The power of personalised information: Evidence from an health behaviour experiment*

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Abstract

While indoor air pollution is one of the leading causes of morbidity and mortality worldwide, its sources and impacts are largely misunderstood by the public. In a randomized controlled trial including 281 households in France, we test two interventions aimed at changing indoor polluting behavior by raising awareness of its health risks: generic and personalised information. While both types of information increase knowledge, only personalised information changes behavior, leading to a reduction of indoor PM2.5 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: Health Behavior, Health Information, Air pollution, Field Experiments, Optimism bias, Smart monitors

JEL classification codes: I12,Q53,D83,C93

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1 Introduction

Exposure to pollution is one of the leading causes of morbidity and mortality worldwide. Diseases caused by PM2.5[1] exposure were responsible for an estimated 9 million premature deaths in 2015, which represents 16% of all deaths worldwide and three times more deaths than from 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 Organisation (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 one when there is no polluting indoor activity, but when household polluting sources are activated it can be up to 5 times worse than outdoor air quality (Ebner et al. 2005). The main sources of PM2.5 emissions are wood burning, cooking, and tobacco smoking, but also to a lesser extent candles and incense burning, and dusting (Nasir et al. 2013). It is currently estimated that an annual loss of 2 million years of healthy life can be attributed to indoor air pollution alone (Asikainen et al. 2016). 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). While it provides only 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).

Yet, the general public is mostly unaware of the negative health consequences of wood burning and other combustion activities. Wood, candles, or incense burning are typically associated with positive feelings and considered natural, healthy, and low-polluting. This

[1] Particulate matter with an aerodynamic diameter smaller or equal to 2.5 µm

strong positive association distorts the perception of health risks and is an obstacle to household behaviour change (Hine et al. 2007; Bhullar et al. 2014). More generally, despite an increased awareness of air pollution, the public still has a limited apprehension of the factors that influence indoor air quality and its effects on health (Daniel et al. 2020; Hofflinger et al. 2019). Therefore, finding levers to increase awareness of the risks associated with wood burning and other household polluting activities is of key public health concern.

This paper tests the effectiveness of two 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. Using a randomized controlled trial in France, we equipped 281 households with air quality micro-monitors and assigned them to three conditions: the *Information* treatment, the *Information + Personalised Emission Profile* treatment, and the control group. The *Information* treatment consisted of weekly leaflets containing generic health-framed information on the risks related to indoor air pollution and multiple combustion activities, with special attention to wood burning. This treatment is expected to change households' behaviour by highlighting the health risks associated with combustion activities. The information was provided on a weekly basis during ten weeks to ensure proper assimilation and salience . The information was formatted in a way that facilitates a simple understanding of indoor polluting sources and its management . An example of the *Information* treatment is shown in Figure A1 of the appendix.

Households in the *Information + Personalised Emission Profile* treatment received the same generic health information along with a weekly Personalised Emission Profile of their indoor pollution levels, consisting of the graph of precise meter readings of the concentration of PM2.5 measured every five minutes over the previous week, as well as statistics to compare their emissions to similar households (the control group). An example of the Personalised Emission Profile is shown in Figure A2 of the appendix. Receiving real-time feedback in the form of a weekly Personalised Emission Profile is expected to reinforce the effect of generic information by activating complementary behavioural levers: first, it makes the hazards of PM2.5 peaks more visible 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 inattention 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 Emission Profile 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.

Both treatments were implemented during ten weeks from January the 6th to March the 9th, 2020. To evaluate the impact of these treatments, we used high-frequency data on households' PM2.5 emissions over almost four months (four weeks before the interventions, ten weeks during the interventions, and two weeks after the interventions). The fixed cost of the conception of the weekly interventions was estimated at 30 EUR per person. The variable cost of the *Information* treatment consists only in printing and mailing the leaflets, which amounts to approximately EUR 15 per person. The variable cost of the *Information + Personalised Emission Profile* leaflets is estimated at EUR 222 per person; this includes printing and mailing the leaflets (as the other treatment), plus renting the monitors, distributing and retrieving them, managing and replacing the defective ones and creating the personalised weekly leaflets.

We find that the *Information + Personalised Emission Profile* 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 3rd 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 down to 5.9 days over the study period. This result is in line with the notion that the *Information + Personalised Emission Profile* 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 health-behavior changes.

Turning to mechanisms, the main channel of behavioural change seems to be the perception of individuals' own indoor air quality. We find 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 Emission Profile* intervention decreased the perceived quality of *own* indoor air. We find no evidence of an impact on the perceived health risk of pollution in general, attitudes toward 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-monitors. 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 real-time 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, our paper contributes to the literature on the effectiveness of information provision in shifting health behaviour. While a number of studies have shown that information provision can effectively lead to the adoption of healthy behaviours (Dupas et al. 2018; Galiani et al. 2016; Jalan et al. 2008; Madajewicz et al. 2007), in many instances information provision has little (Bollinger et al. 2011; Variyam 2008) or no impact on health behaviour (Jacobson et al.

2022; Ashraf et al. 2013; Duflo et al. 2015; Groner et al. 2000). These contrasted results indicate that the content and format of information matter a lot for effectiveness. In fact, some papers directly test different contents or formats and find differential effects on health behaviors (Dupas 2011; Downs et al. 2015; J. Cohen et al. 2018). In this literature, Jalan et al. 2008 and Madajewicz et al. 2007 test personalized information to households on the quality of water and find substantial impacts. We add to this literature by specifically comparing the effectiveness of generic *versus* personalised information on health behavior, which is rare in the literature with the exception of De Vries et al. 2008 and Celis-Morales et al. 2017 who show that receiving personalised feedback and advice on diet and physical activities improves health relative to generic information. Our paper reinforces this result and expands it to a different health issue, indoor pollution.

Our paper also contribute to the literature on knowledge-behavior gaps, whereby greater knowledge about health issues does not necessarily translate in healthier behaviour (Hornik 1989; Kennedy et al. 2004). Although both the *Information* and *Information + Personalised Emission Profile* groups increased knowledge on indoor pollution sources and its detrimental impact on health, only households receiving personalised air quality meter readings changed their behaviour and decreased their indoor pollution. Our paper provides evidence that personalised information can overcome behavioral obstacles such as information disbelief, salience issues, and optimistic bias by making the direct implications of one's behaviour salient. 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. Providing personalised information is definitively more costly than generic information, but this cost may be necessary to overcome the knowledge-behavior gap.

Finally, our paper adds to the limited evidence on the use of smart meters to change health behaviours. The originality of smart meters is that they provide real-time, accurate, high-frequency data on one's energy consumption or emission profile, which may be an effective way to overcome inattention and optimism biases. However, rigorous evidence on the actual effectiveness of smart meters in changing behaviours is scarce.

Two sets of trials have been published showing positive effects of smart meters on water consumption (Tiefenbeck, Goette, et al. 2018; Tiefenbeck, Wörner, et al. 2019) and on indoor smoking (Hovell et al. 2020; Hughes et al. 2018). Our paper innovates by providing first experimental evidence on the effectiveness of micro-monitor 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.

The paper is organized as follows. Section 2 describes the context and barriers to health-behaviour change, the intervention, and the experimental design. Section 3 presents our data sources, outcomes of interest, and sample. Section 4 examines the validity of the experiment and presents the estimation method. Section 5 provides the results on indoor air quality, and section 6 the results on knowledge, attitudes and self-reported behaviour. Section 7 concludes.

2 Context and experimental design

2.1 Context

Wood burning usage. Wood burning is another major source of PM2.5 in France. A recent report estimates that 34% of French dwellings register unsafe levels of PM2.5 and an estimated cost of €19 billion per year attributed to health consequences of indoor air pollution (Boulanger et al. 2017). In the Île de France region, the most populated of the eighteen regions of France centered around the capital Paris, only 16% of households report owning a wood burning equipment but wood burning is responsible for 85% of fine particle emissions of these households, accounting for more than one third of total fine particle emissions in the region (Host 2018). The vast majority of households have not invested in efficient wood burning equipment and have insufficient knowledge of good wood burning practices, which leads to higher levels of indoor pollution. Given that the region is densely populated, occasional wood burning using old equipment by a minority of households generates a great amount of outdoor pollution. Host 2018 also indicates that 83% of households use wood burning as an auxiliary or occasional heating source, not a primary source of heating, which suggests that the use of wood burning could be curbed with little to no adjustment to the budget of these households, with considerable impacts on health (Chafe et al. 2015).

Misperceptions of health risks and indoor air quality. 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 region believe that outdoor air pollution presents a major health risk, less than 50% believe so 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 health 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 stated that this practice has no effect on, or even improves, indoor air quality (Nicolas et al. 2017). This study also shows that only 21% of occasional users of wood burning believe that it has an impact on indoor air quality. The lack of awareness of the negative health impacts of indoor air quality results in low acceptability or effectiveness of environmental policy measures. In fact, 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[2]. Merely informing users about the dangers of wood burning may thus be an effective strategy to change behavior in this context(Daniel et al. 2020; Hofflinger et al. 2019). Households will simply not stop using candles or wood burning if they are unaware that is a source of indoor PM2.5 and subsequent health issues.

Other barriers to change in health behaviour. However, other barriers can prevent households from decreasing indoor air polluting activity even if they are informed of health risks. First, even when households are presented with information about the magnitude of the pollution generated by combustion activities, a positive affect heuristic may generate disbelief because wood, candle, and incense burning are linked to positive feelings (Hofflinger et al. 2019; Hine et al. 2007). Second, as pollutants are invisible to

[2]Laetitia Van Eeckhout. "Pourquoi Ségolène Royal veut revenir sur l'interdiction des feux de cheminée en Île-de-France. *Le Monde*. December 2014. https://www.lemonde.fr/planete/article/2014/12/09/segolene-royale-veut-revenir-sur-l-interdiction-des-feux-de-cheminees_4536996_3244.html

the human eye and their costs on health are often delayed, salience biases can create a discrepancy between intent and actual daily behaviour even when households believe the information and are aware of polluting sources (Allcott and Wozny 2014; Kahneman et al. 1982). For instance, the warmth of a wood fire and the aesthetic of a candle are often more salient than the resulting invisible PM2.5 and the future health costs. Third, optimism bias leads people to underestimate their actual exposure and risk of suffering future health consequences (Weinstein 1980). This has been documented for various health hazards such as having a heart attack, contracting AIDS, being in a traffic accident or developing cancer (Sharot 2011; Fontaine and Smith 1995; Fontaine 1994; DeJoy 1989). In those cases, personalised information may be required to counter these biases and change health behavior. One last barrier that the interventions proposed in this paper do not address is the financial costs of switching to less polluting equipment, which can make it hard for some households to change their behavior.

2.2 The interventions

The goal of the interventions is to examine the effectiveness of information on air quality and health risks in limiting household polluting activities and enhancing indoor air quality. The intervention was developed by researchers in economics and psychology, in collaboration with the Interministerial Directorate for Public Transformation (DITP) and the Île-de-France Regional and Intergovernmental Department of Environment and Energy (DRIEE). The intervention involved mailing eight leaflets[3,4] between January and March 2020. All households participating in the study were equipped with air quality monitors. In order to disentangle the impact of personalised feedback from generic information provision, we implemented two treatments.

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

[3]The first two leaflets were sent two weeks apart, while the following six were sent every week.
[4]All materials can be found in the online appendix: https://osf.io/5br8y/

of indoor air pollution and health risks, and a page providing good practices. The focus, the cover, and the messages were different is each wave. We put an emphasis on wood burning in the last five waves of the intervention (weeks 4 to 8) to overcome households' low awareness of the negative effects of wood burning. The positive image of wood burning was challenged by matching the health risks 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 barriers to household behavioural change: lack of information and salience bias.

The *Information + Personalised Emission Profile* Treatment The second treatment provided households with the same generic information as in the *Information* Treatment, but added people's Personalised Emission Profile based on their real PM2.5 emissions over the previous week. Using data from the air quality monitors, the households' indoor PM2.5 concentration was measured every 5 minutes and represented on a figure along with the date and time of the major pollution peaks. The Personalised Emission Profile also included a ranking of the household in terms of air quality compared to households in the control group. Providing users with their Personalised Emission Profile can alter household's health behaviour through four 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 salience issues and temporal discounting by making the intangible aspect of pollution visible in the present. Fourth, the Personalised Emission Profile can decrease optimism bias by making a household's own pollution visible and readjusting personal perceptions. Finally, the use of social comparison may stimulate behavioural change. Therefore, the *Information + Personalised Emission Profile* intervention addresses most aforementioned barriers: lack of information, information disbelief, salience issue, and optimism bias.

2.3 Experimental design

To measure the differential effect of each treatment, 281 households received a micro air quality monitor and were assigned to the control group, the *Information* treatment, or the *Information + Personalised Emission Profile* treatment. 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[5]. This resulted in 94 triplets. Within each triplet, households were randomly assigned to one of the three groups. 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 Emission Profile for the entire intervention period.

3 Data and Sampling

3.1 Data sources

Micro-monitor indoor pollution data. Every household was equipped with a micro-monitor that retrieved 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 monitor no closer than 1m and no farther than 4m away from their wood burning equipment. In order to minimise the experimenter demand effect, the chosen micro-monitors are discrete, small, and provide no visible indications about the measured air quality.[6] The micro-monitor had two functions: it served as an intervention instrument, allowing us to send personalised summaries of air quality in the *Information + Personalised Emission Profile* group, as well as a reliable way to measure the impact of the intervention.

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 intervention). The endline questionnaire measured the mechanisms of change in indoor air quality between the three groups.

[5]Both smoking and baseline indoor PM2.5 levels highly predict indoor air pollution post-treatment.
[6]Atmotrack Atm01 by 42 Factory: https://atmotrack.fr/

3.2 Outcomes of interest

Indoor air pollution Our main pre-registered hypothesis is that the intervention has an impact on household's PM2.5 emission profiles. 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 outcome is the number of days a household registered higher PM2.5 levels than the WHO 24hrs guidelines (25 µg/m^3).

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, and We expect that both treatments increase the probability that households cite the following sources of pollution 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 neighborhood, and in the region ranges from 1 (worst quality) to 6 (perfect quality). We expect that the *Information + Personalised Emission Profile* treatment has a larger impact on perceived indoor air quality than the *Information* treatment thanks to the graphs with precise emission profiles.

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 expect that both treatments increase all these households' perceptions, but the *Information + Personalised Emission Profile* treatment has a larger impact on the perceived contribution of wood burning on indoor pollution than the *Information* treatment thanks to the 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 at linking the objective measure of indoor air pollution from the micro-monitor to precise behavioral change.

Heterogeneity. The baseline questionnaire also collected information about the household's 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 restrict the heterogeneity analysis to baseline emission profiles 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.

3.3 Sampling strategy

The experiment was presented on a website where applicants could volunteer to install an air quality micro-monitor 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". 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 these households were included in the study, 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-monitor 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.

3.4 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.

4 Validity of the experiment and estimation method

4.1 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 Emission Profile* 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 monitor data. Attrition was very small at endline (4.6%) and was evenly distributed across the three groups[7].

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 population. Our sample is also more educated and wealthier than the national average, and exhibit 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

[7] 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 Table A1

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.

4.2 Estimation method

Final outcomes We measured the Average Treatment Effects 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 Emission Profile* 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 3-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:

$$Y_{i,j,k} = \alpha + \sum_{k=-2}^{11} \beta_k T_{1,i} W_k + \sum_{k=-2}^{11} \gamma_k T_{2,i} W_k + \sum_{k=-2}^{11} W_k + \theta_j + \epsilon_{i,j,k} \tag{2}$$

$\epsilon_{i,j,k}$ 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 Emission Profile* 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 emission may be more likely to respond to the interventions as there is more room for change. On the other hand, their high emission profile 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.

We also hypothesised that impact might vary as a function of outdoor temperatures. 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. To that end, we used household daily outdoor temperature and interacted the treatment variables with three temperature categories: cold days ($<$8 degree C), moderate days (between 8 and 14 degrees) and warm days (more than 14 degrees). Outside local temperature levels were retrieved from the official public administrative institution of meteorology and climatology in France ("Météo France"). The daily temperature was assigned to each household based on the closest meteorological station available.

Mechanisms To measure the treatment effects on outcomes measured in the endline questionnaire, we used an 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:

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

5 Impacts on indoor air quality

5.1 Average treatment effect

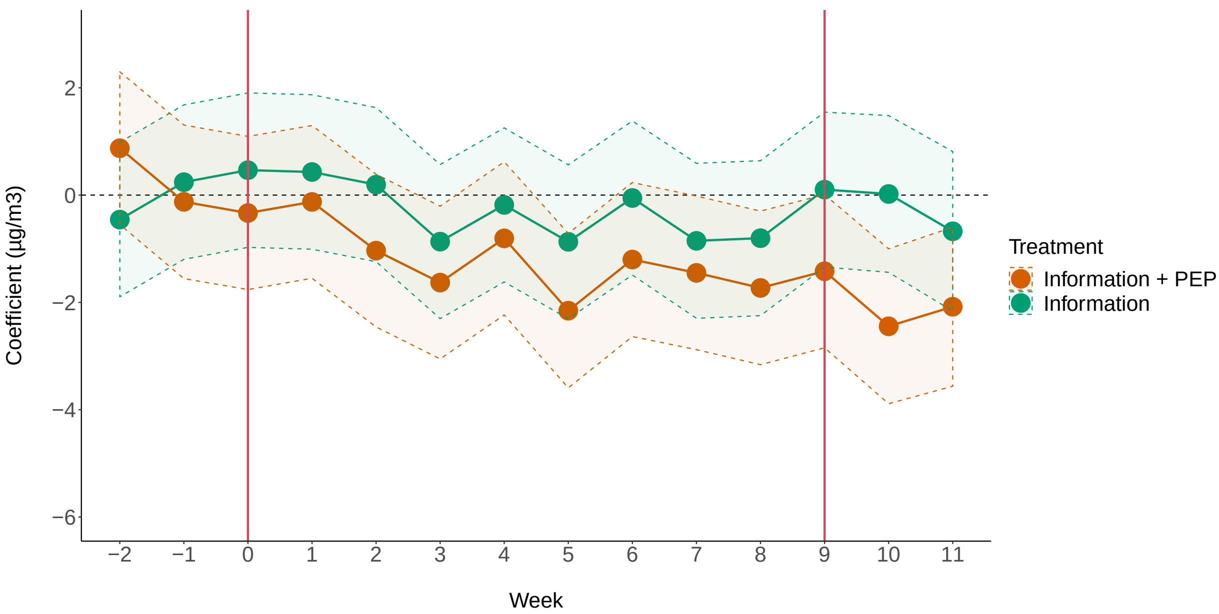
Table 2 presents the impact of the interventions on indoor air quality. Column (1) shows the ATE estimates on average daily PM2.5 level over the whole post-treatment period using the main specification (equation 1). While the *Information* treatment led to a non-significant 0.19 µg/m^3 decrease in average daily PM2.5, the *Information + Personalised Emission Profile* treatment induced a significant 1.315 µg/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 households *Information + Personalised Emission Profile* narrows the gap between households that use wood-burning and households that do not at baseline; the new average level of indoor PM2.5, 4.2µg/m^3, is comparable to the average of 4.3 µg/m^3 observed throughout the same period in the 4th group of comparable households that do not use wood burning. 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 µg/m^3 (non significant) for the *Information* treatment and 1.175 (significant at the 1% level) for the *Information + Personalised Emission Profile* treatment. Based on these estimates, the *Information* treatment appears 2.6 more cost-effective than the *Information* treatment.[8]

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). 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 Emission Profile* intervention started to have an impact on polluting behaviour rather fast: the effect is significant starting the third week after the start of the intervention and is persistent 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 3 months of treatment—if anything rather an amplification,

[8]The *Information + Personalised Emission Profile* treatment's cost is 15 times larger, and its impact 39 times larger, than the *Information* treatment.

indicating that there was no habituation effect to the novelty of the messages or to the monitor.

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 January 6th 2020, when the first message was sent the participants in the *Information* and *Information + Personalised Emission Profile*. The last message was sent on the 9th of March 2020, on week 9.

5.2 Heterogeneous effects

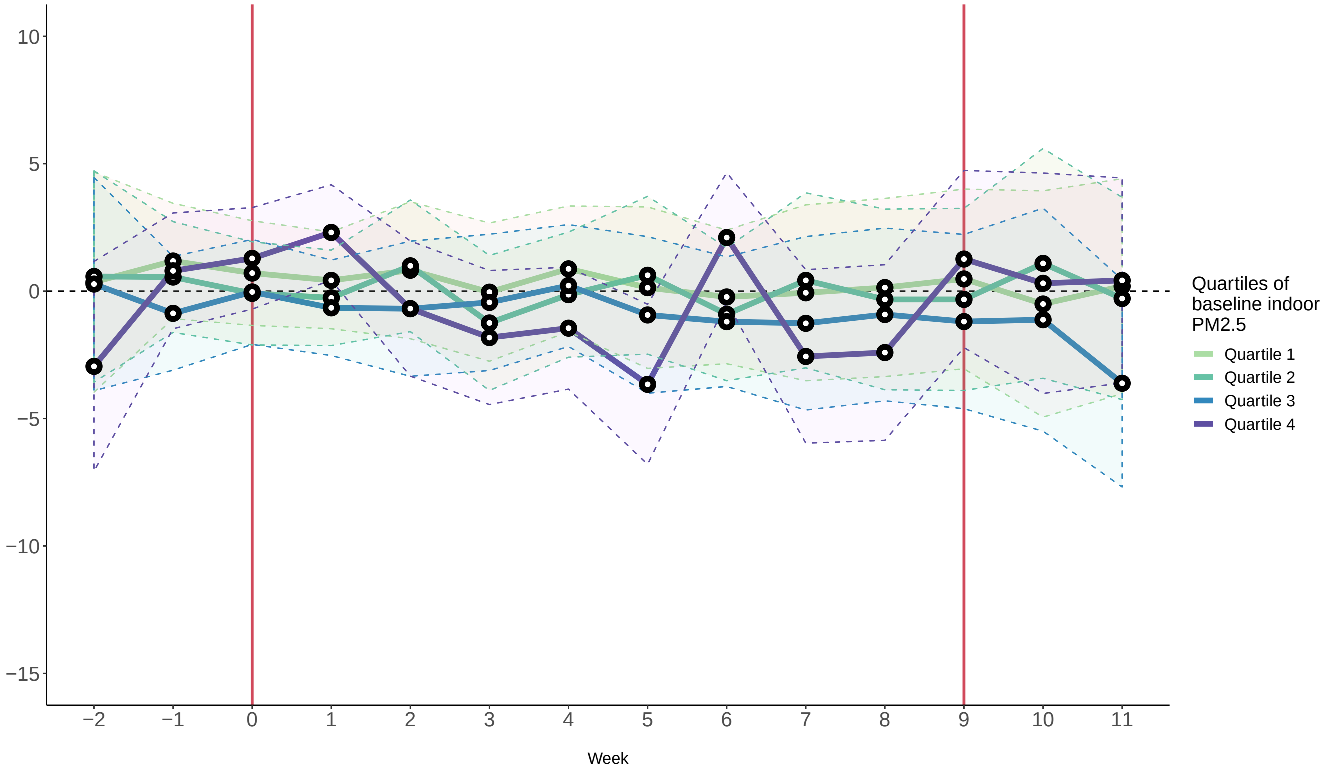
In this section, we tested whether the effectiveness of the intervention depends on the household's initial level of pollution, which is important since households with higher initial levels of PM2.5 are more exposed to health risks. We find that the households that were more polluted to begin with responded more to the *Information + Personalised Emission Profile* intervention. Table 3 shows the treatment effect by quartile of baseline PM2.5 concentration. The treatment effect of the *Information + Personalised Emission Profile* 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 Emission Profile* intervention decreased indoor PM2.5 levels by 4.9 $\mu g/m^3$, a 36% decrease compared to the control group mean, significant at the 95% confidence level. These households are less affluent, reported the presence of a smoker and using wood burning equipment more frequently and reported a better subjective health status (see Appendix Table A2). Households in the third quartile receiving the *Information* treatment decrease their indoor pollution by 18% (-0.78µg/m^3). This decrease is significant at the 10% level and much smaller in absolute size. Finally, the effect was not significantly different than 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 more at risk households respond more 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 Emission Profile* 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.

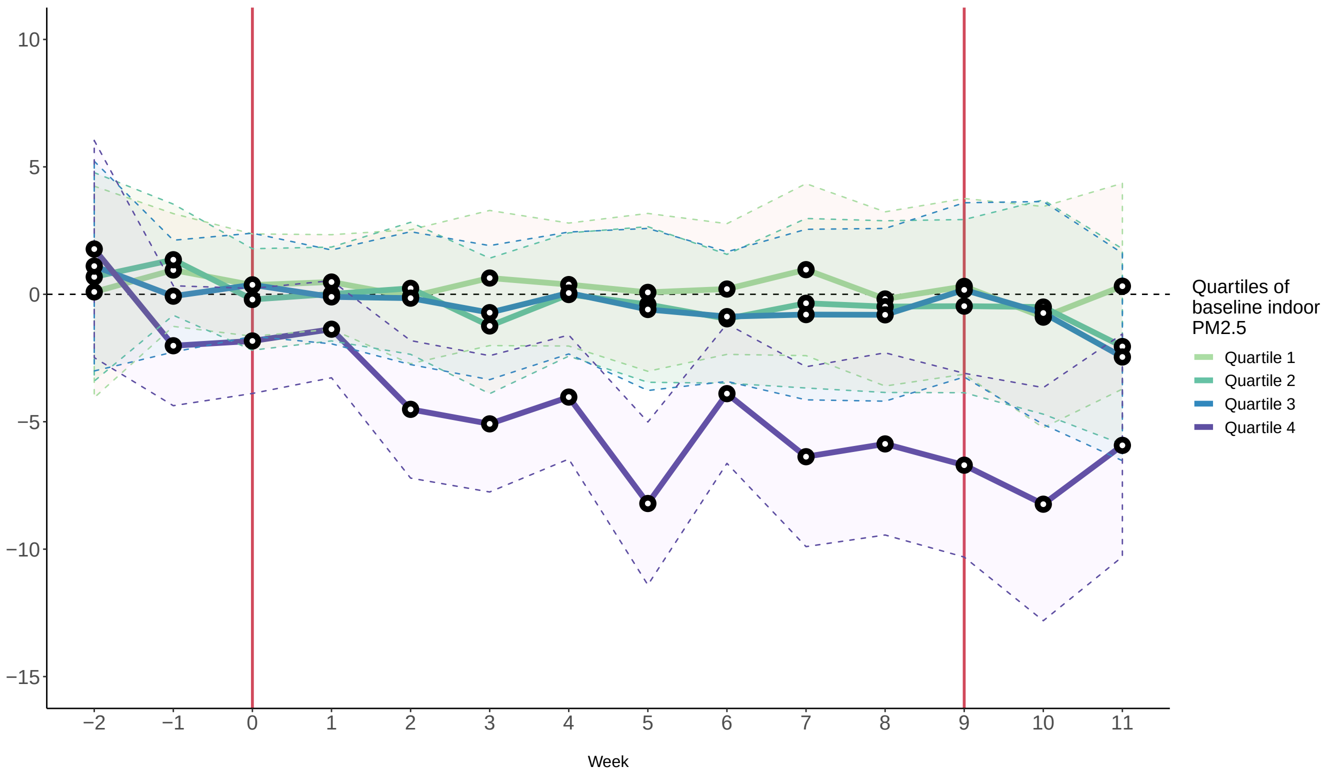
5.3 Number of days over the WHO 24-hour guideline

Another outcome of interest is the number of days a household was exposed to levels of pollutants extremely dangerous for health. The WHO guidelines on PM2.5 24-hour exposure is 25 µg/m^3 not to be exceeded more than 3 days a year. Table 4 reports the average treatment effect 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 Emission Profile* 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 4, Column 1). The effect is greatly

Figure 2: Average treatment effect on Indoor PM2.5 levels, by week and quartile of baseline PM2.5



(a) *Information* treatment



(b) *Information + Personalised Emission Profile* treatment

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 January 6th 2020, when the first message was sent the participants in the *Information* and *Information + Personalised Emission Profile*. The last message was sent on the 9th of March 2020, on week 9.

heterogeneous as it concentrates only on the most polluted households (4th quartile of baseline PM2.5 concentration): for these households, the *Information + Personalised Emission Profile* 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 4, 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.

5.4 Magnitude of the effects and health impacts

The magnitude of the effect of the *Information + Personalised Emission Profile* 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 $70m 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 Emission Profile* 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 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).

6 Mechanisms

6.1 Knowledge about indoor PM2.5 sources

The interventions provided information on the different sources of PM2.5. Table 5 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 Emission Profile* 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 Emission Profile* increased the probability of citing candles, incense and cooking as major indoor PM2.5 sources. This absence of impact is not explained by perfect knowledge of these combustion activities as major sources of pollution, as less than only 4 to 9 percent of households mention candles, incense, and cooking in the control group. Awareness of the risks associated with wood burning and smoking were already more salient and further increased thanks to the intervention.

6.2 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 Emission Profile* group. The top panel of Table 6 details the average treatment effects of both interventions on participants' perceived air quality at home, in their neighborhood 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 0.09 decrease in perceived air quality at home (score from 0 to 6), the *Information + Personalised Emission Profile* treatment induced a significant 0.362 decrease in perceived home air quality, which represents a 9% decrease relative to the control group mean. Heterogeneous effects reveal that the effect is concentrated in the most polluted households, where the *Information +*

Personalised Emission Profile treatment induced a significant 0.828 decrease in perceived home air quality, which represents a 23% decrease relative to the control group mean. We also see an increase in perceived household indoor air quality among the least polluting households, but the effect is not statistically significant. Providing households with their actual levels of indoor PM2.5 increases awareness about own polluting activities and leads households to correctly update their perception of indoor air quality. This in turn could decrease inattention and optimism biases, since individuals are less likely to underestimate their own exposure and its resulting sanitary impacts.

6.3 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 7 details the average treatment effects 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 Emission Profile* 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 Emission Profile* 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 (quartile 4), whose baseline perceived risk of wood burning was lower (the control group mean is 53 in quartile 4 *versus* 59, 65, and 61 in the other quartiles) and was almost twice as big (p-value=0.05) for the *Information + Personalised Emission Profile* 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 points in the *Information* group and by 14.3 points in the *Information + Personalised Emission Profile* group. In quartiles 1, 2 and 3 of baseline PM2.5 concentration, the effects were somewhat larger in the *Information* group than in the *Information + Personalised Emission Profile* group, whereas the opposite was true in the most polluted households (quartile 4). Estimates are quite imprecise though, and thus marginally significant and not always statistically different one from the other.

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 7 presents the impact of the interventions on the probability of 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, 6, and 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 Emission Profile* group.

6.4 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. Table 8 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 Emission Profile* were 12 percentage points less likely to declare that they intended to use wood burning "Once a week or less" next winter (a 25% increase from 48%, significant at the 1% level). This effect seems to concentrate in households in the second quartile of baseline 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 9.

Other activity affecting air quality 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 9). Similarly, we found no significant change in the declared frequency of activities that improve indoor air quality (Table 10). Similarly, we found no change on the extensive margin of polluting and air quality enhancing activities (Tables 11 and 12).

Interpretation Self-reported polluting activities were not affected by any intervention. This result is at odds with PM2.5 micro-monitor data showing a significant reduction in pollution in the *Information + Personalised Emission Profile* 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 that self-reported frequency of polluting or air quality improving activities did not predict levels of PM2.5 (Appendix Table A3). 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 highlight the importance of collecting objective, non self-declared, measures in impact evaluations.

7 Conclusions

We conducted a randomized field experiment among occasional wood burning households to test the effectiveness of generic *versus* personalised information at decreasing indoor air pollution. We use the difference in the level of PM2.5 inside the home as an objective proxy of household polluting behaviour. Our results suggest that information about the health risks associated with combustion activities combined with personalised information on PM2.5 emission profile is effective at improving indoor air, particularly in the most polluted households at baseline. Personalised emission profile and social comparisons could change household behaviour by providing salient direct information that help households update their beliefs and better manage their activity. The improvement in indoor air started the 3rd 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.

Another main finding of our study is that personalised information may be needed to change health behavior. While generic information about indoor air pollutants was effective at increasing households' awareness about the negative impacts of wood burning, it was only effective at changing behaviour when augmented with personalised information on PM2.5 emission profile. This finding points to a knowledge-behavior 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. Indeed, we show that the perceived quality of own indoor air decreases only in households receiving personalised feedback.

As a concluding note, we would like to emphasize that the external validity of our study is limited and affects the generalisability of our estimated effect size. Households in our sample agreed to install an air quality monitor in order to receive information on their home's air quality as well as recommendations on how to improve it. This means that our sample is likely more sensitive to air quality than the total underlying population, which may have affected the impact of the intervention positively or negatively. The treatment effect will have been 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.

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Tables

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

	All	Control	Information	Information + PEP	C=I	C=I+PEP	I=I+PEP
	N=281	N=94	N=93	N=94			
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
BAC+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 3400	0.2(0.4)	0.2 (0.4)	0.2 (0.4)	0.2 (0.4)	0.590	0.401	0.169
3400 to 5000	0.4(0.48)	0.4 (0.5)	0.3 (0.5)	0.4 (0.5)	0.485	0.954	0.521
More than 5000	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
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

Table 1 – *continued from previous page*

	All N=281	Control N=94	Information N=93	Information + PEP N=94	C=I	C=I+PEP	I=I+PEP
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 neighborhood	3.6(1.3)	3.73(1.27)	3.46(1.28)	3.67(1.25)	0.164	0.762	0.275
...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. PEP = Personalised Emission Profile

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	0.033
	(0.539)	(0.564)
Infomation + PEP (I+PEP)	−1.315**	−1.175**
	(0.536)	(0.549)
Mean Control Group	5.55	5.5
p-value of I=I+PEP	0.040**	0.030**
Baseline controls	No	Yes
Observations	280	277
Adjusted R^2	0.725	0.723

Notes: Data from micro-monitors. 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. PEP = Personalised Emission Profile. ***p-value <0.01, **p-value <0.05, *p-value <0.1.

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	Q2	Q3	Q4
Information (I)	0.252	−0.010	−0.783*	−0.304
	(0.304)	(0.313)	(0.39)	(2.046)
Information + PEP (I+PEP)	0.214	−0.382	−0.410	−4.911**
	(0.297)	(0.313)	(0.375)	(2.080)
Mean Control Group	1.90	2.86	4.17	13.49
p-value for I=I+PEP	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		Infomation + PEP	
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-monitors. 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. PEP = Personalised Emission Profile. ***p-value <0.01, **p-value <0.05, *p-value <0.1.

Table 4: 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	Q1	Q2	Q3	Q4
	(1)	(2)	(3)	(4)	(5)
Information (I)	0.401	0.045	0.259	0.01	1.304
	(0.800)	(0.237)	(0.210)	(0.271)	(3.143)
Information + PEP (I+PEP)	−1.440*	0.088	0.081	0.130	−6.461**
	(0.799)	(0.237)	(0.210)	(0.271)	(3.197)
Mean Control Group	2.91	0.17	0.12	0.57	12.39
P-value for I=I+PEP	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 + PEP
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 µg/m^3 recommended by the WHO, not to be exceeded more than 3 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 4 quartiles of baseline PM2.5 levels. Strata fixed effects are used in all specifications. Standard errors (in parentheses) are robust to heteroscedasticity. PEP = Personalised Emission Profile.***p-value <0.01, **p-value <0.05, *p-value <0.1.

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

	Dependent variable: Mentioned ... as indoor polluting source (0/1)				
	wood burning	cigarettes	candles	incense	cooking
	(1)	(2)	(3)	(4)	(5)
Information (I)	0.276***	0.121*	0.062	0.017	0.030
	(0.078)	(0.066)	(0.053)	(0.045)	(0.039)
Information + PEP (I+PEP)	0.215***	0.160**	−0.006	0.006	0.0004
	(0.078)	(0.066)	(0.054)	(0.046)	(0.040)
Mean Control Group	0.458	0.117	0.088	0.058	0.044
p-value of I=I+PEP	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. PEP = Personalised Emission Profile. ***p-value <0.01, **p-value <0.05, *p-value <0.1.

Table 6: Impact on perceived air quality at home, in the neighborhood and in the region

	Dependent variable: Perceived air quality...		
	(1)	(2)	(3)
	...in own home (0-6)	...in neighborhood (0-6)	...in region (0-6)
Full sample			
Information (I)	−0.097	−0.199	0.122
	(0.179)	(0.201)	(0.197)
Information + PEP (I+PEP)	−0.362**	−0.355*	0.029
	(0.171)	(0.194)	(0.190)
Mean Control Group	3.98	3.87	2.77
p-value of I=I+PEP	0.590	0.320	0.890
Observations	276	283	282
Quartile 1			
Information (I)	0.217	0.132	0.802**
	(0.315)	(0.340)	(0.333)
Information + PEP (I+PEP)	0.347	0.038	0.455
	(0.319)	(0.336)	(0.333)
Mean Control Group	4.00	4.04	2.70
p-value of I=I+PEP	0.490	0.700	0.020
Observations	64	68	68
Quartile 2			
Information (I)	−0.026	−0.174	−0.153
	(0.335)	(0.414)	(0.418)
Information + PEP (I+PEP)	−0.521	−0.325	−0.223
	(0.325)	(0.404)	(0.408)
Mean Control Group	4.24	3.96	2.92
p-value of I=I+PEP	0.940	0.680	0.720
Observations	68	69	69
Quartile 3			
Information (I)	−0.461	−0.562	0.123
	(0.348)	(0.410)	(0.392)
Information + PEP (I+PEP)	−0.099	−0.028	0.143
	(0.346)	(0.412)	(0.409)
Mean Control Group	3.95	3.64	2.59
p-value of I=I+PEP	0.190	0.180	0.980
Observations	67	69	68
Quartile 4			
Information (I)	−0.039	−0.112	−0.027
	(0.370)	(0.359)	(0.384)
Information + PEP (I+PEP)	−0.828**	−1.035***	−0.021
	(0.339)	(0.329)	(0.353)
Mean Control Group	3.65	3.80	2.85
p-value of I=I+PEP	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/neighborhood/region?". Standard errors (in parentheses) are robust to heteroscedasticity. PEP = Personalised Emission Profile. ***p-value <0.01, **p-value <0.05, *p-value <0.1.

Table 7: Impacts on perceptions of wood burning and health risks, 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 + PEP (I+PEP)	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+PEP	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 + PEP	3.435	6.13	0.158	0.091	0.043	−0.087	−0.174
	(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+PEP	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 + PEP	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+PEP	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)
Information + PEP	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+PEP	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 + PEP	−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)
Mean Control Group	65.65	53.80	0.35	0.72	3.25	7.80	0.20
p-value of I=I+PEP	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 favor" 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. PEP = Personalised Emission Profile. ***p-value <0.01, **p-value <0.05, *p-value <0.1.

Table 8: Impacts on declared use of wood burning and intention of future use, full sample and by baseline level of indoor pollution

	Declared frequency of wood burning						
	Past winter			Next winter			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Once a month or less	More than once a month	Once a week or more	Never	Once a month or less	More than once a month	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 + PEP (I+PEP)	−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+PEP	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 + PEP	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)
Mean Control Group	0.30	0.35	0.35	0.17	0.39	0.39	0.17
p-value of I=I+PEP	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 + PEP	−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+PEP	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 + PEP	0.011	0.033	−0.040	0.126	0.023	0.030	−0.126
	(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+PEP	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 + PEP	−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+PEP	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) to (3)) and the intention of use next winter (columns (4) to (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. PEP = Personalised Emission Profile.***p-value <0.01, **p-value <0.05, *p-value <0.1.

Table 9: 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) ecigarette	(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 + PEP (I+PEP)	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+PEP	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. PEP = Personalised Emission Profile. ***p-value <0.01, **p-value <0.05, *p-value <0.1.

Table 10: Impacts on the frequency of air quality improving activities in the last week

	Dependent variable: declared weekly frequency of	
	Using the ventilation hood	Opening windows
	(1)	(2)
Information (I)	0.160	0.173
	(0.715)	(0.486)
Information + PEP (I+PEP)	−0.277	−0.362
	(0.709)	(0.481)
Mean Control Group	4.25	6.6
p-value of I=I+PEP	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:"In 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. PEP = Personalised Emission Profile. ***p-value <0.01, **p-value <0.05, *p-value <0.1.

Table 11: Impacts on the incidence of wood burning and other polluting activity in the last week

	Dependent variable: declared weekly incidence of					
	wood burning	cigarette	ecigarette	candles	incense	dusting
Polluting activity						
	(1)	(2)	(3)	(4)	(5)	(6)
Information (I)	−0.073	−0.010	−0.009	0.023	−0.025	0.020
	(0.075)	(0.036)	(0.038)	(0.043)	(0.063)	(0.054)
Information +PEP (I+PEP)	−0.043	−0.013	−0.023	0.020	−0.075	0.047
	(0.074)	(0.035)	(0.037)	(0.043)	(0.063)	(0.054)
Mean Control Group	0.50	0.07	0.08	0.26	0.08	0.82
p-value of I=I+PEP	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. PEP = Personalised Emission Profile.***p-value <0.01, **p-value <0.05, *p-value <0.1.

Table 12: Impacts on the incidence of air quality improving activities in the last week

	Dependent variable: declared weekly incidence of	
	Using the ventilation hood	Opening windows
	(1)	(2)

	Dependent variable:	
	Using the ventilation hood	Opening windows
	(1)	(2)
Information (I)	0.019	0.011
	(0.067)	(0.016)
Information + PEP	0.017	−0.011
	(0.067)	(0.016)
Mean Control Group	0.71	0.99
p-value I=I+PEP	0.980	0.170
Observations	271	270
Adjusted R^2	−0.007	−0.0003

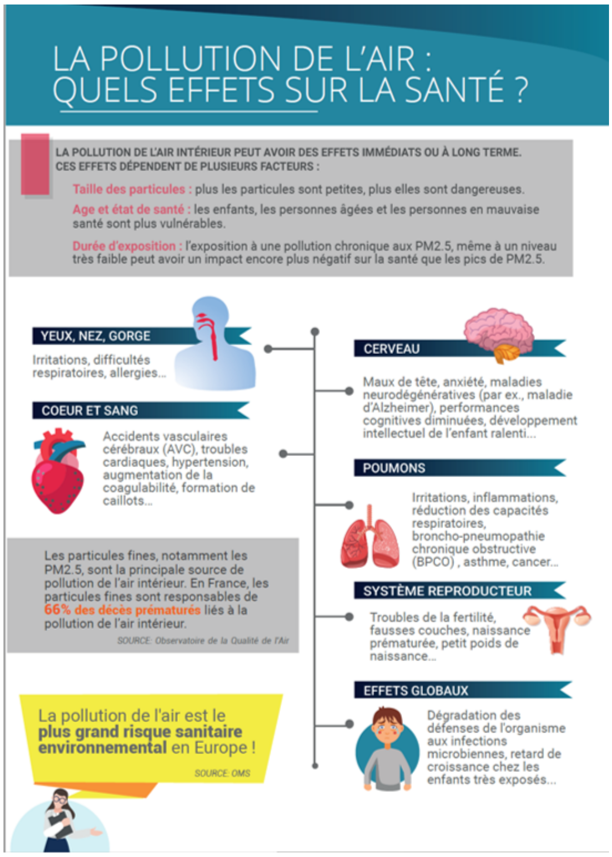
Notes: Data from endline survey. All estimates are derived from OLS regressions (equation 3). Question:"In the last week, How many times inside your dwelling has someone...used the ventilation hood/Opened the windows for aeration".The dependent variable measures the incidence of polluting activity and 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. PEP = Personalised Emission Profile.***p-value <0.01, **p-value <0.05, *p-value <0.1.

Appendix

8 Appendix

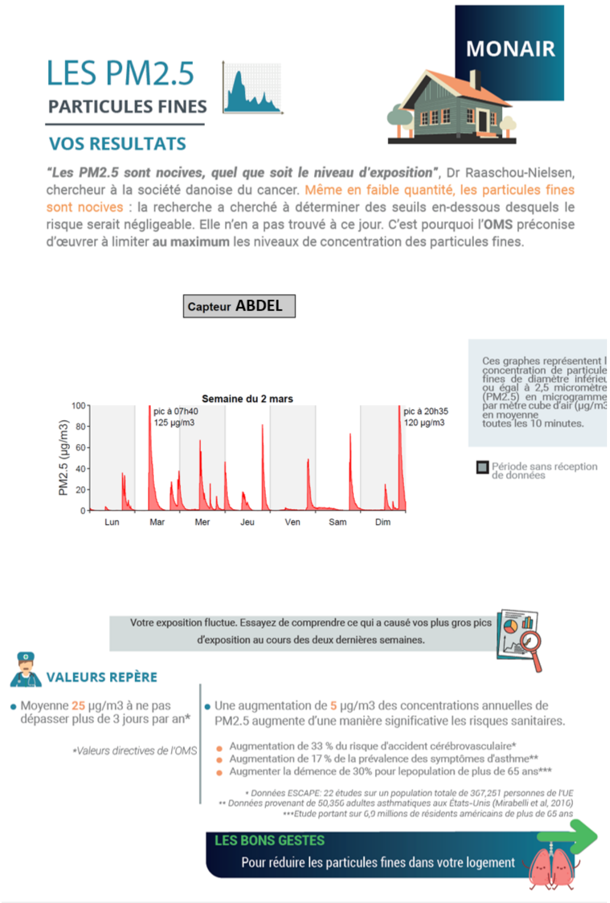
Figure A1: Example of a weekly informational leaflet (*Information* treatment)

(a) Weekly cover of informational leaflet

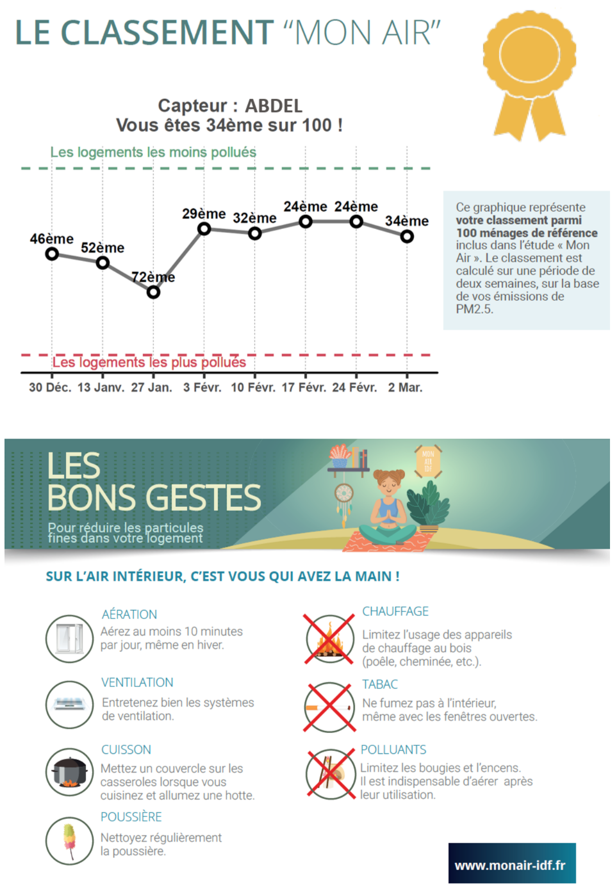


(b) Weekly info-graphics

Figure A2: Example of a weekly Personalised Emission Profile



(a) Weekly PM2.5 emission graph



(b) Weekly social comparison graph

Table A1: Impact of the treatments on the probability of attrition

	Dependent variable:
	Missing endline variables (0/1)
Information (I)	−0.000
	(0.030)
Information + PEP (I+PEP)	0.011
	(0.030)
p-value of I=I+PEP	0.724
Observations	282

Notes : The dependent variable "Missing endline variables" measures the incidence of attrition; it takes the value 0 if the household answered the endline questionnaire and 1 if we received no answer. Coefficients estimated using OLS regression. Standard errors (in parentheses) are robust to heteroscedasticity. PEP = Personalised Emission Profile.

Table A2: Summary descriptives table by quartiles of baseline PM2.5 levels

	Quartiles 1 - 3 N=213	Quartile 4 N=68	p-value of Q1-3=Q4
Age	49.20 (11.82)	48.61 (11.70)	0.717
Household size	3.26 (1.33)	3.28 (1.24)	0.941
Level of education			
Baccalaureate or less	0.13 (0.34)	0.13 (0.34)	0.946
BAC+2 to +4	0.39 (0.49)	0.39 (0.49)	0.997
BAC+5 or more	0.47 (0.50)	0.46 (0.50)	0.982
Income level			
Less than 3400	0.16 (0.37)	0.26 (0.44)	0.086
3400 to 5000	0.40 (0.49)	0.35 (0.48)	0.475
More than 5000	0.35 (0.48)	0.26 (0.44)	0.153
Polluting activity			
Presence of smoker in the household	0.061 (0.23)	0.29 (0.45)	0.00
Use of incense	0.13 (0.33)	0.11 (0.31)	0.65
Presence of a pet	0.50 (0.50)	0.56 (0.49)	0.46
Wood burning frequency			
Once a week or more	0.48 (0.50)	0.65 (0.48)	0.010
More than once a month	0.34 (0.47)	0.26 (0.44)	0.230
Once a month or less	0.19 (0.39)	0.09 (0.28)	0.022
Wood burning equipment type			
Open fireplace	0.22 (0.42)	0.23 (0.43)	0.878
Pollution health risk perception	69.03 (20.20)	63.30 (23.94)	0.078
Investment in health	67.99 (15.73)	67.77 (16.66)	0.925
Wood burning listed as outdoor pollution source	0.56 (0.50)	0.49 (0.50)	0.308

continued on next page

Table A2 – *continued from previous page*

	Quartiles 1 - 3 N=213	Quartile 4 N=68	p-value of Q1-3=Q4
Household member with respiratory problems	0.27 (0.44)	0.25 (0.44)	0.955
Ranking of health in priorities	3.34 (1.42)	3.48 (1.26)	0.452
Subjective health status			
Bad	0.04 (0.20)	0.04 (0.21)	0.891
Acceptable	0.24 (0.43)	0.38 (0.49)	0.037
Good	0.61 (0.49)	0.52 (0.50)	0.213
Excellent	0.11 (0.32)	0.06 (0.24)	0.124

Notes: Data from baseline survey. p-values estimated using independent samples t-tests. Standard errors (in parentheses) are robust to heteroscedasticity.

Table A3: Correlation between indoor levels of PM2.5 and self-reported behaviour

	Dependent variable:
	Average daily PM2.5
Equipment type	
Open fireplace	Ref.
Closed fireplace or insert	−3.255
	(1.279)
Wood stove	−2.902
	(1.368)
Pellet stove	−5.820
	(2.426)
Wood burning frequency baseline	
Once a week or more	Ref.
More than once a month	−1.131
	(0.977)
Once a month or less	−3.701
	(1.278)
Household Income	
Less than 3400	Ref.
3400 to 5000	−3.311
	(1.256)
More than 5000	−4.051
	(1.324)
Education	
Less than BAC+2	Ref.
BAC+2 to +4	0.517
	(1.407)
BAC+5 or more	0.235
	(1.457)
Declared frequency in past week (0/1)	
Wood burning	0.997
	(0.721)
Cigarette	18.142
	(1.572)
E-cigarette	−2.245
	(1.580)
Candles	−0.470
	(0.903)
Encens	0.414
	(1.299)
Dusting	0.869
	(1.047)
Ventilation hood	−0.845
	(0.792)
Window opening	0.623