Know Thy Foe: Information Provision and Air Pollution in Tbilisi*

Sandra Baquié[1], A. Patrick Behrer[1†], Xinming Du[2], Alan Fuchs[1], Natsuko K. Nozaki[1]

[1]The World Bank [2]The National University of Singapore

March 20, 2026

Abstract

Middle income countries host the majority of the world's population exposed to unhealthy levels of air pollution and the majority of this population lives in urban environments. We study the impact of information provision on household behavior regarding indoor and outdoor air pollution in a middle income country's major urban center – Tbilisi, Georgia. We implement a randomized controlled trial (RCT) to assess whether providing households with different levels of pollution information changes their knowledge of air pollution, their avoidance behavior with respect to air pollution, and improves their health outcomes. We evaluate three different treatments: a pamphlet with general information on pollution, the pamphlet combined with daily text messages about local outdoor pollution, and the pamphlet with messages about both indoor and outdoor pollution levels, supplemented with an indoor air pollution monitor. We find that while the pamphlet alone does not lead to behavioral change, daily text messages significantly enhance knowledge of pollution, lead to increased avoidance behaviors, and improve health outcomes. We also examine infiltration rates throughout the city and document three facts: indoor air pollution levels are generally higher than outdoor ones, infiltration rates are high on average, and their variation is driven primarily by behaviors.

JEL Codes: Q53, Q56, 018, 013, I12

Keywords: Air pollution, information provision, avoidance behavior, infiltration, indoor air pollution, PurpleAir, Tbilisi

*We thank Marshall Burke, Sam Heft-Neal, Sefi Roth, Josh Graf-Zivin, Matt Neidell, Teevrat Garg, Jisung Park, and participants at the USC Indoor Air Pollution workshop for valuable feedback. Max Hammond provided excellent research assistance. CRRC was an invaluable partner in conducting the household surveys. Sweden provided generous funding to support this project. The findings, interpretations, and conclusions expressed in this paper are entirely those of the authors. They do not necessarily represent the views of the World Bank and its affiliated organizations, or those of the Executive Directors of the World Bank or the governments they represent.
†Corresponding author, abehrer@worldbank.org.

1 Introduction

Air pollution is one of the leading causes of death worldwide (Weichenthal et al., 2022). Indoor and outdoor air pollution contribute roughly equally to this mortality burden (Fuller et al., 2022). The majority of these deaths, and the vast majority of future mortality from air pollution, will occur in low- and middle-income countries (Shaddick et al., 2020). In these countries outdoor pollution levels regularly exceed WHO recommended limits by as much as a factor of 10 and indoor pollution levels can exceed them by a factor of 20 (Greenstone et al., 2021). Yet, our understanding of the burden of indoor air pollution is mainly based on rural, lower income settings where households rely on burning highly polluting fuels for cooking or illumination. Indoor air pollution sources are likely to differ in more urban, wealthier settings where households often have access to modern infrastructure and relatively-clean cooking and heating fuels.[1]. Indeed, data on indoor air pollution faced by the more than one billion urban residents of middle income countries is sparse. As a result, these settings are relatively understudied, even though our data reveals that air pollution levels are high, particularly indoors. Overcoming this knowledge gap is essential to design policies addressing barriers to adaptation in middle income countries.

A low awareness of exposure to unhealthy levels of pollution could prevent households from reducing their exposure to air pollution. This knowledge gap is likely to be higher in middle income countries than in developed countries due to sparse and/or poorly maintained monitoring networks (Hasenkopf et al., 2023). Addressing this lack of accurate information on pollution levels could yield high benefits in terms of individual welfare (Greenstone et al., 2022; Jha and Nauze, 2022). We assess the effectiveness of providing information about air pollution levels in the context of an upper-middle-income country to see if it (1) leads households to engage in more avoidance behavior and (2) whether this information is valued by households. We also examine the rate of infiltration of outdoor pollution to indoor environments and the drivers of differences in this infiltration rate across households.

[1]Much of the existing work on indoor air pollution has been focused on the role of cook stoves in low-income, often (but not exclusively) in more rural settings (e.g. Hanna et al. (2016)). While it is a substantial challenge in those areas our data suggest indoor air pollution is likely to be elevated for many individuals who live in settings that are more urban, wealthier, and with more modern infrastructure. Cigarette smoking, a routine behavior for more than one billion residents of low- and middle-income countries (WHO, 2021), is likely to be a major driver of indoor pollution in these cases. This is precisely the setting we study. We show that in these settings, where indoor air pollution is driven primarily by behavioral choices, information provision may be an effective approach to reducing exposure.

We conducted a randomized control trail (RCT) in Tbilisi, Georgia, to answer each of these questions. The experiment compares the efficiency of three types of information treatments: (1) receiving a pamphlet with information on pollution harms and avoidance behavior, (2) receiving a pamphlet and daily text messages with information on outdoor air pollution in one's neighborhood, and (3) receiving a pamphlet, daily text messages on indoor and outdoor air pollution levels, and an indoor air pollution monitor. We surveyed households twice before and approximately two months after the treatment. The questionnaire contained questions about socioeconomic status, knowledge about air pollution, avoidance behavior, a cognition exercise, self-reported health, and willingness to pay for protective devices. To ensure that information on air pollution is as accurate as possible, we installed outdoor pollution monitors throughout Tbilisi, multiplying the number of outdoor monitors within the city by 10 for the duration of the intervention. Indoor air pollution monitors were also distributed to nearly 150 randomly selected households. Data from these indoor monitors provides insight into the extent of exposure of households that are representative of Tbilisi inhabitants.

We find that providing information in a pamphlet has no significant impact on our measured outcomes. Receiving daily text messages impacts knowledge of air pollution and the adoption of avoidance behavior. However, only the most intensive information treatment - receiving information about both indoor and outdoor pollution levels - leads to changes in avoidance behavior that result in health improvements during the intervention. These improvements appear to be driven by the fact that households who receive information about indoor air pollution levels reduce their level of indoor cigarette smoking. Consistent with some existing work (Greenstone et al., 2021), but contrary to others (Greenstone et al., 2023; Ahmad et al., 2023), we find that providing information and access to indoor air quality monitors (IAQMs) does not change households' willingness-to-pay for either IAQMs or indoor air purifiers.

To examine the extent of infiltration in Tbilisi, we combine the data from the indoor air pollution monitors with the nearest outdoor monitors and estimate the rates of infiltration of outdoor pollution indoors. Results show that infiltration rates in Tbilisi exceed estimates from the U.S. by approximately 2-4 times (Lunderberg et al., 2023). Compared to the U.S very high infiltration is more common, which may be due to a lower average quality of housing. However, variations in infiltration rates seem to be mainly driven by short-term behavioral differences (e.g. length of time

windows are left open) rather than differences in physical housing or long-term characteristics of the household (e.g. size of the house or income level) (Burke et al., 2021; Greenstone et al., 2021).

Our work contributes to a growing body of literature identifying the impacts of providing real-time information about air pollution on household behaviors. The conclusions from that literature are mixed. Greenstone et al. (2022) and Barwick et al. (2024) study improvements in the provision of information about ambient air pollution in China and find improving information provision results in behavioral changes that improve welfare. Despite improvements in welfare, it is unclear whether households are willing to pay for air pollution information. Ahmad et al. (2023) show households in Lahore are willing to pay a substantial fraction of the monthly cost of mobile internet access to receive air quality forecasts for three months. In contrast, Hanna et al. (2021) find that willingness to pay (WTP) for air quality alerts in Mexico city is only slightly more than a tenth of the cost of providing the alerts for the median respondent. However, once the households receive alerts, they do change their behavior in ways that plausibly reduce their exposure. When looking at willingness to pay for protection, Greenstone et al. (2023) find relatively low WTP for air quality in Delhi - measured by demand for masks - but this WTP increases five-fold when households are informed about the harms of poor air quality. However, Greenstone et al. (2021) find that providing individuals with access to an indoor air quality monitor, also in Delhi, does little to change their willingness-to-pay for an air purifier.

Our analysis adds to this literature by providing evidence that intensive information treatments - daily text messages - about *both* outdoor and indoor pollution leads to meaningful changes in behavior. We show that providing information about indoor pollution leads to more consequential behavioral change than information about outdoor pollution only. In particular, households receiving information about indoor pollution reduce indoor cigarette smoking, which is one of the main drivers of indoor air pollution in Tbilisi. Our results suggest that providing information about pollution that is more easily controlled by the household - indoor pollution - may have a larger impact on behavior than information about outdoor pollution, which households may view as beyond their control.

Turning to infiltration, there is broad agreement that behavioral factors (e.g. opening/closing windows) are major drivers of infiltration (Burke et al., 2021; Lunderberg et al., 2023). We find a similar result in our study, but also that providing information influences behaviors that are

important drivers of infiltration. Much of the literature examining infiltration rates has focused on the United States, where infiltration rates estimates are concentrated between 0.2 and 0.3 (Bi et al., 2021; Liang et al., 2021; Lunderberg et al., 2023).[2] Understanding how infiltration rates may differ in developing countries is critical as these are the parts of the world facing the greatest threats from high levels of ambient air pollution (Shaddick et al., 2020; Fuller et al., 2022). This also contributes to our understanding of how vulnerability to air pollution varies across the income distribution (Behrer and Heft-Neal, 2024). There also remains disagreement about the extent to which infiltration rates vary across SES status. Some studies show notable inequality in infiltration rates during high pollution events (Krebs and Neidell, 2024) and others find no meaningful relationship between infiltration rates and SES (Burke et al., 2021). However, these studies often use crowd-sourced information from publicly available PurpleAir monitor data, a non-random sample of households having bought PurpleAir monitors. In our experiment, we randomly installed monitors in the city and provided them to households that are representative of the broader population.

2 Context and Design

2.1 Air pollution in Tbilisi

Located between Armenia, the Russian Federation, and Azerbaijan, Tbilisi is the capital of the Republic of Georgia and a city of roughly 1.1 million people. Like many cities in the former Soviet Republics, Tbilisi suffers from elevated average levels of ambient air pollution. From 1998 to 2018, average monthly $PM_{2.5}$ levels were approximately 20 $\mu g/m3$ (Van Donkelaar et al., 2019) in Tbilisi, 4x the WHO recommended annual average of 5 $\mu g/m3$.[3] While the level of ambient pollution in Tbilisi is low relative the levels seen in the worst cities in the world (e.g. Delhi), it is similar to levels seen in hundreds of medium and large cities around the world and are high enough to lead to significant negative health consequences for residents.

In Tbilisi, levels of pollution are driven by the geography of the city. The center of Tbilisi sits in a topographic bowl, with high mountains to the West, South and Northeast (Figure 1A). This results in population, wealth, and pollution being concentrated in the central and lower elevation

[2] Although higher (0.4-0.6) (Krebs et al., 2021) and lower (0.14) rates (Burke et al., 2021) have also been estimated.
[3] In recent years this level has fallen, with average levels slightly more than 3x the WHO recommendation in 2023.

part of the city (Figure 1B-D). The positive correlation between wealth and air pollution is similar to many other cities in low- and middle-income countries (Behrer and Heft-Neal, 2024).

The Georgian Ministry of Environmental Protection and Agriculture (MEPA) maintains four pollution monitors in Tbilisi, concentrated in the central part of the city. The location of these monitors is shown in Figure 1E. The data from these monitors is publicly available on MEPA's website but does not seem to be regularly accessed by residents of Tbilisi.[4] Despite not frequently checking outdoor pollution levels, residents of Tbilisi regularly report that pollution is a major issue for them. For instance, a 2017 survey found that 42% of the residents of Tbilisi named pollution as the most important infrastructure issue facing the city (CRRC, 2017). A 2021 follow-up survey found that air pollution followed only unemployment and traffic as the most important issue in Tbilisi (CRRC, 2021).

Tbilisi's built environment was established over three major modern phases of development: the pre-Soviet period in the late 19^{th} and early 20^{th} century, the Soviet period from the 1920s to the early 1990s, and the post-1990 period (Figure A1) (Salukvadze and Golubchikov, 2016). Each period was associated with construction of unique housing types with quality, in particular insulation from the outside environment, tending to increase over time.[5] Housing built prior to 1920 is low rise, 2-3 story structures with large windows and 2^{nd} story balconies. Housing built during the Soviet era largely resembles the large apartment blocks common in most Post-Soviet Republics. Post-1990s housing is similar to much of the modern high rise development throughout Europe with mid-to-large towers that may or may not have small balconies for each unit. In general, housing quality is lower than in the United States or Western Europe but higher than in many other low- and middle- income countries. Our baseline survey indicates that most houses use natural gas for cooking and gas or electric sources for heating and that less than 0.5% of households own an indoor air quality monitor or an air purifier.

2.2 Experimental design

Our experiment was implemented in 3 stages: installation of outdoor air pollution monitors, baseline household survey, and treatment followed by the end-line household survey (Figure A3 shows the

[4] Our household survey indicates that fewer than 5% of households in Tbilisi regularly check outdoor pollution levels at baseline.

[5] We provide images of examples of each housing type in Figure A2.

timeline).

First, we installed 41 outdoor air pollution monitoring devices throughout Tbilisi to improve the monitoring network of the city. These PurpleAir monitors provided a reliable and low-cost way to monitor $PM_{2.5}$.[6] Another advantage is that they allow to have comparable results to other academic studies of air pollution (e.g. Burke et al. (2021); Krebs et al. (2021); Liang et al. (2021)). Figure 1E shows the location of the installed monitoring devices. They were installed by the Caucasus Research Resource Center (CRRC) in collaboration with MEPA and the Tbilisi City Hall. In most cases, outdoor monitors were installed in public schools to ensure reliable access to power and an internet connection. Installation took place during a two-week period at the beginning of January 2023.

The second phase of the intervention was a household survey that took place at the end of March 2023 and beginning of April following the installation of the outdoor monitors. CRRC surveyed 862 randomly selected households within 230 randomly selected census blocks in Tbilisi. Surveyed census blocks are shown in navy in Figure 1 in the bottom portion of Panel E. We describe the details of the selection of census blocks and households in Appendix 1.

Our information intervention was embedded in the survey design. The experiment contained a control and three treatment arms:

> *Control* - Households were surveyed, but no information about air pollution was provided by the survey team.
>
> *Treatment 1 (Leaflet)* - At the end of the baseline survey, households were given a leaflet with information about air pollution: what it is, how it impacts individuals' health, actions that people can take to reduce exposure to air pollution - like using ventilation while cooking or avoiding high traffic areas - and a scale explaining how health effects increase as the level of pollution rises. The information and scale in the leaflet were based on the U.S. EPA brochures on the dangers of air pollution. Households also received a magnet with a QR code that linked to an online version of the leaflet.[7]
>
> *Treatment 2 (Outdoor pollution)* - In addition to the information provided to households

[6] In Figure A5 we plot the readings from the four Ministry of Environment monitoring stations against the readings from the nearest installed PurpleAir monitor. There is broad agreement in the readings, although the PurpleAir monitors appear to have slightly higher readings at high levels of pollution.

[7] An English version of the leaflet is shown in Appendix 7.

in Treatment 1, households received daily text message for approximately two months with information on the level of outdoor air pollution near their house. This information was based on the readings from the nearest PurpleAir monitor to their house from 8am-10am that day and was sent at 10am every day. We document, and report to the household, that the pollution level from 8am-10am was positively correlated with the pollution level for the rest of the day and could be used to inform their expectations about those levels.

Treatment 3 (Outdoor and Indoor pollution) - In addition to the leaflet, households received the same daily text message as Treatment 2 for approximately two months. In the text message, they also received the average level of indoor air pollution over the last 24 hours in their house. To provide this information, households in treatment 3 all received an indoor PurpleAir monitor that recorded the level of $PM_{2.5}$ in their house in real-time. These devices also indicate the quality of air in real-time using a color-scale from green (good) to red (bad). If the household did not consent to host an indoor air pollution monitor, the surveyor ended the survey and followed the same random selection process to select another household. Installation occurred the week following the survey and monitors were installed in a primary living space that was not the kitchen.

The end-line survey was conducted two months later, in late May and early June. At this time, a hundred percent of the surveyed households at baseline were revisited. At this time, all households who completed both surveys received a payment for participation. The size of the payment varied depending on the treatment. Households in the Control group and Treatment 1 received 30 GEL, while the ones in Treatment 2 received 50 GEL and the ones in Treatment 3 received 70 GEL.[8] The survey measured outcomes to assess the effectiveness of the embedded information intervention, such as self-reported health symptoms.

2.3 Balance test

We show in Table A1 that treatments are generally balanced across observables using data from the baseline survey. We report the difference in means between each of the treatment groups and

[8] At the time of the payments, 1 GEL was approximately 0.38USD.

the control and the t-statistic of this difference across 22 observables that summarize household characteristics, behaviors, health outcomes and knowledge of pollution. Of the 66 comparisons we make, five are significant at conventional levels. Households in treatments one and two live one floor lower than those in the control or treatment 3. Of households in treatments two and three, 100% cook with natural gas, compared to 97% in the control and 98% in treatment one. The most meaningful difference is that households in treatment three are slightly wealthier on average than those in the control or other treatment groups. Controlling for wealth in our subsequent analysis does not change any of our results.

3 Empirical strategy

3.1 Information treatment

Our main specification compares outcomes across treatment groups using OLS regressions of the form:

$$\Delta Y_i = \beta_0 + \beta_1 Treatment_i + \epsilon_i \tag{1}$$

where i denotes households and ΔY is the change from survey round one to survey round two in the outcome of interest for that household. $Treatment$ is an indicator for assignment to one of the three treatment groups (*Leaflet*, *Outdoor*, *Outdoor and Indoor*). Our outcomes of interest are three indices of household knowledge, actions, and health. These indices capture a household's performance in the related category across all questions related to this outcome. For example, we ask households whether they experience a variety of health symptoms in the month prior to the survey. Our health index is then the total number of symptoms the household experienced. For more details on these calculations see Appendix 3. Because the health symptoms of pollution exposure and the common cold are similar, to alleviate concerns that our results are driven by seasonal respiratory disease (or COVID-19) we exclude households that have been diagnosed with COVID-19 during our sample period and those that visit the doctor explicitly for a respiratory disease from our analysis.[9] In all analysis we cluster standard errors at the census block level.

[9]Including these households does not meaningfully change our results.

3.2 Measuring infiltration

The random distribution of indoor air pollution monitors in our experiment offers a setting where the ownership of an indoor monitor is not endogenous to household characteristics.[10] To do so we examine the relationship between the indoor pollution measured in the houses of households in Treatment 3 *Outdoor and Indoor* and the level of outdoor pollution measured by the outdoor monitors closest to the household.

To calculate infiltration rates, we estimate a lagged model with the level of indoor pollution in a given household as a function of the previous six hours of outdoor pollution measured by the nearest monitors (Burke et al., 2021). For each household for which we have indoor pollution data, we run the following specification:

$$\text{Indoor pollution}_{hdw} = \sum_{l=0}^{6} \beta_l \text{Outdoor pollution}_{h-l;dw} + \eta_h + \gamma_d + \Delta_w + \epsilon_{hdw} \tag{2}$$

To absorb idiosyncratic variation in indoor pollution that may be due to factors unrelated to infiltration (e.g. cooking), we include hour (η_h), day (γ_d), and week (Δ_w) fixed effects. These fixed effects are specific to each individual household in the sample and capture household-specific details like the typical times at which they return from work or cook meals.

Our measure of infiltration is the sum over all lags of β_l. This provides an estimate of the change in indoor air pollution for a $1\mu g/m^3$ cumulative increase in outdoor pollution over the previous six hours. We include lags because it may take time for outdoor pollution to filter into homes. To assess the sensitivity of our results to our choice of lag structure we estimate several alternative lagged models as in Burke et al. (2021): Our preferred model with six lags of outdoor pollution, one including six lags of indoor pollution and no outdoor lags, one with no lags of indoor or outdoor pollution, and one with ten lags of outdoor pollution. Our estimates of average infiltration are consistent across each of these different specifications (Figure A4).

To understand the drivers of variation in infiltration rates, we estimate the following equation:

$$\text{Infiltration rate}_i = \phi \mathbf{X}_i + \phi \mathbf{Z}_i + \epsilon_i \tag{3}$$

[10] For example, Burke et al. (2021) observe that households in high-income areas in their sample are much more likely to own an indoor monitor than those in low-income areas.

where $\mathbf{X}_i$ is a vector of long-term attributes of the household (i.e. size of the house or education level of the survey respondent) and $\mathbf{Z}_i$ is a vector of short-term behavioral measures (i.e. how long they typically leave the windows open in a day). We run several versions of equation 3 that separately estimate the impact of long-term and short-term characteristics on infiltration and we also jointly estimate their effect. As in our previous analysis, we cluster errors at the census block level. We detail the specific long-term and short-term characteristics that we examine when we discuss the results of these regressions. In all cases we use the level of these characteristics that households provided in response to the first round of our survey, prior to our intervention.

4 Results

4.1 Effectiveness of informational treatments

Existing work indicates that providing information about the negative health effects of air pollution substantially increases willingness-to-pay for reductions in pollution exposure (Greenstone et al., 2023). The *Leaflet* treatment tests this hypothesis by only providing information about the consequences of air pollution exposure and how to avoid it. Table 1A reports the impact of the leaflet treatment on our measure of knowledge of air pollution, avoidance behaviors, and health symptoms. All estimates are insignificant, indicating that we find no evidence that information provided through a leaflet changes knowledge of air pollution or increases avoidance behavior (Columns 1 and 2).

Our *Outdoor* and *Indoor and Outdoor* treatments provided households with information about indoor and outdoor pollution levels. Households appear to have consumed this information. In the survey we asked households about the frequency with which they check information about air pollution levels. Table A5 shows that no household checked indoor or outdoor pollution prior to our intervention. However, after our intervention, 56% of households in the *Outdoor* treatment and 70% in the *Indoor and Outdoor* treatment reported checking outdoor air pollution levels. Similarly, 85% of households in the *Indoor and Outdoor* treatment reported checking indoor pollution levels. In contrast, households in the *Leaflet* treatment did not change their behavior with respect to checking pollution levels in between the survey rounds.

In contrast to the *Leaflet* treatment, the *Outdoor* treatment may have increased households'

knowledge of air pollution and led to an increase in avoidance behavior (Table 1B). Receiving daily text messages with information on outdoor air pollution leads to an estimated 5% increase in knowledge about air pollution, although with wide confidence bounds. However, consistent with some increase in knowledge, the second treatment group increases the number of avoidance behaviors taken by 27%. These changes did not lead to significant improvements in health in the two months separating the two survey rounds. Collectively, our results suggest that receiving daily text messages induces behavioral change but not on actions that lead to significant health improvements within the time period we study.

Our *Indoor and Outdoor* treatment provides daily texts with indoor and outdoor pollution levels, as well as an indoor air pollution monitor and had positive impacts on each of the outcomes we examine (Table 1).The additional information provided about indoor pollution levels appears to make pollution substantially more salient for households. Their knowledge of air pollution improves by 7% between the two survey rounds, and this results in a 21% increase in avoidance behaviors. Notably, these changes translate into substantial improvements in self-reported health, with households in the *Indoor and Outdoor* treatment arm reporting a 21% decline in health symptoms between the two survey rounds.[11]

What drives the differential results for households in the *Indoor and Outdoor* treatment compared to the *Outdoor* treatment? First, we find that households receiving indoor air pollution information report taking weakly more indoor avoidance behaviors than *Outdoor* treated households (difference: 7%, t-stat:1.04). Second, and more importantly, households in the *Indoor and Outdoor* treatment report a 30%-47% reduction in indoor smoking as a consequence of receiving information about indoor air pollution levels in their home.[12] Providing information about indoor air pollution levels, including real-time information via the changing color of the indoor monitor, induced individuals to smoke outside rather than indoors.

This small behavioral change appears to have large impacts on the health of all household

[11] We examine a variety of other outcomes related to exposure to air pollution and information. We report some of these in Table A7. We do not find evidence that our treatments change households' perceptions of the relative importance of pollution as a policy issue in Tbilisi, the number of days they or other members of the household miss school or work, or the amount of time they spend exercising outside.

[12] Unfortunately, only the households in the *Indoor and Outdoor* treatment were asked this question so we cannot compare this magnitude to the change in other treatment arms. However, since no other treatment arm received information about indoor pollution levels, households would have had no reason to reduce smoking. Our informational leaflet did not mention smoking as a source of indoor pollution either.

members. The magnitude of this change is consistent with the important influence that smoking has on indoor air pollution levels. We find that indoor pollution levels are 163.4% (t-test: 4.77) higher in households with at least one member smoking compared to those with none.[13] When, regressing indoor air pollution levels on the presence of a smoker and the vectors of long-term and short-term household characteristics described in equation 3, we find that having a smoker is the most predictive characteristic of levels of indoor air pollution. The presence of a smoker is associated with a greater than one standard deviation increase in indoor pollution levels ($\approx 60\mu g/m^3$ (t-stat: 5.47)).[14] As such, information on indoor air pollution has a strong potential to improve public health in Georgia, given that the country has one of the highest rates of smoking in Europe, with more than 30% of the population smoking (Sturua et al., 2018) and more than 40% regularly exposed to second-hand smoke at home (Foundation for a Smoke Free World, 2021).[15]

4.1.1 Willingness-to-pay

At the end of each survey, we conducted a willingness-to-pay (WTP) exercise with the participants in which they were asked how much they would be willing to pay for an air pollution monitor and, separately, for an air purifier.[16] At baseline, WTP was low relative to the cost of the IAQMs used in the RCT and the cost of air purifiers (Table 2). Households indicate that they are willing to pay less than 25% of the IAQM price and less than 50% of the price of an air purifier. Since the IAQMs have a price similar to low-end smartphones in Tbilisi, the WTP for IAQMs in Georgia is substantially less than the market price of smartphones.

We find little evidence that any of our treatments had a meaningful impact on households' WTP for either IAQMs or air purifiers. None of our point estimates (Table 2) are significant at conventional levels for either the monitor or the purifier. This suggests that providing information, and in some cases access to the technology in question, is not sufficient to change households' WTP for further access to monitoring technology or cleaner air.[17] We offer two hypotheses for this.

[13] We find that outdoor pollution levels at the homes of those who smoke are -4.1% (t-test:1.47) lower compared to those who do not smoke.

[14] Indoor pollution levels declined on average over our sample period for all households but, in households that reported shifting the location of smoking outside, the downward trend was 1.6x larger than in those that did not shift the location of smoking.

[15] In our overall sample 30% of surveyed individuals reported smoking. In the *All* treatment the reported smoking rate is 31%.

[16] They had the option to indicate that they did not know how much they would be willing-to-pay. The specific questions are provided in Appendix 2.

[17] Our results are similar to those of Greenstone et al. (2021) who find that providing individuals with an indoor

First, there is a cognitive cost to knowing that one is living in areas with high levels of air pollution that households may wish to avoid, or at least not pay to be reminded of (Allcott and Kessler, 2019). This could explain the low WTP for IAQMs. Second, households may have realized with the intervention that they can reduce indoor air pollution by changing behavior around smoking, using ventilation while cooking, and closing windows at other times. This knowledge may have reduced their demand for costly technology - indoor air purifiers - that substitutes these actions.[18]

4.2 Infiltration Rates

Effective changes in individual behaviors to mitigate indoor air pollution depend on whether these behaviors are a major source of pollution within their homes. If high levels of infiltration from outdoors are predominant factors, altering individual behaviors may not suffice to protect households effectively.

We estimate that infiltration rates in Tbilisi are substantially higher than those observed in the United States. On average, infiltration rates are 0.6 , which is 4x higher than the lowest estimates in the United States and roughly twice the typical estimates (Burke et al., 2021; Lunderberg et al., 2023). Figure 2A shows the frequency of household specific infiltration rates, obtained by estimating equation 2 individually for each of household with an indoor monitor in our sample.[19] We observe a fairly even distribution of infiltration rates across the full range from 0 to 1, with more mass at the top of the distribution compared to estimates from the U.S. (Burke et al., 2021).

Households that have higher rates of infiltration do have systematically higher levels of indoor air pollution compared to those that have lower levels of infiltration. Figure 2C presents the average level of indoor air pollution during our sample period in households in the top 25% of infiltration rates and those in the bottom 25%. There is a clear difference in the average levels of pollution in high-infiltration households (dark blue line) compared to the level in low-infiltration households

air quality monitor does little to change their willingness-to-pay for a subsidized air purifier.

[18] It is also important to note that our WTP exercise is not incentivized due to limitations in our survey implementation. It is possible that the responses do not reflect households' true WTP. However, even if this resulted in systematically low WTP on average, we'd expect some households to have provided accurate responses. We find that less than 3% of the sample would be willing to pay enough to cover the cost of an air purifier and less than 2% to cover the cost of an IAQM (Figure A6). The qualitative result that WTP is below the cost of these technologies thus appears robust.

[19] For all households where the sum of lags - our estimate of the infiltration rate - is above 1 or below 0 we top- and bottom-code at 1 and 0. Our estimates of the average rate of infiltration do not vary meaningfully based on different lag structures (Figure A4).

(dark orange line) for nearly the entire duration of our measurement period. Indoor pollution levels are 78.6% (t-test: 2.19) higher in high infiltration households compared to low. In contrast, there is no difference in outdoor pollution levels across these two groups (Figure 2D). This is consistent with the spatial distribution of these households in Figure 2B, with households in both quartiles being relatively intermixed throughout Tbilisi.

Table 3 presents evidence on the drivers of differences in infiltration rates across households. The only measure of physical housing characteristics or socioeconomic status that significantly explains variation in infiltration rates is housing size.[20] Larger homes, measured by the size of the home in square meters, tend to have lower levels of infiltration (column 1). This may be due to the fact that there is more space for pollution to disperse in larger homes, which weakens the relationship between changes in outdoor and indoor pollution levels. Other physical features of housing, or the wealth or education level of the household, do not explain variation in infiltration rates.

In contrast, behaviors are significantly correlated with infiltration rates. Ownership of IAQMs and use of ventilation during cooking are both associated with substantially lower infiltration rates (column 2, Table 3). The sign on the relationship between infiltration and both of these behaviors is robust to including our full-set of physical characteristics and SES measures (column 3, Table 3), though owning an IAQM is much less precisely estimated.[21] The correlation between these behaviors and infiltration rates is substantial, with both associated with reductions in infiltration rates of approximately 25%.[22] Opening windows is also associated with substantial increases in infiltration rates. Each additional hour with open windows is associated with an increase in infiltration rates of approximately 5%.[23]

[20] Our other measures include measures of the age of the house, the wealth of the household and the education level of the household.

[21] Curiously we find that owning an air purifier is also associated with higher levels of infiltration in the fully controlled model. This could be a consequence of households with high levels of infiltration, and thus high indoor pollution, seeking to reduce exposure. Only two households in the sample had an indoor air purifier at the beginning of our intervention. Our results are robust to dropping these households from the analysis. We also run this regression controlling for whether anyone in the household smokes. Our results remain unchanged and we do not find that smoking is predictive of infiltration rates.

[22] This is roughly equivalent, in terms of the change in infiltration rates, to owning a home in the 75^{th} percentile of size.

[23] That leaving windows open increases infiltration in an environment with high levels of indoor air pollution may seem strange as it might be expected to reduce indoor pollution. We note that our measure of infiltration is how quickly indoor pollution responds to changes in outdoor pollution, not the level of indoor pollution per se, and because opening windows is likely to make indoor pollution much more responsive to changes in outdoor pollution this result makes sense.

Collectively our results suggest that behaviors, and not the physical characteristics of houses or SES, are the primary drivers of differences in infiltration rates, consistent with evidence from the U.S. (Burke et al., 2021). They suggest that there may be substantial scope for reducing indoor pollution exposure through information provision that do not require substantial investments in changing the built infrastructure.

5 Conclusion

This study provides an analysis of the impact of information provision on knowledge, avoidance behavior and health outcomes related to air pollution in Tbilisi, Georgia, a middle-income country. Our findings indicate that while informational leaflets do not significantly change knowledge or avoidance behaviors, additional information on pollution levels, delivered with high frequency, leads to substantive changes. Households that receive information on both indoor and outdoor pollution levels, coupled with an indoor air pollution monitor, not only increased knowledge and avoidance behaviors by 7% and 21% , respectively, but saw a significant 21% reduction in self-reported health symptoms within two months. The major driver is likely a reduction in indoor cigarette smoking, triggered by increased awareness of indoor air quality. This results highlights the potential of tailored, real-time information in improving public health.

Our study also highlights a persistent challenge, the low willingness-to-pay (WTP) for air quality information or protective devices, even among those who experience the benefits of reduced pollution. Increased awareness of air pollution does not necessarily translate into higher WTP, possibly due to the psychological burden of acknowledging one's pollution exposure or the cost barrier.

We also document that infiltration rates in Tbilisi are higher than those typically recorded in the United States, and that behaviors, rather than the physical characteristics of homes or socioeconomic status, appear to be the primary drivers of high rates of infiltration. The overall high rate of infiltration suggests that regardless of their wealth or education, those living in neighborhoods with high levels of ambient pollution are not substantially more protected from outdoor pollution by their homes than those with lower income or education levels. Our findings emphasize the potential of information provision to enable households to manage their exposure to pollution. Opening win-

dows less and using ventilation while cooking - relatively simple behavioral interventions - are both associated with lower infiltration rates. That suggests that simple behavioral interventions may present an opportunity to reduce exposure to indoor pollution in some settings. Our results show that the adoption of behaviors impacting infiltration, for instance, closing the window when outdoor air pollution levels are high, is increased by information provision through daily text messages.

Overall, this research demonstrates the effectiveness of specific, real-time information in reducing exposure to indoor air pollution and improving health outcomes. But our results leave several important questions unanswered. How long do households remain responsive to information about pollution levels? Existing evidence suggests that the effectiveness of informational and behavioral interventions may decline over time (Allcott and Rogers, 2014). It is unclear if our effects would persist or decline if the intervention had continued for a longer period. It is also unclear whether the behavioral changes we observe in either the *Outdoor* or *Outdoor and Indoor* treatments would lead to long-term improvements in health. It may be the case the behavioral changes households in the *Outdoor* treatment engaged in were not substantial enough to generate short-run improvements in health but would lead to longer-term benefits. Finally, while we demonstrate that behavior seems to matter more than housing characteristics or SES for infiltration rates, our analysis is still able to explain only a small part of the variation in infiltration rates. Work that increases our understanding of the residual variation in infiltration rates would be a valuable contribution.

6 Figures

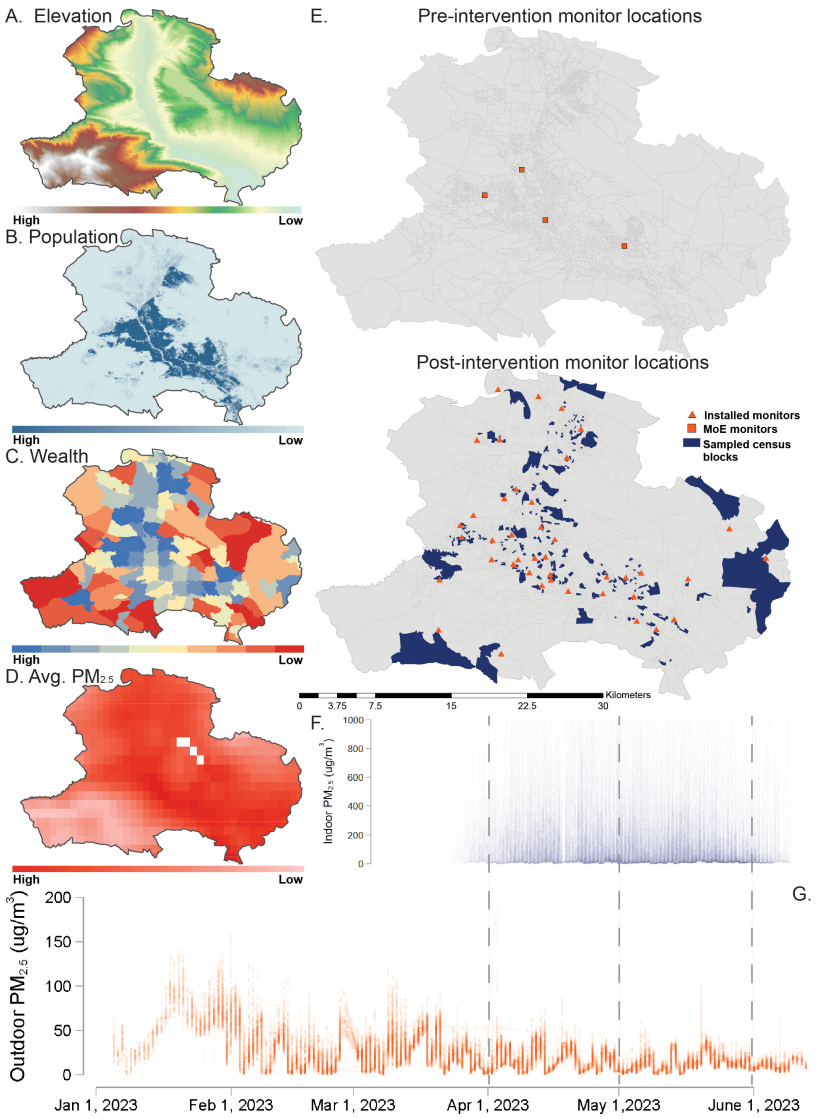


Figure 1: Intervention summary information: Panels **A-D** show the elevation (Abrams, 2000), population distribution (Lloyd et al., 2017), wealth distribution (measured using the RWI (Chi et al., 2022)), and average ambient $PM_{2.5}$ concentrations (Van Donkelaar et al., 2019) throughout Tbilisi. Panel **E** shows the location of the Ministry of Environment monitors, the only pollution monitors in the city prior to our intervention, in the top half and the location of the monitors installed as part of the intervention in the lower half. In the lower half of Panel **E** we also show the census districts that were sampled in the intervention. In Panels **F** and **G** we show the indoor $PM_{2.5}$ levels recorded by the installed monitors and the outdoor levels. The indoor monitors were installed slightly later than the outdoor monitors and so have a shorter period of observation.

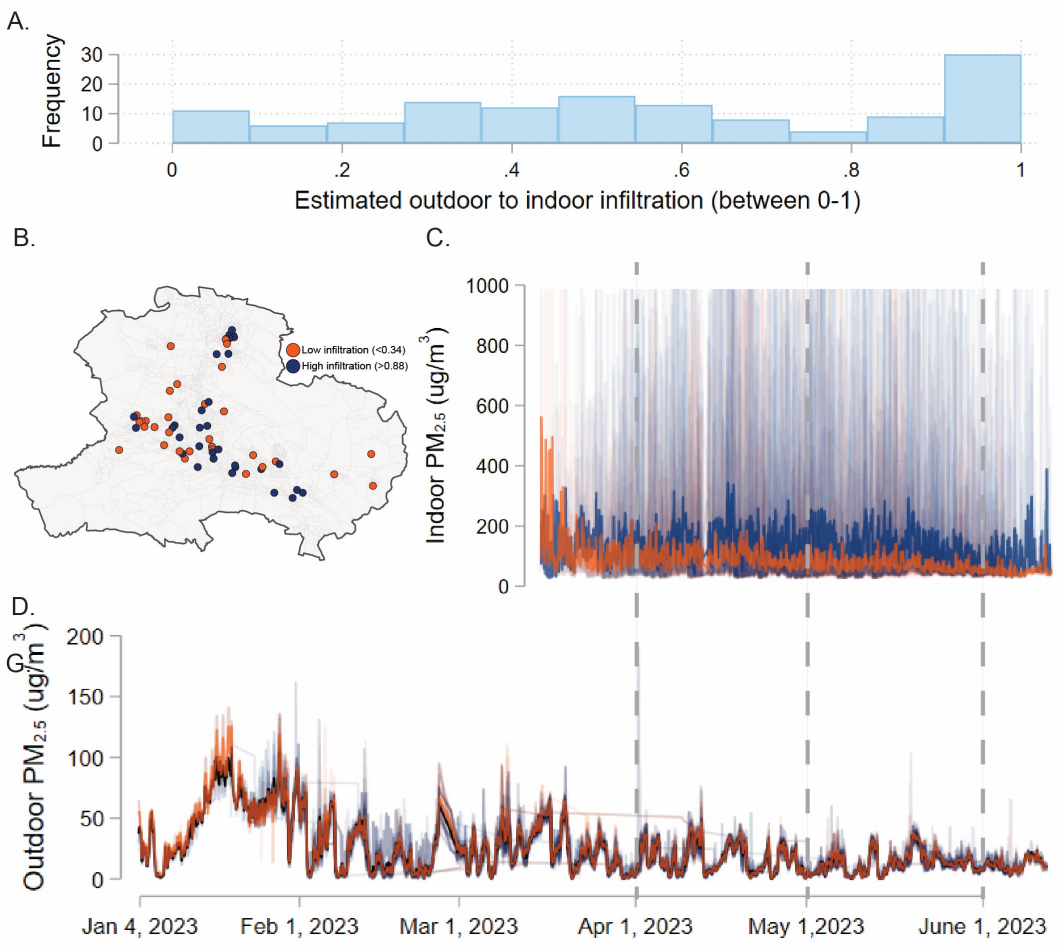


Figure 2: Pollution in high and low infiltration homes: Panel **A** shows the frequency of home specific infiltration rates estimated with Equation 2. We top- and bottom-code estimates outside of the 0-1 range at 0 and 1. Panel **B** shows the distribution of houses across Tbilisi in the bottom quartile of infiltration rates (in orange) and those in the top quartile (in blue). There is no meaningful difference in the spatial distribution of homes across these two quartiles. Panel **C** and **D** show the indoor and outdoor pollution levels recorded by the monitors during our experiments in the same set of homes. Panel **C** clearly shows that indoor pollution levels in high infiltration homes (blue line) are systematically higher than those in low infiltration homes (orange line) while there is no such difference in outdoor levels in Panel **D**. In both figures the dark lines show the average across all households while the lighter lines plot the data from individual monitors.

7 Tables

Table 1: Impact of RCT treatments

	Knowledge of pollution	Actions to avoid pollution	Health symptoms
	Leaflet Treatment		
Treatment effect	-0.3493	-0.0262	-0.0571
	(0.3254)	(0.1350)	(0.1518)
N	458	458	375
	Outdoor Treatment		
Treatment effect	0.4912	0.3107**	0.2468
	(0.3258)	(0.1427)	(0.1575)
N	457	457	368
	Outdoor and Indoor Treatment		
Treatment effect	0.7597**	0.3079*	-0.3692**
	(0.3057)	(0.1566)	(0.1752)
N	375	375	309
Pre-period outcome means:			
Leaflet treatment:	10.90	1.35	1.49
Outdoor treatment:	10.75	1.23	1.30
Outdoor & Indoor treatment:	11.23	1.49	1.77

NOTES: The outcome in all columns is the difference in the count of self-reported knowledge, adaptive behaviors, or health symptoms of pollution exposure from each household in the survey. The omitted group is the control group. The survey asked about adaptive actions and health symptoms during the 30 days prior to each survey round. The actions we ask about are: avoiding busy traffic areas, avoiding high levels of outdoor activity on high pollution days, using a ventilation fan while cooking, opening windows to vent the house. The symptoms we ask about are: eye irritation, sore throat, headache, cough, wheezing, sinus pain, or shortness of breath. Heteroskedasticity robust standard errors clustered by census block - the sampling unit- are in parentheses (* p<.10 ** p<.05 *** p<.01). We report results controlling for household wealth and housing age in Table A2.

Table 2: Impact of treatment on willingness-to-pay

	WTP for air monitor (GEL)	WTP for air purifier (GEL)
Leaflet treatment	-11.19	-103.47
	(20.93)	(135.06)
Outdoor treatment	-33.28	-178.79
	(21.07)	(148.75)
Outdoor & Indoor treatment	-1.37	-84.80
	(15.96)	(126.42)
N	300	314
Pre-period outcome mean (GEL):	80.61	204.11

NOTES: The outcome in all columns is the difference in the household's reported willingness-to-pay to pay for the item between the two rounds measured in Georgian Lahi. We drop all households that answered I don't know in either round or didn't answer the question. In results available upon request we show that these results are robust to alternative measures of dealing with these non-responses. Heteroskedasticity robust standard errors clustered by census district - the sampling block - are in parentheses (* p<.10 ** p<.05 *** p<.01).

Table 3: Characteristics predictive of infiltration rates

	Physical attributes	Actions	Combined
Seperate kitchen	0.002		0.033
	(0.066)		(0.069)
Size of house (m^2)	-0.001*		-0.002**
	(0.001)		(0.001)
After 2010	-0.012		0.093
	(0.168)		(0.218)
1990 -2009	-0.016		-0.035
	(0.135)		(0.135)
1960-1989	-0.041		-0.052
	(0.090)		(0.095)
1930-1959	-0.132		-0.117
	(0.125)		(0.126)
Before 1920			
Floor of dwelling	-0.005		-0.005
	(0.008)		(0.008)
Consumption index	0.006		0.009
	(0.025)		(0.024)
Has fireplace	0.026		0.014
	(0.408)		(0.367)
Greater than secondary schooling	-0.091		-0.092
	(0.068)		(0.066)
Windows open (Hrs)		0.016	0.027**
		(0.011)	(0.012)
Cooks with ventilation		-0.140*	-0.139*
		(0.081)	(0.076)
Owns air purifier		-0.014	0.180*
		(0.037)	(0.098)
Owns indoor monitor		-0.162***	-0.192
		(0.041)	(0.233)
N	129	129	129
Adjusted R^2	-0.009	0.007	0.022
Total SS	12.94	12.94	12.94
Residual SS	11.94	12.46	11.17
Pre-period outcome mean:	0.57	0.57	0.57

NOTES: The outcome in all columns the outcome is the household specific infiltration rate, calculated as described in the text, top-coded at 0 and 1. We use the base estimation of the household infiltration rate in this table. The sample includes all households that received an indoor monitor and whose cleaned indoor data resulted in non-zero indoor measurements. The omitted category for date dwelling was built was pre-1920. The omitted category for education is Windows open indicates the typical number of hours the household leaves the windows open in a day. Heteroskedasticity robust standard errors clustered by census district - the sampling block - are in parentheses (* p<.10 ** p<.05 *** p<.01).

References

Abrams, M (2000), "The advanced spaceborne thermal emission and reflection radiometer (aster): data products for the high spatial resolution imager on nasa's terra platform." *international Journal of Remote sensing*, 21, 847–859.

Ahmad, Husnain F, Matthew Gibson, Fatiq Nadeem, Sanval Nasim, and Arman Rezaee (2023), "Forecasts: Consumption, production, and behavioral responses."

Allcott, Hunt and Judd B Kessler (2019), "The welfare effects of nudges: A case study of energy use social comparisons." *American Economic Journal: Applied Economics*, 11, 236–276.

Allcott, Hunt and Todd Rogers (2014), "The short-run and long-run effects of behavioral interventions: Experimental evidence from energy conservation." *American Economic Review*, 104, 3003–3037.

Barwick, Panle Jia, Shanjun Li, Liguo Lin, and Eric Zou (2024), "From fog to smog: the value of pollution information." *American Economic Review*.

Behrer, A Patrick and Sam Heft-Neal (2024), "Higher air pollution in wealthy districts of most low-and middle-income countries." *Nature Sustainability*, 1–10.

Bi, Jianzhao, Lance A Wallace, Jeremy A Sarnat, and Yang Liu (2021), "Characterizing outdoor infiltration and indoor contribution of pm2. 5 with citizen-based low-cost monitoring data." *Environmental Pollution*, 276, 116763.

Burke, Marshall, Sam Heft-Neal, Jessica Li, Anne Driscoll, Patrick W Baylis, Matthieu Stigler, Joakim Weill, Jennifer Burney, Jeff Wen, Marissa Childs, et al. (2021), "Exposures and behavioral responses to wildfire smoke." Technical report, National Bureau of Economic Research.

Chi, Guanghua, Han Fang, Sourav Chatterjee, and Joshua E Blumenstock (2022), "Microestimates of wealth for all low-and middle-income countries." *Proceedings of the National Academy of Sciences*, 119.

CRRC (2017), "Public attitudes in georgia." Technical report, Caucasus Research Resource Center.

CRRC (2021), "A policy agenda for tbilisi: What voters want." Technical report, Caucasus Research Resource Center.

Foundation for a Smoke Free World (2021), "Georgia country report." Country report, Health Initiatives.

Fuller, Richard, Philip J Landrigan, Kalpana Balakrishnan, Glynda Bathan, Stephan Bose-O'Reilly, Michael Brauer, Jack Caravanos, Tom Chiles, Aaron Cohen, Lilian Corra, et al. (2022), "Pollution and health: a progress update." *The Lancet Planetary Health*.

Greenstone, Michael, Patrick Baylis, Kenneth Lee, and Harshil Sahai (2023), "Is the demand for clean air too low? experimental evidence from delhi." Working paper, Energy Policy Institute of Chicago.

Greenstone, Michael, Guojun He, Ruixue Jia, and Tong Liu (2022), "Can technology solve the principal-agent problem? evidence from china's war on air pollution." *American Economic Review: Insights*, 4, 54–70.

Greenstone, Michael, Kenneth Lee, and Harshil Sahai (2021), "Indoor air quality, information, and socioeconomic status: Evidence from delhi." In *AEA Papers and Proceedings*, volume 111, 420–424, American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203.

Hanna, Rema, Esther Duflo, and Michael Greenstone (2016), "Up in smoke: the influence of household behavior on the long-run impact of improved cooking stoves." *American Economic Journal: Economic Policy*, 8, 80–114.

Hanna, Rema, Bridget Hoffmann, Paulina Oliva, and Jake Schneider (2021), "The power of perception limitations of information in reducing air pollution exposure." Technical report, IDB Working Paper Series.

Hasenkopf, Christa, Nishka Sharma, Farah Kazi, Polash Mukerjee, and Michael Greenstone (2023), "The case for closing global air quality data gaps with local actors: A golden opportunity for the philanthropic community." Working paper, Energy Policy Institute of Chicago.

Jha, Akshaya and Andrea La Nauze (2022), "Us embassy air-quality tweets led to global health benefits." *Proceedings of the National Academy of Sciences*, 119, e2201092119.

Krebs, Benjamin, Jennifer Burney, Joshua Graff Zivin, and Matthew Neidell (2021), "Using crowd-sourced data to assess the temporal and spatial relationship between indoor and outdoor particulate matter." *Environmental Science & Technology*, 55, 6107–6115.

Krebs, Benjamin and Matthew Neidell (2024), "Wildfires exacerbate inequalities in indoor pollution exposure." *Environmental Research Letters*, 19, 024043.

Liang, Yutong, Deep Sengupta, Mark J Campmier, David M Lunderberg, Joshua S Apte, and Allen H Goldstein (2021), "Wildfire smoke impacts on indoor air quality assessed using crowdsourced data in california." *Proceedings of the National Academy of Sciences*, 118, e2106478118.

Lloyd, Christopher T, Alessandro Sorichetta, and Andrew J Tatem (2017), "High resolution global gridded data for use in population studies." *Scientific data*, 4, 1–17.

Lunderberg, David M, Yutong Liang, Brett C Singer, Joshua S Apte, William W Nazaroff, and Allen H Goldstein (2023), "Assessing residential pm2. 5 concentrations and infiltration factors with high spatiotemporal resolution using crowdsourced sensors." *Proceedings of the National Academy of Sciences*, 120, e2308832120.

Salukvadze, Joseph and Oleg Golubchikov (2016), "City as a geopolitics: Tbilisi, georgia—a globalizing metropolis in a turbulent region." *Cities*, 52, 39–54.

Shaddick, G, ML Thomas, P Mudu, G Ruggeri, and S Gumy (2020), "Half the world's population are exposed to increasing air pollution." *NPJ Climate and Atmospheric Science*, 3, 1–5.

Sturua, Lela, Nino Maglakelidze, and Amiran Gamkrelidze (2018), "Smoking prevalence in georgian adults: results of non-communicable disease risk factors steps 2016 survey." *Tobacco Prevention & Cessation*, 4.

Van Donkelaar, Aaron, Randall V Martin, Chi Li, and Richard T Burnett (2019), "Regional estimates of chemical composition of fine particulate matter using a combined geoscience-statistical method with information from satellites, models, and monitors." *Environmental science & technology*, 53, 2595–2611.

Weichenthal, Scott, Lauren Pinault, Tanya Christidis, Richard T Burnett, Jeffrey R Brook, Yen Chu, Dan L Crouse, Anders C Erickson, Perry Hystad, Chi Li, et al. (2022), "How low can you go? air pollution affects mortality at very low levels." *Science Advances*, 8, eabo3381.

WHO (2021), "Who global report on trends in prevalence of tobacco use 2000–2025."

Appendix – For Online Publication

Table of Contents

Appendix 1	**Census block & household selection process**	**25**
Appendix 2	**Survey implementation details**	**25**
Appendix 3	**Creation of outcome indices**	**26**
Appendix 4	**PurpleAir data cleaning**	**28**
Appendix 5	**Additional tables**	**28**
Appendix 6	**Additional figures**	**33**
Appendix 7	**Air pollution informational leaflet**	**38**

Appendix 1 Census block & household selection process

Census blocks were randomly selected to be surveyed after stratifying census blocks in Tbilisi based on average block elevation above sea level and average household consumption in the block in the last reported census. We stratified census blocks into above and below median of each of these categories to ensure that surveyed blocks were balanced across high and low consumption and high and low elevation blocks. After randomization we selected 56 or 59 blocks in each of the four strata. The location of the outdoor monitors was chosen such that the average distance between a selected census block and the nearest outdoor monitor was less than 1 kilometer.

To select households within census blocks, interviewers followed a random walk process. Starting points were marked on all maps and trainers instructed enumerators on the direction of the random walk. Depending on the number of apartment blocks and houses to be sampled, interviewers were instructed to conduct interviews in different buildings or, if there were only one building in the sampled block, they were asked to use different entrances. All enumerators had to follow instructions provided by CRRC and a randomized post-survey back check was conducted to ensure quality. Households were assigned to control or treatment groups based on the order they were encountered. The first household encountered was assigned to control and subsequent households were selected for each of the treatment groups. Because of limits on the size of treatment group three not all surveyed census blocks had four households contacted. Those that were limited to three household contacts were selected randomly within strata.

Appendix 2 Survey implementation details

The survey was collected through face-to-face interviews using Computer Assisted Personal Interviewing (CAPI). The interview lasted approximately 20 minutes. CRRC Georgia coordinated the survey implementation. They recruited 22 enumerators, two supervisors and one technical assistant

for installing indoor air monitors. CRRC conducted two four-hour trainings before the start of the fieldwork. During the trainings, interviewers practiced the questionnaire, sampling instructions, familiarized themselves with the maps and recording air quality with the help of the portable air monitors. They also discussed possible problems or challenges that might arise during the fieldwork.

The training covered the following topics:

- Sampling instructions
- Becoming familiarized with maps
- Indoor monitor installment procedure
- Usage of portable air monitors
- Respondent selection
- Overview of the questionnaire with special attention to problematic questions
- Conducting test interviews

Trainings were provided by CRRC staff. Before the actual fieldwork, all enumerators were provided with tablets, maps for every cluster, letter to the respondent explaining the aim of the project, name tags and portable air monitors that they had to carry with them during the whole fieldwork. The technical assistant received indoor monitors and a detailed manual on installation.

Appendix 3 Creation of outcome indices

The survey included three questions intended to elicit households understanding of their ability to reduce their exposure to air pollution by changing their behavior, the extent to which they engaged in these behaviors, and the health symptoms related to pollution that they experienced in the month prior to each round of the survey. The exact wording of these questions was as follows:

Knowledge question:

Do you think that the following behavior can impact someone's health (Yes/no/not sure for each)?

1. *Avoid going out on high air pollution hours and days?*
2. *Avoid opening windows during high air pollution hours?*
3. *Avoid busy roads when walking, running, or cycling?*
4. *Increase ventilation at home?*

Behavior question:

In the last 30 days, have you taken any of the following actions more than twice?

1. *Avoided going out on high air pollution hours and days?*
2. *Avoided opening windows during high air pollution hours?*
3. *Avoided busy roads when walking, running, or cycling?*
4. *You increased ventilation at home?*

These questions were specifically worded to focus on the actions that the informational leaflet that all households received highlighted as potential ways for households to reduce their exposure to air pollution. We asked the following about health symptoms:

> *Have you had any asthma attacks during the last month?*

and

> *Have you had any of the following symptoms in the last month? (Specify which)*
>
> 1. *Eye irritation*
> 2. *Sore throat*
> 3. *Headaches*
> 4. *Coughing*
> 5. *Wheezing*
> 6. *Sinus irritation*
> 7. *Shortness of breath during physical activity*

For each category - knowledge, behavior, and health - we count the number of affirmative answers the household gives and sum these to create the index. So a household that indicated they did not think that any of the actions could improve health but had avoided going out on high pollution days would have scores of 0 and 1 in the knowledge and behavior indices respectively. If they then indicated they had suffered an asthma attack and headaches but no other symptoms they would receive a score of 2 in the health index.

In Table A7 we examine how treatment impacts households' ranking air pollution in a list of issues facing Tbilisi, whether treatment reduces missed school or work due to illness and whether households have exercised outside. To measure these we ask the following questions. // For exercise:

> *In the last week, how many hours have you spent practicing outdoor physical activity?*

For health concerns impacting work or school:

> *Did a health concern affect your normal work pattern in the last month?*

or:

> *Have you or anyone in the household missed school due to health concerns in the last month?*

For the importance of air pollution:

> *How important do you think the following issues are in Tbilisi? Please scale from 1 (least important) to 5 (most important)*
>
> 1. *Prices*
> 2. *Poverty*
> 3. *Air pollution*
> 4. *Crime*
> 5. *Immigration*

Appendix 4 PurpleAir data cleaning

We follow both Burke et al. (2021) and Krebs et al. (2021) and filter the data from our PurpleAir monitors to eliminate data that is likely to have been generated by errors in the monitors. To do so we use the following steps:

1. For indoor monitors we require that a monitor report data for at least 30% of the sample period to be included. All outdoor monitors are included because they report over this threshold.

2. For both indoor and outdoor monitors we replace with missing all observations, after the first, where the value is the same for five periods in a row. Pollution levels are unlikely to be stable enough to generate that consistency in readings and these are likely due to monitors experiencing momentary losses of connectivity.

3. For both indoor and outdoor monitors we top-code pollution levels at 1000 $\mu g/m^3$. This is the accuracy threshold reported by PurpleAir.

Appendix 5 Additional tables

Table A1: Balance table

	Control Mean	T1 T1-Con.	t-stat	T2 T2-Con.	t-stat	T3 T3-Con.	t-stat
House & Neighborhood characteristics							
District elevation (m)	500.74	0.00	0.00	-0.17	-0.02	1.98	0.20
Lives in apartment. (Y/N)	0.72	-0.00	-0.10	0.02	0.50	-0.04	-0.78
Lives in house. (Y/N)	0.17	0.01	0.25	-0.00	-0.11	0.03	0.80
Apt. floor (#)	5.18	-0.75	-1.97	-1.05	-2.84	-0.23	-0.53
Seperate kitchen. (Y/N)	0.84	-0.03	-0.86	0.03	0.92	-0.02	-0.53
House built prior to 1959. (Y/N)	0.17	-0.02	-0.51	0.02	0.51	0.06	1.49
House built 1960-1989. (Y/N)	0.48	0.02	0.47	-0.02	-0.52	0.02	0.45
House build post-1989. (Y/N)	0.06	0.00	0.00	-0.03	-1.36	0.03	0.96
Consumption in 000s GEL	19.45	0.00	0.00	0.61	0.45	3.20	2.00
Level of education	0.58	-0.01	-0.19	0.06	1.21	0.07	1.35
Knowledge index	10.82	0.07	0.32	-0.08	-0.32	0.41	1.70
Avg. outdoor PM_2.5	21.95	0.00	0.00	-0.01	-0.04	-0.02	-0.07
Behaviors							
Cook with natural gas	0.97	0.01	0.91	0.03	2.14	0.03	2.14
Do you use ventilation when cooking	0.83	0.02	0.63	-0.00	-0.02	0.04	0.97
Does anyone smoke inside? (Y/N)	0.22	-0.03	-0.93	0.02	0.58	0.01	0.33
Use air monitor at home	0.01	0.01	1.01	0.00	0.01	-0.01	-0.57
Adaptive actions index	1.28	0.04	0.32	-0.11	-0.81	0.15	0.96
Health outcomes							
Health index	1.62	-0.14	-0.87	-0.32	-2.09	0.15	0.81
Has anyone missed school for health? (Y/N)	0.11	-0.00	-0.15	-0.00	-0.12	-0.02	-0.76
Have health concerns impacted your work? (Y/N)	0.10	-0.01	-0.33	-0.03	-0.68	0.05	1.00
Knowledge of pollution							
Knowledge of air purifier. (Y/N)	0.41	0.00	0.02	0.02	0.48	0.05	0.93
Knowledge of air monitor. (Y/N)	0.35	-0.02	-0.44	0.02	0.39	-0.01	-0.16
Checked outdoor pollution? (Y/N)	0.01	-0.00	-0.58	-0.00	-0.57	0.01	0.46
Checked indoor pollution? (Y/N)	0.00	-0.00	-1.00	0.00	0.01	-0.00	-0.80

NOTES: Means of each variable for the control group are reported as labeled in column 1. Columns 2, 4, and 6 report the difference in the means between the control and treatment groups. Columns 3, 5, and 7 report the t-stat of the difference in means. For all Y/N questions, 1 indicates Yes. Each of the health questions was asked about the previous 2 weeks. Education is an index measuring the level of education completed wtih 1 indicating completion of at least college.

Table A2: Impact of Leaflet treatment

	Knowledge of pollution	Actions to avoid pollution	Health symptoms
Leaflet treatment	-0.3330	-0.0602	-0.0602
	(0.3269)	(0.1364)	(0.1517)
N	458	458	375
Pre-period outcome mean:	10.90	1.32	1.49
Controls for wealth & building age:	Yes	Yes	Yes

NOTES: The outcome in all columns is the difference in the count of self-reported knowledge, adaptive behaviors, or health symptoms of pollution exposure from each household in the survey. The omitted group is the control group. The survey asked about adaptive actions and health symptoms during the 30 days prior to each survey round. The actions we ask about are: avoiding busy traffic areas, avoiding high levels of outdoor activity on high pollution days, using a ventilation fan while cooking, opening windows to vent the house. The symptoms we ask about are: eye irritation, sore throat, headache, cough, wheezing, sinus pain, or shortness of breath. Heteroskedasticity robust standard errors clustered by census block - the sampling unit- are in parentheses (* p<.10 ** p<.05 *** p<.01).

Table A3: Impact of Outdoor treatment

	Knowledge of pollution	Actions to avoid pollution	Health symptoms
Outdoor treatment	0.5046	0.3232**	0.2588
	(0.3226)	(0.1450)	(0.1591)
N	457	457	368
Pre-period outcome mean:	10.75	1.16	1.30
Controls for wealth & building age:	Yes	Yes	Yes

NOTES: The outcome in all columns is the difference in the count of self-reported knowledge, adaptive behaviors, or health symptoms of pollution exposure from each household in the survey. The omitted group is the control group. The survey asked about adaptive actions and health symptoms during the 30 days prior to each survey round. The actions we ask about are: avoiding busy traffic areas, avoiding high levels of outdoor activity on high pollution days, using a ventilation fan while cooking, opening windows to vent the house. The symptoms we ask about are: eye irritation, sore throat, headache, cough, wheezing, sinus pain, or shortness of breath. Heteroskedasticity robust standard errors clustered by census block - the sampling unit- are in parentheses (* p<.10 ** p<.05 *** p<.01).

Table A4: Impact of All treatment

	Knowledge of pollution	Actions to avoid pollution	Health symptoms
All treatment	0.8116***	0.2844*	-0.3308*
	(0.3037)	(0.1582)	(0.1785)
N	375	375	309
Pre-period outcome mean:	11.23	1.49	1.77
Controls for wealth & building age:	Yes	Yes	Yes

NOTES: The outcome in all columns is the difference in the count of self-reported knowledge, adaptive behaviors, or health symptoms of pollution exposure from each household in the survey. The omitted group is the control group. The survey asked about adaptive actions and health symptoms during the 30 days prior to each survey round. The actions we ask about are: avoiding busy traffic areas, avoiding high levels of outdoor activity on high pollution days, using a ventilation fan while cooking, opening windows to vent the house. The symptoms we ask about are: eye irritation, sore throat, headache, cough, wheezing, sinus pain, or shortness of breath. Heteroskedasticity robust standard errors clustered by census block - the sampling unit- are in parentheses (* p<.10 ** p<.05 *** p<.01).

Table A5: Impact of treatment on whether HH checked pollution levels

	Checked outdoor	Checked indoor
Leaflet treatment	0.0175	0.0044
	(0.0107)	(0.0044)
Outdoor treatment	0.5638***	-0.0000
	(0.0336)	(0.0062)
All treatment	0.6984***	0.8526***
	(0.0380)	(0.0310)
N	830	829
Within adjusted R^2	0.45	0.81
Pre-period outcome mean:	0.01	0.00

NOTES: The outcome in all columns is the difference in whether the household reports checking either the indoor or outdoor pollution level in the 30 days before the survey. Heteroskedasticity robust standard errors clustered by census district - the sampling block - are in parentheses (* p<.10 ** p<.05 *** p<.01).

Table A6: Impact of average pollution levels

	Without controls					
	Knowledge of pollution		Actions to avoid pollution		Health symptoms	
Avg. outdoor $PM_{2.5}$	-0.008		0.038*		-0.046***	
	(0.042)		(0.020)		(0.017)	
Avg. indoor $PM_{2.5}$		0.007*		0.004*		0.002
		(0.004)		(0.002)		(0.002)
N	832	131	832	131	688	113
	With controls for wealth & building age					
Pre-period outcome mean:	10.89	11.24	1.28	1.39	1.27	1.51

NOTES: The outcome in all columns is the difference in the count of self-reported knowledge, adaptive behaviors, or health symptoms of pollution exposure from each household in the survey. The survey asked about adaptive actions and health symptoms during the 30 days prior to each survey round. The actions we ask about are: avoiding busy traffic areas, avoiding high levels of outdoor activity on high pollution days, using a ventilation fan while cooking, opening windows to vent the house. The symptoms we ask about are: eye irritation, sore throat, headache, cough, wheezing, sinus pain, or shortness of breath. We measure average outdoor pollution based on the average level of pollution over the full sample period from the nearest installed PurpleAir monitors. Avearage indoor pollution is measured as the average from the household's indidivual indoor PurpleAir monitor over the full period that it was installed. Heteroskedasticity robust standard errors clustered by census block - the sampling unit- are in parentheses (* p<.10 ** p<.05 *** p<.01).

Table A7: Impact of treatment on other outcomes

	Importance of pollution	Missed work	Missed school	Exercised outside
Treatment group 1	0.045	-0.059	0.000	0.047
	(0.066)	(0.045)	(0.030)	(0.042)
Treatment group 2	-0.002	-0.019	-0.009	0.001
	(0.063)	(0.045)	(0.032)	(0.041)
Treatment group 3	-0.025	-0.076	0.040	-0.032
	(0.081)	(0.053)	(0.035)	(0.044)
N	783	318	832	832
Pre-period outcome mean:	4.88	0.10	0.11	0.16
Controls for wealth & building age:	Yes	Yes	Yes	Yes

NOTES: The outcome in all columns is the change in the measured named in the column heading. "Importance" is the ranking of air pollution by the household on a list of items (i.e. inflation, crime, etc.) facing Tbilisi. Lower ranks indicate the issue was more important. "Missed work" and "Missed school" indicate someone in the household missed work or school due to a health concern in the previous 30 days. "Exercised outside" indicates the surveyed individual exercised outside in the previous week. Details of the constructin of these measures are provided in Appendix Appendix 3. The omitted group is the control group. Heteroskedasticity robust standard errors clustered by census block - the sampling unit- are in parentheses (* p<.10 ** p<.05 *** p<.01).

Appendix 6 Additional figures

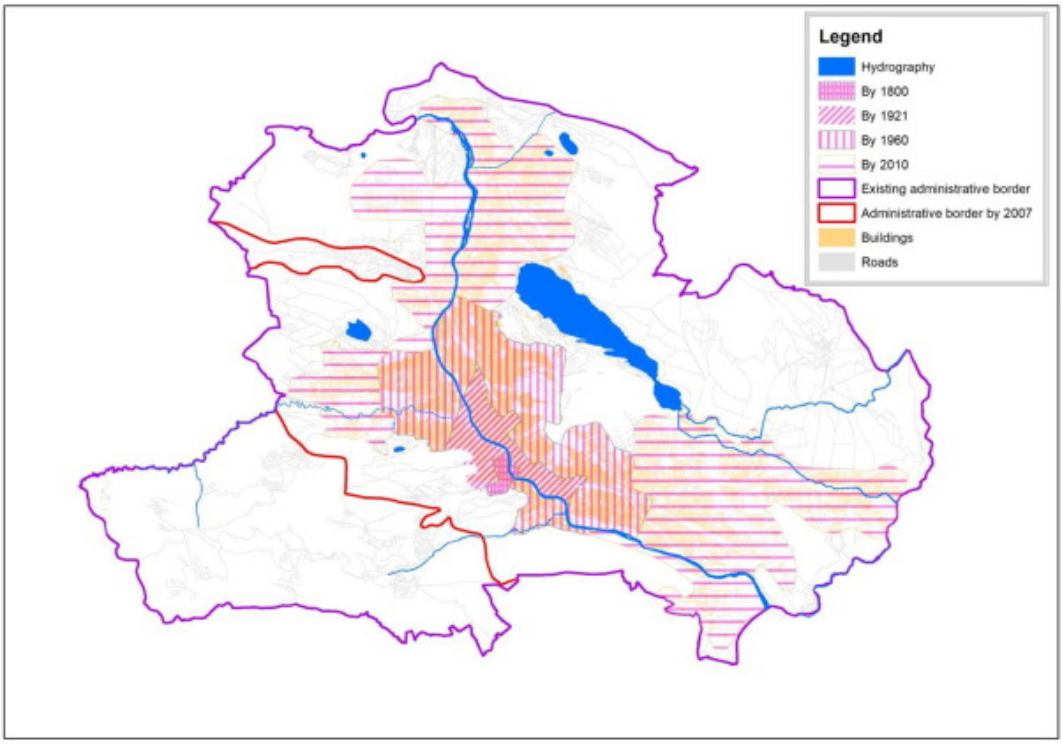
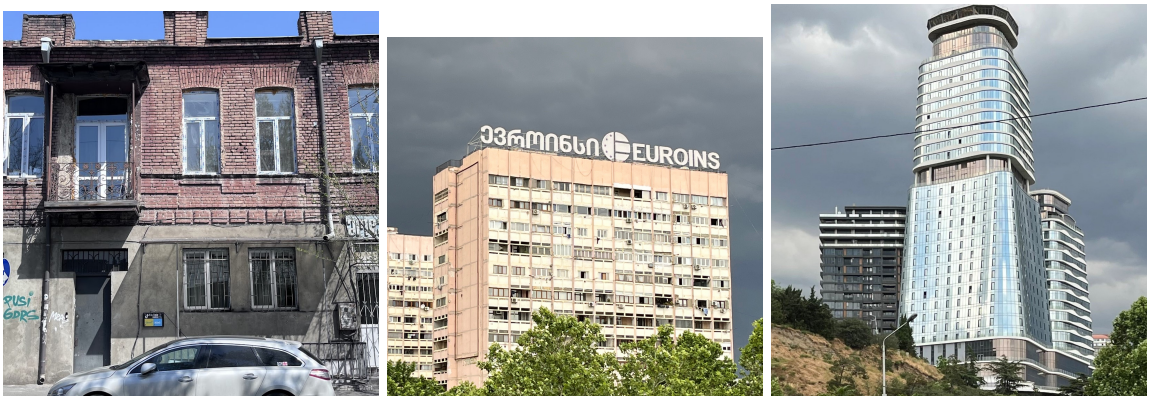


Figure A1: Map of housing vintages in Tbilisi. Reproduced from Salukvadze and Golubchikov (2016).



(a) **(b)** **(c)**

Figure A2: Examples of housing types in Tbilisi. Panel **A** shows a second story single family home above commercial real estate. Panel **B** is an example of the Soviet era apartment blocks still found throughout Tbilisi. Panel **C** is an example of the new, more modern towers constructed since the early 1900s.

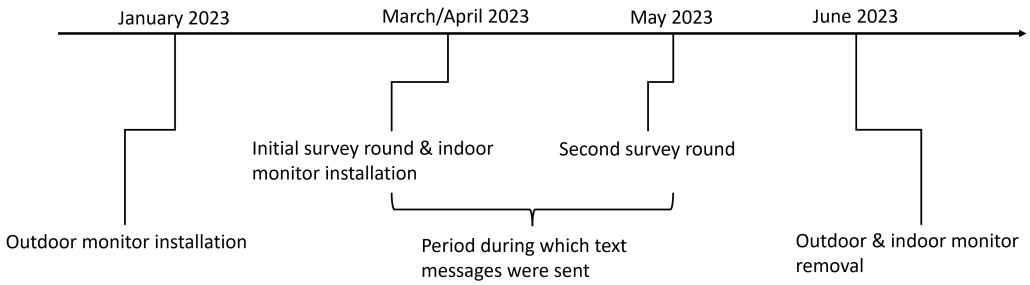


Figure A3: RCT Timeline Overview of the timing of survey rounds and monitor installation.

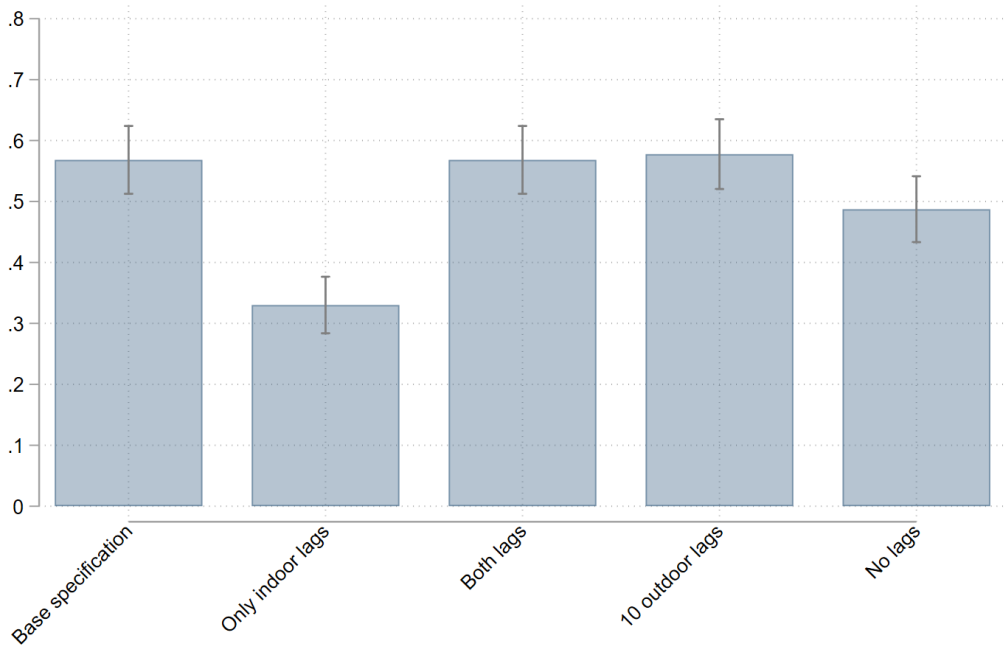


Figure A4: Alternative lag specifications for infiltration estimates: We show the mean infiltration rate and 95% confidence interval of the mean over all the households for which we can estimate infiltration in our sample. We estimate infiltration as described in Equation 2 in the main text. The "Base" estimates are from a specification exactly as described in Equation 2. "Only indoor lags" includes six lags of indoor pollution and no outdoor lags. "Both lags" includes six lags of both indoor and outdoor pollution. "10 outdoor lags" includes ten lags of outdoor pollution. "No lags" includes only contemporaneous indoor and outdoor pollution.

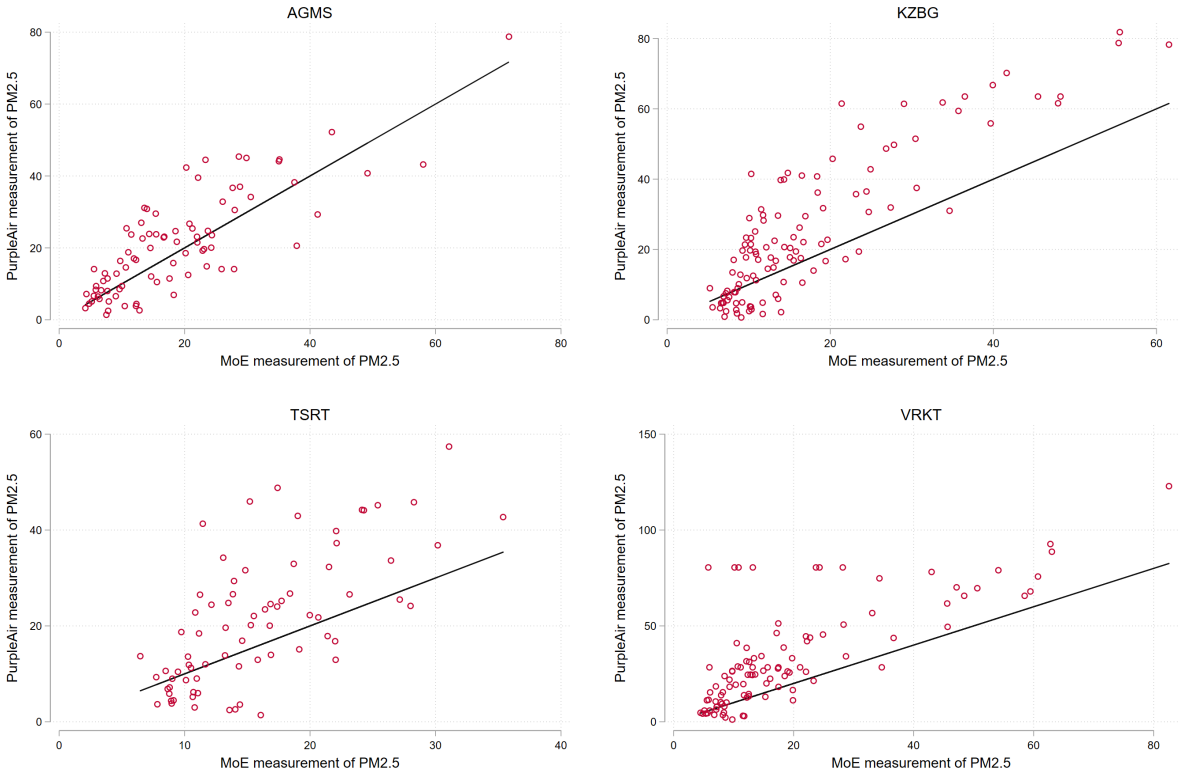


Figure A5: PurpleAir and MoE monitor comparison For each of the four Ministry of Environment run monitors in Tbilisi we plot the daily pollution readings against the corresponding closest PurpleAir monitor. The names of the four MoE monitors are taken from the MoE reporting website.

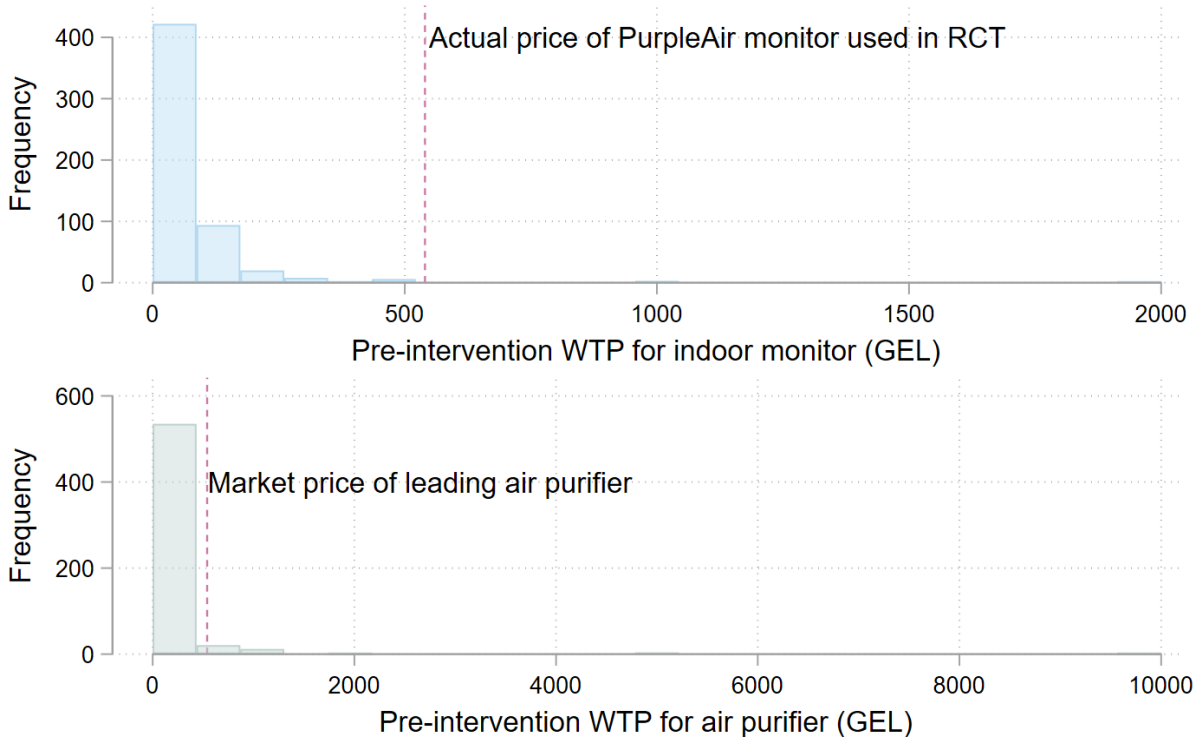


Figure A6: WTP for IAQMs or purifiers These figures show the frequency of WTP amounts for indoor air quality monitors (a) and air purifiers (b) prior to our experimental intervention. In both figures we show the actual price of the devices with a dashed vertical line. The price for air monitors is the price for the PurpleAir monitors used in our intervention. For the air purifiers we use the price of a market leading air purifier. In both figures we omit households that said they did not know how much they would be willing to pay or did not answer the question.

Appendix 7 Air pollution informational leaflet



Figure A7: Information leaflet A copy of the English translation of the leaflet that was provided to treated households. The leaflet was translated into Georgian by the survey firm. The QR code magnet is shown in the center of the figure.