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ARTICLE

The power of personalised feedback: evidence from an indoor air quality experiment

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Abstract
Indoor air pollution is one of the leading causes of morbidity and mortality worldwide, but its sources and impacts are largely misunderstood by the public. In a randomised controlled trial including 281 households in France, we test two interventions aimed at changing indoor polluting behaviour by raising households' awareness of health risks associated with indoor air pollution. While both generic and personalised information increased knowledge, only personalised information including social comparison feedback changed behaviour, leading to a reduction of indoor PM2.5 (particulate matter with an aerodynamic diameter $\leq$2.5 μm) emissions by 20% on average. Heterogeneous treatment effects show that this effect is concentrated on the most polluted households at baseline, for whom the reduction reaches 40%.

Keywords: air pollution; field experiments; health behaviour; health information; personalised information; social comparison feedback

Introduction

Exposure to air pollution is one of the leading causes of morbidity and mortality worldwide. Diseases caused by PM2.5 (particulate matter with an aerodynamic diameter $\leq$2.5 μm) exposure were responsible for an estimated nine million premature deaths in 2015, which represents 16% of all deaths worldwide and three times more deaths than AIDS, tuberculosis and malaria combined (Burnett *et al.*, 2018; Landrigan *et al.*, 2018). Despite improvements in air quality over the past 10 years, 90% of European countries still record levels of PM2.5 above the safety threshold set by the World Health Organization (Ortiz *et al.*, 2020). Recent estimates show that PM2.5 exposure causes a loss of life expectancy that rivals that of tobacco smoking, especially through cardiovascular and respiratory diseases (Lelieveld *et al.*, 2020). Given that residents in high-income countries spend more than 80% of their time in closed environments, exposure to air pollutants is largely determined by indoor air quality (Hoek *et al.*, 2008). Indoor air quality is roughly the same as outdoor air quality when there is no polluting indoor activity, but when household polluting sources are activated, it can be up to five times worse than outdoor air quality (Ebner *et al.*, 2005). The main indoor sources of PM2.5 are wood burning, cooking and tobacco smoking, and, to a lesser extent, candles, incense burning and dusting (Nasir *et al.*, 2013). Residential wood burning, in particular, releases far more abundant and harmful volumes of pollutants than other activities such as car exhausts or cigarettes (Chafe *et al.*, 2015), even when using certified, high-efficiency equipment (Frasca *et al.*, 2018). Beyond sanitary risks for individual users, residential wood burning is also a major source of outdoor pollution, which means that private heating choices have collective consequences. While it only provides 3% of energy needs, residential wood burning is responsible for more than 45% of PM2.5 concentration in Europe, which makes it the leading source of outdoor air pollution, above transportation and the industry (Amann *et al.*, 2018). The general public is mostly unaware of the negative health consequences of wood burning and other combustion activities and has limited knowledge of the factors that influence indoor air quality and its effects on health (Hofflinger *et al.*, 2019; Daniel *et al.*, 2020). Such lack of awareness results in low acceptability and effectiveness of policies aiming to reduce PM2.5 pollution. To name just one example, a ban on wood burning by the City of Paris in 2014 was faced with intense public and political backlash, leading to a lift of the ban by the Minister of the Environment (Eeckhout, 2014). Finding levers to increase awareness of the risks associated with wood burning and other household polluting activities is therefore of key environmental and public health concern. Several barriers can hinder the adoption of behaviours that limit air pollution. First, structural barriers, such as financial costs, can make it hard for a household to change their habits. For instance, wood burning is still one of the cheapest heating methods in the world (Thomson *et al.*, 2015) and switching to less polluting methods or equipment might be out of reach for many households. In addition to structural barriers, informational and psychological barriers can prevent households from avoiding activities that increase indoor air pollution.

1) Lack of information: Despite being an important health hazard, there is limited awareness of indoor air pollution, its sources and its health impacts. While almost 90% of residents in the Île-de- France region (i.e. Paris and its suburbs) believe that outdoor air pollution presents a major health risk, less than 50% hold that belief about indoor air pollution (Menard *et al.*, 2008). Most households overestimate indoor air quality, show limited understanding of the different sources of indoor pollution, and underestimate its associated sanitary risks (Langer *et al.*, 2017; Daniel *et al.*, 2020). For example, although burning incense and candles can release up to 10 times more PM2.5 than a cigarette, 68% of candle users and 58% of incense users state that this practice has no effect on or even improves indoor air quality (Nicolas *et al.*, 2017). This study also showed that only 21% of occasional users of wood burning believe that it has an impact on indoor air quality. Better informing users about the dangers of wood burning

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thus appears necessary to change behaviour (Hofflinger *et al.*, 2019; Daniel *et al.*, 2020). However, even when households are informed and aware of the risks, they may not change their behaviour due to other psychological biases.

2) Positive affect heuristic: Wood, candles or incense burning is typically associated with positive feelings and considered natural, healthy and low-polluting. This positive affect heuristic likely distorts the perception of health and environmental risks, generates disbelief and works as an obstacle to household behaviour change (Hine *et al.*, 2007; Bhullar *et al.*, 2014). These positive feelings are widespread and well-entrenched given that humans have burned wood for heating purposes for 350,000 years (Rolland, 2004).
3) Salience of the risks: The risks of PM2.5 exposure may not be salient both because of the invisibility of pollutants (except when found in very high concentrations) and because their costs on health are often delayed. For instance, the visible warmth of a wood fire and the aesthetic of a candle are more salient than the resulting invisible PM2.5 and the future health costs.
4) Optimism bias: This bias may lead people to underestimate their actual exposure and risk of suffering future health consequences relative to other people (Weinstein, 1980). Such optimism biases have been documented for various health hazards such as having a heart attack, contracting AIDS, being in a traffic accident or developing cancer (DeJoy, 1989; Fontaine, 1994; Fontaine *et al.*, 1995; Sharot, 2011).

These psychological biases might contribute to discrepancies between households' intent and their actual daily behaviour, even when households believe the information and are aware of polluting sources (Kahneman *et al.*, 1982; Allcott *et al.*, 2014). Personalised information may thus be required to counter these individual biases and change behaviour.

A number of studies have indeed shown that the content and format of information matter a lot for effective information provision. Information provision can have little (Variyam, 2008; Bollinger *et al.*, 2011) to no impact on health behaviour (Groner *et al.*, 2000; Ashraf *et al.*, 2013; Duflo *et al.*, 2015; Jacobson *et al.*, 2022), or it can effectively lead to the adoption of healthy behaviours (Dupas *et al.*, 2018; Jalan *et al.*, 2008; Madajewicz *et al.*, 2007). Some papers directly test different contents or formats and find differential effects on behaviours (Dupas, 2011; Downs *et al.*, 2015; Cohen et al., 2018; Madajewicz *et al.*, 2007; Hine *et al.*, 2007). However, only two studies specifically compare the effectiveness of generic vs personalised information on health behaviour (De Vries et al., 2008; Celis-Morales et al., 2017). These studies show that, relative to generic information, personalised information on diet and physical activities has a larger impact on health behaviour. But while most people are now aware that diet and physical activity have an impact on health, public awareness of the impact of indoor air pollution might be comparatively less well-understood, in particular the negative role of combustion activities, which might further increase the importance of personalised feedback.

In this paper, we equipped households that occasionally use woodheating with air quality micro-sensors to objectively test the impact of generic vs personalised interventions using a randomised controlled trial. We tested the effectiveness of two

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interventions aimed at raising households' awareness of the health risks associated with wood burning and other indoor pollutants, changing their behaviour, and ultimately decreasing indoor air pollution. We equipped 281 French households with air quality micro-sensors and randomly assigned them to three conditions: the *Information* treatment, the *Information + Personalised Feedback* treatment and the control group. The *Information* treatment consisted of weekly leaflets containing generic information about the risks related to indoor air pollution and multiple combustion activities, with special attention to wood burning. The *Information + Personalised Feedback* treatment received the same generic information along with personalised feedback about their emission profile and social comparison feedback. The personalised feedback consisted of two elements: (i) a personalised graph displaying the concentration of PM2.5 measured every five minutes over the previous week by their personal micro-sensor and (ii) a personalised graph displaying how their average emissions stood in comparison to similar households in the control group. Receiving such personalised feedback is expected to reinforce the effect of generic information by activating complementary behavioural levers: first, it makes the hazards of PM2.5 peaks more salient and allows people to think about which household activities are associated with subsequent PM2.5 peaks. Given that feedback is sent weekly, it is easy for households to remember what they did the previous week, which allows them to learn the precise consequences of their actions and to overcome salience and optimism biases. Second, building on prior research in environmental economics showing that social norms are an efficient lever of behavioural change (Allcott, 2011; Ferraro *et al.*, 2013), the personalised feedback activates social comparisons by providing participants with their rank compared to other households included in the study. Social comparison addresses biased beliefs about one's own consumption behaviour in comparison to others and can counter the optimism bias. We found that the *Information + Personalised Feedback* treatment was successful at decreasing indoor levels of PM2.5 by more than 20% over the four-month period, with a sustained and significant decrease starting on the third week after the beginning of the intervention. A heterogeneous impact analysis revealed that the effect was concentrated on the most polluted households who exhibit a 40% decrease in PM2.5 concentration levels. For that group, the number of days over the WHO threshold – not to be exceeded more than three days per year – decreased by 52%, from 12.4 down to 5.9 days over the study period. This result is in line with the notion that the *Information + Personalised Feedback* treatment helps eliminate 'slack' in combustion activities. In contrast, we observed no significant change in indoor air quality for households receiving the *Information* treatment, suggesting that generic information about the health risks of combustion activities was not sufficient to induce behavioural changes.

Turning to mechanisms, the main channel of behavioural change seems to be the perception of individuals' own indoor air quality. We found that both interventions were successful at increasing the perceived detrimental impact of wood burning and smoking on health risks, and at decreasing self-reported frequency of wood burning in the future. However, only the *Information + Personalised Feedback* intervention decreased the perceived quality of one's *own* indoor air. We found no evidence of an impact on the perceived health risk of pollution in general, attitudes towards wood burning regulation, pleasure when lighting a fire, or on the intention to change wood

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burning equipment in the future. Self-reported frequency of combustion activities was not different between the control group and both treatment groups, as well as air quality improvement efforts, which is at odds with the objective reduction in PM2.5 concentration measured by the micro-sensors. Our interpretation is that self-reported combustion and air quality improvement efforts were not precise enough to capture the behavioural changes that took place in the households and led to an objective decrease in PM2.5 concentration. Overall, both generic information and personalised feedback were efficient at improving knowledge about the risks associated with combustion activities but only personalised feedback induced actual behavioural changes. This finding suggests that general knowledge is not sufficient to change behaviour, and that the combination of personalised emission measures and personalised social comparisons is a powerful lever to overcome biased beliefs.

The paper is organised as follows. The 'Methods' section describes the material and experimental design of our study. The 'Data and sampling' section presents our data, outcomes of interest, hypotheses and sample. The 'Validity of the experiment and estimation' section examines the validity of the experiment and presents the estimation method. The 'Results' section provides the results on indoor air quality and on mechanisms. The 'Discussion' section concludes.

Methods

Materials

Both interventions involved mailing eight leaflets between January and March 2020 (i.e., winter season in the north hemisphere). The information was formatted in a way that facilitates a simple understanding of indoor polluting sources and its management. The first two leaflets were sent two weeks apart, while the following six were sent every week. In order to disentangle the impact of personalised feedback from generic information provision, we implemented two treatments. Examples are shown in the Appendix, and the full campaign can be found in the online appendix: https://osf.io/5br8y/.

The *Information* Treatment. In the *Information* treatment, we sent households informational leaflets about PM2.5 emitting activities, their associated health risks, as well as tips to improve indoor air quality. Each leaflet was composed of a cover page containing an illustration and a catchy slogan, a page containing infographics on sources of indoor air pollution and health risks, and a page providing information on good practices. The focus, the cover and the messages were different in each wave. We put an emphasis on wood burning in the last five waves of the interventions (weeks 4–8) to overcome households' low awareness of the negative effects of wood burning. The positive image of wood burning was challenged by matching the pollution produced by wood burning to that of other sources that are already perceived as detrimental, such as cigarettes and car exhausts. The weekly *Information* intervention addresses two potential informational and psychological barriers to household behavioural change: lack of information and positive affect towards combustion activities.

The *Information* + *Personalised Feedback* Treatment. The second treatment provided households with the same generic information as in the *Information* Treatment, but added people's personalised feedback. This included a graph showing precise meter

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readings of the concentration of PM2.5 measured every five minutes over the previous week in their household, as well as statistics comparing their emissions to similar households (the control group). Providing users with personalised feedback can alter household's polluting behaviour through different channels. First, the graphs help households identify pollution peaks that occurred in the previous week and encourage them to link these peaks to domestic activities, which provides a better understanding and management of indoor air quality. Second, personalised statements could reinforce the overall credibility of the generic information. Third, the graphs can help households further overcome issues linked to the low salience of risks and optimism bias, by making a household's own pollution visible in the present and readjusting personal perceptions. Finally, the use of social comparison may stimulate behaviour change by addressing biased beliefs about one's own consumption behaviour in comparison to others and can counter optimism biases. Therefore, the *Information + Personalised Feedback* intervention addresses all aforementioned informational and psychological barriers: lack of information, positive affect towards wood burning, salience bias and optimism bias.

Experimental design

To measure the differential effect of each treatment, 281 households received a micro air quality sensor. Using a baseline questionnaire, households were stratified by the presence of a smoker in the household and then matched into the best triplets according to their average weekly PM2.5 levels at baseline (both smoking and baseline indoor PM2.5 levels highly predict indoor air pollution post-treatment). This resulted in 94 triplets. Within each triplet, households were randomly assigned to one of the three groups: the control group, the *Information* treatment group and the *Information + Personalised Feedback* treatment group. At the end of the intervention, the control households were given access to the informational campaign, and both the *Information* and control groups received their indoor air quality personalised feedback for the entire intervention period.

Data and sampling

Data sources

Micro-sensor indoor pollution data. Every household was equipped with a micro-sensor that retrieved highly precise PM1, PM2.5, PM10, temperature and humidity levels every five minutes and transmitted it to an online platform set up by the manufacturer, using the 2G Network. Participating households were asked to place the sensor no closer than 1 m and no further than 4 m away from their wood burning equipment. In order to minimise the experimenter demand effect, the chosen micro-sensors were discrete, small ($140 \times 140 \times 46.5\ mm$), and provided no visible indications about the measured air quality (Atmotrack Atm01 by 42 Factory). The micro- sensor had two functions: it served as an intervention instrument, allowing us to send personalised summaries of air quality in the *Information + Personalised Feedback* group, as well as a reliable way measuring the impact of the interventions. As stated in the pre-analysis plan, we chose to limit the analyses to PM2.5 measures, which our sensors measure very accurately and for which the health-related literature is abundant.

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Self-reported questionnaire data. Households completed two online questionnaires, at baseline from August to December 2019, and at endline at the end of March 2020 (3 weeks after the end of the interventions). The endline questionnaire measured the mechanisms of change in indoor air quality between the three groups.

Outcomes of interest and hypotheses

Indoor air pollution. Our main pre-registered hypothesis was that the interventions would have an impact on households' PM2.5 feedbacks. The difference in PM2.5 emissions between the treatment group and the control group is the most reliable indicator of change in household behaviour. Our main outcome is households' average daily PM2.5 level over the whole post-treatment period. Another complementary outcome is the difference in the number of days a household registered higher PM2.5 levels than the WHO 24 hours guidelines (25 $\mu g/m^3$). Both variables capture the difference in indoor air pollution, which is influenced by how much people ventilate, whether they burn wood or engage in other polluting activities, and by the level of outdoor air pollution (indoor and outdoor pollution are indeed highly interconnected).

Knowledge about indoor air pollution sources. The baseline and endline questionnaires included questions about households' knowledge of main indoor and outdoor sources of pollution. We asked each respondent to cite all indoor PM2.5 emitting sources. We predicted that both treatments would increase the probability that households cite the following sources of pollution, which are mentioned in the leaflets: wood burning, cigarettes, candles, incense, and cooking.

Perceptions of indoor air quality. The baseline and endline questionnaires included questions about the household's perceived indoor and outdoor air quality. Scores of perceived air quality in the house, in the neighbourhood, and in the region ranges from 1 (worst quality) to 6 (perfect quality). We predicted that the *Information + Personalised Feedback* treatment would have a larger impact on perceived indoor air quality than the *Information* treatment thanks to the two graphs providing households with precise feedback about their emission profile.

Perceptions of wood burning and health risks. The baseline and endline questionnaires included a set of variables reflecting the household's perception on the contribution of wood burning to indoor pollution and perceived impact on health, knowledge of good wood burning practices, attitude towards wood burning regulation, pleasure when lighting a fire, as well as the intention to change wood burning equipment in the future. We predicted that both treatments would increase all these households' perceptions, but that the *Information + Personalised Feedback* treatment would have a larger impact on the perceived contribution of wood burning on indoor pollution than the *Information* treatment thanks to the possibility to link pollution peaks on the graphs with precise polluting activities.

Self-reported polluting activities. Finally, we collected information about households' self- reported polluting activities, such as the number of times they engaged into smoking, wood burning, candles, incense and dusting over the past week; overall frequency of wood burning over the past winter, and intended use in the future. These questions aim to link the objective measure of indoor air pollution from the micro-sensor to specific behavioural changes.

Heterogeneity. The baseline questionnaire also collected information about the households' socioeconomic and demographic characteristics (age and educational level of the respondent, monthly household income, number of residents), self-reported health status (subjective health status, the presence of a person with respiratory problems in the household, investment in health, the presence of a smoker in the household), environmental beliefs and attitudes and type of wood burning equipment. However, we restricted the heterogeneity analysis to baseline emissions to conform to our pre-analysis plan and avoid multiple hypothesis testing issues. See online appendix for a full list of baseline and endline questions.

Sampling strategy and statistical power

The experiment was presented on a website where applicants could volunteer to install an air quality micro-sensor in their homes for six months and receive information on ways to decrease indoor pollution. Participants who wished to be part of the study were asked to fill out the recruitment survey, which also served as the baseline questionnaire. The call for volunteers was advertised through multiple channels: first, the Regional and Intergovernmental Department of the Environment and Energy passed on our call for volunteers to local communities, authorities and institutions. Second, we emailed a list of households identified as wood burning households by the Agency for the Environment and Energy Management. Finally, we relied on a collaborative network of brands and consumers, 'Wedoolink'. The recruitment campaign took place during the autumn (from September to December). The recruitment stop-date was chosen to allow us to implement our four-month long study during the winter season. The study included 2 weeks of pre-treatment baseline indoor air pollution measurement, 16 weeks of intervention and 2 weeks of post-intervention indoor air pollution measurement. A total of 4,200 people volunteered to take part in the study. Within this sample, 558 people used wood burning, of whom 370 reported using wood burning as an occasional heating method. Only the households that burn wood occasionally were included in the eligible sample, whereas those using wood burning as their only source of heating were excluded. We chose to restrict the study sample to households that burn wood occasionally for two main reasons: first, when a household's main heating source is wood burning, a change in behaviour is constrained by additional barriers, including financial ones; second, the primary aim of the intervention was to limit *avoidable* burning of wood. Due to technical issues related to the strength of the 2G signal, 36 households could not be included because their micro-sensor did not transmit data consistently. We also asked participants to tell us whether they knew people taking part in the study and identified 13 clusters of 'friends'. In order to avoid spillovers, only one individual in each cluster was randomly included in the study. The final sample included 281 households, mostly residents of the Ile-de-France region. We then checked whether that sample was adequate to detect a meaningful effect size. We found that our sample size allowed us to obtain a minimum detectable effect of 41% of a standard deviation of the dependent variable (with type-I error of 20% and type-II of 5%). The minimum detectable effect is large when expressed in per cent of a standard deviation, but we leveraged our stratification strategy based on baseline PM2.5 emissions to get a small standard deviation in the outcome and therefore a reasonable statistical

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power: when we include triplet fixed effects in the model, the standard deviation of the dependent variable is reduced from 7.9 μg/m^3 down to 3.7 μg/m^3, which allowed us to detect a minimum effect of 1.53 μg/m^3 out of a baseline average of 5.4 μg/m^3.

Sample characteristics

Column (1) in Table 1 presents the characteristics of the households at baseline. The sample characteristics are comparable to those of the population of occasional users of wood burning in the Île-de-France region (BVA/ADEME, 2015), which means that it is not representative of the entire French population. Respondents have a mean age of 49 years, they are highly educated (46% have a masters degree or more), and they are of middle-high to high income status (80% earn more than €3400 per month). In the sample, air quality at home is wrongly perceived as being better than air quality in the neighbourhood, which is itself perceived as better than the air quality of the entire Île-de-France region. Regarding wood burning, 55% of respondents believe it to be an important source of outdoor pollution, and 36% list it as an important source of indoor pollution. Half of the households use wood burning more than once a week, 32% use it more than once a month, and 17% use it once a month or less. The baseline picture thus shows large margins of improvement in households' knowledge and behaviour.

Validity of the experiment and estimation method

Validity of the experiment

Balance checks. Table 1 presents balance tests of household characteristics across treatment arms. We found some imbalances in the Environmental Attitudes score and respiratory problems in the household between the *Information* treatment and control groups, the perception of air quality in the region between both treatment groups and the control group, and the type of equipment between the *Information* treatment and control groups as well as between the *Information* and the *Information + Personalised Feedback* treatment groups. We found eight significant differences in means out of a total of 81 tests, which is exactly what we expect under the hypothesis that all groups are drawn from identical underlying distributions and that differences are purely due to chance sampling fluctuations. The balance checks did not reject the assumption that each treatment group is statistically identical to the control group. We ran the analyses both including and excluding these variables as controls and found qualitatively and quantitatively similar estimates across specifications, which suggests that the bias introduced by these baseline differences do not account for our results.

Attrition. There was no attrition for indoor air quality sensor data. Attrition was very small at endline (4.6%) and was evenly distributed across the three groups. A linear probability model regression failed to reject the null hypothesis that the probability of having baseline data was similar between the three groups. Results are shown in the Appendix.

External validity. One limitation of our paper relates to its external validity. We focus on voluntary households and on households who use wood burning as a complementary (and not primary) heating source. Households who volunteer to be part of a study on air pollution are probably more interested in air pollution than the general

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Table 1. Summary statistics and balance check of household characteristics between the three treatment groups

	All *N* = 281	Control *N* = 94	Information *N* = 93	Information + PF *N* = 94	C = I	C = I + PF	I = I + PF
Panel A: Sociodemographic							
Age	48.94(11.7)	47.9(11.5)	48.1(11.4)	51.0(12.1)	0.889	0.072	0.096.
Household size	3.25(1.32)	3.4(1.4)	3.3(1.2)	3.2(1.3)	0.596	0.325	0.625
Education level: Baccalaureate or less	0.1(0.34)	0.2(0.4)	0.1(0.3)	0.1(0.3)	0.141	0.527	0.395
BAC +2 to +4	0.39(0.49)	0.3(0.5)	0.4(0.5)	0.4(0.5)	0.210	0.322	0.787
BA +5 or more	0.46(0.5)	0.5(0.5)	0.5(0.5)	0.5(0.5)	0.947	0.947	0.894
Monthly income (€): Less than 3,400	0.2(0.4)	0.2 (0.4)	0.2 (0.4)	0.2 (0.4)	0.590	0.401	0.169
3,400 to 5,000	0.4(0.48)	0.4 (0.5)	0.3 (0.5)	0.4 (0.5)	0.485	0.954	0.521
More than 5,000	0.3(0.47)	0.3 (0.5)	0.4 (0.5)	0.3 (0.5)	0.259	0.963	0.239
Panel B: Health status and attitudes							
Household with resp. problems	0.27(0.44)	0.34 (0.48)	0.22 (0.41)	0.26 (0.44)	0.056	0.204	0.519
Subjective health status: Bad	0.04 (0.2)	0.04 (0.20)	0.05 (0.23)	0.03 (0.18)	0.722	0.702	0.464
Acceptable	0.27(0.45)	0.34(0.48)	0.26(0.44)	0.22(0.42)	0.221	0.075	0.582
Good	0.59(0.49)	0.52 (0.50)	0.55 (0.50)	0.68 (0.47)	0.712	0.025	0.063
Excellent	0.1(0.3)	0.10 (0.30)	0.14 (0.35)	0.06 (0.25)	0.353	0.422	0.087

(*Continued*)

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Table 1. (*Continued.*)

	All $N = 281$	Control $N = 94$	Information $N = 93$	Information + PF $N = 94$	C = I	C = I + PF	I = I + PF
Investment in health	68.32(15.92)	69.70 (16.12)	66.91 (17.18)	68.11 (14.62)	0.254	0.478	0.610
Ranking of health in priorities	3.38(1.38)	3.20 (1.31)	3.49 (1.31)	3.45 (1.53)	0.125	0.235	0.817
Panel C: Environmentalism							
Environmental attitude	3.68(0.7)	3.57 (0.77)	3.82 (0.63)	3.66 (0.66)	0.016	0.395	0.087
Environmental behaviour	0.59(0.24)	0.57 (0.24)	0.60 (0.26)	0.60 (0.21)	0.451	0.403	1.000
Panel D: Pollution perception							
Pollution health risk perception	68(21)	70.39 (20.47)	67.80 (19.69)	64.86 (22.27)	0.411	0.102	0.376
Wood burning listed as: An outdoor pollution source	0.55(0.5)	0.54 (0.50)	0.49 (0.50)	0.54 (0.50)	0.539	0.953	0.582
An indoor pollution source	0.36(0.5)	0.37 (0.49)	0.32 (0.47)	0.38 (0.49)	0.483	0.984	0.475
Air quality (1–5 score) ..at home	3.8(1.1)	3.84(1.12)	3.68 (1.09)	3.85(1.06)	0.343	0.969	0.315
..in the neighbour-hood	3.6(1.3)	3.73(1.27)	3.46(1.28)	3.67(1.25)	0.164	0.762	0.275

(*Continued*)

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Table 1. (*Continued.*)

	All $N = 281$	Control $N = 94$	Information $N = 93$	Information + PF $N = 94$	C = I	C = I + PF	I = I + PF
..in Île-de-France	2.44(1.2)	2.73(1.32)	2.36(1.14)	2.27(1.16)	0.052	0.019	0.648
Panel E: Wood burning practices							
Frequency of wood burning: More than once a week	0.52(0.5)	0.49 (0.50)	0.57 (0.50)	0.48 (0.50)	0.303	0.885	0.240
More than once a month	0.32(0.47)	0.34 (0.48)	0.29 (0.46)	0.33 (0.47)	0.494	0.878	0.595
Once a month or less	0.17(0.37)	0.17 (0.38)	0.14 (0.35)	0.19 (0.40)	0.589	0.707	0.361
Type of equipment: Open fireplace	0.22(0.42)	0.18 (0.39)	0.32 (0.47)	0.19 (0.39)	0.034	0.944	0.041
Panel F: Indoor Pollution							
Baseline PM2.5	4.96(7.89)	5.41(11.01)	4.67(5.58)	4.82(5.99)	0.520	0.607	0.893

Notes: Data from baseline survey. p-values of pairwise *t*-tests. Mean values are shown and Standard deviation in parentheses. PF = Personalised Feedback

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population. Our sample is also more educated and wealthier than the national average, and exhibits lower levels of indoor air pollution. This may affect treatment effects both upwards or downwards, either because volunteering households might be more willing to change, which would inflate the impact of our intervention, or because they might have already implemented many pollution-reduction strategies, which would decrease the impact of our intervention. This paper can thus pave the way for replications on more representative samples.

Estimation method

Final outcomes

We measured the average treatment effects (ATE) of both interventions on indoor air quality by running the following regression:

$$Y_{i,j,post} = \alpha + \beta T_{1,i} + \gamma T_{2,i} + \theta_j + \epsilon_{i,j} \tag{1}$$

where $Y_{i,j,post}$ represents the outcomes of interest for household i in triplet j, $T_{1,i}$ is a dummy indicating that the household is in the *Information* group, $T_{2,i}$ is a dummy indicating that the household is in the *Information + Personalised Feedback* group, θ_j is a vector of triplet fixed effects aimed at improving the precision of the treatment effect estimators, and $\epsilon_{i,j}$ is the heteroscedasticity robust error term.

To exploit longitudinal variations in indoor PM2.5 levels, we estimated how the treatment effect varied over the three-month intervention period. The permanency of behavioural changes following information campaigns is often questioned, as the effect is expected to be concentrated in the ‘hot phase’ of decision making, the first weeks following the beginning of the intervention, but might then decay as the novelty effect dissipates. By contrast, the intervention could alter beliefs and attitudes and lead to long-lasting behavioural changes. To capture the short-run dynamics of the effect, we interacted both treatment variables $T_{1,i}$ and $T_{2,i}$ with a set of weekly indicator variables W_k, with k denoting the week since the start of the intervention:

$$Y_{i,j,k} = \alpha + \sum_{k=-2}^{11} \beta kT1, iWk + \sum_{k=-2}^{11} \gamma kT2, iWk + \sum_{k=-2}^{11} Wk + \theta_j + \epsilon_{i,j,k} \tag{2}$$

$\epsilon_{i,j,k}$ is clustered at the household level and at the week level, and robust to heteroscedasticity. β_k thus provides the impact of *Information* treatment in week k, while γ_k provides the impact of *Information + Personalised Feedback* in week k.

Heterogenous treatment effects

As intended in the pre-analysis plan, we tested whether treatment effects were different depending on the initial level of PM2.5 emission. On the one hand, people with a high baseline level of PM2.5 may be more likely to respond to the interventions as there is more room for change. On the other hand, their high emission level may reflect constraints that render their beliefs and behaviour more persistent (e.g., less education, lower income or lower level of trust). Theoretically, how the initial level of PM2.5 emission affects treatment effects is thus ambiguous. To test it, we added dummy variables indicating the quartile of baseline PM2.5 level, as well as the interaction between each of these dummies and the treatment variables.

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We also hypothesised that impact might vary as a function of outdoor temperature. While on very cold days, a household has to use wood burning for complementary heating, on warmer days the use of wood burning is more likely to be limited to recreational purposes, leading to a larger margin of improvement. Similarly, ventilation is likely less frequent on cold days, during which people are less inclined to be willing to open their windows. To that end, we used household daily outdoor temperature and interacted the treatment variables with three temperature categories: cold days ($<8^{\circ}$C), moderate days (between 8° and 14°) and warm days ($>14^{\circ}$). Outside local temperature levels were retrieved from the official public administrative institution of meteorology and climatology in France ('Météo France'). The average daily temperature over 24 hours was assigned to each household based on the closest meteorological station available.

Mechanisms

To measure the treatment effects on intermediary outcomes measured in the endline questionnaire (i.e., knowledge about indoor air pollution sources, perceptions of indoor air quality, perceptions of wood burning and health risks, attitudes towards woodburning and self-reported polluting activities), we used an ordinary least squares (OLS) regression without including triplet fixed effect in order to avoid a loss of observations and statistical power due to attrition in the endline questionnaire:

$$Y_{i,post} = \alpha' + \beta' T_{1,i} + \gamma' T_{2,i} + \epsilon'_i \tag{3}$$

Results

Impacts on indoor air quality

Average treatment effect. Table 2 presents the impact of the interventions on indoor air quality. Column (1) shows the ATE estimates on average daily PM2.5 level over the whole post-treatment period using the main specification (equation 1). While the *Information* treatment led to a non-significant 0.19 $\mu g/m^3$ decrease in average daily PM2.5, the *Information* + *Personalised Feedback* treatment induced a significant 1.315 $\mu g/m^3$ decrease in average daily PM2.5 over the post-treatment period, representing a 24% decrease relative to the control group mean. The observed decrease in indoor PM2.5 in the *Information* + *Personalised Feedback* households narrows the gap between households that use wood-burning and households that do not use wood burning at baseline. The average level of indoor PM2.5 in that group (4.2 $\mu g/m^3$) is indeed comparable to that observed among comparable households that do not use wood burning over the same time period (4.3 $\mu g/m^3$). This was robust to the inclusion of controls to correct for baseline imbalances (Column (2)): the reduction in average daily PM2.5 is 0.03 $\mu g/m^3$ (non-significant) for the *Information* treatment and 1.175 (significant at the 1% level) for the *Information* + *Personalised Feedback* treatment. The cost of the *Information* + *Personalised Feedback* treatment is 15 times larger, and its impact 39 times larger, than the *Information* treatment. Based on these estimates, the *Information* treatment appears 2.6 more cost-effective than the *Information* treatment.

Figure 1 provides insights on the dynamics of the impact across time: it displays the ATE estimates interacted with dummies indicating the number of weeks since the first message, after adjustment for triplet and week fixed effects (equation 2).

Table 2. Impacts on indoor air quality measured by average indoor PM2.5 levels

	Dependent variable: Average daily PM2.5 (µg/m^3)	
	(1)	(2)
Information (I)	−0.193 (0.539)	0.033 (0.564
Information + PF (I + PF)	−1.315** (0.536)	−1.175** (0.549)
Mean control group	5.55	5.5
p-value of I = I + PF	0.040**	0.030**
Baseline controls	No	Yes
Observations	280	277
Adjusted R^2	0.725	0.723

Notes: Data from micro-sensors. Column (1) shows estimates from equation 1. Specification in Column (2) includes imbalanced baseline variables as controls: the presence of a household member with respiratory problems, subjective health status, the perceived air quality in the region and wood burning equipment type. Strata fixed effects are used in all regressions. Standard errors (in parentheses) are robust to heteroscedasticity. *Significance at 10% level. **Significance at 5% level. ***Significance at 1% level. PF = Personalised Feedback.

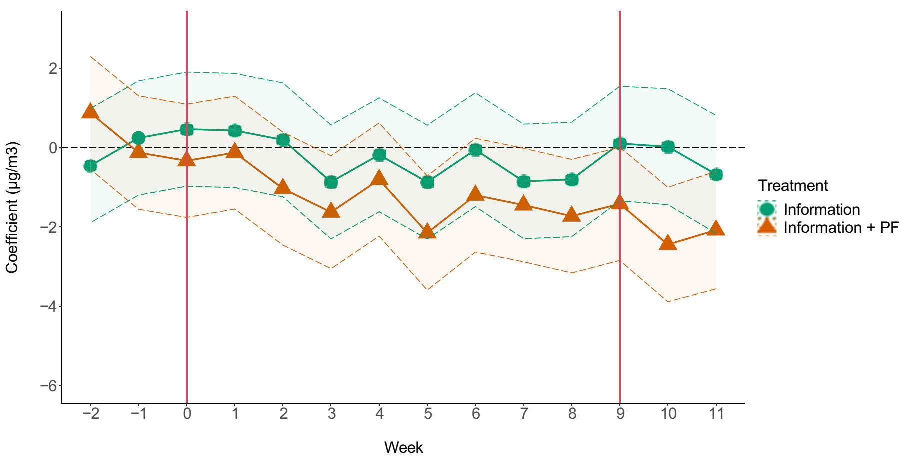

Figure 1. Average treatment effects on indoor daily PM2.5 levels, by week since the first message.
Notes: Confidence intervals are computed at the 95% confidence level. The figure represents the coefficients on the interaction between each intervention dummy and weekly dummies. Triplet and weekly fixed effects are included. Standard errors are clustered at the household and week levels. The two solid vertical lines represent the start and the end of the intervention. Week 0 starts on 6 January 2020, when the first message was sent the participants in the *Information* and *Information + Personalised Feedback* groups. The last message was sent on 9 March 2020, on week 9.

While the households receiving the *Information* treatment show no difference in indoor air quality compared to the control group in any week throughout the whole intervention period, the *Information + Personalised Feedback* intervention started to have an impact on polluting behaviour rather fast: the effect was significant starting the third week after the start of the intervention and persisted throughout weeks 5, 6 and 8 of the intervention, and weeks 10 and 11 after the end of the intervention. There is no noticeable decay of the effect throughout the three months of treatment – if anything

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Table 3. Heterogeneous impacts on indoor air quality measured by average indoor PM2.5 levels, by baseline level of indoor pollution

	Dependent variable: Average daily PM2.5 (μg/m^3)			
	Quartiles of baseline PM2.5 levels			
	Q1 (1)	Q2 (2)	Q3 (3)	Q4 (4)
Information (I)	0.252 (0.304)	−0.010 (0.313)	−0.783* (0.39)	−0.304 (2.046)
Information + PF (I + PF)	0.214 (0.297)	−0.382 (0.313)	−0.410 (0.375)	−4.911** (2.080)
Mean control group	1.90	2.86	4.17	13.49
p-value for I = I + PF	0.90	0.25	0.32	0.03**
Observations	70	71	71	68
Adjusted R^2	−0.12	−0.10	0.06	0.64
	Information		Information + PF	
p-value for Q1 = Q2	0.86		0.69	
p-value for Q1 = Q3	0.49		0.67	
p-value for Q1 = Q4	0.71		0.00**	
p-value for Q2 = Q3	0.59		0.98	
p-value for Q2 = Q4	0.84		0.00**	
p-value for Q3 = Q4	0.74		0.00**	

Notes: Data from micro-sensors. Columns (1) to (4) show the treatment effect from equation 1 estimated in subsamples of households in the 4 quartiles of baseline PM2.5 levels. The bottom panel shows the p-values of the difference in treatment effects between each pair of quartiles, derived from interactions between each of the quartile dummies and the treatment dummies. Strata fixed effects are used in all regressions. Standard errors (in parentheses) are robust to heteroscedasticity. *Significance at 10% level. **Significance at 5% level. ***Significance at 1% level. PF = Personalised Feedback.

rather an amplification, indicating that there was no habituation effect to the messages or to the micro-sensor.

Heterogeneous effects. We found that the households that were more polluted at baseline were the only group affected by the *Information + Personalised Feedback* intervention. Table 3 shows the treatment effect by quartile of baseline PM2.5 concentration. The treatment effect of the *Information + Personalised Feedback* intervention was concentrated in households in the 4th quartile of baseline PM2.5 concentration, i.e., the highest polluters. In that group, the *Information + Personalised Feedback* intervention decreased indoor PM2.5 levels by 4.9 μg/m^3, a 36% decrease compared to the control group mean, significant at the 5% level. These households are less affluent, and reported the presence of a smoker and using wood burning equipment more frequently (see Appendix). Households in the third quartile receiving the *Information* treatment decrease their indoor pollution by 18% (−0.78 μg/m^3). This decrease is significant at the 10% level and much smaller in absolute size. Finally, the effect was not significantly different from 0 in the households with the best indoor air quality, which indicates that the boomerang effect found in other normative feedback experiments, which leads households that are better than average to pollute more, was not found here

(Ayres *et al.*, 2013). Our finding that the impact concentrates on more at-risk households is in line with other personalised feedback and social comparison interventions (Allcott, 2011; Ferraro *et al.*, 2013).

Figure 2 shows the dynamics of the treatment effect (equation 2) by quartile of baseline indoor pollution level. Regarding households exposed to the *Information* treatment, there was no significant difference relative to the control group for any quartile of baseline level of pollution. In contrast, regarding households exposed to the *Information + Personalised Feedback* intervention, the treatment effect is significant for the highest quartile of baseline indoor pollution every week starting the second week after the reception of the first leaflet. The difference in the effect between cold, moderate and warm days is not statistically significant (Table 4).

Number of days over the WHO 24-hour guideline. Another outcome of interest is the number of days a household was exposed to extremely dangerous levels of pollutants. The WHO guidelines on PM2.5 24-hour exposure is 25 μg/m^3 not to be exceeded more than three days a year.

Table 5 reports the ATE of the interventions on the number of days exceeding this threshold over the study period, i.e., 77 days. Note that in the control group, the average number of days above the threshold was 2.9 days over four months only, thus well above the WHO recommendation. There was no impact of the *Information* treatment, which confirms that this intervention was insufficient to induce a change in behaviour. In contrast, the *Information + Personalised Feedback* treatment reduced the number of days exceeding the WHO threshold by 1.44 days, a 50% decrease compared to the control group mean, significant at the 10% level (Table 5, Column (1)). The effect is greatly heterogeneous as it concentrates only on the most polluted households (fourth quartile of baseline PM2.5 concentration): for these households, the *Information + Personalised Feedback* treatment induced a decrease of days above the WHO threshold from 12.4 days down to 5.9 days over a period of four months, a change significant at the 5% level (Table 5, Column (5)). For the other less polluted households, the number of days above the WHO threshold was already very small and in line with WHO recommendations (0.12–0.57 days over four months on average), and we see no impact of the treatments. Overall, our data show that the households who responded to and benefited from the intervention were those who needed it the most.

Magnitude of the effects and health impacts. The magnitude of the effect of the *Information + Personalised Feedback* intervention is sizeable. From a public health perspective, a decrease of 1.315 μg/m^3 in average exposure to PM2.5 is noteworthy. In fact, studies have shown that an increase in exposure of as little as 1 μg/m^3 can have serious health consequences. For instance, an increase of 1 μg/m^3 in PM2.5 was associated with a dementia incidence of a 1.55 hazard ratio (Oudin *et al.*, 2018) and an 11% increase in COVID-19 mortality rates (Wu *et al.*, 2020). A review on Medicare patients in the U.S. showed that an increase in short-term exposure to PM2.5 of 1 μg/m^3 is associated with an annual increase of 3,642 hospital admissions, 20,000 extra hospitalisation days and almost $70 m in care cost at the country level (Wei *et al.*, 2019). The sanitary impacts are even more important for the most polluted households where the *Information + Personalised Feedback* intervention led to a decrease in average daily PM2.5 levels of 4.9 μg/m^3. In fact, an improvement in PM2.5 exposure of 5 μg/m^3 is associated with a 16% decreased incidence of hypertension and the total annual

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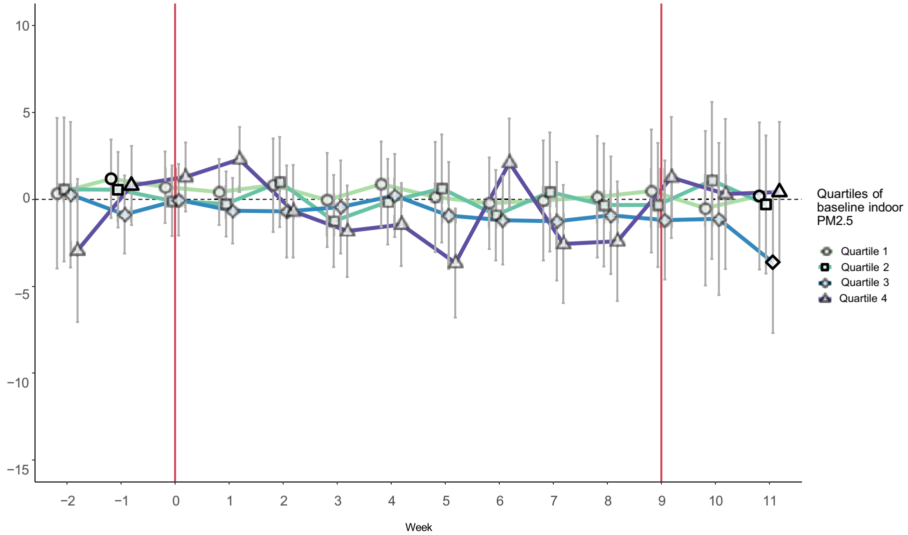
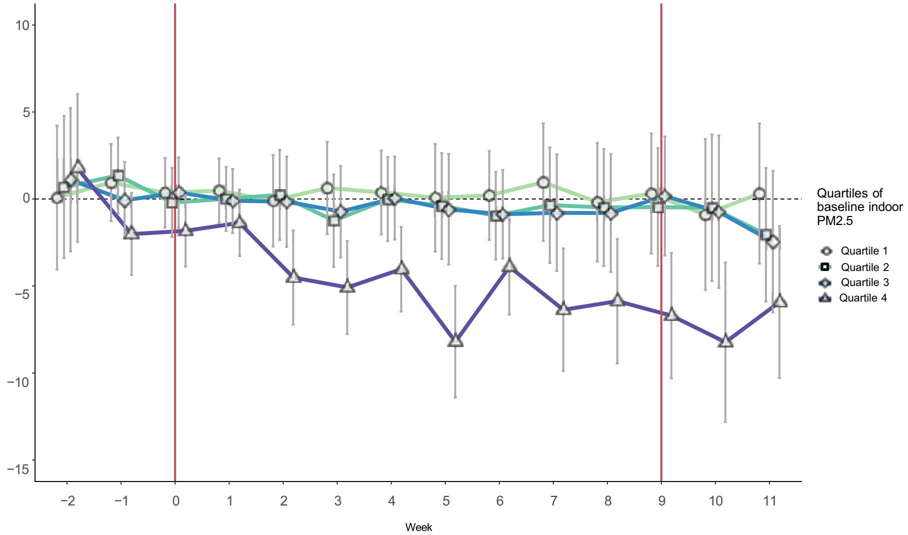


(a) *Information* treatment



(b) *Information* + *Personalised Feedback* treatment

Figure 2. Average treatment effect on indoor PM2.5 levels, by week and quartile of baseline PM2.5. *Notes*: Confidence intervals are computed at the 95% confidence level. The figure represents the coefficients on the interaction between each intervention dummy and weekly dummies. Triplet and weekly fixed effects are included. Standard errors are clustered at the household and week levels. The two solid vertical lines represent the start and the end of the intervention. Week 0 starts on 6 January 2020, when the first message was sent the participants in the *Information* and *Information* + *Personalised Feedback*. The last message was sent on the 9th of March 2020, on week 9.

economic benefits of decrease of ambient air pollution by 5 μg/m^3 in Paris is estimated to be around €3.6 billion, including reductions in health spending, productivity loss and immaterial costs namely quality of life and life-expectancy (Pascal *et al.*, 2013).

Table 4. Heterogeneous impacts on indoor air quality measured by average indoor PM2.5 levels, by outside temperature

	Dependent variable: daily PM2.5 ($\mu g/m^3$)		
	Cold days *temperature* < 8°C (1)	Moderate days 8°C < *temperature* < 14°C (2)	Warm days *temperature* > 14°C (3)
Information (I)	0.010 (0.388)	−0.043 (0.507)	0.385 (0.661)
Information + PF (I + PF)	−0.738** (0.368)	−1.304*** (0.452)	−0.760 (0.511)
Mean control group	5.05	5.15	4.60
p-value for I = I + PF	0.03**	0.01**	0.14
Observations	10,338	5,647	789
Adjusted R^2	0.423	0.497	0.546
	Information	Information + PF	
p-value for Cold = Moderate	0.84	0.19	
p-value for Cold = Warm	0.88	0.68	
p-value for Moderate = Warm	0.65	0.57	

Notes: Data from micro-sensors and Météo France. Columns (1)–(3) show the treatment effects using daily PM2.5 household-level data, restricting the observations to days in which a household recorded an outside temperature smaller than 8°C, between 8°C and 14°C and above 14°C, respectively. The bottom panel shows the p-values of the difference of treatment effects between each pair of temperature levels; the p-values shown estimates shown are derived from an interaction between each of the temperature dummies and the treatment dummies. Strata and region fixed effects are included. Standard errors (in parentheses) are robust to heteroscedasticity and clustered at the household and day level. *Significance at 10% level. **Significance at 5% level. ***Significance at 1% level. PF = Personalised Feedback.

Mechanisms

Knowledge about indoor PM2.5 sources. The interventions provided information on the different sources of PM2.5. Table 6 displays treatment impact on the probability of correctly citing different indoor PM2.5 emitting sources. Both treatments led to an important increase in the probability of reporting wood burning and cigarette smoking as a main source of indoor PM2.5; households that received the *Information + Personalised Feedback* were 50% and 136% more likely to cite wood burning and cigarette smoking compared to the control group. The *Information* treatment led to a similar increase in the reporting of wood burning as a main source of PM2.5, and an increase of 100% when it comes to cigarettes, though only significant at the 10% level. Conversely, neither the *Information* nor the *Information + Personalised Feedback* increased the probability of citing candles, incense and cooking as major indoor PM2.5 sources. This absence of impact was not explained by perfect knowledge of these combustion activities as major sources of pollution, as less than only 4–9% of households mention candles, incense and cooking in the control group. Awareness of

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Table 5. Impacts on the number of days that exceed the WHO 24-hour guideline, full sample and by baseline level of indoor pollution

	Dependent variable: Number of days exceeding 24hr WHO PM2.5 limit				
		Quartiles of baseline PM2.5 levels			
	Full sample (1)	Q1 (2)	Q2 (3)	Q3 (4)	Q4 (5)
Information (I)	0.401 (0.800)	0.045 (0.237)	0.259 (0.210)	0.01 (0.271)	1.304 (3.143)
Information + PF (I + PF)	−1.440* (0.799)	0.088 (0.237)	0.081 (0.210)	0.130 (0.271)	−6.461** (3.197)
Mean control group	2.91	0.17	0.12	0.57	12.39
p-value for I = I + PF	0.02**	0.85	0.41	0.63	0.02**
Observations	281	71	71	71	68
Adjusted R^2	0.702	−0.116	−0.159	0.063	0.658
	Information		Information + PF		
p-value for Q1 = Q2	0.92		0.99		
p-value for Q1 = Q3	0.98		0.98		
p-value for Q1 = Q4	0.57		0.00***		
p-value for Q2 = Q3	0.90		0.98		
p-value for Q2 = Q4	0.63		0.00***		
p-value for Q3 = Q4	0.55		0.00***		

Notes: Data from micro-sensors. The estimates depict the treatment effects measured using equation 1 on the number of days a household records PM2.5 levels higher than the 25 $\mu g/m^3$ recommended by the WHO, not to be exceeded more than three days a year. Column (1) presents the estimates in the full sample while Columns (2) to (5) present the estimates in subsamples of households in the four quartiles of baseline PM2.5 levels. Strata fixed effects are used in all specifications. Standard errors (in parentheses) are robust to heteroscedasticity. *Significance at 10% level. **Significance at 5% level. ***Significance at 1% level. PF = Personalised Feedback.

the risks associated with wood burning and smoking were already more salient and further increased thanks to the intervention.

Perception of indoor air quality. Even though knowledge of polluting activities increased following both interventions, perceived indoor air quality decreased only in the *Information* + *Personalised Feedback* group. The top panel of Table 7 details the ATE of both interventions on participants' perceived air quality at home, in their neighbourhood and in their region, while the bottom four panels show the treatment effect by quartile of baseline PM2.5. While the *Information* treatment led to a non-significant decrease in average perceived air quality at home, the *Information* + *Personalised Feedback* treatment induced a significant 9% decrease in perceived home air quality relative to the control group mean. Heterogeneous effects reveal that the effect is concentrated in the most polluted households, where the *Information* + *Personalised Feedback* treatment induced a significant 23% decrease in perceived home air quality relative to the control group mean. We also see a non-significant increase in perceived household indoor air quality among the least polluting households. Providing households with their actual levels of indoor PM2.5 increases awareness about own polluting

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Table 6. Impacts on knowledge of indoor PM2.5 sources

	Dependent variable: Mentioned ... as indoor polluting source (0/1)				
	wood burning (1)	cigarettes (2)	candles (3)	Incense (4)	cooking (5)
Information (I)	0.276*** (0.078)	0.121* (0.066)	0.062 (0.053)	0.017 (0.045)	0.030 (0.039)
Information + PF (I + PF)	0.215*** (0.078)	0.160** (0.066)	−0.006 (0.054)	0.006 (0.046)	0.0004 (0.040)
Mean control group	0.458	0.117	0.088	0.058	0.044
p-value of I = I + PF	0.43	0.55	0.21	0.812	0.45
Observations	202	202	202	202	202
Adjusted R^2	0.098	0.097	0.011	0.061	−0.010

Notes: Data from baseline and endline survey. All estimates are derived from OLS regressions (equation 3). Controls for baseline response are included in all regressions. Question: 'Are you aware of any sources of indoor air pollution in your home or in others? If so, please give one to three examples'. Standard errors (in parentheses) are robust to heteroscedasticity. *Significance at 10% level. **Significance at 5% level. ***Significance at 1% level. PF = Personalised Feedback.

activities and leads households to correctly update their perception of indoor air quality. This in turn could decrease salience and optimism biases, since individuals are less likely to underestimate their own exposure and its resulting health impacts.

Perceptions of wood burning and health risks. The intervention provided information on the health and environmental risks of PM2.5 emissions with an important focus on wood burning. The top panel of Table 8 details the ATE of both interventions on beliefs, knowledge and attitudes towards wood burning, while the bottom four panels show the treatment effect by quartile of baseline PM2.5. Neither the *Information* nor the *Information + Personalised Feedback* interventions had an impact on the perception of the health risks associated with air pollution (Column (1)). In contrast, both interventions increased the perceived negative impact of wood burning on indoor air quality, by 6 points (on a score from 0 to 100) in the *Information* group (significant at the 10% level), and by 9 points in the *Information + Personalised Feedback* group (significant at the 1% level), off a base score of perceived risk of 60 in the control group. This effect was concentrated on the most polluted households (fourth quartile), whose baseline perceived risk of wood burning was lower (the control group mean is 53 in the fourth quartile vs 59, 65 and 61 in the other quartiles) and was almost twice as big (p-value = 0.05) for the *Information + Personalised Feedback* treatment (20-point increase, significant at the 1% level) as for the *Information* treatment (12-point increase, significant at the 5% level). Providing the household with direct information about their indoor PM2.5 profile thus decreased disbelief in the information and reinforced the overall credibility of the generic messages more in households where pollution is high.

The belief that wood burning is a major source of outdoor pollution also increased in both treatment groups (Column (3)): while 45% of households in the control group believed that wood burning is a major source of outdoor pollution, the intervention increased that proportion by 18.7 percentage points in the *Information* group

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Table 7. Impact on perceived air quality at home, in the neighborhood and in the region

	Dependent variable: Perceived air quality		
	(1) ... in own home (0 − 6)	(2) ... in neighbourhood (0–6)	(3) ... in region (0–6)
Full sample			
Information (I)	−0.097 (0.179)	−0.199 (0.201)	0.122 (0.197)
Information + PF (I + PF)	−0.362** (0.171)	−0.355* (0.194)	0.029 (0.190)
Mean control group	3.98	3.87	2.77
p-value of I = I + PF	0.590	0.320	0.890
Observations	276	283	282
Quartile 1			
Information (I)	0.217 (0.315)	0.132 (0.340)	0.802** (0.333)
Information + PF (I + PF)	0.347 (0.319)	0.038 (0.336)	0.455 (0.333)
Mean control group	4.00	4.04	2.70
p-value of I = I + PF	0.490	0.700	0.020
Observations	64	68	68
Quartile 2			
Information (I)	−0.026 (0.335)	−0.174 (0.414)	−0.153 (0.418)
Information + PF (I + PF)	−0.521 (0.325)	−0.325 (0.404)	−0.223 (0.408)
Mean control group	4.24	3.96	2.92
p-value of I = I + PF	0.940	0.680	0.720
Observations	68	69	69
Quartile 3			
Information (I)	−0.461 (0.348)	−0.562 (0.410)	0.123 (0.392)
Information + PF (I + PF)	−0.099 (0.346)	−0.028 (0.412)	0.143 (0.409)
Mean control group	3.95	3.64	2.59
p-value of I = I + PF	0.190	0.180	0.980
Observations	67	69	68
Quartile 4			
Information (I)	−0.039 (0.370)	−0.112 (0.359)	−0.027 (0.384)

(*Continued*)

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Table 7. (*Continued.*)

	Dependent variable: Perceived air quality		
	(1) … in own home (0 – 6)	(2) … in neighbourhood (0–6)	(3) … in region (0–6)
Information + PF (I + PF)	−0.828** (0.339)	−1.035*** (0.329)	−0.021 (0.353)
Mean control group	3.65	3.80	2.85
p-value of I = I + PF	0.920	0.760	0.940
Observations	77	77	77

Notes: Data from baseline and endline survey. All estimates are derived from OLS regressions (equation 3). Controls for baseline response are included in all regressions. Question: 'How do you evaluate the quality of air … in your home / neighbourhood / region?'. Standard errors (in parentheses) are robust to heteroscedasticity. *Significance at 10% level. **Significance at 5% level. ***Significance at 1% level. PF = Personalised Feedback.

and by 14.3 percentage points in the *Information + Personalised Feedback* group. The leaflet also provided information on how to decrease PM2.5 in general and good practices to decrease emissions from wood burning in particular. Column (4) in Table 8 presents the impact of the interventions on the proportion of households mentioning one good practice for more efficient wood burning. While 67% of households in the control group name at least one good wood burning practice, this proportion increased by 13 percentage points in both treatment groups – significant at the 10% level. The effect was larger in less polluted households (quartiles 1 and 2 of baseline PM2.5), which may be related to lower baseline knowledge of good practices, especially in quartile 2.

The intervention had no significant impact on households' attitude towards wood burning regulation, the pleasure felt when lighting a fire or the intention to change wood burning equipment (Columns (5)–(7)). Overall, these results show that both interventions improved awareness of the role of wood burning in generating PM2.5 pollution and good practices to reduce pollution. These positive effects were not restricted to a particular group of households, although some effects were particularly pronounced for most polluted households in the *Information + Personalised Feedback* group.

Self-reported polluting activities.

Wood burning. We asked households about the frequency of use of wood burning this past winter, and their intended frequency of use in the future (next winter). Table 9 shows the results of the declared frequency of use regressed on the two treatment dummies, controlling for baseline frequency. We found no difference in the frequency of use of wood burning throughout the treatment period. However, both treated groups reported that they intended to decrease wood burning in the future. Compared to the control group, households exposed to *Information* or *Information + Personalised Feedback* were 12 percentage points less likely to declare that they intended to use wood burning 'Once a week or more' next winter (a 28% decrease from 49%, significant at the 1% level). This effect seems to concentrate in households in the 2nd quartile of baseline

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Table 8. Impacts on beliefs, knowledge and attitudes towards wood burning and indoor pollution, full sample and by baseline level of indoor pollution:

	Dependent variable						
	(1) Impact of pollution on health (0–100)	(2) Impact of wood burning on indoor pollution (0–100)	(3) Wood burning is a source of outdoor pollution (0/1)	(4) Good practices knowledge (0/1)	(5) Attitude towards wood burning regulation (1–5)	(6) Pleasure derived from wood burning (1–10)	(7) Equipment change intention (0/1)
Full sample							
Information (I)	0.208	6.169*	0.187***	0.125*	0.226	−0.068	−0.011
	(2.795)	(3.142)	(0.070)	(0.066)	(0.182)	(0.274)	(0.061)
Information + PF (I + PF)	3.785	9.079***	0.143**	0.129*	0.187	−0.140	−0.049
	(2.802)	(3.142)	(0.070)	(0.067)	(0.181)	(0.273)	(0.061)
Mean control group	65.61	60.00	0.47	0.67	3.3	7.64	0.22
p-value of I = I + PF	0.200	0.360	0.450	0.970	0.840	0.810	0.350
Observations	271	271	271	271	271	271	271
Adjusted R^2	0.268	0.028	0.129	0.012	−0.006	−0.093	−0.001
Quartile 1							
Information	−6.599	5.60	0.253*	0.218*	0.020	−0.642	−0.077
	(5.530)	(4.6)	(0.131)	(0.128)	(0.333)	(0.557)	(0.125)
Information + PF	3.435	6.13	0.158	0.091	0.043	−0.087	−0.174

(*Continued*)

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Table 8. (*Continued.*)

	Dependent variable						
	(1) Impact of pollution on health (0–100)	(2) Impact of wood burning on indoor pollution (0–100)	(3) Wood burning is a source of outdoor pollution (0/1)	(4) Good practices knowledge (0/1)	(5) Attitude towards wood burning regulation (1–5)	(6) Pleasure derived from wood burning (1–10)	(7) Equipment change intention (0/1)
	(5.484)	(6.6)	(0.130)	(0.125)	(0.329)	(0.550)	(0.123)
Mean Control Group	65.52	59.30	0.48	0.68	3.43	7.87	0.30
p-value of I = I + PF	0.240	0.400	0.060	0.090	0.950	0.260	0.540
Quartile 2							
Information	1.076	−2.251	0.264*	0.217*	0.434	−0.050	0.126
	(6.204)	(6.358)	(0.145)	(0.129)	(0.366)	(0.499)	(0.107)
Information + PF	1.714	5.233	0.099	0.232*	0.242	0.195	−0.117
	(5.964)	(6.206)	(0.141)	(0.125)	(0.358)	(0.487)	(0.104)
Mean control group	67.52	64.68	0.44	0.625	3.28	7.24	0.16
p-value of I = I + PF	0.860	0.720	0.070	0.100	0.240	0.260	0.240
Quartile 3							
Information	8.820*	10.121	0.101	0.072	0.564*	0.189	−0.102
	(4.815)	(6.273)	(0.148)	(0.140)	(0.306)	(0.523)	(0.122)

(*Continued*)

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Table 8. (*Continued.*)

	Dependent variable						
	(1) Impact of pollution on health (0–100)	(2) Impact of wood burning on indoor pollution (0–100)	(3) Wood burning is a source of outdoor pollution (0/1)	(4) Good practices knowledge (0/1)	(5) Attitude towards wood burning regulation (1–5)	(6) Pleasure derived from wood burning (1–10)	(7) Equipment change intention (0/1)
Information + PF	9.627*	7.824	0.014	0.048	0.121	−0.032	0.077
	(4.925)	(6.338)	(0.147)	(0.143)	(0.309)	(0.528)	(0.124)
Mean control group	63.50	61.05	0.59	0.67	3.23	7.73	0.23
p-value of I = I + PF	0.070	0.110	0.500	0.610	0.070	0.260	0.410
Quartile 4							
Information	−2.297	11.745**	0.129	−0.008	−0.159	0.018	0.027
	(5.959)	(5.866)	(0.139)	(0.138)	(0.370)	(0.692)	(0.122)
Information + PF	−2.848	20.243***	0.253*	0.135	0.141	−0.843	−0.070
	(5.902)	(5.805)	(0.138)	(0.138)	(0.366)	(0.685)	(0.121)

(*Continued*)

Table 8. (*Continued.*)

	Dependent variable						
	(1) Impact of pollution on health (0–100)	(2) Impact of wood burning on indoor pollution (0–100)	(3) Wood burning is a source of outdoor pollution (0/1)	(4) Good practices knowledge (0/1)	(5) Attitude towards wood burning regulation (1–5)	(6) Pleasure derived from wood burning (1–10)	(7) Equipment change intention (0/1)
Mean control group	65.65	53.80	0.35	0.72	3.25	7.80	0.20
p-value of I = I + PF	0.700	0.050	0.360	0.950	0.670	0.260	0.820
Observations	69	69	69	65	69	69	69

Notes: Data from endline survey. All estimates are derived from OLS regressions (equation 3). Controls for baseline levels are included in columns (1) and (3). The impact of pollution on health and of wood burning on indoor air pollution (columns (1) & (2)) were measured on a scale from 0 – 'Not at all impactful' to 100 – 'Extremely impactful'. Column (3) shows the treatment effect on the probability of mentioning woodburning as an outdoor source of pollution and column (4) the probability of mentioning at least one good practice in wood burning management. Respondent's attitudes towards wood burning policy (column (5)) is measured using a score from 1 – 'Not at all in favour' to 5 – 'Completely in favour', while the pleasure derived from lighting a fireplace (column (6)) is measured on a scale from 0 – 'No pleasure' to 10 – 'A lot of pleasure'. The upper panel shows treatment effects estimated on the full sample, while the bottom 4 panels show the estimates on subsamples of quartiles of baseline PM2.5. Standard errors (in parentheses) are robust to heteroscedasticity. *Significance at 10% level. **Significance at 5% level. ***Significance at 1% level. PF = Personalised Feedback.

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Table 9. Impacts on declared use of wood burning and intention of future use, full sample and by baseline level of indoor pollution

	Past winter			Declared frequency of wood burning			
	(1) Once a month or less	(2) More than once a month	(3) Once a week or more	(4) Never	(5) Once a month or less	(6) More than once a month	(7) Once a week or more
Full sample							
Information (I)	0.036	0.043	−0.082	0.012	0.089	0.020	−0.138**
	(0.053)	(0.065)	(0.057)	(0.039)	(0.056)	(0.066)	(0.056)
Information + PF (I + PF)	−0.010	0.066	−0.062	0.034	0.035	0.066	−0.140**
	(0.053)	(0.064)	(0.057)	(0.039)	(0.056)	(0.066)	(0.056)
Mean control group	0.170	0.340	0.490	0.060	0.160	0.300	0.490
p-value of I = I + PF	0.390	0.720	0.730	0.630	0.490	0.970	0.340
Observations	267	267	267	268	267	267	267
Adjusted R^2	0.388	0.130	0.410	−0.004	0.092	0.122	0.428
Quartile 1							
Information	0.012	−0.002	−0.053	0.012	0.082	−0.014	−0.097
	(0.091)	(0.127)	(0.108)	(0.038)	(0.123)	(0.140)	(0.106)
Information + PF	0.050	0.016	−0.100	0.031	0.074	0.048	−0.187*
	(0.090)	(0.125)	(0.107)	(0.038)	(0.122)	(0.138)	(0.105)

(*Continued*)

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Table 9. (*Continued.*)

	Past winter			Declared frequency of wood burning			
	(1) Once a month or less	(2) More than once a month	(3) Once a week or more	(4) Never	(5) Once a month or less	(6) More than once a month	(7) Once a week or more
Mean control group	0.30	0.35	0.35	0.17	0.39	0.39	0.17
p-value of I = I + PF	0.680	0.890	0.670	0.950	0.660	0.400	0.950
Observations	68	68	68	271	68	68	68
Quartile 2							
Information	0.027	0.102	−0.160	0.095	0.196*	−0.026	−0.247**
	(0.114)	(0.138)	(0.105)	(0.061)	(0.111)	(0.140)	(0.110)
Information + PF	−0.025	0.318**	−0.275***	0.043	0.084	0.150	−0.269**
	(0.111)	(0.133)	(0.101)	(0.059)	(0.108)	(0.135)	(0.106)
Mean control group	0.28	0.28	0.44	0.16	0.36	0.48	0.16
p-value of I = I + PF	0.660	0.130	0.290	0.330	0.220	0.850	0.330
Quartile 3							
Information	0.176	0.098	−0.178	0.034	0.083	0.087	−0.181
	(0.117)	(0.128)	(0.113)	(0.105)	(0.125)	(0.127)	(0.111)
Information + PF	0.011	0.033	−0.040	0.126	0.023	0.030	−0.126

(*Continued*)

Table 9. (*Continued.*)

	Past winter			Declared frequency of wood burning			
	(1) Once a month or less	(2) More than once a month	(3) Once a week or more	(4) Never	(5) Once a month or less	(6) More than once a month	(7) Once a week or more
	(0.118)	(0.128)	(0.115)	(0.106)	(0.126)	(0.127)	(0.113)
Mean control group	0.32	0.18	0.50	0.18	0.18	0.55	0.18
p-value of I = I + PF	0.160	0.610	0.220	0.630	0.650	0.620	0.630
Quartile 4							
Information	−0.121	0.033	0.077	−0.100*	−0.013	0.083	−0.029
	(0.097)	(0.114)	(0.122)	(0.053)	(0.083)	(0.120)	(0.120)
Information + PF	−0.109	−0.104	0.209*	−0.100*	−0.008	0.032	0.064
	(0.094)	(0.112)	(0.119)	(0.052)	(0.080)	(0.119)	(0.117)
Mean control group	0.25	0.30	0.45	0.10	0.25	0.55	0.10
p-value of I = I + PF	0.160	0.610	0.220	0.630	0.650	0.620	0.630

Notes: Data from endline survey. All estimates are derived from OLS regressions (equation 3) on the declared frequency of use of wood burning equipment the past winter (columns (1)–(3)) and the intention of use next winter (columns (4)–(7)). The responses of the categorical variable were turned into dummy variables and used as the outcome variables in separate regressions. For all regressions, declared baseline response is added as control. The upper panel shows treatment effects estimated on the full sample, while the bottom 4 panels show the estimates on subsamples of quartiles of baseline PM2.5. Standard errors (in parentheses) are robust to heteroscedasticity. *Significance at 10% level. **Significance at 5% level. ***Significance at 1% level. PF = Personalised Feedback.

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Table 10. Impacts on the frequency of wood burning and other polluting activity in the last week

	Dependent variable: declared weekly frequency of						
	(1) wood burning	(2) cigarette	(3) e-cigarette	(4) candles	(5) incense	(6) dusting	(7) Polluting activity
Information (I)	−0.095	0.542	0.711	0.109	−0.042	0.043	1.271
	(0.371)	(0.625)	(0.643)	(0.135)	(0.235)	(0.283)	(1.150)
Information + PF (I + PF)	0.141	−0.124	−0.128	−0.011	0.048	−0.024	−0.106
	(0.371)	(0.621)	(0.639)	(0.135)	(0.235)	(0.283)	(1.144)
Mean control group	1.59	0.60	0.62	0.33	0.30	1.82	5.30
p-value of I = I + PF	0.530	0.290	0.190	0.370	0.700	0.810	0.230
Observations	268	265	266	265	268	268	261
Adjusted R^2	−0.006	−0.003	−0.0001	−0.004	−0.007	−0.007	−0.001

Notes: Data from endline survey. All estimates are derived from OLS regressions (equation 3). Question: 'In the last week, How many times inside your dwelling has someone … burned wood/smoked a cigarette/smoked an e-cigarette/lit a candle/lit incents/dusted'. Polluting activity (column (7)) designates the number of times a household engaged in *any* of the mentioned polluting behaviours over the past week. Standard errors (in parentheses) are robust to heteroscedasticity. *Significance at 10% level. **Significance at 5% level. ***Significance at 1% level. PF = Personalised Feedback.

indoor pollution. In the endline questionnaire, we also asked 'How many times in the last week have you used wood burning?'. The treatment effects on this variable is shown in Column (1) of Table 10.

Other activities. The declared frequency of other PM2.5 emitting activities did not differ significantly between the three groups. Households receiving weekly messages were not different from the control households in their declared frequency of use of electronic and tobacco cigarettes, candles, incense or dusting (Table 10). Similarly, we found no significant change in the declared frequency of activities that improve indoor air quality (Table 11). Similarly, we found no change on the extensive margin of polluting and air quality enhancing activities (Tables 12 and 13).

Interpretation. Self-reported polluting activities over the intervention period were not affected by any intervention. This result is at odds with PM2.5 micro-sensor data showing a significant reduction in pollution in the *Information + Personalised Feedback* group. The discrepancy between objective PM2.5 measures and self-declared polluting activities may be due to the fact that households may not report their behaviour accurately, maybe because of memory issues or social desirability biases. Alternatively, our questions were not precise enough to capture the changes in behaviour. We also found that self-reported frequency of polluting or air quality improving activities did not predict levels of PM2.5 (see Appendix). A third interpretation is that the decrease in indoor PM2.5 levels is not associated with a decrease in wood burning, a better management of firewood or a decrease in indoor smoking, incense and candle, but to better ventilation and wood burning management. Although we observe that the frequency of ventilation has not changed between following the treatment, it is possible that treated households ventilate for a longer or at more appropriate times. Overall, these results

Table 11. Impacts on the frequency of air quality improving activities in the last week

	Dependent variable: declared weekly frequency of	
	Using the ventilation hood (1)	Opening windows (2)
Information (I)	0.160 (0.715)	0.173 (0.486)
Information + PF (I + PF)	−0.277(0.709)	−0.362(0.481)
Mean control group	4.25	6.6
p-value of I = I + PF	0.539	0.270
Observations	271	270
Adjusted R^2	−0.006	−0.003

Notes: Data from endline survey. All estimates are derived from OLS regressions (equation 3). Question 'n the last week, How many times inside your dwelling has someone … used the ventilation hood/Opened the windows for aeration'. Standard errors (in parentheses) are robust to heteroscedasticity. *Significance at 10% level. **Significance at 5% level. ***Significance at 1% level. PF = Personalised Feedback.

Table 12. Impacts on the incidence of wood burning and other polluting activity in the last week

	Dependent variable: declared weekly incidence of					
Polluting activity	wood burning (1)	cigarette (2)	e-cigarette (3)	candles (4)	incense (5)	dusting (6)
Information (I)	−0.073 (0.075)	−0.010 (0.036)	−0.009 (0.038)	0.023 (0.043)	−0.025 (0.063)	0.020 (0.054)
Information + PF (I + PF)	−0.043 (0.074)	−0.013 (0.035)	−0.023 (0.037)	0.020 (0.043)	−0.075 (0.063)	0.047 (0.054)
Mean control group	0.50	0.07	0.08	0.26	0.08	0.82
p-value of I = I + PF	0.690	0.930	0.700	0.430	0.940	0.620
Observations	271	268	269	271	268	271
Adjusted R^2	−0.004	−0.007	−0.006	−0.006	−0.002	−0.005

Notes: Data from endline survey. All estimates are derived from OLS regressions (equation 3). Question: 'In the last week, How many times inside your dwelling has someone … burned wood/smoked a cigarette/smoked an e-cigarette/lit a candle/lit incense/dusted'. The dependent variable measures the incidence of polluting activity and is an indicator variable that takes the value 1 if the household declared undertaking the activity at least once in the past week. Standard errors (in parentheses) are robust to heteroscedasticity. *Significance at 10% level. **Significance at 5% level. ***Significance at 1% level. PF = Personalised Feedback.

highlight the importance of collecting objective, non–self-declared measures in impact evaluations.

Discussion

We conducted a randomised field experiment among occasional wood burning households to test the effectiveness of generic vs personalised information in decreasing indoor air pollution. We used the difference in the level of PM2.5 inside the home as an objective proxy of household air polluting behaviour. Our results suggest that information about the health risks associated with combustion activities combined

Table 13. Impacts on the incidence of air quality improving activities in the last week

	Dependent variable: declared weekly incidence of	
	Using the ventilation hood (1)	Opening windows (2)
	Dependent variable	
	Using the ventilation hood (1)	Opening windows (2)
Information (I)	0.019 (0.067)	0.011 (0.016)
Information + PF	0.017 (0.067)	−0.011 (0.016)
Mean control group	0.71	0.99
p-value I = I + PF	0.980	0.170
Observations	271	270
Adjusted R^2	−0.007	−0.0003

Notes: Data from endline survey. All estimates are derived from OLS regressions (equation 3). Question: 'In the last week, How many times inside your dwelling has someone … used the ventilation hood/Opened the windows for aeration'. The dependent variable measures the incidence of polluting activity and is an indicator variable that takes the value 1 if the household declared undertaking the activity at least once in the past week. Standard errors (in parentheses) are robust to heteroscedasticity. *Significance at 10% level. **Significance at 5% level. ***Significance at 1% level. PF = Personalised Feedback.

with personalised information on indoor air quality is effective in improving indoor air, particularly in the most polluted households at baseline. Personalised feedback on PM2.5 households' emissions and how they compare to others could change household behaviour by providing salient information that help households update their beliefs and better manage their activity. The improvement in indoor air started the third week after the beginning of the intervention, and did not decay throughout the intervention period as well as two weeks after the end of the intervention, which is noteworthy given that other studies have found behavioural interventions to have a short-term impact only (Gneezy *et al.*, 2006; Ferraro and Price, 2013). Another main finding of our study is that personalised information may be needed to change health behaviour. While generic information about indoor air pollutants was effective in increasing households' awareness about the negative impacts of wood burning, it was only effective in changing behaviour when augmented with personalised feedback on households' PM2.5 emission levels. This finding points to a knowledge-behaviour gap whereby greater knowledge about health issues does not necessarily translate in adequate behaviour. People's optimism bias might explain this phenomenon. Generic information successfully increases awareness of PM2.5 emitting sources, but if people are over-optimistic about their own situation, they likely will not change their behaviour. Sending detailed information about PM2.5 emissions in participants' own living room could therefore help counter people's optimism bias by increasing the salience of the actual risk they are exposed to. We found that the *Information + Personalised Feedback* treatment was successful at decreasing indoor levels of PM2.5 by more than 20% over the four-month period, with a sustained and

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significant decrease starting on the third week after the beginning of the intervention. A heterogeneous impact analysis revealed that the effect is concentrated on the most polluted households who exhibit a 40% decrease in PM2.5 concentration levels. For that group, the number of days over the WHO threshold – not to be exceeded more than 3 days per year – decreased by 52%, from 12.4 days down to 5.9 days over the study period. This result is in line with the notion that the *Information + Personalised Feedback* treatment helps eliminate 'slack' in combustion activities. In contrast, we observed no significant change in indoor air quality for households receiving the *Information* treatment, suggesting that generic information about the health risks of combustion activities is not sufficient to induce behavioural changes. The main channel of behavioural change seems to be the perception of individuals' own indoor air quality. We found that both interventions were successful at increasing the perceived detrimental impact of wood burning and smoking on indoor and outdoor air, and at decreasing self-reported frequency of wood burning in the future. However, only the *Information + Personalised Feedback* intervention decreased the perceived quality of *own* indoor air. We found no evidence of an impact on the perceived health risk of air pollution, attitudes towards wood burning regulation, pleasure when lighting a fire or on the intention to change wood burning equipment in the future. Self-reported frequency of combustion activities was not different between the control group and both treatment groups, as well as air quality improvement efforts, which is at odds with the objective reduction in PM2.5 concentration measured by the micro-sensors. Our interpretation is that self-reported combustion and air quality improvement efforts are not precise enough to capture the behavioural changes that took place in the households and did lead to a decrease in PM2.5 concentration. Overall, both generic and personalised information were efficient at improving knowledge about the health risks associated with combustion activities, but only personalised information induced actual behavioural changes. This finding suggests that general knowledge is not sufficient to change behaviour, and that the combination of feedback and social comparison is a powerful lever to overcome biased beliefs about one's own emissions and inattention. Our paper makes several contributions to the literature. First, it adds to the limited evidence on the use of smart meters to change behaviour. The originality of smart meters is that they provide accurate and high-frequency data on one's energy consumption or emission levels, which may be an effective way to overcome inattention and optimism biases by making the implications of one's salient. However, rigorous evidence on the actual effectiveness of smart meters in changing behaviour is scarce. Two sets of trials show positive effects of smart meters on water consumption (Tiefenbeck *et al.*, 2018, 2019) and on indoor smoking (Hughes *et al.*, 2018; Hovell *et al.*, 2020). Our paper innovates by providing first experimental evidence on the effectiveness of micro-sensor technology in reducing PM2.5 emissions. It adds to the nascent literature showing how new technologies in our everyday lives can help individuals improve their health by providing relevant information to households.

Second, our paper contributes to the literature on the effectiveness of information provision in shifting by specifically comparing the effectiveness of generic vs personalised information. Our paper adds to this literature by testing two different information contents against a control group and comparing their relative effectiveness. We show that generic information is not enough to shift; although both the

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Information and *Information + Personalised Feedback* groups received similar information on indoor pollution sources and its detrimental impact on health, only households receiving personalised air quality meter readings changed their and decreased their indoor pollution. This result further adds to the literature on the awareness – gap, whereby individuals are aware of an issue, like climate change, air pollution or the importance of preventive behaviours, but fail to implement concrete actions to curb the issue (Kennedy *et al.*, 2004; Schwarzer, 2008; Gifford *et al.*, 2011). Our paper shows that this gap can be reduced by providing individuals with accurate feedback on their emission levels and social comparisons. These results may be of particular interest for policymakers in a context where micro-sensor technologies that detect ambient PM2.5 levels are increasingly available and affordable (Jiang *et al.*, 2011).

There are, however, several limitations to the current study. First, one may be concerned by an experimenter demand effect because all volunteering households, including the controls, were aware that the overall goal of the study was indoor air quality. Providing this information truthfully was necessary given that participants needed to agree to installing an air quality monitor in their home. However, the mere presence of the sensor, combined with people's knowledge of the overall goal of the study, may have led people to try to improve air quality in their homes by paying more attention than usual or by searching information about indoor air quality on their own. If that happened similarly in the control and treatment groups, the effect reported in this paper should not be affected. Yet, if that happened more (resp. less) in the control group than in the treatment groups, the effect reported in this paper is underestimated (resp. overestimated).

Second, our sample is of relatively modest size and non-representative, which may limit the generalisability of our findings to a broader population. While every effort was made to ensure the internal validity of our analyses, their external validity is limited. Specifically, our sample is more educated and wealthier than the national average, and exhibits lower levels of indoor air pollution. Moreover, households in our sample agreed to install an air quality sensor in order to receive information on their home's air quality as well as recommendations on how to improve it, so they are likely more sensitive to air quality than the total underlying population. As a consequence, the treatment effect may be overestimated if our households reacted more to the treatment because of their baseline interest in air pollution, or underestimated if our sample's preexisting effort to reduce air pollution decreased their margin of behavioural change compared to a more representative sample.

Third, our experimental design does not allow us to disentangle the distinct effects of the two elements that constitute the personalised information treatment: the personalised graph displaying both households' emission levels over the previous week and how it stands compared to the control group. Teasing these two pieces of information apart would have required adding two additional experimental arms in the study (one group receiving the first graph only, another group receiving the second graph only), which was not feasible due to material constraints. As a starting point, we prioritised testing the most promising treatment, which bundles two elements of personalisation. Future research should seek to tease apart and compare these components.

Finally, while the effect holds for two weeks after the end of the intervention, we do not know whether our findings capture changes that extend over longer time periods.

Longitudinal studies or research conducted over multiple time points may provide a more comprehensive understanding of the dynamics of behavioural change following such an intervention.

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