Making the Invisible Visible: The Impact of Revealing Indoor Air Pollution on Behavior and Welfare*

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Abstract

Exposure to ambient air pollution has been shown to be detrimental to human health and productivity, and has motivated many policies to reduce such pollution. However, given that humans spend 90% of their time indoors, it is important to understand the degree of exposure to Indoor Air Pollution (IAP), and, if high, ways to reduce it. We design and implement a field experiment in London that monitors households' IAP and then randomly reveals their IAP in real-time. At baseline, we find that IAP is worse than ambient air pollution when residents are at home and that for 38% of the time, IAP is above World Health Organization standards. Additionally, we observe a large household income-IAP gradient, larger than the income-ambient pollution gradient, highlighting large income disparities in IAP exposure. During our field experiment, we find that the randomized revelation reduces IAP by 17% (1.9 $\mu g/m^3$) overall and 34% (5 $\mu g/m^3$) during occupancy time. We show that the mechanism is households using more natural ventilation as a result of the feedback (i.e., opening up doors and windows). Finally, in terms of welfare, we find that: (i) households have a willingness to pay of £4.8 ($6) for every 1 $\mu g/m^3$ reduction in indoor PM2.5; (ii) households have a higher willingness to pay for mitigation than for full information; (iii) households have a price elasticity of IAP monitor demand around -0.75; and (iv) a £1 subsidy for an IAP monitor or an air purifier has an infinite marginal value of public funds, i.e., a Pareto improvement.

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1 Introduction

The adverse impacts of ambient air pollution and its associated costs have received substantial policy and academic attention (Chay and Greenstone, 2003, 2005; Luechinger, 2009; Currie and Walker, 2011; Graff Zivin and Neidell, 2012; Currie et al., 2015; Chang et al., 2016; Schlenker and Walker, 2016; Ebenstein et al., 2016; Deschenes et al., 2017; Zhang et al., 2018; Deryugina et al., 2019; Clay et al., 2021; Bishop et al., 2023; Borgschulte et al., 2024; Miller et al., 2024). However, the issue of Indoor Air Pollution (IAP) is often overlooked in these discussions. This oversight is particularly concerning given that individuals in the developed world spend approximately 80 (90) percent of their time in their home (indoors) (Klepeis et al., 2001; Sundell, 2004; Spalt et al., 2016), a figure which has been increasing since 2020 with the trend to work-from-home (Barrero et al., 2023; Morris et al., 2023, 2024; Zarate et al., 2024). Furthermore, the U.S. government predicts that IAP concentrations are often two to five times higher than those outdoors (EPA, 1987), exacerbating the risks of exposure. Therefore, as most air pollution exposure for humans occurs indoors, the full welfare impact of air pollution may be vastly underestimated (Jeuland et al., 2015).

The relatively limited academic research on this subject has shown that IAP is correlated with or linked to a range of health outcomes, including respiratory diseases, heart disease, cancer, and milder effects such as headaches, dizziness, and fatigue (Monn, 2001; Pope III et al., 2011; Zheng et al., 2015; Li et al., 2017), as well as reduced cognitive performance (Stafford, 2015; Künn et al., 2023; Xu et al., 2024).[1] It has also been argued that IAP is likely to be as dangerous for human health as ambient air pollution (WHO et al., 2010), and studies have shown that IAP contains a variety of inflammatory and carcinogenic metals (Bandowe et al., 2021). Despite these potentially substantial impacts on mortality, morbidity, productivity, and well-being, the true scale of IAP and whether it can be mitigated remains uncertain due to insufficient monitoring, reporting, and experimentation. Recent advancements in residential IAP measuring technology have led to high levels of validity and reliability of pollution monitors (Wang et al., 2020),[2] so

[1] There is also a large literature suggesting that ambient air pollution is detrimental to cognitive ability, human capital formation, and productivity (Currie et al., 2009; Graff Zivin and Neidell, 2012; Davis et al., 2013; Ebenstein et al., 2016; Bharadwaj et al., 2017; Chang et al., 2019; Huang et al., 2020; Bedi et al., 2021; Carneiro et al., 2021; Persico and Venator, 2021; Duque and Gilraine, 2022; Krebs and Luechinger, 2024; Chen, 2025; La Nauze and Severnini, 2025)

[2] The cost of IAP monitors have also declined over time (U.S. Environmental Protection Agency, 2025). This cost reduction can be attributed to multiple factors including learning-by-doing in the production process, the development of low-cost sensors, and the overall increasing market size for IAP monitors, which causes more innovation (Acemoglu and Linn, 2004), as there is growing awareness about poor air quality arising from many sources, such as wildfires.

estimating the true scale of the issue and assessing potential solutions is now possible.[3]

IAP is a largely unobserved good. One where both awareness and information are limited, yet technological advancements have the potential to drive significant improvements. In many contexts, the introduction of new information through technology has shifted market equilibria (Jensen, 2007; Jessoe and Rapson, 2014). Similarly, information providing insights into others' beliefs (Cantoni et al., 2019; Bursztyn et al., 2020) and information from the new advancement in modeling (Fairweather et al., 2024) have been shown to influence market behavior. A key feature of the IAP context is that information is becoming increasingly known and observable due to the declining cost of air quality monitoring. This cost reduction, coupled with growing demand for air quality improvements, has likely driven innovation (Acemoglu and Linn, 2004), enabling households to monitor their IAP affordably. However, because this information remains only observable to private individuals, governments are unable to monitor or regulate it directly. While individuals can now have access to better indoor air pollution data, broader societal benefits may arise from policies that increase the adoption of monitors and motivate reductions in IAP.

In this study, we conduct a field experiment in London to achieve three primary objectives. First, to document essential descriptive facts about IAP, including its scale, its relationship with ambient pollution, and the key predictors of IAP based on household and dwelling characteristics. Second, to investigate how the provision of real-time indoor air pollution information can motivate behavioral changes that improve indoor air quality, and thereby enhance overall health and well-being. Third, to understand households' willingness to pay for IAP monitoring and mitigation.

Achieving these objectives is empirically challenging for several reasons. One major challenge is data availability. Since monitors are not mandatory in people's homes, IAP levels often remain invisible. Moreover, even if we were to obtain data from individuals who have purchased monitors, such as crowd-sourced data, this introduces selection bias, as middle- to low-income areas and households are typically under-represented in such data sets (Graff Zivin et al., 2024). Furthermore, the existing data does not allow us to assess the magnitude of the issue across heterogeneous households and to estimate the causal effects of possible interventions to reduce IAP. The diverse sources and physical complexities of IAP also make it extremely difficult, if not impossible, to accurately

[3] The World Health Organization (WHO) estimates that IAP accounts for around three percent of the burden of disease and causes over three million premature deaths annually across a sample of developing countries (*WHO*, 2021).

model indoor air pollution in residential settings without data from indoors.[4] Additionally, the interaction between indoor and outdoor pollutants combined with unobserved and potentially unpredictable human behaviors (such as opening windows) adds further layers of complexity. Together, these factors create a highly dynamic and variable environment, making precise prediction and effective management of IAP exceptionally difficult without the indoor exposure data.

We overcome these empirical challenges by partnering with the local government of the London Borough of Camden, which distributed recruitment letters to a randomly selected sample of Camden's residents. Individuals who were interested in the topic completed an online survey on demographics, dwelling specifics, and health and were then randomly assigned to either a control or treatment group. Control group households received air pollution monitors that recorded real-time IAP levels but had their displays blinded. Treatment group households received the same monitors to collect baseline information, but after two weeks, the real-time IAP information became visible on their monitors. Additionally, households in this group received a two-page information sheet on interpreting the data and possible ways to reduce indoor pollution.

The treatment is a full knowledge treatment of IAP. This consists of many channels, such as real-time information on IAP (which has both knowledge and salience components), Hawthorne effects from monitoring, and information on how bad IAP is for human health. While we do not have experimental variation to separate these channels apart, we will provide evidence that the real-time feedback is what is driving any treatment effects we find. Moreover, both the control and treatment group understand that their IAP is being measured, so there is no difference in the intensity or incidence of monitoring between the groups,[5] and they placed the monitors in the same location in their homes.

Our treatment can be seen as "making the invisible visible," as the air pollution that we measure is undetectable to households without specialized monitoring equipment. By providing real-time feedback in the treatment group, our intervention can be framed as full knowledge of the risks from indoor pollution, which can enter into the utility maximizing health production model (Pattanayak and Pfaff, 2009; Graff Zivin and Neidell, 2013). Individuals will choose the optimal risk-averting behaviors, which will be a func-

[4]Indoor pollution arises from numerous sources, such as cooking, heating (e.g., fireplaces), smoking, and the burning of candles and incense.

[5]Previous research has shown that monitoring can itself have important consequences on behavior, especially in environmental markets (Gosnell et al., 2020; Zou, 2021).

tion of time, resources, and knowledge of the averting behaviors. We posit that many individuals do not even have knowledge about how to measure IAP, less the averting behaviors that reduce IAP. So our treatment is a direct test of the the knowledge function in these health models, since if people are fully aware and knowledgeable, the treatment will have no impact on behavior and indoor pollution levels.

Our field experiment allows us to monitor indoor Fine Particulate Matter (PM2.5), the US Air Quality Index (US AQI), temperature and relative humidity, for a duration of four weeks among 258 households. We also elicit a whole range of beliefs about the incidence of IAP, people's subjective health status, household and building composition, a range of behaviors and residents' willingness to pay for information on and mitigation of indoor air pollution. To-date, this is one of the largest IAP experiments ever completed in the developed world and to the best of our knowledge, the first paper to successfully provide real-time information feedback on indoor air quality, estimate the willingness to pay (WTP) for reduction in indoor PM2.5, and show the welfare effects of subsidies for technology that monitors and reduces indoor PM2.5.

1.1 Our Findings

We begin our empirical analysis by documenting four novel descriptive facts from the IAP data. First, for our random sample in London, we find that average indoor PM2.5 concentrations (10.5 $\mu g/m^3$) are very similar to ambient PM2.5 concentrations (10.8 $\mu g/m^3$), with both exceeding The WHO and US EPA annual standards of 5 and 9 $\mu g/m^3$ respectively.[6] Second, we find that during occupancy hours (16:00-23:00), when residents are actually exposed to the air quality in their dwellings, indoor pollution levels are significantly higher than outdoor pollution (14.6 vs. 12.2 $\mu g/m^3$), likely due to household activities such as cooking, cleaning, heating, smoking, using candles, etc. Since the health and productivity effects are driven by exposure rather than average concentrations, we demonstrate that during time spent at home when exposure is very high, IAP is significantly higher than ambient air pollution.[7]

Third, our analysis reveals that ambient air pollution is not a main predictor of IAP. While we find a positive correlation between hourly indoor and hourly outdoor PM2.5

[6] The Environmental Targets Regulations (2023) for PM2.5 in England require that the annual average of 10 $\mu g/m^3$ for PM2.5 will not exceeded at any monitoring station by the end of 2040.

[7] These results are in contrast to the work by Krebs et al. (2021), who document that outdoor concentrations of PM are higher than indoor concentrations using crowd-sourced data from California.

levels, outdoor levels do not explain indoor variations very well ($R^2 < 0.1$) and do not explain overall averages, emphasizing the important role of indoor PM2.5 sources. Fourth, there are several important predictors of indoor PM2.5, such as smoking, household income, and property ownership. This suggest a socioeconomic dimension to IAP, where lower-income households face higher exposure to indoor PM2.5, which has also been documented in previous studies (Ferguson et al., 2020; Burke et al., 2022). This relationship can be explained by numerous factors, such as poor housing quality, and thus can exacerbate existing inequalities in health, education, and productivity. To put this into perspective, households with below-median income levels have indoor PM2.5 concentrations that are 20 $\mu g/m^3$ higher than those of above-median income households. Expressed differently, for every £1,000 decrease in income, PM2.5 concentrations rise by 0.1 $\mu g/m^3$ (a 1% increase in income is associated with a 0.034% reduction in PM2.5).[8]

Turning to the results from the field experiment itself, we have five main findings. First, we find that randomized real-time feedback leads to a significant reduction in overall PM2.5 concentrations by 1.9 $\mu g/m^3$, translating to an 17% decrease from baseline levels. We also find that the treatment effect is much larger during occupancy hours, when people are typically at home and exposed to PM2.5, with a significant reduction of 5.0 $\mu g/m^3$, or 33.9% reduction from baseline. These reductions are very meaningful, especially considering the WHO annual mean standard for PM2.5 is 5 $\mu g/m^3$ and that our observed reductions exceed the effect of many large-scale interventions aimed at reducing air pollution.[9] When we re-weight our estimates to match our experimental sample to the population sample in terms of income, we find an even larger reduction in PM2.5 concentrations during occupancy time.[10]

Second, we show that the mechanism for these large reductions in PM2.5 came primarily through improved home ventilation. We show this in three different ways. First, we surveyed the treatment group about their actions to reduce PM2.5 levels. An over-

[8]In addition, we find that cooking technologies and ventilation opportunities are also important predictors of IAP. These findings highlight the complexity of IAP and reveal that, while behavioral factors are significant predictors of IAP, ambient air pollution is not a primary determinant. This is in contrast to some of the older in-situ measurements of IAP from small selected samples (Hanley et al., 1994; Riley et al., 2002; Chen and Zhao, 2011).

[9]For example, the 2005 US Clean Air Act amendment for PM2.5 and the congestion pricing in Stockholm resulted in reductions of 3% and 15%, respectively, in particulate matter pollution (Sager and Singer, 2022; Simeonova et al., 2021). Specifically, Sager and Singer (2022) found a 0.4 $\mu g/m^3$ reduction in PM2.5, while Simeonova et al. (2021) observed a 4.56 $\mu g/m^3$ decline in PM10.

[10]This increase in the treatment effect with re-weighting suggests that our experimental sample estimates might be lower than the estimate if everyone in the country adopted the IAP monitor. However, there will be selection into adoption (with and without subsidies) so our experimental sample might be more externally-valid than extrapolating the average consumer.

whelming majority (72%) stated that they increased ventilation as their primary strategy to reduce pollution mainly through the opening of windows. Second, we utilize our data on indoor and outdoor air temperature before and after the treatment and show that the treatment group's indoor air temperature is more correlated with outdoor air temperature during the treatment period compared to the control group. This suggests that people are indeed opening windows to ventilate and dilute PM2.5 concentrations in their homes. Lastly, we examine the characteristics of peak indoor pollution events to determine whether the intervention led participants to modify their pollution-generating activities or implement strategies to curb high pollution levels. We do not find that the number of peak PM2.5 events is different between the treatment and control. However, their intensity, which we defined as the maximum PM2.5 level of an event, was reduced. These results suggest that most people do not stop conducting their daily activities, such as cooking and heating behaviors that emit high levels of PM2.5 in the home (these activities are integral to their utility). Instead, households are changing how they respond to the high levels or taking preventive action to avoid a high level of pollution(e.g., opening windows during or after cooking). This result is a novel test of the averting behaviors entering the utility function directly–i.e., people still want to cook as it provides utility. Given the universality of this ventilation mechanism across all households, our results provide some external validity and possibility of scaling to other samples in the developed world (List, 2020, 2024).

The above result on ventilation at peak times also allows us to say something about the channels of the treatment effect. Treatment does not reduce baseline level of IAP or change the number of peak events–which would be consistent with an overall health knowledge channel from our treatment. But treatment changes the response to a peak PM2.5 event and that this response is only possible with real-time feedback. Therefore, we believe the main channel is the salient real-time feedback.

Third, we find that residents in the treatment group updated their beliefs about their home's IAP, realizing it is significantly worse than they originally believed. Interestingly, the effectiveness of our treatment in not only altering participants' perceptions of air quality but also affecting the confidence level of these perceptions, offering valuable insights into the psychological impact of air quality awareness interventions. For outdoor air quality, we find no significant effects, which is reassuring since we only provided information about indoor pollution.

Fourth, we conduct a comprehensive welfare analysis by examining the intervention's impact on human health, estimating households' WTP for clean air, and evaluating the welfare implications of subsidies for adopting an IAP monitor or an air purifier. Using our average treatment effect estimates, we show that the mortality savings from implementing the intervention across all UK households could reach £39.73 billion (£582 per capita). In terms of WTP, we find that for the control group, the average WTP for the IAP monitor and for an air purifier (that reduces IAP to zero) is £36.65 and £44.65 respectively. For the treatment group, the average WTP for the IAP monitor and the purifier is £38.84 and £50.39 respectively. These findings indicate that households value mitigation measures (air purifiers) more than simply acquiring information on their indoor air quality. Translating these into a WTP for 1 $\mu g/m^3$ reduction, we find values of £4.06 for the control group and £5.54 for the treatment group (with perfect information), suggesting that real-time information enhances the perceived value of air quality improvements.

Finally, we assess the welfare impacts of subsidies for adopting an IAP monitor or an air purifier. We incorporate the price elasticities of demand derived from our WTP estimates, combined with our health and productivity impact estimates, reductions in healthcare spending by the National Health Service (NHS), and increased tax revenue from higher earnings to estimate a marginal value of public funds (MVPF) of a £1 subsidy for an IAP monitor or purifier (Hendren and Sprung-Keyser, 2020; Hahn et al., 2024). Under a range of different scenarios and assumptions, a £1 change in a subsidy for an IAP monitor or air purifier leads to an outcome where the productivity increases that flow back to the government more than offsets the upfront subsidy cost. That is, a £1 subsidy pays for itself just through the benefits to the government from reductions in IAP. This indicates that these subsidies would constitute a Pareto improvement by fully paying for themselves and this result occurs because the fiscal externalities from reducing PM2.5 are larger than the cost of the subsidy. There are two things to note here with our estimates. First, even if our treatment effect decreased by 90% (which is outside of our 95% confidence intervals), we would still estimate an MVPF of infinity for the £1 government subsidy for the IAP monitor. Second, even if people meaningfully underestimate the health benefits from reducing PM2.5 concentrations, the MVPF remains infinite.

1.2 Relationship to Existing Literature

Our study connects and contributes to several strands of research. In the context of IAP, we think that the closest study to ours is by Greenstone et al. (2021), who conducted a field experiment in Delhi, India. They randomly assigned indoor air quality monitors to households and offered the opportunity to rent subsidized air purifiers. Their findings indicated that access to indoor air pollution monitors did not affect the take-up of subsidized air purifier rentals. However, their study faced significant survey non-response and attrition issues, and the authors themselves noted that the results should be interpreted with caution and considered suggestive. It is also worth highlighting that their study was conducted in Delhi, which is very different to London in terms of many characteristics including the housing stock, population, income and pollution levels.[11]

Our work also contributes to the small but growing literature on air pollution and education outcomes and the housing market (Gilraine, 2023; Pinchbeck et al., 2023). There have been many studies in the developing world on the role of cooking technologies (Duflo et al., 2008). In particular, several field experimental studies have explored the causal impacts of cleaner cooking technologies in developing countries on greenhouse gas emissions and household well-being, though the results have been mixed (Smith et al., 2011; Mobarak et al., 2012; Bensch and Peters, 2015; Hanna et al., 2016; Barron and Torero, 2017; Pattanayak et al., 2019; Berkouwer and Dean, 2022; Beltramo et al., 2023). However, none of these studies measure IAP directly and assess its exposure to humans. A novel and notable exception is Berkouwer and Dean (2023), who place mobile PM2.5 monitors on human backpacks for 48 hours to assess exposure and show how cookstove technologies affect that exposure.

Furthermore, our study supports the previous work that show that air pollution monitoring can have an impact on air pollution levels in the U.S. (Mu et al., 2021; Zou, 2021). Similar research has shown that access to outdoor air pollution information in China can reduce air pollution through avoidance behaviors (Greenstone et al., 2022; Jha and Nauze, 2022; Barwick et al., 2024) and political pressure (Axbard and Deng, 2024; Li et al., 2024;

[11] There are two other related studies. First, Sater et al. (2021) installed IAP monitors in French homes with wood-burning fireplaces, providing static feedback on PM2.5. They found that personalized information reduced indoor pollution by over 20%. Our study differs in key ways: (1) we analyze a general population sample, while they focused on fireplace users; (2) our recruitment was via randomized government letters, whereas they used targeted outreach; (3) we provide real-time feedback, while they used weekly delayed reports; (4) we examine the mechanisms behind pollution reduction, which they do not; and (5) we assess the economic welfare effects of IAP changes. Second, Baquie et al. (2024) conducted an RCT in Tbilisi testing how different air pollution information affects awareness, avoidance behaviors, and self-reported health. While their findings highlight the role of awareness in behavioral change, they did not study the impact on actual indoor pollution concentrations.

Yang et al., 2024).[12] We also relate to the work of Burke et al. (2022) and Lunderberg et al. (2023), who show that wildfire smoke can infiltrate homes and raise PM2.5 levels to 3-4 times the health-based guidelines. Notably, our findings in London demonstrate that indoor PM2.5 levels can reach 10 times the health-based guidelines for extended periods in many households. However, we find that ambient air pollution is not the primary source of this indoor pollution in London, rather it is generated by the behaviors of the residents themselves.

We also contribute to the literature on the valuation of clean air. To the best of our knowledge, we are the first to estimate the WTP for reductions in indoor PM2.5. The only other study estimating WTP for indoor air pollution more broadly is Ito and Zhang (2020) which examined the willingness to pay for indoor air quality improvements in China by leveraging data on air purifiers' effectiveness in reducing indoor PM10 and the price elasticity of demand. Ito and Zhang (2020) estimated an annual WTP of \$1.34 to remove 1 $\mu g/m^3$ of PM10.[13]

We also relate to the literature on environmental justice. There are existing papers showing the income-pollution relationship for ambient air pollution (Banzhaf et al., 2019; Hsiang et al., 2019; Colmer et al., 2020; Jbaily et al., 2022; Currie et al., 2023; Colmer et al., 2024). We show that lower-income households have significantly higher IAP levels than above median-income levels (whilst controlling for ambient air pollution), suggesting that environmental justice is not just an ambient phenomena, it is an indoor phenomena as well. Furthermore, the size of the gradient of the income-IAP relationship is much larger than the size of the income-ambient pollution relationship. As such, our paper leaves open the possibility that the observed differences in health impacts across income levels from ambient PM2.5 could, at least in part, be attributable to disparities in IAP exposure.

Finally, our paper also relates to the work on how knowledge is a costly input to the utility-maximizing health production models, and that there seems to be real costs of

[12] There is also research from Mexico (Hanna et al., 2021) and Uganda (Bassi et al., 2022) showing that there is generally a lack of information or knowledge about PM2.5 concentrations, meaning that people are not adequately compensated for the damage. However, information provided by Government sources on PM2.5 concentrations to citizens is not always trusted, as Imtiaz et al. (2025) show for Pakistan. This is a potential benefit of private indoor IAP monitors (which is beyond the scope of our study)–the inability of Government or external sources to manipulate the data.

[13] There have been a range of hedonic estimates of the valuation of ambient air pollution (Smith and Huang, 1995; Bayer et al., 2009; Freeman et al., 2019). However, IAP is one of the environmental amenities that cannot be estimated from hedonic markets because most IAP exposure is generated from indoor sources and not location-specific sources (unless pollution comes from the ground, such as Radon (Pinchbeck et al., 2023)).

monitoring IAP and acquiring knowledge of the averting behaviors for IAP. This supports the previous work suggesting that this knowledge/awareness mechanism is important for the improvement in health of many populations (Smith et al., 1990; Jalan and Somanathan, 2008; Pattanayak and Pfaff, 2009; Ashraf et al., 2013; Brown et al., 2017; Keskin et al., 2017; Bennett et al., 2018; Goeb et al., 2020; Ito and Zhang, 2020; Weitz et al., 2020). From our field experiment, these costs seems real and potentially large. Whether policymakers nudge people to adopt technologies that provide real-time feedback because of this information asymmetry (Loewenstein et al., 2007), or provide subsidies or standards for reducing the cost of real-time monitoring and feedback, there is a real need for policymakers around the world to help make the invisible visible. These policies will likely end up paying for themselves.

2 Background, Experimental Design, and Data

In this section, we provide some background on indoor PM pollution (section 2.1), the design of the field experiment (section 2.2), and details on sampling, data, randomization, and estimation (section 2.3).

2.1 Background on Indoor Particulate Matter Pollution

Particulate matter, especially fine particles (PM2.5), is a key air pollutant due to its prevalence and substantial impact on public health. PM2.5 consists of a complex mixture of tiny particles and liquid droplets suspended in the air with a diameter of 2.5 micrometers or less (about three percent of the diameter of a human hair). The size of the particles is important for three main reasons: First, these tiny particles are able to bypass the body's natural defenses and penetrate deep into the lungs and even the bloodstream, posing serious health risks. There is overwhelming evidence that PM2.5 is incredibly harmful for human health and well-being (Pope III and Dockery, 2006; Currie et al., 2014; Aguilar-Gomez et al., 2022). Second, PM2.5 is not visible to the naked eye, which means that individuals are often unaware of its presence and concentration levels in their immediate environment, leaving them unable to take measures to mitigate and adapt to exposure. Third, the small size of these particles allows them to better travel through small cracks and openings, enabling some outdoor-generated PM2.5 to infiltrate the indoor environment.

There are many sources of indoor PM2.5, including ambient (outdoor) pollution which stems from both natural and anthropogenic sources including transportation, industrial processes, wildfires, and dust storms. However, indoor PM2.5 is not simply a byproduct of ambient pollution as there are many indoor sources of PM2.5, originating from everyday activities such as cooking, heating, smoking, and even the burning of candles. Particulates can also be continually resuspended through the daily physical activity taking place within indoor settings (Tran et al., 2020). The overwhelming proportion of indoor PM emissions is thought to originate from smoking, heating, and cooking practices (Tran et al., 2020).[14] Cooking appliances themselves, including electric cookers, induction hobs and toasters, comprise a dimension of this, though the heating of utensils and pans themselves when cooking has also been tied to the release of PM, as has the heating of food products; particularly meats and oils (Wallace et al., 2004; Rohr and McDonald, 2016; Cheung et al., 2019). The cooking method is also important, with oil-based cooking (such as deep-frying, pan-frying and sautéing), especially when using low smoke-point oils, being a particularly significant contributor to PM emissions when cooking. These activities contribute to indoor PM2.5 concentrations, which are often significantly higher than outdoor levels due to contained environments and inadequate ventilation-especially during colder months (O'Leary et al., 2019).

Interestingly, while some might think that indoor PM2.5 is "less dangerous" than its ambient counterpart due to its potentially different composition, there is no scientific backing for this claim. In fact, the steering group aiding the WHO in formulating indoor air quality guidelines determined that there is no convincing evidence that particulate matter from indoor sources is less hazardous than that from outdoor sources (WHO et al., 2010).[15] While we have a good knowledge of ambient PM pollution, we do not have a good understanding of the indoor environment because we do not have consistent indoor PM measures. Nevertheless, we do know that some of the ambient PM2.5 penetrates inside and we also have some limited knowledge that everyday indoor activities that produce fine particulate matter generate some very harmful components of PM2.5. For example, PM produced by cooking is thought to be comprised of Organic Carbon

[14] In the UK, domestic combustion is also a major source of ambient particulate matter as well. According to the UK Department for Environment Food and Rural Affairs, emissions from this source (mainly from burning wood in closed stoves and open fires) account for 29 percent of ambient PM2.5 emissions (DEFRA, 2024).

[15] Epidemiological and public health studies have shown a positive association between elevated levels of indoor PM2.5 and an array of health problems, including asthma symptoms and medication use in children in Baltimore (McCormack et al., 2009, 2011), wheezing in children in New York (Jung et al., 2012), and exacerbated respiratory symptoms and Chronic Obstructive Pulmonary Disease (COPD) in the United Kingdom (Osman et al., 2007). See also Rohr and McDonald (2016) for a review of the association between PM emissions from cooking and an increased risk of lung cancer and low birth weight babies.

(OC) (Klimont et al., 2017; Zhao et al., 2019; Alves et al., 2021) and various inflammatory and carcinogenic heavy metals, elements, and Polycyclic aromatic hydrocarbons (PAHs) are also present (See and Balasubramanian, 2008; Zhang et al., 2017; Cheung et al., 2019; Bandowe et al., 2021). Furthermore, the effect of exposure to indoor PM2.5 might have a much bigger effect on our health and well-being than ambient fine particulates because individuals tend to spend the majority of their time indoors, leading to prolonged exposure to potentially high levels of PM2.5.

2.2 Experimental Design

We conducted a field experiment in the London Borough of Camden, England, which is one of the 32 local authorities that make up the administrative area of Greater London. Camden presents an ideal setting for our study, due to its geography, diverse population, and wide range of dwelling types and characteristics. These factors provide a unique opportunity to examine how indoor air quality and our intervention vary across different households and dwelling types in a relatively large urban area. From 2021, we partnered with The Local Government of Camden to recruit participants for our study, using their mailing system for random distribution of recruitment letters to households across the whole borough. Interested individuals were prompted to complete an online survey gathering baseline data on demographic characteristics, dwelling specifics, and health and well-being assessments as seen in Appendix Figure A1. We followed up with a reminder letter for households that did not respond to the first invitation. This two-step communication strategy significantly improved our recruitment efforts, culminating in a response rate of about 20% (i.e., almost 20% of a representative population were interested in taking part in the research). Additionally, we also offered a payment of £20 for taking part, which may also have led to this good response rate (see Appendix A2 for the initial letter).

Following the collection of baseline data from the survey, participants were stratified and randomly assigned to either the control or treatment group, ensuring demographic and health balance in addition to balance across all beliefs about ambient and indoor air pollution.[16]

[16] We blocked on the following variables: large household, children, income, education, tenure, happiness, anxiety, health, pain, calm, energy, health, sleep, health condition, open plan kitchen, hob type, fireplace, indoor and outdoor air pollution belief and confidence, comparative indoor air quality belief. We then balanced on the same variables.

Control Group: Households in the control group were equipped with a Kaiterra air pollution monitor (and accompanying equipment) that recorded real-time indoor air pollution levels for four weeks and transmitted this information to us (the researchers). However, the screen display on the monitor was covered with a security sticker which prevented participants from viewing this data in real-time (see Appendix Figure A3).[17] These households were informed of their indoor air pollution levels at the very end of the experiment and after they completed the end-line survey.

Treatment Group: Households in the treatment group received the same onboarding procedure with the exact same technology and sticker.[18] However, after two weeks of baseline data collection, participants were given access to their real-time pollution readings through an identical pollution monitor which did not have the screen-obstructing security sticker and with an information sheet detailing some basic information about the interpretation of their monitor readings, the health effects of pollution exposure, and potential measures that can be adopted to reduce air pollution within the home (see Appendix Figure A4). This information sheet was based on data that is publicly available on the Camden and the Kaiterra websites but we make this information more salient.

In terms of the indoor air pollution monitor, households received a Kaiterra Laser Egg Air Pollution Monitor that measures and presents information on Fine Particulate Matter concentrations (PM2.5), temperature, and relative humidity but also measures PM10. Importantly, the monitor converts the pollution metrics into the United States (US) Air Quality Index (AQI), with the display altering its color based on AQI levels and explicitly indicating the AQI category, such as 0-50 AQI for 'Good', through to 'Hazardous' for higher values of above 300 AQI. See Figure A5 below which demonstrates the screen on good and bad levels of AQI.

The IAP monitor collects real-time information on the above air quality measures every second and feeds it into an online database which we use in our analysis. We used the Kaiterra Laser Egg series for several reasons. First, we verified that it is a very reliable monitor of PM via testing against other (more expensive) monitors and also through consultations with experts in the field.[19] Second, the monitor was relatively affordable,

[17] The use of the security sticker also enabled us to check if participants tried to remove it and reassuringly, we found no evidence of tempering

[18] The use of the same sticker in both the control and treatment groups nullified any differences in Hawthorne effects or attention placed on monitoring.

[19] Following our decision to use this monitor we also found out that Greenstone et al. (2021) also used the same monitor in their experiment in India. This is very reassuring as we both choose the same monitor independently.

with a price tag of around $150 (2021 prices). Finally, the monitor has a very consumer friendly and clear display that transmits the air quality data in real-time to the consumer. This design was ideal for our research question of making the invisible visible, and we could remotely track all of the data from the monitors during the study period.

We conducted the experiment in five waves due to the limited number of monitors available to deploy. Additionally, all households were provided with Wi-Fi routers and SIM cards, a crucial step as we determined we could not rely on household Wi-Fi access and quality. To address logistical challenges, we also supplied USB plugs and adapters, enabling the connection of both the router and the monitor to a single electrical socket. This consideration stemmed from feedback received during our pilot study.[20] To further streamline the process and ensure the secure delivery and setup of the equipment, we utilized a professional courier service for delivering the initial kits. Our own research team personally conduct the swap of monitors for the treatment group. By managing these exchanges ourselves, we were able to maintain the integrity of the study conditions and minimize any potential disruptions for participants, ensuring that the experiment ran as smoothly and effectively as possible.

At the end of the field experiment, all participants completed a final endline survey focusing on their experience, behavioral changes, and a re-assessment of their beliefs and subjective health and well-being. This survey also included questions on their willingness to pay for air pollution mitigation technologies, allowing us to understand the welfare effects of such technologies. Following the completion of the endline survey and once we received the equipment back, participants in the control and treatment groups received debriefing information on their pollution levels in their home during the study period as well as a £20 voucher to compensate them for participating in the experiment.

2.3 Further Experimental Details

2.3.1 Sample and Data

Our study was initiated by dispatching recruitment letters to 3,000 random households in the London Borough of Camden. Overall, we received a response from 566 households, which translates to a response rate of 19%. This figure aligns with the expected

[20]Prior to the main field experiment, we conducted a pilot study involving 40 households, recruited via the Camden's website and social media channels. This initial phase aimed to test the air pollution monitors, refine the survey questions, and address any potential procedural issues, ensuring the main experiment's smooth execution.

response for studies of this nature, where participants are required to commit to a data collection process in their own homes. Importantly, this response rate also offers insights into policy implications, particularly regarding household willingness to engage with air quality monitoring initiatives.[21] In our approach, we offered air monitoring equipment for free for four weeks, which sheds light on the potential uptake of such devices if the government would subsidize a similar initiative. This aspect of our findings could inform policymakers about the feasibility and public interest in subsidized air quality monitoring programs within residential settings.

From the pool of respondents, we selected 262 households that were available during the study period (i.e., not on holiday) and contributed to optimizing the balancing process (see below for more details). The study experienced minimal attrition, with only three households failing to complete the study in accordance with our research protocol. Additionally, we excluded one participant who was identified as an extreme outlier in terms of PM2.5 levels. As a result, our final sample consists of 127 households in the control group and 131 households in the treatment group.

Table A1 provides a comparison of various characteristics between our study sample and the broader population of Camden, thereby facilitating an evaluation of our study's external validity (Camden Council, 2023). The table reveals notable differences that illustrate the composition of our sample relative to the general demographic and socioeconomic fabric of Camden. Specifically, our sample is characterized by a higher proportion of individuals with advanced educational attainment and higher earners, compared to the general Camden population. Furthermore, there is a reduced presence of social housing occupants and single households within our sample, alongside a higher prevalence of homeownership. In terms of heating, our sample exhibits more gas heating and less electric heating in comparison to the broader Camden population.

While these discrepancies do not undermine the validity of our findings within the sample context (the internal validity), they do suggest caution when generalizing our main results to the entire Camden population and indicate that our study's insights may be most applicable to similar demographic segments. Despite this limitation in representativeness, it is important to acknowledge that our study represents a significant advancement over previous research efforts in the field of indoor air quality monitoring. Prior studies have often relied on samples comprising households that independently

[21] There is selection into the research based on their preferences and constraints, which means that we have a framed field experiment (Harrison and List, 2004). We will understand the importance of this selection when we re-weight our estimates to match the population sample.

decided to purchase air monitors or recruited participants exclusively via social media channels. These methods are likely to introduce a much larger selection bias into the study, limiting the diversity and generalizability of the research findings. In contrast, our approach, while not perfectly mirroring the Camden population, offers a more systematic and controlled method of participant selection, thereby reducing the likelihood of such biases. Moreover, the characteristics of our sample provide valuable insights into the types of households that are willing to engage with air quality monitoring initiatives. This understanding can inform future outreach and engagement strategies for air quality monitoring projects, ensuring they effectively reach and resonate with a broader segment of the population. Finally, in the robustness section, we address this external validity threat directly by reweighting our estimate based on observable demographic characteristics, ensuring it is more representative of the entire Camden population.

We complemented our indoor air quality data which we collected ourselves with information on ambient pollution and weather from government-regulated measuring stations. These stations are managed by the UK Environment Agency on behalf of the Department for Environment Food and Rural Affairs (Defra) and the Devolved Administrations. Given the extensive network of monitors in London, we utilised four different measuring sites for this information which are situated within relatively close proximity to the households in our study (median distance of 2km). Overall, our comprehensive dataset encompassing 150,079 hours of air pollution and weather data across 258 households.

2.3.2 Randomization

In each wave of our study, the procedure for randomizing households was as follows. Initially, four seeds were chosen through a random selection process. Subsequently, households were categorized (blocked on) based on a variety of characteristics to ensure a balanced distribution across treatment and control groups. These characteristics included household size (specifically identifying households with more than three members), the presence of children, levels of education and income, the gender composition and number of occupants, housing tenure, responses to surveys on beliefs and welfare, kitchen layout (notably the presence of an open-plan design), the type of heating system and main cooking appliance (the kind of fireplace used and cooking hob), whether an extractor hood was installed, the total number of rooms and windows, existing air purifiers, and whether smokers resided within the household.

To achieve an optimal randomization balance concerning these factors, we employed a block randomization technique, executing 5,000 iterations for each of the four seeds. In each iteration, we replaced the previous assignment if it showed an improved balance across our specified blocking variables. Upon completing the randomization for a wave, we checked for balance with the previous waves that had already been completed and selected the treatment assignment among the four options that best maintained balance across waves.

Table A2 presents the number of observations and means of a range of characteristics across the treatment and control groups. The final column reports the p-values from statistical tests assessing whether the mean differences between the two groups are statistically significant. The results show that there are no significant differences between the treatment and control groups, confirming that the randomization process was successful. This balance across key characteristics underscores the robustness of our randomization process and reinforces the internal validity of our intervention's effects analysis.

2.3.3 Estimation

Our main empirical strategy employs a differences-in-differences (DiD) methodology to estimate the causal effect of air quality information on household behavior and subsequent indoor air pollution levels. Formally, we estimate the following model:

$$
\begin{aligned}
PM_{2.5,it} = \beta_0 + \beta_1 \text{Treatment}_i + \beta_2 \text{Post}_t + \beta_3 (\text{Post} \times \text{Treatment})_{it} \\
+ \beta_4 \text{AmbientPM}_{it} + \delta_t + \varepsilon_{it}
\end{aligned}
\tag{1}
$$

where $PM_{2.5,it}$ represents indoor PM2.5 for household i at time (hour) t, Treatment_i is a dummy indicating that the household is in the treatment group, Post_t is a dummy indicating the post treatment period, $(\text{Post} \times \text{Treatment})_{it}$ is the DiD interaction term, AmbientPM_{it} is ambient PM2.5 concentrations for household i at time t, δ_t is time (day of week and month) fixed effects, and ε_{it} is an idiosyncratic error term. Standard errors are heteroskedastic-consistent and (two way) clustered by household and date.

The inclusion of ambient PM2.5 allows us to control for external air quality conditions, ensuring that our estimates are not confounded by outdoor pollution levels that may independently affect indoor PM2.5 levels. The day of week fixed effect captures any systematic variation in air quality that could be attributed to different days of the week, thereby controlling for weekly patterns in household activities that could affect pollution levels. Additionally, the inclusion of month fixed effects helps address seasonality, which can influence pollution through factors such as ventilation practices for example.

We employ the differences-in-differences (DiD) methodology for several important reasons that align with the specific constraints and objectives of our study. First, the DiD approach inherently controls for the Hawthorne Effect, the phenomenon where individuals alter their behavior simply because they are aware they are being observed, which is a concern in any experimental study. By comparing changes over time between the treatment and control groups, any behavioral modifications among participants due to their awareness of being studied will be differenced out in the estimation process. Second, the reliance on differential changes over time as the basis for estimation helps to circumvent potential measurement errors that could distort the analysis. Since DiD estimates are derived from changes in the dependent variable, rather than its levels, any constant measurement error is differenced out, thereby purifying our estimates from such noise. This attribute of the DiD methodology is particularly important given the complexities associated with accurately measuring indoor air pollution levels. Third, our sample is sufficiently large but perhaps not large enough to completely eradicate all concerns about randomization and the potential for the imbalance between treated and control groups. Our balancing test reported in Table A2 suggests that our treatment and control groups are balanced on observables but the DiD methodology allows us also to control for unobservable factors that are constant over time, thereby mitigating potential biases.

3 Descriptive Statistics and Baseline Analysis

In this section, we conduct a descriptive analysis focusing first on the comparison and interactions between ambient and indoor air pollution (Section 3.1). We then estimate the determinants of IAP, focusing on household and dwelling characteristics as predictors (Section 3.2).

3.1 The Relationship Between Indoor and Ambient Air Pollution

We start by examining the relationship between indoor and outdoor air pollution. Table A3 provides a summary of 150,079 hours of air pollution and weather data collected from 258 households. The left side of the table presents information for the full sample, covering the entire four-week duration of the field experiment, while the right side focuses exclusively on the pre-treatment period (the first two weeks). This distinction is critical, as the treatment is designed to reduce indoor pollution, making the pre-treatment data vital for establishing baseline conditions. Column 4 aggregates data across all hours of the day and indicates that indoor and ambient PM2.5 concentrations are relatively similar during the pre-treatment period, averaging 10.85 $\mu g/m^3$ and 11.61 $\mu g/m^3$, respectively. These two numbers are important because they highlight that, despite London being a modern developed city with ambitious and effective policies to reduce pollution (mainly traffic related policies such as the Low Emission Zone, expanded cycling infrastructure, and strict emission standards for taxis) pollution levels remain above recommended international health guidelines. To put it in perspective, the annual US EPA and WHO guidelines are currently set at 9 and 5 g/m^3, respectively. In England, the Environmental Targets Regulations 2023 mandate reducing PM2.5 concentrations to 10 g/m^3 or lower by 2040, but this higher target must be achieved across all Automatic Urban and Rural Network (AURN) monitoring sites in England, not just on average.

In columns 5 and 6 of Table A3 we further analyze the pre-treatment pollution data by stratifying it into two distinct time frames: occupancy time (16:00-24:00) and non-occupancy time (all other hours). This temporal distinction is essential because we are particularly interested in periods when people are at home, active, and near the pollution monitor. The results reveal an important pattern: indoor pollution levels are significantly higher during occupancy hours compared to non-occupancy hours (14.6 vs. 8.9 $\mu g/m^3$).[22] This 65 percent increase in pollution during occupancy hours is critical for several reasons. First, elevated pollution levels during occupancy time are particularly concerning, as this is when individuals are most likely to be at home (back from school and/or work) and actively using their home. Because participants were instructed to place their monitors in the room where they spend most of their awake time, the data also closely approximate their real-world exposure to indoor air pollution, providing meaningful insights into potential health and well-being impacts. [23]

Second, the notable increase in pollution during active household hours suggests that human behavior significantly contributes to the observed air quality degradation (note that ambient pollution levels do not exhibit the same sizable increase in concentrations

[22] We also plot the average PM2.5 levels by hour in Figure A6 to illustrate how PM2.5 fluctuates throughout the day. The figure clearly shows a sharp peak in indoor PM2.5 during the evening hours. Ambient PM2.5 also rises during this time, possibly due to vehicle emissions, though to a much lesser extent.

[23] We also present histograms of indoor PM2.5 concentrations for the entire day and specifically during occupancy in Figures A7 and A8, respectively.

and are not very well correlated with IAP as we document more formally below). As mentioned before, activities, such as cooking and heating, can release pollutants, intensifying indoor air pollution during these hours. Moreover, ventilation may also play a crucial role in the evolution of indoor air quality, with its effectiveness potentially being dependent on human behavior as well, such as the opening and closing of windows. This behavior-driven pattern of pollution highlights the influence of daily activities on indoor air quality, suggesting a clear link between human behavior and environmental health impacts. These findings emphasize the need for targeted strategies to mitigate exposure to indoor air pollutants, especially during peak times when people are at home and engaged in activities that contribute to their indoor air quality.

Our temporal analysis also reveals that during occupancy hours (16:00-23:00), when residents are actually exposed to the air quality in their dwellings, indoor pollution levels are in fact *higher* than the pollution outside (14.6 vs. 12.2 g/m3), with indoor concentrations exceeding outdoor levels for a significant proportion of the time. This is evident in Table A3 as described above and also in Figure A9 where we show a histogram of the hourly difference between indoor and ambient pollution during occupancy hours. The figure reveals that for 22% of the time, indoor PM2.5 is higher than ambient PM2.5 during this time.[24] This result suggests that pollution spikes during these episodes are not only sharp enough to meaningfully elevate the overall average but also frequent enough to be a major concern. While there are not many studies that can accurately compare the two measures, our finding is consistent with the work of Greenstone et al. (2021) for India. However, our result is in contrast to the work by Krebs et al. (2021), who document that outdoor concentrations of PM are higher than indoor concentrations using crowd-sourced data from the PurpleAir Real-Time Air Quality Monitoring Network in California. There could be many reasons as to why the Krebs et al. (2021) study differs from ours and the Greenstone et al. (2021) study.[25] Overall, our indoor finding demonstrates the severity of indoor air pollution levels in a developed city and their potential health impacts. This highlights the urgent need for interventions to reduce exposure to particulate matter in indoor environments, which may be an even more pressing issue than addressing ambient pollution.

[24]Figure 1, which presents the histogram of the hourly difference between indoor and ambient pollution for the entire day (not just during occupancy hours), reveals that indoor pollution exceeds outdoor pollution 16% of the time.

[25]The divergence between the our findings and Krebs et al. (2021) could be because: (1) theirs is based in a different location with different climatic conditions, housing stock, and human activity indoors; (2) their sample is based on a very selected (but important) group of people who decided to purchase an air pollution monitor whilst our sample is based on a more represented pool of households; and (3) some combination of both.

Following our analysis of temporal pollution patterns and the discussion around the potential role of human behavior in shaping indoor air quality, we further delve into the relationship between indoor and outdoor pollution levels. This examination is visualised in Figure 2, where we plot hourly outdoor PM2.5 concentrations on the x-axis against hourly indoor PM2.5 concentrations on the y-axis. To illustrate the correlation between these two variables, we have fitted a linear regression line, depicted in green, against a 45-degree black dashed line, which would indicate a direct one-to-one relationship. This analysis reveals a positive relationship between indoor and outdoor PM2.5 levels, suggesting that outdoor pollution does contribute to indoor pollution levels to some extent. However, the relatively low coefficient of determination associated with the fitted line (R^2=0.098) indicates that outdoor PM2.5 levels explain very little of the variations in indoor PM2.5 concentrations. This finding implies that while there is a correlation as suggested by prior studies (Krebs et al., 2021; Burke et al., 2022), a significant portion of indoor air pollution can be attributed to sources within the indoor environment itself.[26]

Figure 2 further supports the statement that indoor air pollution is not that related to ambient air pollution conclusion in two notable ways. First, the scale of the axes is markedly different, with indoor pollution levels reaching up to 999 µg/m³, whereas outdoor levels remain well below 100 µg/m³. This disparity underscores the potential for indoor activities and sources to significantly elevate pollution levels beyond what is observed outdoors. Second, on the left-hand side of the figure, we observe many cases where very high levels of indoor pollution occur while ambient pollution remains relatively low. This also suggests that the source of the pollution in these cases is likely to be indoors. Together, these insights highlight the complexity of indoor air pollution dynamics and the critical role that indoor sources and activities play in determining the healthiness of indoor environments.

We continue by econometrically estimating the extent to which ambient air pollution infiltrates homes, contributing to IAP, and the duration of its impact on indoor pollution levels. To do so, we replicate Krebs et al. (2021), which investigates the penetration rates of ambient PM2.5 into the indoor environment. Using their methodology, we regress

[26]Given that ambient air monitors provide pollution concentration measurements for specific locations, which may not accurately reflect individual exposure due to the distance between the monitor and the individual's actual environment (Fowlie et al., 2019), we investigate the outdoor-indoor pollution relationship in Appendix Figure A10 but separately for households located below and above the median distance to the nearest ambient pollution monitor. This allows us to test whether proximity to the monitor explains the low explanatory power of this relationship, despite the relatively close location of the monitors to the households in our study. The results indicate that even for households in closer proximity to the ambient monitors, the R^2 value remain very low, suggesting that proximity alone does not account for the weak relationship observed.

indoor PM2.5 levels on lagged outdoor PM2.5 values (up to 12 hours) while controlling for outdoor temperature, dew point temperature, wet-bulb temperature, and including fixed effects for hour, day, and month.[27] This is displayed in figure A11, where we plot the coefficients of the lagged outdoor PM2.5 values. We get very similar results to Krebs et al. (2021), with bigger point estimates. Consistent with their findings, the primary influence of the outdoor environment lasts for approximately 5 hours and dissipates entirely within 9 hours. We also look at this over the first two weeks of our data - the pre-treatment period, to avoid the effect of the experiment, and we get an identical looking graph as seen in Figure A12. Furthermore, we investigate the effect of the treatment of this experiment in the post-treatment period on penetration rates. This can be seen in Figure A13a and A13b, where the penetration rates are higher in the control group and the effects last longer. This indicates that some households in the treatment group have altered their behavior and ensured that outdoor pollution affects them less.

We also look at this effect on different time periods to show how outside air temperature affects penetration rates. Similar to Krebs et al. (2021), we show that penetration rates are much higher in warmer weather. We can see this when comparing Winter and Summer in Figure A14b and Figure A14a. In these graphs, it is clear that penetration rates are higher in summer, and that indoor PM2.5 stays higher for longer. This could be due people keeping their windows open for longer hours.

3.2 Predictors of Indoor Air Pollution

We next turn our attention to identifying the principal predictors of indoor PM2.5 levels, as detailed in Tables A4 and A5. These tables, which focus solely on the pre-treatment occupancy period, examine the influence of various household and dwelling characteristics on indoor air pollution concentrations. We begin by examining household characteristics in Table A4. Our descriptive analysis reveals that smoking is the most significant predictor of elevated indoor PM2.5 levels. This finding highlights the substantial impact that indoor smoking can have on air quality and is aligned with existing research in this area

[27] The regression equation we use is $PM2.5_{it} = \sum_j \beta_j \overline{AmbientPM2.5}_{it-j} + \gamma X_{it} + \delta_t + \theta_i + \varepsilon_{it}$. Standard errors are clustered at the household and day levels.

which tends to be based on a much smaller sample size.[28]

Following smoking, the household's income level (measured as above and below median for the area) is the next biggest predictor of higher IAP. We further explore the income dimension in Figure A15, which shows PM2.5 concentrations across different income groups during our pre-treatment period. The figure reveals a pronounced downward-sloping relationship between income and PM2.5 concentrations, highlighting how pollution exposure decreases significantly as income levels rise. In particular, we find that for every £1000 increase in income, indoor PM2.5 falls by $0.1\mu g/m^3$ (a 1% increase in income is associated with a 0.034% reduction in PM2.5). To put this in perspective, below median income households have a PM2.5 level 20 $\mu g/m^3$ units higher than above median income households. Although similar patterns have been observed in ambient pollution (Jbaily et al., 2022; Colmer et al., 2020), the relationship between income and pollution is much larger for indoor than ambient. It is important to document that this disparity exists for indoor pollution in the developed world but also potentially larger than ambient.[29]

Our analysis in Table A4 also shows that renters experience higher levels of indoor PM2.5 compared to homeowners. This disparity could reflect differences in the quality of living conditions, including the age and maintenance of rented versus owned properties, as well as potential restrictions on modifications that could improve indoor air quality, or it could be personal behaviors associated with renters. Overall, these results suggest a socioeconomic dimension to indoor air quality, where lower-income households renters and smokers (who are more prevalent among disadvantaged groups (Auld, 2005; Hiscock et al., 2012; DeCicca et al., 2022) may face higher exposure to indoor PM2.5.

Next, we examine how dwelling characteristics are linked with indoor PM2.5 levels in Table A5. Notably, certain household appliances emerge as significant predictors of indoor air pollution levels. In particular, we find that having an electric or gas stove is positively correlated with higher indoor air pollution levels. These appliances, commonly

[28]For example, a study by Semple et al. (2015) in Scotland analyzed PM2.5 concentrations in homes with smokers compared to those without and revealed that the average PM2.5 levels in the 93 smoking homes were about ten times higher than in the 17 non-smoking homes. Importantly, the findings reported by the study in Scotland and our findings presented here not only highlight the substantial role of cigarette smoking in elevating indoor PM2.5 concentrations but also the severe exposure risks for non-smokers residing in these environments. According to Semple et al. (2015), non-smokers living in smoking households typically experienced average PM2.5 exposure levels more than three times higher than the World Health Organization's (WHO) guidance for annual PM2.5 exposure.

[29]When we look at ambient PM2.5 we find no evidence for statistically and economically significant relationship between income and ambient pollution over the course of the data collection period. The ambient PM2.5 gradient is -7.312873e-06 which means that for every £1000 increase in income, outdoor PM2.5 falls by 0.0073.

used for cooking and food preparation, contribute to the indoor emission of particulates, thereby elevating PM2.5 concentrations. Interestingly, induction hobs appear to have a relatively lower impact on indoor PM2.5 levels. This finding aligns with their design, as induction hobs heat cookware directly through electromagnetic fields, reducing heat loss and cooking time. This efficiency minimizes overheating, which in turn produces lower emissions of PM2.5 compared to electric hobs. Furthermore, induction hobs lack exposed heating elements, preventing particulate emissions from surface oxidation. Their efficient heating also reduces ambient heat buildup, a factor supported by our observation of a positive correlation between higher indoor temperatures and elevated PM2.5 levels.

In contrast to the impact of cooking appliances, the presence of more windows in a dwelling is associated with lower baseline pollution levels. This can be attributed to improved air circulation and the dispersion of indoor-generated pollutants, effectively mitigating indoor air pollution. Interestingly, we do not find a statistically significant association between the presence of an air purifier and indoor PM2.5 levels. While air purifiers are known to reduce indoor pollution when properly used and maintained, this result may reflect factors such as human behavior (as ownership does not guarantee regular use) and selection bias.

Overall, our results highlight the complexity of factors affecting indoor air quality and underscore the significance of household and dwelling characteristics in influencing indoor air quality. As such, interventions to improve indoor air quality might require a tailored approach through architectural design, lifestyle modifications, informed appliance choices, and personalized information about indoor pollution.

4 Main Results

4.1 Impact of Real-time Feedback on Indoor Air Quality

In this section, we investigate the impact of our intervention designed to provide residents with real-time, personalized feedback on indoor PM2.5 pollution levels within their homes. Our primary aim is to assess whether such feedback can effectively reduce indoor PM2.5 concentrations. Figure 3 shows our main point estimates and confidence intervals for three regression equations.[30] The left estimate shows the average treatment

[30] Appendix Table A6 presents these results in a table format, including versions with and without bootstrapped standard errors for robustness.

effect of our intervention on total PM2.5 concentrations. As evident from the figure, we find that providing real-time indoor pollution information reduces overall pollution concentration by 1.9 $\mu g/m^3$ (microgram per cubic meter), representing an effect size of 17.3% of mean PM2.5 of the control group post treatment or 17.6% of baseline pollution (i.e. pre-treatment).

In the next two estimates presented in Figure 3, we differentiate (as in the previous section) between occupancy time (16:00-23:00) and non-occupancy time (all other hours) respectively. This differentiation is crucial, given that our occupancy hours typically represent time when individuals are at home, active and near their pollution monitor which gives us a very good indication to their actual pollution exposure during this time. Our results demonstrate a much more pronounced effect during occupancy hours, compared to our overall estimate reported for the all day. This estimate is also statistically significant at the 1 percent level and very large. In particular, we find that our intervention reduces indoor PM2.5 concentrations by 5 $\mu g/m^3$, equivalent to a 34% or 0.11 of a standard deviation reduction from baseline during the same hours or 32.5% reduction compared to mean PM2.5 in the control group post treatment. This is a sizable reduction, especially when compared to other prominent interventions. For example, the 2005 US Clean Air Act amendment for PM2.5 achieved a reduction of only 3% (or 0.4 $\mu g/m^3$) over five years, congestion pricing in Stockholm reduced PM10 pollution by 10-15%, and the introduction of Low Emission Zones (LEZ) in Germany reduced PM10 levels by 9%. (Sager and Singer, 2022; Simeonova et al., 2021; Wolff, 2014). Conversely, the effect observed during non-occupancy hours is much smaller and not statistically significantly different from zero, suggesting the intervention's effectiveness is only heightened when residents are likely to be home and awake.

We further delve into the temporal dynamics of the intervention's efficacy through Figure 4, which shows the average treatment effects segmented by hour of the day. This graphical representation corroborates the findings outlined in Table A6, particularly highlighting the concentration of negative effects during occupancy hours. These temporal insights enrich our understanding of the intervention's impact, emphasizing the significance of daily household routines on indoor air quality. We also explore the effect over time in Figures 5 and 6. These graphs indicate that (1) our parallel trends assumption holds reasonably well and (2) the effect size remains consistently high throughout the post-treatment period, with a more pronounced and concentrated impact observed during occupancy hours. In Figure 7 we further analyze this temporal dimension and find that the intervention's impact during the first and second weeks is nearly identical, highlighting once more the consistency of the treatment effect over time. Finally, in Figure 8, we examine the impact of our intervention by season and find that our results are entirely driven by the intervention during the winter months. During this period, dwellings typically have lower levels of ventilation (due to closed windows) and higher usage of heating sources, both of which contribute to elevated indoor pollution levels.

Next, we explore the potential non-linear effects of our intervention through a probit model analysis, focusing on the time households spend within various Air Quality Index (AQI) categories. The US AQI, a scale that quantifies air quality, spans from 0 to 500, categorizing air quality into six levels: Good (0-50), Moderate (51-100), Unhealthy for Sensitive Groups (101-150), Unhealthy (151-200), Very Unhealthy (201-300), and Hazardous (301-500), with lower scores indicating healthier air quality. A unique feature of our intervention is the air quality monitor's ability to visually display AQI categories, altering its color and displaying category names (e.g., "Good" in green for PM2.5 levels at 8 $\mu g/m^3$). We hypothesize that this visual and categorical representation of air quality may nudge households to improve their indoor air to the safest AQI category achievable.

Our analysis, detailed in Figure 9 and Appendix Table A7, specifically investigates these effects during occupancy hours, a period of heightened indoor activity and potential pollutant exposure as we documented before. The findings suggest that the intervention effectively encourages households to maintain air quality within the "Good" and "Moderate" PM2.5 ranges (below 100 AQI which is equivalent to 35.4 $\mu g/m^3$), increasing the likelihood of air quality falling within these safer ranges. Conversely, there is a significant decrease in the time spent in all higher AQI categories, such as "Unhealthy" and "Hazardous." In particular, we find that the intervention reduced the likelihood of time spent in the Unhealthy, Very Unhealthy, or Hazardous ranges by 0.06, 0.05, and 0.04 standard deviations, respectively, compared to pre treatment baseline. Overall, these results highlight the intervention's efficacy in nudging household behavior towards maintaining healthier indoor air quality levels and more generally the efficacy of providing real-time pollution feedback in significantly lowering indoor PM2.5 concentrations, especially during critical periods when individuals are present and active in their homes.

In order to understand the variation in household responses to our treatment, we also perform a heterogeneity analysis to investigate the Average Treatment Effect (ATE) across different household characteristics. The results, presented in Figure 10, reveal that households with below-median income experience the largest reductions in indoor pollution exposure. Specifically, the ATE for these households is 19.6 $\mu g/m^3$ during occupancy time, compared to 5 $\mu g/m^3$ for the full sample. This substantial impact is likely because these households started with significantly higher levels of indoor pollution in the pre-treatment period, as highlighted in Section 3.2 above, requiring more drastic actions to address their pollution problem.

We further explore this dimension in Table A8, where we stratify results based on whether households had above- or below-median PM2.5 levels at baseline (the first two weeks). The findings for households with above-median PM2.5 levels are consistent to those for below-median-income households, strongly supporting the argument that households with higher pre-treatment pollution levels require more significant reductions. Interestingly, households with below-median PM2.5 levels at baseline showed an increase in pollution exposure post-treatment. We hypothesize that this increase may be due to households learning through the intervention that their pollution levels were lower than they had initially perceived and consequently adjusting their behaviors. In other words, these households might have been operating below their efficient pollution level and used the information provided by the treatment to re-optimize. Later in the paper (in Section 4.3), we present empirical evidence from our survey data on beliefs, which supports this hypothesis. Beyond the income-related findings, we also observe significantly higher reductions in indoor pollution (exceeding 5 $\mu g/m^3$) among specific demographic groups, including households without a college education, renters, single-occupant households, households without children, and those with pre-existing health conditions.

4.2 Mechanisms

Following our main results showing how the treatment reduced indoor pollution, we move to empirically explore the mechanisms driving our main results by examining participant-stated answers and revealed actions in detail. We begin with the former as we elicited direct insights from the participants themselves. In particular, individuals in the treatment group were surveyed about the specific steps, if any, they undertook to mitigate indoor pollution levels. This inquiry is pivotal, as it provides first-hand accounts of the behavioral changes or preventive measures adopted by residents when faced with immediate feedback on their indoor air quality. Figure A16, which summarizes the answers we received from participants, shows that a significant majority, 72.1%, reported increasing ventilation as their primary strategy to reduce pollution. This mainly involved opening windows to allow fresh air to circulate and dilute indoor pollution, which highlights the intuitive and accessible nature of enhancing ventilation as a potential first-line response to air quality concerns. Conversely, a small segment of the sample, 9.3%, reported decreasing ventilation as their main strategy to reduce pollution. This might seem a contradictory response at first glance but as mentioned above, indoor pollution could be influenced by external factors such as outdoor air quality (e.g. a window opening into a major road) or weather conditions, suggesting a complex decision-making process regarding air quality management and the importance of real-time monitoring.

We also find that 11.6% of respondents indicated they had reduced activities known to contribute to indoor pollution, such as cooking, dusting, and the use of candles and aerosols. This reduction reflects a conscious effort to decrease the generation of pollutants at the source. Interestingly, only 2.3% of participants turned to air purifiers as a solution, leveraging technology to filter out pollutants from indoor air. Finally, 4.7% of the respondents adopted multiple strategies, combining various measures to tackle indoor pollution effectively. These findings highlight the range of actions individuals are willing to take to improve their living environments, demonstrating the critical role of real-time air quality feedback in empowering residents to make informed decisions about their indoor air quality.

Whilst the analysis above provides great insight into the behavior responses, it is important to note that the response rate for this specific survey question was 32%. As such, we proceed with two additional methods to examine the behavioral response, both of which utilize data collected from all participants in our study and focus on revealed rather than stated behaviors. First, we analyze our collected data on indoor and outdoor temperatures as an indirect measure of ventilation habits. By evaluating the absolute difference between these two measures of temperatures before and after the intervention, we aim to deduce changes in household ventilation strategies. A narrowing of this temperature gap suggests an increase in activities like opening windows, a straightforward method for reducing indoor pollutant concentrations by allowing in cleaner outdoor air. Table 1 shows the results of such analysis, utilizing our main empirical approach (DiD) but with absolute temperature difference (between indoor and outdoor) as the outcome variable instead of Indoor PM2.5. The results, which are in Table 1, clearly show a narrowing of this temperature gap, echoing the results found in Figure A16.

Finally, we investigate the characteristics of peak indoor pollution events, focusing on their magnitude and frequency. We define pollution events by observing rolling 5 hour windows of the monitor files to find the local maximum within that window. This is saved in the data as a potential peak. If the PM2.5 measurement is greater than $35 \mu g/m^3$ (meaning the monitor is no longer reporting a "good" rating), we define the entire event by the entire period the monitor reported a non-good range around this peak. This analysis helps us to assess whether the intervention led participants to modify pollution-generating activities or implement strategies to curb high pollution levels (e.g. by increasing ventilation). A decline in the intensity and frequency of these events would imply that households took effective steps in response to or anticipation of high pollution levels. We start with intensity and check if the height of peaks (defined as the maximum PM2.5 level of an event) changes following our intervention. The results are presented in column 1 of Table 2 and show that the peak is on average 36.9 $\mu g/m^3$ lower following our intervention suggesting that households might have taken preventive action (such as opening windows in advance) to avoid high pollution levels or acted very fast in response to high readings. In column 2 of Table 2, we test for the frequency of these peak events to explore if residents changed the way they perform their indoor activities (e.g. change their cooking and/or heating practices). We find no evidence to support this channel as the results are not statistically significant. Together, these results further support our earlier conclusion that the ventilation channel is the key margin of behavioral change and provide a comprehensive view of how real-time feedback on air pollution levels influences household behaviors and practices related to indoor air quality management. Understanding these mechanisms is crucial for assessing the broader applicability and efficacy of such interventions in promoting public health through improved air quality.

4.3 Impact on Beliefs

We also study the impact of our treatment on participants' perceptions and confidence regarding indoor and outdoor air quality, as measured through the difference in air quality beliefs between the baseline and end-line surveys. In particular, our "Air Quality Belief" variable captures the participants' perceived level of air quality using a spectrum from "Good" with no health risk, to "Hazardous", both indoors and outdoors, while our "Confidence" variable assesses the certainty with which participants hold these beliefs.

Table 3 shows the estimated coefficients of the treatment effect, quantifying how the intervention influenced participants' beliefs about air quality in their home environments and their confidence. The results show that residents updated their beliefs, realizing that their indoor air is in fact worse than they originally thought. This estimate is statistically significant at the 5% level and is fairly large - this translates to 33% of the standard deviation of the variable (mean is 0.17, sd is 0.79). Importantly, the effectiveness of our treatment in not only altering participants' perceptions of air quality but also affecting the confidence level of these perceptions, offering valuable insights into the psychological impact of air quality awareness interventions. For ambient (outdoor) air quality, the results differ. The estimates do not show statistically significant effects, implying that the intervention did not alter beliefs or confidence regarding outdoor air quality. This distinction in findings between indoor and outdoor air quality perceptions makes sense as we only provided information about indoor pollution and not ambient pollution. In fact, given that most of the indoor pollution we observed in our study is generated indoors in conjunction with the fact that we only provided information on indoor pollution, one can describe this analysis as a placebo test and the results of this exercise are very reassuring.

Finally, we revisit our earlier findings from Section 4.1, which show that households with initially low levels of pollution actually slightly increased their pollution exposure following the treatment. We hypothesized that this occurred because they learned their pollution levels were better than they had previously believed and, as a result, adjusted their air quality at home (via behavioral change) to align with their efficient level of pollution. Since we have data on their initial beliefs, we can now empirically test this explanation. In Figure A17, we present the correlation between pre-treatment beliefs about indoor air quality and the actual pre-treatment indoor air quality for households below- and above-median PM2.5 levels separately. The results reveal that households with below-median PM2.5 levels tend to believe their pollution levels are worse than they actually are, while those with above-median PM2.5 levels perceive their pollution to be better than it truly is. This finding strongly supports (though does not causally prove) our hypothesis that households with low baseline PM2.5 levels adjust their behavior to increase pollution exposure in an effort to reach their optimal level of pollution.

4.4 Robustness

We conduct a series of robustness checks to validate the reliability of our primary findings. These checks are designed to ensure that our results are not driven by specific model specifications or sample selections. We employ four key strategies: adding household fixed effects to our preferred DiD estimator, omitting ambient pollution controls, using two-way clustering technique without bootstrapped standard errors and re-evaluating our analysis using a reduced sample size as outlined in our pre-regitration plan. Given that the majority of the effects observed in our study occur during occupancy evening hours when residents are typically at home, we will focus on this time period in the subsequent analysis and we will also examine our estimates when we modify this definition.

We begin by re-estimating our model using household fixed effects to account for unobservable household-specific characteristics that could potentially bias our estimates. While our original DiD strategy remains our preferred approach due to its suitability for our data, the fixed effects specification offers a valuable robustness check. This approach controls for all time-invariant heterogeneity across households, which may not have been fully addressed by our randomization procedure for some unclear reason. As a robustness test, we aim to determine whether this alternative specification yields results consistent with our original findings. Figure A18 and Table A10 show that the household fixed effects model produces an estimate of 3.45 $\mu g/m^3$ during occupancy time, which is similar to our main estimate reported in Table A6.

We also re-run our main analysis using a reduced sample of households, as specified in our pre-registration plan (N=150).[31] Aside from necessary adjustments to the specified date ranges due to logistical constraints, this is the only deviation from the original plan.[32] The primary reasons for increasing the sample size were to enable heterogeneity analysis and to ensure sufficient statistical power for our willingness-to-pay analysis. Additionally, the original choice of 150 households was based on preliminary results from our pilot study, as we did not have prior literature to guide our power calculations. Notably, the pilot study employed a different recruitment process-advertising on social media rather than randomly distributing letters-which resulted in significantly higher estimates, possibly due to selection bias. By adhering to this predefined sample and comparing it with the full dataset, we rigorously evaluate the stability of our findings across different sample configurations and ensure transparency. The results, presented in Column 2 of Table 4, closely mirror those obtained from the full sample, which is very

[31]The results presented here are actually based on the first three waves of our experiment (N=175). However, we also conducted the same analysis after randomly dropping 25 households from the third wave to exactly match the pre-specified sample size of 150 households. The results remained virtually identical. We present the findings using the slightly larger sample size for reproducibility purposes.

[32]Our pre-registration mistakenly stated that we would run the experiment for four weeks post-treatment. However, this was never our actual intention for this study. As evident from our recruitment letters to residents, we consistently communicated that the study duration was one month overall (including the pre-treatment period).

reassuring.

The final three columns of Table 4 present an analysis of our estimates across alternative time windows of the day. This analysis produces very similar results, with the effect being primarily concentrated during the PM hours. Finally, Panel B of Table A6 reports the main results without bootstrapped standard errors. While the estimates are less precisely estimated in this specification, the ATE during occupancy hours remains highly statistically significant at the 5 percent level.

The outcomes from all the above robustness checks - the household fixed effects model, the omission of ambient pollution controls, and the analysis with a reduced sample size and our different clustering - consistently align with our main results, reaffirming the strong effect of our intervention. The persistence of the treatment effect across these varied specifications and sample criteria underscores the robustness of our primary findings. Notably, the treatment effect for the occupancy hours remains statistically significant and economically meaningful in all scenarios tested, bolstering the credibility of our original conclusions and the internal validity of our study.

Finally, as we mentioned earlier in the paper, our study sample does not fully align with the demographic composition of the broader Camden population. Table A1 highlights these differences (see section 2.3 for a full discussion). While these discrepancies do not compromise the internal validity of our findings, they do raise concerns about the external validity of our results. To address this threat head-on, we re-weight our estimates using detailed knowledge of our sample's demographics and the demographic characteristics of Camden as a whole, ensuring that our results are more representative of the broader population. If we re-weight on income, assuming the other characteristics of households are relatively similar across the UK, we can see that the whole day ATE increases to -4.43 and the occupancy time rises to -9.91 (compared to -1.9 and -5.0 in the unweighted sample).[33] This requires the assumption that the population of Camden is similar to the rest of England and air pollution levels would be similar since we do not have data on people who did not participate in our study. When re-weighting by the other variables in Table A1 we find that the whole day ATE estimates range from -1.67 to -1.95 and the occupancy time ATEs range from -3.02 to -4.86.

[33] This is calculated by re-weighting the sample to ensure 50% of households have income below the median level, rather than 24% as in our sample.

5 Welfare Analysis

In this section, we examine the impact of the intervention on human health, residents' willingness to pay for improvements in indoor air and information about it, and the overall marginal value of public funds (MVPFs) for a government subsidy of indoor air pollution monitors.

5.1 Impact on Health

We first focus on the intervention's impact on health. To analyze this dimension, we follow Carozzi and Roth (2023) and begin by applying the point estimates derived in our study to Concentration-Response (C-R) functions extracted from the existing literature. This synthesis of empirical data from our intervention with established C-R functions allows for a robust estimation of the health impacts due to changes in indoor air pollution. Next, we use the UK Government Value of a Prevented Fatality (VPF) and combining this with the C-R functions to quantify the potential mortality benefit of our intervention.[34]

We draw from the literature to estimate the upper and lower bound mortality C-R functions as in Fowlie et al. (2019). Lepeule et al. (2012) provided a pivotal extension of the Harvard Six Cities study and estimate that an annual increment of $10\mu g/m^3$ in PM2.5 concentrations correlates with a 14% increase in the risk of mortality from all causes compared to baseline (this is our upper bound C-R function).[35] Complementing this, Krewski et al. (2009) conducted an extensive cohort analysis,[36] and estimated that an annual increment of $10\mu g/m^3$ PM2.5 concentrations correlates with a 6% increase in the risk of mortality from all causes (this is our lower bound C-R function). While these studies focus on ambient PM2.5, there is currently no evidence to suggest that particulate matter originating indoors is less harmful than outdoor sources. As mentioned in the background section, the WHO advisory group on indoor air quality guidelines similarly concluded that there is no compelling evidence to indicate that indoor particulate matter poses a lower health risk than its outdoor counterpart (WHO et al., 2010). As such, we

[34] For more details on VPF and its relationship with the Value of a Life Year (VOLY) for the UK Government, please see:https://www.gov.uk/government/publications/valuation-of-risks-to-life-and-health-monetary-value-of-a-life-year-voly/annexe-5. This overall approach also aligns with the US EPA in their Regulatory Impact Analysis.

[35] Utilizing a Cox proportional hazards model, Lepeule et al. (2012) reported a Relative Risk (RR) of 1.14, with a 95% confidence interval of [1.07,1.22].

[36] They employed a random-effects Cox model to articulate the concentration-response relationship. They identified a lower mortality RR of 1.06, with a 95% confidence interval of [1.04,1.08], which is our lower bound C-R function.

reasonably assume that these C-R functions are also applicable to indoor PM2.5.

More formally, we can outline the calculation as follows. We begin by defining the relationship between air pollution and mortality risk:

$$\ln(y) = \alpha + \beta \cdot PM2.5$$

where $\ln(\cdot)$ is the natural logarithm and β is the coefficient of interest which measures the estimated average effect of PM2.5 on mortality. Defining y_0 as the baseline mortality incidence rate, we can now express the relationship between changes in $PM_{2.5}$ (ΔPM) and the mortality incidence rate (Δy) as:

$$\Delta y = y_0 \cdot \left(1 - \frac{1}{\exp(\beta \cdot \Delta PM2.5)}\right)$$

By multiplying the change in the mortality incidence rate by the relevant population, we calculate the total change in mortality. Multiplying this change by the VPF then provides a monetary estimate of the mortality benefit.

Using this approach, we estimate the monetary health benefits of our intervention and generalize them to the UK population. Utilizing the two C-R functions discussed earlier, our main estimates from Figure 3, and assuming that this effect remains constant (as suggested by our analysis in Figure 7), we evaluate the impact of providing all households in the UK with the same treatment implemented in our study.[37] Our analysis considers two key reductions in PM2.5 concentrations: a 5 $\mu g/m^3$ reduction observed during occupancy hours and a 1.9 $\mu g/m^3$ reduction calculated as the all-day average. These reflect the treatment effects measured during periods of maximum exposure (occupancy time) and across the full day, respectively.

Using these reductions, our results suggest that the annual mortality benefit of such an intervention, based on the high and low C-R functions from Lepeule et al. (2012) and Krewski et al. (2009), in conjunction with the UK VPF recommended estimate of £2.4 million (2023 GBP), would be £102.4 billion and £46.4 billion (or £1,501 and £680 per capita), respectively, for the 5 $\mu g/m^3$ reduction. For the smaller 1.9 $\mu g/m^3$ reduction, the annual mortality benefits are estimated at £39.73 billion and £17.79 billion (or £582.05 and £260.63 per capita), respectively.

[37] We also assume that the treatment effect observed in our London-based study applies to the United Kingdom as a whole.

Given the substantial uncertainty surrounding the C-R functions, we adopt a midpoint C-R function of 1.10. Furthermore, there is also uncertainty surrounding the correct estimated pollution reduction that we should use for our calculation, as we do not observe individuals' exposure throughout the entire day. For instance, individuals might be at school or work during certain hours, where indoor air quality may differ significantly from that observed in their homes. To address this, we adjust our ATE by weighting the observed reduction during occupancy hours (16:00–23:00), which represents one-third of the day. In other words, we divide the 5 $\mu g/m^3$ reduction we observed during occupancy time by 3, resulting in an adjusted ATE of 1.67 $\mu g/m^3$. Using this adjusted ATE and the midpoint C-R function, the estimated annual mortality benefit is £25.52 billion.

5.2 Impact on Economic Welfare

In this last section of the paper, we estimate the willingness to pay (WTP) of both the IAP monitor and an air purifier, and the welfare impacts of a subsidy for both technologies. This setting is particularly attractive for estimating such values and impacts, because those households in the treatment group will have the correct and full information about the air quality in their home, without any misinformation or biased beliefs.

To ensure the accuracy of our estimates and overcome common valuation issues such as hypothetical bias, we employed the following incentive-compatible Becker et al. (1964) elicitation procedure. Participants were informed that we would randomly select one person to receive a £100 Amazon voucher. They were then asked how much of the voucher they would be willing to sacrifice to: (1) acquire the Kaiterra Laser Egg air monitor, which displays real-time air pollution readings for their home; and (2) own a Philips 800 Series Air Purifier, which is claimed to purify the air in a single room within 16 minutes, filtering out 99% of pollutants. We also provided a link for participants to learn more about the air purifier if they wished. Furthermore, we explained that if this question were selected to be enacted upon them, the computer would choose a random number from a specified list provided to them. If their chosen monetary value is above that random number, they would receive the air purifier/monitor, along with the difference between the computer-generated number and their chosen amount (equivalent to a second-price sealed bid auction). This method ensures that responses are financially consequential for participants, and provides more truthful and considerate responses regarding their true valuation.

We present the demand curves for the Kaiterra Laser Egg monitor and the Philips air purifier in Figure A19. The figure clearly illustrates that people are willing to pay more for a technology that directly reduces pollution exposure compared to one that solely provides information about it.[38,39] In Figures A20a and A20b, we delve deeper into the demand for these technologies by plotting the demand functions separately for the treatment and control groups for both the monitor and the air purifier. While the demand curves are relatively similar between the groups, the treatment group exhibits a higher average WTP for both technologies. Specifically, for the control group, the average WTP for the IAP monitor and the air purifier is £36.65 and £44.65, respectively. In the treatment group, the average WTP increases to £38.84 and £50.39, respectively. We also calculate the WTP for a 1 $\mu g/m^3$ reduction in indoor PM2.5 by dividing the mean WTP for the air purifier in the control and treatment groups by their respective mean PM2.5 concentrations (11 $\mu g/m^3$ and 9.1 $\mu g/m^3$). The results show that the WTP for a 1 $\mu g/m^3$ reduction in PM2.5 is £4.06 for the control group and £5.54 for the treatment group (£4.8 on average).[40]

If we re-weight the WTP numbers to match the proportion of people with the characteristics from Table A1, we find that average WTP for the air purifier ranges from £38.94-44.14 for the control group and £48.91-52.01 for the treatment group. These numbers range from £34.25-39.28 and £36.06-39.30 respectively for the IAP monitor, all of which are very similar to our sample estimates since we do not find much heterogeneity in WTP by income, education or other characteristics.

To the best of our knowledge, this is the first study to estimate the WTP for reductions in indoor PM2.5. Only one other study, by Ito and Zhang (2020), has estimated the WTP for indoor air pollution more broadly.[41] Their study uses revealed preference approach (complementing our experimental approach) to estimates the willingness to pay for re-

[38] It is worth noting that the Philips air purifier also provides information about PM2.5 levels through an air quality light, which indicates different PM2.5 air quality levels.

[39] We find that there is no bunching of WTP at zero (where we only had a one-sided BDM), meaning that people did not feel an overriding value of shame in having or potentially experiencing very high IAP levels (Butera et al., 2022).

[40] Please note that this calculation is based on the assumption that the WTP is linear.

[41] Another related paper by (Pinchbeck et al., 2023) uses the housing market in England to estimate the cost of radon, an indoor air pollutant formed by the natural decay of uranium from soil and rocks. Radon is the second leading cause of lung cancer after smoking. To overcome the empirical challenges in estimating this relationship, the authors exploit a natural experiment stemming from updates to the radon risk map, which induce exogenous variation in published radon risk levels. They find that reclassification of a property from being in a radon-risk-free category to being in a radon-affected category reduces property prices by about 0.8%. However, because this paper examines a very different type of pollutant and lacks home-specific measures of indoor air pollution, it is impossible to compare their estimates with ours. There are also a few papers that estimate the WTP for reduction in outdoor (as opposed to indoor) pollution including Chay and Greenstone (2005); Deschenes et al. (2017); Freeman et al. (2019).

ductions in PM10 by analyzing air purifier sales data (defensive investments) in China. Leveraging the fact that air purifier filters provide both consumers and researchers with information about their effectiveness in reducing indoor PM10, and using instrumental variable (IV) approaches to address endogeneity concerns regarding pollution and price, they find that households in China are willing to pay \$6.3 (around £5.1) to reduce 1 $\mu g/m^3$ of PM10.[42] While the nominal value of this estimate is slightly larger than our average estimate (£5.1 vs £4.8), the comparison is not entirely straightforward due to substantial differences in price levels between the UK and China. Using Purchasing Power Parity (PPP) for a more like-for-like comparison, we find that our WTP estimate in the UK is equivalent to approximately £1.91 in China. This comparison suggests that Chinese households value reductions in indoor air pollution more highly than households in the UK. This difference may be attributed to several factors. First, there may be greater awareness of air pollution issues in China compared to the UK. Second, the severity of air pollution is higher in China, making the benefits of indoor air quality improvements more tangible and urgent. We posit that these contextual differences likely play a role in shaping the observed disparities in WTP between the two populations. However, we cannot completely rule out the possibility that the difference between the two estimates arises because Ito and Zhang (2020) estimate the WTP for PM10 rather than PM2.5. We consider this unlikely, given that the two pollutants are very closely related (PM2.5 is a subset of PM10) and that most purifiers filter both.[43]

Next, we estimate the Marginal Value of Public Funds (MVPF) of providing a £1 subsidy for the IAQ monitor using the above WTP in conjunction with the health estimates from section 5.1. The MVPF is the ratio of the societal WTP for the subsidy to the net cost incurred by the government in providing that subsidy. This metric allows us to analyze what are the most welfare enhancing policies for reducing air pollution, and how do those policies compare to other non-environmental policies.

[42] According to Ito and Zhang (2020), air purifiers typically have a lifespan of five years. This implies that their estimate can also be expressed as an annual WTP of \$1.2.

[43] Specifically, PM10 includes particulate matter with a diameter of 10 micrometers or smaller, encompassing finer particles with a diameter of 2.5 micrometers or smaller, which are classified as PM2.5.

Mathematically, the MVPF is calculated as follows (following Hahn et al. (2024)):

$$MVPF = \frac{xds + Vdx + Idx + Cdx}{xds + Hdx + Tdx + Pdx} \tag{2}$$

$$= \frac{1 + \frac{V+I+C}{p}(-\epsilon)}{1 + \frac{H+T+P}{p}(-\epsilon)} \tag{3}$$

where x is the quantity of monitors used and s is the subsidy. The MVPF formula in equation 2 is composed of six key components: the individual benefit from the subsidy transfer for the inframarginal consumer (xds),[44] the individual health benefit for marginal consumers who purchase the monitor due to the subsidy (Vdx), the individual income benefit for marginal consumers who work more after an improvement in their health (Idx), the government cost of providing the subsidy (xds), the government savings from reduced healthcare spending (Hdx), and the government benefit from increased income tax revenue resulting from improved health and higher earnings (Tdx). Using p as the price of the monitor and ϵ as the price elasticity of demand, we re-write the MVPF expression in equation 3.

We should note that we are uncertain as to whether the price elasticity of demand incorporates the health and productivity benefits of the air monitor to individuals. It might be reasonable to assumes that consumers are not aware of the full extent of the long-term health benefits which will ensue once they buy a monitor or purifier. However, if we assume that individuals do possess this perfect information, those benefits would be baked into their price elasticity for demand that we calculate. Therefore, the numerator of the equation 2 would just be $1 + \frac{C\epsilon}{p}$. However, we show below that this assumption does not matter for the calculation of the MVPF due to the presence of very large fiscal externalities.[45] We also assume that the £1 subsidy would get fully passed through to the consumers.

We now proceed to calculate the MVPF. The demand function for the IAP monitor provides us the price elasticity of demand (ϵ), which ranges between -0.22 at the 25th percentile to -1.31 at the 75th percentile (Figure A20a). For our analysis, we use -0.75 which is the mean elasticity. For V, which is the WTP for one monitor in terms of the health benefits, we use the analysis in Section 5.1 and quantify per capita WTP as fol-

[44]This represents the benefit received by individuals who would have purchased a monitor even without the subsidy. Since the subsidy is standardized to £1, an inframarginal consumer is effectively £1 better off.

[45]Further note that we do not calculate the morbidity and other well-being costs associated with air pollution (such as the effect on education and crime).

lows. We use our low and high mortality C-R function which yield cost estimates of £260.63 - £582.05 for our whole day ATE of -1.9. This range increases to between £679.73 - £1501.72 for the occupancy time ATE of 5.0. We then multiply this by the UK mean number of people per household (2.41) to find our average household WTP. We also need to calculate the price of the monitor (p) discounted over a 10 year period.[46] To do so, we make the conservative assumptions that a monitor lasts 2 years and costs £135 to purchase, which translates to a discounted cost of £624.57 over 10 years.[47]

For the Philips air purifier, we conduct a similar analysis. Since the Air Purifier cleans 99.5% of air (and we made sure that households understood this efficacy), we assume that the purifier decreases PM2.5 down to 0. Since the baseline indoor PM2.5 throughout the day is 11.0, this translate to ATE of 11.0. Using this ATE and the average price elasticity of demand which is equal to -0.81 (Figure A20b), we recalculate the mortality cost estimates and find a per capita WTP ranging between £1469.61 - £3177.42. when we focus on the occupancy period only, the ATE is even higher at 15.4, bringing the per capita WTP at £2031.69 - 4325.57. Finally, we calculate the price of the purifier over a 10-year period. The Philips Air Purifier costs approximately £135, with an additional £25 annual cost for replacing the filter, as recommended.[48] We also assume the air purifier has a lifespan of 5 years (as per Ito and Zhang (2020)), after which it needs to be replaced. Adding these costs results in a total discounted price of £438.69 over the 10-year period.

We also estimate the change in income for marginal consumers, accounting for the portion of income not subject to taxation (I). We draw on estimates from Borgschulte et al. (2024), who find that a 1 $\mu g/m^3$ increase in PM2.5 decreases earnings by 1.81%.[49] Using the UK average income of £35,393, as reported by ONS (2023), and the average marginal income tax rate in the UK of 23.4%, we estimate the additional annual tax rev-

[46]We calculate the MVPF over a decade with a discount rate of 2%. This comes from using the discount rate 3.5% used by the His Majesty's Treasury (2022) Green Book and accounting for the 1.5% inflation rate. We calculate the MVPF by household, since each household would receive the subsidy. From ONS (2024), there were 28.4 million households in the UK and 68.4 million people, this gives a mean of 2.41 people per household, which aligns with our sample average of 2.33.

[47]Air pollution monitors can often last much longer than 2 years; however, their accuracy may diminish over time. The assumption of a 2-year lifespan is based on manufacturer recommendations to replace (or recalibrate where possible) sensors every 18–24 months. Since the Kaiterra Laser Egg is discontinued, we cannot provide updated pricing, but the £135 estimate reflects the most recent price available to us.

[48]The frequency of filter replacement depends on usage, but it is reasonable to assume yearly replacements for households that use the purifier regularly.

[49]Borgschulte et al. (2024) demonstrate that the implied elasticity of 0.18 identified in their study aligns with the average elasticity reported across nine related causal studies that examine the impact of air pollution on labor market outcomes.

enue collected by the government per unit decrease in PM2.5.[50] Specifically, consumers retain 76.6% of the income change, which is incorporated into the consumer WTP, under the assumption that these consumers were not previously aware of the associated health benefits. This income change remains constant over the time horizon we are using, since the median age of the primary resident in our study is in the range 31-45, therefore it is reasonable to assume they will work for 20 years after acquiring a monitor.

We now also consider the impact of reductions in PM2.5 on crime using Bondy et al. (2020) where they demonstrate that a 10 unit rise in AQI leads to a 2.6% increase in crime in the UK. Translating this to PM2.5, a $1\mu g/m^3$ reduction in PM2.5 leads to a 1.04% fall in the crime rate. We find the individual social cost of crime from Heeks et al. (2018) to be £58.8 billion across all types of crime. This includes costs of prevention, insurance costs, property damage costs, psychological costs, cost of lost output and police/prison costs. Since we have already included the impact of PM2.5 on labor income, we exclude the cost of lost output. In the numerator of our MVPF we include all the other costs apart from police costs, since those are fiscal externalities. This totals to £36.0 billion for the whole country in £2016, and therefore £1268 per household, which is £1665 in 2023. This expenditure falls by 1.04% for a $1\mu g/m^3$ reduction in PM2.5 (£13.18), and we scale this by the ATE, discounting it over the years that these costs are saved. Then we work out how much this will change for a £1 subsidy for an IAP monitor/purifier using the demand elasticities and prices above ($\frac{C*\epsilon}{p}$).

Next we focus on the denominator of the MVPF equation to understand and estimate the fiscal externalities. We calculate two types of fiscal externalities: (1) the benefits from reduced healthcare spending by the National Health Service (NHS) and (2) the increased tax revenue from higher earnings. To estimate healthcare savings, we use our upper and lower bound average treatment effects in conjunction with cost estimates based on data from Public Health England (PHE). Specifically, PHE (2018) estimates that, over a 10-year horizon (2015–2025), a 1 $\mu g/m^3$ reduction in PM2.5 saves the NHS £0.72 million per 100,000 people in 2015£ (£0.952 million in 2023).[51] With an average of 2.4 residents per household in the UK, the NHS benefit of reducing PM2.5 by 1.9 $\mu g/m^3$ per household (our whole day ATE) is estimated at £43.41 over a 10-year period. Reductions of 5.0 $\mu g/m^3$ (our occupancy ATE), 11.0 $\mu g/m^3$ (whole day pollution at baseline), and 15.4

[50] The 23.4% marginal tax rate is derived by calculating a weighted average of the proportion of UK workers paying each tax rate in 2023. Specifically, 1.6% paid 0%, 80.4% paid 20%, 15.6% paid 40%, and 2.4% paid 45%. A weighted average of these rates gives an overall marginal tax rate of 23.4%.

[51] PHE (2018) provides this estimate specifically for England; however, we assume the same cost per household applies to the rest of the UK.

$\mu g/m^3$ (occupancy time pollution at baseline) yield savings of £114, £251, and £352 per household, respectively. We also conduct the same analysis for a 20 year time horizon.

For the second fiscal externality, the increased tax revenue resulting from higher earnings, we use the method above using Borgschulte et al. (2024) estimation that a 1 $\mu g/m^3$ increase in PM2.5 decreases earnings by 1.81%. we estimate the additional annual tax revenue collected by the government per unit decrease in PM2 using the UK average income of £35,393 ONS (2023) and the average marginal income tax rate in the UK of 23.4%. This amounts to £149.90 per capita (or £361.27 per household). We also calculate the cumulative tax revenue increase over 10 and 20 years, estimating it to rise by £3,310 and £6,025 per household, respectively.

The final fiscal externality we calculate is the cost savings associated with crime reduction Bondy et al. (2020), which comes from police costs, healthcare costs and victim service costs. Heeks et al. (2018) show this is equal to £8.01 billion, which is £281.69 per household. This is equivalent to £369.95 in 2023. Since crime falls by 1.04% using Bondy et al. (2020), each household will save £3.85 annually per $\mu g/m^3$ reduction in PM2.5. We discount this over the time frame using a 2% discount rate and multiply by the ATE and then use the demand elasticity and price to show the crime fiscal externality which occurs due to a £1 subsidy ($\frac{P*\epsilon}{P}$).

Using all of above estimated components, we calculate the MVPFs for the different scenarios and display them in Table 5. We will focus on the third row in Table 5 as our baseline (see also Fig 11). This scenario is the lower bound 20 years MVPF estimate using the low C-R function combined with an ATE of -1.9 (the daily ATE from our field experiment). The transfer consumers receive is £1, and they get health benefits of £0.75 from this if they choose to buy a monitor as well as income benefits equal to £44.83. Additionally, consumers save £0.50 in crime externalities due to the decrease in criminal activity. Therefore the total benefit is £47.08. Then we calculate costs to the government: the cost of the subsidy is £1, and over a 20 year horizon, this will compound to save the NHS £0.18 per £1 of subsidy based on the elasticity of demand for the monitor. Finally, once we incorporate labor force participation and calculate the change in income tax over a 20 year horizon, we find that the government increases revenue by £13.69 per £1 of subsidy. Also, the police and government save £0.15 due to crime costs.

Therefore the overall effect from a £1 subsidy on ther IAP monitor on government revenue is £13.02. Figure 11, which presents all these costs for our lower bound MVPF estimate, shows that government costs are negative due to the significant reduction in

Government healthcare costs and increased tax revenue from increased productivity. The figure shows the bars for the individual health benefits and income changes as lighter blue to reflect how these components may be included within the MVPF implicitly due to the WTP demand elasticities. As evident from Table 5, the MVPF is ∞ across all scenarios, meaning that these subsidies would be a Pareto improvement (they pay for themselves). This holds true even if we assume that consumers have full information and so the health benefits they get are incorporated into their price elasticity of demand.[52] Moreover, the MVPF remains infinite with different assumptions on the fiscal externality (the FE would have to decrease by 86% to stop being infinite).

We also show how sensitive the MVPF is to the ATE and the price elasticity of demand. In Figure 12, we plot the MVPF for the IAP monitor against different levels of treatment effects and show that even small reductions in PM2.5 will be beneficial over a 20 year horizon. The three lines represent the quartiles of price elasticity of demand: -0.22 (25^{th} percentile), -0.75 (median) and -1.31 (75^{th} percentile). These estimates show that an ATE as small as -0.14 can still have an infinite MVPF for a $1 subsidy for the IAP monitor, and the most inelastic price elasticity of demand still leads to an MVPF of ∞ at ATE = -0.46 $\mu g/m^3$. This shows that our result is very robust to different levels of treatment effects and demand elasticities. At the whole day ATE of -1.9 $\mu g/m^3$ as shown in Figure 3, we can see that a $1 subsidy on an IAP monitor will always pay for itself, mainly due to the increase in income taxes over the time horizon.

It is quite unusual to find MVPFs that are infinite. Many of the health, labor, and education policies have an MVPF around 1, although some have infinite MVPFs, such as child health insurance and early years education (Hendren and Sprung-Keyser, 2020). For environmental policies, Hahn et al. (2024) do not find any polices having an infinite MVPFs, so to the best of our knowledge this is the first environmental policy that could pay for itself.

6 Conclusion

There is a large literature on the contributors to ambient air pollution and on the health and welfare consequences of such pollution. This literature has been important in shaping air pollution policy around the World. However, we have limited knowledge on in-

[52] In this case the numerator decreases, but the tax revenue increases such that the policy pays for itself.

door air pollution (IAP), in terms of the levels, its predictors, but also what can causally change it and whether such interventions/policies are welfare enhancing. Using a field experiment in London, UK, we are able to demonstrate IAP levels, its predictors, and what can causally change it. On levels, we find that for 38% of the time, IAP is above World Health Organization standards. We find that there are many predictors of high IAP, such as smoking, income, several households appliances and dwelling characteristics. in our field experiment, we show that real-time feedback reduces IAP by 34% (5 $\mu g/m^3$) during occupancy time where people are at home and exposed to this pollution.

Our data and results also point to a very important mechanism: ventilation. We find numerous pieces of evidence that ventilation is important for regulating high levels of IAP. We explore the mechanisms for our findings and show that people are using more natural ventilation as a result of the feedback (i.e., opening up doors and windows to the outside world). Furthermore, we find that the treatment leads to change in beliefs about exposure to IAP and that the willingness to pay for every 1 $\mu g/m^3$ of PM2.5 is of £4.80. Finally, we show that subsidies to adopt an IAP monitor or an indoor air purifier have an infinite MVPF. This infinite MVPF means that subsidies for such technologies pay for themselves.

While further research on this issue is urgently needed given the extremely limited empirical evidence, our analysis already provides critical insights into both the scale and sources of indoor air pollution, as well as the economic evaluation of potential policy interventions to address this issue. These findings are particularly important for policymakers, as they highlight the urgent need to tackle this significant public health and economic challenge and provide possible solutions.

In the context of policy, it is also important to highlight the role of ventilation in mitigating indoor pollution. Policymakers should carefully evaluate proposed housing policies aimed at improving energy efficiency, such as increased insulation and weatherization measures to reduce drafts. While these measures may help reduce energy use and greenhouse gas emissions, they could inadvertently increase indoor air pollution exposure by reducing ventilation. We strongly recommend that this potential trade-off be empirically assessed and integrated into future housing and environmental policies. Additionally, potential technological solutions that could minimize or even eliminate such trade-offs should be explored to ensure a balanced approach that advances both climate goals and public health priorities.

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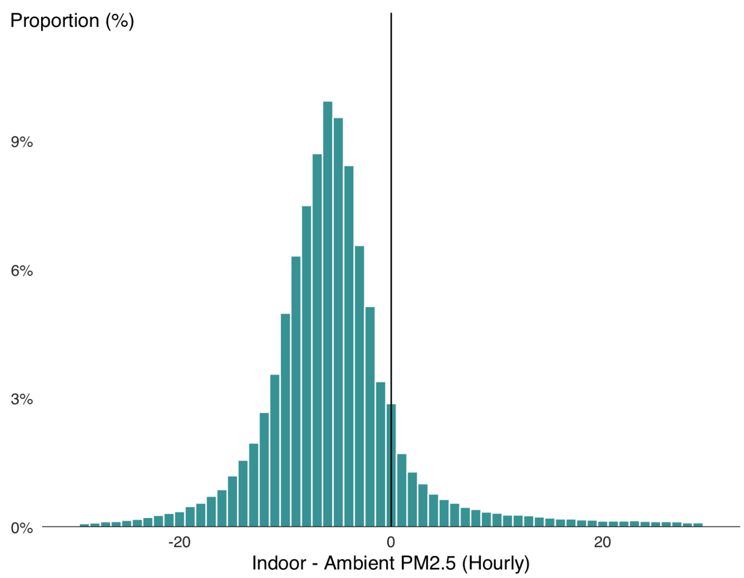
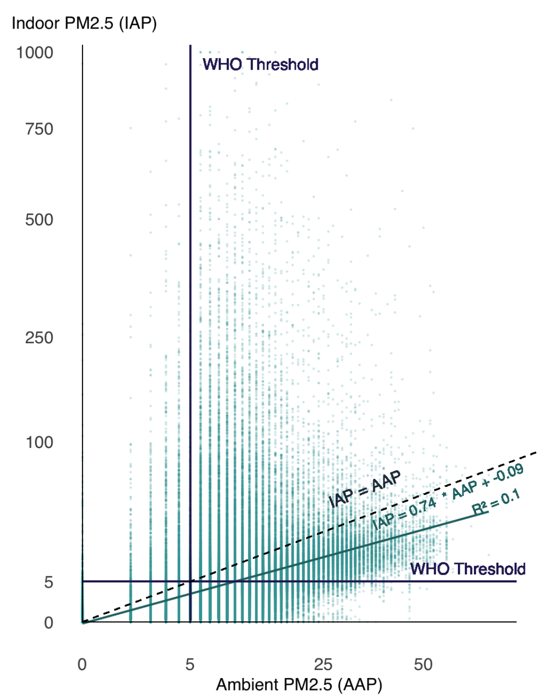
Figure 1: Indoor PM2.5 minus Ambient PM2.5 per hour



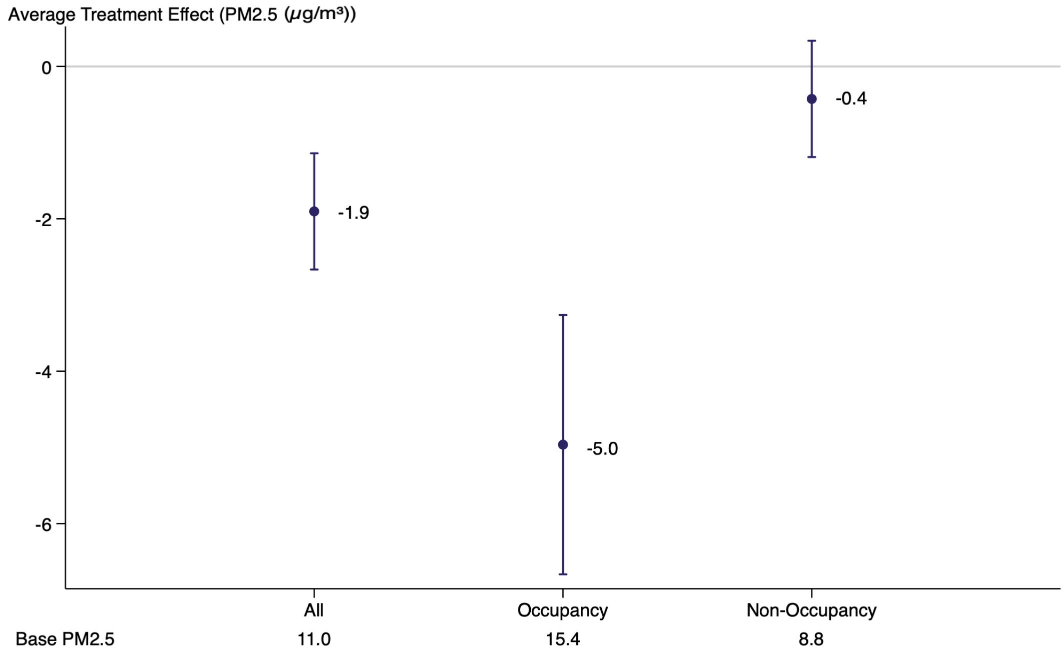
Note: This figure displays the distribution of the difference between indoor and ambient air pollution during the pre-treatment period.

Figure 2: The Relationship Between Indoor and Ambient Air Pollution



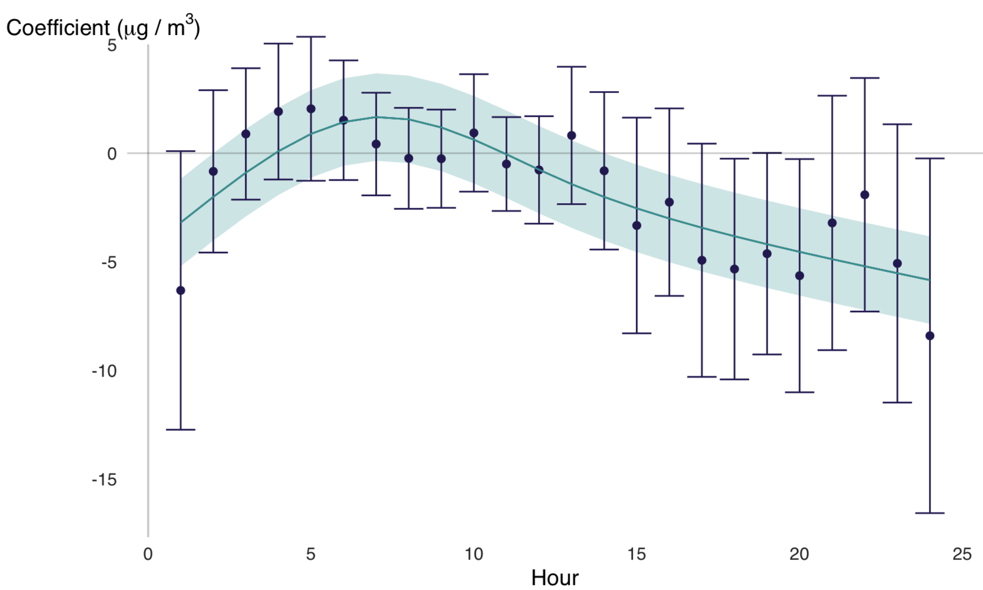
Note: This figure displays the relationship between indoor and ambient air pollution during the pre-treatment period.

Figure 3: Average Treatment Effects of The Treatment (IAP Monitor)



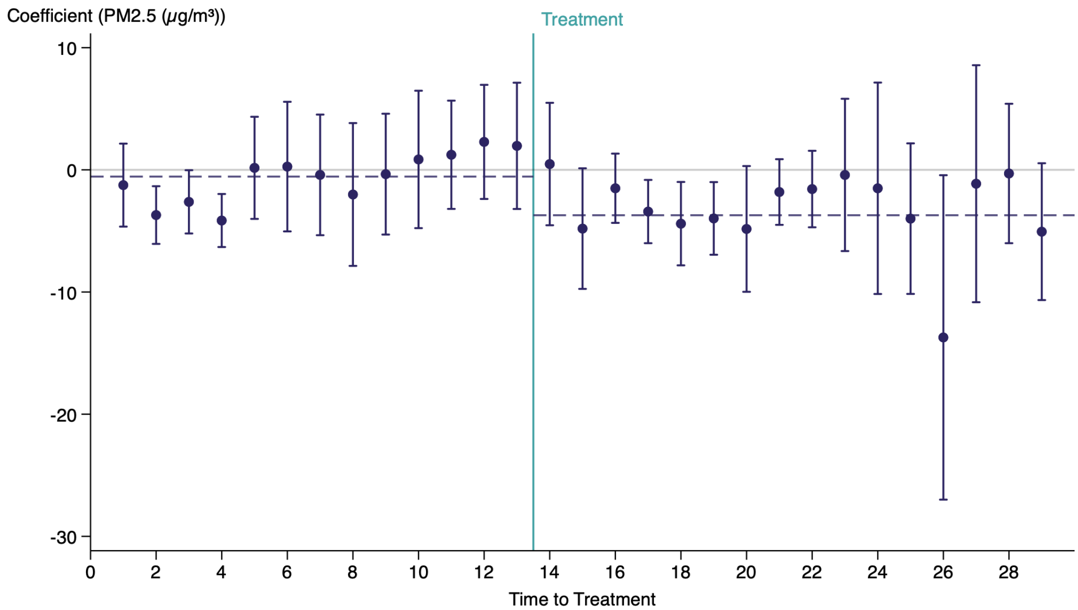
Note: This figure displays estimates of the coefficients of the average treatment effect by day respective to treatment time bootstrapped 1000 times. Ambient pollution levels as well as day and month fixed effects have been controlled for. 95% confidence intervals are presented clustered at a household and date level. Occupancy time here refers to 16:00-23:00. Base PM2.5 refers to the post-treatment time control group average PM2.5 levels.

Figure 4: Average Treatment Effects by Hour of The Day



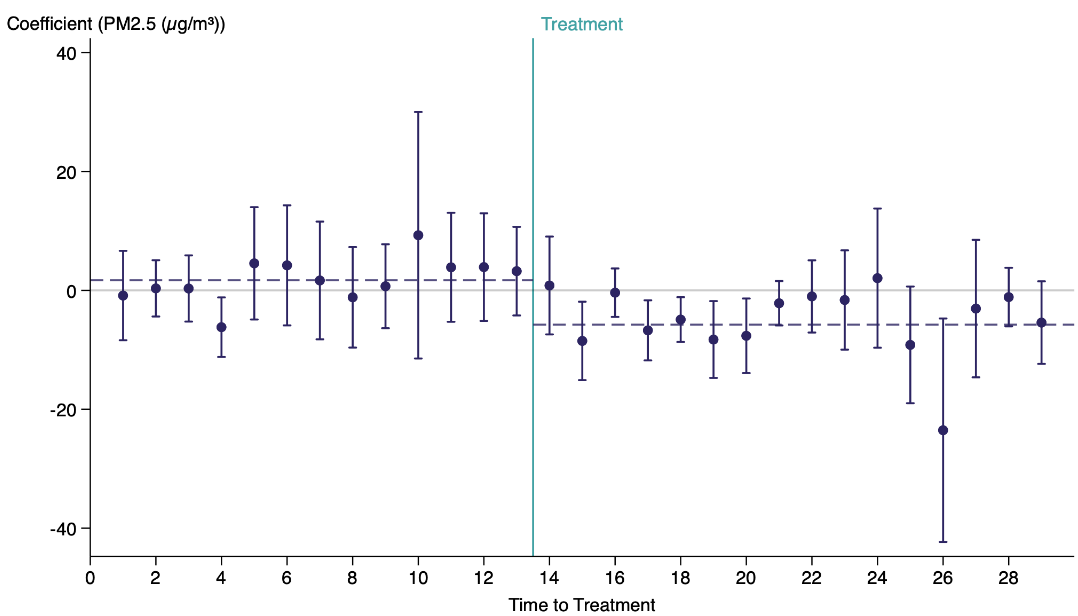
Note: This figure shows the coefficient on Treatment x Post, and uses our main specification, separated by hour of the day. 95% confidence intervals are presented, clustered at the household and date level. The light blue ribbon shows the bootstrapped standard errors.

Figure 5: Average Treatment Effect by Day



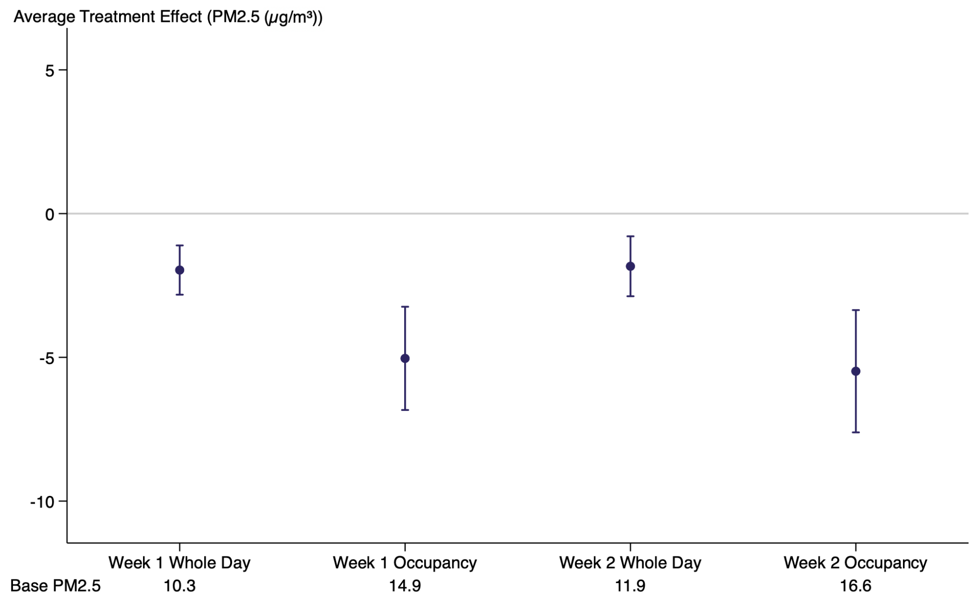
Note: This figure displays estimates of the coefficients of the average treatment effect by day respective to treatment time, controlling for ambient PM2.5 and day and month fixed effects. 95% confidence intervals are presented, clustered at the household and date level.

Figure 6: Average Treatment Effects by Day (occupancy hours only)



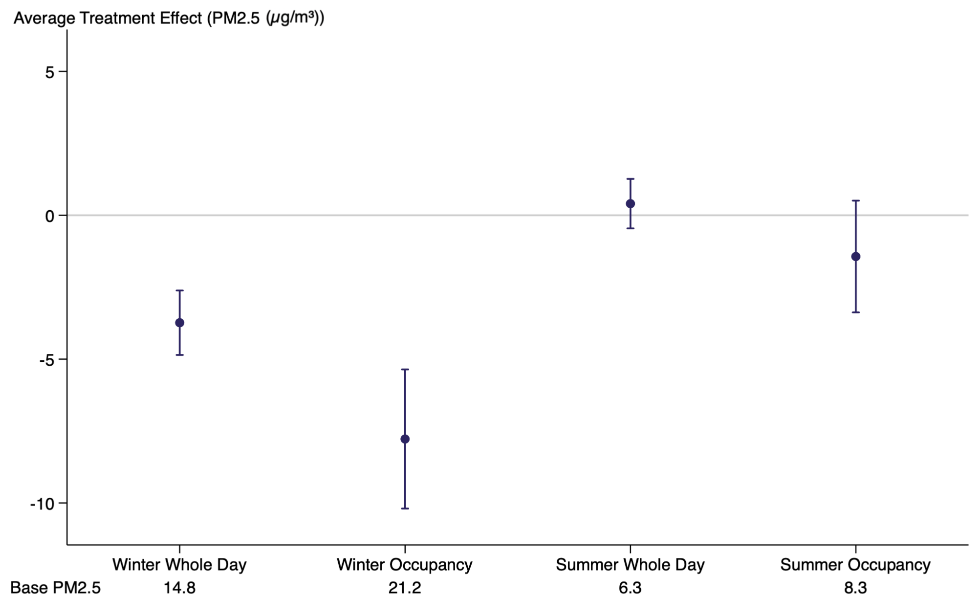
Note: This figure displays estimates of the coefficients of the average treatment effect by day respective to treatment time from 4pm-11pm. 95% confidence intervals are presented.

Figure 7: Average Treatment Effect by Week of the Experiment



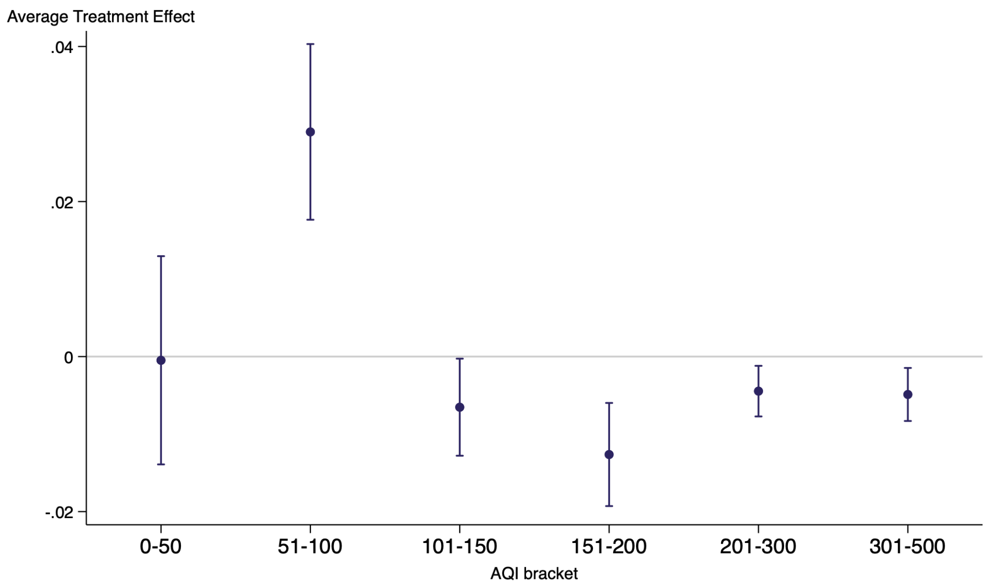
Note: This figure displays the average treatment effect by week after treatment and time of day bootstrapped 1000 times, controlling for ambient PM2.5 and day and month fixed effects. 95% confidence intervals are presented, clustered at the household and date level.

Figure 8: Average Treatment Effect by Season



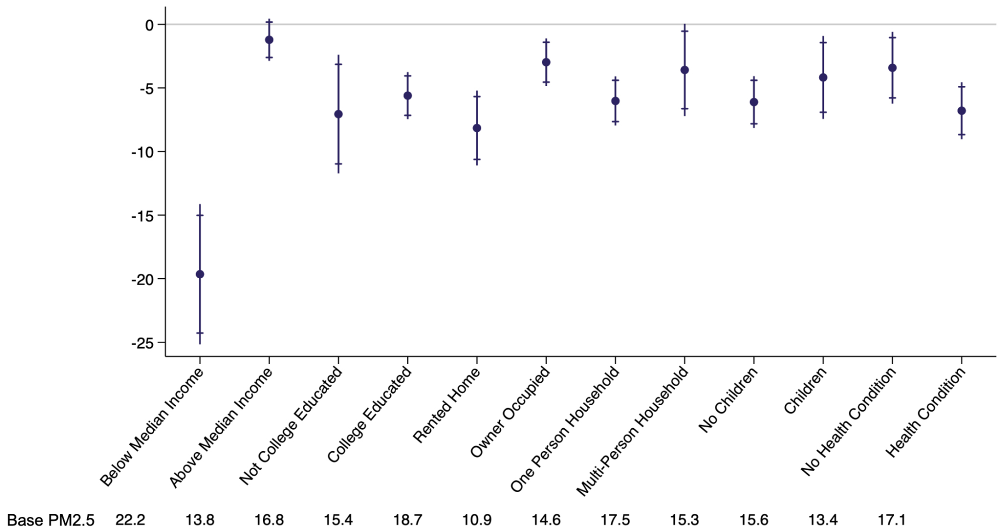
Note: This figure displays the average treatment effect by season and time of day bootstrapped 1000 times, controlling for ambient PM2.5 and day and month fixed effects. 95% confidence intervals are presented, clustered at the household and date level.

Figure 9: Average Treatment Effect by Air Quality Index (AQI) Bracket



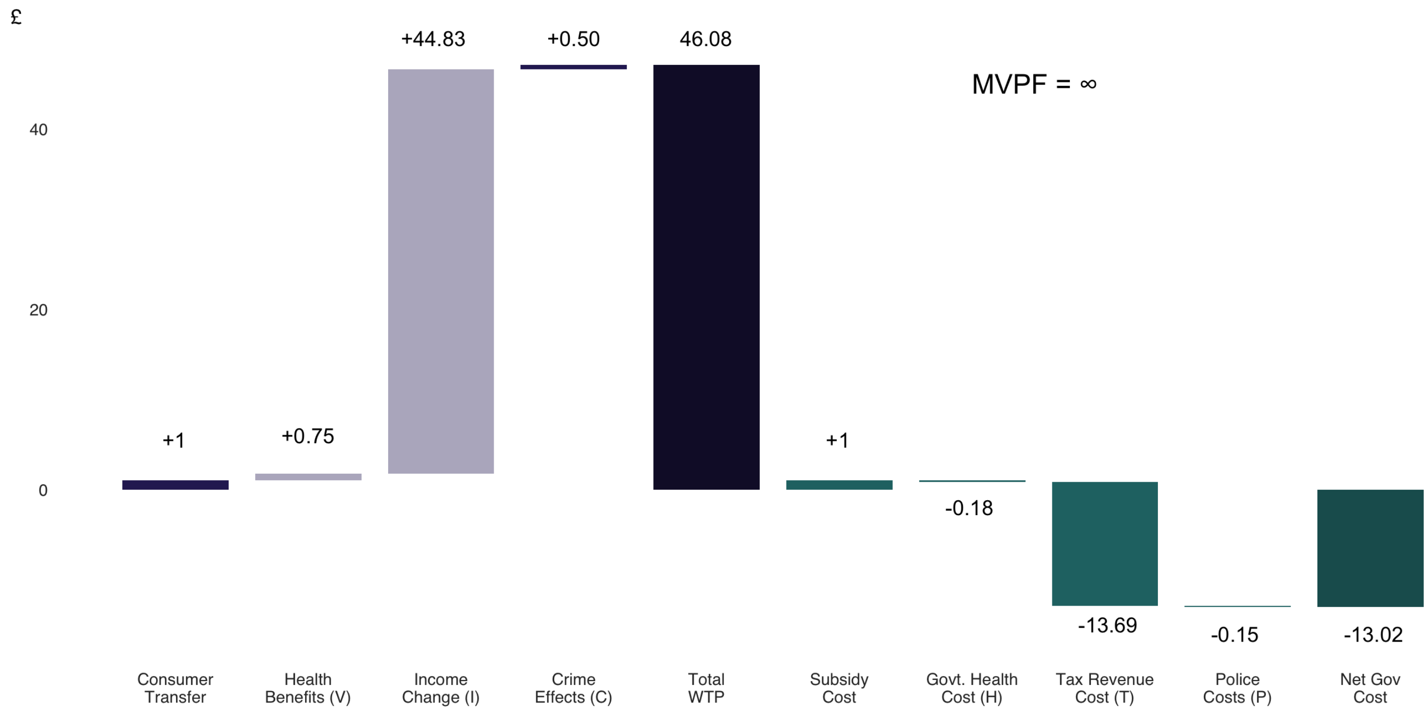
Note: This figure displays estimates of the coefficients of Treatment x Post on AQI brackets. This is a linear probability model, where each coefficient shows the probability that a household's AQI level will be within a certain bracket. Day and month fixed effects are controlled for, as well as ambient levels of PM2.5. The observations restricted to occupancy time (16:00-23:00) to reflect times when the average person is at home and near the monitor. Standard errors bootstrapped 1000 times and clustered two way at the household level and by date. 95% confidence intervals are presented.

Figure 10: Average Treatment Effect by Household Characteristics



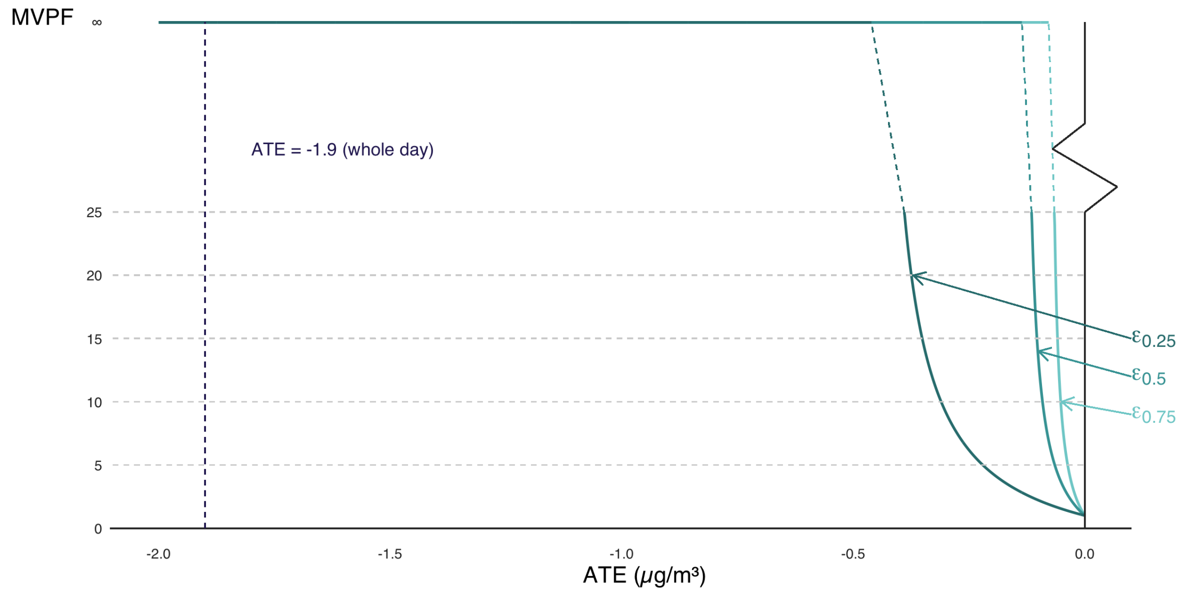
Note: This figure displays estimates of the coefficients of the average treatment effect for each characteristic in the occupancy period bootstrapped 1000 times, controlling for ambient PM2.5, all the other household characteristics (below median income dummy, number of smokers, asthma, children, number of residents, health conditions, if the house is owned by the resident and education). Day of week and month fixed effects are also included, with standard errors clustered at the household level and by date. 95% confidence intervals are presented.

Figure 11: Marginal Value of Public Funds for an Air Pollution Monitor Subsidy



Note: This figure displays the MVPF waterfall chart for the lower bound estimate of the MVPF of the whole day average treatment effect for the Kaiterra Monitor over a 20 year horizon. The health (V) and Income benefits (I) are depicted as a different shade of blue because there is uncertainty as to whether consumers fully value these in the purchase of the air monitor. Even if individuals have perfect information on these benefits (so zero H and I), the MVPF would remain being infinite.

Figure 12: MVPF by the ATE and price elasticity of IAP monitor demand



Note: This figure displays how the MVPF varies with the ATE for the IAP monitor across the interquartile ranges of elasiticies with the darkest shade referring to a PED of -0.22 and the lightest shade corresponding to a PED of -1.31. This is specifically relating to the third row of Table 5, as described in the text and shown in Figure 11. With our median elasticity of 0.75, we show that MVPF = ∞ for ATE = -1.9 over a 20 year horizon. These results are robust to a 10 year horizon too. This shows that an ATE as small as -0.14 can still have an infinite MVPF for the IAP monitor.

Table 1: Impact of treatment on indoor and outdoor temperature difference

	Total	Occupancy	Non-Occupancy
Treatment x Post	-0.714***	-0.570**	-0.767***
	(0.24)	(0.24)	(0.25)
Treatment	0.121	0.117	0.132
	(0.29)	(0.27)	(0.30)
Post	0.765***	0.580**	0.913***
	(0.26)	(0.28)	(0.28)
Ambient PM2.5	0.050***	0.026*	0.079***
	(0.01)	(0.01)	(0.01)
Constant	7.587***	6.299***	8.023***
	(0.31)	(0.32)	(0.32)
Observations	149,044	49,776	99,268

Note: This table displays estimates of the coefficients of binary variables treatment and post as well as an interaction between the treatment and post on hourly levels of indoor PM2.5. Day and month fixed effects are controlled for, as well as ambient levels of PM2.5. The observations that are restricted to occupancy time (16:00-23:00) are to reflect times when the average person is at home. Standard errors clustered two way at the household level and by date are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 2: IAP peak analysis

	Peak Height	Peak Frequency
Treatment x Post	-37.907*	1.179
	(20.97)	(1.24)
Treatment	2.196	-0.821
	(17.97)	(0.89)
Post	12.994	-0.568
	(11.69)	(0.88)
Ambient PM2.5	-0.256	-0.037
	(0.39)	(0.05)
Constant	154.646***	6.531***
	(10.59)	(0.94)
Observations	10,697	377

Note: This table displays estimates of the coefficients of binary variables treatment and post as well as an interaction between the treatment and post on hourly levels of indoor PM2.5. Day and month fixed effects are controlled for, as well as ambient levels of PM2.5. Standard errors clustered two way at the household level and by date are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Peaks are defined as local maximum levels of AQI levels being above 100 over at least a 5 hour period.

Table 3: Belief Outcomes

	Indoor		Ambient	
	Air Quality Belief	Confidence	Air Quality Belief	Confidence
Treatment	0.259**	0.302**	0.155	0.115
	(0.10)	(0.13)	(0.12)	(0.14)
Constant	0.051	0.026	-0.000	0.076
	(0.07)	(0.09)	(0.08)	(0.10)
Observations	234	233	234	233

Note: This table displays estimates of the coefficients of treatment on the difference in air quality beliefs in the baseline and endline survey. Air quality belief represents a participants perception of indoor and outdoor air quality. Confidence represents how certain a participant is about this level of air quality. Standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 4: Robustness regressions

	Occupancy			Non-Occupancy	12am-11am	12pm-11pm
	No Ambient	First Waves	All			
Treatment x Post	-4.495*	-6.528**	-4.964**	-0.426	-0.133	-3.798*
	(2.34)	(2.84)	(2.33)	(1.06)	(1.03)	(1.96)
Treatment	1.007	0.439	1.261	-0.980	-1.292	0.852
	(2.67)	(2.52)	(2.65)	(1.35)	(1.37)	(2.18)
Post	1.215	4.871**	2.525*	-0.129	-0.390	2.035
	(1.55)	(2.03)	(1.51)	(0.83)	(0.85)	(1.36)
Ambient PM2.5		0.560***	0.549***	0.519***	0.547***	0.554***
		(0.07)	(0.08)	(0.03)	(0.03)	(0.07)
Constant	14.423***	5.370***	7.385***	3.969***	3.293***	6.411***
	(1.51)	(1.38)	(1.55)	(0.97)	(1.11)	(1.28)
Observations	50,085	32,491	50,085	99,994	75,002	75,077

Note: This table displays estimates of the coefficients of binary variables treatment and post as well as an interaction between the treatment and post on hourly levels of indoor PM2.5. Day and month fixed effects are controlled for, as well as ambient levels of PM2.5. The first column doesn't control for outdoor PM2.5, the second column only includes the participants from the first 3 waves to match our pre-analysis plan. The third column is our normal specification as shown in 1 and the fourth column does this for non-occupancy time. The last two columns focus on time periods 12pm-11pm and 12am-11am respectively. Standard errors clustered two way at the household level and by date are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 5: MVPF estimates for a $1 subsidy for either an IAP monitor or purifer

	Transfer	Health Benefits (V)	Income Change (I)	Crime (C)	Total WTP	Subsidy Cost	Govt. Health Cost Savings (H)	Tax Revenue (T)	Gov Crime Costs (P)	Net Government Cost	MVPF
IAP monitor: Whole Day ATE (-1.9)											
Lower Bound 10 Year	1	0.75	24.63	0.27	26.65	1	0.05	7.52	0.08	-6.65	∞
Upper Bound 10 Year	1	1.68	24.63	0.27	27.58	1	0.05	7.52	0.08	-6.65	∞
Lower Bound 20 Year	1	0.75	44.83	0.50	47.08	1	0.18	13.69	0.15	-13.02	∞
Upper Bound 20 Year	1	1.68	44.83	0.50	48.01	1	0.18	13.69	0.15	-13.02	∞
IAP monitor: Occupancy Time ATE (-5.0)											
Lower Bound 10 Year	1	1.96	64.81	0.72	68.49	1	0.14	64.81	0.21	-64.16	∞
Upper Bound 10 Year	1	4.33	64.81	0.72	70.86	1	0.14	64.81	0.21	-64.16	∞
Lower Bound 20 Year	1	1.96	117.97	1.31	122.24	1	0.46	36.04	0.38	-35.88	∞
Upper Bound 20 Year	1	4.33	117.97	1.31	124.61	1	0.46	36.04	0.38	-35.88	∞
IAP purifier: Whole Day ATE (-11.0)											
Lower Bound 10 Year	1	6.56	220.75	2.46	230.77	1	0.47	67.44	0.72	-67.63	∞
Upper Bound 10 Year	1	14.18	220.75	2.46	238.39	1	0.47	67.44	0.72	-67.63	∞
Lower Bound 20 Year	1	6.56	401.85	4.48	413.89	1	1.57	122.76	1.31	-124.64	∞
Upper Bound 20 Year	1	14.18	401.85	4.48	421.51	1	1.57	122.76	1.31	-124.64	∞
IAP purifier: Occupancy Time ATE (-15.4)											
Lower Bound 10 Year	1	9.07	309.05	3.44	322.56	1	0.65	94.41	1.01	-95.07	∞
Upper Bound 10 Year	1	19.31	309.05	3.44	332.80	1	0.65	94.41	1.01	-95.07	∞
Lower Bound 20 Year	1	9.07	562.58	6.27	578.92	1	2.20	171.86	1.83	-173.49	∞
Upper Bound 20 Year	1	19.31	562.58	6.27	589.16	1	2.20	171.86	1.83	-173.49	∞

Note: This table displays estimates of MVPFs from equation 2. All the numbers are inflation adjusted to 2023£. We consider the 10 and 20 year horizons for the government health cost savings for the NHS and for the change in income tax revenue due to labor force participation. The upper and lower bound estimates are derived from the C-R mortality function, which tell us the WTP for a reduction in mortality. The varying degrees of ATE's is derived from the effectiveness we calculate of the Kaiterra Monitor through our experiment and is assumed for the Philips Air Purifier.

Appendices

Contents of Appendices

A Figures

Figure A1: Preliminary Survey Questions

Preliminary Survey

Thank you for participating in the Camden Household Air Monitoring Project (CHAMP), we're really excited to have you on board. Before we get started with the project, we just need a little more information from you, so please feel in as much as you can of this survey. It shouldn't take more than 10 minutes to complete.

Dr Sefi Roth
Department of Geography and Environment
London School of Economics and Political Science
geog.iaq@lse.ac.uk

1. What is the research about?

    • This study will observe the scale of indoor air pollution in homes throughout Camden for a four-week period. You will be given a small air pollution monitor for the main room in your home, and a 3G router to send the air pollution data from the device to our database.

    • You will also complete two short surveys. This first survey will determine your eligibility for the project, and the second will ask your experience with the monitors and the project. At the end of the project when you complete the second survey and give back the monitor, as a thank you, you will be rewarded with a £20 Amazon voucher.

    • We will also notify you of your indoor air pollution levels, how they compare to the average Camden resident in the study, and how to reduce the pollution levels.

2. What will my information be used for?

    We will use the collected information to write scientific papers on the topic of indoor air pollution and to guide future research in the area. The records from this study will be kept confidential. Only the researchers conducting the project will have access to the information you have provided. Your data will be anonymised – your name will not be used in any reports or publications resulting from this study.

3. What if I have a question or complaint?

    If you have any questions regarding this project, please contact the team on geog.iaq@lse.ac.uk. This study has undergone ethics review in accordance with the LSE Research Ethics Policy and Procedure. If you have any concerns or complaints regarding the conduct of this research, please contact the LSE Research Governance Manager via research.ethics@lse.ac.uk.

    You can withdraw from the study at any point.

    The air pollution monitors are the ownership of the London School of Economics, and we will be retrieving the monitors from all participants at the end of the four-week period.

    If you are happy to take part in this study, please tick the consent question below.

Thank so much!

Dr Sefi Roth
Department of Geography and Environment
London School of Economics and Political Science
geog.iaq@lse.ac.uk

Please tick the box: I have read and understood the study information and consent voluntarily to be a participant in this study. As part of this consent, I allow researchers at the London School of Economics to analyse the data for scientific purposes only.

I have read and understood the study information and consent voluntarily to be a participant in this study. As part of this consent, I allow researchers at the London School of Economics and University of Southern California (US), to analyse the data for scientific purposes only.

1. How many people usually live in your household?
   1
   2
   3
   4
   5
   6
   7+
   Prefer not to say

2. How old are the residents living in your household? (Resident 1)

3. How old are the residents living in your household? (Resident 2)

4. How old are the residents living in your household? (Resident 3)

5. How old are the residents living in your household? (Resident 4)

6. How old are the residents living in your household? (Resident 5)

7. How old are the residents living in your household? (Resident 6)

8. How old are the residents living in your household? (Residents 7 and above)

9. Of the adults in your household, how many are…
   Female
   Male
   Other

10. What is your highest level of education held?
    GCSE/O Levels or equivalent
    A-Levels or equivalent

Undergraduate degree
Postgraduate degree
Other
None

11. What is your gross (pre-tax) household income level?
    £0-£15,000
    £15,001-£35,000
    £35,001-£50,000
    £50,001-£65,000
    £65,001-£80,000
    £80,001-£95,000
    Over £95,000

12. What is your housing tenure?
    Owner-occupied
    Privately rented
    Socially rented
    Other

13. Overall, how happy did you feel yesterday?
    0-10 not at all happy – extremely happy)

14. Overall, how anxious did you feel yesterday?
    0-10 (not at all anxious – extremely anxious)

15. In general, what is the quality of your health?
    Very good
    Good
    Fair
    Bad
    Very bad

16. During the past 2 weeks, how much did pain interfere with your normal work including both work outside the home and housework? Did it interfere...
    Not at all
    A little bit
    Moderately
    Quite a bit
    Extremely

17. How much of the time during the past 2 weeks have you felt calm and peaceful?
    All of the time
    Most of the time
    Some of the time
    A little of the time
    None of the time

18. How much of the time during the past 2 weeks did you have a lot of energy?
    All of the time

Most of the time
Some of the time
A little of the time
None of the time

19. During the past 2 weeks, how much of the time has your physical health or emotional problems interfered with your social activities like visiting friends or relatives?
    All of the time
    Most of the time
    Some of the time
    A little of the time
    None of the time

20. During the past 2 weeks, how would you rate your sleep quality overall?
    Very good
    Fairly good
    Fairly bad
    Very bad

21. Do you or any of the people in your household have any underlying health conditions?
    Yes
    No
    Unsure
    Prefer not to say

22. What are therse conditions?

23. How many smokers are there in your household?
    None
    1
    2
    3
    4
    5+

24. In total, how many rooms are in your home?

25. Do you have an open plan kitchen (that is, where the kitchen and living room are not separated by a wall)?
    Yes
    No

26. How many windows can be opened in your home?

27. What is the primary appliance used for cooking in your home? (multiple answers allowed)
    Stovetop
    Oven
    Microwave

Toaster
Grill
Other

28. Do you have a hob in your kitchen?
    Yes
    No

29. What kind of hob do you have?
    Induction
    Gas
    Electric
    Other
    Unsure

30. Do you have an extractor hood in your kitchen?
    Yes
    No

31. Do you have a fireplace in your home?
    Yes
    No

32. What type of fireplace do you have?
    Open fireplace
    Wood burning stove
    Electric fireplace
    Gas fireplace
    Other

33. Do you have any working air purifiers in your home?
    Yes
    No

34. How many?

35. On average, do you think the air quality **in your home** is:
    Good (no health risk)
    Moderate (acceptable but some health concern)
    Unhealthy for sensitive people (such as children, asthmatics, and those with breathing difficulties)
    Unhealthy for all people (harmful for all people)
    Very unhealthy (emergency levels for all people)
    Hazardous

36. How confident are you about your answer to the question above?
    Very confident
    Somewhat confident
    Neither confident nor unconfident
    Somewhat unconfident

Very unconfident

37. On average, do you think the air quality **outside your home** is:
    - Good (no health risk)
    - Moderate (acceptable but some health concern)
    - Unhealthy for sensitive people (such as children, asthmatics, and those with breathing difficulties)
    - Unhealthy for all people (harmful for all people)
    - Very unhealthy (emergency levels for all people)
    - Hazardous

38. How confident are you about your answer to the question above?
    - Very confident
    - Somewhat confident
    - Neither confident nor unconfident
    - Somewhat unconfident
    - Very unconfident

39. In comparison to the average Camden home, do you think the air quality in your home is:
    - A lot better
    - Somewhat better
    - About the same
    - Worse
    - A lot worse
    - Unsure

40. In order to deliver your indoor air monitor, we need your contact details. Please provide below:
    - Full name
    - Full address
    - Mobile number
    - Preferred contact email

All done! Thank you very much for completing this survey. We'll be in touch shortly with more information on the next steps.

Figure A2: Initial Recruitment Letter

Camden

Air Quality
London Borough of Camden
5 Pancras Square
LONDON
N1C 4AG

Phone: 020 7974

camden.gov.uk

email: AirQuality@camden.gov.uk

Date:

Our reference: [ID]

Your reference: [ID}

OCCUPIER
[Add1]
[Add2]
[Add3]
[Add4]
[PostCode]

An invitation to participate in an indoor air pollution study

Dear Camden Resident,

You have been randomly selected to take part in an indoor air pollution research study taking place in Camden in a collaboration between the London School of Economics and Camden Council. The study will expand our scientific knowledge around indoor air pollution and help to improve your knowledge about the health and wellbeing effects of indoor air pollution.

We are looking for Camden residents like yourself to take part in this exciting project. You will be given a small device to monitor the air pollution in your home over a four week period. Installing the monitor is very straightforward, and we will provide technical support if needed. The information collected in this study will only be used for research purposes by approved researchers at the London School of Economics. Identifiable information will never be shared with any other party.

At the end of the study, you will receive a personalised report of the pollution levels within your home and some information around what this means for your health and wellbeing. Involvement in this study will put you at the forefront of scientific knowledge production and will be valuable in driving policy changes addressing the pollution problem and supporting public health. As a thank you for your time, you will also receive a voucher payment of £20.
If you are willing to participate in this study, please visit our website to register and to learn more. Scan the QR code below or visit the URL https://www.lse.ac.uk/geography-and-environment/news/indoor-air-pollution-in-camden. You can also email geog.iaq@lse.ac.uk or call 07472 740612 if you have any questions.

We look forward to hearing from you.

Kind regards,

The Camden Household Air Monitoring Project (CHAMP) team

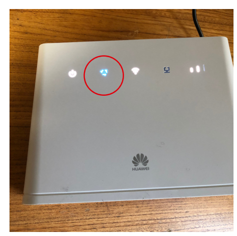
CHAMP Camden Household Air Monitoring Project   LSE The London School of Economics and Political Science   Camden   USC

Figure A3: Monitor Instructions

HOW TO SET UP YOUR MONITOR

Set up your monitor in the room where you spend the most amount of time.

Open the WiFi router box. Insert the black cable at the back of the router and plug the cable into a socket. After a few minutes, you should see the second symbol at the front turn blue.



Take the pollution monitor out of the box. Insert the white cable into the back of the monitor and plug it into a nearby socket.

Press and hold the power button at the top of the monitor for three seconds to turn it on. It wont look like anything has changed, but it should be working.

IF YOU NEED ANY HELP OR HAVE ANY QUESTIONS PLEASE CALL **07472 740612** OR EMAIL **GEOG.IAQ@LSE.AC.UK**

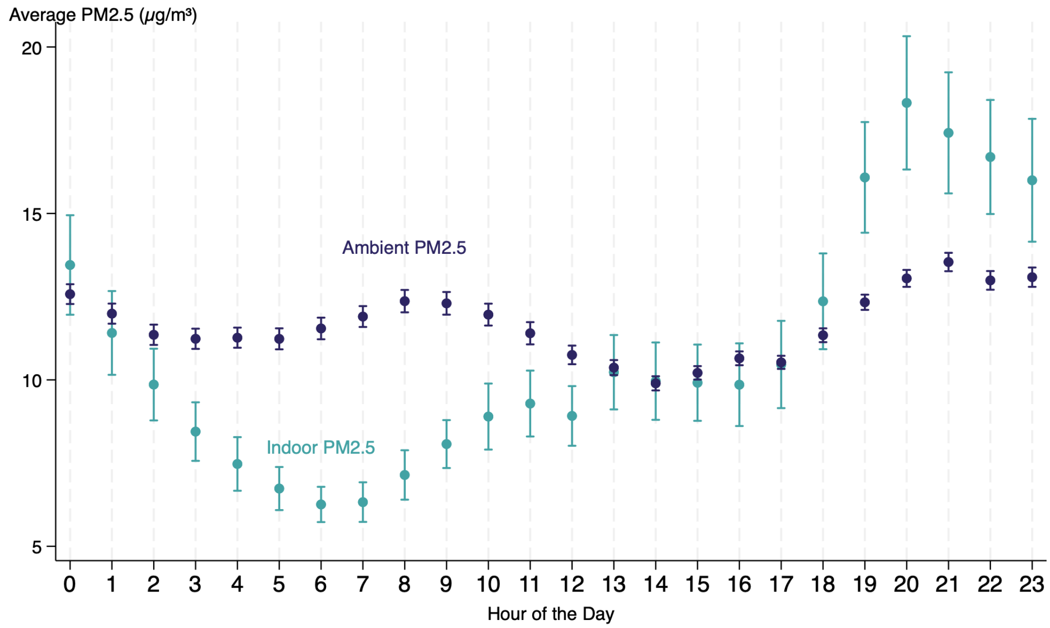
CHAMP Camden Household Air Monitoring Project · LSE · USC University of Southern California · Camden

Figure A4: Information Sheet

Figure A5: Monitor Picture

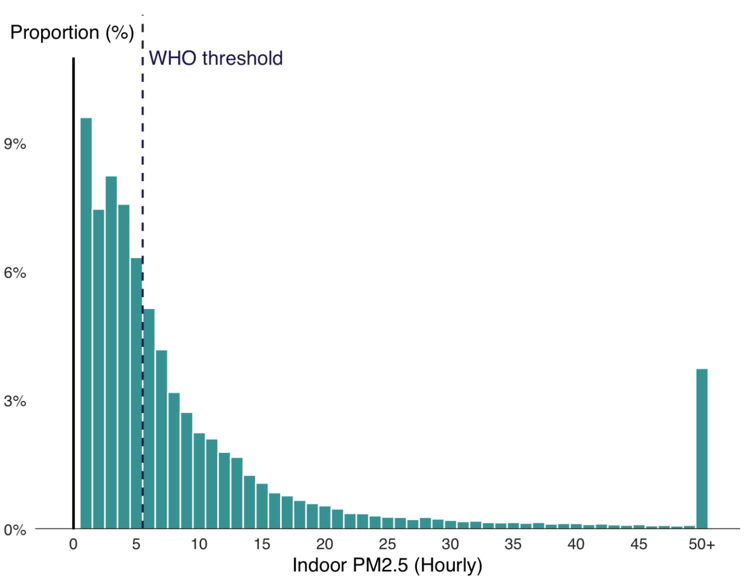
Note: This figure displays a picture of the Kaiterra Laser Egg Air Pollution Monitor.

Figure A6: Average PM2.5 by Hour of the Day



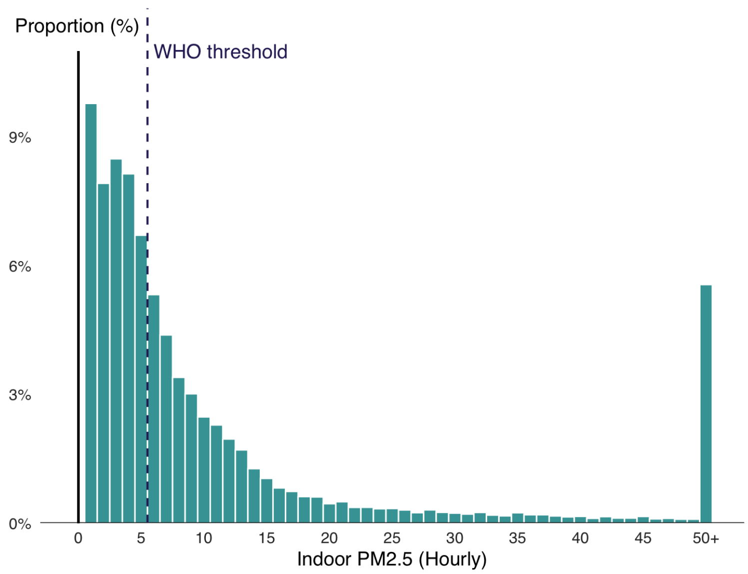
Note: This figure displays average indoor and ambient PM2.5 by hour of the day during the pre-treatment period.

Figure A7: Histogram of Indoor PM2.5 Whole Day



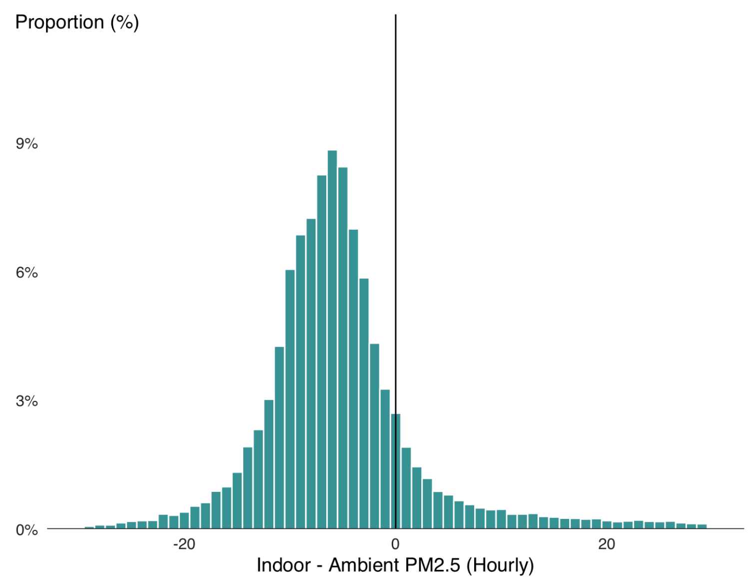
Note: This figure displays the distibution of the difference between IAP and AAP. Indoor PM2.5 is higher than ambient PM2.5 16% of the time.

Figure A8: Histogram of Indoor PM2.5 Occupancy Time



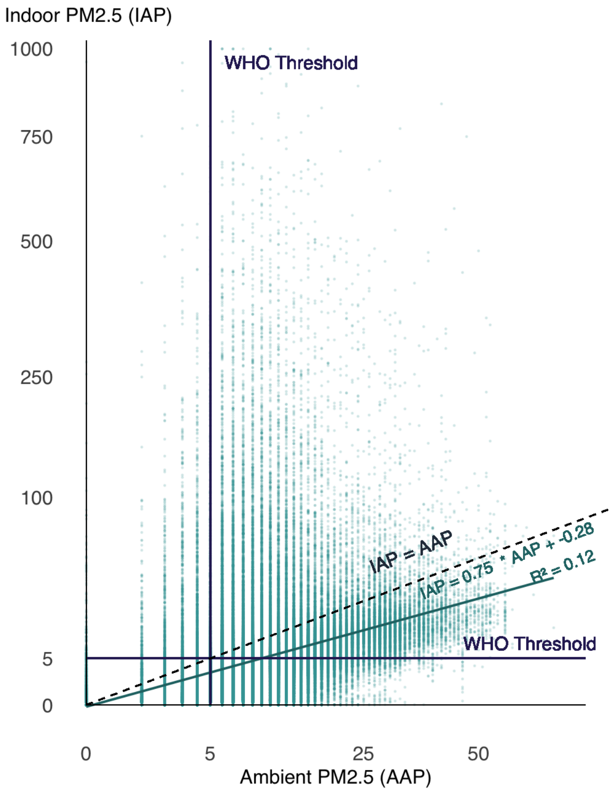
Note: These figure displays the distribution of the difference between IAP and AAP. Indoor PM2.5 is higher than ambient PM2.5 22% of the occupancy time.

Figure A9: Occupancy Time Indoor PM2.5 minus Ambient PM2.5

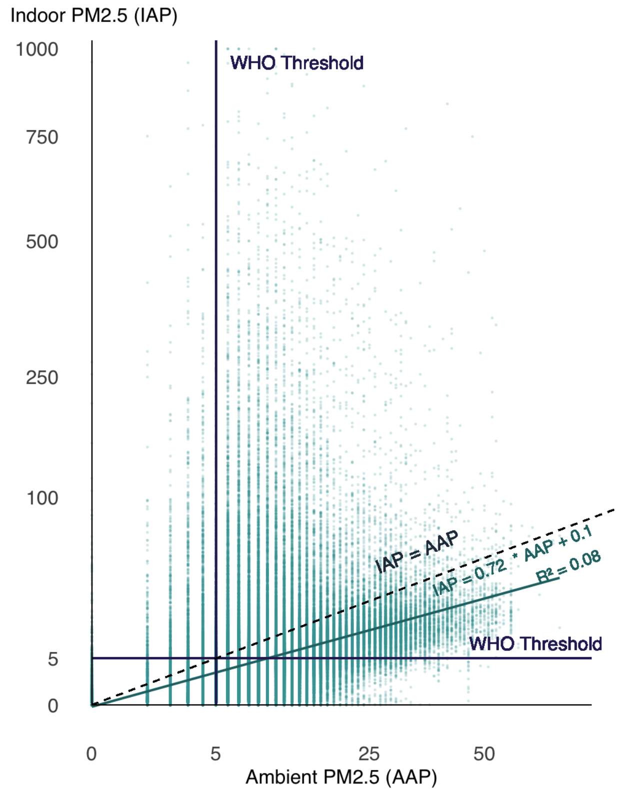


Note: These figure displays the distribution of indoor PM2.5 from 4pm-11pm.

Figure A10: Scatter Plots of Ambient and Indoor PM2.5 by Distance to Air Pollution Monitor



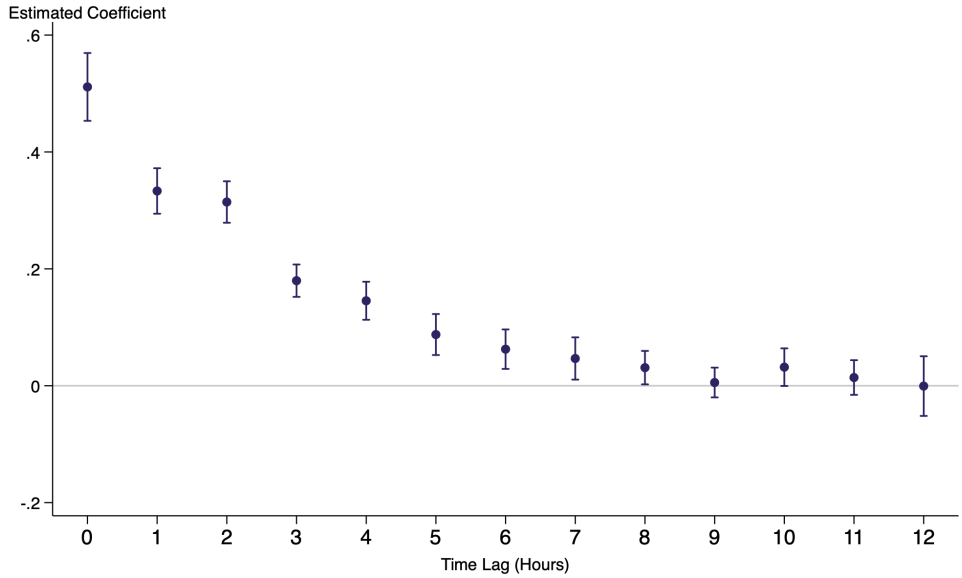
(a) Below Median Distance (1.79km)



(b) Above Median Distance (1.79km)

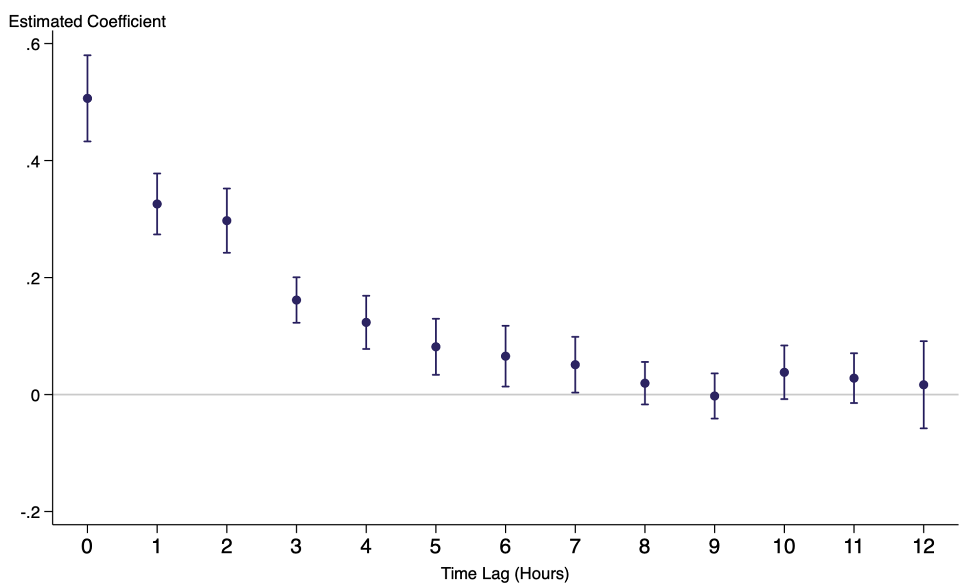
Note: These figures display scatter plots of ambient and indoor PM2.5. The first figure shows this relationship for households which live within 1.79km of their nearest air pollution monitor, and the second figure shows this for households who live further away.

Figure A11: How Ambient PM2.5 Affects Indoor PM2.5 Over Time



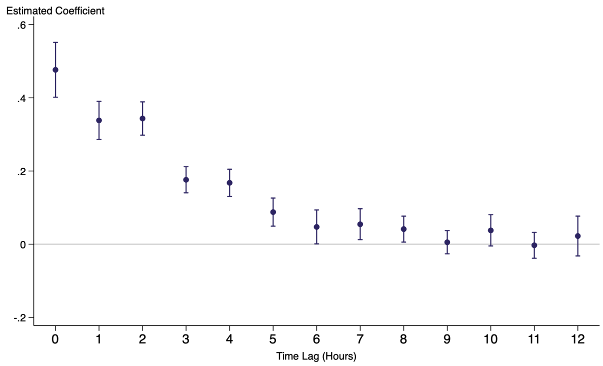
Note: This figure displays estimates of the coefficients of the effect of Ambient PM2.5 at different times on indoor PM2.5, controlling for outside temperature, dew point temperature, wet-bulb temperature, hour, day, month and household fixed effects. Standard errors clustered at the household level and by date. 95% confidence intervals are presented.

Figure A12: How Ambient PM2.5 Affects Indoor PM2.5 Over Time Pre-Treatment

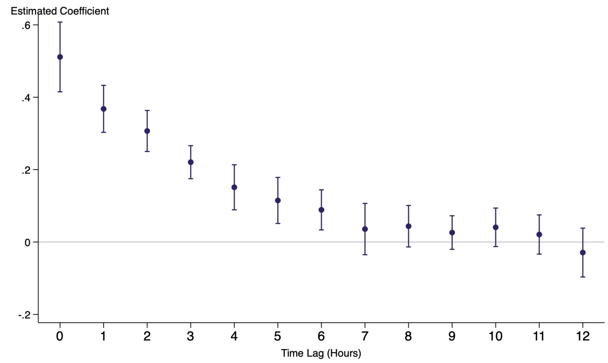


Note: This figure displays estimates of the coefficients of the effect of Ambient PM2.5 at different times on indoor PM2.5 for the first two weeks of the experiment, controlling for outside temperature, dew point temperature, wet-bulb temperature, hour, day, month and household fixed effects. Standard errors clustered at the household level and by date. 95% confidence intervals are presented.

Figure A13: Post-Treatment Time Analysis



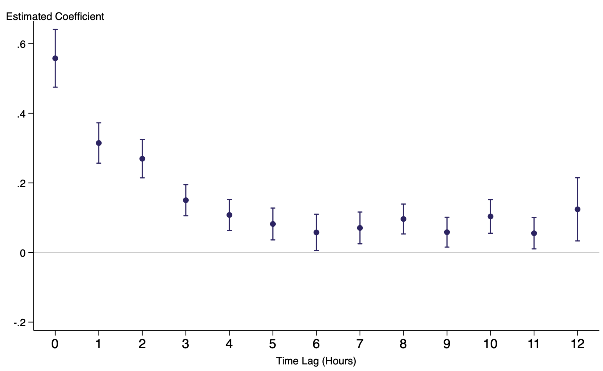
(a) Post-Treatment Time: Treatment



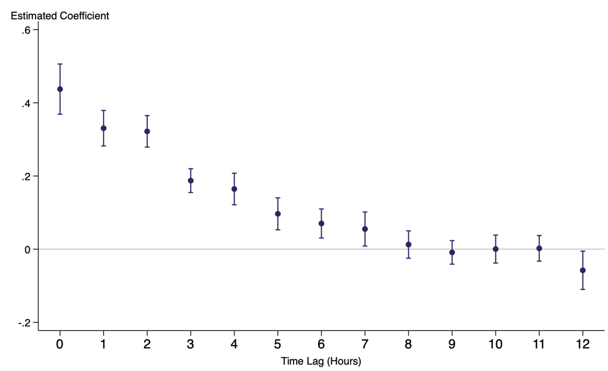
(b) Post-Treatment Time: Control

Note: These figures display the penetration rate of ambient PM2.5 to indoor PM2.5 categorized by treatment and control.

Figure A14: Seasonal Analysis of PM2.5 Penetration Rates



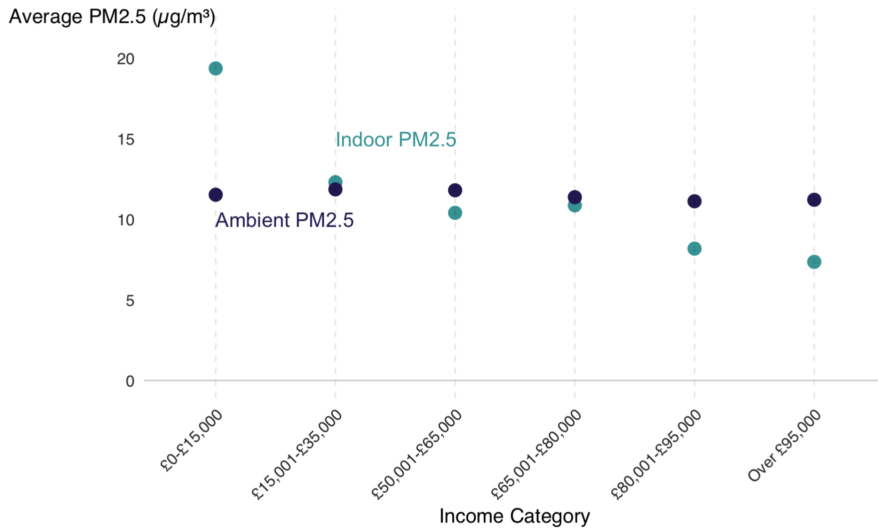
(a) Summer



(b) Winter

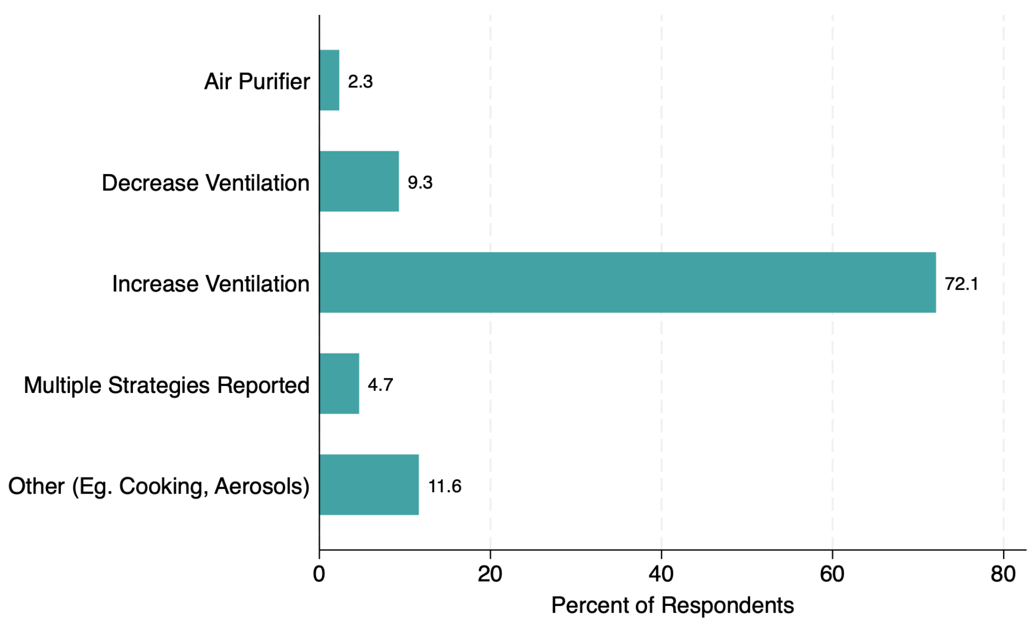
Note: These figures display the penetration rate of ambient PM2.5 to indoor PM2.5 categorized by different seasons.

Figure A15: Average PM2.5 by Income



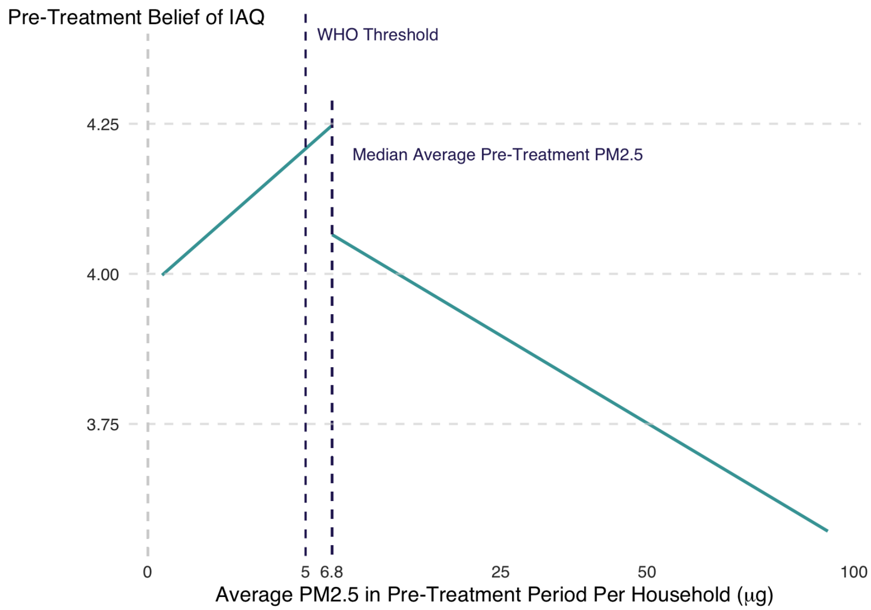
Note: This figure displays average indoor and ambient PM2.5 by income category.

Figure A16: Changes Implemented by Treatment Group



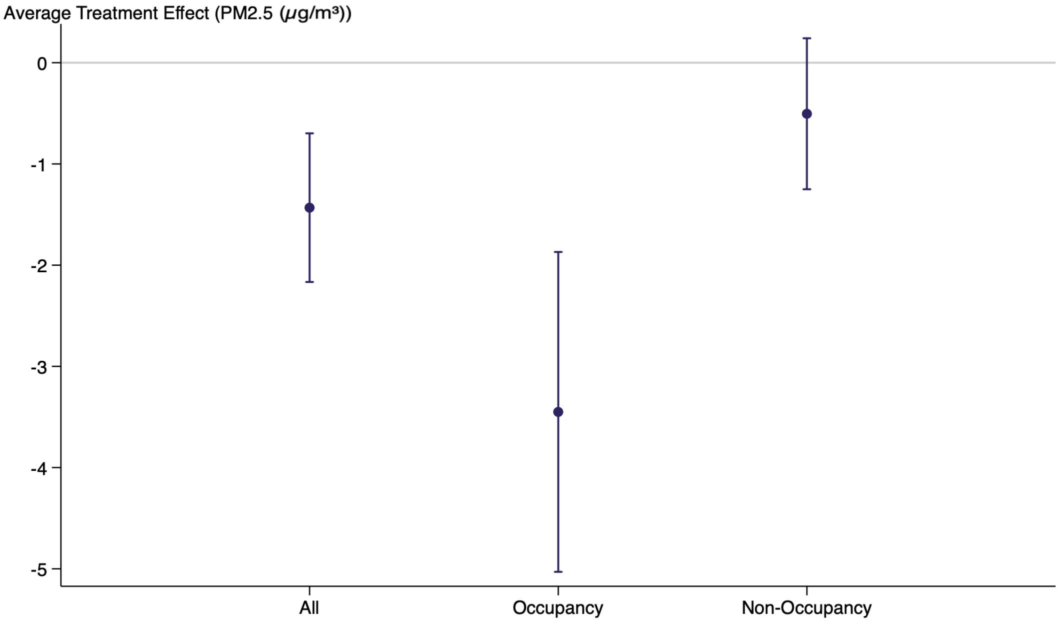
Note: This figure displays any changes implemented by the treatment group. This is analysed by the endline survey.

Figure A17: Mean PM2.5 vs Belief



Note: This figure displays lines of best fit between the mean of PM2.5 for each household in the pre-treatment period and how the household answered in the survey about their PM2.5. The higher this belief is, the worse they believe their atmosphere is for their health. The options ranged from 1-5, with 5 being the worst. Here, we have split the graph into two sections: the first half shows households who had lower average pollution levels pre-treatment and the second half shows households who had higher average pollution levels pre-treatment. We can see from this graph that people who had better pollution in their environment actually believed it was worse.

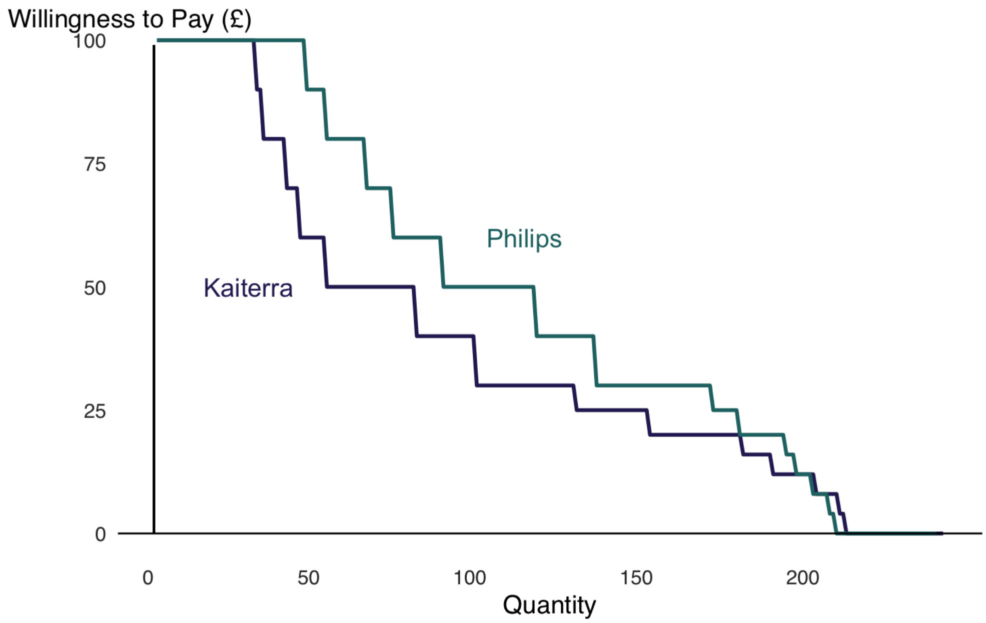
Figure A18: Main Results with Household Fixed Effects



Base PM2.5 11.0 15.4 8.8

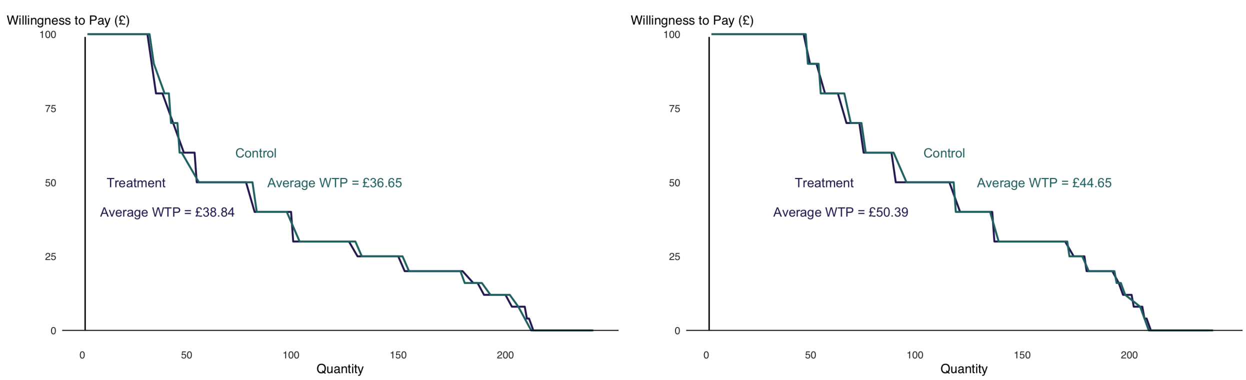
Note: This figure displays estimates of the coefficients of the average treatment effect by day respective to treatment time bootstrapped 1000 times with household fixed effects. Ambient pollution levels as well as day and month fixed effects have been controlled for. 95% confidence intervals are presented clustered at a household and date level. Occupancy time here refers to 16:00-23:00. Base PM2.5 refers to the post-treatment time control group average PM2.5 levels.

Figure A19: WTP



Note: This figure displays the WTP demand curves. The quantity demanded signifies the number of households who answered how much they were willing to pay. There were 237 households who answered this question, with answers ranging between £0-100.

Figure A20: Histograms of Households by Monitor Type



(a) WTP Kaiterra (b) WTP Philips

Note: This figure displays the WTP demand curves for the Kaiterra Air Pollution Monitor and the Philips Air Purifier.

B Tables

Table A1: External Validity

Characteristic	Camden	England	Our Sample
Single Household	34%	30%	24%
Socially Rented	34%	17%	13%
Homeowners	30%	63%	51%
Gas Heated	66%	73%	81%
Electric Heated	13%	8%	10%
Percent Below Median Income	45%	50%	24%
NVQ Level 4 or Above	72%	43%	86%

Note: This table displays the Camden and England averages of various household characteristics relative to the sample studied.

Table A2: Balance Test by Treatment

	Control		Treatment		Comparison		
	Mean	N	Mean	N	Difference	Standard Error	P-Value
Female	1.24	106	1.33	107	-0.09	(0.10)	0.36
Male	1.31	105	1.28	95	0.03	(0.10)	0.76
Number of Rooms	4.63	120	4.92	118	-0.28	(0.32)	0.37
Number of Windows	7.21	117	7.06	112	0.14	(0.53)	0.79
Number of Smokers	0.12	120	0.11	119	0.02	(0.05)	0.74
Open Plan Kitchen	0.53	120	0.48	119	0.05	(0.06)	0.48
College Educated	0.88	121	0.85	121	0.02	(0.04)	0.58

Note: This table shows the difference between the demographics between the treatment and control groups. Standard errors are reported in parentheses.

Table A3: Summary Statistics

	All			Pre-Treatment		
	All	Occupancy	Non-Occupancy	All	Occupancy	Non-Occupancy
Indoor PM2.5	10.539	14.281	8.664	10.815	14.649	8.899
	(36.60)	(45.92)	(30.72)	(34.92)	(46.26)	(27.36)
Indoor AQI	28.328	35.409	24.781	29.787	36.602	26.382
	(47.01)	(55.72)	(41.53)	(46.74)	(56.28)	(40.72)
Indoor Temperature	21.280	21.672	21.084	21.702	22.113	21.497
	(3.67)	(3.70)	(3.64)	(3.77)	(3.82)	(3.74)
Outdoor PM2.5	10.774	11.578	10.371	11.661	12.188	11.398
	(7.17)	(6.68)	(7.36)	(7.95)	(6.95)	(8.39)
Outdoor Temperature	12.992	15.115	11.928	13.825	16.054	12.709
	(6.11)	(6.56)	(5.58)	(6.20)	(6.66)	(5.63)

Note: This table displays the descriptive statistics from both the overall and pre-treatment periods. Standard deviations are reported in parentheses.

Table A4: Household Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Below Median Income	10.410**									9.894*
	(4.59)									(5.64)
College Educated		-0.983								5.382
		(3.47)								(4.95)
Owner Occupied			-5.884**							-3.692
			(2.55)							(2.91)
Single Household				0.000						-3.078
				(2.81)						(4.33)
Children Dummy					-2.301					-0.918
					(2.59)					(3.14)
Asthma Dummy						5.541				6.938
						(5.81)				(5.06)
Health Condition							0.857			-0.316
							(1.55)			(2.07)
Number of Residents								-0.885		-0.483
								(0.96)		(1.57)
Number of Smokers									19.894***	17.885***
									(6.92)	(6.78)
Observations	22,701	22,701	24,093	24,093	24,093	22,701	24,093	22,591	22,488	22,378

Note: This table displays estimates of the coefficients of binary variables treatment and post as well as an interaction between the treatment and post on hourly levels of indoor PM2.5. Day and month fixed effects and ambient PM2.5 levels are controlled for. The observations are restricted to occupancy time (16:00-23:00) to reflect times when the average person is at home. Standard errors clustered two way at the household level and by date are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A5: Dwelling Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Fireplace	-3.682**												-2.238
	(1.83)												(2.72)
Purifiers		0.502											1.311
		(3.38)											(3.35)
Gas Hob			-3.560										13.291***
			(2.67)										(4.49)
Electric Hob				8.920**									19.238***
				(4.16)									(6.01)
Induction Hob					-4.167								9.811*
					(2.78)								(5.60)
Indoor Temperature						0.358							0.550*
						(0.34)							(0.31)
Number of Windows							-0.781**						-0.780***
							(0.31)						(0.29)
Open Plan Kitchen								0.639					3.158
								(2.77)					(2.72)
Stovetop									-3.768				0.801
									(4.80)				(4.43)
Oven										1.320			0.576
										(2.85)			(3.07)
Microwave											2.216		1.511
											(2.85)		(3.09)
Toaster												0.769	1.557
												(2.97)	(3.29)
Observations	24,093	22,376	20,913	20,913	20,913	24,093	21,506	22,488	22,701	22,701	22,701	22,701	20,041

Note: This table displays estimates of the coefficients of binary variables treatment and post as well as an interaction between the treatment and post on hourly levels of indoor PM2.5. Day and month fixed effects and ambient PM2.5 levels are controlled for. The observations are restricted to occupancy time (16:00-23:00) to reflect times when the average person is at home. Standard errors clustered two way at the household level and by date are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A6: Main Results

	Total Indoor PM2.5	Occupancy Indoor PM2.5	Non-Occupancy Indoor PM2.5
Panel A: Bootstrapped Estimates			
Treatment x Post	-1.903***	-4.964***	-0.426
	(0.39)	(0.87)	(0.39)
Treatment	-0.233	1.261**	-0.980***
	(0.27)	(0.62)	(0.24)
Post	0.827***	2.525***	-0.129
	(0.31)	(0.64)	(0.30)
Ambient PM2.5	0.557***	0.549***	0.519***
	(0.02)	(0.04)	(0.01)
Constant	-0.885*	-1.460	-0.060
	(0.53)	(1.23)	(0.52)
Panel B: Non-Bootstrapped Estimates			
Treatment x Post	-1.903	-4.964**	-0.426
	(1.34)	(2.33)	(1.06)
Treatment	-0.233	1.261	-0.980
	(1.67)	(2.65)	(1.35)
Post	0.827	2.525*	-0.129
	(0.95)	(1.51)	(0.83)
Ambient PM2.5	0.557***	0.549***	0.519***
	(0.04)	(0.08)	(0.03)
Constant	4.772***	7.385***	3.969***
	(1.03)	(1.55)	(0.97)
Base PM2.5	10.95	15.36	8.80
Observations	150,079	50,085	99,994

Note: This table displays estimates of the coefficients of binary variables treatment and post as well as an interaction between the treatment and post on hourly levels of indoor PM2.5. Day and month fixed effects are controlled for, as well as ambient levels of PM2.5. The observations that are restricted to occupancy time (16:00-23:00) are to reflect times when the average person is at home. Base presents the mean level of PM2.5 in the control group in the post-treatment period. Standard errors clustered two way at the household level and by date are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A7: AQI Brackets

	0-50	51-100	101-150	151-200	201-300	301-500
Panel A: Bootstrapped Estimates						
Treatment x Post	-0.000	0.029***	-0.007**	-0.013***	-0.004***	-0.005***
	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Treatment	0.019***	-0.014***	-0.009***	0.006**	-0.001	-0.001
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Post	0.006	-0.023***	0.002	0.010***	0.003**	0.002*
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Ambient PM2.5	-0.015***	0.012***	0.001***	0.001***	0.000*	0.000***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	1.129***	-0.125***	0.002	-0.006	0.000	-0.000
	(0.02)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)
Panel B: Non-Bootstrapped Estimates						
Treatment x Post	-0.000	0.029**	-0.007	-0.013**	-0.004	-0.005
	(0.02)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)
Treatment	0.019	-0.014	-0.009	0.006	-0.001	-0.001
	(0.03)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)
Post	0.006	-0.023**	0.002	0.010**	0.003*	0.002
	(0.02)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Ambient PM2.5	-0.015***	0.012***	0.001***	0.001***	0.000**	0.000**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	0.951***	-0.006	0.023**	0.018***	0.007***	0.007***
	(0.02)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)
	(1.03)	(1.55)	(0.97)			
Observations	50,085	50,085	50,085	50,085	50,085	50,085

Note: This table displays estimates of the coefficients of binary variables treatment and post as well as an interaction between the treatment and post on hourly levels of AQI. This is a linear probability model, where each coefficient shows the probability that a household's AQI level will be within a certain bracket. Day and month fixed effects are controlled for, as well as ambient levels of PM2.5. The observations that restricted to occupancy time (16:00-23:00) to reflect times when the average person is at home. Standard errors clustered two way at the household level and by date are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A8: Below vs Above Median Base PM2.5

	Above		Below	
	Whole Day PM.5	Occupancy PM2.5	Whole Day PM.5	Occupancy PM2.5
Treatment x Post	-4.342***	-10.567***	0.819***	0.816***
	(0.75)	(1.57)	(0.16)	(0.31)
Treatment	-0.302	3.185***	-0.050	-0.277
	(0.50)	(1.16)	(0.09)	(0.20)
Post	1.687***	4.813***	-0.029	0.334
	(0.57)	(1.18)	(0.14)	(0.26)
Ambient PM2.5	0.629***	0.641***	0.425***	0.384***
	(0.02)	(0.06)	(0.01)	(0.01)
Constant	2.287***	0.099	-1.753***	-0.526
	(0.74)	(1.52)	(0.53)	(1.16)
Observations	77,644	25,933	72,435	24,152

Note: This table displays estimates of the coefficients of binary variables treatment and post as well as an interaction between the treatment and post on hourly levels of indoor PM2.5. Day and month fixed effects are controlled for, as well as ambient levels of PM2.5. The observations that are restricted to occupancy time (16:00-23:00) are to reflect times when the average person is at home. Standard errors bootstrapped 1000 times and clustered two way at the household level and by date are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A9: Belief Outcomes Above vs Below

	Above Median Base PM2.5				Below Median Base PM2.5			
	Indoor		Outdoor		Indoor		Outdoor	
	Belief	Confidence	Belief	Confidence	Belief	Confidence	Belief	Confidence
Treatment	0.040	0.207	0.081	-0.154	0.494***	0.409**	0.242	0.411**
	(0.14)	(0.18)	(0.18)	(0.20)	(0.14)	(0.19)	(0.15)	(0.19)
Constant	0.169	0.034	-0.017	0.186	-0.068	0.017	0.017	-0.034
	(0.10)	(0.13)	(0.13)	(0.14)	(0.10)	(0.13)	(0.10)	(0.13)
Observations	121	120	121	121	113	113	113	112

Note: This table displays estimates of the coefficients of treatment on the difference in air quality beliefs in the baseline and endline survey. Air quality belief represents a participants perception of indoor and outdoor air quality. Confidence represents how certain a participant is about this level of air quality. Standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A10: Household Fixed Effects

	Total Indoor PM2.5	Occupancy Indoor PM2.5	Non-Occupancy Indoor PM2.5
Treatment x Post	-1.432***	-3.450***	-0.505
	(0.37)	(0.81)	(0.38)
Post	1.016***	2.844***	-0.023
	(0.30)	(0.65)	(0.29)
Ambient PM2.5	0.587***	0.612***	0.537***
	(0.02)	(0.04)	(0.01)
Constant	-2.031***	-2.128	-1.844**
	(0.72)	(1.49)	(0.78)
Observations	150,079	50,085	99,994

Note: This table displays bootstrapped estimates of the coefficients of binary variable post as well as an interaction between the treatment and post on hourly levels of indoor PM2.5. The treatment variable is not included due to the inclusion of household fixed effects. Day, month and household fixed effects are controlled for, as well as ambient levels of PM2.5. The observations that are restricted to occupancy time (16:00-23:00) are to reflect times when the average person is at home. Standard errors (bootstrapped 1000 times) clustered two way at the household level and by date are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.