes change mechanically as covariates are added even absent any confounding; the fixed-effects-

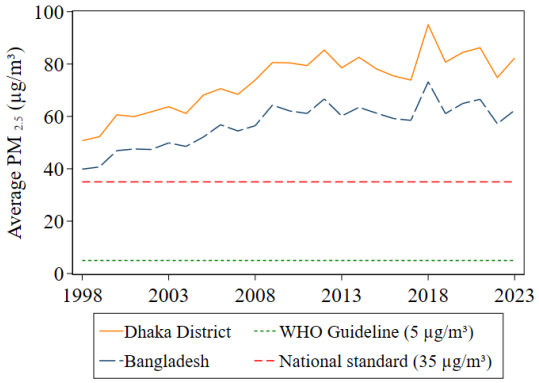
stability diagnostic of Table A.11 is therefore conducted in the linear model, where coefficients are directly comparable across specifications.

From hourly flows to seasonal and annual values. The ratio $-\beta_{PM}/\beta_c$ is a flow value in BDT per $\mu g/m^3$ per hour. Seasonal values multiply by the 24×90 hours of the 90-day winter season, annual values by 24×365 hours, and both are converted to PPP USD at the 2023 PPP rate (BDT 30.75 per USD). Standard errors and confidence bounds for these transformed ratios are computed by the delta method.

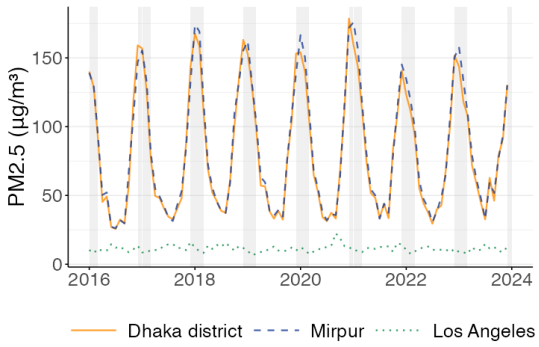
E Additional Figures and Tables

Figure A.1: Air Pollution in Bangladesh and at the Study Sites

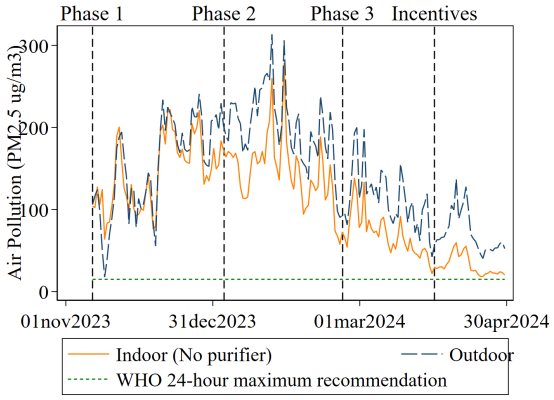
(a) Bangladesh over time



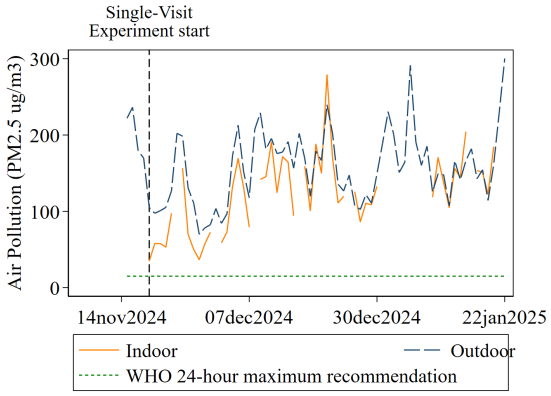
(b) Seasonality in Bangladesh



(c) Indoor vs. outdoor pollution: Longitudinal Experiment

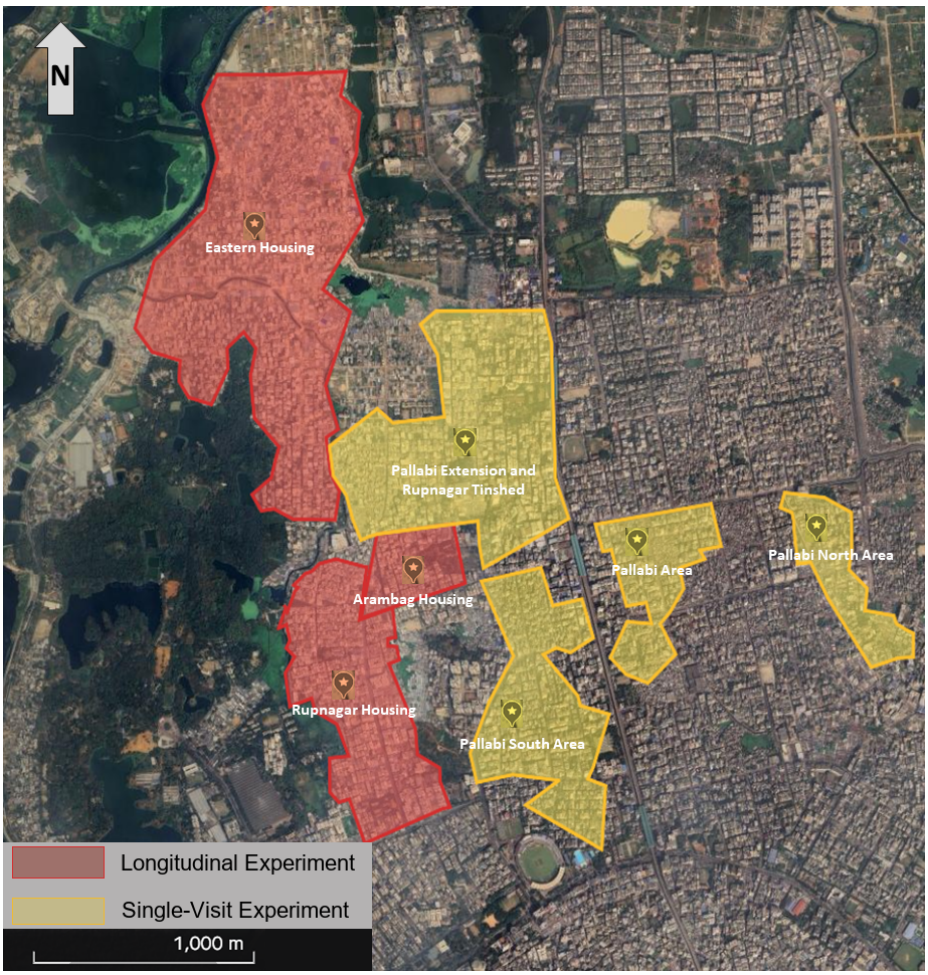


(d) Indoor vs. outdoor pollution: Single-Visit Experiment



Notes: This figure provides an overview of air pollution in Bangladesh and at the study sites. Panel (a) shows annual satellite-derived PM2.5 across Bangladesh and in Dhaka district, compared to the WHO annual guideline and Bangladesh's National Standard. Panel (b) shows monthly satellite-derived PM2.5 in Dhaka, Mirpur (the locality in Dhaka where the experiments were carried out), and Los Angeles (for reference); the months when most of the experiments took place (December, January, and February) are shaded in gray. Data in Panels (a) and (b) are from van Donkelaar et al. (2021). Panel (c) shows average daily indoor and outdoor PM2.5, measured by our monitors and compared to the WHO 24-hour guideline, for households without air purifiers during the Longitudinal Experiment; the four vertical dashed lines indicate the start of the Phase 1, 2, and 3 surveys and the start of the incentive experiment, and outdoor data from November 1 to November 30, 2023 are imputed from US Embassy monitor readings. Panel (d) shows average daily outdoor PM2.5 and the indoor measurements collected during the Single-Visit Experiment; because surveys were not conducted every day, the indoor series has gaps. See discussion in Section 2.2.

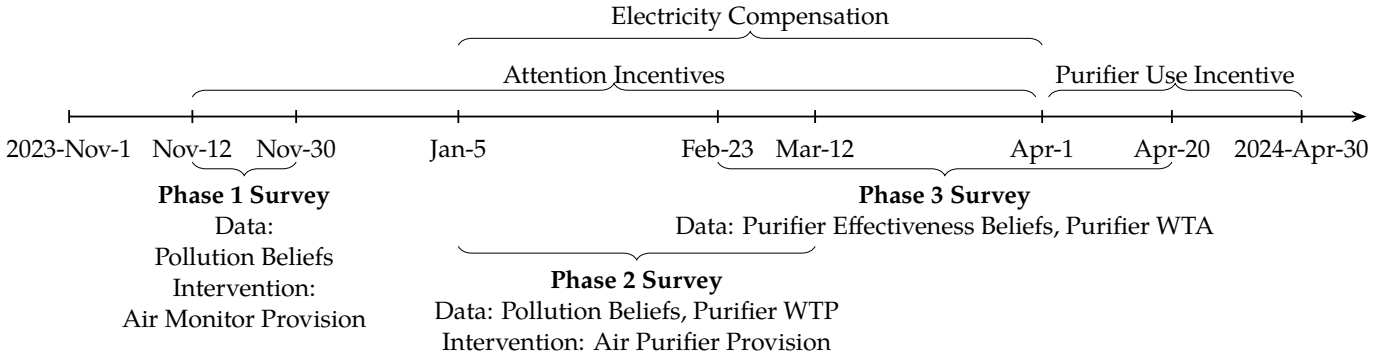
Figure A.2: Map of Study Area



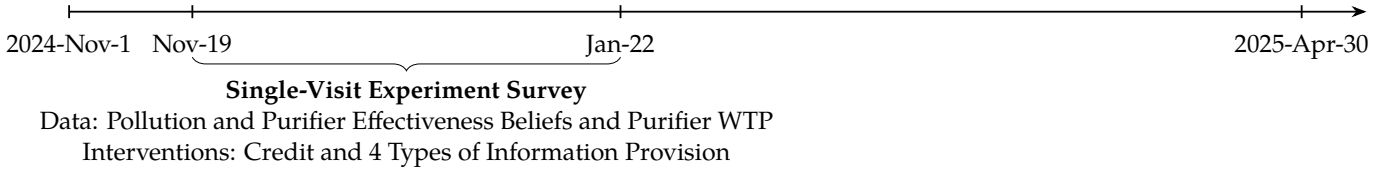
Notes: This is a map of the seven housing associations in which the two experiments were conducted. All of the housing associations are located in the Mirpur area of Dhaka, Bangladesh. See discussion in Section 2.2.

Figure A.3: Timing of Interventions and Survey Data Collection

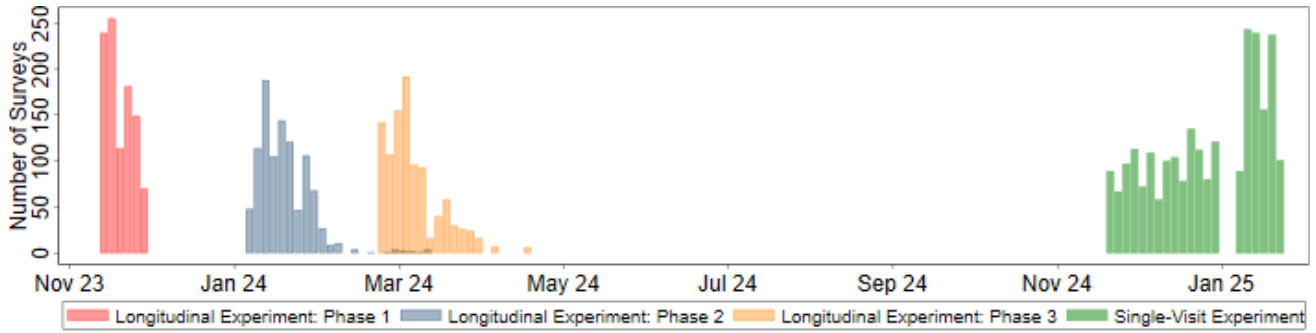
(a) Longitudinal Experiment interventions and survey data collection



(b) Single-Visit Experiment interventions and survey data collection



(c) Distribution of survey dates



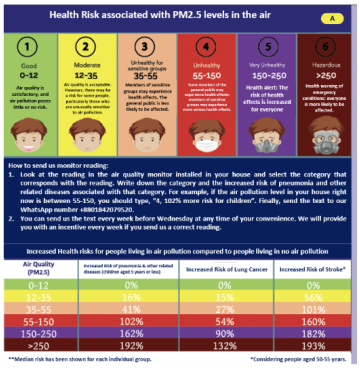
Notes: This figure shows the timing of the interventions and data collection for the Longitudinal and Single-Visit Experiments. Panels (a) and (b) show the intervention and survey timelines for the Longitudinal and Single-Visit Experiments, respectively. Panel (c) shows the distribution of individual survey dates for each survey; in the Longitudinal Experiment, the surveys were carried out in the same sequence, so that the households first surveyed in Phase 1 were also contacted first in Phases 2 and 3. See discussion in Section 2.

Figure A.4: Devices and Information Materials Provided to Households

(a) Air quality monitor



(b) Information chart



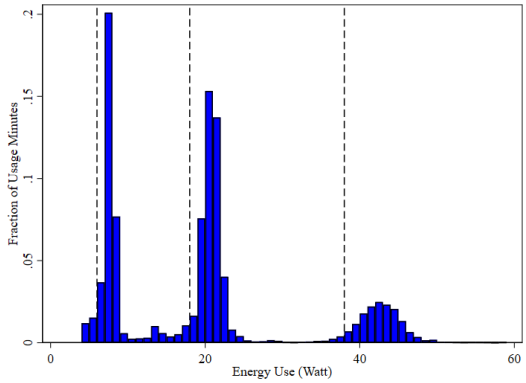
(c) Sqair air purifier



(d) Smart socket

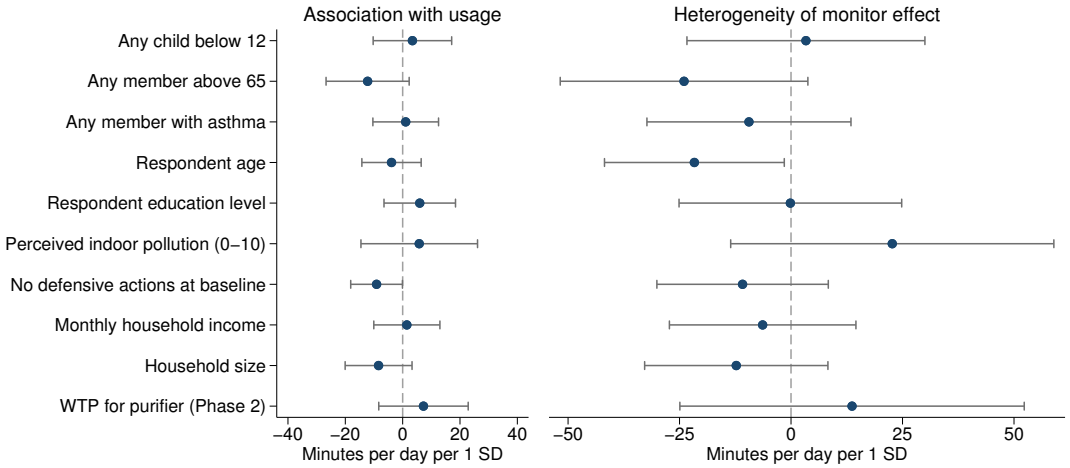


(e) Purifier wattage when in use



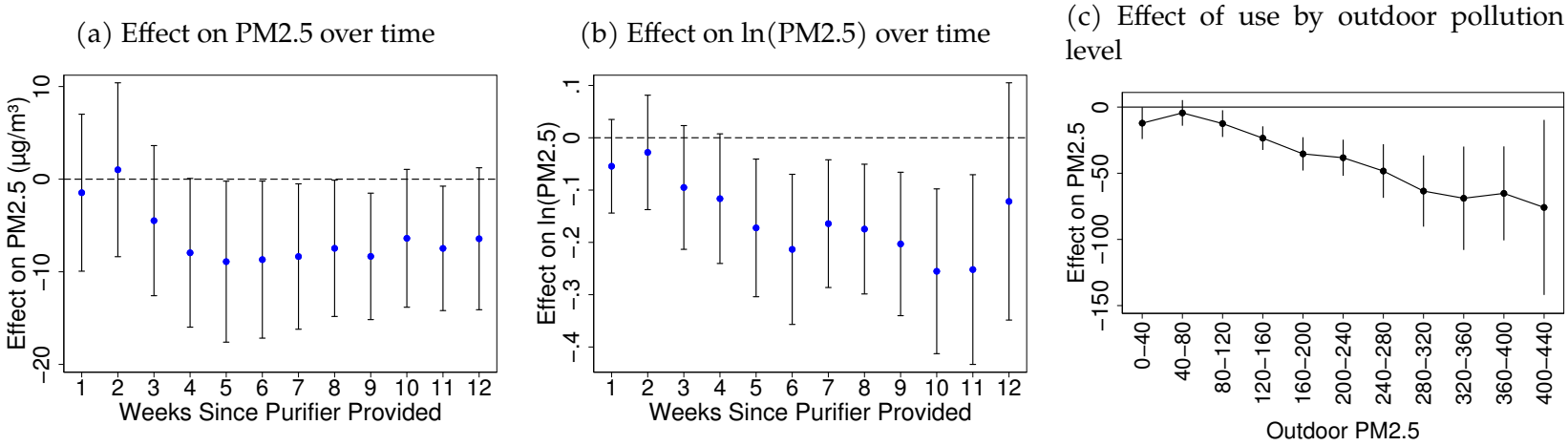
Notes: This figure shows the devices and information materials provided to households in the Longitudinal Experiment, and the electricity use recorded by the smart sockets. Panel (a): the air quality monitor provided to the monitor treatment group (for details, see https://www.qingping.co/air-monitor-lite/overview). Panel (b): the English translation of the information chart provided together with the monitor; the version shown was given to attention-treatment households, and the version for other monitor households was identical except that the instructions for reporting readings were replaced by a contact number. Panel (c): the air purifier model provided to the purifier treatment group (Smart Air "Sqair"; for details, see https://smartairfilters.com/en/product/sqair-air-purifier/). Panel (d): the smart socket used to measure purifier usage; each purifier's electricity cord was glued into a smart socket, which transmits minute-by-minute usage data to the research team via Wi-Fi. Panel (e): the distribution of wattage across household-minute smart-socket readings with the purifier in use, between the Phase 2 survey and 1 April 2024; the three vertical dashed lines mark the manufacturer's stated wattage on the low, medium, and high settings. See discussion in Sections 2.3.1 and 2.4.

Figure A.5: Purifier Usage and Baseline Household Characteristics



Notes: This figure relates air purifier usage to baseline household characteristics among Longitudinal Experiment households that received a purifier (N = 304). The outcome in both panels is the household's average minutes of purifier use per day, measured by the smart sockets between the Phase 2 survey and 1 April 2024. Each characteristic is standardized to mean zero and standard deviation one in the estimation sample, so coefficients are minutes per day per one-standard-deviation difference. The left panel shows coefficients from separate regressions of usage on each characteristic, controlling for monitor and attention-incentive assignment. The right panel shows the coefficient on the interaction between monitor assignment and the characteristic, from regressions of usage on monitor assignment, the characteristic, their interaction, and attention-incentive assignment. "No defensive actions at baseline" indicates the household reported taking no actions against air pollution in the Phase 1 survey. Household income is winsorized at the 1st and 99th percentiles. Bars are 95% confidence intervals based on heteroskedasticity-robust standard errors. See discussion in Section 5.1.

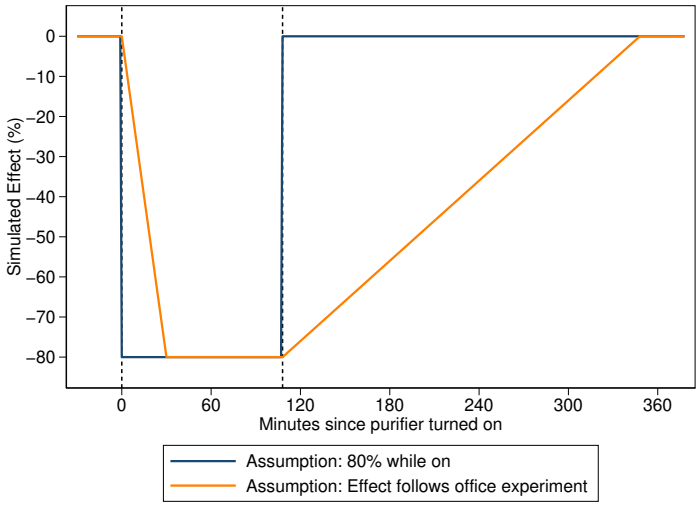
Figure A.6: Effect of Purifiers on Indoor Air Pollution



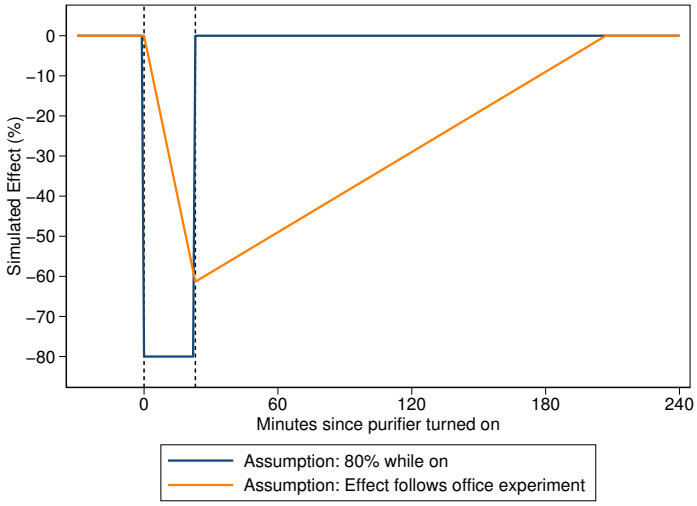
Notes: This figure shows the effect of air purifiers on indoor PM2.5, using imputed values for pollution when monitors are turned off. The imputed values multiply the outdoor pollution reading in that hour by the average indoor-outdoor pollution ratio in households without an air purifier. In Panels (a) and (b), the coefficients come from one regression at the hour-by-household level with time fixed effects, where the coefficients are on the purifier indicator interacted with the week since the Phase 2 survey; the outcome is the hourly PM2.5 level in Panel (a) and its log in Panel (b), and data run from the Phase 2 survey until 1 April 2024. Panel (c) shows the estimated effect of purifier use on indoor PM2.5 at different outdoor pollution levels, from a regression at the hour-by-household level among households with both a purifier and a monitor, of indoor PM2.5 on the share of the hour the purifier was used interacted with the outdoor PM2.5 bins shown; outdoor PM2.5 is the average reading of our two outdoor monitoring stations, and data run from the Phase 2 survey until 1 April 2024. 95% confidence intervals are based on standard errors clustered at the household level. See discussion in Section 6.

Figure A.7: Simulated Effect of Purifier Use

(a) Simulated effect of 108 min purifier use

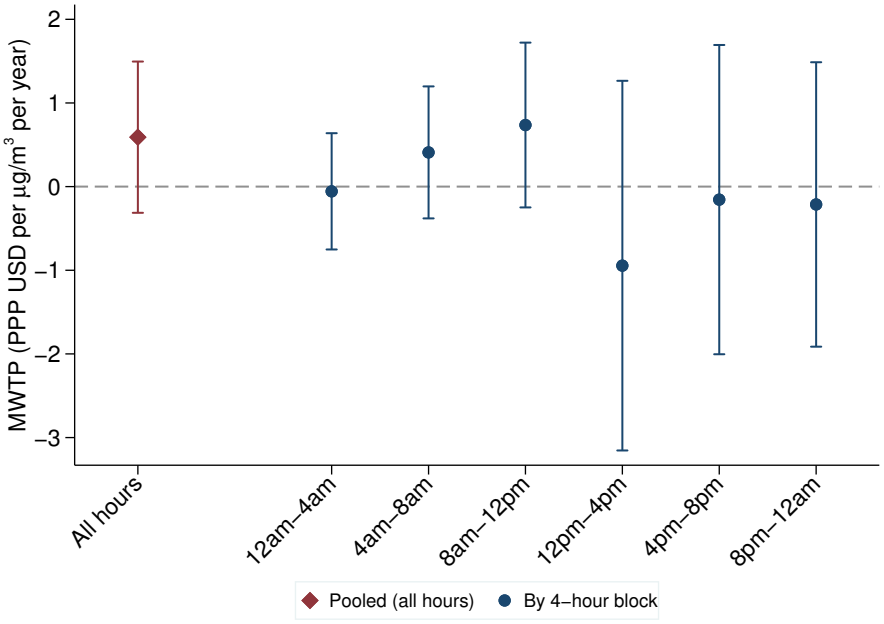


(b) Simulated effect of 23 min purifier use



Notes: This figure shows the simulated effect on air pollution of turning a purifier on for a limited amount of time. For the "80% while 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. For the simulated series, we assume that air pollution decreases linearly for 30 minutes after the purifier is turned on until it has reduced air pollution by 80%, and that when the purifier is turned off, air pollution increases linearly at a rate such that an 80% reduction completely disappears after 4 hours. Panel (a) shows the simulated reduction when turning the purifier on for 108 minutes, the average length of a purifier session in our data. Panel (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 7.2.

Figure A.8: Use-Based MWTP by Time of Day



Notes: This figure reports the use-based MWTP for clean air estimated separately for each of six four-hour blocks of the day, using our main 108-minute simulated-effectiveness specification (Equation 6, estimated as in Column (1) of Table 4). Each point is the annualized MWTP for that block, in PPP USD per $\mu g/m^3$ per year, with its 95% confidence interval; the dashed line marks zero. Estimates are statistically indistinguishable from zero in every block. The wider intervals around midday and the afternoon reflect smaller within-block variation in the potential pollution reduction at those hours, which identifies β_{PM} less precisely. See discussion in Section 7.2.

Table A.1: Single-Visit Experiment: 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)	48.0	47.5	47.0	48.1	46.6	46.5	0.863
	(0.741)	(0.748)	(0.693)	(0.764)	(0.688)	(0.750)	0.505
Highest Education Level	13.5	13.2	13.6	13.3	13.7	13.0	0.582
	(0.290)	(0.402)	(0.290)	(0.299)	(0.268)	(0.293)	0.714
HH Members (#)	4.43	4.37	4.37	4.50	4.27	4.37	0.888
	(0.089)	(0.084)	(0.078)	(0.088)	(0.083)	(0.081)	0.488
Beliefs about Severity of	6.65	6.52	6.56	6.37	6.35	6.62	1.04
Outdoor Air Pollution	(0.120)	(0.119)	(0.114)	(0.120)	(0.118)	(0.120)	0.394
Beliefs about Severity of	4.32	4.29	4.48	4.45	4.18	4.35	1.01
Indoor Air Pollution	(0.115)	(0.116)	(0.106)	(0.110)	(0.105)	(0.114)	0.410
Beliefs about Indoor v.	4.48	4.42	4.54	4.45	4.14	4.70	2.23**
Outdoor Air Pollution	(0.122)	(0.125)	(0.116)	(0.118)	(0.119)	(0.123)	0.049
Indoor PM2.5 (50 ug/m3)	2.61	2.77	2.78	2.69	2.85	2.75	1.31
	(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	1.71
	(0.025)	(0.024)	(0.025)	(0.025)	(0.025)	(0.024)	0.128
WTP (Practice Round)	12.9	13.5	11.9	11.6	12.6	13.5	1.61
	(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	2,400

Omnibus test (multinomial logit LR): $\chi^2(65) = 69.92$, p = 0.316

Notes: This table provides balance test for the baseline variables in the Single-Visit Experiment. 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. $***p < 0.01; **p < 0.05; *p < 0.1$. See discussion in Section 2.3.2.

Table A.2: Effects on Perceived Purifier Effectiveness and Beliefs about Outdoor Air Pollution

Panel A: Longitudinal Experiment				
	(1) Perceived Reduction: $> 0\%$	(2) Perceived Reduction: $> 25\%$	(3) Perceived Reduction: $> 75\%$	(4) Beliefs about Severity of OAP
Monitor	0.114**	0.125**	-0.007	0.161
	(0.055)	(0.054)	(0.030)	(0.161)
Purifier	0.279***	0.304***	0.134***	
	(0.052)	(0.052)	(0.039)	
Purifier x Monitor	0.018	-0.052	0.098	
	(0.083)	(0.086)	(0.069)	
Observations	758	758	758	818
Control mean	0.357	0.281	0.080	7.05

Panel B: Single-Visit Experiment				
	(1) Perceived Reduction: $> 0\%$	(2) Perceived Reduction: $> 25\%$	(3) Perceived Reduction: $> 75\%$	(4) Beliefs about Severity of OAP
Credit Only	-0.025	-0.037	0.030*	-0.110
	(0.035)	(0.033)	(0.016)	(0.169)
Monitor Only	0.015	0.013	0.020	0.493***
	(0.035)	(0.034)	(0.015)	(0.163)
Purifier Only	0.130***	0.120***	0.068***	-0.142
	(0.035)	(0.034)	(0.018)	(0.169)
Both (Separately)	0.135***	0.140***	0.040**	0.245
	(0.035)	(0.035)	(0.017)	(0.168)
Both (Together)	0.183***	0.200***	0.060***	0.563***
	(0.035)	(0.034)	(0.018)	(0.163)
Observations	2,400	2,400	2,400	2,400
Control Mean	0.45	0.34	0.04	6.66

Notes: This table reports the columns omitted from Tables 1 and 2: the perceived-effectiveness thresholds ($> 0\%$, $> 25\%$, $> 75\%$) in Columns (1)–(3) and beliefs about the severity of outdoor air pollution in Column (4). Specifications are as in those tables. In Panel A, the effectiveness thresholds are measured in the Phase 3 survey; outdoor-pollution beliefs are measured in the Phase 2 survey and regressed on the monitor treatment only, as in Panel A of Table 2, so the purifier rows in Column (4) are empty. Standard errors clustered at the household level. $***p < 0.01; **p < 0.05; *p < 0.1$. See discussion in Sections 4.1 and 4.2.

Table A.3: Effect of Monitor and Attention Incentives on Household Perception of Indoor and Outdoor Air Quality (Longitudinal Experiment, 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	0.030*
	(0.151)	(0.161)	(0.018)
Monitor X Attention	-0.161	-0.070	-0.0056
	(0.176)	(0.181)	(0.021)
Observations	818	818	818
Control mean	4.54	7.05	0.43

Notes: This table shows the effect of the air quality monitor and of incentives for attention to the monitor on households' perception of indoor and outdoor air pollution (IAP and OAP). All outcome variables are measured during the Phase 2 survey of the Longitudinal Experiment. 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 the corresponding question for outdoor air quality. 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?" $***p < 0.01; **p < 0.05; *p < 0.1$. See discussion in Section 4.2.

Table A.4: Effect of Compensation for Electricity Costs on Purifier Use (Longitudinal Experiment, Smart Socket Data)

	Minutes of Usage per Day		
	(1)	(2)	(3)
Purifier x Any Compensation	17.3	12.9	19.9**
	(16.0)	(18.3)	(8.31)
Purifier x Daily Compensation		9.01	
		(23.9)	
Time FE	Yes	Yes	Yes
Sample	Full	Full	Without monitor
Observations	22,840	22,840	10,853
Clusters	304	304	145
Control mean	55.1	55.1	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. Columns (1) and (2) include 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 5.2.

Table A.5: Effects of Use Incentives and Air Monitor on Air Purifier Use

	(1) Minutes per Day	(2) Minutes per Day
Any Incentive	113***	82.0**
	(29.8)	(36.9)
Monitor	72.4**	72.9**
	(32.4)	(32.3)
BDT 10 Incentive		60.2
		(46.9)
Time FE	Yes	Yes
Observations	9,120	9,120
Clusters	304	304
Control mean	25.2	25.2

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 5.4.

Table A.6: Effect of Purifiers on Pollution (Longitudinal Experiment)

	PM2.5 ($\mu g/m^3$)		ln(PM2.5)	
	(1)	(2)	(3)	(4)
Purifier	-6.21**	-5.75	-0.153***	-0.128*
	(3.16)	(4.53)	(0.054)	(0.075)
Imputed values	Yes	No	Yes	No
Baseline PM2.5 control	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	744,862	474,554	744,862	474,554
Clusters	416	376	416	376
Control mean	112	111	112	111

Notes: This table shows the effect of providing air purifiers on indoor PM2.5 during the Longitudinal Experiment. The outcome is the average air pollution in the hour in Columns (1)–(2) and the log of that average in Columns (3)–(4). Columns (1) and (3) use imputed indoor PM2.5, filling gaps when the monitor is off by multiplying outdoor PM2.5 in that hour by the average indoor-outdoor pollution ratio observed in non-purifier households; Columns (2) and (4) use only observed monitor readings. Each observation is at the hour-by-household level among households who remained in the survey until the Phase 2 survey (when the purifiers were provided); all days are included, regardless of whether the purifier was turned on. All regressions control for the household's baseline PM2.5 (in the same units as the outcome). 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 6.

Table A.7: Effect of Purifier on Monitor Usage

	(1) Usage per Day (Minutes)
Purifier	113**
	(54.2)
Time FE	Yes
Observations	31,501
Clusters	419
Control mean	858

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 6.

Table A.8: Effect of Monitor and Purifier on Health Outcomes and Specific Symptoms

	Panel A: 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	0.26	-0.09
	(1.59)	(1.02)	(0.08)	(1.51)	(0.07)	(0.65)	(218)	(0.18)	(0.09)
Purifier	1.22	-0.10	-0.10	-0.58	0.11**	-0.81	496**	-0.04	0.06
	(1.76)	(1.00)	(0.08)	(1.36)	(0.05)	(0.57)	(236)	(0.18)	(0.09)
Purifier x Monitor	-0.97	-0.52	0.12	1.79	-0.08	-0.26	-164	-0.21	0.10
	(2.59)	(1.55)	(0.13)	(2.28)	(0.10)	(0.91)	(412)	(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	121	81.6	2.53	90.5	98.8	2.34	998	0.62	0.00
	Panel B: 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, Dizziness, or Vomiting	(9) Symptom free
Monitor	0.052	-0.0005	0.0003	0.0011	-0.015	-0.0017	0.012	0.0099	-0.014
	(0.037)	(0.0058)	(0.013)	(0.013)	(0.021)	(0.014)	(0.010)	(0.039)	(0.042)
Purifier	-0.0023	0.0019	-0.0076	-0.0050	0.020	-0.0039	-0.0053	-0.025	-0.0045
	(0.034)	(0.0063)	(0.0086)	(0.013)	(0.024)	(0.011)	(0.0071)	(0.036)	(0.041)
Purifier x Monitor	-0.022	0.0017	0.0030	-0.013	0.028	0.0062	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

Notes: This table reports the effects of the monitor and purifier treatments, as well as their interaction, on health outcomes (Panel A) and on whether a household member experienced a specific symptom in the past 30 days (Panel B). 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; data are from the Phase 3 survey of the Longitudinal Experiment. In Panel A, Forced Vital Capacity (FVC) is the total amount of 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 to the FVC, and 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 signed so that a higher value represents a better outcome. Standard errors clustered at the household level. $***p < 0.01; **p < 0.05; *p < 0.1$. See discussion in Section 6.

Table A.9: Effect of Monitor and Purifier on Labor Supply, Labor Income, Mental Health, and Sleep

	(1) Days worked past 7 days	(2) Income past month	(3) Sleep Index	(4) Mental Health Index
Monitor	-0.066	1,921	-0.134	0.189
	(0.261)	(7,332)	(0.119)	(0.136)
Purifier	-0.139	2,800	-0.012	0.0042
	(0.264)	(5,224)	(0.109)	(0.113)
Purifier x Monitor	-0.187	790	0.121	-0.262
	(0.458)	(10,204)	(0.182)	(0.198)
Observations	830	829	1,852	1,852
Clusters	721	720	758	758
Control Mean	5.07	42,372	0.00	0.00

Notes: This table reports the effects of the monitor and purifier treatments, and their interaction, controlling for the attention incentive and its purifier interaction. Each observation is a household member sleeping in the bedroom of the household head at the time of the Phase 2 survey; Columns (1)–(2) additionally restrict to members who held a job at baseline. Outcomes: days worked in the past 7 days, labor income in the past month, and the sleep and mental-health indices (sums of ten questions each, signed so that a higher value represents a better outcome and normalized to mean zero and standard deviation one in the control group). Data are from the Phase 3 survey. Standard errors clustered at the household level. $***p < 0.01; **p < 0.05; *p < 0.1$. See discussion in Section 6.

Table A.10: 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 (PPP USD)		MWTP for 1 μg/m^3 reduction per season (PPP USD)
		Assumption	Value	Assumption	Value	Assumption	Value	Assumption	Value	Assumption	Value	
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1)	Longitudinal Experiment: All	Full information	111	All the time	100%	HEPA filter	99%	Calculated	109	WTP	44.3	0.40
(2)	Longitudinal Experiment: All	Stated	69	All the time	100%	Stated	66%	Calculated	46	WTP	44.3	0.97
(3)	Longitudinal Experiment: All	Stated	69	Stated Ex-Ante	40%	Stated	66%	Calculated	18	WTP	44.3	2.41
(4)	Longitudinal Experiment: All	Stated	69	Stated Ex-Post	29%	Stated	66%	Calculated	14	WTP	44.3	3.28
(5)	Longitudinal Experiment: All	Stated	69	Actual	5%	Stated	66%	Calculated	2	WTP	44.3	21.3
(6)	Longitudinal Experiment: Both	N/A	N/A	N/A	N/A	N/A	N/A	Actual	6	WTP	39.1	6.29

Notes: This table shows the results of calculating Equations 1 and 2 under different assumptions about indoor air pollution beliefs, expectations of purifier use, and purifier effectiveness beliefs. The data source "Longitudinal Experiment: All" refers to all households in the Longitudinal Experiment, "Longitudinal Experiment: Both" refers to households that received both a purifier and a monitor. See discussion in Section 7.1.

Table A.11: Robustness of Use-Based MWTP Estimates

	Use Purifier (%)										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Potential PM2.5 Improvement	0.0009	0.0020	0.0018	0.0006	-0.0016	0.0049	0.0014	0.0039*	0.0008	0.0029	0.0016
	(0.0044)	(0.0050)	(0.0042)	(0.0011)	(0.0010)	(0.0035)	(0.0010)	(0.0023)	(0.0029)	(0.0019)	(0.0019)
Cost of Use	-1.09***	-1.10***	-1.15***	-0.977***	-0.722**	-1.21***	-1.21***	-0.971**	-1.56***	-1.21***	-1.30***
	(0.322)	(0.323)	(0.279)	(0.226)	(0.285)	(0.345)	(0.345)	(0.437)	(0.557)	(0.345)	(0.411)
Hour of Day FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Monitor	Monitor	Monitor	All	No Monitor	Monitor	Monitor	Monitor	Monitor	Monitor	Monitor
PM2.5 Improvement Assumption	Sim.: 108 min	Sim.: 108 min	Sim.: 108 min	Sim.: 108 min	Sim.: 108 min	80%	Sim.: 23 min	Sim.: 108 min	Sim.: 108 min	Sim.: 108 min	Sim.: 108 min
Phase-2 WTP subgroup	All	All	All	All	All	All	All	Above median	Below median	All	All
Weather controls	No	No	No	No	No	No	No	No	No	Outdoor	Indoor
$-\beta_{PM}/\beta_c$ (BDT per μg/m^3-hour)	0.0008	0.0018	0.0016	0.0006	-0.0022	0.0041	0.0012	0.0040	0.0005	0.0024	0.0012
MWTP per season (PPP USD)	0.06	0.13	0.11	0.04	-0.15	0.29	0.08	0.28	0.04	0.17	0.09
MWTP per year (PPP USD)	0.23	0.52	0.45	0.17	-0.62	1.17	0.34	1.14	0.15	0.69	0.35
P-value: MWTP	0.84	0.68	0.67	0.60	0.21	0.20	0.20	0.21	0.78	0.16	0.44
Upper bound 95% CI: MWTP/year	2.46	3.00	2.54	0.78	0.35	2.95	0.85	2.93	1.17	1.65	1.24
Observations	399,864	399,864	399,864	762,638	362,774	399,864	399,864	221,847	178,017	399,864	257,918
Clusters	159	159	159	304	145	159	159	88	71	159	152
Outcome Variable Mean	8.15	8.15	8.15	5.87	3.35	8.15	8.15	8.23	8.04	8.15	8.98

Notes: This table assesses the robustness of our main use-based MWTP estimate. All columns use the 108-minute simulated effectiveness unless noted otherwise. Columns (1)–(3) progressively add hour-of-day and household fixed effects for monitor households; adding date fixed effects yields the main specification, which is omitted here because it appears as Column (1) of Table 4. Columns (4) and (5) report the full-fixed-effects specification for all households and for households without monitors. Columns (6) and (7) vary the effectiveness assumption, using a constant 80% reduction and the 23-minute median-session effectiveness. Columns (8) and (9) report the main specification separately for households with above- vs. below-median willingness to pay for the purifier in the Phase 2 BDM (median BDT 500); households with missing Phase-2 WTP fall in neither column. Columns (10) and (11) add linear controls for hourly temperature and relative humidity, measured by the two outdoor monitors in Column (10) and by the household's indoor monitor in Column (11). Column (11) uses only the hours in which the indoor monitor reported; on those hours, the specification without these controls yields an MWTP of PPP USD 0.27 per year. Potential PM2.5 improvement is the purifier's assumed effectiveness multiplied by outdoor air pollution and the average indoor-outdoor pollution ratio. Before the incentive period, the cost of using the purifier equals 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, it is 0.24 per hour for the control group and the difference between the electricity cost and the incentive (-4.76 or -9.76) for the incentive group. Standard errors clustered at the household level. $***p < 0.01; **p < 0.05; *p < 0.1$. See discussion in Sections 7.2 and 7.3.

Table A.12: Comparison of MWTP Estimates Across Contexts and Methodologies

Study Context	**Household Income** (PPP USD)	**Methodology**	**Adjustment Scenarios**	**MWTP** (PPP USD/$\mu g/m^3$/yr)
Bangladesh				
Chowdhury et al. (2025)	24,122	Use-based	Point estimate	0.59
			Upper bound (95% CI)	1.50
China				
Ito and Zhang (2020)	11,804	Purchase-based	Baseline	6.39
			Expected usage adjustment ($\times 2.5$)	15.9
			Actual usage adjustment ($\times 8.8$)	141
India				
Baylis et al. (2023)	9,454	Purchase-based	Baseline	3.11
			Actual usage adjustment ($\times 6.5$)	20.1
USA				
Tarduno and Walker (2025)	65,000	Purchase-based	Baseline	2.68
			Expected usage adjustment ($\times 2.5$)	6.67
			Actual usage adjustment ($\times 8.8$)	58.9

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. For Bangladesh we report our use-based point estimate and the upper bound of its 95% confidence interval (the 108-minute main specification, Column (1) of Table 4). MWTP values in the table are reported in PPP USD (2023 PPP-adjusted). 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 the assumed use is replaced by the expected use our households stated before receiving the device and by the actual use we measure with smart plugs. The multiplication factors are relative to the estimate on the row above. For example, if the subjects of Ito and Zhang (2020) or Tarduno and Walker (2025) had anticipated the use our households stated before receiving the device rather than continuous use, the implied MWTP would be 2.5 times the published figures; had they anticipated the use we measure in Dhaka, it would be 22 times ($2.5 \times 8.8 = 22$). Usage in Dhaka may not transfer to their settings, but the direction of the adjustment, upward whenever anticipated use falls short of the assumed divisor, applies to all purchase-based estimates. For Ito and Zhang (2020), the baseline uses their post-2013 estimate, which they originally report as USD 1.44 per year (after the January 2013 expansion of air-pollution information; their full-2006–2014-sample estimate is USD 1.34) and which we convert to PPP USD in the table, for comparability with our monitor-equipped (informed) households and the information-treatment estimate of Baylis et al. (2023).

Table A.13: Effect of Treatments on Attrition

	Phase 1 to 2 Attrition	Phase 2 to 3 Attrition		
	(1)	(2)	(3)	(4)
	All	All	Monitor HHs	Purifier HHs
Monitor	-0.024			-0.011
	(0.030)			(0.023)
Monitor x Attention	0.021			-0.011
	(0.034)			(0.021)
Purifier		-0.056**	-0.044	
		(0.022)	(0.029)	
Purifier x Monthly Compensation		-0.022	-0.042*	
		(0.024)	(0.024)	
Purifier x Daily Compensation		-0.045**	-0.042*	
		(0.018)	(0.024)	
Observations	1,008	818	419	306
Control mean	0.196	0.102	0.085	0.034

Notes: This table shows the effects of the randomized treatments on survey attrition. Column (1): attrition between the Phase 1 and Phase 2 surveys, all households. Column (2): attrition between the Phase 2 and Phase 3 surveys, all Phase 2 households. Columns (3) and (4) repeat Column (2) within monitor households and within purifier households, respectively. Observations are at the household level; heteroskedasticity-robust standard errors in parentheses. $***p < 0.01; **p < 0.05; *p < 0.1$. See discussion in Appendix B.

Table A.14: Balance Among Unattrited Households in Phase 2: Monitor Treatment

	(1)		(2)		(2)-(1)	
	No-Monitor Group		Monitor Group		Pairwise t-test	
Variable	N	Mean/(SE)	N	Mean/(SE)	N	Mean difference
College Graduate	399	0.474	419	0.480	818	0.006
		(0.025)		(0.024)		
Age	399	37.6	419	39.0	818	1.42
		(0.696)		(0.700)		
Beliefs about Risk of Lung Cancer	380	1.65	401	1.63	781	-0.021
and Stroke from Air Pollution		(0.024)		(0.023)		
Beliefs about Risk of ARI for	390	1.74	410	1.72	800	-0.017
Children from Air Pollution		(0.029)		(0.029)		
Beliefs about Severity of	399	7.38	419	7.57	818	0.190
Outdoor Air Pollution		(0.102)		(0.101)		
Beliefs about Severity of	399	4.79	419	4.69	818	-0.097
Indoor Air Pollution		(0.105)		(0.105)		
Beliefs about Indoor v.	388	1.65	412	1.69	800	0.047
Outdoor Air Pollution		(0.056)		(0.056)		
F-test of joint significance (P-value)						0.315
F-test, number of observations						761

Notes: This table provides balance test for Phase 1 survey data for households unattrited by Phase 2 survey in the Longitudinal Experiment 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. $***p < 0.01; **p < 0.05; *p < 0.1$. See discussion in Appendix B.

Table A.15: Balance Among Unattrited Households in Phase 2: Attention Treatment

	(1)		(2)		(2)-(1)	
	No-Attention Group		Attention Group		Pairwise t-test	
Variable	N	Mean/(SE)	N	Mean/(SE)	N	Mean difference
College Graduate	213	0.479	206	0.481	419	0.002
		(0.034)		(0.035)		
Age	213	37.6	206	40.4	419	2.85**
		(0.943)		(1.03)		
Beliefs about Risk of Lung Cancer	204	1.65	197	1.60	401	-0.050
and Stroke from Air Pollution		(0.032)		(0.032)		
Beliefs about Risk of ARI for	209	1.76	201	1.69	410	-0.066
Children from Air Pollution		(0.042)		(0.039)		
Beliefs about Severity of	213	7.46	206	7.67	419	0.215
Outdoor Air Pollution		(0.138)		(0.147)		
Beliefs about Severity of	213	4.63	206	4.76	419	0.128
Indoor Air Pollution		(0.143)		(0.154)		
Beliefs about Indoor v.	212	1.67	200	1.72	412	0.050
Outdoor Air Pollution		(0.079)		(0.079)		
F-test of joint significance (P-value)						0.384
F-test, number of observations						394

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

Table A.16: 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	61,813	298	58,236	758	-3,578
		(2,490)		(2,677)		
Education	460	14.2	298	14.6	758	0.359
		(0.273)		(0.325)		
Age	460	43.6	298	44.5	758	0.873
		(0.628)		(0.780)		
WTP	459	1,399	296	1,362	755	-36.7
		(112)		(149)		
HH Size	460	4.18	298	4.11	758	-0.072
		(0.068)		(0.073)		
Beliefs about Risk of Lung Cancer and Stroke from Air Pollution	440	1.92	290	1.94	730	0.020
		(0.035)		(0.043)		
Beliefs about Risk of ARI for Children from Air Pollution	449	2.17	291	2.25	740	0.081
		(0.043)		(0.056)		
Donate to Clean Air NGO (0/1)	460	0.246	298	0.268	758	0.023
		(0.020)		(0.026)		
Clean Air Priority (Z-score)	460	-0.002	298	0.034	758	0.035
		(0.046)		(0.061)		
Beliefs about Indoor v. Outdoor Air Pollution	460	0.446	298	0.448	758	0.002
		(0.010)		(0.012)		
Beliefs about Severity of Indoor Air Pollution	460	4.71	298	4.69	758	-0.022
		(0.084)		(0.103)		
Beliefs about Severity of Outdoor Air Pollution	460	7.04	298	7.17	758	0.130
		(0.088)		(0.117)		
Health Index (ICW)	460	0.056	298	0.080	758	0.023
		(0.028)		(0.030)		
F-test of joint significance (P-value)						0.924
F-test, number of observations						725

Notes: This table provides balance test for Phase 2 survey data for households unattrited by Phase 3 survey of the Longitudinal Experiment 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. $***p < 0.01; **p < 0.05; *p < 0.1$. See discussion in Appendix B.

Table A.17: Balance Among Unattrited Households in Phase 3: Purifier Treatment By Compensation

	(1) No Compensation		(2) Daily Compensation		(3) Monthly Compensation		F-test for balance across all groups	
Variable	N	Mean/(SE)	N	Mean/(SE)	N	Mean/(SE)	N	F-stat/P-value
Monthly Income	127	58,200	86	57,029	85	59,510	298	0.061
		(4,414)		(4,404)		(5,027)		0.941
Education	127	14.7	86	14.5	85	14.4	298	0.076
		(0.524)		(0.585)		(0.588)		0.927
Age	127	44.9	86	46.2	85	42.0	298	2.17
		(1.15)		(1.52)		(1.45)		0.117
WTP	126	1,663	85	1,044	85	1,235	296	1.64
		(268)		(186)		(273)		0.197
HH Size	127	4.20	86	4.13	85	3.96	298	0.875
		(0.116)		(0.133)		(0.132)		0.418
Beliefs about Risk of Lung Cancer	122	1.96	85	2.01	83	1.85	290	0.980
and Stroke from Air Pollution		(0.067)		(0.093)		(0.066)		0.377
Beliefs about Risk of ARI for	123	2.22	85	2.39	83	2.15	291	1.48
Children from Air Pollution		(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	1.77
		(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.	127	0.450	86	0.467	85	0.426	298	0.808
Outdoor Air Pollution		(0.020)		(0.022)		(0.023)		0.447
Beliefs about Severity of	127	4.58	86	4.94	85	4.60	298	1.20
Indoor Air Pollution		(0.159)		(0.186)		(0.197)		0.302
Beliefs about Severity of	127	7.09	86	7.55	85	6.92	298	2.28
Outdoor Air Pollution		(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 test (multinomial logit LR): $\chi^2(26) = 27.93$, p = 0.362								

Notes: This table provides balance test for Phase 2 survey data for households unattrited by Phase 3 survey of the Longitudinal Experiment within the purifier group by type of compensation (none, daily, monthly). For each variable, we report the F-test of equality of means across the three groups with its p-value. We also report an omnibus test of joint significance. $***p < 0.01; **p < 0.05; *p < 0.1$. See discussion in Appendix B.

Table A.18: 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	63,087	158	61,338	394	-1,749
		(3,589)		(3,875)		
Education	236	14.7	158	14.8	394	0.121
		(0.376)		(0.421)		
Age	236	44.6	158	43.8	394	-0.798
		(0.879)		(1.05)		
WTP	236	1,392	158	1,177	394	-215
		(157)		(166)		
HH Size	236	4.07	158	4.09	394	0.027
		(0.089)		(0.103)		
Beliefs about Risk of Lung Cancer and Stroke from Air Pollution	225	2.00	156	1.97	381	-0.035
		(0.055)		(0.065)		
Beliefs about Risk of ARI for Children from Air Pollution	228	2.21	156	2.30	384	0.093
		(0.063)		(0.082)		
Donate to Clean Air NGO (0/1)	236	0.271	158	0.253	394	-0.018
		(0.029)		(0.035)		
Clean Air Priority (Z-score)	236	0.029	158	0.079	394	0.050
		(0.068)		(0.084)		
Beliefs about Indoor v. Outdoor Air Pollution	236	0.470	158	0.449	394	-0.022
		(0.014)		(0.017)		
Beliefs about Severity of Indoor Air Pollution	236	5.00	158	4.75	394	-0.253
		(0.116)		(0.145)		
Beliefs about Severity of Outdoor Air Pollution	236	7.16	158	7.12	394	-0.041
		(0.116)		(0.153)		
Health Index (ICW)	236	0.009	158	0.044	394	0.035
		(0.044)		(0.043)		
F-test of joint significance (P-value)						0.835
F-test, number of observations						379

Notes: This table provides balance test for Phase 2 survey data for monitor households unattrited by Phase 3 survey of the Longitudinal Experiment 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. $***p < 0.01; **p < 0.05; *p < 0.1$. See discussion in Appendix B.

Table A.19: 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	54,735	158	61,338	298	6,603
		(3,645)		(3,875)		
Education	140	14.3	158	14.8	298	0.515
		(0.504)		(0.421)		
Age	140	45.2	158	43.8	298	-1.36
		(1.16)		(1.05)		
WTP	138	1,575	158	1,177	296	-398
		(256)		(166)		
HH Size	140	4.13	158	4.09	298	-0.034
		(0.103)		(0.103)		
Beliefs about Risk of Lung Cancer and Stroke from Air Pollution	134	1.92	156	1.97	290	0.047
		(0.056)		(0.065)		
Beliefs about Risk of ARI for Children from Air Pollution	135	2.19	156	2.30	291	0.109
		(0.073)		(0.082)		
Donate to Clean Air NGO (0/1)	140	0.286	158	0.253	298	-0.033
		(0.038)		(0.035)		
Clean Air Priority (Z-score)	140	-0.017	158	0.079	298	0.096
		(0.090)		(0.084)		
Beliefs about Indoor v. Outdoor Air Pollution	140	0.448	158	0.449	298	0.001
		(0.019)		(0.017)		
Beliefs about Severity of Indoor Air Pollution	140	4.63	158	4.75	298	0.118
		(0.146)		(0.145)		
Beliefs about Severity of Outdoor Air Pollution	140	7.23	158	7.12	298	-0.108
		(0.180)		(0.153)		
Health Index (ICW)	140	0.120	158	0.044	298	-0.076
		(0.043)		(0.043)		
F-test of joint significance (P-value)						0.432
F-test, number of observations						288

Notes: This table provides balance test for Phase 2 survey data for purifier households unattrited by Phase 3 survey of the Longitudinal Experiment 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. $***p < 0.01; **p < 0.05; *p < 0.1$. See discussion in Appendix B.

Table A.20: Effect of Treatments on Withdrawals from Study

	(1) Purifier Status: Withdrawn	(2) Purifier Status: Withdrawn	(3) Monitor Status: Withdrawn
Monitor	0.011		
	(0.011)		
Monitor x Attention	0.0010		
	(0.017)		
Purifier x Any Compensation		-0.014	-0.013
		(0.010)	(0.013)
Purifier x Daily Compensation		-0.0000315	0.0000182
		(0.0000547)	(0.0000296)
Purifier			0.0091
			(0.014)
Time FE	Yes	Yes	Yes
Observations	22,983	22,983	31,501
Control mean	0	0.014	0.0043

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. $***p < 0.01; **p < 0.05; *p < 0.1$. See discussion in Appendix B.

Table A.21: 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*	0.519*	0.143**
	(0.311)	(0.281)	(0.066)
Data	Self-reported	Actual	Self-reported
Observations	292	297	292
Control mean	5.10	0.94	0.244

Notes: This table shows the effect of monitors on self-reported and actual air purifier use during the Phase 3 survey of the Longitudinal Experiment. 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 the Phase 3 survey, households who received the air purifier were asked how often they used the air purifier; the options 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 used the air purifier "all the time when home". $***p < 0.01; **p < 0.05; *p < 0.1$. See discussion in Appendix C.