High Returns, Low Adoption: Air Purifiers in Bangladeshi Firms*

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Abstract

Even under the most optimistic regulatory scenarios, many developing countries will continue to face decades of dangerously elevated pollution levels. This reality makes private defensive technologies like workplace air purifiers—which can improve indoor air quality despite poor ambient conditions—potentially critical for sustaining productivity growth. Yet we lack causal evidence on their effectiveness. Our year-long randomized field experiment in Dhaka's ready-made garment (RMG) manufacturing sector provides the first causal evidence of air purifiers' impact on labor productivity and firm profit. We installed air purifiers at no cost in 50 randomly selected firms (out of 100 total), finding severe indoor PM2.5 pollution levels averaging 75 $\mu g/m^3$, 15 times WHO's annual guidelines. Firms used purifiers for 4-6 hours daily, increasing usage during pollution peaks. This proactive use resulted in a 15% decrease in PM2.5 levels, a 10% increase in daily labor productivity, and a 18% increase in monthly profits compared to control firms. During peak production months, productivity increased by 23% and profits by 39%, suggesting that returns on air purifier investment are highest when firms have little production slack. Overall, our results suggest that the average owner would recover purifier costs in less than three months of high production. Despite this, fewer than 1% of firms own an air purifier. To understand barriers to adoption, we conducted a second experiment with 2500 additional RMG manufacturing firms in Dhaka during the peak production months. We find that information about generalized returns from our first experiment, access to credit, or a free two-year full warranty did little to raise firm owners' willingness-to-pay (WTP). Purchase contracts enabling low-risk personalized learning about returns, e.g., a 30-day free trial, increased WTP by 20–30%, though this remained at only 15% of the retail price. One year after returning their purifiers, treatment firms from our first experiment showed 81% higher WTP for the same model compared to control firms, consistent with first-hand experience resolving firm-specific uncertainty about the purifier's return on investment. However, even this elevated WTP remained at only 23% of the retail price.

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1 Introduction

Air pollution represents a paradox of modern economic development. While pollution is an inevitable byproduct of economic transformation, mounting evidence reveals that it simultaneously undermines the very economic growth it accompanies.[1] This tension is nowhere more acute than in South Asia, where rapid economic growth has occurred alongside severe deterioration in ambient air quality. Traditional regulatory responses have proven insufficient despite their ambition (Duflo et al., 2013, 2018; Piette, 2018). Indeed, even under the most optimistic policy scenarios, these countries will face decades of dangerously elevated pollution levels (The World Bank, 2024). This makes private defensive technologies like workplace air purifiers—which can improve indoor air quality despite poor ambient conditions—potentially critical for sustaining productivity growth. However, we possess no causal evidence on air purifiers' returns to firms or the barriers preventing their adoption. To address this gap, we conducted two field experiments with microenterprises in Bangladesh's ready-made garment (RMG) manufacturing sector.

Bangladesh exemplifies the pollution-growth paradox at its most extreme. As its economy has expanded rapidly over the past decade, ambient PM2.5 levels now routinely exceed WHO's annual guidelines by 15-fold and surpass US annual average levels by nine-fold (IQAir, 2024), imposing economic costs equivalent to 4% of GDP (Raza, Mahmud and Rabie, 2021). We focus on microenterprises because they constitute the backbone of non-farm employment in Bangladesh as well as other developing countries (Hsieh and Olken, 2014; Rajagopalan and Shah, 2024; Tybout, 2000). Enterprises with fewer than 10 workers account for 97% of all non-farm economic units and employ 68% of the non-farm workforce (Bakht and Basher, 2015). The RMG manufacturing sector alone employs 4 million workers across thousands of factories, generating 80% of exports and 10% of GDP (Export Promotion Bureau, 2020; Farhana, Syduzzaman and Munir, 2015; Wing, 2023; Zaman, 2024).

Firms in our sample are typical microenterprises in this sector, operating in modest 500-square-foot facilities with approximately 10 workers each. These predominantly male operators work independently at piece rates, a common feature of developing-country labor markets (Baland, Drèze and Leruth, 1999; Ortiz, 2002), completing diverse products from simple underwear to elaborate two-piece garments. The piece-rate system reflects differences in time and effort required for each garment and allows workers flexibility—upon completing tasks, they can leave or move to another firm. Production fluctuates with seasonal demand and order flow. Oper-

[1] Recent evidence shows that air pollution reduces life expectancy (Chen et al., 2013; Ebenstein et al., 2017), increases infant mortality (Arceo, Hanna and Oliva, 2016; Greenstone and Hanna, 2014; Heft-Neal et al., 2018; Jayachandran, 2009), damages cognitive performance (Ebenstein, Lavy and Roth, 2016; Zhang, Chen and Zhang, 2018), and decreases labor supply and productivity (Adhvaryu, Kala and Nyshadham, 2022; Graff Zivin and Neidell, 2012; Hanna and Oliva, 2015; Hoffmann and Rud, 2024); see Oliva, Alexianu and Nasir (2019) for a review.

ational constraints include frequent power outages and reliance on natural ventilation through open doors and windows. As a consequence of the piece-rate system, these firms maintain detailed daily records of worker-level output.

In our first year-long experiment, we installed air purifiers for free in 50 randomly selected firms (out of 100 total) on April 1, 2023, and removed them on April 1, 2024. Treatment firms received both an air purifier and an air monitor, while control firms received only an air monitor.[2] At the time of installation, the purifier retailed for BDT 70,000 (approximately USD 600), equivalent to about one month's average profit for control firms in our sample. We collected extensive data from all firms between April 1, 2023, and March 31, 2024: minute-by-minute air purifier usage from smart plugs, hourly readings from outdoor and indoor air pollution monitors, daily worker-level output from firm records, and monthly revenue and cost data from owner surveys. We also collected pre-period data between February and March 2023: daily worker-level output from firm records and monthly revenue and cost data from owner surveys.

Our data reveals severe air pollution levels in Dhaka, both outdoors and indoors. Using high-frequency monitors at three sites, we recorded outdoor PM2.5 levels ranging from the WHO's 24-hour safe limit of 15 $\mu g/m^3$ to over 275 $\mu g/m^3$. On a typical day, the 24-hour outdoor average exceeded 84 $\mu g/m^3$, routinely surpassing 150 $\mu g/m^3$ from December to March. Indoor air quality, monitored in every firm in our sample, showed about 90% of hourly PM2.5 readings ranging from 15 $\mu g/m^3$ to over 225 $\mu g/m^3$, with median 24-hour levels over 55 $\mu g/m^3$. During the winter months, indoor levels regularly topped 100 $\mu g/m^3$. Overall, these patterns resulted in annual average outdoor and indoor PM2.5 levels of 110 $\mu g/m^3$ and 75 $\mu g/m^3$, respectively, which are 22 and 15 times higher than the WHO's annual safe limit of 5 $\mu g/m^3$.

In response, treatment firms extensively used air purifiers. The typical firm operated air purifiers for 4 to 6 hours daily, mainly during work hours, with over 40% using them for over six hours. Notably, usage increased when outdoor PM2.5 levels spiked, suggesting that firms responded to higher pollution levels. Specifically, firms were 3 percentage points (12.5%) more likely to use the purifier when outdoor PM2.5 ranged from 100 $\mu g/m^3$ to 150 $\mu g/m^3$, 4 percentage points (16.67%) more likely between 200 $\mu g/m^3$ and 250 $\mu g/m^3$, and over 11 percentage points (45.83%) more likely when levels exceeded 500 $\mu g/m^3$, compared to levels below 50 $\mu g/m^3$.

This proactive use led to lower indoor air pollution, and higher labor productivity and firm profits in treatment firms compared to control firms. Treatment firms saw hourly indoor PM2.5 levels drop to 63.55 $\mu g/m^3$—a 15% improvement over the 74.46 $\mu g/m^3$ recorded in control firms.

[2]Our experimental design estimates the effect of air purifiers conditional on air quality monitoring, as both treatment and control firms received air monitors. This design choice eliminates differential monitoring effects unrelated to purifier use between groups but allows treatment firms to optimize purifier usage. Our estimates should therefore be interpreted as the effect of air purifiers when firms can monitor and respond to air quality levels. Indeed, many commercial air purifier models include a display panel with indoor air quality measurements.

The hour-of-day effects during work hours were highly correlated with hour-of-day indoor PM2.5 levels in control firms ($\rho \approx 0.87$), as were month-by-month effects with month-by-month indoor PM2.5 levels ($\rho \approx 0.95$), consistent with increased purifier use in response to higher indoor PM2.5 levels. These effects are highest in January and February: between 9 am and 6 pm, indoor PM2.5 levels in treatment firms are roughly 38 $\mu g/m^3$ (25%) lower than in control firms.

Consequently, treatment firms observed a 10% increase in daily worker output without any change in labor supply. The impacts peaked in February (18%) and March (28%), tracking closely with seasonal production patterns in control firms ($\rho \approx 0.89$). This alignment suggests that production slack moderates the returns to air purifiers: when workers complete tasks faster in treatment firms, owners can capitalize on this speed only when demand is high enough to secure additional orders. During low-demand periods, faster task completion cannot translate into higher output. Indeed, consistent with this mechanism, treatment firms strategically adjust operations to match productivity gains with market demand: more treatment firms remain open during high-production months and more treatment firms close during low-production months. The output gains correlate less strongly with pollution levels, but the magnitude is still large ($\rho \approx 0.44$)—effects are largest when outdoor pollution is worst and purifier use intensifies.[3]

These labor productivity gains translate directly into higher profits. Treatment firms make approximately BDT 11,000 more in monthly profits than control firms, an 18% increase, peaking in February (BDT 30,000 or 48%) and March (BDT 24,000 or 35%). The month-by-month profit increases correlate strongly with both market-level production ($\rho \approx 0.56$) and our output estimates ($\rho \approx 0.70$). This alignment reinforces the key role played by production slack: air purifiers generate returns for owners only when firms can convert faster production into additional orders.

Overall, these results suggest that the average owner would recover costs of purchasing and running a purifier within three months during high production periods. Yet adoption remains virtually nonexistent: of 2,500 RMG manufacturing firms we contacted for our second experiment, fewer than 10 owned air purifiers. Furthermore, when we used an incentive-compatible mechanism to elicit willingness to pay (WTP), firms bid just BDT 8,439 on average, roughly 12% of the retail price.

Our survey of owners' beliefs about purifier profitability revealed uncertainty and heterogeneity in expected returns: 20% were uncertain about returns, another 20% expected no profit gains, and 5% anticipated gains but couldn't quantify them. Among the 55% who expected specific increases, most predicted only 5-10% gains—far below our experimental estimate of 18%.

Firm owners who expected no profit gains cited two primary reasons: profits depend on or-

[3]Indeed, when we examine heterogeneous effects on labor productivity by outdoor air pollution levels, we find that air purifiers have larger productivity effects when outdoor air pollution is worse. This dose-response relationship, where treatment effects scale with pollution exposure, is inconsistent with Hawthorne or placebo effects, which are unlikely to vary systematically with pollution levels.

ders which makes purifiers less relevant during slack periods and purifiers seem unnecessary for productivity. This reasoning reveals nuanced understanding – owners recognize that purifier returns depend critically on capacity utilization (precisely what our first experiment demonstrated), yet they are uncertain about or underestimate the peak-period benefits.

To investigate the reasons for low demand, we randomized access to information, credit, or contracts offering free two-year full warranties, money-back guarantees, and free trials, before eliciting WTP from these 2,500 firms. This experiment was fielded during late January to early March 2025, the peak production season when purifier returns are highest.

We find that relaxing information constraints alone doesn't increase WTP: providing detailed flyers that credibly document profit gains for the average RMG manufacturing firm from our first experiment left willingness to pay unchanged. Credit constraints prove equally unimportant: offering 12-month loans at 1% monthly interest (the lending rate for scheduled banks in Bangladesh), even when paired with information flyers, had zero effect on demand. Product durability concerns are also not first-order: a free two-year full-service warranty, even when paired with information flyers, failed to increase valuations.

Only purchase contracts enabling low-risk experiential learning during peak production periods proved effective, though the resulting WTP remained well below the market price. The treatment that paired the information flyer with a month-long money-back guarantee increased WTP by 20-25%, reaching 15% of the retail price. The guarantee contract stipulated that firms could return the purifier within this period for a full refund with no questions asked, effectively allowing them to observe actual impacts on their specific workers, production processes, and profit margins during high production months with minimal financial risk. Interestingly, the standalone money-back guarantee failed to increase valuation. This contrast suggests that guarantees require credibility: without the legitimacy conferred by the research context in the information flyer, firms likely perceived high counterparty risk and doubted the refund would be honored.

The free one-month trial treatment without the information flyer generated similar results to the treatment that paired the information flyer with a month-long money-back guarantee. Unlike the money-back guarantee, the free trial eliminates all upfront costs and associated financial risk, and doesn't require the credibility generated by the information flyer. Adding the information flyer to the trial yielded the highest point estimate of 30%, but this estimate is not statistically different from the effect of the free trial without information.

Consistent with these results, we also show that actual experience generates higher WTP. When we returned to our original experimental firms in March 2025—one year after removing purifiers—we found dramatic differences in WTP. Treatment firms that had used purifiers for a year bid 81% higher for the same device compared to control firms. However, even this elevated

WTP was only about 23% of the retail price.

The persistence of severe undervaluation even after experience points to additional barriers beyond informational uncertainty.[4] In volatile environments where 60% of firms report year-over-year production swings, driven by unpredictable order volume and political upheaval like Bangladesh's 2024 mass uprising that forced a government collapse, even demonstrated profits from one good year cannot guarantee future returns. Combined with model-specific uncertainty (our experiment tested just one purifier among many), these compounding risks trap firms in a rational but inefficient equilibrium: they know the technology works but reasonably doubt whether it will pay off in their uncertain operating and market environment.

Contributions. This paper contributes to the literature on firm-level upgrading in developing countries (for reviews, see Atkin et al., 2024; Verhoogen, 2023). Despite the "advantages of backwardness" that Gerschenkron (1962) identified, whereby developing countries could rapidly adopt proven technologies from advanced economies, firms in low- and middle-income countries (LMICs) persistently fail to adopt seemingly profitable innovations. The diffusion process remains slow and incomplete (Comin and Hobijn, 2010), and significant barriers continue to hinder technological catch-up (Verhoogen, 2023). Our study directly addresses this puzzle by examining one such technology, workplace air filtration, which, despite being widely adopted in high-income countries, e.g., through Heating, Ventilation, and Air Conditioning (HVAC) systems (Biasi, Lafortune and Schönholzer, 2025), has only recently become prominent in developing countries amid growing concerns about ambient air quality (Mukherjee, 2024; Verma, 2024).

One key reason why the adoption of any technology might be low is that the returns, while high in an idealized setting, do not manifest in the real-world. Indeed, aside from management or worker training programs (McKenzie, 2021; McKenzie and Woodruff, 2014), few firm-level interventions in LMICs have been shown to boost productivity and profitability in field experiments (Atkin et al., 2024). Similarly, the returns to workplace filtration may be limited in high-pollution LMICs due to physiological, technical, or organizational reasons. First, the dose-response relationship between pollution and productivity may be non-linear. Air purifiers provide only localized protection, leaving workers exposed during commutes and at home, so if the effects are non-linear in exposure duration, workplace filtration may yield limited benefits. Or, if the relationship is non-linear in absolute pollution levels, even double-digit reductions from extreme baselines may yield minimal productivity gains. Second, firms in these contexts face frequent power outages and rely on natural ventilation through open doors and windows—factors that

[4] This pattern is common across developing economy contexts where multiple market failures compound (Kremer, 1993). For example, Berkouwer and Dean (2022) find that while access to credit doubles willingness-to-pay for energy-efficient cookstoves in Kenya, average WTP remains well below market prices—suggesting that even when financial constraints are partially addressed, other barriers prevent efficient technology adoption.

reduce purifier effectiveness. Third, organizational barriers may prevent firms from realizing the full potential of air purifiers. Owners who make technology decisions may infrequently visit the shop floor, and implementation may be delegated to managers—such as less-experienced family members or fixed-wage employees—who do not internalize the productivity gains. Consistent usage also requires monitoring systems that these firms lack. Finally, profit-focused owners may undervalue any worker health benefits that purifiers might provide. To test this explanation, we provide the first causal evidence on the productivity and profitability returns to air purifiers in a year-long field experiment. Unlike the technology in Atkin et al. (2017), which reduces material waste in production but also reduces earnings for piece-rate workers, we find that air purifiers increase both hourly wages for piece-rate workers and profits for firm owners.

This result contributes to the extensive literature examining how technological adoption affects worker productivity (Autor, Katz and Krueger, 1998; Bartel, Ichniowski and Shaw, 2007; Bloom et al., 2014; Brynjolfsson and Hitt, 2000). While much of this literature has focused on information technologies and their complementarity with skilled workers (Acemoglu and Restrepo, 2020; Akerman, Gaarder and Mogstad, 2015; Bresnahan, Brynjolfsson and Hitt, 2002), and more recently on AI-based tools that often show mixed results for productivity and human-technology collaboration (Acemoglu et al., 2022; Brynjolfsson, Li and Raymond, 2025; Kanazawa et al., 2022; Noy and Zhang, 2023; Vaccaro, Almaatouq and Malone, 2024), our study examines a different type of technology—workplace air filtration—that enhances productivity by improving the physical work environment, benefiting all workers regardless of skill level. The closest paper to ours is Adhvaryu, Kala and Nyshadham (2020), who leverage the staggered replacement of factory floor lighting with LED bulbs to show that cooler factory temperatures from LED adoption raised productivity on hotter days in a Bangalore garment manufacturing firm.

It also contributes to a broader scientific literature that has documented the human health impacts of purifiers in residential settings. These studies typically feature samples selected based on pre-existing health conditions in high-income, low-pollution countries, establish idealized conditions (e.g., closing doors and windows), and ensure high compliance with purifier use, thereby failing to evaluate real-world usage patterns (for a review, see EPA, 2018). In effect, these are efficacy rather than effectiveness trials. A new economics literature has begun to fill this gap.[5] For instance, a recent field experiment from Dhaka found that household purifier use of roughly 110 minutes daily, while achieving double-digit percentage decreases in indoor PM2.5,

[5]New or ongoing randomized controlled trials in public settings like schools, where users don't bear operational costs, have examined air purifiers' effects on educational outcomes and find mixed results. Bonan et al. (2025) find improved student attendance under controlled, non-discretionary use over 6 months. In contrast, studies examining cognitive outcomes show initial but unsustained benefits: Bharti et al. (2025), using controlled implementation for 3 months, document cognitive performance improvements 3 weeks into the intervention that disappeared 6 weeks later, while Kremer, Romero and Saavedra (2025), who allowed discretionary use but are unable to measure it, find test score gains on high-stakes exams at 3 months that had vanished by the following year.

may be too modest to generate significant health benefits given extreme baseline pollution and potential non-linearities in the dose-response relationship (Chowdhury et al., 2025). However, no prior research has measured the causal real-world productivity and profitability returns to air purifiers for firms, where impacts are mediated by the market structure, production processes, organizational barriers, and the unique physical environment of a shop floor.

Second, we examine why demand remains low for this win-win technology. We show that production slack, a pervasive feature of firms in developing countries (Walker et al., 2024), significantly moderates the returns to air purifiers for firms. The efficiency gains from cleaner air only translate into higher firm profits when firms have enough orders to capitalize on faster production. This result demonstrates how firm-level returns to a new technology are critically dependent on market structure and capacity utilization. Moreover, we document that this reality is reflected in owners' beliefs: we find significant uncertainty and heterogeneity in perceived returns, with many owners correctly intuiting that slack periods would limit profitability, yet systematically underestimating the magnitude of the benefits during peak season.

Third, we show that while standard interventions fail, experiential learning increases WTP, though not enough to drive adoption. We find that providing credible information on purifier profitability, offering subsidized credit, and providing free full warranty contracts are all ineffective at increasing firm owners' willingness to pay (Banerjee and Duflo, 2014; Bloom et al., 2010; de Mel, McKenzie and Woodruff, 2008; Spence, 1977). In contrast, purchase contracts that allow for low-risk experiential learning, such as free trials or credible money-back guarantees, are somewhat effective. This finding contributes directly to the nascent literature on how firms learn and accumulate knowledge in low-income settings (Atkin, Khandelwal and Osman, 2017; Chaurey et al., 2025). While extensive evidence documents "learning-by-doing" in developed-country firms (e.g., Hendel and Spiegel, 2014; Irwin and Klenow, 1994; Levitt, List and Syverson, 2013) and in developing-country agriculture (e.g., Foster and Rosenzweig, 1995; Hanna, Mullainathan and Schwartzstein, 2014), there is far less detailed evidence for non-agricultural firms in developing countries. Our paper provides experimental evidence on the value of "learning-by-using," where firms resolve their specific uncertainty about a technology's value only through direct, first-hand experience within their own production environment. However, the magnitude of undervaluation even after direct experience, with WTP reaching only 23% of retail price, suggests that experiential learning alone cannot solve the technology adoption puzzle.

2 Context and Background

We conduct two experiments with microenterprises in Dhaka, Bangladesh. Two key factors motivated this choice of setting. First, air pollution levels are extremely high in Bangladesh, with

the capital city, Dhaka, routinely ranked among the world's most polluted cities (AQLI, 2023). Second, micro, small, and medium enterprises (MSMEs) provide more than 80% of non-farm employment in Bangladesh. These features, however, are not unique to Dhaka; indeed, its air pollution levels and economic structure are emblematic of many cities in low- and middle-income countries. Understanding these settings is crucial because the documented health effects of air pollution on respiratory, cardiovascular, and cognitive functions—effects that purifiers have been shown to mitigate—likely translate into substantial productivity losses for enterprises and would suggest a high return on investment for air purifiers.

2.1 Air Pollution in Dhaka, Bangladesh

We observe levels of outdoor air pollution at three different sites within the Greater Dhaka district over one year, from April 1, 2023, to March 31, 2024. These sites include Baridhara, where the US Embassy's air pollution monitor is located, and the study areas of Kamrangirchar and Narayanganj, where we installed outdoor air pollution monitors.[6]

The data reveal alarming air pollution levels across all three sites (Figure 1). Roughly 75% of hourly outdoor PM2.5 levels were above 45 $\mu g/m^3$, three times the WHO 24-hour safe limit of 15 $\mu g/m^3$ (Figure 1, Panel (a)). Less than 5% of hourly readings during this period, almost exclusively in rainy months, were below the WHO 24-hour safe limit. The annual average outdoor PM2.5 level for Greater Dhaka district in 2023-24 was 110 $\mu g/m^3$, which is 22 higher than the WHO's annual safe limit of 5 $\mu g/m^3$. Remarkably, there was not a single day in the entire year when the daily average PM2.5 levels fell below the World Health Organization's (WHO) 24-hour safe limit of 15 $\mu g/m^3$ (Figure 1, Panel (b)). Moreover, hour-of-day PM2.5 levels throughout the year were typically at least five and fifteen times higher than the WHO's 24-hour and annual recommended levels, respectively (Figure 1, Panel (c)). Outdoor PM2.5 levels during the winter months are particularly acute. From December to February, daily PM2.5 levels frequently exceeded the WHO's 24-hour recommended levels by more than tenfold, with peaks of more than 275 $\mu g/m^3$. In fact, monthly average PM2.5 levels exceeded 100 $\mu g/m^3$ between November and April (Figure 1, Panel (d)).

[6]We installed outdoor air monitors in Kamrangirchar and Narayanganj in late August 2023. Therefore, we rely on hourly outdoor PM2.5 data from the US Embassy in Dhaka, located less than 25 kilometers from both study sites, for the period between April 2023 and August 2023.

2.2 MSMEs in the Ready-Made Garment (RMG) Manufacturing Sector in Bangladesh

Our study was conducted with microenterprises in the RMG manufacturing sector at two different sites within the Greater Dhaka district: Kamrangirchar and Narayanganj.

Micro, small, and medium enterprises (MSMEs). MSMEs play a crucial role in Bangladesh's economy. Over the last decade, the impact of MSMEs has grown significantly, with their contribution to GDP rising from about 2.3 percent in 1992 to 22.4 percent in 2020. Furthermore, these enterprises employ around 24 million people, accounting for approximately 80% of industrial employment and 25-30% of the total employed labor force in Bangladesh (Andrianaivo and Ndiaye, 2019; Bidisha, 2024; Dallakoti, 2023).

Within MSMEs, microenterprises play a critical role supporting both the broader economy and the manufacturing sector in Bangladesh. In 2013, enterprises with fewer than 10 workers constituted nearly 97% of all non-farm economic units and 93% of manufacturing units.[7] Employment data from 2003 further reinforces their significance, showing that these small enterprises accounted for 68% of non-farm employment and 40% of manufacturing employment (Bakht and Basher, 2015).

Ready-made garment (RMG) manufacturing sector. The RMG manufacturing sector, where Bangladesh ranks second globally only to China, is the nation's largest manufacturing industry (OECD/UNCTAD, 2023). It accounts for 80% of the country's exports, generating $28 billion in national export earnings, and about 10% of its GDP (Export Promotion Bureau, 2020). Within this sector, about 4,000 factories employ 4 million workers, many in MSMEs, highlighting their role as major employment providers (Farhana, Syduzzaman and Munir, 2015; Wing, 2023; Zaman, 2024). Dhaka, the political and financial capital as well as the largest city in Bangladesh, serves as the central hub of RMG manufacturing, hosting the vast majority of operations.[8]

2.3 Air Pollution and Human Health

Particulate matter (PM) pollution has been extensively studied and linked to numerous adverse health effects and increased mortality (see, for example, Bell, Samet and Dominici, 2004; Dockery and Pope, 1994; Pope and Dockery, 2006; Pope, Dockery et al., 1999, for a review). PM is categorized by particle size into coarse (greater than 2.5 μm), fine (2.5 μm or less), and ultra-fine (less

[7] This is similar to other developing economies (Hsieh and Olken, 2014; Tybout, 2000). For example, in India, 95% of all industrial units employ fewer than 10 workers (Rajagopalan and Shah, 2024).

[8] https://mappedinbangladesh.org/

than 0.1 μm) particles. Fine PM (PM2.5), the focus of this study, primarily originates from the combustion of fossil fuels, such as emissions from power plants, industrial facilities, and vehicles, especially when exhaust gases interact in the atmosphere.

PM2.5 poses significant health risks due to several key characteristics: it can be inhaled more deeply into the lungs compared to larger particles (Bell, Samet and Dominici, 2004), remains airborne for a much longer duration, can be transported over greater distances (Wilson and Suh, 1997), tends to have a more toxic chemical composition, and can more readily penetrate indoor environments (Ozkaynak et al., 1996; Vette et al., 2001).

Both long-term and short-term exposure to PM has been linked to a wide range of adverse health effects and impaired cognitive function (see Environmental Protection Agency, 2004, for a review). These risks primarily arise from changes in pulmonary and cardiovascular functioning (Seaton et al., 1995); if PM2.5 particles enter the bloodstream and central nervous system (CNS), they can cause inflammation, cortical stress, and cerebrovascular damage (Oberdörster et al., 2004; Peters et al., 2006).

Long-term exposure to PM is associated with an increased mortality risk, mainly due to a higher incidence of cardiovascular events and chronic inflammatory lung injury (Souza et al., 1998), negatively impacting the respiratory system.

Short-term exposure to PM has been linked to a range of detrimental physical and cognitive effects (see Adhvaryu, Kala and Nyshadham, 2022, for a review). Studies have shown that PM2.5 exposure can reduce intelligence, increase the likelihood of errors, especially under time pressure, and impair performance across various cognitive domains (Künn, Palacios and Pestel, 2019; Lewis et al., 1970; Power et al., 2011; Shehab and Pope, 2019; Suglia et al., 2008; Weuve et al., 2012). In terms of physical health, short-term PM2.5 exposure can elevate blood pressure (Chang et al., 2015; Soppa et al., 2017), trigger inflammatory responses (Ghio, Kim and Devlin, 2000; Kubesch et al., 2015), affect cardiac function (Wu et al., 2010, 2011), and decrease lung function in individuals with respiratory conditions (McCreanor et al., 2007). Even relatively low levels of exposure may impact physical health through changes in blood pressure, irritation of the ear, nose, throat, and lungs, and mild headaches (Ghio, Kim and Devlin, 2000; Pope, 2000). Symptoms can manifest within a few hours of exposure or be triggered after several days of elevated exposure, especially in individuals with pre-existing cardiovascular and respiratory conditions.

2.4 Air Purifiers and Human Health

Air purifiers offer a powerful defense against the threat of air pollution, trapping 99.97% of microscopic particles (EPA, 2024). They are even more effective for larger particles, such as PM2.5 (particles with a diameter of ≤ 2.5 μm) and PM10 (particles with a diameter of ≤ 10 μm). Mul-

tiple recent research efforts—including experimental studies, observational studies, and meta-analyses—find that air purifiers in residential settings decrease PM2.5 levels and improve human health outcomes. Health benefits include reduced allergy and asthma symptoms (measured via peak expiratory flow, bronchial inflammation markers, self-reported medication use and symptoms) as well as decreased cardiovascular morbidity (assessed via lung function, exhaled breath condensate, blood pressure, heart rate, microvascular endothelial function, inflammation, oxidative stress) (Allen et al., 2011; EPA, 2018; Lanphear et al., 2011; Li et al., 2018; Park et al., 2020; Sublett, 2011; Walzer et al., 2020; Xia et al., 2021). Importantly, while the majority of the experimental literature that demonstrates these improvements features small samples (fewer than 30 participants) selected based on pre-existing health conditions, there exist nine studies with larger sample sizes and no selection based on pre-existing conditions (for a review, see EPA, 2018). Of these, four are in developed countries with PM2.5 levels below 15 $\mu g/m^3$ (the WHO recommended annual guideline), three are in developed countries with PM2.5 levels between 15 and 45 $\mu g/m^3$. The remaining two from urban China examined intervention periods of 2 days to 2 weeks with baseline PM2.5 levels of 95 and 60 $\mu g/m^3$, respectively. The first of these is worth emphasizing: Chen et al. (2015) found that just 48 hours of air purifier exposure produced measurable cardiopulmonary benefits in healthy young adults living in severely polluted Chinese dormitories, including improvements in inflammatory, thrombogenic, and vasoconstriction biomarkers, lung function, blood pressure, and fractional exhaled nitric oxide.

3 Impact of Air Purifiers on Worker Productivity and Firm Profits

Our first experiment, conducted from April 1, 2023, to March 31, 2024, involved 124 microenterprises within the RMG manufacturing sector at two sites in the Greater Dhaka district: Kamrangirchar and Narayanganj. To select these firms, we carried out a listing survey targeting firm owners who expressed interest in participating and compensated their workers on a piece-rate basis. We then applied several criteria for inclusion in the study: firms needed to maintain and be willing to share daily worker-level output records; their production facilities had to be no larger than 1500 square feet, which is the recommended size for the air purifiers used in the study; they must use individual production methods that are not automated to facilitate matching of output to specific workers; and they could not experience more than 20 hours of power outages per week. After excluding firms that did not meet these criteria, we were left with a sample of 124 firms. Figure A.1 shows the location of each of the 124 firms in our sample. Table A.1 presents the baseline characteristics of these firms.

3.1 Sample Characteristics

Firms in our sample, typical of the microenterprises in the RMG manufacturing sector, generally employ about 10 workers, with a workforce composition of 80% male and 20% female. The standard workweek is six days, with Friday off.

The individual production methods employed by microenterprises in our sample contrasts sharply with larger firms' assembly lines, where garment production is segmented among approximately 65-70 workers, each specializing in a specific part of the garment, such as sleeves or collars for shirts.[9] In line production, materials for about 10-20 garments are processed in bundles through each segment of the line, and the product systematically moves from one station to the next until completion. In contrast, in our microenterprises, each worker is responsible for independently completing the entire garment or a specific component of the garment and does not follow a fixed sequence or have a fixed location within the factory. That is, workers are not arranged in a vertical formation; they may be dispersed throughout the facility, working at their own pace; and upon completing their task, workers have the option to leave or move to another firm, offering flexibility not present in line production setups.

The product range in these enterprises is diverse, including t-shirt, underwear, shirt, one-piece garment (e.g., nightgowns), two-piece garment (e.g., salwar kameez), pants, and burkha. Orders dictate production volumes for most firms, with each firm tailoring its output accordingly. In turn, orders are heavily influenced by seasonal demand, typically peaking before Eid-ul-Fitr between February and April, and macroeconomic conditions.

Operational conditions in these microenterprises are characterized by modest facilities. The average production floor measures about 500 square feet, typically equipped with one door and three windows, which are kept open for ventilation. Electricity supply is erratic, with up to roughly 6 power cuts per week, with an average duration of 40 minutes.

Every firm in our sample maintains daily worker-level records (Table A.2).[10] These records include details of output, product produced, piece rate, breaks, rejected pieces, and work hours. Workers typically work for 9 to 12 hours, with the vast majority of firms operational between 9 AM and 6 PM. Workers take two breaks totaling approximately 120 minutes each day.

In terms of staff roles, the vast majority of employees are operators focused on sewing. The remaining employees serve as helpers, who are responsible for support tasks such as folding, aligning, and material feeding, or cutting or pattern masters, who are responsible for the fabric cutting, layout, and design. A typical firm in our study employs two helpers and one cutting or

[9] See Figure A.2 for an example of production layout in a treatment firm.

[10] Only 6% of 124 firms in our sample did not share any daily records before leaving the study. 14% of firms in our sample did not use the air monitor at any point before leaving the study. 19% of firm owners never participated in the monthly telephonic owner survey.

pattern master. Lastly, few factory floors have a dedicated manager, as managerial responsibilities are typically handled by the owner or a family member.

Both helpers and cutting or pattern masters typically receive fixed weekly or monthly salaries. Operators, however, are compensated on a piece-rate basis that varies significantly between product types, reflecting differences in time and effort required (Figure A.3).

For example, operators producing underwear earn approximately 1.75 BDT per piece and manufacture over 350 pieces daily, while operators producing two-piece garments earn about 45 BDT per piece but produce only 20 pieces daily. This inverse relationship between piece rate and daily output is consistent across products: garments that can be sewn quickly with less effort command lower piece rates but allow for higher daily production volumes. As a result, despite the 25-fold difference in piece rates between underwear and two-piece garments, the gap in daily earnings is much narrower—approximately 550 versus 750 BDT.[11]

Even within product categories, piece rates vary substantially based on the specific requirements of types and components (Figure A.4). Among workers responsible for manufacturing the entire product, where a piece is the entire garment, those handling more labor-intensive variations produce fewer units daily but receive proportionally higher piece rates. For instance, operators manufacturing two-piece garments earn different rates depending on skill requirements—those working on garments with specialized techniques like fine embroidery (zari-work) receive higher piece rates to compensate for the additional time required. Similarly, among workers tasked with manufacturing specific components of a product, those handling more labor-intensive components produce fewer units daily but receive proportionally higher piece rates. For example, t-shirt production involves eight distinct components (sleeve joints, collar, side joints, cuffs, hem, and armholes), each with its own piece rate reflecting its complexity (Figure A.5).

Our study focuses on the productivity of operators, who constitute the bulk of employment within these firms and whose output is systematically recorded every day on the factory floor. For all other types of workers, we do not observe any measures of output or productivity, so we cannot estimate the effects of air purifiers on their output or productivity.

Overall, between April 1, 2023 and March 31, 2024, firms in our control group operated for an average of 231 days (Figure A.6). Firms that remained operational through the end of our intervention (March 31, 2024) averaged 256 operational days, reflecting the exclusion of firms that shut down temporarily or permanently during the study period.[12] More striking is the se-

[11] This translates to roughly 19,000 BDT per month for an operator exclusively producing underwear, which exceeds the minimum wage for garment workers in Bangladesh, set at 12,500 BDT per month.

[12] While the three-week October-November 2023 garment worker protests disrupted operations across our sample firms (Al Jazeera, 2023), the impact was limited: firms that remained operational through March 2024 averaged 256 operational days, only slightly below the 266 days recorded for 2,500 RMG manufacturing firms in the same areas during the calendar year 2024 (Experiment 2).

vere worker turnover in this sector. Operators typically work at the same firm for only 45 days per year, indicating that most workers stay for just 1-2 months before moving to other factories.[13] Correspondingly, the operator-to-operational days ratio for the typical firm is around 0.2, meaning firms employ approximately 5 different operators for each full-time equivalent position annually. This extreme transience reflects the sector's order-driven production model and flexible hiring practices, where workers routinely move between firms as specific tasks or orders are completed.

3.1.1 Research Design, Data Collection, and Balance

Intervention. We procured 100 air monitors, and 50 air purifiers with smart plugs for our intervention. Then, we randomly divided the 124 firms in our sample into four groups: two main groups of 50 firms each (treatment and control), and two smaller buffer groups of 12 firms each (treatment buffer and control buffer). That is, firms within the smaller groups were randomly ordered and designated as sequential replacements to account for any attrition, because a firm temporarily or permanently shut down, from the 50 firms in both the main treatment and control groups (Figure A.7).[14]

On April 1, 2023, we equipped all 100 firms from the main treatment and control groups with air quality monitors that measure indoor PM2.5 levels, displaying the readings in micrograms per cubic meter ($\mu g/m^3$) on a small screen (Figure A.8).[15] Our field team assisted in setting up these monitors and ensuring they were connected to WiFi for data transmission. Firms were provided with a WiFi dongle, solely for transmitting data from our devices. Importantly, on the same date, we installed the the "Blast Mk II Air Purifier" from Smart Air in each of the 50 firms from the main treatment group (Figure A.9).[16] At the time of the study, the purifier retailed at BDT 70,000 (approximately USD 600), equivalent to about one month's average profit for firms in our sample. Each air purifier was connected to a smartplug (Figure A.10), enabling us to directly monitor their minute-by-minute usage. Our field team removed all devices from the firms still participating in our sample on April 1, 2024.

Our experimental design estimates the effect of air purifiers conditional on air quality moni-

[13] We used worker names to generate unique worker identifiers.

[14] In our core analysis, we will combine the two treatment and control groups, respectively, since we used all the buffer firms during the course of the intervention. However, our results are not sensitive to the exclusion of the buffer treatment and control groups.

[15] We purchased 86 Qingping Lite monitors, a model that has performed well in tests in other highly polluted environments: https://smartairfilters.com/en/blog/how-accurate-are-qingping-qp-pm2-5-air-quality-monitors/. Additionally, we deployed 14 Kaiterra Laser Egg monitors, which were leftovers from our pilot conducted before COVID in January 2020 and have now been discontinued: https://support.kaiterra.com/laser-egg-discontinued. We randomly assigned whether Kaiterra or Qingping monitors were installed in each firm.

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

toring, as both treatment and control firms received air monitors. This design choice strengthens our causal interpretation in key ways. First, it eliminates differential monitoring effects unrelated to purifier use between treatment and control groups, for example, if seeing pollution levels motivates firms to improve ventilation or adjust work schedules. Second, the monitors allow targeted purifier usage: we find that treatment firms use purifiers more intensively when pollution is worse, a behavioral response that might not occur without air quality feedback. In a purifier-only design, firms might run purifiers constantly (wasting electricity) or insufficiently (missing productivity benefits), whereas our design captures the effect when firms can optimize usage based on need. Third, if control firms responded to high pollution readings by implementing other mitigating behaviors, this would bias our estimates downward, making our results conservative. The fact that we still find large productivity gains suggests that behavioral responses to pollution information alone are insufficient substitutes for air purification technology. Our estimates should therefore be interpreted as the effect of air purifiers when firms can monitor and respond to air quality levels, a common feature in many commercial models.

To address the electricity costs from using air purifiers, we compensated the treatment firms. However, we did not encourage the use of air purifiers. Each firm received a *flat* 500 BDT (4.25 USD) per month, with average compensation calculated at the commercial electricity rate of 16 BDT (0.14 USD) per kWh, based on the wattage range used by the devices. Although this approach was designed to closely match the actual electricity expenses tracked via smart plugs and prevent attrition due to under-compensation of electricity costs, firms faced the full marginal cost of electricity—thereby maintaining real-world incentives. In fact, treatment firms were overcompensated to cover the additional electricity costs of using air monitors. Payments were made monthly, with the electricity cost compensation for a typical treatment firm amounting to less than 0.3% of their total monthly production costs. Control firms, in contrast, received 150 BDT (1.28 USD) per month to cover the electricity costs associated with air monitor usage. Both treatment and control firms received these compensations regardless of whether they actually used the air purifier and/or air monitor.

Lastly, we provided each firm owner in our study with an incentive to share photographs of their daily worker-level productivity data via WhatsApp. All 124 firms received 50 BDT (0.43 USD) for each day they shared their records. This strategy was designed to encourage consistent participation and ensure compliance throughout the experiment. Payments were distributed monthly. The monthly incentive payments received by a typical firm in our sample amounted to less than 0.8% of their monthly production costs.

Data collection. We collected data from multiple sources. Initially, we conducted a baseline survey with all 124 firms involved in the study. Following this, we collected detailed daily worker-

level productivity data and monthly firm-level revenue and cost data from these firms. In addition, we monitored indoor air pollution continuously at the hour-by-firm level using air quality monitors installed within each enterprise. We also installed outdoor air pollution monitors in the study areas to assess environmental conditions externally. Lastly, we tracked the usage of air purifiers at each firm minutely through smart sockets connected to these devices.

Baseline survey. In December 2022, we conducted a comprehensive baseline survey with all 124 firms in our sample. This survey, carried out with the firm owners, gathered detailed information on factory space, such as production floor size and ceiling height; worker characteristics, including the number of workers and the proportion of male and female workers; compensation mechanisms, such as whether workers were paid by piece rates; product types ranging from basic T-shirts to more complex garments like burkhas and salwar kameez; and operational specifics, such as typical workdays, electricity availability, and power cuts.

Daily worker-level productivity. Starting intermittently in February 2023, and continuing until March 31, 2024, all firms provided daily worker-level records. These records included work hours, worker breaks, products produced, output generated, units rejected, and piece rates. The daily records also contained information on power cuts and number of workers by designation.

Monthly firm-level data. We conducted a monthly telephonic survey with firm owners from October 2023 to March 2024 to collect information on production costs and revenues for the preceding month. In the initial October 2023 survey, we also requested recall data on monthly production costs and revenues from February 2023 to September 2023.

Indoor air pollution. We collected indoor air pollution data via monitors installed in all firms in our sample. These devices were designed to record and transmit hourly data on PM2.5, PM10, temperature, and humidity to our server. Data collection from these air monitors spanned from April 1, 2023, to March 31, 2024.

Outdoor air pollution. In both study regions, we installed outdoor air pollution monitors in late August 2023, which provided us with hourly PM2.5 level data until March 31, 2024.[17] Additionally, we accessed hourly outdoor environmental data from the US embassy in Dhaka, located less than 25 kilometers from both Kamrangirchar and Narayanganj (Figure A.11), covering the

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

period from April 1, 2023, to March 31, 2024.[18]

Air purifier use. Each air purifier was connected to a smart plug. The smart plugs were connected to WiFi and recorded electricity usage of the device connected to them and pushed data onto the server on how many watts were used by the plug each minute. We classify electricity usage between 40 and 160 watts as indicative of air purifier operation. Figure A.12 shows that while smart plugs were occasionally used with other devices, the vast majority of readings were consistent with the manufacturer's specifications for air purifier consumption at each speed setting. Importantly, because air purifiers could be used without smart plugs, our data captures only a lower bound of actual air purifier usage.

Balance. First, we show that the firm characteristics are balanced across treatment and control firms (Table A.3). Notably, the dropout rate—8% of control firms did not share any air worker records—is consistent across both groups, showing no statistically significant difference. The magnitude of the difference is also small: 5 control firms exited without sharing any daily records compared to 2 treatment firms. Similarly, 16% of control firms exited the project without ever sharing air monitor data, but this rate does not statistically differ between the treatment (7 firms) and control groups (10 firms). Lastly, 19% of control firm owners never responded to the monthly owner survey, with a similar non-response rate of 18% among treatment firm owners.

Daily worker-level data. Second, we examine the frequency with which treatment and control firms were open and shared their daily worker-level records (Figure A.13). Several points stand out: First, on no day did we receive daily worker records from all 124 firms. This was either because there was no day when all firms were open, or because some firms temporarily or permanently closed operations. Second, as mentioned earlier, starting intermittently in February 2023 and continuing until March 31, 2024, 117 firms provided daily worker-level records on at least one day. Third, almost no firms operated during the holidays for the two Eid festivals: Eid-ul-Fitr in late April and Eid-ul-Adha in late June to early July. This is typical for MSMEs in Dhaka. Fourth, as expected, significantly fewer firms were open on Fridays every week (due to religious observance), and therefore, did not provide worker data on those days.

Third, we find no evidence that treatment firms were more or less likely to share daily worker-level records than control firms (Table A.4).[19] Furthermore, the baseline characteristics of treat-

[18]We also downloaded hourly outdoor temperature, precipitation, and humidity data for Dhaka from Visual Crossing. For more information, see https://www.visualcrossing.com/.

[19]We secured complete records for all operational days. Therefore, this result also indicates that treatment and control firms had similar overall operational rates. However, operational status may be an outcome rather than a balance variable. Indeed, while aggregate operational rates were similar, as we show later, monthly patterns differed

ment firms that shared their daily records largely resembled those of control firms that did the same. However, there were a few differences: treatment firms that shared daily records were more likely to be engaged in shirt manufacturing than control firms that shared their daily records. Similarly, treatment firms that shared daily records had slightly larger floor sizes. Nevertheless, the p-value of the joint test is 0.34, indicating no significant difference between baseline characteristics of treatment and control firms that shared daily records.

Finally, roughly the same number of treatment and control firms were operational on the final day of the intervention (March 31, 2024): 36 control firms and 37 treatment firms.

Hourly air monitor data. Third, not all open firms turned on their monitors at some point during the day, but the daily pattern of use of air monitors closely followed the daily pattern of firm openings and closings (Figure A.14). However, we find that treatment firms were less likely to turn on their air monitors compared to control firms (Table A.5). Nevertheless, the baseline characteristics of treatment firms that did activate their monitors closely resembled those of control firms that did likewise. The p-value of the joint test is 0.13, indicating no significant difference between the baseline characteristics of treatment and control firms that turned on their air monitors. Furthermore, we demonstrate that when accounting for the approximately 12,000 hours (4% of total hours for which smartplug data is available for treatment firms) during which purifiers were turned on, as indicated by smartplug data, but indoor monitors were turned off, there is no statistical difference in the availability of any monitoring data (air monitor or smart plug) between treatment and control firms.

Using available outdoor PM2.5 data, and indoor PM2.5 data for control firms, we estimated an infiltration rate of 0.64 between outdoor and indoor PM2.5 levels meaning a reading of 10 $\mu g/m^3$ outdoors would correspond to an indoor reading of 6.4 $\mu g/m^3$. We then used this rate to impute indoor PM2.5 levels for hours when indoor monitors were off for both treatment and control firms, generating data for all but less than 1% of the sample hours for which both indoor and outdoor pollution data were unavailable. It is important to note that we implicitly assume treatment firms are not using air purifiers during hours when the monitors are turned off, even though the smartplug data indicate the purifiers are on, yielding a conservative estimate of the treatment effect. There are no differences in baseline characteristics of control and treatment firms for hours for which we have either observed or imputed indoor PM2.5 values (Table A.6).

Monthly firm-level data. Lastly, we find that non-response to the monthly owner survey is small (roughly 5%) and balanced across treatment and control firms for months when firms

significantly: treatment firms were more likely to operate during high-demand months and less likely during low-demand months. This pattern is consistent with production slack moderating air purifier returns; when firms cannot secure additional orders to capitalize on increased worker productivity, they rationally suspend operations.

were operational and in the sample (Table A.7). Moreover, the baseline characteristics of treatment firms whose owners responded to monthly surveys closely resembled those of control firms whose owners also responded. The p-value of the joint test is 0.39, indicating no significant difference between the baseline characteristics of treatment and control firms whose owners answered the monthly surveys.

3.2 Air Pollution and Purifier Use

3.2.1 Indoor Air Pollution

From April 1, 2023, to March 31, 2024, indoor air pollution monitors across firms in our sample recorded hourly air pollution levels. These monitors reveal persistently high levels of PM2.5, far exceeding the WHO's 24-hour safe limit of 15 $\mu g/m^3$ (Figure 2, Panel (a)). Roughly nine-tenths of hourly PM2.5 levels ranged between 15 $\mu g/m^3$ and 225 $\mu g/m^3$. Only about 11% of hourly readings during this period, almost exclusively in rainy months, were below the WHO 24-hour safe limit.

Our data also show that the 24-hour indoor PM2.5 levels closely tracked the severe ambient air pollution conditions, though they were modestly mitigated indoors (Figure 2, Panel (b)). Alarmingly, fewer than 10 days throughout the year recorded indoor PM2.5 levels below the 24-hour safe limit, with a median 24-hour value at 57.43 $\mu g/m^3$, nearly four times the recommended limit. During the winter months, especially from December to February, the 24-hour indoor PM2.5 levels regularly exceeded 100 $\mu g/m^3$.

Hour-of-day data revealed a pattern of PM2.5 levels peaking late in the evening and dropping to their lowest just before dawn, suggesting that cyclical environmental changes significantly affect air quality (Figure 2, Panel (c)). The average hourly indoor levels by hour-of-day always remained above 50 $\mu g/m^3$ but were about 40 $\mu g/m^3$ lower than the outdoor levels.

Finally, a monthly breakdown of the data corroborates daily patterns, showing sharp increases in indoor PM2.5 levels during the winter documented, particularly from December through February, when the average exceeded 100 $\mu g/m^3$ (Figure 2, Panel (d)). In the months of October, November, March, and April, the levels remained consistently high, above 50 $\mu g/m^3$.

Overall, the annual average indoor PM2.5 level in our sample for 2023-24 was 75 $\mu g/m^3$, which is 15 times higher than the WHO's annual safe limit of 5 $\mu g/m^3$.

3.2.2 Purifier Use

We collected minute-by-minute usage data through smart plugs from April 1, 2023, to March 31, 2024, which show extensive use of air purifiers by treatment firms.[20] Typically, firms started

[20] As mentioned earlier, because air purifiers could be used by firms without smart plugs, our data captures only a lower bound of actual air purifier usage.

operating their air purifiers at 9 am when the factory floors opened (Figure 3, Panel (a)). Usage peaked between noon and 2 pm, with over 40% of firms using their air purifiers during this period. However, usage declined to below 30% by 9 pm and further dropped to under 20% after midnight. Notably, approximately 15% of firms left their air purifiers running overnight.

The daily usage patterns of air purifiers varied significantly throughout the year (Figure A.15, Panel (a)). Usage was highest in March and April, when a typical firm used their air purifiers for more than 8 hours a day (Figure A.15, Panel (b)). In February, September, and November, usage averaged between 7 and 8 hours, while in July, October, and January, it was lowest, at about 3-5 hours per day.[21]

Lastly, we show the number of hours air purifiers were used at the firm-day level (Figure 3, Panel (b)). Most firms, on most days, use the air purifier, with roughly 65% of firm-days seeing some air purifier usage. Firm-level data reveal extensive use (Figure 3, Panel (c)). Over 85% of firms used an air purifier for more than 2 hours daily, with the median firm operating air purifiers between 4 to 6 hours daily, and more than 40% using them for over six hours.

Though we likely capture a lower bound since purifiers could operate without the smartplug we used to monitor their use, several factors may explain why the treatment firms did not use purifier all the time. First, the cultural norm of switching off unused appliances creates cognitive load, requiring someone to remember to turn purifiers back on each day. Second, owners who make technology decisions rarely visit shop floors, delegating implementation to managers – often less experienced family members or fixed-wage employees, who don't internalize productivity gains. Third, consistent usage requires monitoring systems these firms lack. Finally, other operational frictions—power outages, shifting workspaces, or simply forgetting during busy periods—further limit usage. These implementation challenges suggest that even when firms own productivity-enhancing technologies, organizational and behavioral constraints prevent round-the-clock use.

Econometric specification. Next, we examine whether treatment firms respond to higher indoor PM2.5 levels, observable via their air monitor, by increasing their air purifier use. To test this hypothesis, we leverage hour-by-hour variation in outdoor PM2.5 levels, which indoor PM2.5 level track closely, after controlling for seasonal confounders (e.g., religious festivals) and time-of-day confounders (e.g., typical opening hour) common across firms via date and hour-of-day fixed effects, respectively. We also control for site specific confounders that are time-invariant (e.g., distance to city center) via firm fixed effects. That is, we leverage plausibly random hourly fluctuations in outdoor PM2.5 levels. We separately estimate the following linear and non-para

[21] These patterns are consistent with the number of firms that used the air purifier for any amount of time (Figure A.16). Additionally, similar to the data from indoor air monitors, the daily pattern of air purifier usage closely followed the pattern of firm openings and closings.

metric regression specifications:

$$\mathbf{1}(Use)_{iswdhm} = \beta_1(OutdoorPM2.5)_{swdh} + X_{wdh} + \mu_i + \omega_d + \theta_h + \epsilon_{isw} \tag{1}$$

$$\begin{aligned}\mathbf{1}(Use)_{iswdhm} = &\sum_{k=1}^{9} \beta_k \mathbf{1}(50k < OutdoorPM2.5 \leq 50(k+1))_{swdh} \\ &+ \beta_{10}\mathbf{1}(OutdoorPM2.5 > 500)_{swdh} + X_{wdh} + \mu_i + \omega_d + \theta_h + \epsilon_{isw}\end{aligned} \tag{2}$$

where $\mathbf{1}(Use)_{iswdhm}$ is an indicator variable that takes the value 1 if firm i in site s uses the air purifier during week-of-year w on date d in hour h in minute m, 0 otherwise. To test robustness, we generate an alternative version of $\mathbf{1}(Use)_{iswdhm}$ where we assign missing values rather than zeros when the smart plug was not connected, as indicated by missing electricity use data. In Equation (1), $OutdoorPM2.5_{swdh}$ indicates outdoor PM2.5 level for site s during week-of-year w on date d in hour h; β_1 represents the marginal effect of an increase of 100 $\mu g/m^3$ in outdoor PM2.5 levels on air purifier use.

The notation in Equation (2) is the same as in Equation (1). The key difference is our coefficients of interest: $\mathbf{1}(50k < OutdoorPM2.5 \leq 50(k+1))_{swdh}$ is an indicator variable that takes the value 1 if outdoor PM2.5 level for site s during week-of-year w on date d in hour h was between $50k$ and $50(k+1)$ $\mu g/m^3$ for $k \in [1, 9]$. Similarly, $\mathbf{1}(OutdoorPM2.5 > 500)_{swdh}$ is an indicator variable that takes the value 1 if outdoor PM2.5 level for site s during week-of-year w on date d in hour h is greater than 500 $\mu g/m^3$. The omitted category is $\mathbf{1}(OutdoorPM2.5 < 50)_{swdh}$. All other categories are interpreted relative to this category.[22] For example, β_4 is the marginal effect of outdoor PM2.5 levels between 200 $\mu g/m^3$ and 250 $\mu g/m^3$ relative to when these levels are less than 50 $\mu g/m^3$. By estimating this flexible approach we avoid imposing restrictive assumptions on the functional relationship (e.g., linear) between outdoor PM2.5 levels and air purifier use. μ_i, ω_d, and θ_h indicate firm, date, and hour-of-day fixed effects, respectively, in both Equation (1) and (2). We also control for precipitation, outdoor humidity, and outdoor temperature at the date-hour level in both specifications (X_{wdh}).

We cluster standard errors by week-of-year to account for the predominantly seasonal variation in outdoor PM2.5 levels (ϵ_{isw}). The identifying assumption is that hourly outdoor PM2.5 levels are exogenous to unobservable site-specific characteristics that vary over time. The assumption is plausible given the conditional randomness of hour-by-hour changes in outdoor PM2.5

[22] Figure A.17 shows the distribution of outdoor PM2.5 levels across various categories, based on the number of site-hour readings within each range. Approximately 25% of readings showed PM2.5 levels below 50 $\mu g/m^3$; around 35% ranged between 50 $\mu g/m^3$ and 100 $\mu g/m^3$; 15% were between 100 $\mu g/m^3$ and 150 $\mu g/m^3$; 8% fell between 200 $\mu g/m^3$ and 250 $\mu g/m^3$; 3% were between 300 $\mu g/m^3$ and 350 $\mu g/m^3$; and 1% exceeded 500 $\mu g/m^3$.

levels and the inability of firms to predict such fluctuations beyond common spatial features or seasonal trends. Nevertheless, we control for potential firm-specific seasonal confounders and firm-specific hour-of-day confounders via firm-by-date fixed effects and firm-by-hour-of-day fixed effects, respectively, in robustness tests.

Increase in outdoor PM2.5 levels increases air purifier use. We find air purifier usage increased in response to rising outdoor PM2.5 levels (Figure A.18, Panel (a)). Our linear specification finds that an hourly 100 $\mu g/m^3$ increase in outdoor PM2.5 led to a 2 percentage point (7.7%) increase in air purifier usage (Table 1).

Estimates from our non-parametric specification also show that firms actively increased their use of air purifiers as outdoor PM2.5 levels rose (Figure A.19). We find that when outdoor PM2.5 levels ranged from 100 $\mu g/m^3$ to 150 $\mu g/m^3$, firms were 3 percentage points (12.5%) more likely to use the purifier. Between 200 $\mu g/m^3$ and 250 $\mu g/m^3$, they were 4 percentage points (16.67%) more likely, and they were over 6 percentage points (25%) more likely when outdoor PM2.5 levels ranged from 350 $\mu g/m^3$ to 400 $\mu g/m^3$, compared to levels below 50 $\mu g/m^3$. Lastly, their response to pollution spikes, particularly to the most extreme outdoor pollution levels or peaks exceeding 500 $\mu g/m^3$, is significantly more pronounced: firms were 11 percentage points (45.83%) more likely to use the purifier when outdoor PM2.5 levels were above 500 $\mu g/m^3$, compared to levels below 50 $\mu g/m^3$. Our findings remain stable when accounting for firm-by-date and firm-by-hour-of-day fixed effects.

Overall, compared to levels below 50 $\mu g/m^3$, usage significantly increases when outdoor PM2.5 levels rise above 100 $\mu g/m^3$, then somewhat stabilizes until PM2.5 levels reach 300 $\mu g/m^3$, after which it jumps again, suggesting a stronger response by firms to pollution spikes.

Finally, our estimates from both the parametric (linear) and non-parametric specifications are robust to excluding, rather than zeroing out, observations with missing smart plug energy use data (Figure A.18, Panel (b); Figure A.19; Table A.8).

3.3 Impact of Purifier Installation on Indoor Air Pollution

In this section, we investigate the impact of air purifiers on indoor PM2.5 levels in treatment versus control firms.

Econometric specification. We exploit the random variation in air purifier assignment across firms, and estimate the difference in indoor PM2.5 levels between treatment and control firms on days they were open. Our preferred approach leverages differences in indoor PM2.5 levels between treatment and control firms in the same site via site fixed effects, while controlling for

seasonal and time-of-day fluctuations (e.g., in outdoor air pollution) that could influence indoor PM2.5 levels via date and hour-of-day fixed effects, respectively. We estimate the following regression specification:

$$IndoorPM2.5_{isdh} = \beta_1 Treatment_i + \mu_s + \omega_d + \theta_h + \epsilon_i \quad (3)$$

where $IndoorPM2.5_{isdh}$ captures the indoor PM2.5 levels as measured by indoor air pollution monitors in firm i located in site s on date d in hour h. We impute indoor PM2.5 levels for days when indoor monitors were turned off but firms were open: using available hourly outdoor PM2.5 data, and hourly indoor PM2.5 data for control firms, we estimated an infiltration ratio of 0.64 between outdoor and indoor PM2.5 levels. We then used this rate to impute indoor PM2.5 levels for hours when indoor monitors were off but firms were open, generating data for all but less than 1% of the sample hours for which both indoor and outdoor pollution data were unavailable. The embedded assumption here is that purifier was also turned off during hours when the treatment firms were open but the monitor was off, yielding a conservative estimate of the treatment effect. We will show that our estimates remain qualitatively robust to restricting the sample to observations where indoor air monitors were turned on.

$Treatment_i$ takes the value 1 if firm i was randomly assigned to receive an air purifier, either as part of the main treatment group or the buffer treatment group, and 0 otherwise. β_1 represents the effect of the air purifier installation on indoor PM2.5 levels. μ_s, ω_d, and θ_h represent fixed effects for site, date, and hour-of-day, respectively. Finally, we cluster standard errors at the firm level (ϵ_i). We demonstrate that our results are not sensitive to the exclusion of site, date, and hour-of-day fixed effects; we also confirm that they are robust to the inclusion of date-by-hour fixed effects.

Falsification test. Before we estimate Equation (3), we confirm that there are no differences in indoor environment (temperature and humidity) between treatment and control firms on days they are open (Table A.9).

Air purifier installation decreases indoor PM2.5 levels. We find evidence for significantly lower indoor air pollution in treatment firms compared to control firms. Treatment firms saw hourly indoor PM2.5 levels drop to 63.55 $\mu g/m^3$—a 14.65% improvement over the 74.46 $\mu g/m^3$ recorded in control firms. Our estimates are robust to the exclusion of site, date, and hour-of-day fixed effects, as well as to the inclusion of date-by-hour fixed effects (Table 2, Panel A).

To ensure that our estimates are not influenced by the approximately 15% of treatment firms that use air purifiers overnight when closed, we also estimated impacts on hourly PM2.5 lev-

els during typical work hours (9 am to 6 pm), when the vast majority of firms are operational. We find that our estimates are slightly larger—treatment firms saw hourly indoor PM2.5 levels between 9 am and 6 pm decrease by 12.69 $\mu g/m^3$, which represents an 18.11% improvement compared to the 70.08 $\mu g/m^3$ recorded in control firms (Table 2, Panel B). Restricting the sample to the main treatment and control groups, that is excluding the buffer groups, does not appreciably alter our findings (Table A.10).

Figure A.20 shows the difference in PM2.5 levels between treatment and control firms by hour of day. The level effects are largest—approximately 15 $\mu g/m^3$—between 12 pm and 9 pm. This pattern closely correlates with average hourly indoor PM2.5 levels in control firms ($\rho \approx 0.43$), consistent with increased purifier use when indoor PM2.5 levels are worse, as observed via air monitors. The correlation is even stronger when excluding 10 pm to 8 am ($\rho \approx 0.87$), when most firms are not operational.

We also show that our results are qualitatively robust but somewhat larger when we restrict our sample to observations for which indoor air pollution monitors were turned on (Table A.11, Panel A). Specifically, we find that treatment firms experienced a reduction in hourly indoor PM2.5 levels by 18.91 $\mu g/m^3$—a 23.59% improvement over the 80.16 $\mu g/m^3$ recorded in control firms. The corresponding estimate for hourly PM2.5 levels between 9 am and 6 pm was 20.29 $\mu g/m^3$, which is a 26.19% improvement (Table A.11, Panel B).

Month-by-month estimates. Finally, we examine the month-by-month impacts of air purifier installation on indoor PM2.5 levels (Figure A.21). We find that the effects are highest in the winter months, especially in January and February: for instance, between 9 am and 6 pm, indoor PM2.5 levels in treatment firms are roughly 38 $\mu g/m^3$ lower than in control firms. Between September and December, and from March to April, the decrease in PM2.5 levels is about 8-16 $\mu g/m^3$. In May and August, we observe a roughly 6 $\mu g/m^3$ decrease, and there are no effects in June and July.[23] These patterns are strongly correlated ($\rho \geq 0.94$) with average monthly indoor PM2.5 levels in control firms throughout the year (Figure A.21, Panel (d)), which is exactly what one would expect if purifier usage—affected by indoor PM2.5 levels, as observed via air monitors—were driving the variations in these month-by-month impacts.

3.4 Impact of Purifier Installation on Labor Productivity

In this section, we investigate the impact of air purifiers on worker productivity in treatment versus control firms.

[23]Our estimates also remain consistent when we limit the analysis to observations where indoor air pollution monitors were turned on (Figure A.22).

Econometric specification. We exploit the random variation in treatment assignment across firms; we estimate the difference in log output at the worker-date level for the same product type between treatment and control firms on days they were open. Our preferred method leverages differences in log output for the same product type, using product and piece rate fixed effects, and controls for time-invariant site-specific characteristics with site fixed effects. Moreover, we account for seasonal variations (e.g., in outdoor air pollution or temperature) that could affect worker productivity using date fixed effects. We estimate the following regression specification:

$$LogOutput_{jprisd} = \beta_1 Treatment_i + \alpha_p + \gamma_r + \mu_s + \omega_d + \epsilon_i \quad (4)$$

where $LogOutput_{jprisd}$ captures output, as captured by daily worker-level records, for a worker j producing product p for piece rate r in firm i located in site s on date d. $Treatment_i$ takes the value 1 if firm i was randomly assigned to receive an air purifier, either as part of the main treatment group or the buffer treatment group, and 0 otherwise. β_1 represents the effect of the air purifier installation on worker output. α_p and γ_r represent fixed effects for product and piece rate, respectively, to ensure that we are comparing daily worker-level output between treatment and control firms for the same product.[24] μ_s and ω_d represent fixed effects for site and date, respectively. Finally, we cluster standard errors at the firm level (ϵ_i). We demonstrate that our results are not sensitive to the exclusion of site and date fixed effects; we also confirm that they are robust to the inclusion of site-by-date fixed effects.

Falsification test. Before we estimate Equation (4), we confirm that there are no differences in product types produced, piece rates, or electricity access between treatment and control firms on days they are open in both the pre- and post-periods (Table A.12; Table A.13). This is consistent with the market setting: production is order-dependent and relies on exogenous factors. Piece rates are consistent across the market and set based on the time and effort required for each garment or component. Furthermore, output data was missing for roughly 3-5% of the sample, and this rate is not differential between treatment and control firms. The likelihood of producing other products and power cuts was higher in treatment firms in the post-period, but the p-value of the joint test is 0.37, indicating no significant difference in daily production characteristics between treatment and control firms.

Air purifier installation increases worker productivity. We find that workers in treatment firms produce greater output than those in control firms. Specifically, workers in treatment firms

[24] As previously mentioned, operators are compensated based on the piece rate, which varies significantly both between and within different product types. This variation reflects the differing time and effort required, with fewer units produced per worker-date for product types and subtypes that command higher piece rates.

produce 10% more units per day than those in control firms (Table 3, Panel A). Our estimates are robust to the exclusion of site and date fixed effects, as well as to the inclusion of site-by-date fixed effects.[25] Furthermore, as expected, our findings are qualitatively and quantitatively robust to restricting the sample to the main treatment and control groups (excluding the buffer groups) (Table A.15).

Importantly, before the intervention started on April 1, 2023, there was no difference in output between workers in treatment and control firms during February and March—impacts were both close to zero and statistically insignificant. This stands in stark contrast to the 23% increase in output observed in treatment firms during the same months in 2024 (Table 3, Panels B and C).

We find no average differences in the number of operational days, number of daily workers, or worker hours between treatment and control firms (Table A.16). We also find no evidence of differences in the number of breaks taken or the minutes spent on breaks. Overall, this suggests that the increase in output indicates an improvement in labor productivity. Furthermore, we find no impact on rejection rates, which is not surprising since the daily rejection rate per worker for control firms is only about 2%.

We also examine impacts on hourly wages (Table A.17). To calculate hourly wages, we first multiply each worker's daily output by their piece rate for that day, then divide by hours worked. Consistent with increased output and unchanged work hours, we find that hourly wages for workers in treatment firms are 12% higher than those in control firms.

Month-by-month estimates. Lastly, we examine the month-by-month relationship between air purifier installation and worker productivity. We find that the impacts are greatest in March (28%), followed by February (18%), and April (16%) (Figure A.23, Panel (a)). Between November and January, as well as in May, June, and September, the improvement in worker productivity is between 7-10%. In August, we observe a roughly 6% increase, while no effects are observed in July and October.

Correlation with market-level production. Interestingly, these patterns are almost perfectly correlated with monthly market-level production ($\rho \approx 0.89$), as proxied by production costs in control firms (Figure A.23, Panels (b) and (c)). This is consistent with production slack due to seasonal demand patterns moderating the productivity returns of air purifiers. That is, in treatment firms, workers complete their tasks faster compared to control firms. When demand for ready-made garments is high, treatment firm owners can secure additional orders to take advantage of their workers' increased speed, leading to the observed increase in output. However,

[25] We also show that our results are quantitatively robust when restricting the sample to observations where indoor air pollution monitors were turned on (Table A.14). This reinforces previous evidence that production on days when firms were open but air purifiers were turned off was no different than on days when firms were open but air purifiers were turned on.

when demand is low, treatment firm owners may be unable to procure sufficient additional orders, limiting the extent to which faster task completion translates into higher output.

This interpretation aligns with month-by-month operational differences between treatment and control firms (Figure A.24). We find no differences in work hours or piece rates, which is expected in this market setting where full-day work is the norm and piece rates are standardized across firms based on garment complexity (Figure A.24, Panels (a) and (b)). However, we do observe strategic operational adjustments (Figure A.24, Panels (c) and (d)): more treatment firms tend to remain open during high-production months and more treatment firms close during low-production months. This pattern is consistent with our interpretation: when workers complete tasks faster but owners cannot secure enough additional orders to capitalize on this increased speed, firms choose to suspend operations.[26] Furthermore, treatment firms employ fewer workers during some low-production months compared to control firms, suggesting further operational adjustments to manage the productivity-demand mismatch.

Correlation with air pollution levels. The correlation between monthly productivity estimates and air pollution levels, as proxied by indoor air pollution in control firms, is also positive and large ($\rho \approx 0.44$), though smaller than the correlation with production levels (Figure A.23, Panel (d)). This is consistent with increased air purifier use when indoor air pollution levels are higher. Indeed, when we examine heterogeneous effects on labor productivity by outdoor air pollution levels, we find that air purifiers have larger productivity effects when outdoor air pollution is worse (Table A.18). This dose-response relationship, where treatment effects scale with pollution exposure, is inconsistent with Hawthorne or placebo effects, which would not vary systematically with pollution levels.

3.5 Impact of Purifier Installation on Firm Profits

In this section, we examine whether the labor productivity gains observed in treatment firms translate into higher profits relative to control firms. Given that labor productivity increases are significantly larger during months with higher demand for ready-made garments, we expect profit effects to follow a similar pattern.

Econometric specification. To test this, we exploit the random variation in air purifier assignment across firms; we estimate the difference in monthly profits between treatment and control firms for months they were operational. Our preferred specification leverages variation in firm profits among firms with similar baseline characteristics; we also control for product mix using

[26] These effects are robust to excluding firms that temporarily or permanently shut down before the end of the intervention on April 1, 2024 (Figure A.24, Panel (e)).

product type fixed effects and account for time-invariant site-specific factors with site fixed effects. Lastly, we include month fixed effects to control for seasonal variations in demand and other temporal factors that could influence firm profits. We estimate the following regression specification:

$$Profit_{ipsm} = \beta_1 Treatment_i + \mathbf{X}_i + \alpha_p + \mu_s + \omega_m + \epsilon_i \tag{5}$$

where $Profit_{ipsm}$ captures profit (in BDT), as recorded in the monthly owner surveys, for firm i producing product mix p located in site s for month m. $Treatment_i$ takes the value 1 if firm i was randomly assigned to receive an air purifier, either as part of the main treatment group or the buffer treatment group, and 0 otherwise. β_1 represents the effect of the air purifier installation on firm profits. $\mathbf{X}_i$ includes controls for the following baseline firm characteristics: monthly profit (in BDT), weekly output (# of units), and floor area (in sq ft). α_p represents product-type fixed effects for products manufactured in any given month, ensuring that we compare profits between treatment and control firms with the same product mix. μ_s and ω_m represent fixed effects for site and month, respectively. Finally, we cluster standard errors at the firm level (ϵ_i). We demonstrate that our results are not sensitive to the exclusion of site and month fixed effects; we also confirm that they are robust to the inclusion of site-by-month fixed effects.

Air purifier installation increases firm profits. We find that treatment firms generate higher profits than control firms (Table 4, Panel A). Specifically, treatment firms earn approximately BDT 11,000 more in monthly profits than control firms, representing a roughly 18% increase. While our preferred specification yields marginally significant results (p-value = 0.11), the estimates become statistically significant and remain quantitatively similar when we exclude site and/or month fixed effects. Our estimates also remain quantitatively similar when we include site-by-date fixed effects.[27]

Importantly, before the intervention began on April 1, 2023, there was no difference in profits between treatment and control firms during February and March—effects were both close to zero and statistically insignificant. This contrasts sharply with the statistically significant increase of approximately BDT 26,000 (nearly 40%) in monthly profits observed in treatment firms during the same months in 2024 (Table 4, Panels B and C).

Higher profits result from increased production efficiency: air purifiers enable workers to produce more output, allowing firms to fulfill existing orders faster and take on additional orders. The revenue from this expanded production exceeds the marginal costs (Tables A.20 and A.21).

[27]Our findings are qualitatively and quantitatively robust to restricting the sample to the main treatment and control groups (excluding the buffer groups) (Table A.19).

Month-by-month estimates. Lastly, we examine the month-by-month relationship between air purifier installation and firm profits. Closely mirroring our month-by-month productivity estimates, we find that the effects are largest in February (approx. BDT 30,000 or 48%) and March (approx. BDT 24,000 or 35%) (Figure A.25, Panel (a)). In April and June, as well as September through December, firm profits increased by double digits. However, no effects are observed in January, May, July, or August.

These patterns are highly correlated with monthly market-level production ($\rho \approx 0.56$), as proxied by production costs in control firms (Figure A.25, Panel (b)), consistent with production slack moderating returns to air purifier investment. That is, returns on air purifier investment are highest when firms have little production slack but evaporate when faster production cannot be monetized by procuring additional orders. These estimates are even more strongly correlated with month-by-month productivity estimates ($\rho \approx 0.70$) (Figure A.25, Panel (c)).

4 Barriers to Demand for Air Purifiers

Our first experiment reveals that air purifiers generate substantial productivity and profit gains for RMG manufacturing firms in Bangladesh. Treated firms achieved sustained reductions in indoor air pollution, resulting in a 10% increase in daily output per worker and an 18% (BDT 11,000) increase in monthly profits. Effects peaked during the high-production months of February and March, with productivity rising 23% and profits increasing 39% (BDT 26,000).

These returns far exceed the device cost of BDT 70,000. Firms could recover their full investment through profits from three high production months. Yet adoption remains virtually nonexistent: of 2,500 firms we contacted in late January to early March 2025, fewer than 10 owned air purifiers. This stark gap between profitability and adoption is puzzling: why do firms fail to invest in a technology with such demonstrably high returns? To explore this, we conducted a second experiment measuring firms' willingness to pay (WTP) for air purifiers and examining barriers to demand.

4.1 Sample Characteristics

Unlike the first experiment, we imposed no restrictions on firm selection beyond requiring that they operate in the RMG manufacturing sector at two sites in the Greater Dhaka district: Kamrangirchar and Narayanganj.

Despite this difference in sampling criteria, the two samples exhibit similarity in observable characteristics (Table A.22). The vast majority of firms use piece-rate compensation and individual production methods, with only 11% employing automated production. The median firm

employs 9 workers, predominantly operators, mirroring our earlier sample. Infrastructure challenges persist: few firms have access to uninterrupted power, with the median firm experiencing 5 power cuts per week, each lasting approximately 30 minutes.

The samples do differ in one notable dimension: physical space. Firms in the second experiment occupy larger facilities, with an average floor size of approximately 900 square feet compared to 500 square feet in Experiment 1. This difference is expected, given that we removed the 1,500-square-foot ceiling restriction applied in the first experiment.

The product range remains diverse, encompassing t-shirts, underwear, shirts, one-piece garments (such as nightgowns), two-piece garments (such as salwar kameez), pants, and burkhas.

Production variability. As in the first experiment, customer orders drive production volumes in these firms, with output fluctuating based on seasonal demand—peaking before Eid-ul-Fitr between February and April—and year-over-year variability due to broader market conditions.

Indeed, 78% of firm owners acknowledged seasonality in production. When asked to identify high and low production months in a typical year, owners most frequently cited January through April as peak months and July through November as low production periods (Figure A.26). This pattern aligns with the seasonality observed in monthly production costs amongst control firms in Experiment 1, which we used as a proxy for market demand. Firm owners attributed this seasonality primarily to fluctuations in orders and customer demand.

Furthermore, 60% of owners reported year-over-year variability in production. Again, broader market demand emerged as the leading cause of this variability, followed by political instability.

Beliefs about impacts on profits. We also surveyed firm owners about their beliefs regarding impact of consumer-grade air purifiers on profits, revealing strikingly heterogeneous views (Figure A.27). Twenty percent admitted uncertainty about profit effects, another 20% believed purifiers would not increase profits, and 5% expected profit gains but could not estimate the magnitude. Among the remaining 55% who expected specific profit increases, most predicted gains of 5% or 10%, much lower than the estimates 18% increase observed in Experiment 1, while roughly 25% of all firms anticipated increases between 15% and 50%.

Firm owners who expected no profit gains cited two primary reasons: first, they argued that profits depend on production orders, making purifiers irrelevant during periods with few orders; second, they doubted air purifiers were necessary for productivity improvements.

These heterogeneous beliefs, combined with owners' explicit recognition that returns depend on order availability, suggest that firms understand how production seasonality shapes purifier profitability—a key insight from our first experiment. That is, owners appear acutely aware that slack capacity during low-demand periods would limit purifier returns, and underestimate the

returns during high-demand periods.

4.2 Research Design

To elicit valuations under real financial stakes, we implemented a Becker-DeGroot-Marschak (BDM) mechanism during the peak production months: late January to early March. This timing was strategic for three reasons. First, interventions enabling low-risk experiential learning would have maximum impact during high-production months when returns are greatest. Second, firms face greater liquidity constraints during busy periods, making credit-based interventions more salient. Third, we needed to complete surveying before Ramadan fasting began, which could affect response rates.

Each firm owner was informed that the market price of the air purifier was BDT 70,000 and asked to state their maximum willingness to pay.[28] A lottery price was then randomly drawn from a known distribution using a tablet. If the firm's bid equaled or exceeded the lottery price, they could purchase the purifier at the lower lottery price; otherwise, no transaction occurred. This incentive-compatible mechanism ensures truthful reporting as a dominant strategy (Berry, Fischer and Guiteras, 2020), allowing us to estimate the full demand curve across heterogeneous firms. To ensure comprehension of the mechanism, enumerators first conducted a real-stakes practice round using a common production item—a box of threads. The market price of the thread box was BDT 60. Only after confirming understanding during the practice round did we proceed to the air purifier valuation.

Firms were randomly assigned to one of ten experimental groups (250 firms per group), with treatments designed to isolate specific barriers to adoption:

- **Control:** Provides a basic description of the air purifier alongside a picture of the air purifier.
- **T1: Information**: Provides a flyer with a summary of results from the first experiment, emphasizing documented improvements in air quality, productivity, and profits in similar firms from the same device. The flyer clearly identified the research team to build credibility about the information being delivered.
- **T2: Access to Credit**: Provides a contract offering a 12-month loan with 1% monthly interest to finance the purchase. This corresponds to 12% per year, which was very close to the weighted average lending rate for scheduled banks in Bangladesh in February 2025 of 11.92% (CEIC Data, 2025).
- **T3: Access to Credit + Information**: Information provision with access to credit.

[28] This is the same air purifier we installed in treatment firms in Experiment 1.

- **T4: Free Full Warranty**: Provides a free 2-year full warranty contract including scheduled servicing and part (including filters) replacement.
- **T5: Free Full Warranty + Information**: Information with the free full warranty contract.
- **T6: Money-Back Guarantee**: Provides a contract requiring upfront payment but allows returns after one month for a full refund.
- **T7: Money-Back Guarantee + Information**: Information with the money-back option.
- **T8: Free Trial**: Provides a contract requiring no upfront payment, where firms could return the purifier after one month or pay to keep the device.
- **T9: Free Trial + Information**: Information with the free trial.

Trained enumerators visited all firms in person, administering the experiment through a structured, tablet-based protocol. Each visit proceeded in four stages: (i) a brief survey collecting firm characteristics and baseline perceptions of purifier effectiveness, (ii) the practice BDM round to ensure comprehension, (iii) treatment provision and explanation, and (iv) the actual BDM elicitation for the air purifier under the assigned treatment condition.[29]

Random assignment ensures that differences in WTP can be causally attributed to the specific frictions addressed. The factorial design allows separate identification of the following effects:

- Comparing T1 (information only) to Control isolates the pure effect of generalized information. If firms are unsure about technical quality of the device or returns to purifier investment due to lack of credible information, providing experimental results from the same device, demonstrating productivity gains and profit increases for similar firms in the RMG sector, should increase WTP.
- T2 (credit) vs. Control identifies the role of liquidity. Despite high returns, the 70,000 BDT upfront cost may exceed available cash for credit-constrained firms. If WTP increases substantially with credit access, this indicates that financing barriers—rather than low perceived returns—limit adoption. The 12-month loan at 1% monthly interest approximates local lending conditions, making the investment feasible for liquidity-constrained firms.
- T4, T6, and T8 progressively reduce different dimensions of risk under uncertain and heterogeneous returns.

[29] We set up the random price draw to sell two purifiers for BDT 1,000. We sold one purifier each in T6 (money-back) and T9 (free trial w/ information). Both firms opted to keep the purifier at the end of the 30-day period.

  - T4 (warranty) addresses concerns about product durability; firms may worry about longer-term functionality of the product, their ability to maintain equipment, or potential repair or filter replacement costs.
  - T6 (money-back) allows firms to test actual returns during peak production while maintaining an exit option, reducing uncertainty about productivity gains in their specific context. However, firms still bear residual financial risks arising from the possibility that the seller might refuse to honor the refund agreement, delay reimbursement, or impose additional conditions upon return.
  - T8 (free trial) further eliminates this financial risk, allowing firms to verify technical aspects and benefits during peak production without bearing any upfront financial exposure before committing resources.

- Arms combining features (T3, T5, T7, T9) test whether constraints interact with the information treatment. For instance, T3 examines whether credit is more effective when firms have credible information on the device's returns observed by other firms.

Econometric specification. We estimate the effect of each treatment arm on firm owners' willingness to pay for air purifiers using the following specification:

$$WTP_i = \sum_{k=1}^{9} \beta_k \mathbf{1}(Tk)_i + X_i + \epsilon_i$$

where WTP$_i$ denotes the stated willingness to pay for the air purifier by firm i in the BDM mechanism, and $\mathbf{1}(Tk)_i$ is an indicator for assignment to treatment group $k \in 1, \ldots, 9$, with the control group serving as the omitted category. The scalar X_i controls for baseline willingness to pay for the thread box. The coefficients β_k capture the intention-to-treat effect of each experimental contract on WTP relative to the control group. We report heteroskedasticity-robust standard errors.

Balance. We assess the validity of the randomization by examining balance on baseline covariates across the ten experimental arms. Overall, we find good balance on observable characteristics collected prior to the experiment. Table A.23 reports group specific means for number of workers and operators, payment characteristics, production characteristics, infrastructure, and willingness to pay for a box of thread. Mean differences between treatment groups and the control are generally small and not statistically significant. An omnibus F-test fails to reject the null hypothesis of joint equality across groups (p-value = 0.21), suggesting that the randomization successfully generated comparable groups at baseline.

There are a few notable exceptions: The p-values for binary indicators of whether the firm is located in Kamrangirchar, makes shirts, or makes burkhas are statistically significant at conventional levels. However, these differences are small in magnitude and economically minor given the variety of products manufactured by these firms. On average, only 6% of firms make shirts and 8% make burkhas, which makes some imbalance across these characteristics plausible by chance. Furthermore, the skills required and the production facilities used remain comparable across treatment groups. Collectively, these findings reinforce the internal validity of the experimental design and support a causal interpretation of the treatment effects on willingness to pay.

Uncertainty about returns to their specific firm is one reason for low demand. The average WTP in the control group was just 8,439 BDT, roughly 12% of the purifier's retail price. The WTP distribution is sharply right-skewed, with most firms bidding below 10,000 BDT (Figure A.28). Very few express willingness to pay more than 15,000 BDT, consistent with non-ownership of air purifiers. Firms' stated WTP is modestly positively correlated with their beliefs about the impact of purifiers on profits ($\rho = 0.23$); owners who report higher expected returns place somewhat higher bids. These descriptive results paired with considerable skepticism and heterogeneity about returns suggest that demand appears to be constrained by at least some combination of belief heterogeneity, perceived risk, and limited experiential learning.

Indeed, we find that providing information (T1), access to credit (T2/T3), or a free full warranty contract (T4/T5) did little to raise WTP (Table 5).[30] However, two approaches proved effective at increasing WTP, though it remained far below the market price: pairing benefit information with a 30-day money-back guarantee or offering a 30-day free trial option (with or without information)—both increased WTP by 20–30%. Figure A.29 illustrates how WTP varies across the T7, T8, and T9 arms relative to Control. Consistent with the regression results, the figure shows that these treatments shift the entire WTP distribution to the right. These effects are largest when free one-month trial is paired with information about purifier effectiveness but not statistically different from the effects for the other two groups (free trial without information and money-back with information).

This pattern of null results can be rationalized by a model in which firm owners must overcome uncertainty about the technology's expected returns to their specific firm. The failure of the information-only treatment suggests that even when data is perceived as credible, it is in-

[30]The coefficient for the 'Free Full Warranty w/o Information' group is positive and large, albeit not statistically significant. However, the 'Free Full Warranty w/ Information' group is small and negative; given that there is no obvious theoretical reason why information should minimize the positive effect of free full warranty, the large positive coefficient for the 'Free Full Warranty w/o Information' group is likely noise. Moreover, we test for the joint significance of both the access to credit (T2/T3) groups and the free full warranty (T4/T5) groups in Column 3; the effects are positive, but relatively small and statistically insignificant.

sufficient to drive adoption.[31] Owners may accept the statistics on the pamphlet we provided as factually accurate for the firms in the original study, yet remain uncertain about the technology's external validity and its performance within their own unique operational context. The investment remains too risky when returns are merely a statistical average, not a personalized certainty. Similarly, the failure of credit and full warranty treatments indicates that neither liquidity nor longer-term product durability are the binding constraints; the primary barrier is this fundamental uncertainty about the purifier's firm-specific profitability.

In contrast, purchase contracts that provided a mechanism for owners to resolve this uncertainty through low-risk, experiential learning during peak production proved highly effective. The failure of the stand-alone money-back guarantee (T6) is interesting, as it suggests that such mechanisms must first clear the hurdle of credibility. Without the legitimacy signaled by the research context, the guarantee likely suffered from high perceived counterparty risk and was not trusted. The success of T7 (Money-Back Guarantee + Information), however, may point to the solution: the information flyer appears to have served primarily to establish the seller's credibility, which in turn made the guarantee a believable promise. This credible guarantee then empowered owners to test the purifier's applicability in their own firms without financial exposure.

The free one-month trial (T8) offered the most direct path to this same end, providing the ultimate tool for personalized learning. While adding information to the trial (T9) yielded the highest point estimate for WTP, as mentioned above, the difference from the trial alone was not statistically significant. This suggests that the risk-free opportunity for direct experience during peak production months is the dominant driver of adoption. Any complementary role of information in this context appears to be secondary to the powerful effect of the trial itself, which single-handedly allows firms to resolve the critical uncertainty around the technology's personalized returns.

However, importantly, the average WTP across all three arms remained below 15% of the retail price. In fact, no firm owner in any treatment arm was willing to pay the full retail price.

4.3 Own Experience Increases Purifier WTP

We further corroborate our second experiment results through a real-stakes willingness-to-pay exercise with firms from the Experiment 1 sample. This exercise took place in in early March 2025, approximately one year after we removed air purifiers and monitors from treatment firms and

[31] We tried to build credibility about the information being delivered by clearly identifying the research context as well as the research team, both local and international, involved. Furthermore, as we discuss below, the success of T7 (money-back + information) compared to T6 (money-back only) suggests that the legitimacy signaled by the research context laid out in the information flyer appears to have served primarily to establish the seller's credibility, which in turn made the guarantee a believable promise. However, without direct measures of perceived credibility, we cannot definitively know how credible firm owners found the information flyer.

air monitors from control firms. We employed the same BDM mechanism described earlier to elicit valuations under real financial stakes, using the identical air purifier model (market price: BDT 70,000) that had been installed in treatment firms.[32] As in Experiment 2, we conducted a practice round with real stakes using a box of thread valued at BDT 60.

Econometric Specification We estimate the treatment effect on firm owners' willingness to pay for air purifiers using the following specification:

$$WTP_i = \beta_1 \cdot \text{Treatment}_i + \mathbf{X}_i + \epsilon_i \tag{6}$$

where WTP_i denotes firm i's stated willingness to pay in the BDM mechanism, Treatment_i is an indicator variable equal to 1 if firm i was randomly assigned to receive an air purifier (either in the main or buffer treatment group) and 0 otherwise, and $\mathbf{X}_i$ controls for baseline willingness to pay for the thread box. The coefficient β_1 captures the effect of air purifier installation on willingness to pay. We report heteroskedasticity-robust standard errors.

Sample, Attrition, and Balance. We contacted 107 firms that were operational on April 1, 2023, when we initially installed air purifiers and monitors (52 control, 55 treatment). Of these, 73 remained operational at intervention end on April 1, 2024 (36 control, 37 treatment). One year later, we successfully contacted 68 of the original 107 firms, including 50 of the 73 firms that had remained operational through April 1, 2024.[33]

Our analysis examines both samples (68 and 50 firms), finding quantitatively similar patterns for attrition, balance, and treatment effects. We observe significant differential attrition: control firms were 15–18 percentage points more likely to be contacted than treatment firms, depending on the sample (Tables A.24 and A.25).

Despite differential attrition, participating firms remain well-balanced on most observable characteristics. Crucially, the WTP for thread box is comparable across the two groups. The primary imbalance concerns floor size, with treatment firms having larger floor space than control firms. However, joint tests confirm that the groups remain comparable overall.[34] In addition, to address attrition concerns, we construct bounds for treatment effects following Lee (2009).

Results. Treatment firms exhibit significantly higher willingness to pay for the air purifier compared to control firms (Table 6). Among firms operational on April 1, 2023, treatment firms re-

[32] We set up the random price draw to sell one purifier for BDT 1,000.

[33] This was because firms were either temporarily or permanently closed, or because the firm owner was not available for the survey.

[34] Given the large number of observables relative to observations, we follow Kerwin, Rostom and Sterck (2025) by employing omnibus tests with randomization inference rather than relying on regression standard errors.

port a willingness to pay that is BDT 7,241 higher than control firms—an 81% increase. This result remains robust when controlling for willingness to pay for the thread box.

This pattern persists in the subsample of firms operational through March 31, 2024: treatment firms demonstrate 88% higher WTP compared to control firms. Our Lee (2009) bounds analysis addresses differential attrition concerns: the lower bound estimate is significant, BDT 5,068–5,317 (roughly 60% of control WTP), confirming that selective attrition does not drive our results.

Figure A.30 illustrates the WTP distribution across treatment and control arms for firms operational through March 31, 2024. Consistent with our regression results, the treatment shifts the entire WTP distribution rightward.

4.4 Higher Valuation Falls Well Short of Adoption

While experience increased WTP by over 80%, this substantial gain proved insufficient to drive adoption. Even after a year of direct experience with proven returns, treatment firms' WTP reached only 23% of retail price, a gap too large to bridge through learning alone. Indeed, no treatment firm owner was willing to pay the full retail price. This is reflected in actual purchasing behavior: only one treatment firm purchased an air purifier between the interim period of April 2024 and March 2025, compared to zero among control firms.[35]

This adoption failure despite substantial WTP gains reflects a broader pattern across developing economies, where multiple market failures compound (Kremer, 1993). Multiple studies document similar dynamics where interventions successfully increase technology valuation but fail to achieve market-viable adoption levels. For example, Berkouwer and Dean (2022) find that while access to credit doubles willingness-to-pay for energy-efficient cookstoves in Kenya, average WTP remains well below market prices—suggesting that even when financial constraints are partially addressed, other barriers prevent efficient technology adoption.

Our results reveal that the binding constraint is not fundamental unprofitability—firms could recover costs in under three months during peak production—but rather firms' inability to accurately value returns before experiencing them firsthand. Both the 80% WTP increase from long-term experience and the 20-30% increase from short-term trial contracts point to the same mechanism: direct experience (or low-risk personalized learning) partially resolve uncertainty about firm-specific benefits.

Yet even direct experience cannot overcome the structural uncertainties inherent in volatile business environments. Firms may rationally discount future returns given production volatility and political instability—exemplified by Bangladesh's government being deposed by a mass uprising in August 2024 after month-long protests. With 60% of owners reporting year-over-year

[35]The purchased purifier was a much cheaper model than the one we tested in Experiment 1.

production variability, largely due to market demand and political instability, investing based on one year's results carries substantial risk. Furthermore, our experiment only reduced uncertainty about the specific model tested; firms may reasonably doubt whether other available models would deliver similar returns. These compounding uncertainties create a rational underinvestment equilibrium where firms recognize the technology's value but cannot justify the upfront cost given their uncertain operating environment. This explains why even firms that experienced substantial profits from air purifiers remain unwilling to pay market prices for the technology.

5 Conclusion

This paper demonstrates that air purifiers can dramatically boost productivity and profits in polluted developing-country manufacturing, yet firms systematically fail to adopt them. Our findings reveal a nuanced adoption puzzle: while purifiers generate 39% profit gains during peak production periods, enough to recover costs within three high-production months, returns evaporate during slack periods when faster production cannot be monetized without additional orders. Firm owners understand this constraint but are uncertain about or underestimate peak-period benefits, creating a market failure that traditional interventions cannot solve. Neither information provision, credit access, nor product warranties increase WTP. Only purchase contracts enabling low-risk experiential learning, e.g., a 30-day free trial, prove effective, allowing firms to discover returns within their specific production environment. However, even this elevated WTP remained significantly below the retail price, perhaps due to uncertainty about production demand even in peak months in future years. These results underscore how the interplay between technology characteristics (returns contingent on capacity utilization) and learning constraints (inability to assess firm-specific benefits) can trap profitable technologies in low-adoption equilibria. More broadly, they highlight why the "advantages of backwardness" remain elusive: even when technologies exist to mitigate growth-constraining problems like air pollution, their diffusion depends critically on mechanisms that allow firms to learn about heterogeneous, context-specific returns across multiple draws from the market demand distribution.

Given these findings, the optimal policy response likely requires government intervention through subsidies or regulation rather than relying on market-based solutions. Subsidies that reduce the effective price to match firms' willingness-to-pay (approximately 75-80% subsidy) could unlock these productivity gains while potentially paying for themselves through increased tax revenues from higher profits and employment. Alternatively, workplace air quality regulations mandating maximum PM2.5 exposure levels would create demand for defensive technologies regardless of firms' undervaluation. Such regulatory approaches have proven effective in

high-income countries and could be particularly justified in settings like Bangladesh where ambient pollution will remain hazardous for decades. The choice between subsidies and regulation depends on implementation capacity and political economy constraints, but either approach appears necessary given that market mechanisms alone cannot overcome the severe undervaluation of technologies that could substantially improve firm productivity in polluted industrial regions.

Beyond immediate policy implications, our study also opens a few directions for future research: First, our year-long experiment documents impacts on productivity and profitability; however, the broader general equilibrium effects are not yet clear. Investments in air filtration technologies could enable adopting firms to embark on a growth path, potentially outpacing slower-moving incumbents who may be forced to exit. Understanding the dynamics of firm growth in response to the adoption of air filtration offers a promising avenue for further investigation. Second, our findings likely understate the total returns of air filtration. While we document firm-level profits from increased productivity, these figures may not capture the full range of benefits. Crucially, the primary beneficiaries of cleaner air may not be the ones making the investment. Firm owners, who are often absent from the daily production environment, may not fully internalize the health and well-being benefits that accrue directly to their workers. Future research should investigate whether firms with air filtration can more easily attract and retain high-quality talent. If so, air purifiers are not just a productivity tool, but a strategic investment in human capital—strengthening the business case for their adoption even further. Third, our findings point to a broader research agenda on how production slack, a pervasive feature of developing country manufacturing, systematically impedes technology adoption. Many productivity-enhancing technologies may share the characteristic we document for air purifiers: returns that materialize only when firms operate near capacity. If widespread slack prevents firms from capturing the benefits of available technologies, this could represent a general barrier to technological catch-up in developing economies. Future work should examine this mechanism across different technologies and sectors to test whether the capacity utilization constraint we identify for air purifiers applies more broadly.

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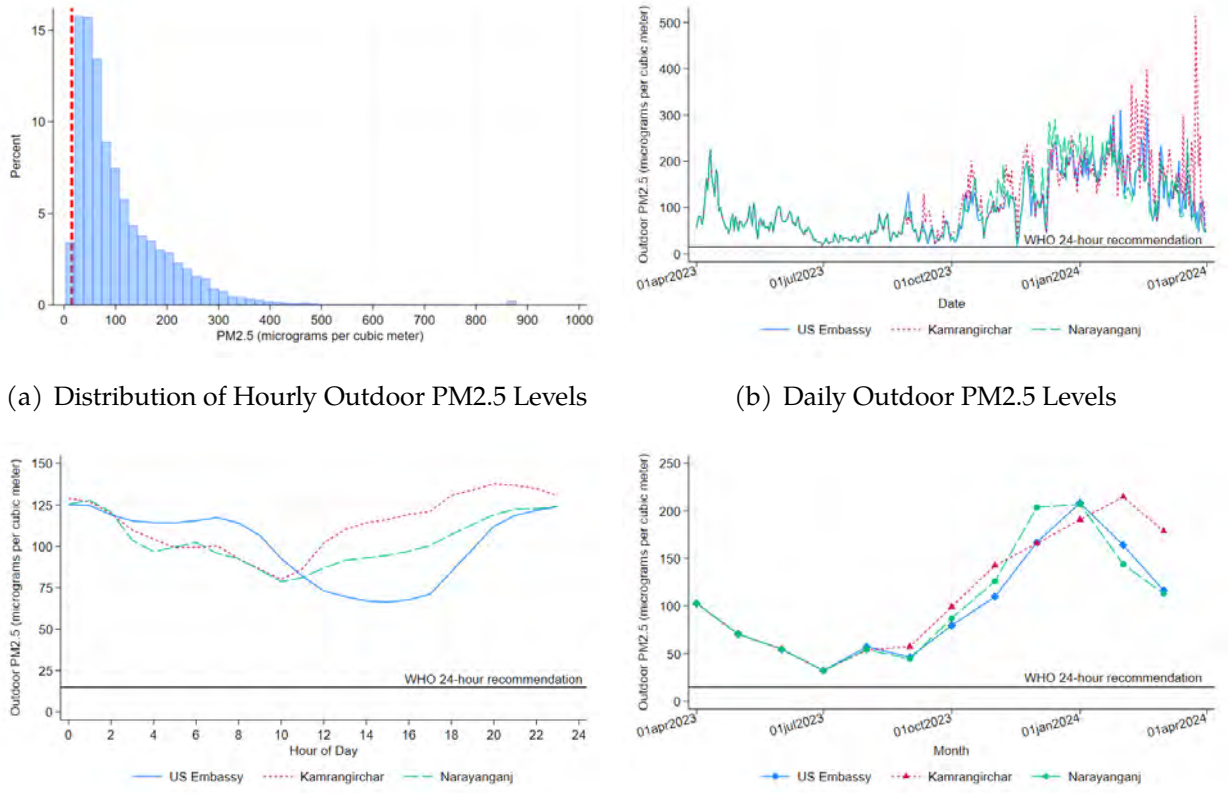
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Tables and Figures

Figure 1: Outdoor PM2.5 Levels Across Sites in Greater Dhaka



(a) Distribution of Hourly Outdoor PM2.5 Levels

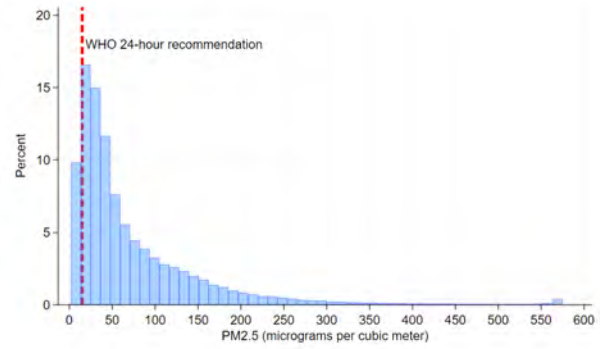
(b) Daily Outdoor PM2.5 Levels

(c) Hourly Outdoor PM2.5 Levels

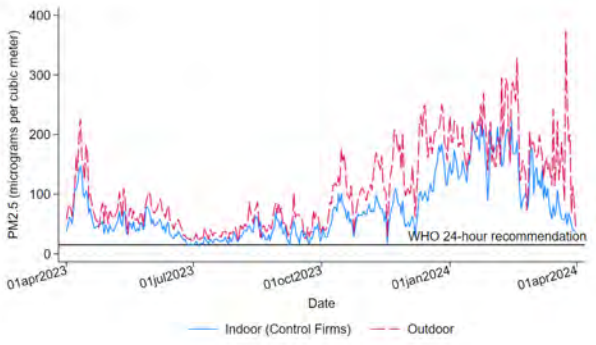
(d) Monthly Outdoor PM2.5 Levels

Notes: Panel (a) presents the distribution of hourly outdoor PM2.5 levels across three sites in Greater Dhaka district from April 2023 to March 2024. The vertical dashed line represents the WHO's 24-hour guideline of 15 $\mu g/m^3$. Panel (b) presents the daily outdoor PM2.5 levels across three sites in Greater Dhaka district from April 2023 to March 2024. Panel (c) presents outdoor PM2.5 levels by hour-of-day across three sites in Greater Dhaka district from April 2023 to March 2024. Panel (d) displays the monthly average outdoor PM2.5 levels across three sites in Greater Dhaka district from April 2023 to March 2024. Measurements from Kamrangirchar and Narayanganj were supplemented with data from the US Embassy in Dhaka, which is less than 25 kilometers away, particularly for the period from April to August before local monitors were installed. The solid lines in Panels (b)-(d) represent data from the US Embassy, while the dashed and dot-dashed lines show the levels in Kamrangirchar and Narayanganj, respectively. The horizontal lines in Panels (b)-(d) indicate the WHO's 24-hour recommended safe limit of 15 $\mu g/m^3$.

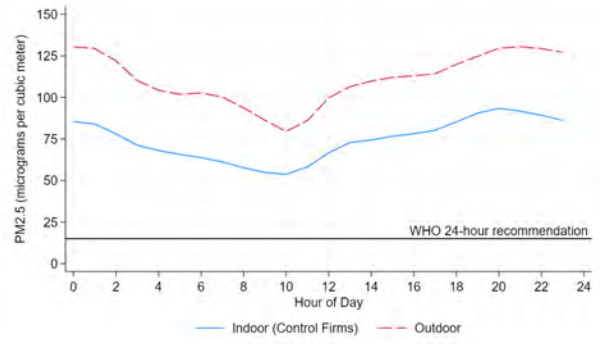
Figure 2: Indoor PM2.5 Levels in Control Firms



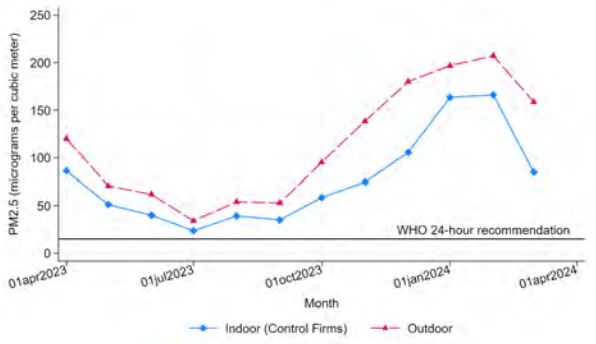
(a) Distribution of Hourly Indoor PM2.5 Levels in Control Firms



(b) Daily Indoor PM2.5 Levels



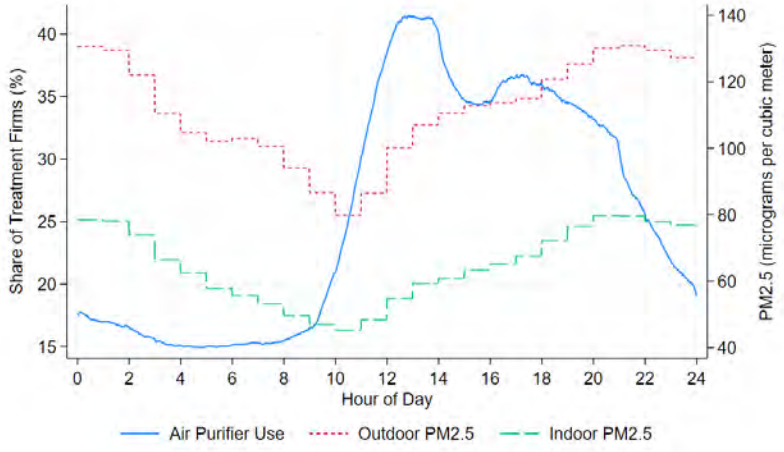
(c) Hour-of-Day Indoor PM2.5 Levels



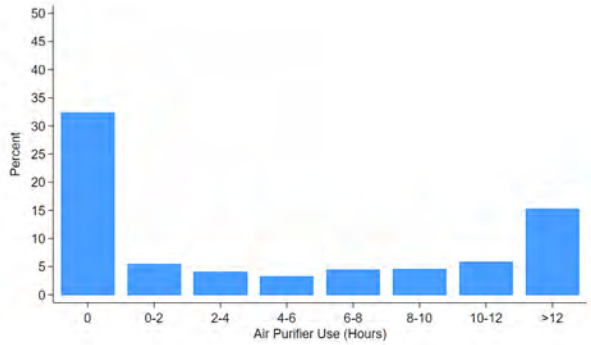
(d) Monthly Indoor PM2.5 Levels

Notes: Panel (a) shows the distribution of hourly indoor PM2.5 levels in control firms from April 2023 to March 2024. The vertical line represents the WHO's 24-hour guideline of 15 $\mu g/m^3$. Panel (b) tracks daily indoor and outdoor PM2.5 levels in control firms from April 2023 to March 2024. Panel (c) displays the hourly variation of PM2.5 levels inside and outside control firms from April 2023 to March 2024. Panel (d) presents monthly average indoor and outdoor PM2.5 levels for control firms from April 2023 to March 2024. The dashed lines in Panels (b)-(d) represent outdoor PM2.5 levels, while the dashed lines show the indoor PM2.5 levels in control firms. The horizontal lines in Panels (b)-(d) indicate the WHO's 24-hour recommended safe limit of 15 $\mu g/m^3$.

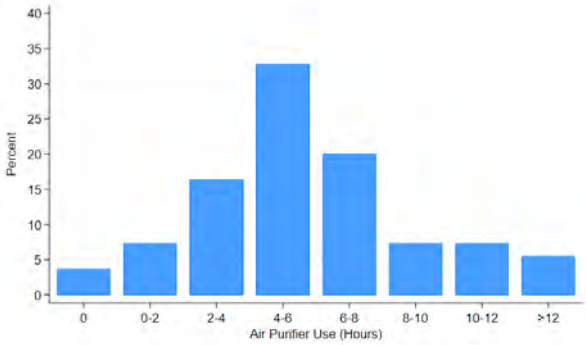
Figure 3: Air Purifier Use in Treatment Firms



(a) Hourly Air Purifier Use and PM2.5 Levels



(b) Distribution of Purifier Use at the Firm-Date Level



(c) Distribution of Purifier Use at the Firm Level

Notes: Panel (a) illustrates the share of treatment firms using air purifiers by hour of day between April 1, 2023, and March 31, 2024, alongside hourly average indoor and outdoor PM2.5 levels for the same period. Panel (b) displays the distribution of air purifier usage hours per firm-date from April 2023 to March 2024. Panel (c) illustrates the distribution of daily average air purifier usage hours among treatment firms from April 2023 to March 2024.

Table 1: Treatment Firms Increase Purifier Use in Response to Higher Outdoor PM2.5 Levels

	(1) Use (0/1) β / SE	(2) Use (0/1) β / SE	(3) Use (0/1) β / SE	(4) Use (0/1) β / SE
Outdoor PM2.5 (x100)	0.02***			
	(0.00)			
50 < Outdoor PM2.5 <= 100		0.01	0.01***	0.01***
		(0.01)	(0.01)	(0.00)
100 < Outdoor PM2.5 <= 150		0.03***	0.04***	0.04***
		(0.01)	(0.01)	(0.01)
150 < Outdoor PM2.5 <= 200		0.03***	0.04***	0.04***
		(0.01)	(0.01)	(0.01)
200 < Outdoor PM2.5 <= 250		0.04***	0.04***	0.04***
		(0.01)	(0.01)	(0.01)
250 < Outdoor PM2.5 <= 300		0.04***	0.04***	0.04***
		(0.01)	(0.01)	(0.01)
300 < Outdoor PM2.5 <= 350		0.04***	0.04***	0.04***
		(0.02)	(0.01)	(0.01)
350 < Outdoor PM2.5 <= 400		0.06**	0.05**	0.06***
		(0.02)	(0.02)	(0.02)
400 < Outdoor PM2.5 <= 450		0.08***	0.08***	0.08***
		(0.02)	(0.02)	(0.02)
450 < Outdoor PM2.5 <= 500		0.09***	0.09***	0.10***
		(0.02)	(0.02)	(0.02)
Outdoor PM2.5 > 500		0.11***	0.11***	0.12***
		(0.02)	(0.02)	(0.03)
Weather Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	No	No
Date FE	Yes	Yes	No	No
Hour of Day FE	Yes	Yes	Yes	No
Firm-Date FE	No	No	Yes	Yes
Firm-Hour of Day FE	No	No	No	Yes
Control Mean	0.26	0.24	0.24	0.24
Observations	17361000	17361000	17361000	17361000
R^2	0.191	0.191	0.604	0.635

Notes: This table shows the linear and non-parametric relationship between outdoor PM2.5 levels and air purifier use in treatment firms. Estimates in Column (1) are from Equation (1). Estimates in Columns (2) to (4) are from a specification that extended Equation (2) to include 50 unit bins between 300 and 500 $\mu g/m^3$. All columns include controls for precipitation, outdoor temperature, and outdoor humidity. Columns (1) and (2) include firm, date, and hour-of-day fixed effects. Column (3) includes firm-by-date and hour-of-day fixed effects. Column (4) includes firm-by-date and firm-by-hour-of-day fixed effects. Standard errors are clustered at the week-of-year level. Significance levels are denoted by $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$.

Table 2: Lower Indoor Air Pollution Levels in Treatment Firms

	(1) Indoor PM2.5 β / SE	(2) Indoor PM2.5 β / SE	(3) Indoor PM2.5 β / SE	(4) Indoor PM2.5 β / SE	(5) Indoor PM2.5 β / SE
Panel A: 24-Hour					
Treatment = 1	-9.86***	-10.31***	-10.91***	-10.91***	-10.91***
	(3.52)	(3.31)	(3.15)	(3.15)	(3.17)
Control Mean	74.46	74.46	74.46	74.46	74.46
Observations	577255	577255	577255	577255	577039
R^2	0.004	0.010	0.350	0.373	0.455
Panel B: 9am - 6pm					
Treatment = 1	-11.71***	-12.13***	-12.70***	-12.69***	-12.70***
	(3.18)	(2.98)	(2.84)	(2.84)	(2.86)
Control Mean	70.08	70.08	70.08	70.08	70.08
Observations	240196	240196	240196	240196	240106
R^2	0.007	0.014	0.376	0.395	0.447
Site FE	No	Yes	Yes	Yes	Yes
Date FE	No	No	Yes	Yes	No
Hour-of-Day FE	No	No	No	Yes	No
Date-Hour FE	No	No	No	No	Yes

Notes: This table shows the effect of purifier assignment on hourly indoor PM2.5 levels. Panel A analyzes the 24-hour impact, while Panel B focuses on the 9am to 6pm window, when the vast majority of firms are open. Columns (1) through (5) progressively include more controls and fixed effects: Column (1) is the simplest model without controls, Column (2) includes site fixed effects, Column (3) includes site and date fixed effects, Column (4) includes site, date, and hour-of-day fixed effects, and Column (5) includes site and date-hour fixed effects. Standard errors are clustered at the firm level. Significance levels are denoted by $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$.

Table 3: Increased Output Per Worker in Treatment Firms

	(1) Ln Output β / SE	(2) Ln Output β / SE	(3) Ln Output β / SE	(4) Ln Output β / SE
Panel A: Post-Period				
Treatment = 1	0.09**	0.10***	0.10***	0.10***
	(0.04)	(0.04)	(0.04)	(0.04)
Control Mean	108.69	108.69	108.69	108.69
Observations	125510	125510	125509	125509
R^2	0.903	0.907	0.909	0.910
	(1) Ln Output β / SE	(2) Ln Output β / SE	(3) Ln Output β / SE	(4) Ln Output β / SE
Panel B: Post-Period (Feb-Mar)				
Treatment = 1	0.21***	0.23***	0.23***	0.23***
	(0.04)	(0.04)	(0.04)	(0.04)
Control Mean	109.79	109.79	109.79	109.79
Observations	16635	16635	16635	16635
R^2	0.977	0.978	0.978	0.979
	(1) Ln Output β / SE	(2) Ln Output β / SE	(3) Ln Output β / SE	(4) Ln Output β / SE
Panel C: Pre-Period (Feb-Mar)				
Treatment = 1	-0.01	-0.01	-0.01	-0.00
	(0.08)	(0.08)	(0.07)	(0.07)
Control Mean	100.15	100.15	100.15	100.15
Observations	18431	18431	18431	18431
R^2	0.823	0.843	0.846	0.851
Piece Rate FE	Yes	Yes	Yes	Yes
Product Type FE	Yes	Yes	Yes	Yes
Site FE	No	Yes	Yes	No
Date FE	No	No	Yes	No
Site-Date FE	No	No	No	Yes

Notes: This table shows the impact of air purifier assignment on log daily worker-level output. Panel A examines impacts on output during the entire post-period (April 23 to Mar 24). Panel B examines impacts on output during the final two months of the post-period (Feb 24 to Mar 24). Panel C examines impacts on output during the pre-period (Feb 23 to Mar 23). All columns include piece rate and product type fixed effects. Column (1) includes no other controls. Column (2) also includes site fixed effects. Column (3) includes site and date fixed effects. Column (4) includes site-by-date fixed effects. Standard errors are clustered at the firm level. Significance levels are denoted by $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$.

Table 4: Increased Profit in Treatment Firms

	(1) Profits (BDT) β / SE	(2) Profits (BDT) β / SE	(3) Profits (BDT) β / SE	(4) Profits (BDT) β / SE
Panel A: Post-Period				
Treatment = 1	11927.29*	11827.82*	10933.65	10992.72
	(6969.54)	(6859.52)	(6862.70)	(6872.31)
Control Mean	63507.40	63507.40	63507.40	63507.40
Observations	1044	1044	1044	1044
R^2	0.065	0.076	0.151	0.167
	(1) Profits (BDT) β / SE	(2) Profits (BDT) β / SE	(3) Profits (BDT) β / SE	(4) Profits (BDT) β / SE
Panel B: Post-Period (Feb-Mar)				
Treatment = 1	25839.59**	25803.12**	25810.74**	25842.49**
	(9999.33)	(9945.41)	(9953.97)	(9983.10)
Control Mean	66240.26	66240.26	66240.26	66240.26
Observations	158	158	158	158
R^2	0.219	0.228	0.231	0.232
	(1) Profits (BDT) β / SE	(2) Profits (BDT) β / SE	(3) Profits (BDT) β / SE	(4) Profits (BDT) β / SE
Panel C: Pre-Period (Feb-Mar)				
Treatment = 1	580.11	537.74	399.18	705.91
	(25281.88)	(25343.48)	(25420.59)	(25572.38)
Control Mean	108677.71	108677.71	108677.71	108677.71
Observations	166	166	166	166
R^2	0.256	0.257	0.260	0.261
Baseline Controls	Yes	Yes	Yes	Yes
Product Type FE	Yes	Yes	Yes	Yes
District FE	No	Yes	Yes	No
Year-Month FE	No	No	Yes	No
District-Year-Month FE	No	No	No	Yes

Notes: This table shows the impact of air purifier assignment on monthly profit at the firm level. Panel A examines impacts on profits during the entire post-period (April 23 to Mar 24). Panel B examines impacts on profits during the last two months of the post-period (Feb 24 to Mar 24). Panel C examines impacts on profits during the pre-period (Feb 23 to Mar 23). All columns include controls from the baseline survey (monthly profits in BDT, output in weekly units, flood size in sq ft) and product type fixed effects. Column (1) includes no other controls. Column (2) also includes site fixed effects. Column (3) includes site and date fixed effects. Column (4) includes site-by-date fixed effects. Standard errors are clustered at the firm level. Significance levels are denoted by $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$.

Table 5: Experiment 2: Money-Back Guarantee (w/ Information) and Free Trial Increases Willingness to Pay for Air Purifier

	(1) WTP (BDT) β / SE	(2) WTP (BDT) β / SE	(3) WTP (BDT) β / SE
Information Only = 1	-75.06	26.21	26.26
	(961.23)	(927.64)	(927.27)
Access to Credit w/o Information = 1	57.88	235.10	
	(963.87)	(946.94)	
Access to Credit w/ Information = 1	302.79	559.11	
	(974.34)	(949.47)	
Free Full Warranty w/o Information = 1	664.76	992.29	
	(1002.78)	(970.22)	
Free Full Warranty w/ Information = 1	-512.64	-117.86	
	(929.95)	(907.07)	
Money-Back w/o Information = 1	20.18	3.57	3.56
	(943.52)	(921.12)	(920.75)
Money-Back w/ Information = 1	1793.74*	2136.30**	2136.46**
	(1028.39)	(1008.57)	(1008.16)
Free Trial w/o Information = 1	1627.82	1837.47*	1837.57*
	(1063.84)	(1029.08)	(1028.66)
Free Trial w/ Information = 1	2560.38**	2580.95**	2580.96**
	(1069.80)	(1059.38)	(1058.96)
WTP for Thread Box (BDT)		197.78***	197.87***
		(20.14)	(20.15)
Access to Credit w/ or w/o Information = 1			397.21
			(823.70)
Free Full Warranty w/ or w/o Information = 1			437.38
			(819.27)
Control Mean	8438.66	8438.66	8438.66
Observations	2500	2500	2500
R^2	0.007	0.049	0.049

Notes: This table shows the effect of information about purifier impacts, 12-month loan with 1% monthly interest (w/ or w/o information), free 2-year full warranty contract (w/ or w/o information), 30-day money-back guarantee (w/ or w/o information), and 30-day free trial (w/ or w/o information) on willingness-to-pay (WTP) for air purifier. Column (1) includes no other controls. Column (2) includes WTP for a thread box as a control. Column (3) combines the credit groups (with and without information) into a single group, and similarly combines the free full warranty groups. Heteroskedasticity robust standard errors are presented. Significance levels are denoted by $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$.

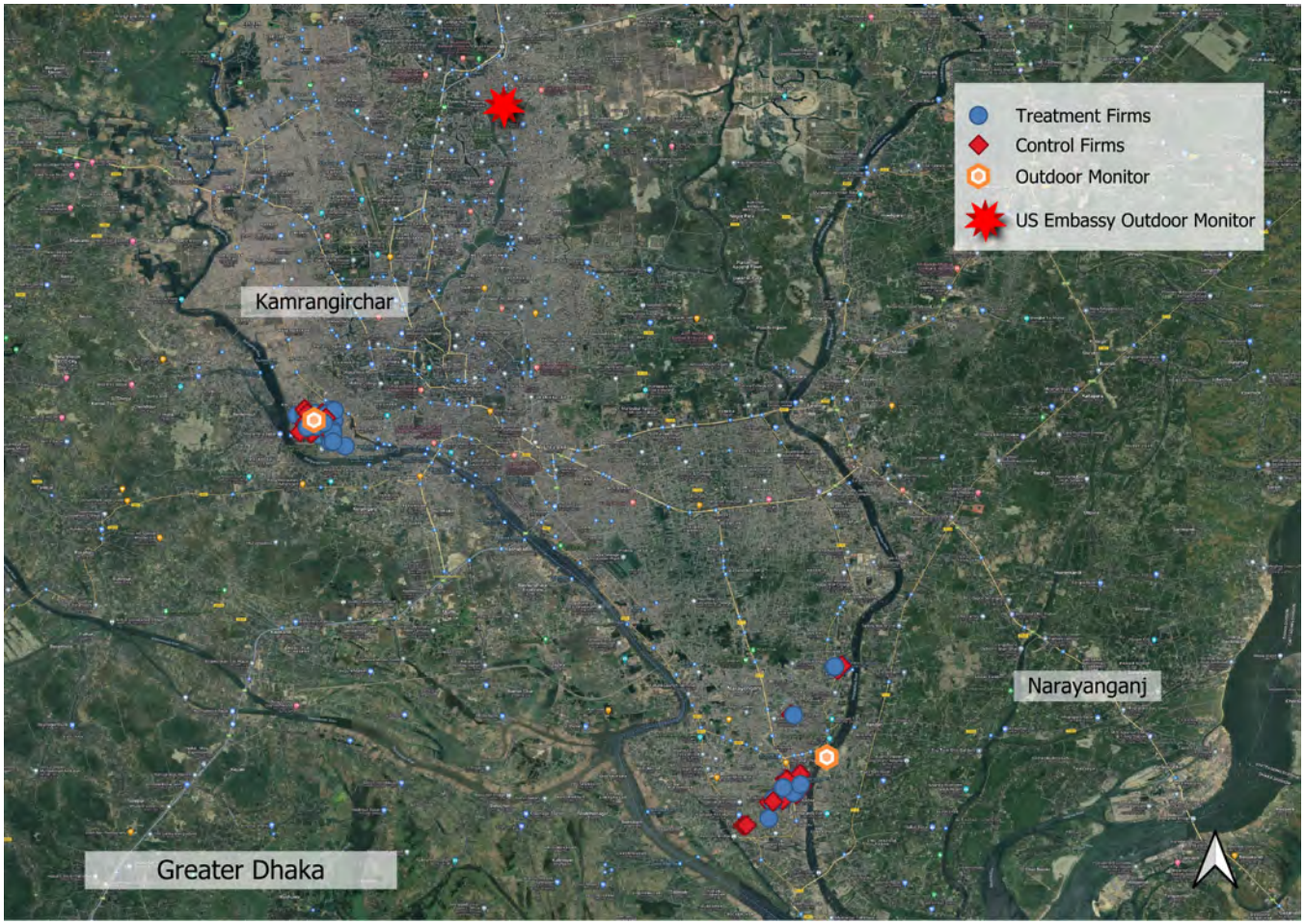
Table 6: Higher Willingness-to-Pay for Air Purifier in Treatment Firms 1 Year After its Removal

	(1) Open 1 April 23 β / SE	(2) Open 1 April 23 β / SE	(3) Open 31 March 24 β / SE	(4) Open 31 March 24 β / SE
Treatment = 1	7240.63**	6901.29**	7856.82*	7791.89*
	(3473.49)	(3428.62)	(4009.83)	(4003.65)
WTP for Thread Box (BDT)		237.91**		165.27
		(106.12)		(118.59)
Control Mean	8943.24	8943.24	8925.00	8925.00
Lee Lower Bound	5067.56		5317.17	
Lee Upper Bound	12359.74		13093.31	
Observations	68	68	50	50
R^2	0.066	0.112	0.081	0.104

Notes: This table shows the impact of air purifier installation on willingness to pay for air purifiers one year after removal from firms. Columns (1) and (2) include firms that were open on April 1, 2023, and therefore either received an air purifier and air monitor (treatment) or an air monitor only (control). Columns (3) and (4) include firms that were open on March 31, 2024; that is, firms that did not close temporarily or permanently (attrition) during Experiment 1. Columns (2) and (4) include willingness to pay for a thread box as a control. Heteroskedasticity-robust standard errors are presented. Significance levels are denoted by $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$.

A Online Appendix: Tables and Figures

Figure A.1: Firm Locations in Kamrangirchar and Narayanganj, Dhaka



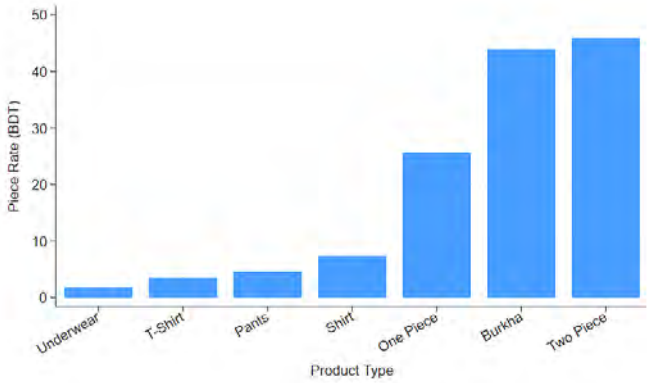
Notes: This map displays the geographical distribution of 124 firms participating in our study across Kamrangirchar and Narayanganj in the Greater Dhaka district. Treatment firms are marked with blue circles, control firms with red diamonds, and locations of the outdoor air monitors are shown with orange circles. The red star marks the position of the US Embassy outdoor air monitor.

Figure A.2: Individual Production Layout in a Treatment Firm

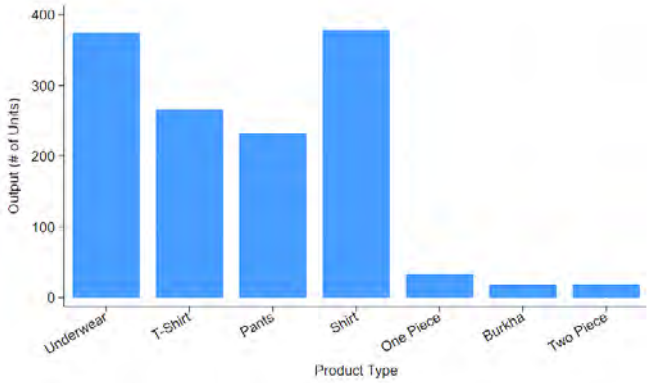


Notes: Distinct from larger firms in the ready-made manufacturing sector in Bangladesh, microenterprises employ individual production methods rather than line production. That is, workers are not arranged in a vertical formation; they may be dispersed throughout the facility, working at their own pace; and upon completing their task, workers have the option to leave or move to another firm, offering flexibility not present in line production setups.

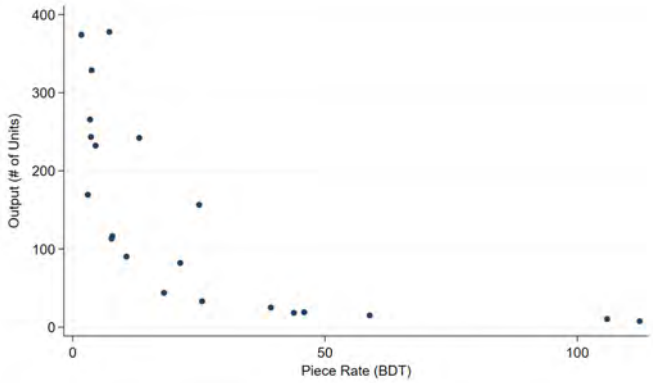
Figure A.3: Differences in Piece Rate and Output Between Products



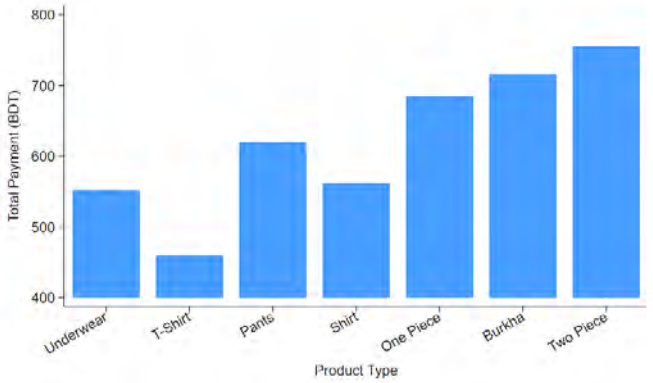
(a) Piece Rate by Product



(b) Output by Product



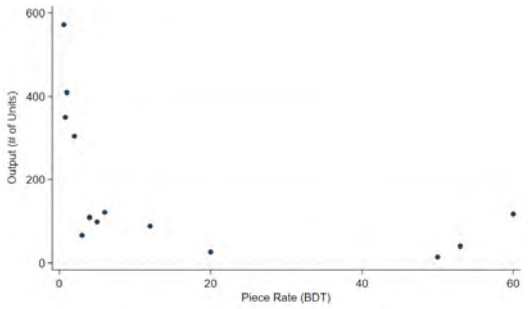
(c) Output by Product (All)



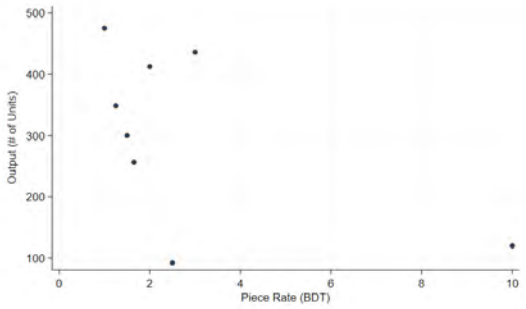
(d) Daily Payment to Workers by Product

Notes: Panel (a) shows the average piece rate paid to workers by product type. Panel (b) shows the average output produced per day by the typical worker by product type. Panel (c) plots a binned scatterplot to examine the relationship between piece rate and output between (all) product types. Panel (d) shows the average daily payment made to the typical worker by product type. All panels use data between February 2023 and March 2024 from control firms.

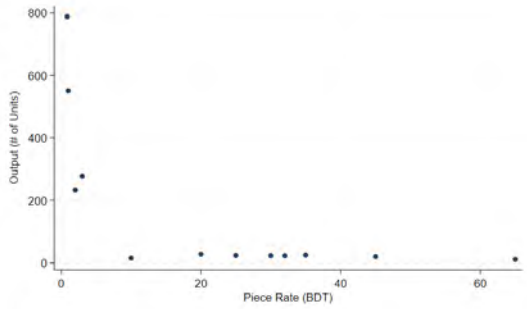
Figure A.4: Variation in Piece Rate and Output Within Products



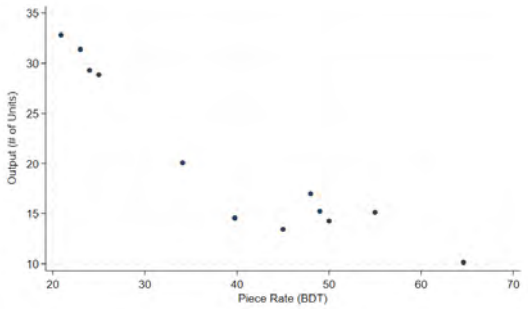
(a) T-shirt



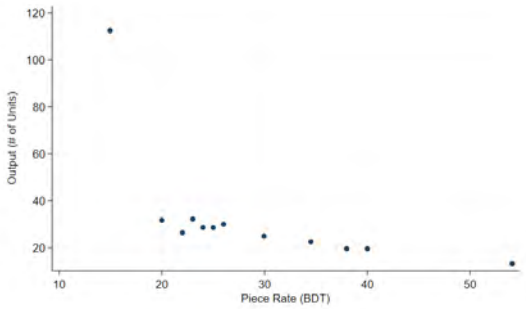
(b) Underwear



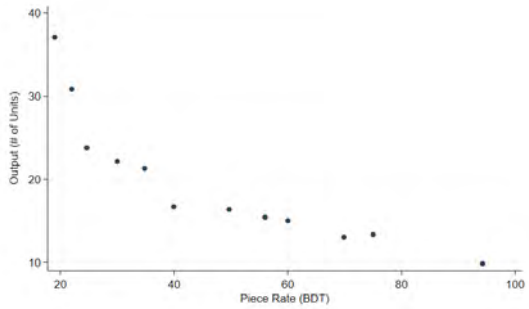
(c) Shirt



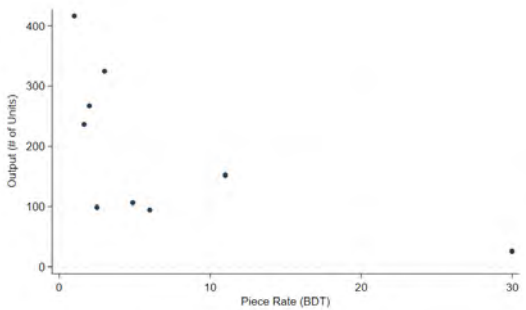
(d) Burkha



(e) One-piece



(f) Two-piece



(g) Pants

Notes: This figure plots binned scatterplots by product type to examine the relationship between piece rate and output within products. It uses data between February 2023 and March 2024 from control firms.

Figure A.5: Piece Rate by Component for a T-Shirt (in BDT)

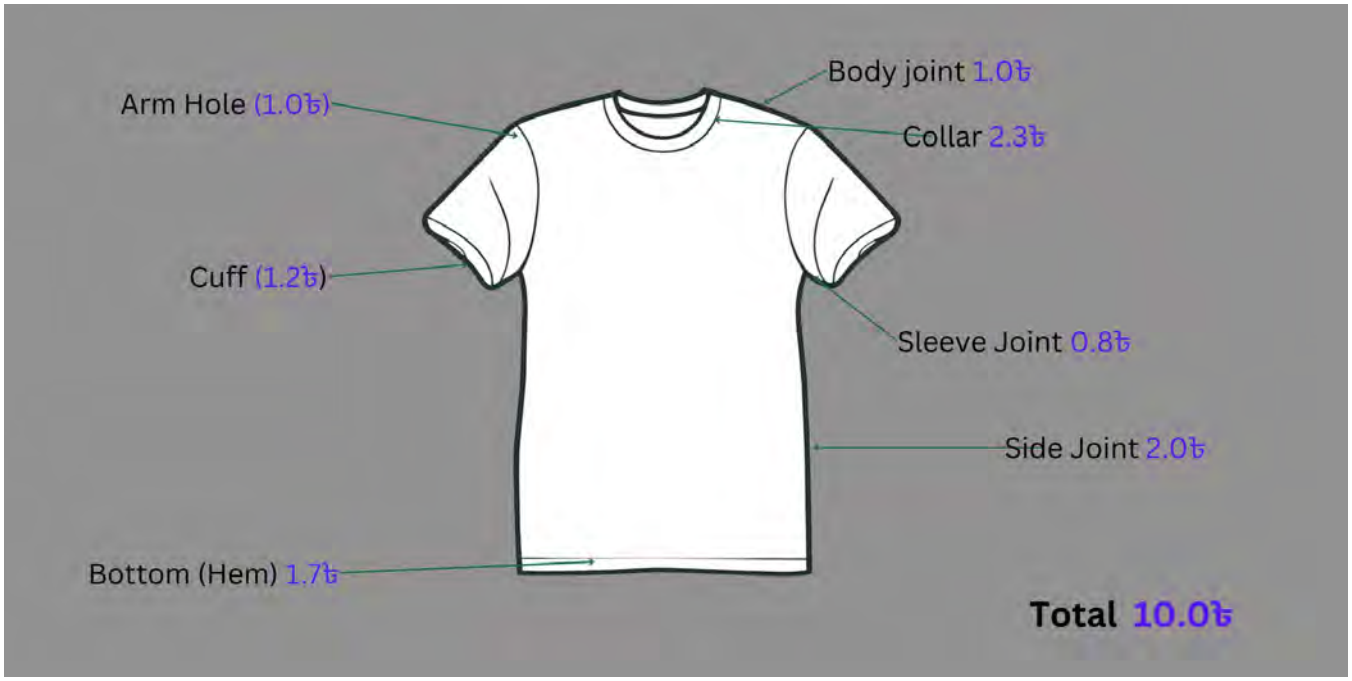
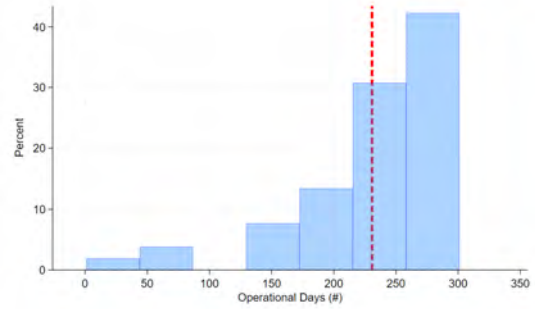
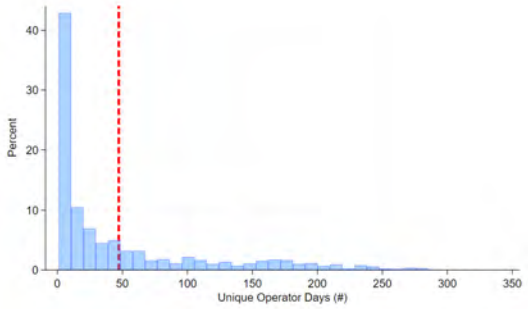


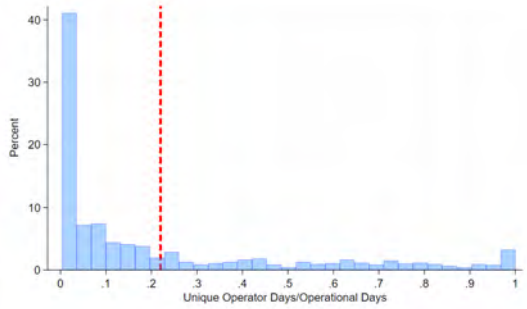
Figure A.6: Operational Days and Worker Turnover in Control Firms



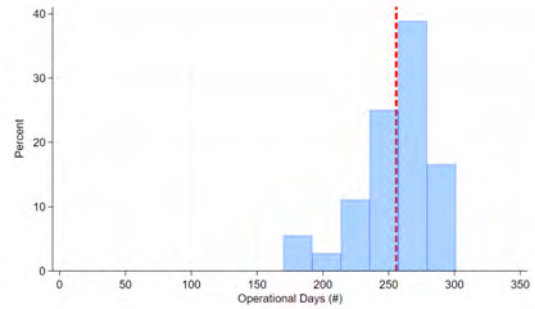
(a) Operational Days (#)



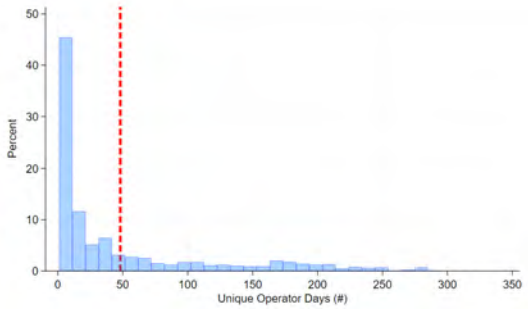
(b) Unique Operator Days (#)



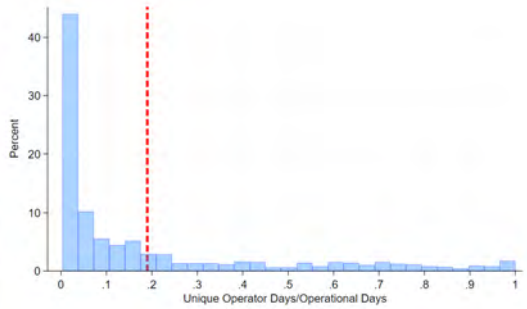
(c) Unique Operator/Firm Operational Days



(d) Operational Days (#) (Firms Operational on March 31, 2024)



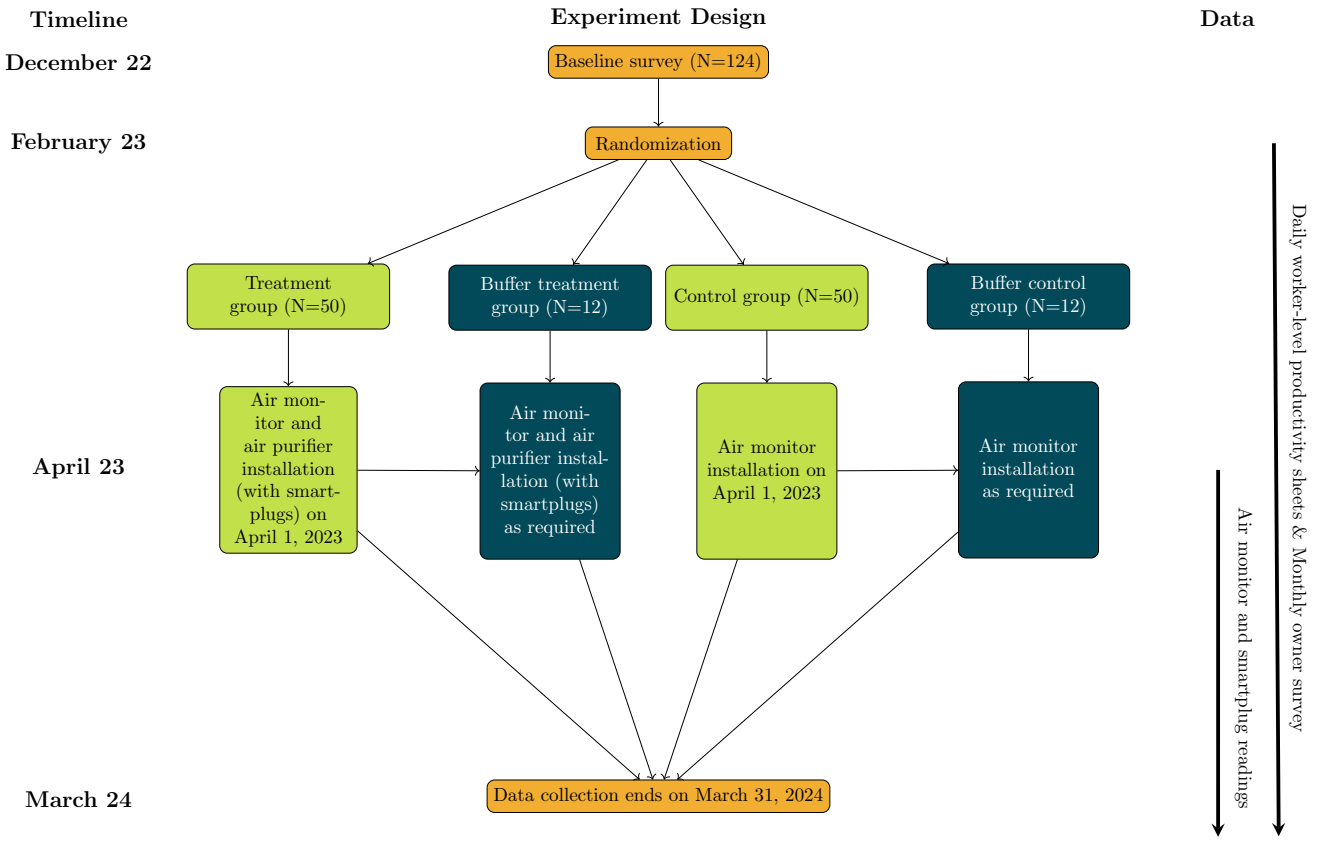
(e) Unique Operator Days (#) (Firms Operational on March 31, 2024)



(f) Unique Operator/Firm Operational Days (Firms Operational on March 31, 2024)

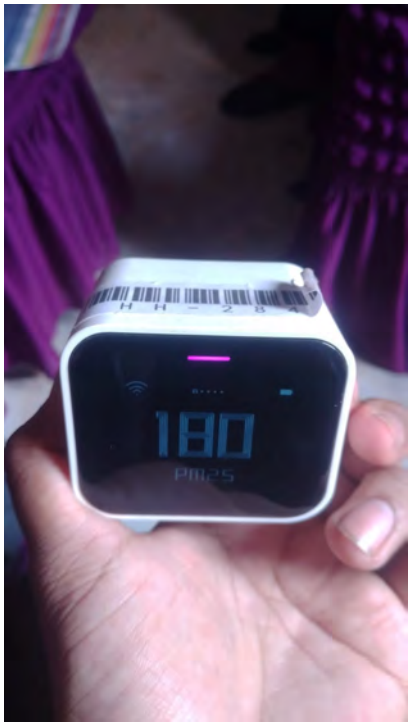
Notes: Panel (a) shows the distribution of operational days for control firms between April 2023 and March 2024. Panel (b) shows the distribution of days operators were working in the same firm during this period. Panel (c) shows the distribution of share of days operators were working in the same firm during this period. Panels (d), (e), (f) show the same distributions for firms that were operational on March 31, 2024. In all panels, the red dashed vertical line represents the sample mean for the corresponding outcome.

Figure A.7: Overview of Research Design for Studying Impact of Air Purifiers on Firms

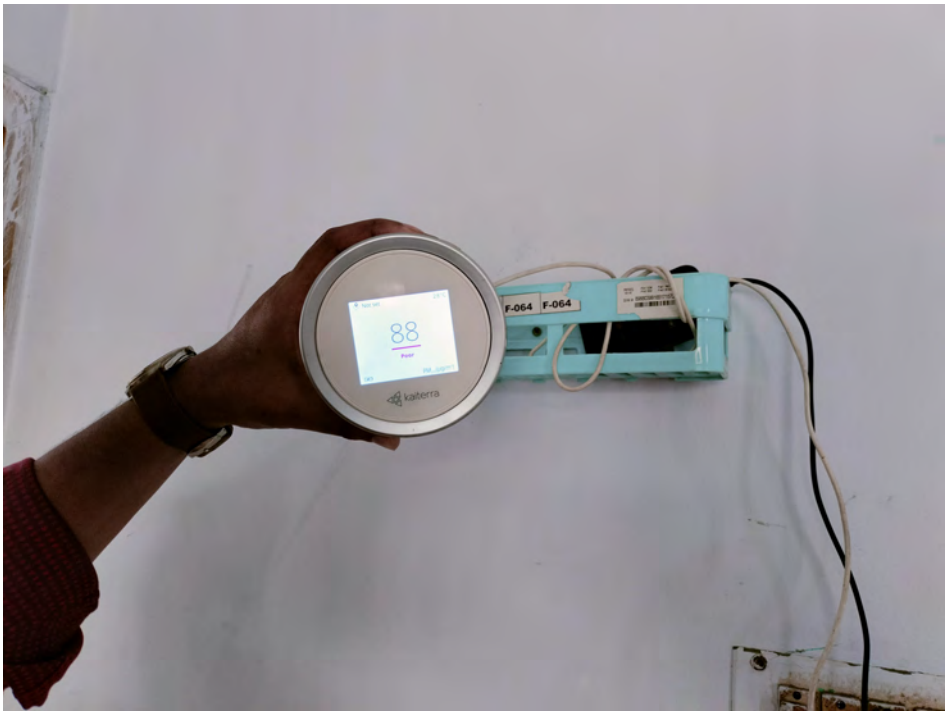


Notes: Baseline survey was administered in December 2022. We started collecting daily worker-level records from February 2023. We started monthly telephonic surveys with firm owners from October 2023; in the initial October 2023 survey, we collected information from owners covering the period from February 2023 to September 2023. The intervention started on April 1, 2023, and ended on March 31, 2024.

Figure A.8: Types of Air Monitors Used in the Experiment



(a) Qingping



(b) Kaiterra

Notes: Panel (a) shows a Qingping monitor used in our experiment. Panel (b) shows a Kaiterra monitor used in our experiment. Both monitors measure indoor PM2.5 levels, displayed in micrograms per cubic meter ($\mu g/m^3$), PM10 levels, temperature, and humidity.

Figure A.9: Air Purifier Used in the Experiment



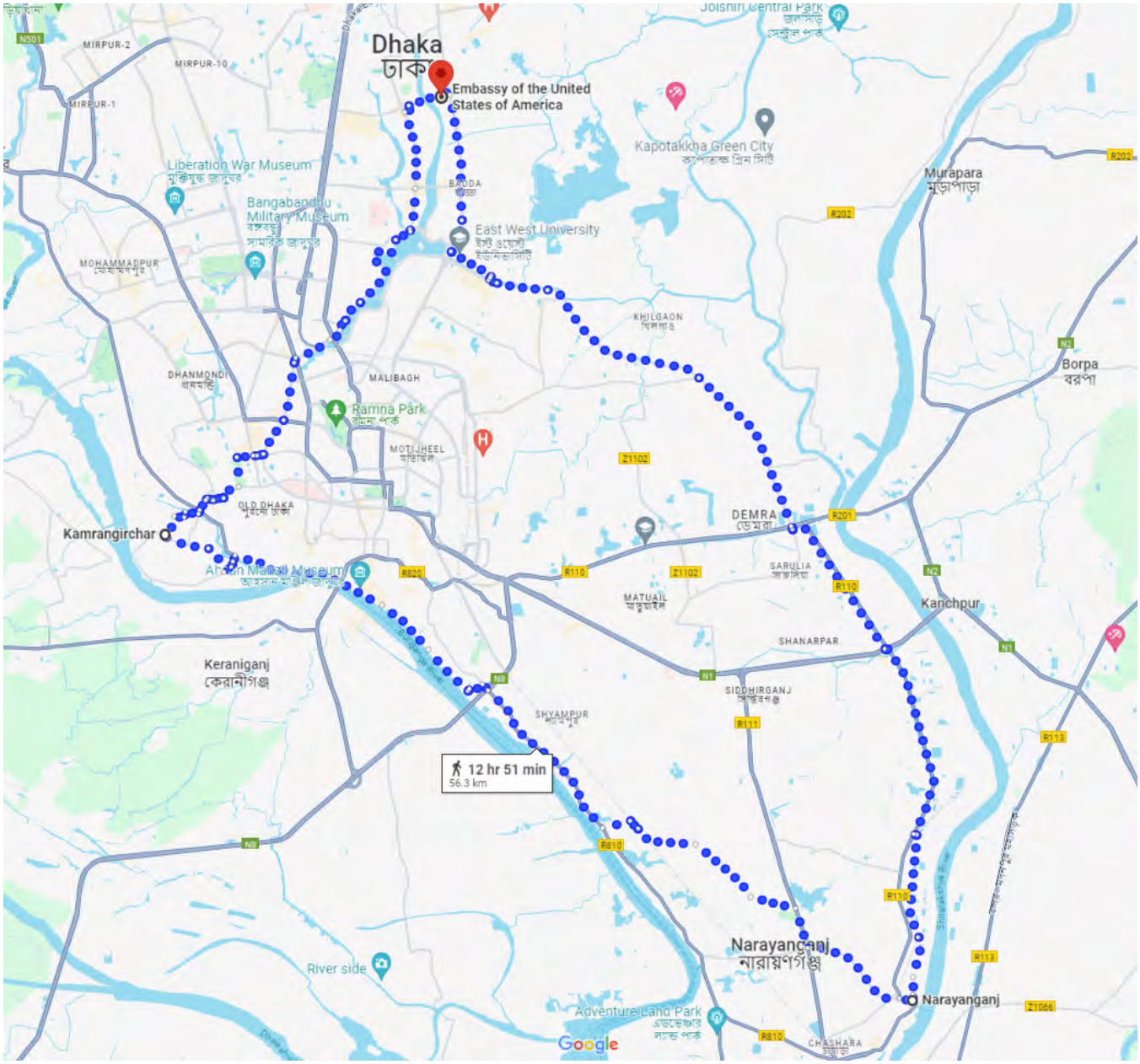
Notes: This figure shows a "Blast Mk II Air Purifier" from Smart Air that was used in our experiment.

Figure A.10: Smartplug Used in the Experiment



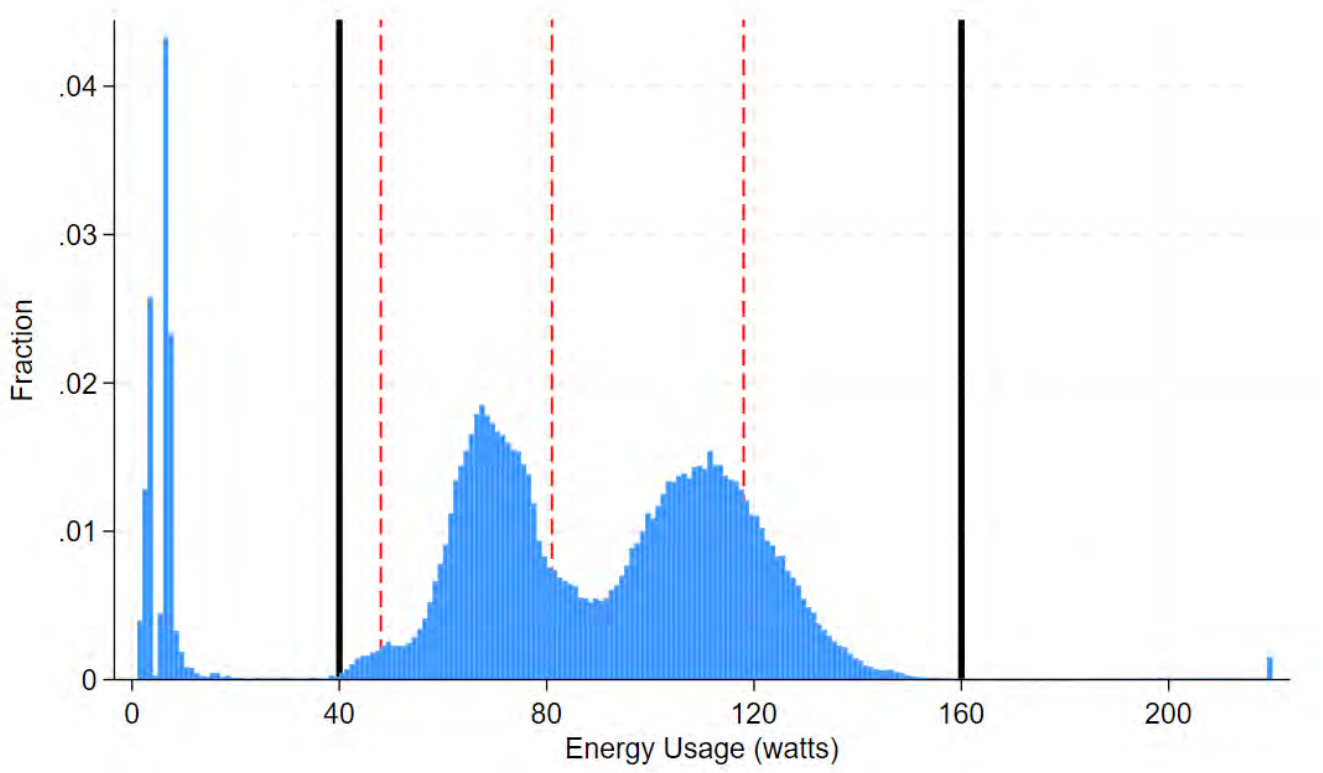
Notes: This figure shows a smartplug used in our experiment.

Figure A.11: Locations of Outdoor PM2.5 Monitoring Sites in Greater Dhaka District



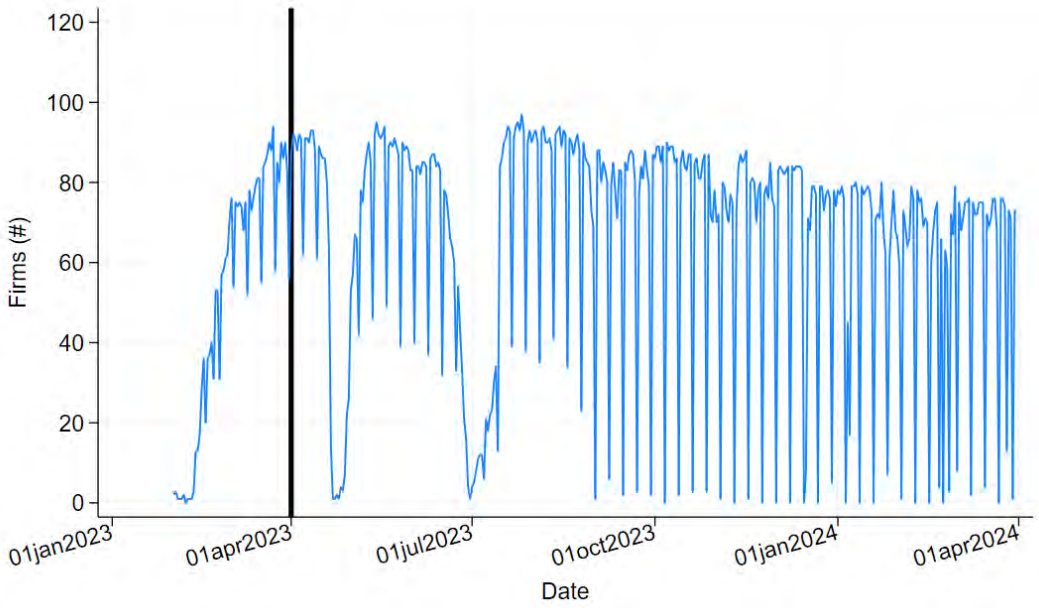
Notes: The US embassy in Dhaka is located less than 25 kilometers from both Kamrangirchar and Narayanganj, the two study sites in Greater Dhaka district.

Figure A.12: Energy Consumption Patterns Recorded via Smart plugs

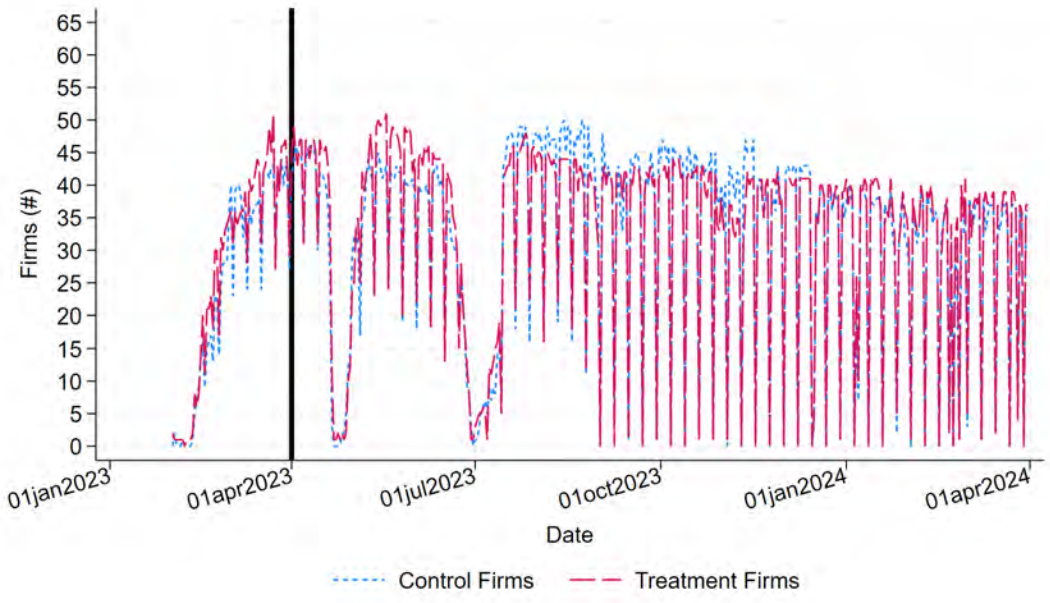


Notes: This figure shows electricity usage (watts) that the smart plugs recorded between April 1, 2023 and March 31, 2024. As per Smart Air's labeling, the "Blast Mk II Air Purifier"uses 48, 81, and 118 watts of electricity at low, medium, and high speeds (indicated by the dashed vertical lines), respectively. We classify electricity usage between 40 and 160 watts (indicated as the solid vertical lines) as indicative of the purifier being used.

Figure A.13: Daily Firm Openings and Record Sharing



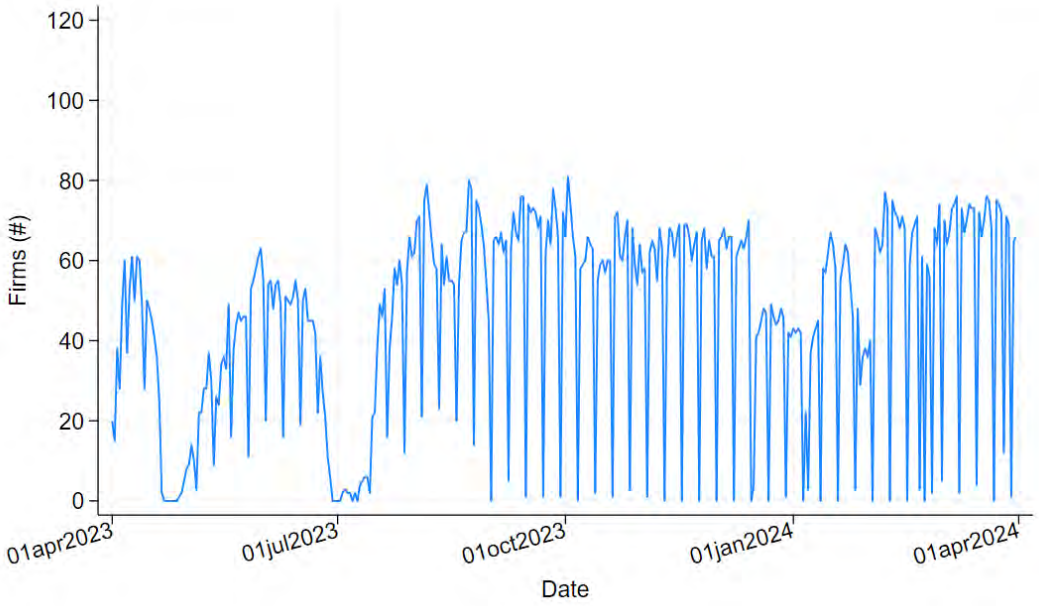
(a) All firms



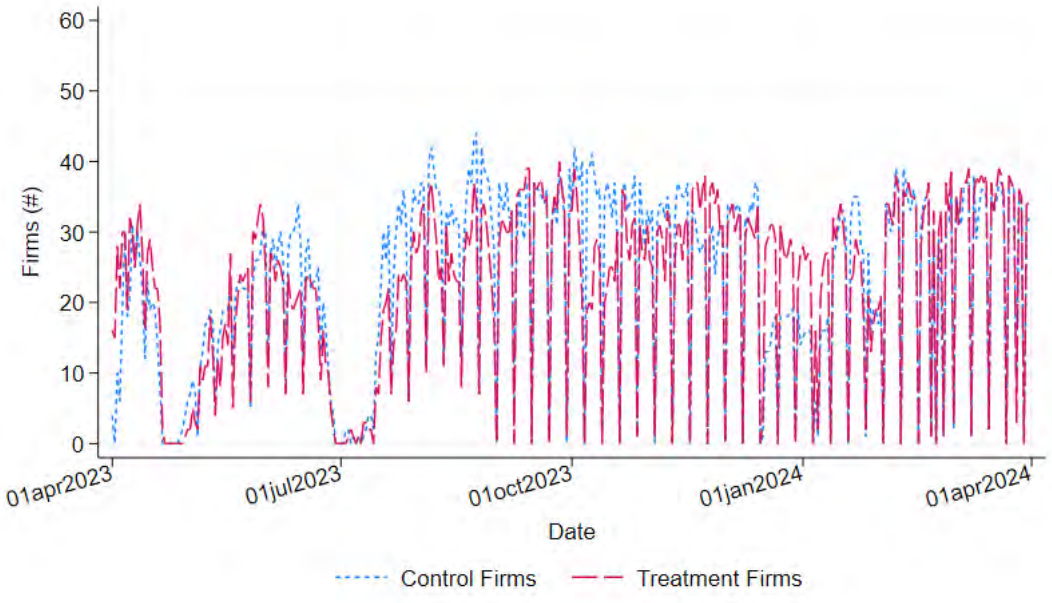
(b) Treatment vs. control firms

Notes: Panel (a) displays the number of firms open and sharing daily records on each date from February 1, 2023, to March 31, 2024. Panel (b) further categorizes these firms by treatment status for the same period. A dashed vertical line marks the start of the intervention on April 1, 2023.

Figure A.14: Daily Openings and Monitor Usage by Firms



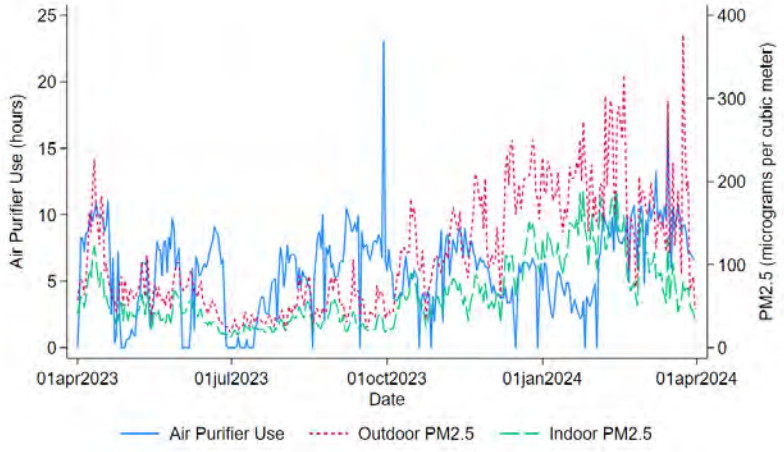
(a) All firms



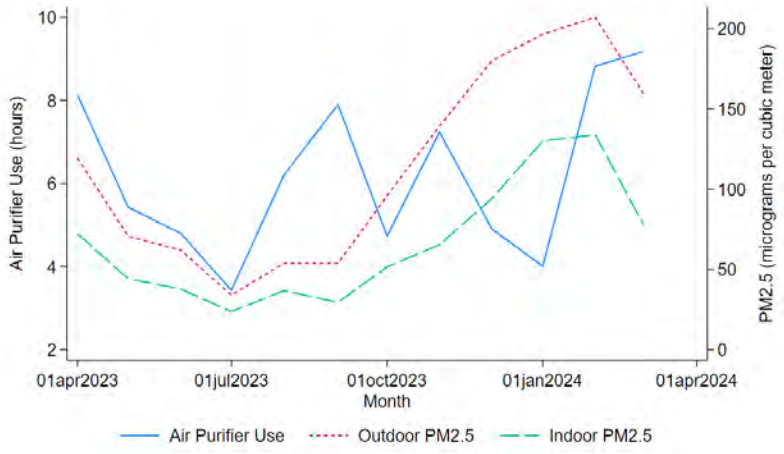
(b) Treatment vs. control firms

Notes: Panel (a) displays the number of firms open and turned on their indoor air monitor each date from April 1, 2023, to March 31, 2024. Panel (b) further categorizes these firms by treatment status for the same period.

Figure A.15: Air Purifier Use and PM2.5 Levels



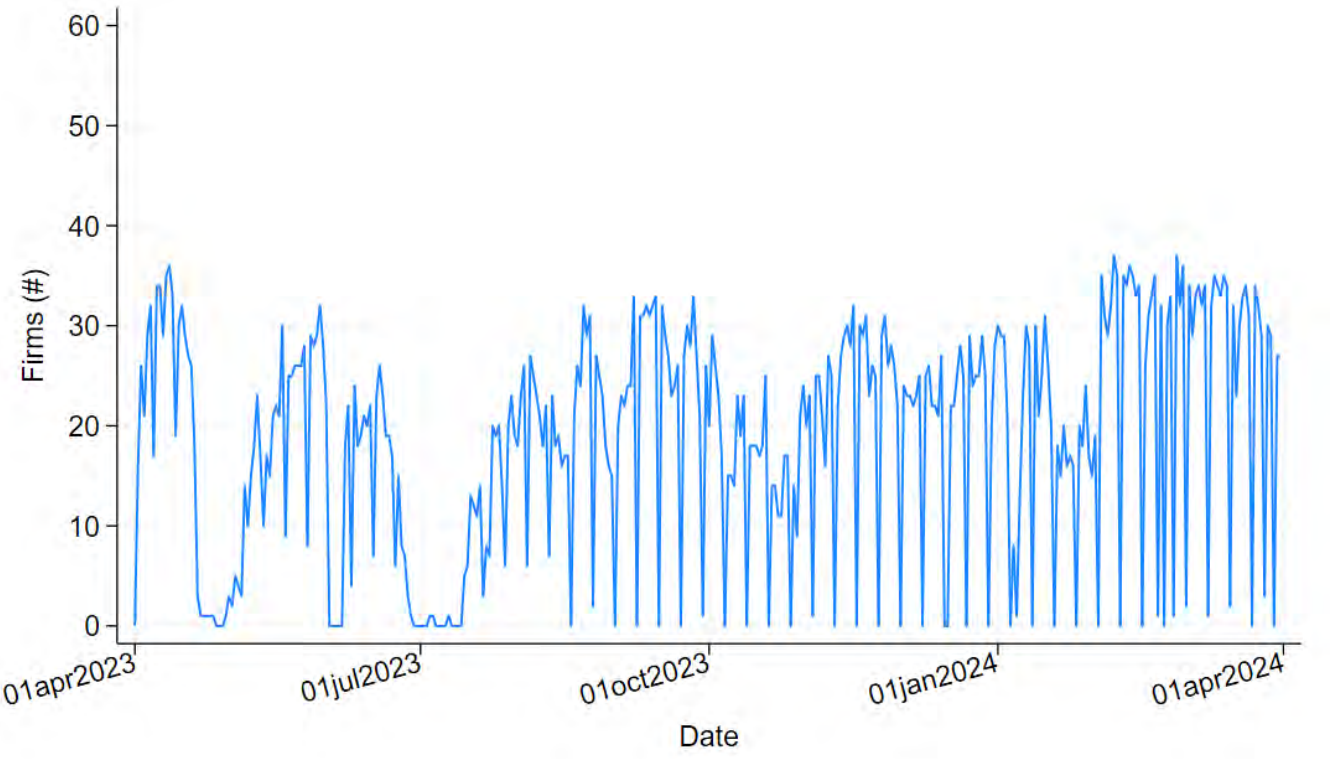
(a) Daily Trends in Air Purifier Use and PM2.5 Levels



(b) Monthly Trends in Air Purifier Use and PM2.5 Levels

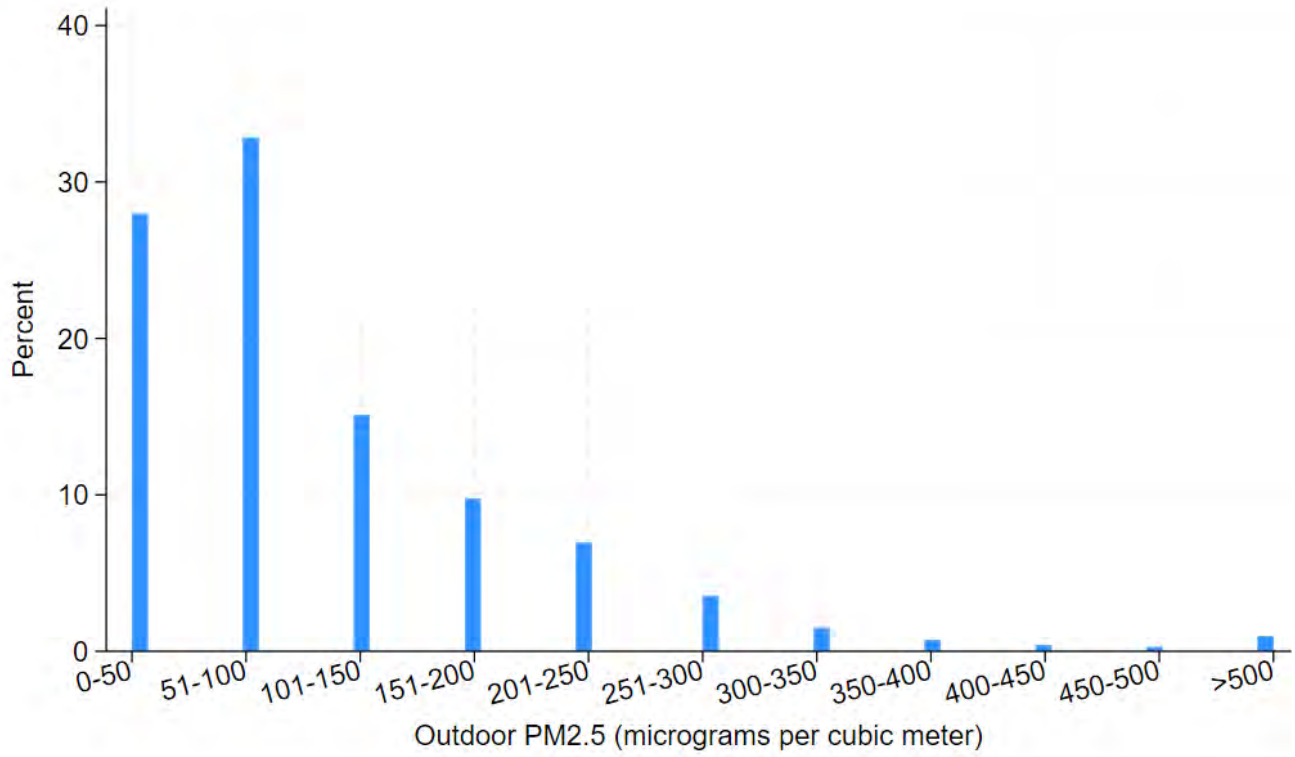
Notes: Panel (a) shows the daily average air purifier use by treatment firms between April 2023 and March 2024. It also shows daily average indoor and outdoor PM2.5 levels for treatment firms for same period. Panel (b) shows the monthly average air purifier use by treatment firms between April 2023 and March 2024. It also shows monthly average indoor and outdoor PM2.5 levels for treatment firms for same period.

Figure A.16: Number of Treatment Firms Using Air Purifiers for at Least One Minute



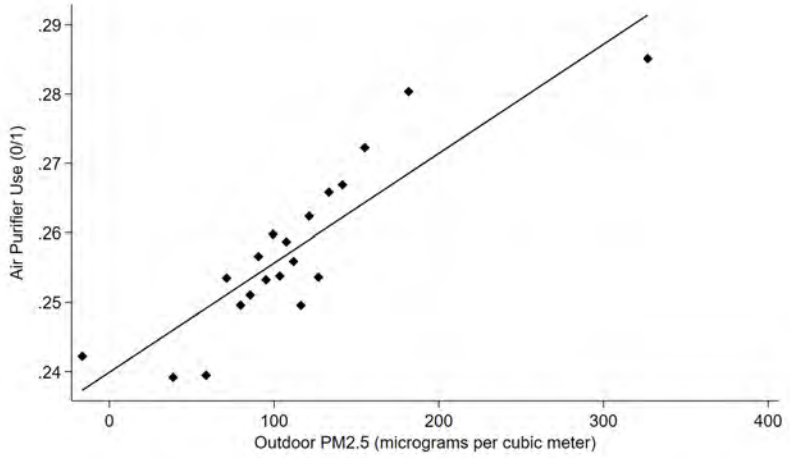
Notes: This figure shows the number of treatment firms that used an air purifier for at least one minute each day between April 1, 2023, and March 31, 2024.

Figure A.17: Distribution of Outdoor PM2.5 Levels at the Site-Hour Level

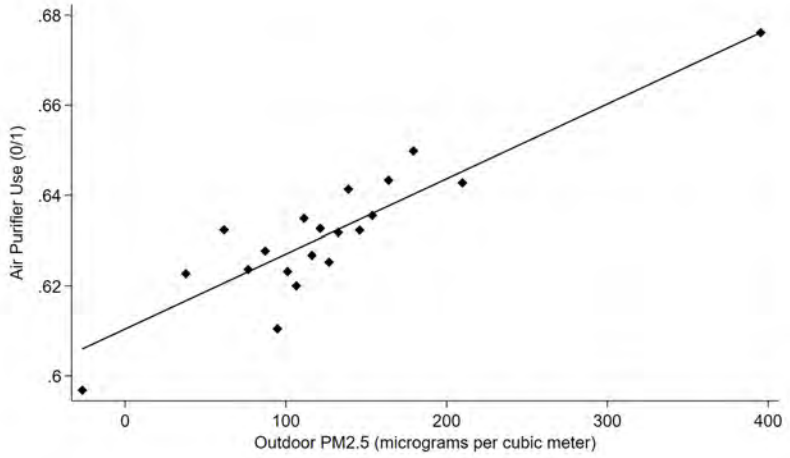


Notes: This figure shows the distribution of outdoor PM2.5 levels across various categories, based on the number of site-hour readings within each range.

Figure A.18: Treatment Firms Increase Purifier Use in Response to Higher Outdoor PM2.5 Levels



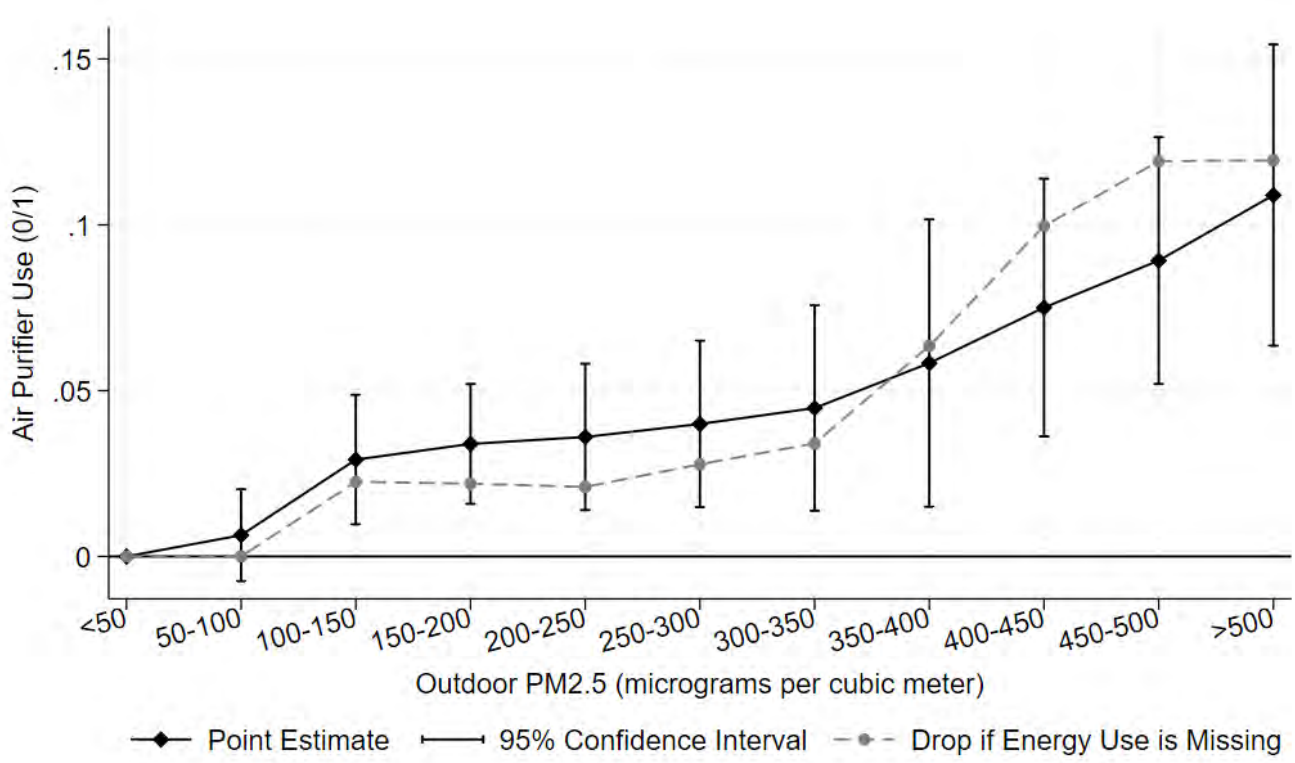
(a) Missing Energy Use Data = 0



(b) Drop Missing Energy Use Data

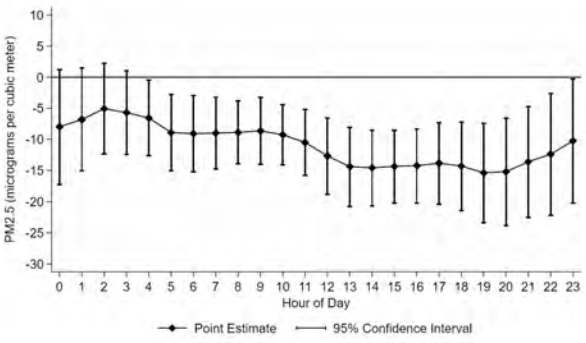
Notes: This figure presents binned scatterplots illustrating the relationship between outdoor PM2.5 levels and air purifier use in treatment firms. The analysis includes firm, date, and hour-of-day fixed effects. In Panel (a) we assume no air purifier use when energy use data from smart plugs is missing. In Panel (b) we drop observations where energy use data from smart plugs is missing.

Figure A.19: Treatment Firms Increase Purifier Use in Response to Higher Outdoor PM2.5 Levels

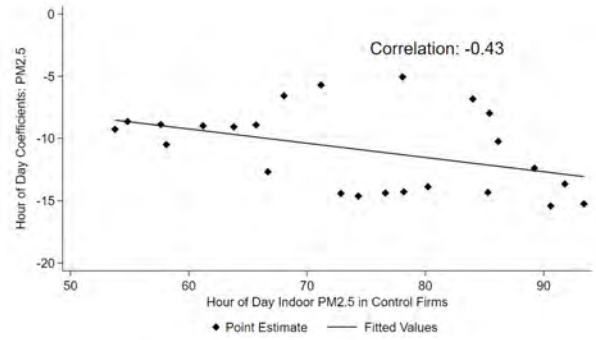


Notes: This figure shows the non-parametric relationship between air purifier use and outdoor PM2.5 levels in treatment firms. Estimates are from a specification extending Equation (2) to include 50-unit bins between 0 and 500 $\mu g/m^3$. The solid line presents estimates derived from data in which we assume zero air purifier use when energy usage data from smart plugs is missing. The dashed line presents estimates derived from data that exclude observations with missing energy use data from smart plugs. Our analysis includes firm, date, and hour-of-day fixed effects, as well as controls for precipitation, outdoor temperature, and outdoor humidity. 95% confidence intervals are constructed with standard errors clustered at the week-of-year level.

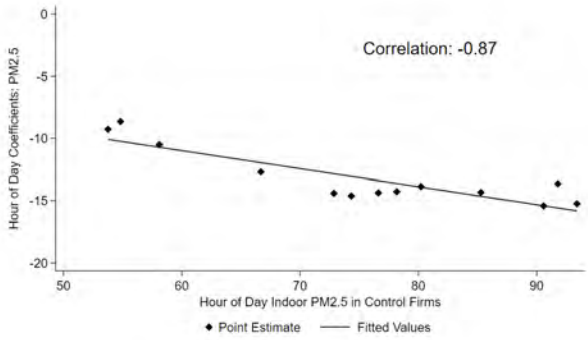
Figure A.20: Hour of Day Estimates: Lower Indoor Air Pollution Levels in Treatment Firms



(a) Hour-of-Day Estimates



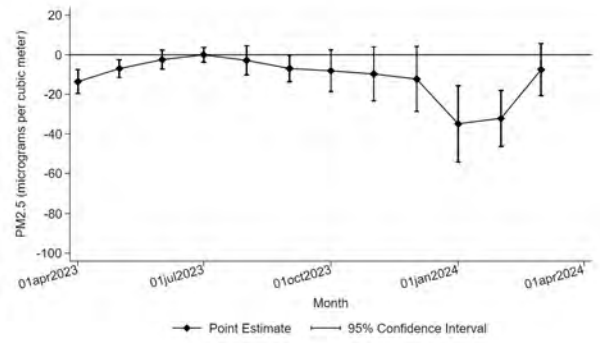
(b) Control Indoor PM2.5 and Hour-of-Day Estimates



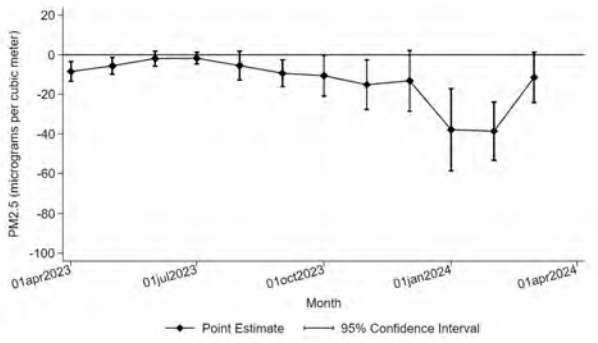
(c) Control Indoor PM2.5 and Hour-of-Day Estimates (9am-9pm)

Notes: Panel (a) shows hour-of-day estimates for the impact of treatment assignment on indoor PM2.5 levels from April 1, 2023, to March 31, 2024. We present estimates that include controls for site and date fixed effects. 95% confidence intervals are constructed with standard errors clustered at the firm level. Panel (b) presents a binned scatterplot to show the relationship between hour-of-day estimates from Panel (a) and the hour-of-day average indoor PM2.5 levels in control firms. Panel (c) shows a similar relationship as Panel (b) but excluding estimates between 10 pm and 8 am, when the vast majority of firms are not operational.

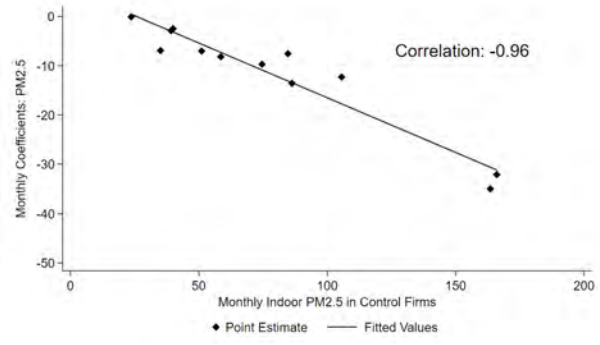
Figure A.21: Month-by-Month Estimates: Lower Indoor Air Pollution Levels in Treatment Firms



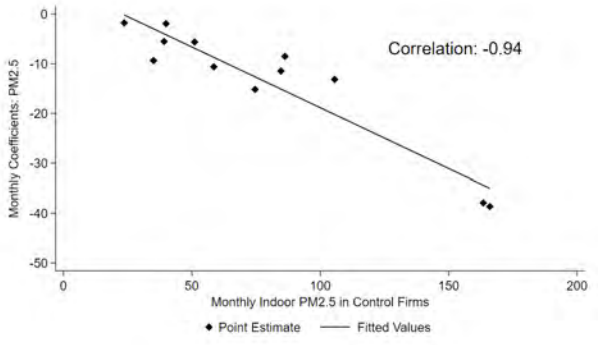
(a) 24-hour



(b) 9am - 6pm



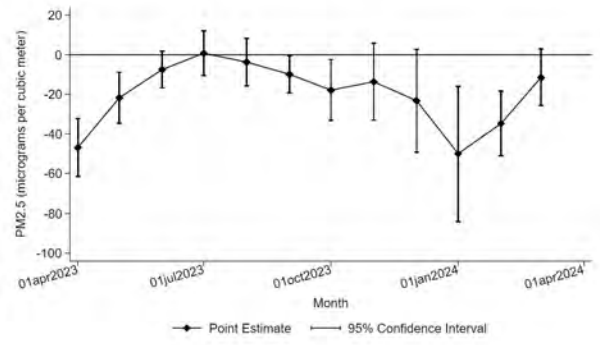
(c) Control Indoor PM2.5 and 24-hour Estimates



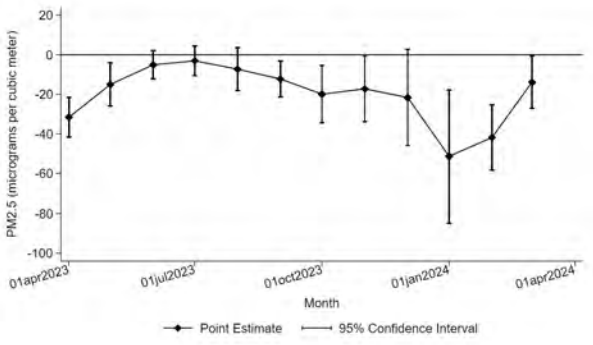
(d) Control Indoor PM2.5 and 9am-6pm Estimates

Notes: Panel (a) shows month-by-month estimates for the impact of air purifier assignment on hourly indoor PM2.5 levels from April 2023 to March 2024. Panel (b) restricts the analysis to 9 am to 6 pm, when the vast majority of firms are operational. Both panels present estimates that include controls for site and date fixed effects. 95% confidence intervals are constructed with standard errors clustered at the firm level. Panel (c) presents a binned scatterplot to show the relationship between month-by-month estimates from Panel (a) and the monthly average indoor PM2.5 levels in control firms. Panel (d) shows a similar relationship as Panel (c) but for the estimates presented in Panel (b).

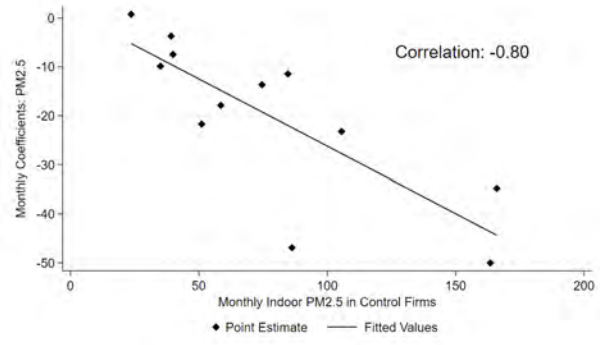
Figure A.22: Month-by-Month Estimates: Lower Indoor Air Pollution Levels in Treatment Firms



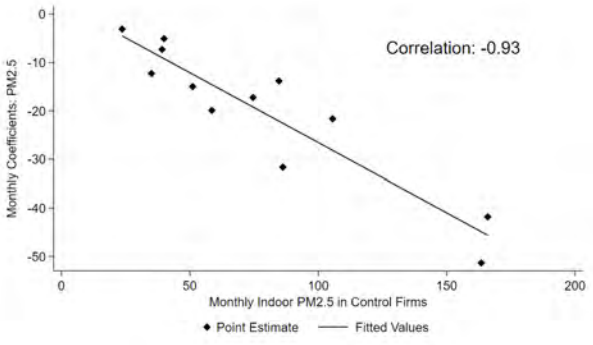
(a) 24-hour



(b) 9am - 6pm



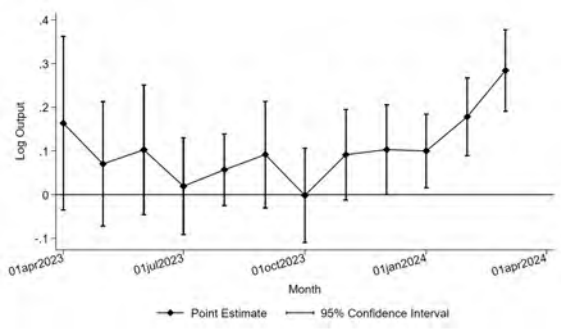
(c) Control Indoor PM2.5 and 24-hour Estimates



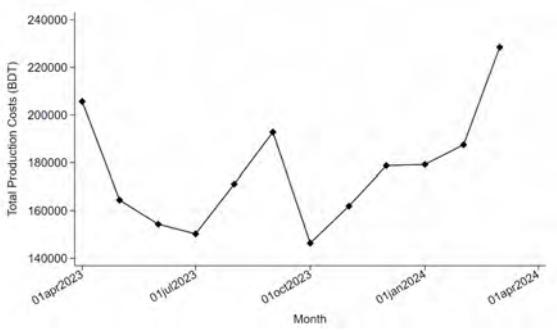
(d) Control Indoor PM2.5 and 9am-6pm Estimates

Notes: In this figure, all panels restrict the sample to observations where hourly indoor PM2.5 data is available. Panel (a) shows month-by-month estimates for the impact of air purifier assignment on hourly indoor PM2.5 levels from April 2023 to March 2024. Panel (b) restricts the analysis to 9 am to 6 pm, when the vast majority of firms are operational. Both panels present estimates that include controls for site and date fixed effects. 95% confidence intervals are constructed with standard errors clustered at the firm level. Panel (c) presents a binned scatterplot to show the relationship between month-by-month estimates from Panel (a) and the monthly average indoor PM2.5 levels in control firms. Panel (d) shows a similar relationship as Panel (c) but for the estimates presented in Panel (b).

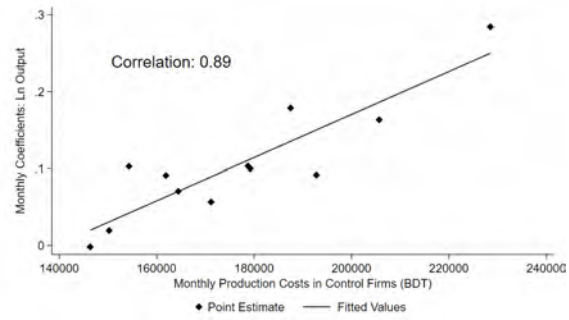
Figure A.23: Month-by-Month Estimates: Increased Output Per Worker in Treatment Firms



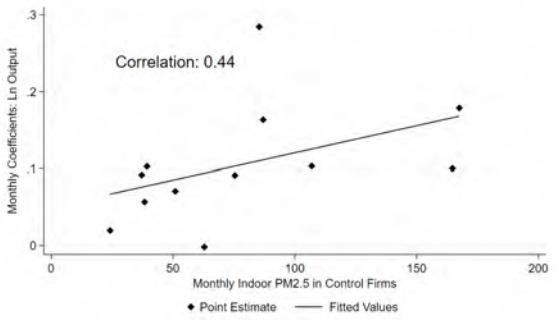
(a) Month-by-Month Estimates



(b) Month-by-Month Mean Production Costs in Control Firms



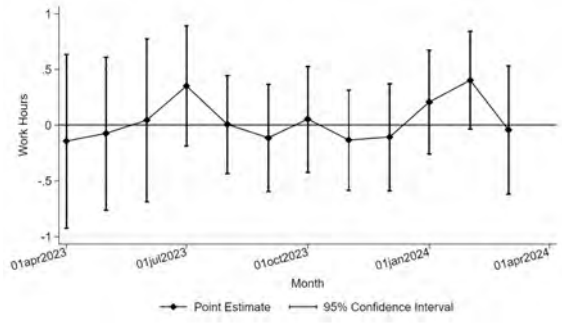
(c) Control Production Costs and Output Impacts



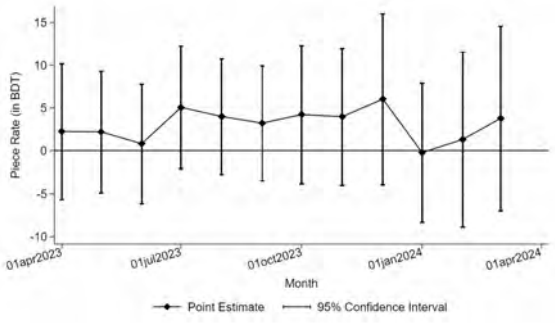
(d) Control Indoor PM2.5 and Output Impacts

Notes: Panel (a) shows the month-by-month estimates for the impact of air purifier assignment on daily worker-level output from April 2023 and March 2024. 95% confidence intervals are constructed with standard errors clustered at the firm level. Panel (b) displays the month-by-month average production costs for control firms. Panel (c) is a binned scatterplot that examines the relationship between month-by-month estimates of the impact on worker output from April 23 to March 24 and the month-by-month average of total production costs in control firms. Panel (d) is a binned scatterplot that examines the relationship between month-by-month estimates of the impact on worker output from April 23 to March 24 and the month-by-month average of indoor PM2.5 levels in control firms.

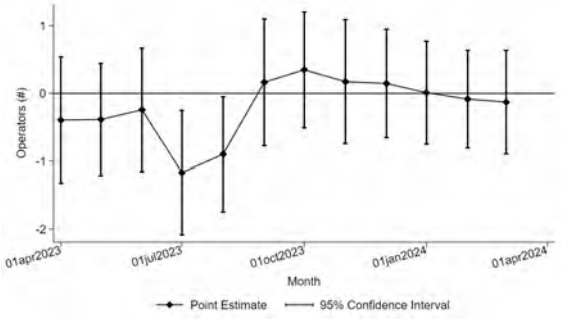
Figure A.24: Month-by-Month Estimates: Operational Differences Between Treatment and Control Firms



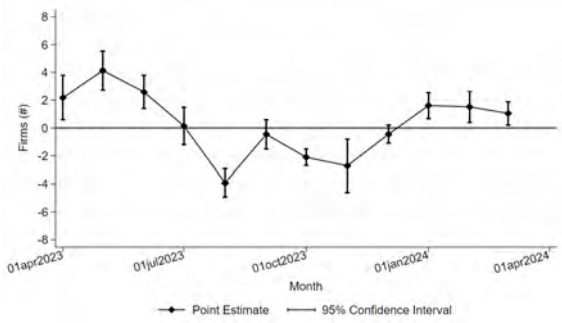
(a) Work Hours



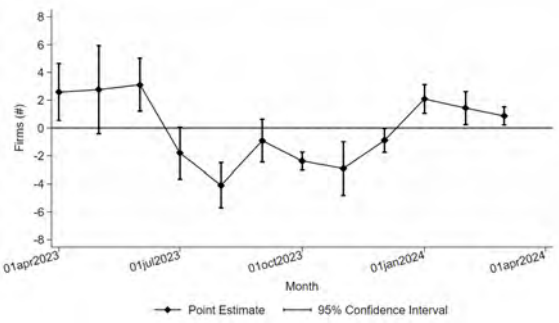
(b) Piece Rate (in BDT)



(c) Number of Operators



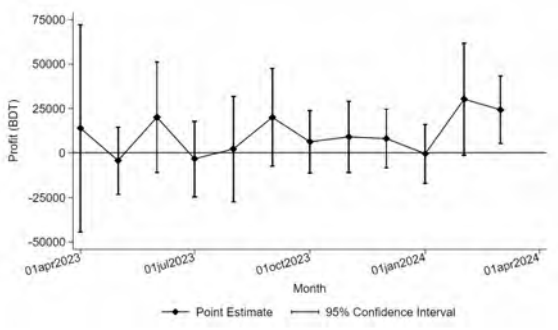
(d) Number of Firms Operational



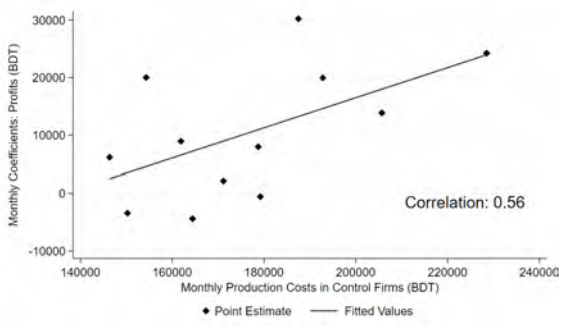
(e) Number of Firms Operational (excludes firms not operational on March 31, 2024)

Notes: Panel (a) shows the month-by-month estimates for the impact of air purifier assignment on daily worker-level hours worked from April 2023 and March 2024. Panel (b) shows the month-by-month estimates for the impact of air purifier assignment on daily worker-level piece rates from April 2023 and March 2024. Panel (c) shows the month-by-month estimates for the impact of air purifier assignment on daily firm-level number of operators from April 2023 and March 2024. Panel (d) shows the month-by-month estimates for the impact of air purifier assignment on daily number of firms open for production from April 2023 and March 2024. Panel (e) is similar to Panel (d) except it excludes firms that were not operational on March 31, 2024. 95% confidence intervals are constructed with standard errors clustered at the firm level.

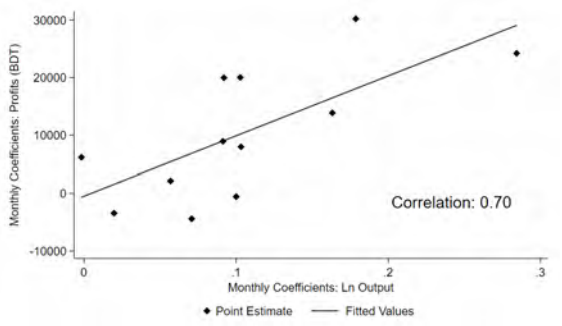
Figure A.25: Month-by-Month Estimates: Higher Monthly Profit in Treatment Firms



(a) Month-by-Month Estimates



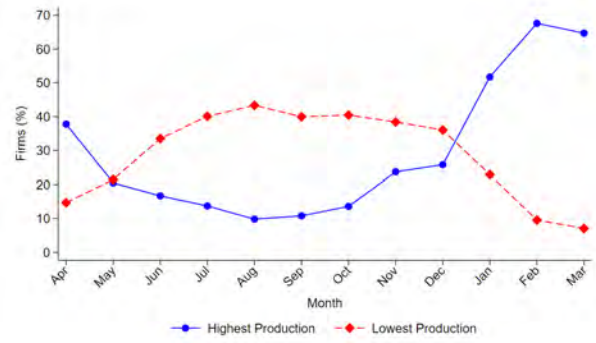
(b) Control Production Costs and Profit Impacts



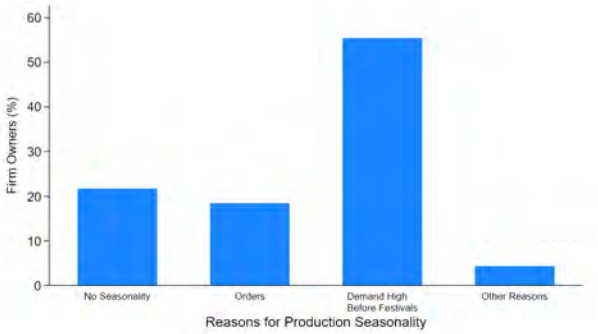
(c) Output Impacts and Profit Impacts

Notes: Panel (a) shows the month-by-month estimates for the impact of air purifier assignment on firm profits for from April 2023 to March 2024. 95% confidence intervals are constructed with standard errors clustered at the firm level. Panel (b) is a binned scatterplot that examines the relationship between month-by-month estimates of the impact on firm profits from April 23 to March 24 and the month-by-month average of total production costs in control firms. Panel (c) is a binned scatterplot that examines the relationship between month-by-month estimates of the impact on firm profits from April 23 to March 24 and month-by-month estimates of the impact on worker output from April 23 to March 24.

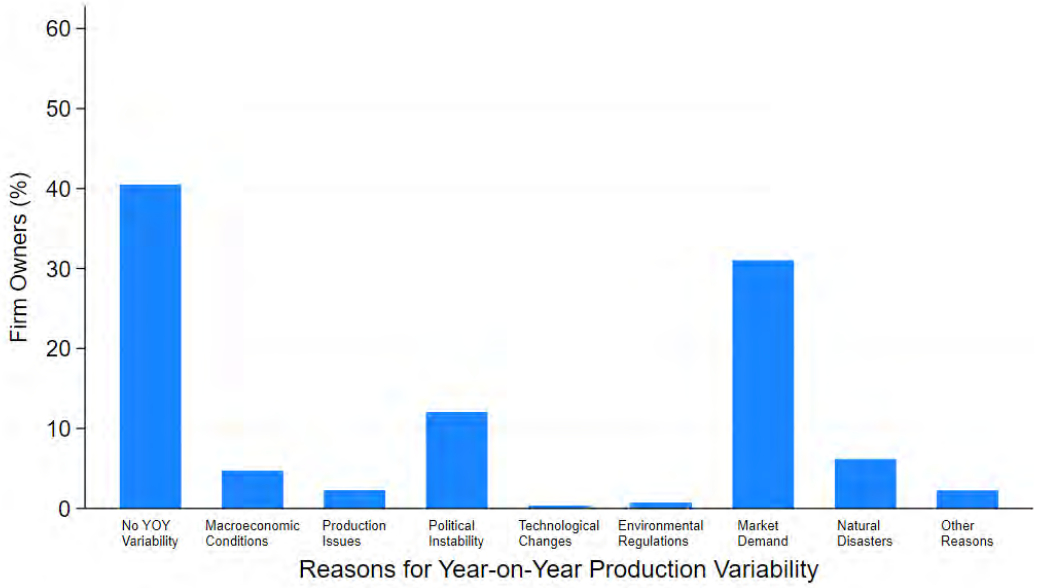
Figure A.26: Experiment 2: Production Variability Within and Across Years



(a) Highest and Lowest Production Months



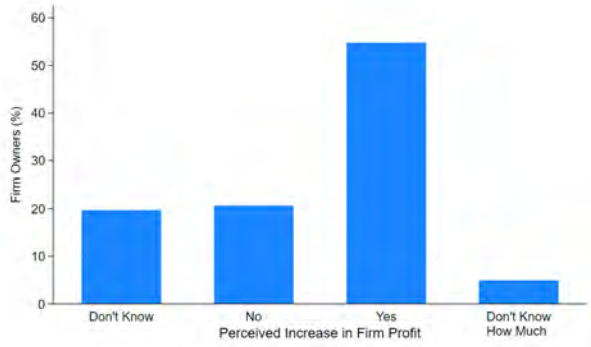
(b) Why is Production Seasonal?



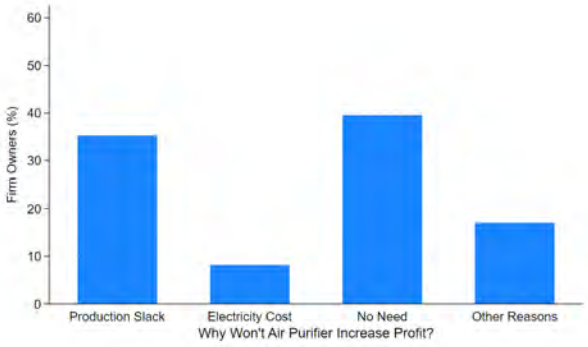
(c) Why is Production Variable Year-on-Year?

Notes: Panel (a) shows the highest and lowest production months in a typical year according to firm owners. Panel (b) shows reasons why firm owners believe production is seasonal. Panel (c) shows reasons why firm owners believe there is production variability across years.

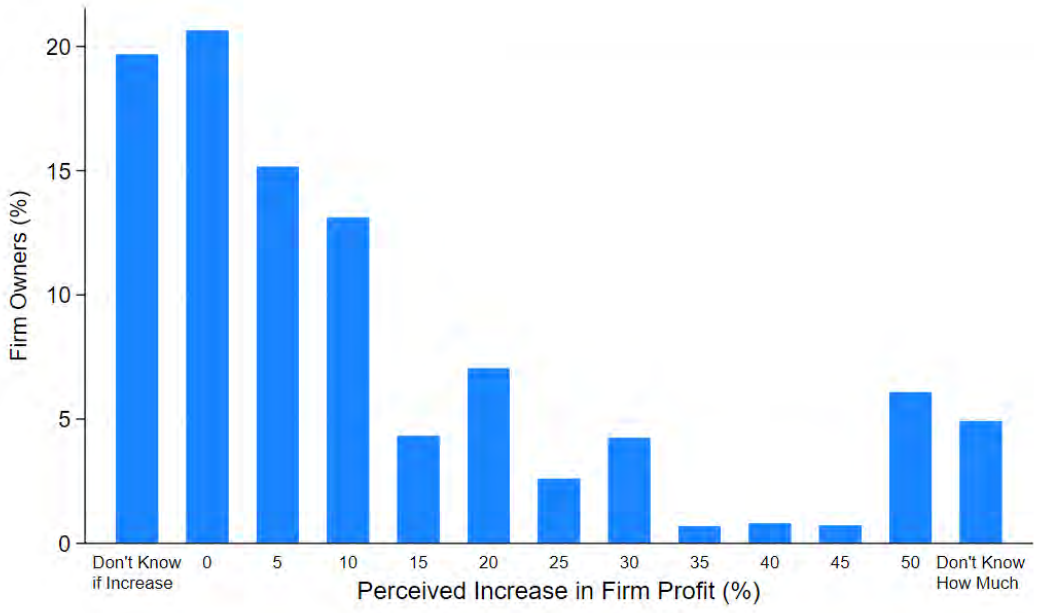
Figure A.27: Experiment 2: Beliefs about Purifier-Induced Profit Increases



(a) Firm Owners Perceptions of Purifier-Induced Profit Increases



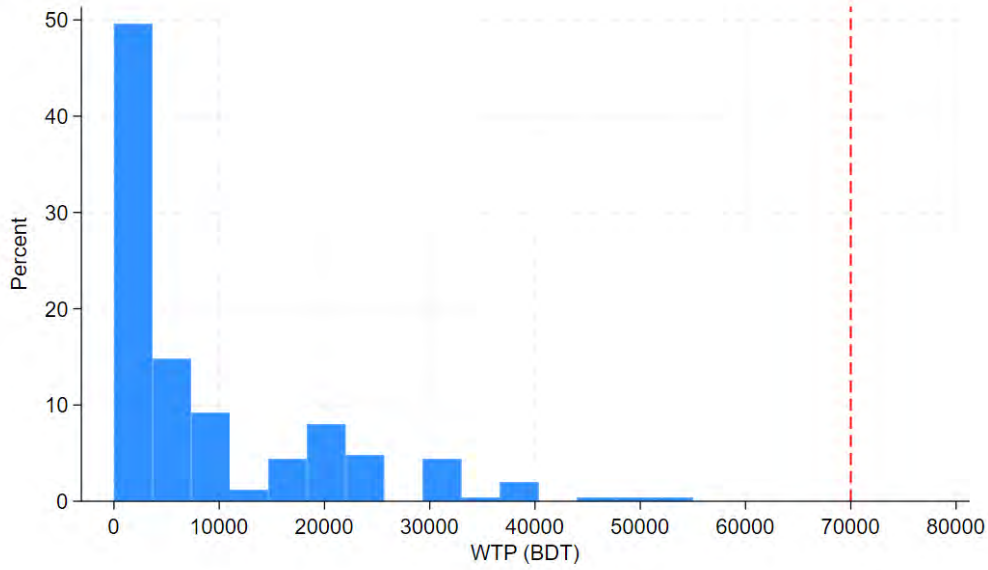
(b) Reasons Why Purifiers Won't Increase Profit



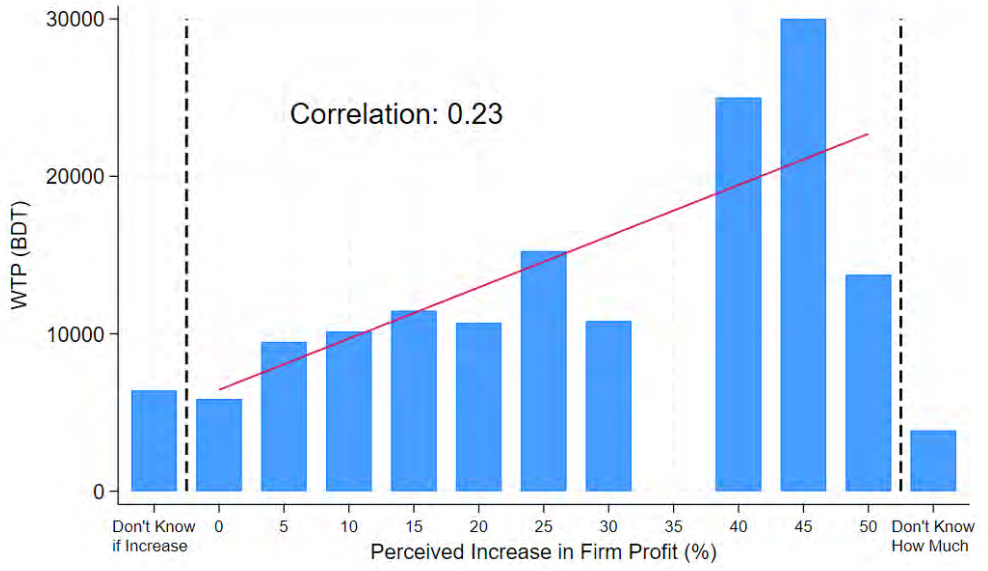
(c) Firm Owners Perceptions of Purifier-Induced Profit Increases

Notes: Panel (a) shows the percentage of firm owners who believe air purifiers would increase firm profits. Panel (b) shows the reasons why firm owners believe air purifiers will not increase firm profits among owners who hold this belief. Panel (c) shows the distribution of perceived profit increases among owners who believe purifiers will increase profits.

Figure A.28: Experiment 2: Willingness to Pay for Air Purifiers



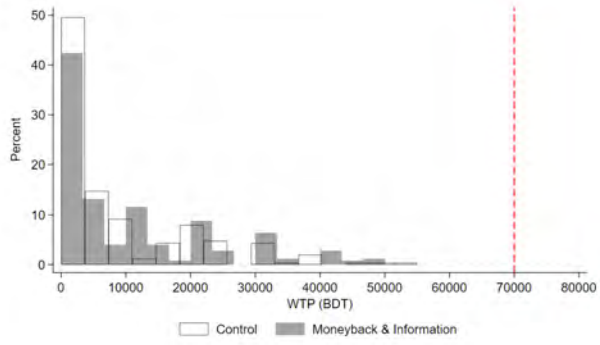
(a) Distribution of Willingness to Pay in Control Group



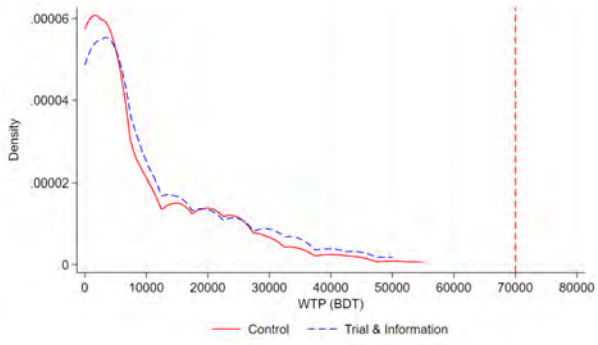
(b) Correlation Between Perceived Profit Increases and Willingness to Pay for Air Purifier in Control Group

Notes: Panel (a) shows the distribution of willingness to pay for an air purifier in the control group. The red dashed line indicates the market value of the air purifier (BDT 70,000). Panel (b) shows the correlation between perceived profit increases and willingness to pay for an air purifier among firm owners in the control group.

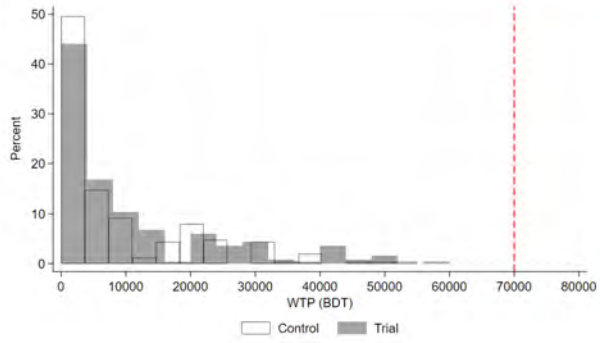
Figure A.29: Experiment 2: Differences in Willingness to Pay for Air Purifiers Between Control and Treatment Groups



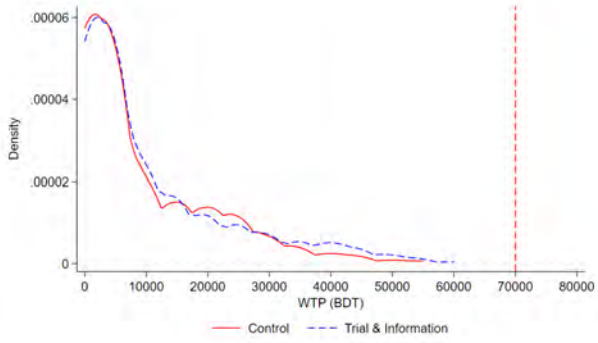
(a) Control vs. Money-Back + Information



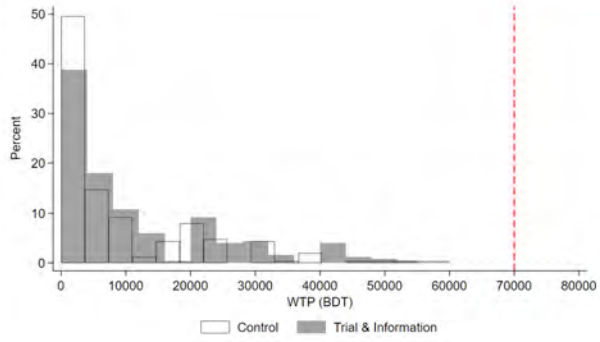
(b) Control vs. Money-Back + Information



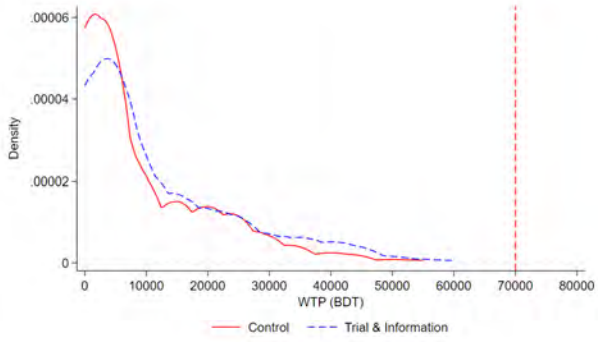
(c) Control vs. Free Trial



(d) Control vs. Free Trial



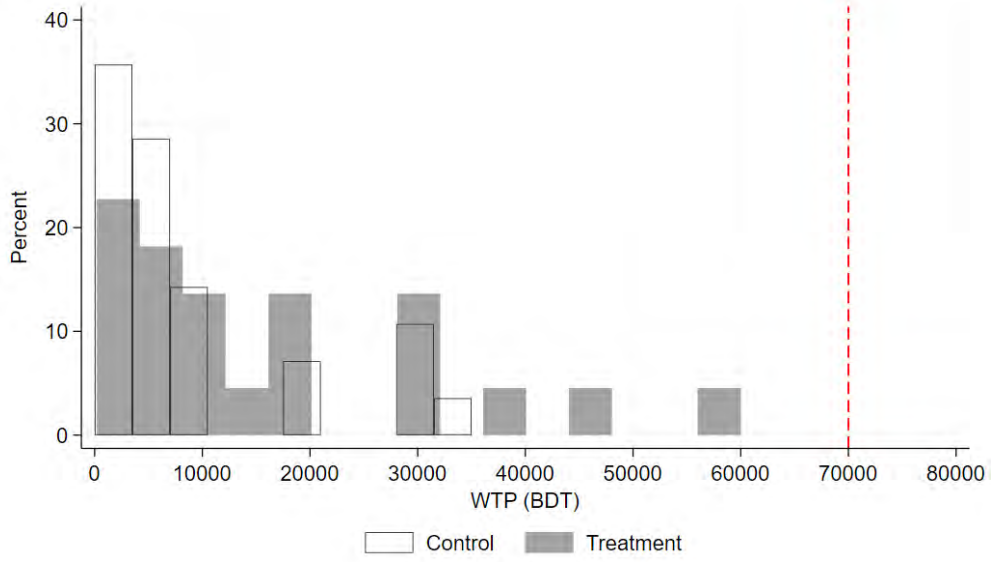
(e) Control vs. Free Trial + Information



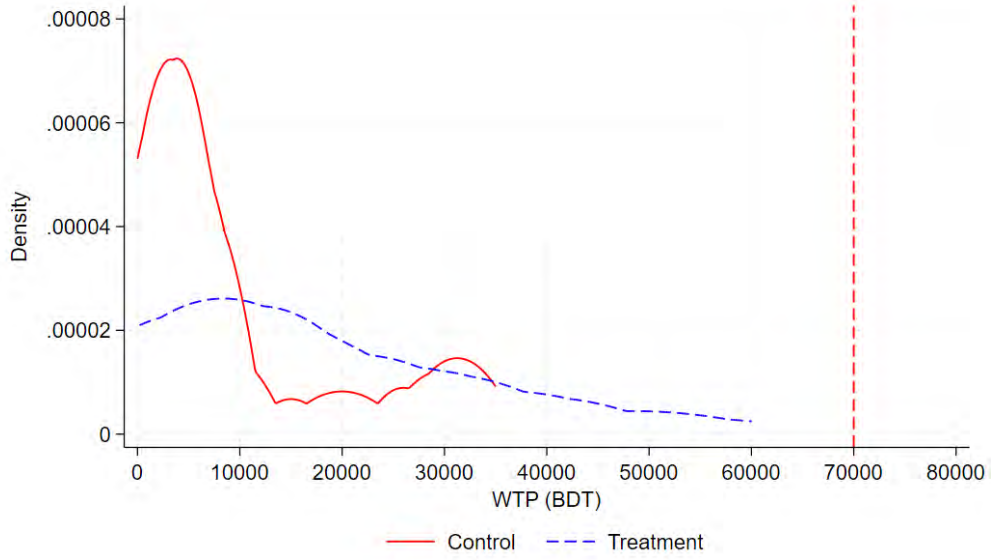
(f) Control vs. Free Trial + Information

Notes: Panels (a) and (b) show the distributions and kernel density plots of willingness to pay for an air purifier in the control and money-back + information group. Panels (c) and (d) show the distributions and kernel density plots of willingness to pay for an air purifier in the control and free trial (w/o information) group. Panels (e) and (f) show the distributions and kernel density plots of willingness to pay for an air purifier in the control and free trial w/ information group. The red dashed line indicates the market value of the air purifier (BDT 70,000).

Figure A.30: Difference in Willingness to Pay for Air Purifiers Between the Control and Treatment Firms 1 Year After Removal



(a) Distribution



(b) Kerney Density Plot

Notes: Panels (a) and (b) show the distributions and kernel density plots of willingness to pay for an air purifier in the control and treatment group. The red dashed line indicates the market value of the air purifier (BDT 70,000).

Table A.1: Baseline Characteristics of the 124 Firms in Our Sample

	Mean	Std dev	Min	Median	Max
RMG Sector (0/1)	1.00	0.00	1.00	1.00	1.00
Keep Daily Records (0/1)	1.00	0.00	1.00	1.00	1.00
Piece Rate Payments (0/1)	1.00	0.00	1.00	1.00	1.00
Individual Production (0/1)	1.00	0.00	1.00	1.00	1.00
Automated Production (0/1)	0.00	0.00	0.00	0.00	0.00
Kamrangirchar (0/1)	0.67	0.47	0.00	1.00	1.00
Workers (#)	10.36	2.94	8.00	9.00	20.00
Female Workers (#)	2.15	1.77	0.00	2.00	8.00
Male Workers (#)	8.21	2.65	2.00	8.00	16.00
Workdays in Week (#)	6.01	0.09	6.00	6.00	7.00
Friday Workday (0/1)	0.05	0.22	0.00	0.00	1.00
T-Shirt (0/1)	0.11	0.32	0.00	0.00	1.00
Underwear (0/1)	0.06	0.23	0.00	0.00	1.00
Shirt (0/1)	0.19	0.40	0.00	0.00	1.00
Burkha (0/1)	0.10	0.30	0.00	0.00	1.00
One Piece (0/1)	0.31	0.46	0.00	0.00	1.00
Two Piece (0/1)	0.06	0.23	0.00	0.00	1.00
Pant (0/1)	0.08	0.27	0.00	0.00	1.00
Other Products (0/1)	0.10	0.30	0.00	0.00	1.00
Piece Rate (BDT)	36.37	29.45	2.00	30.00	180.00
Order-Dependent Production (0/1)	0.68	0.47	0.00	1.00	1.00
Production Highest Before Eid in Feb-April (0/1)	0.80	0.40	0.00	1.00	1.00
Production Floor Size (sq ft)	524.62	317.39	100.00	450.00	1500.00
Ceiling Height (ft)	10.85	1.56	6.00	11.00	15.00
Doors (#)	1.45	0.87	0.00	1.00	5.00
Doors Open (0/1)	0.76	0.43	0.00	1.00	1.00
Windows (#)	3.19	2.12	0.00	3.00	10.00
Windows Open (0/1)	0.69	0.46	0.00	1.00	1.00
Uninterrupted Electricity (0/1)	0.20	0.40	0.00	0.00	1.00
Weekly Power Cuts (#)	5.62	5.06	0.00	5.00	20.00
Typical Power Cut Duration (Mins)	40.73	27.12	0.00	50.00	180.00
No Daily Records Shared (0/1)	0.06	0.23	0.00	0.00	1.00
No Air Monitor Use (0/1)	0.14	0.35	0.00	0.00	1.00
No Owner Survey (0/1)	0.19	0.39	0.00	0.00	1.00
Observations					124

Notes: This table presents the summary statistics (mean, standard deviation, minimum, and maximum values) for the 124 firms in our sample. The data was collected through a baseline owner survey administered in December 2022.

Table A.2: Daily Production Characteristics for Control Firms

	Mean	Std dev	Min	Median	Max
Panel A: Worker-Date Level Data					
T-Shirt (0/1)	0.06	0.24	0.00	0.00	1.00
Underwear (0/1)	0.01	0.11	0.00	0.00	1.00
Shirt (0/1)	0.02	0.14	0.00	0.00	1.00
Burkha (0/1)	0.04	0.21	0.00	0.00	1.00
One Piece (0/1)	0.36	0.48	0.00	0.00	1.00
Two Piece (0/1)	0.12	0.33	0.00	0.00	1.00
Pants (0/1)	0.06	0.23	0.00	0.00	1.00
Other Products (0/1)	0.28	0.45	0.00	0.00	1.00
Piece Rate (BDT)	24.30	21.80	0.60	22.00	400.00
Breaks (#)	1.84	0.72	0.00	2.00	12.00
Time on Break (Mins)	117.00	39.72	0.00	120.00	420.00
Work Hours	11.36	1.64	1.00	12.00	17.00
Any Rejection (0/1)	0.02	0.15	0.00	0.00	1.00
Missing Output Data (0/1)	0.04	0.18	0.00	0.00	1.00
Observations					74796
Panel B: Date Level Data					
Power Cut (0/1)	0.48	0.50	0.00	0.00	1.00
Power Cut (Mins)	32.45	52.16	0.00	0.00	420.00
Workers (#)	8.04	2.72	0.00	8.00	40.00
Operators (#)	5.56	2.25	1.00	5.00	15.00
Other Workers (#)	2.32	1.76	0.00	2.00	10.00
Observations					13446

Notes: This table presents the daily production characteristics (mean, standard deviation, minimum, and maximum values) for control firms between February 2023 and March 2024. Panel A provides worker-date level data, while Panel B presents date-level data. This data was collected through daily production records maintained by each firm.

Table A.3: Differences in Baseline Characteristics of Treatment and Control Firms

	Full sample	Control firms	Treatment firms	Difference of means	p-value on difference
Kamrangirchar (0/1)	0.67	0.65	0.69	0.05	0.57
Workers (#)	10.36	10.35	10.37	0.02	0.98
Female Workers (#)	2.15	1.95	2.35	0.40	0.21
Male Workers (#)	8.21	8.40	8.02	-0.39	0.42
Workdays in Week (#)	6.01	6.02	6.00	-0.02	0.32
Friday Workday (0/1)	0.05	0.05	0.05	0.00	1.00
T-Shirt (0/1)	0.11	0.13	0.10	-0.03	0.57
Underwear (0/1)	0.06	0.06	0.05	-0.02	0.70
Shirt (0/1)	0.19	0.13	0.26	0.13	0.07
Burkha (0/1)	0.10	0.06	0.13	0.06	0.23
One Piece (0/1)	0.31	0.31	0.31	-0.00	1.00
Two Piece (0/1)	0.06	0.08	0.03	-0.05	0.25
Pant (0/1)	0.08	0.11	0.05	-0.06	0.19
Other Products (0/1)	0.10	0.11	0.08	-0.03	0.55
Piece Rate (BDT)	36.37	34.24	38.50	4.26	0.42
Order-Dependent Production (0/1)	0.68	0.71	0.65	-0.06	0.45
Production Highest Before Eid in Feb-April (0/1)	0.80	0.82	0.77	-0.05	0.51
Production Floor Size (sq ft)	524.62	470.50	578.74	108.24	0.06
Ceiling Height (ft)	10.85	10.63	11.07	0.44	0.11
Doors (#)	1.45	1.40	1.50	0.10	0.54
Doors Open (0/1)	0.76	0.77	0.74	-0.03	0.68
Windows (#)	3.19	3.15	3.23	0.08	0.83
Windows Open (0/1)	0.69	0.74	0.65	-0.10	0.25
Uninterrupted Electricity (0/1)	0.20	0.19	0.21	0.02	0.82
Weekly Power Cuts (#)	5.62	5.61	5.63	0.02	0.99
Typical Power Cut Duration (Mins)	40.73	39.11	42.34	3.23	0.51
No Daily Records Shared (0/1)	0.06	0.08	0.03	-0.05	0.25
No Air Monitor Use (0/1)	0.14	0.16	0.11	-0.05	0.44
No Owner Survey (0/1)	0.19	0.19	0.18	-0.02	0.82
Joint Test (p-value)					0.55
Observations					124

Notes: This table shows the mean values of baseline characteristics for the 124 firms in our sample, categorized by treatment status. The data was collected via a baseline owner survey administered in December 2022. The table also provides the difference in means and the corresponding p-values to test for significant differences between treatment and control firms.

Table A.4: Differences in Baseline Characteristics of Treatment and Control Firms that Shared Their Daily Records

	Full sample	Control firms	Treatment firms	Difference of means	p-value on difference
Data Unavailable (0/1)	0.44	0.42	0.45	0.02	0.60
Observations					42822
Kamrangirchar (0/1)	0.68	0.66	0.70	0.03	0.72
Workers (#)	10.38	10.23	10.52	0.29	0.63
Female Workers (#)	2.19	1.92	2.45	0.54	0.12
Male Workers (#)	8.19	8.31	8.07	-0.25	0.66
Workdays in Week (#)	6.00	6.00	6.00	0.00	
Friday Workday (0/1)	0.05	0.03	0.07	0.04	0.39
T-Shirt (0/1)	0.09	0.11	0.07	-0.04	0.47
Underwear (0/1)	0.05	0.07	0.04	-0.03	0.47
Shirt (0/1)	0.19	0.11	0.27	0.16	0.04
Burkha (0/1)	0.10	0.06	0.14	0.07	0.23
One Piece (0/1)	0.31	0.33	0.29	-0.03	0.72
Two Piece (0/1)	0.06	0.08	0.04	-0.04	0.35
Pants (0/1)	0.10	0.13	0.07	-0.06	0.35
Other Products (0/1)	0.10	0.11	0.09	-0.03	0.67
Piece Rate (BDT)	35.91	32.95	38.84	5.89	0.32
Order-Dependent Production (0/1)	0.66	0.71	0.61	-0.11	0.28
Production Highest Before Eid in Feb-April (0/1)	0.83	0.87	0.80	-0.07	0.34
Production Floor Size (sq ft)	519.87	453.40	585.86	132.45	0.03
Ceiling Height (ft)	10.84	10.64	11.04	0.39	0.22
Doors (#)	1.38	1.30	1.45	0.15	0.39
Doors Open (0/1)	0.75	0.74	0.75	0.00	1.00
Windows (#)	3.37	3.16	3.58	0.42	0.34
Windows Open (0/1)	0.72	0.74	0.69	-0.04	0.63
Uninterrupted Electricity (0/1)	0.23	0.22	0.24	0.02	0.79
Weekly Power Cuts (#)	4.97	5.23	4.71	-0.52	0.60
Typical Power Cut Duration (Mins)	39.26	35.72	42.77	7.06	0.23
Joint Test (p-value)					0.34
Observations					24085

Notes: This table shows the differences in baseline characteristics for firms that shared daily records, categorized by treatment status, between February 1, 2023, and March 31, 2024. The data was collected via a baseline owner survey administered in December 2022. The table includes the difference of means and the p-value on the difference to assess statistical significance.

Table A.5: Differences in Baseline Characteristics of Treatment and Control Firms with Indoor Air Monitor Turned On

	Full sample	Control firms	Treatment firms	Difference of means	p-value on difference
Monitor Turned Off (0/1)	0.43	0.39	0.46	0.07	0.02
Monitor or Smartplug Turned Off (0/1)	0.41	0.39	0.42	0.03	0.33
Observations					578040
Kamrangirchar (0/1)	0.70	0.68	0.73	0.05	0.59
Workers (#)	10.29	10.10	10.50	0.40	0.51
Female Workers (#)	2.14	1.82	2.50	0.68	0.05
Male Workers (#)	8.15	8.28	8.00	-0.28	0.61
Workdays in Week (#)	6.00	6.00	6.00	0.00	
Friday Workday (0/1)	0.05	0.03	0.07	0.04	0.33
T-Shirt (0/1)	0.09	0.11	0.06	-0.05	0.41
Underwear (0/1)	0.05	0.08	0.02	-0.06	0.24
Shirt (0/1)	0.21	0.13	0.31	0.18	0.05
Burkha (0/1)	0.10	0.06	0.15	0.09	0.17
One Piece (0/1)	0.29	0.31	0.27	-0.04	0.66
Two Piece (0/1)	0.07	0.09	0.04	-0.05	0.31
Pants (0/1)	0.08	0.10	0.06	-0.05	0.39
Other Products (0/1)	0.10	0.11	0.08	-0.03	0.63
Piece Rate (BDT)	37.01	33.52	40.93	7.40	0.26
Order-Dependent Production (0/1)	0.65	0.70	0.59	-0.11	0.29
Production Highest Before Eid in Feb-April (0/1)	0.83	0.86	0.80	-0.07	0.41
Production Floor Size (sq ft)	515.38	445.73	593.68	147.95	0.02
Ceiling Height (ft)	10.84	10.59	11.13	0.54	0.11
Doors (#)	1.36	1.26	1.48	0.22	0.27
Doors Open (0/1)	0.74	0.76	0.73	-0.03	0.75
Windows (#)	3.36	3.03	3.74	0.72	0.13
Windows Open (0/1)	0.72	0.75	0.68	-0.07	0.49
Uninterrupted Electricity (0/1)	0.23	0.23	0.23	-0.00	0.99
Weekly Power Cuts (#)	5.09	5.39	4.75	-0.63	0.54
Typical Power Cut Duration (Mins)	39.61	35.16	44.62	9.46	0.12
Joint Test (p-value)					0.13
Observations					331981

Notes: This table shows the differences in baseline characteristics for firms that had their indoor air monitor turned on and for which hourly indoor PM2.5 readings were available, categorized by treatment status, between April 1, 2023, and March 31, 2024. The data was collected via a baseline owner survey administered in December 2022. The table includes the difference of means and the p-value on the difference to assess statistical significance.

Table A.6: Differences in Baseline Characteristics of Treatment and Control Firms for which Observed or Imputed Indoor PM2.5 Readings are Available

	Full sample	Control firms	Treatment firms	Difference of means	p-value on difference
Indoor PM2.5 Unavailable (0/1)	0.00	0.00	0.00	0.00	0.32
Observations					578040
Kamrangirchar (0/1)	0.68	0.66	0.70	0.04	0.72
Workers (#)	10.38	10.23	10.52	0.29	0.63
Female Workers (#)	2.19	1.92	2.45	0.54	0.12
Male Workers (#)	8.19	8.31	8.07	-0.24	0.66
Workdays in Week (#)	6.00	6.00	6.00	0.00	
Friday Workday (0/1)	0.05	0.03	0.07	0.04	0.38
T-Shirt (0/1)	0.09	0.11	0.07	-0.04	0.47
Underwear (0/1)	0.05	0.07	0.04	-0.03	0.47
Shirt (0/1)	0.19	0.11	0.27	0.16	0.04
Burkha (0/1)	0.10	0.06	0.14	0.07	0.23
One Piece (0/1)	0.31	0.33	0.29	-0.03	0.72
Two Piece (0/1)	0.06	0.08	0.04	-0.04	0.35
Pants (0/1)	0.10	0.13	0.07	-0.06	0.35
Other Products (0/1)	0.10	0.11	0.09	-0.03	0.67
Piece Rate (BDT)	35.91	32.95	38.85	5.89	0.32
Order-Dependent Production (0/1)	0.66	0.71	0.61	-0.11	0.28
Production Highest Before Eid in Feb-April (0/1)	0.83	0.87	0.80	-0.07	0.34
Production Floor Size (sq ft)	519.88	453.45	585.85	132.40	0.03
Ceiling Height (ft)	10.84	10.64	11.04	0.39	0.22
Doors (#)	1.38	1.30	1.45	0.15	0.39
Doors Open (0/1)	0.75	0.74	0.75	0.00	1.00
Windows (#)	3.37	3.16	3.58	0.43	0.34
Windows Open (0/1)	0.72	0.74	0.69	-0.04	0.63
Uninterrupted Electricity (0/1)	0.23	0.22	0.24	0.02	0.79
Weekly Power Cuts (#)	4.97	5.23	4.71	-0.52	0.60
Typical Power Cut Duration (Mins)	39.26	35.72	42.78	7.06	0.23
Joint Test (p-value)					0.34
Observations					577255

Notes: This table shows the differences in baseline characteristics for firms with observed or imputed hourly indoor PM2.5 readings available by treatment status between April 1, 2023, and March 31, 2024. The data was collected via a baseline owner survey administered in December 2022. The table includes the difference of means and the p-value on the difference to assess statistical significance.

Table A.7: Differences in Baseline Characteristics of Treatment and Control Firms where Owners Responded to Monthly Surveys

	Full sample	Control firms	Treatment firms	Difference of means	p-value on difference
Owner Survey Unavailable (0/1)	0.06	0.05	0.07	0.02	0.65
Observations					1290
Kamrangirchar (0/1)	0.70	0.67	0.72	0.05	0.60
Workers (#)	10.40	10.22	10.58	0.36	0.57
Female Workers (#)	2.19	1.93	2.45	0.52	0.14
Male Workers (#)	8.21	8.29	8.13	-0.16	0.78
Workdays in Week (#)	6.00	6.00	6.00	0.00	
Friday Workday (0/1)	0.05	0.03	0.06	0.03	0.43
T-Shirt (0/1)	0.10	0.11	0.08	-0.04	0.52
Underwear (0/1)	0.04	0.07	0.02	-0.05	0.29
Shirt (0/1)	0.19	0.10	0.27	0.17	0.04
Burkha (0/1)	0.10	0.06	0.13	0.07	0.25
One Piece (0/1)	0.31	0.32	0.30	-0.02	0.83
Two Piece (0/1)	0.06	0.09	0.04	-0.05	0.31
Pants (0/1)	0.10	0.13	0.07	-0.06	0.37
Other Products (0/1)	0.10	0.11	0.09	-0.03	0.68
Piece Rate (BDT)	36.46	33.27	39.71	6.44	0.28
Order-Dependent Production (0/1)	0.67	0.73	0.61	-0.11	0.25
Production Highest Before Eid in Feb-April (0/1)	0.83	0.86	0.80	-0.06	0.45
Production Floor Size (sq ft)	517.57	453.80	582.19	128.39	0.05
Ceiling Height (ft)	10.84	10.66	11.02	0.36	0.26
Doors (#)	1.36	1.30	1.43	0.13	0.44
Doors Open (0/1)	0.74	0.74	0.73	-0.02	0.87
Windows (#)	3.39	3.20	3.59	0.38	0.39
Windows Open (0/1)	0.70	0.73	0.68	-0.05	0.57
Uninterrupted Electricity (0/1)	0.23	0.23	0.24	0.02	0.85
Weekly Power Cuts (#)	4.82	5.08	4.57	-0.51	0.60
Typical Power Cut Duration (Mins)	39.17	35.42	42.97	7.56	0.21
Joint Test (p-value)					0.39
Observations					1212

Notes: This table shows the differences in baseline characteristics for firms where the owners answered the survey that collected revenue and cost data in months the firm was open, categorized by treatment status, between February 1, 2023, and March 31, 2024. The data was collected via a baseline owner survey administered in December 2022. The table includes the difference of means and the p-value on the difference to assess statistical significance.

Table A.8: Treatment Firms Increase Purifier Use in Response to Higher Outdoor PM2.5 Levels

	(1) Use (0/1) β / SE	(2) Use (0/1) β / SE	(3) Use (0/1) β / SE	(4) Use (0/1) β / SE
Outdoor PM2.5 (x100)	0.02***			
	(0.00)			
50 < Outdoor PM2.5 <= 100		0.00	0.01**	0.01*
		(0.01)	(0.01)	(0.01)
100 < Outdoor PM2.5 <= 150		0.02*	0.03***	0.03***
		(0.01)	(0.01)	(0.01)
150 < Outdoor PM2.5 <= 200		0.02	0.03***	0.02**
		(0.02)	(0.01)	(0.01)
200 < Outdoor PM2.5 <= 250		0.02	0.03**	0.02**
		(0.02)	(0.01)	(0.01)
250 < Outdoor PM2.5 <= 300		0.03	0.03*	0.02
		(0.02)	(0.02)	(0.01)
300 < Outdoor PM2.5 <= 350		0.03	0.03	0.02
		(0.02)	(0.02)	(0.02)
350 < Outdoor PM2.5 <= 400		0.06*	0.05*	0.04
		(0.03)	(0.03)	(0.02)
400 < Outdoor PM2.5 <= 450		0.10***	0.08***	0.06***
		(0.03)	(0.02)	(0.02)
450 < Outdoor PM2.5 <= 500		0.12***	0.10***	0.07***
		(0.03)	(0.02)	(0.02)
Outdoor PM2.5 > 500		0.12***	0.10***	0.08***
		(0.03)	(0.03)	(0.03)
Weather Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	No	No
Date FE	Yes	Yes	No	No
Hour of Day FE	Yes	Yes	Yes	No
Firm-Date FE	No	No	Yes	Yes
Firm-Hour of Day FE	No	No	No	Yes
Control Mean	0.26	0.24	0.24	0.24
Observations	7078118	7078118	7078117	7078116
R^2	0.361	0.362	0.765	0.789

Notes: This table shows the linear and non-parametric relationship between outdoor PM2.5 levels and air purifier use in treatment firms. We drop observations where energy use data from smart plugs is missing. Estimates in Column (1) are from Equation (1). Estimates in Columns (2) to (4) are from a specification that extended Equation (2) to include 50 unit bins between 300 and 500 $\mu g/m^3$. All columns include controls for precipitation, outdoor temperature, and outdoor humidity. Columns (1) and (2) include firm, date, and hour-of-day fixed effects. Column (3) includes firm-by-date and hour-of-day fixed effects. Column (4) includes firm-by-date and firm-by-hour-of-day fixed effects. Standard errors are clustered at the week-of-year level. Significance levels are denoted by $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$.

Table A.9: Falsification Test: No Differences in Indoor Environment Between Treatment and Control Firms on Days They Are Open

	Control mean	Estimate	p-value on difference
Indoor Temperature (C)	29.47	-0.17	0.27
Indoor Humidity (%)	73.76	0.26	0.69
Observations			331690

Notes: The table presents differences in indoor environmental conditions between treatment and control firms on days they are open. All regressions include date and hour-of-day fixed effects. Standard errors are clustered at the firm level.

Table A.10: Lower Indoor Air Pollution Levels in Main Treatment Firms

	(1) Indoor PM2.5 β / SE	(2) Indoor PM2.5 β / SE	(3) Indoor PM2.5 β / SE	(4) Indoor PM2.5 β / SE	(5) Indoor PM2.5 β / SE
Panel A: 24-Hour					
Treatment = 1	-8.55**	-9.57**	-9.83***	-9.83***	-9.83***
	(3.91)	(3.73)	(3.54)	(3.54)	(3.57)
Control Mean	72.96	72.96	72.96	72.96	72.96
Observations	477605	477605	477605	477605	477389
R^2	0.003	0.009	0.352	0.375	0.458
Panel B: 9am - 6pm					
Treatment = 1	-10.32***	-11.27***	-11.56***	-11.56***	-11.56***
	(3.51)	(3.33)	(3.19)	(3.19)	(3.21)
Control Mean	68.52	68.52	68.52	68.52	68.52
Observations	198726	198726	198726	198726	198636
R^2	0.006	0.011	0.381	0.400	0.454
Site FE	No	Yes	Yes	Yes	Yes
Date FE	No	No	Yes	Yes	No
Hour-of-Day FE	No	No	No	Yes	No
Date-Hour FE	No	No	No	No	Yes

Notes: This table shows the effect of purifier assignment on hourly indoor PM2.5 levels. The sample is restricted to only include firms that are part of the main treatment and control groups. Panel A analyzes the 24- hour impact, while Panel B focuses on the 9am to 6pm window, when the vast majority of firms are open. Columns (1) through (5) progressively include more controls and fixed effects: Column (1) is the simplest model without controls, Column (2) includes site fixed effects, Column (3) includes site and date fixed effects, Column (4) includes site, date, and hour-of-day fixed effects, and Column (5) includes site and date-hour fixed effects. Standard errors are clustered at the firm level. Significance levels are denoted by $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$.

Table A.11: Lower Indoor Air Pollution Levels in Treatment Firms Compared for Observations Where Indoor PM2.5 Levels Are Recorded

	(1) Indoor PM2.5 β / SE	(2) Indoor PM2.5 β / SE	(3) Indoor PM2.5 β / SE	(4) Indoor PM2.5 β / SE	(5) Indoor PM2.5 β / SE
Panel A: 24-Hour					
Treatment = 1	-14.55**	-15.71***	-19.14***	-18.91***	-18.91***
	(5.96)	(5.61)	(5.18)	(5.18)	(5.21)
Control Mean	80.16	80.16	80.16	80.16	80.16
Observations	331981	331981	331981	331981	331690
R^2	0.007	0.019	0.336	0.364	0.433
Panel B: 9am - 6pm					
Treatment = 1	-16.29***	-17.06***	-20.24***	-20.29***	-20.24***
	(5.07)	(4.77)	(4.44)	(4.43)	(4.47)
Control Mean	77.46	77.46	77.46	77.46	77.46
Observations	146331	146331	146331	146331	146218
R^2	0.010	0.021	0.370	0.398	0.440
Site FE	No	Yes	Yes	Yes	Yes
Date FE	No	No	Yes	Yes	No
Hour-of-Day FE	No	No	No	Yes	No
Date-Hour FE	No	No	No	No	Yes

Notes: This table shows the effect of purifier assignment on hourly indoor PM2.5 levels. The sample only includes observations for which indoor PM2.5 readings were available. Panel A analyzes the 24- hour impact, while Panel B focuses on the 9am to 6pm window, when the vast majority of firms are open. Columns (1) through (5) progressively include more controls and fixed effects: Column (1) is the simplest model without controls, Column (2) includes site fixed effects, Column (3) includes site and date fixed effects, Column (4) includes site, date, and hour-of-day fixed effects, and Column (5) includes site and date-hour fixed effects. Standard errors are clustered at the firm level. Significance levels are denoted by $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$.

Table A.12: Falsification Test: No Differences in Daily Production Characteristics Between Control and Treatment Firms on Days They Are Open Before April 2023

	Control mean	Estimate	p-value on difference
T-Shirt (0/1)	0.06	-0.01	0.83
Underwear (0/1)	0.01	0.04	0.15
Shirt (0/1)	0.00	0.02	0.08
Burkha (0/1)	0.04	0.02	0.59
One Piece (0/1)	0.36	-0.02	0.85
Two Piece (0/1)	0.10	0.04	0.52
Pants (0/1)	0.08	-0.02	0.47
Other Products (0/1)	0.30	-0.08	0.34
Piece Rate (BDT)	26.21	3.86	0.28
Missing Output Data (0/1)	0.05	-0.01	0.82
Observations			19186
Power Cut (0/1)	0.28	0.02	0.67
Power Cut (Mins)	15.37	4.98	0.23
Observations			3035
Joint Test (p-value)			0.59

Notes: This table presents estimates for the differences in daily production characteristics between control and treatment firms on days they are open between February 2023 and March 2023. All regressions include site and date fixed effects. Standard errors are clustered at the firm level.

Table A.13: Falsification Test: No Differences in Daily Production Characteristics Between Control and Treatment Firms on Days They Are Open Between April 2023 and March 2024

	Control mean	Estimate	p-value on difference
T-Shirt (0/1)	0.06	-0.01	0.85
Underwear (0/1)	0.01	0.02	0.19
Shirt (0/1)	0.02	0.04	0.12
Burkha (0/1)	0.05	0.05	0.33
One Piece (0/1)	0.36	-0.02	0.84
Two Piece (0/1)	0.12	0.00	0.94
Pants (0/1)	0.05	0.01	0.69
Other Products (0/1)	0.28	-0.10	0.09
Piece Rate (BDT)	24.03	3.14	0.36
Missing Output Data (0/1)	0.03	-0.01	0.70
Observations			129236
Power Cut (0/1)	0.50	0.07	0.08
Power Cut (Mins)	34.52	3.76	0.18
Observations			24085
Joint Test (p-value)			0.37

Notes: This table presents estimates for the differences in daily production characteristics between control and treatment firms on days they are open between April 23 and March 24. All regressions include site and date fixed effects. Standard errors are clustered at the firm level.

Table A.14: Increased Output Per Worker in Treatment Firms

	(1) Ln Output β / SE	(2) Ln Output β / SE	(3) Ln Output β / SE	(4) Ln Output β / SE
Treatment = 1	0.09**	0.10***	0.09**	0.09***
	(0.04)	(0.04)	(0.04)	(0.04)
Piece Rate FE	Yes	Yes	Yes	Yes
Product Type FE	Yes	Yes	Yes	Yes
Site FE	No	Yes	Yes	No
Date FE	No	No	Yes	No
Site-Date FE	No	No	No	Yes
Control Mean	108.69	108.69	108.69	108.69
Observations	83318	83318	83317	83317
R^2	0.923	0.926	0.928	0.930

Notes: This table shows the impact of air purifier assignment on log daily worker-level output during the entire post-period (April 23 to Mar 24). We restrict the sample to dates when indoor air monitor readings were available. All columns include piece rate and product type fixed effects. Column (1) includes no other controls. Column (2) also includes site fixed effects. Column (3) includes site and date fixed effects. Column (4) includes site-by-date fixed effects. Standard errors are clustered at the firm level. Significance levels are denoted by $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$.

Table A.15: Increased Output Per Worker in Main Treatment Firms

	(1) Ln Output β / SE	(2) Ln Output β / SE	(3) Ln Output β / SE	(4) Ln Output β / SE
Treatment = 1	0.09**	0.11***	0.11***	0.11***
	(0.04)	(0.04)	(0.04)	(0.04)
Piece Rate FE	Yes	Yes	Yes	Yes
Product Type FE	Yes	Yes	Yes	Yes
District FE	No	Yes	Yes	No
Date FE	No	No	Yes	No
District-Date FE	No	No	No	Yes
Control Mean	115.20	115.20	115.20	115.20
Observations	102095	102095	102095	102095
R^2	0.923	0.924	0.925	0.927

Notes: This table shows the impact of air purifier assignment on log daily worker-level output during the entire post-period (April 23 to Mar 24). We restrict the sample to include firms in only the main treatment and control groups. All columns include piece rate and product type fixed effects. Column (1) includes no other controls. Column (2) also includes site fixed effects. Column (3) includes site and date fixed effects. Column (4) includes site-by-date fixed effects. Standard errors are clustered at the firm level. Significance levels are denoted by $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$.

Table A.16: No Aggregate Change in Firm Operations, Labor Supply, or Rejection Rates for Treatment Firms

	(1) Firms Operational (#) β / SE	(2) Workers (#) β / SE	(3) Operators (#) β / SE	(4) Other Workers (#) β / SE	(5) Breaks (#) β / SE	(6) Time on Break (Mins) β / SE	(7) Work Hours β / SE	(8) Any Rejection (0/1) β / SE
Treatment = 1	0.24	-0.18	-0.20	0.08	-0.11*	-1.51	-0.06	-0.01
	(0.23)	(0.44)	(0.32)	(0.27)	(0.06)	(3.09)	(0.13)	(0.01)
Piece Rate FE	No	No	No	No	Yes	Yes	Yes	Yes
Product Type FE	No	No	No	No	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control Mean	39.88	8.49	6.30	2.14	1.83	115.89	11.48	0.02
Observations	678	24076	24076	24076	125515	125515	125515	125515
R^2	0.977	0.033	0.120	0.050	0.247	0.558	0.218	0.138

Notes: This table shows the impact of air purifier assignment on the number of days firms were operational, number of workers, number of operators, number of other workers, number of breaks, time on breaks, work hours, and rejection rates during the entire post-period (April 23 to Mar 24). All columns include piece rate, product type, site, and date fixed effects. Standard errors are clustered at the firm level. Significance levels are denoted by $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$.

Table A.17: Increased Hourly Earnings Per Worker in Treatment Firms

	(1) Log Hourly Wage β / SE	(2) Log Hourly Wage β / SE	(3) Log Hourly Wage β / SE	(4) Log Hourly Wage β / SE	(5) Log Hourly Wage β / SE
Treatment = 1	0.13**	0.12**	0.13**	0.12**	0.12**
	(0.06)	(0.05)	(0.05)	(0.05)	(0.05)
Product Type FE	No	Yes	Yes	Yes	Yes
District FE	No	No	Yes	Yes	No
Date FE	No	No	No	Yes	No
District-Date FE	No	No	No	No	Yes
Control Mean	58.65	58.65	58.65	58.65	58.65
Observations	125512	125512	125512	125511	125511
R^2	0.018	0.108	0.114	0.155	0.169

Notes: This table shows the impact of air purifier assignment on log hourly worker-level earnings during the entire post-period (April 23 to Mar 24). Column (1) includes no controls. Column (2) includes product type fixed effects. Column (3) also includes site fixed effects. Column (4) includes product type, site, and date fixed effects. Column (4) includes product type and site-by-date fixed effects. Standard errors are clustered at the firm level. Significance levels are denoted by $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$.

Table A.18: Heterogeneity by Outdoor PM2.5 Levels: Daily Output Per Worker in Treatment Firms Higher Compared to Control Firms on Worse Pollution Days

	(1) Ln Output β / SE	(2) Ln Output β / SE	(3) Ln Output β / SE	(4) Ln Output β / SE
Treatment*Outdoor PM2.5 <= 50	0.05	0.06	0.07*	0.08*
	(0.04)	(0.04)	(0.04)	(0.04)
Treatment*50 < Outdoor PM2.5 <= 100	0.10**	0.10**	0.10**	0.09**
	(0.04)	(0.04)	(0.04)	(0.04)
Treatment*100 < Outdoor PM2.5 <= 150	0.11**	0.12***	0.11**	0.10**
	(0.04)	(0.04)	(0.04)	(0.04)
Treatment*150 < Outdoor PM2.5 <= 200	0.11**	0.12***	0.12***	0.12***
	(0.04)	(0.04)	(0.05)	(0.04)
Treatment*200 < Outdoor PM2.5 <= 250	0.10**	0.12**	0.14**	0.13**
	(0.05)	(0.05)	(0.05)	(0.06)
Treatment*Outdoor PM2.5 > 250	0.12**	0.14***	0.18***	0.17***
	(0.05)	(0.05)	(0.05)	(0.05)
Piece Rate FE	Yes	Yes	Yes	Yes
Product Type FE	Yes	Yes	Yes	Yes
District FE	No	Yes	Yes	No
Date FE	No	No	Yes	No
District-Date FE	No	No	No	Yes
Control Mean	108.69	108.69	108.69	108.69
Observations	125516	125516	125515	125515
R^2	0.904	0.907	0.909	0.911

Notes: This table shows the impact of air purifier assignment on log daily worker-level output by outdoor PM2.5 levels during the entire post-period (April 23 to Mar 24). All columns include piece rate and product type fixed effects. Column (1) includes no other controls. Column (2) also includes site fixed effects. Column (3) includes site and date fixed effects. Column (4) includes site-by-date fixed effects. Standard errors are clustered at the firm level. Significance levels are denoted by $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$.

Table A.19: Higher Daily Output Per Worker in Main Treatment Firms Compared to Main Control Firms

	(1) Profits (BDT) β / SE	(2) Profits (BDT) β / SE	(3) Profits (BDT) β / SE	(4) Profits (BDT) β / SE
Treatment = 1	11776.03	11150.18	10192.87	10498.95
	(7994.50)	(7888.18)	(7855.18)	(7884.86)
Baseline Controls	Yes	Yes	Yes	Yes
Product Type FE	Yes	Yes	Yes	Yes
District FE	No	Yes	Yes	No
Year-Month FE	No	No	Yes	No
District-Year-Month FE	No	No	No	Yes
Control Mean	62205.17	62205.17	62205.17	62205.17
Observations	858	858	858	858
R^2	0.067	0.080	0.160	0.175

Notes: This table shows the impact of air purifier assignment on monthly profit at the firm level during the entire post-period (April 23 to Mar 24). We restrict the sample to include firms in only the main treatment and control groups. All columns include controls from the baseline survey (monthly profits in BDT, output in weekly units, flood size in sq ft) and product type fixed effects. Column (1) includes no other controls. Column (2) also includes site fixed effects. Column (3) includes site and date fixed effects. Column (4) includes site-by-date fixed effects. Standard errors are clustered at the firm level. Significance levels are denoted by $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$.

Table A.20: Increased Revenues in Treatment Firms

	(1) Revenues (BDT) β / SE	(2) Revenues (BDT) β / SE	(3) Revenues (BDT) β / SE	(4) Revenues (BDT) β / SE
Panel A: Post-Period				
Treatment = 1	37659.72*	37437.27*	36004.49*	36066.41*
	(21634.46)	(21389.51)	(21542.14)	(21610.38)
Control Mean	267823.53	267823.53	267823.53	267823.53
Observations	1044	1044	1044	1044
R^2	0.148	0.156	0.229	0.232
	(1) Revenues (BDT) β / SE	(2) Revenues (BDT) β / SE	(3) Revenues (BDT) β / SE	(4) Revenues (BDT) β / SE
Panel B: Post-Period (Feb-Mar)				
Treatment = 1	59155.29	58931.55	58988.03	59243.10
	(37671.22)	(37470.42)	(37334.57)	(37409.03)
Control Mean	302545.45	302545.45	302545.45	302545.45
Observations	158	158	158	158
R^2	0.221	0.251	0.263	0.266
	(1) Revenues (BDT) β / SE	(2) Revenues (BDT) β / SE	(3) Revenues (BDT) β / SE	(4) Revenues (BDT) β / SE
Panel C: Pre-Period (Feb-Mar)				
Treatment = 1	5371.69	5152.58	4790.44	5033.99
	(60722.17)	(60846.55)	(61042.07)	(61229.58)
Control Mean	349204.82	349204.82	349204.82	349204.82
Observations	166	166	166	166
R^2	0.320	0.322	0.324	0.324
Baseline Controls	Yes	Yes	Yes	Yes
Product Type FE	Yes	Yes	Yes	Yes
District FE	No	Yes	Yes	No
Year-Month FE	No	No	Yes	No
District-Year-Month FE	No	No	No	Yes

Notes: This table shows the impact of air purifier assignment on monthly revenues at the firm level. Panel A examines impacts on revenues during the entire post-period (April 23 to Mar 24). Panel B examines impacts on revenues during the last two months of the post-period (Feb 24 to Mar 24). Panel C examines impacts on revenues during the pre-period (Feb 23 to Mar 23). All columns include controls from the baseline survey (monthly profits in BDT, output in weekly units, flood size in sq ft) and product type fixed effects. Column (1) includes no other controls. Column (2) also includes site fixed effects. Column (3) includes site and date fixed effects. Column (4) includes site-by-date fixed effects. Standard errors are clustered at the firm level. Significance levels are denoted by $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$.

Table A.21: Increased Costs in Treatment Firms

	(1) Costs (BDT) β / SE	(2) Costs (BDT) β / SE	(3) Costs (BDT) β / SE	(4) Costs (BDT) β / SE
Panel A: Post-Period				
Treatment = 1	27229.56	27101.96	26931.67	26927.56
	(17075.06)	(16969.87)	(16930.53)	(16978.83)
Control Mean	202536.24	202536.24	202536.24	202536.24
Observations	1044	1044	1044	1044
R^2	0.188	0.192	0.247	0.252
	(1) Costs (BDT) β / SE	(2) Costs (BDT) β / SE	(3) Costs (BDT) β / SE	(4) Costs (BDT) β / SE
Panel B: Post-Period (Feb-Mar)				
Treatment = 1	19318.52	19113.99	19179.87	19440.88
	(30142.61)	(29948.66)	(29782.20)	(29868.74)
Control Mean	236305.19	236305.19	236305.19	236305.19
Observations	158	158	158	158
R^2	0.277	0.316	0.344	0.348
	(1) Costs (BDT) β / SE	(2) Costs (BDT) β / SE	(3) Costs (BDT) β / SE	(4) Costs (BDT) β / SE
Panel C: Pre-Period (Feb-Mar)				
Treatment = 1	100.87	-77.86	-308.27	-269.04
	(39133.56)	(39245.33)	(39370.64)	(39404.60)
Control Mean	241671.69	241671.69	241671.69	241671.69
Observations	166	166	166	166
R^2	0.363	0.365	0.367	0.367
Baseline Controls	Yes	Yes	Yes	Yes
Product Type FE	Yes	Yes	Yes	Yes
District FE	No	Yes	Yes	No
Year-Month FE	No	No	Yes	No
District-Year-Month FE	No	No	No	Yes

Notes: This table shows the impact of air purifier assignment on monthly costs at the firm level. Panel A examines impacts on costs during the entire post-period (April 23 to Mar 24). Panel B examines impacts on costs during the last two months of the post-period (Feb 24 to Mar 24). Panel C examines impacts on costs during the pre-period (Feb 23 to Mar 23). All columns include controls from the baseline survey (monthly profits in BDT, output in weekly units, flood size in sq ft) and product type fixed effects. Column (1) includes no other controls. Column (2) also includes site fixed effects. Column (3) includes site and date fixed effects. Column (4) includes site-by-date fixed effects. Standard errors are clustered at the firm level. Significance levels are denoted by $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$.

Table A.22: Experiment 2: Baseline Characteristics of the 2500 Firms in Our Sample

	Mean	Std dev	Min	Median	Max
Kamrangirchar (0/1)	0.58	0.49	0.00	1.00	1.00
Workers (#)	11.93	9.03	0.00	9.00	148.00
Operators (#)	6.97	5.71	0.00	5.00	50.00
Piece Rate Payments (0/1)	0.77	0.42	0.00	1.00	1.00
Individual Production (0/1)	0.75	0.43	0.00	1.00	1.00
Automated Production (0/1)	0.11	0.31	0.00	0.00	1.00
T-Shirt (0/1)	0.29	0.45	0.00	0.00	1.00
Underwear (0/1)	0.03	0.16	0.00	0.00	1.00
Shirt (0/1)	0.06	0.24	0.00	0.00	1.00
Burkha (0/1)	0.08	0.27	0.00	0.00	1.00
One Piece (0/1)	0.13	0.33	0.00	0.00	1.00
Two Piece (0/1)	0.18	0.38	0.00	0.00	1.00
Pants (0/1)	0.18	0.38	0.00	0.00	1.00
Other Products (0/1)	0.40	0.49	0.00	0.00	1.00
Order-Dependent Production (0/1)	0.60	0.49	0.00	1.00	1.00
Seasonality in Production (0/1)	0.78	0.41	0.00	1.00	1.00
Production Highest Before Eid in Feb-April (0/1)	0.85	0.36	0.00	1.00	1.00
Year-on-Year Fluctuations in Production (0/1)	0.60	0.49	0.00	1.00	1.00
Production Floor Size (sq ft)	882.88	741.90	100.00	700.00	10000.00
Operational Days (#)	265.57	50.80	0.00	280.00	360.00
Uninterrupted Electricity (0/1)	0.09	0.29	0.00	0.00	1.00
Weekly Power Cuts (#)	7.60	7.35	0.00	5.00	70.00
Typical Power Cut Duration (Mins)	38.84	34.39	0.00	30.00	480.00
Observations					2500

Notes: This table presents the summary statistics (mean, standard deviation, minimum, and maximum values) for the 2500 firms in our sample. The data was collected through a baseline owner survey administered in January-March 2025.

Table A.23: Experiment 2: Differences in Baseline Characteristics of Treatment and Control Firms

	Control	Information	Credit	Credit + Info	Warranty	Warranty + Info	Money-Back	Money-Back + Info	Trial	Trial + Info	p-value
Kamrangirchar (0/1)	0.64	0.58	0.57	0.58	0.62	0.61	0.55	0.64	0.53	0.53	0.09
Workers (#)	13.13	11.72	11.43	11.02	12.52	11.74	11.84	12.27	12.06	11.55	0.35
Operators (#)	7.69	6.96	6.38	6.36	7.52	7.11	6.82	7.06	7.02	6.79	0.13
Piece Rate Payments (0/1)	0.81	0.79	0.76	0.70	0.80	0.74	0.78	0.78	0.75	0.77	0.18
Individual Production (0/1)	0.75	0.75	0.78	0.75	0.78	0.74	0.76	0.76	0.73	0.72	0.87
Automated Production (0/1)	0.08	0.10	0.09	0.12	0.10	0.18	0.09	0.11	0.11	0.09	0.16
T-Shirt (0/1)	0.26	0.26	0.31	0.31	0.26	0.28	0.32	0.26	0.30	0.31	0.64
Underwear (0/1)	0.04	0.03	0.02	0.02	0.04	0.02	0.04	0.04	0.02	0.02	0.41
Shirt (0/1)	0.03	0.09	0.08	0.04	0.07	0.07	0.08	0.06	0.06	0.05	0.07
Burkha (0/1)	0.12	0.08	0.10	0.08	0.05	0.10	0.04	0.07	0.10	0.08	0.02
One Piece (0/1)	0.14	0.13	0.13	0.12	0.17	0.13	0.11	0.12	0.10	0.13	0.65
Two Piece (0/1)	0.23	0.17	0.19	0.20	0.19	0.16	0.14	0.19	0.14	0.17	0.24
Pants (0/1)	0.16	0.17	0.16	0.15	0.19	0.17	0.20	0.24	0.16	0.18	0.37
Other Products (0/1)	0.37	0.42	0.38	0.39	0.42	0.36	0.40	0.39	0.43	0.40	0.85
Order-Dependent Production (0/1)	0.60	0.58	0.64	0.62	0.61	0.60	0.60	0.58	0.58	0.59	0.91
Seasonality in Production (0/1)	0.80	0.76	0.79	0.80	0.78	0.83	0.77	0.75	0.74	0.81	0.34
Production Highest Before Eid in Feb-April (0/1)	0.84	0.87	0.88	0.84	0.81	0.83	0.85	0.85	0.82	0.87	0.35
Year-on-Year Fluctuations in Production (0/1)	0.57	0.57	0.60	0.61	0.59	0.61	0.59	0.55	0.62	0.64	0.75
Production Floor Size (sq ft)	910.33	841.66	870.04	887.07	872.00	924.42	881.67	884.47	919.60	837.56	0.92
Operational Days (#)	266.70	263.26	265.16	264.52	266.06	261.20	265.12	267.44	270.19	266.06	0.80
Uninterrupted Electricity (0/1)	0.10	0.10	0.08	0.07	0.11	0.08	0.08	0.08	0.10	0.08	0.92
Weekly Power Cuts (#)	6.93	7.51	7.47	7.43	7.54	7.60	7.51	8.21	8.22	7.60	0.76
Typical Power Cut Duration (Mins)	36.95	37.83	38.14	36.91	39.48	38.26	38.68	44.82	39.00	38.28	0.56
WTP for Thread Box (BDT)	17.28	16.77	16.38	15.98	15.62	15.28	17.36	15.55	16.22	17.18	0.36
Joint Test (p-value)											0.21
Observations											2500

Notes: This table shows the mean values of baseline characteristics for the 2,500 firms in our sample, categorized by treatment status. The data were collected via a baseline owner survey administered in January-March 2023. The table also provides the p-values from the joint test for significant differences between control and treatment groups.

Table A.24: Firms Open on April 1, 2023: Differences in Baseline Characteristics of Treatment and Control Firms

	Full sample	Control firms	Treatment firms	Difference of means	p-value on difference
WTP Missing (0/1)	0.36	0.29	0.44	0.15	0.11
Observations					107
Kamrangirchar (0/1)	0.66	0.65	0.68	0.03	0.81
Workers (#)	10.47	10.35	10.61	0.26	0.74
Female Workers (#)	2.29	1.84	2.84	1.00	0.02
Male Workers (#)	8.18	8.51	7.77	-0.74	0.28
Workdays in Week (#)	6.00	6.00	6.00	0.00	.
Friday Workday (0/1)	0.03	0.00	0.06	0.06	0.15
T-Shirt (0/1)	0.13	0.14	0.13	-0.01	0.94
Underwear (0/1)	0.04	0.05	0.03	-0.02	0.66
Shirt (0/1)	0.19	0.14	0.26	0.12	0.21
Burkha (0/1)	0.07	0.03	0.13	0.10	0.13
One Piece (0/1)	0.29	0.32	0.26	-0.07	0.55
Two Piece (0/1)	0.07	0.11	0.03	-0.08	0.22
Pant (0/1)	0.10	0.14	0.06	-0.07	0.33
Other Products (0/1)	0.09	0.08	0.10	0.02	0.82
Piece Rate (BDT)	35.16	33.27	37.42	4.15	0.59
Order-Dependent Production (0/1)	0.66	0.73	0.58	-0.15	0.21
Production Highest Before Eid in Feb-April (0/1)	0.82	0.86	0.77	-0.09	0.34
Production Floor Size (sq ft)	518.94	437.51	616.13	178.62	0.02
Ceiling Height (ft)	10.68	10.41	11.02	0.61	0.10
Doors (#)	1.25	1.19	1.32	0.13	0.49
Doors Open (0/1)	0.76	0.76	0.77	0.02	0.87
Windows (#)	3.01	2.78	3.29	0.51	0.34
Windows Open (0/1)	0.71	0.73	0.68	-0.05	0.64
Uninterrupted Electricity (0/1)	0.24	0.27	0.19	-0.08	0.46
Weekly Power Cuts (#)	5.09	5.05	5.13	0.07	0.95
Typical Power Cut Duration (Mins)	37.94	31.76	45.32	13.57	0.07
WTP for Thread Box (BDT)	21.35	20.70	22.13	1.43	0.65
Joint Test (Randomization Inference) (p-value)					1.00
Observations					68

Notes: This table shows the mean values of baseline characteristics for firms in our sample that were open on April 1, 2023, and were available for the willingness to pay exercise in March 2025, categorized by treatment status. The data were collected via a baseline owner survey administered in December 2022. The table also provides the difference in means and the corresponding p-values to test for significant differences between treatment and control firms.

Table A.25: Firms Open on March 31, 2024: Differences in Baseline Characteristics of Treatment and Control Firms

	Full sample	Control firms	Treatment firms	Difference of means	p-value on difference
WTP Missing (0/1)	0.32	0.22	0.41	0.18	0.09
Observations					73
Kamrangirchar (0/1)	0.64	0.64	0.64	-0.01	0.96
Workers (#)	10.40	10.32	10.50	0.18	0.85
Female Workers (#)	2.16	1.79	2.64	0.85	0.10
Male Workers (#)	8.24	8.54	7.86	-0.67	0.39
Workdays in Week (#)	6.00	6.00	6.00	0.00	
Friday Workday (0/1)	0.04	0.00	0.09	0.09	0.15
T-Shirt (0/1)	0.12	0.11	0.14	0.03	0.76
Underwear (0/1)	0.04	0.07	0.00	-0.07	0.16
Shirt (0/1)	0.20	0.14	0.27	0.13	0.28
Burkha (0/1)	0.06	0.04	0.09	0.06	0.45
One Piece (0/1)	0.28	0.29	0.27	-0.01	0.92
Two Piece (0/1)	0.08	0.11	0.05	-0.06	0.41
Pant (0/1)	0.12	0.14	0.09	-0.05	0.57
Other Products (0/1)	0.10	0.11	0.09	-0.02	0.85
Piece Rate (BDT)	36.60	33.50	40.55	7.05	0.46
Order-Dependent Production (0/1)	0.64	0.64	0.64	-0.01	0.96
Production Highest Before Eid in Feb-April (0/1)	0.86	0.86	0.86	0.01	0.95
Production Floor Size (sq ft)	527.36	448.86	627.27	178.42	0.04
Ceiling Height (ft)	10.64	10.43	10.91	0.48	0.31
Doors (#)	1.24	1.18	1.32	0.14	0.57
Doors Open (0/1)	0.78	0.79	0.77	-0.01	0.91
Windows (#)	3.16	2.64	3.82	1.18	0.07
Windows Open (0/1)	0.74	0.79	0.68	-0.10	0.42
Uninterrupted Electricity (0/1)	0.24	0.25	0.23	-0.02	0.85
Weekly Power Cuts (#)	5.54	5.93	5.05	-0.88	0.55
Typical Power Cut Duration (Mins)	38.00	31.96	45.68	13.72	0.15
WTP for Thread Box (BDT)	22.78	22.61	23.00	0.39	0.91
Joint Test (Randomization Inference) (p-value)					1.00
Observations					50

Notes: This table shows the mean values of baseline characteristics for firms in our sample that were open on March 31, 2024, and were available for the willingness to pay exercise in March 2025, categorized by treatment status. The data were collected via a baseline owner survey administered in December 2022. The table also provides the difference in means and the corresponding p-values to test for significant differences between treatment and control firms.