IDB WORKING PAPER SERIES Nº IDB-WP-1260

The Power of Perception

Limitations of Information in Reducing Air Pollution Exposure

Rema Hanna
Bridget Hoffmann
Paulina Oliva
Jake Schneider

Inter-American Development Bank
Department of Research and Chief Economist

July 2021

Inter-American Development Bank

The Power of Perception

Limitations of Information in Reducing Air Pollution Exposure

Rema Hanna*
Bridget Hoffmann**
Paulina Oliva***
Jake Schneider***

* Harvard University
** Inter-American Development Bank
*** University of Southern California

July 2021

Cataloging-in-Publication data provided by the
Inter-American Development Bank
Felipe Herrera Library

The power of perception: limitations of information in reducing air pollution exposure / Rema Hanna, Bridget Hoffmann, Paulina Oliva, Jake Schneider.
p. cm. — (IDB Working Paper Series ; 1260)
Includes bibliographic references.
1. Air-Pollution-Mexico-Econometric models. 2. Willingness to pay-Mexico-Econometric models. 3. Text messages (Cell phone systems)-Mexico-Econometric models. I. Hanna, Rema. II. Hoffmann, Bridget. III. Oliva, Paulina. IV. Schneider, Jake. V. Inter-American Development Bank. Department of Research and Chief Economist. VI. Series.
IDB-WP-1260

Abstract

We conduct a randomized controlled trial in Mexico City to determine willingness to pay (WTP) for SMS air quality alerts and to study the effects of air quality alerts, reminders, and a reusable N95 mask on air pollution information and avoidance behavior. At baseline, we elicit WTP for the alerts service after revealing whether the household will receive an N95 mask and participant compensation, but before revealing whether they will receive alert or reminder services. While we observe no significant impact of mask provision on WTP, higher compensation increases WTP, suggesting a possible cash-on-hand constraint. The perception of high pollution days prior to the survey is positively correlated with WTP, but the presence of actual high pollution days is not correlated with WTP. Follow-up survey data demonstrate that the alerts treatment increases reporting of receiving air pollution information via SMS, a high pollution day in the past week, and staying indoors on the most recent perceived high pollution day. However, we observe no significant effect on the ability to correctly identify which specific days had high pollution. Similarly, households that received an N95 mask are more likely to report utilizing a mask with filter in the past two weeks, but we observe no effect on using a filter mask on the specific days with high particulate matter. Although we find that air quality alerts increased the salience of air quality and avoidance behavior, these results illustrate the difficulty that information treatments face in overcoming perceptions to effectively reduce exposure to air pollution.

JEL classifications: Q53; Q56; D83

Keywords: Air pollution, Information, Alerts, Willingness to pay, Avoidance behavior, Randomized control trial, Mexico

Acknowledgements: We would like to thank Daniel Velez-Lopez, Karla Hernández, and María Paula Medina for excellent research assistance and IPA Mexico, especially Cosma Gabaglio, for implementing the data collection.

1 Introduction

Air pollution levels in Mexico City regularly exceed WHO recommendations. High levels of air pollution negatively impact health (Chay and Greenstone, 2003; Bell et al., 2004; Currie and Neidell, 2005), labor supply (Hanna and Oliva, 2015; Aragón et al., 2017), productivity (Graff Zivin and Neidell, 2012; Chang et al., 2016; Chang et al., 2019), and educational outcomes (Lavy et al., 2014; Bharadwaj et al., 2017). In the longer term, governments can implement policies to mitigate air pollution, but in the short term, air quality alerts may allow individuals to engage in avoidance behavior on high pollution days to reduce their exposure to air pollution.

We conduct a randomized controlled trial in Mexico City to determine willingness to pay for real-time air quality alerts and to study the effects of air quality alerts and reminders and the provision of a reusable N95 mask on pollution information and avoidance behavior. In the study, 1,869 households are randomly assigned to four cross-cutting treatment groups and their respective control groups: (1) a one-year subscription to pollutant-specific SMS air quality alerts, (2) a free N95 mask, (3) a one-year subscription to monthly pollution trend and avoidance behavior SMS reminders, and (4) 50% higher compensation for baseline survey participation. Therefore, a pure control group consists of individuals assigned to the control group of each of the four treatments.

During the baseline survey, we elicit WTP for the SMS alert service after revealing the participants' compensation and whether they will receive a free N95 mask, but before revealing whether the participant will receive the SMS alert or reminder services. We use a novel variation of the Becker-De-Groot-Marshak (BDM) method (Becker et al., 1964) to elicit willingness to pay (WTP). Our design allows us to obtain an incentive-compatible measure of WTP, allows unconditional randomization of participants into the four cross-cutting treatment groups, and allows us to identify the effect of the compensation treatment and the mask treatment on WTP.

We observe no significant impact of the provision of a reusable N95 mask on WTP for the SMS alert service. Given the non-negligible cost of purchasing an N95 mask, lack of a mask that protects against particulate matter could be a barrier to taking effective avoidance measures against particulate matter. This would suggest that the N95 mask and the air quality alerts are complements. Although we estimate a positive coefficient, the coefficient is not significant at conventional levels. However, we find that higher compensation increases WTP, suggesting that

cash on hand may be a binding constraint.

We also investigate the correlates of WTP for the SMS alert service. WTP is negatively correlated with age and positively correlated with income, being male, and the perception that there was a high pollution day prior to the baseline survey regardless of whether there were actual high pollution days prior to the survey. The correlations between participant characteristics and WTP suggests that WTP for real-time air quality alerts may increase in the future with economic growth and as younger generations comprise a larger share of the population. The perception of high pollution days matters more than actual high pollution days in determining WTP for air quality alerts. We are able to rule out the specific channel that negative short-term health impacts of high pollution increase WTP for air quality information, concluding that participants with a stronger preference for clean air or who generally experience more pollution have both a higher WTP for air quality alerts and a greater likelihood of perceiving high air pollution.

We conduct two rounds of follow-up surveys approximately five months after the baseline survey to measure air pollution information and avoidance behavior. Data from the follow-up survey demonstrate that the SMS alerts increased the salience of air pollution. Households assigned to the alerts treatment are more likely to report that they received air pollution information from SMS alerts, less likely to report that they received air pollution information from television, and more likely to report that there was a high air pollution day in the past week. However, we cannot attribute the increased reporting of high pollution days to an increase in the accuracy of air pollution information, as we observe no significant effect on the ability to correctly recall which specific days had high pollution. Rather, it suggests an increase in the general salience of air pollution for households in the alerts treatment. In contrast, we find no effect of the reminders treatment on information outcomes, indicating that the reminders treatment was not frequent or prominent enough to increase the salience of air pollution.

Consistent with an increase in the general salience of air pollution, households in the alert and mask treatment are more likely to report engaging in air pollution avoidance behavior but these behavior changes are unlikely to significantly reduce exposure to air pollution. Households in the alerts treatment are more likely to report a change in behavior on the last perceived high pollution day, particularly that they stayed inside with windows closed. Similarly, households that received an N95 mask at baseline are more likely to report utilizing a mask with filter in the two weeks

before the follow-up survey, but we observe no effect on using a filter mask on the specific days with high PM. Consistent with the null effect on information outcomes, the reminder treatment had no effect on avoidance behavior outcomes, indicating that it was not sufficiently salient to motivate a change in behavior. This suggests that in a context of high ambient air pollution in which the population is already concerned about air quality, air pollution information that is not frequent and salient is ineffective. These results illustrate the strength of perceptions and the difficulty of using information treatments to effect behavioral change that could significantly lower air pollution exposure.

This paper contributes to the literature on the value of air pollution information and the effects of air pollution information on avoidance behavior in three ways. First, previous studies of pollution information (Barwick et al., 2020; Delmas and Kohli, 2020; Saberian et al., 2017; Janke, 2014; Noonan, 2014; Graff Zivin and Neidell, 2009; Neidell, 2009; Stieb et al., 1996; Skov et al., 1991) do not provide any empirical evidence on how households value air pollution information because the air quality information was provided for free. We make a novel contribution to this literature by providing a fine, incentive-compatible measure of WTP for real-time actionable air quality information and documenting the correlates of WTP. Second, relative to the existing literature that studies the effects of air quality alerts disseminated through the media (Saberian et al., 2017; Janke, 2014; Graff Zivin and Neidell, 2009; Neidell, 2009; Skov et al., 1991) and air quality information displayed on websites and smartphone applications (Barwick et al., 2020; Delmas and Kohli, 2020) on avoidance behavior, we study passive SMS alerts delivered directly to participants' phones. This limits concerns regarding inattention because participants do not need to remember to consult sources of air pollution information on a regular basis. Third, our study contributes empirical evidence for a large city in a developing country with a long and well-publicized history of high air pollution. Despite the fact that the cities with the highest pollution are located in developing countries, with the exception of Barwick et al. (2020), the empirical evidence on the effect of air pollution information on avoidance behavior comes from high-income countries.

Our paper extends this literature by providing novel empirical evidence of the strength of perceptions in air pollution knowledge and avoidance behavior. In particular, three results demonstrate that although masks and SMS alerts provide the technology and information to engage in effective avoidance behavior on high pollution days, powerful perceptions limit the impacts on exposure and

health outcomes that we can expect. First, we find that the perception of a recent high pollution day increases WTP for the alert service, but actually experiencing a recent high pollution day does not. Second, we find the alert treatment increases reported high pollution days and avoidance behavior but that participants in the alerts group are no more likely to be able to correctly identify recent high pollution days. Third, we find that the mask treatment increases reported use of a mask with a filter but has no effect on the use of a mask with a filter on days with high levels of particulates. Our findings are consistent with Semenza et al. (2008), which documents that a greater share of respondents in Portland, Oregon and Houston, Texas reported that they changed their behavior due to the perception of high pollution and not due to an advisory.[1]

The remainder of the paper proceeds as follows. Section 2 describes the experimental design, and data. Section 3 presents the empirical methods. Section 4 presents the distribution of WTP for the air quality alerts service, the correlates of WTP, and the effects of the mask and compensation treatments on WTP. Section 5 presents the treatment effects on air pollution information and avoidance behavior. Section 6 concludes.

2 Experimental Design and Data

2.1 Experimental Design

Our experimental design leverages a novel variation of the Becker–DeGroot–Marschak (BDM) method (Becker et al., 1964) to elicit an incentive-compatible measure of willingness to pay (WTP) for the air quality alerts service while allowing unconditional randomization of participants into four cross-cutting treatment arms – including the alerts service. Our approach allows us to (1) recover the demand curve for the alerts service, (2) study baseline correlates of WTP for alerts, (3) estimate treatment effects of the mask and higher compensation on WTP, and (4) estimate the causal impact of the alerts service on pollution knowledge and avoidance behaviors at followup.

The experimental design randomly assigned households to four cross-cutting treatment groups and their respective group groups: (1) the provision of a free, reusable, N95 mask (the *mask* treatment), (2) the provision of 50% higher compensation for baseline survey participation (*compensation* treatment), (3) a year-long subscription to pollutant-specific SMS air quality alerts (*alerts*

[1] Air quality advisories were publicized through the media, emails to subscribers, and electronic freeway signs.

treatment), and (4) a year-long subscription to monthly pollution trend and avoidance behavior SMS reminders (*reminders* treatment).[2] The structure of overlapping treatment arms allows us to study potential interactions between the experimental interventions. Appendix Figure A.2 depicts the division of the total sample into treatment arms. Overall, 50% of participants were assigned to each of the mask, alerts and reminders treatments and 30% were assigned to the compensation treatment. A pure control group comprised of households assigned to the control group for all of the four treatments contains 162 participants (8.7%).

All treatment arms were revealed to participants during the course of the baseline survey. First, baseline covariates were collected and information regarding trends, health impacts, and avoidance behavior of air pollution was provided to all respondents. Second, immediately *prior* to the elicitation of WTP, individuals randomly assigned to the mask treatment group were informed of the gift of an N95 mask and individuals randomly assigned to the compensation treatment group were informed of that their compensation would be 150 pesos. For consistency across treatment groups, individuals who were not randomly assigned to the compensation group were reminded of their 100 peso compensation. Third, willingness to pay for the alerts service was elicited. Fourth, *after* the WTP module, the alerts and reminders treatments were revealed. The timing of revealing each treatment is depicted in Appendix Figure A.1. The staggered timing allows for estimation of treatment effects of the mask and compensation treatments on willingness to pay for the alerts service. Appendix Figure A.1 depicts the experimental timeline.

2.1.1 Interventions

Appendix Figure A.3 provides a brief description of each treatment arm. In the *mask* treatment, participants were provided a free, reusable, N95 mask at the time of the baseline survey. N95 masks are proven effective against PM2.5; they do not, however, protect against ozone. At the time of purchase (2017) the cost per mask was approximately $4 USD. At baseline, while 32% of respondents report having previously used a mask with filter, only 6% report having done so in the recent air pollution contingencies in Mexico City (which occurred within a few weeks of the start

[2] Households were assigned to their particular treatment arms based on a survey ID associated with a random treatment status prior to baseline data collection. To avoid potential differential treatment of households, enumerators were unaware of the treatment status of the current household until it was revealed to the respondent during the course of the survey. The treatment status associated with the current survey ID was stored on the enumerator tablet.

of the baseline survey).[3]

The *compensation* treatment was designed to determine whether there is anchoring of WTP around the value of the compensation and/or cash-on-hand is a binding constraint for willingness to pay for the alerts service. All participants were recruited to participate in the baseline survey with an offer of 100 pesos of compensation on a prepaid debit card.[4] Participants who were not assigned to the *compensation* treatment received 100 pesos (approximately $5 USD) and participants who were assigned to the *compensation* treatment received 150 pesos (approximately $7.50 USD). To avoid having the survey team carry cash and to facilitate the implementation of the BDM module, for participants assigned to the *alerts* treatment, the amount of compensation loaded on a participant's debit card was reduced by the amount that he/she paid for the alerts service. Participants were informed of their higher compensation of 150 pesos or reminded of their compensation 100 pesos immediately prior to eliciting WTP for the alerts service in the baseline survey.

In the *alerts* treatment, participants received a year subscription to SMS alerts providing notification of elevated levels of air pollutants in the household's neighborhood. Alerts were sent at 7am on days when pollutants were measured at (or projected to) reach harmful levels by one of the four air pollution monitoring stations nearest to a household's AGEB (Área Geoestadística Básica). Messages were specific to particulate matter (PM) and ozone. The PM alert read *"Suspended particles near your house are high and likely will remain high for the rest of the day. Take precautions. Remember: the mask DOES protect against suspended particles."* For a high ozone forecast the alert read *"It is forecasted that the IMECA, and likely ozone, will be high near your house today. Take precautions. Remember: the mask DOES NOT protect against ozone."*[5] The amount that households in the *alerts* treatment paid for the service was determined through the Becker-DeGroot-Marshak mechanism. Nineteen households (4%) cancelled the SMS service before the 12-month subscription ended.

The *reminders* treatment was a year-long subscription to monthly SMS notifications describing

[3]Environmental "*contingencias*" in Mexico City are days when pollution levels rise above a determined threshold resulting in a public announcement and the imposition of certain emissions restrictions to mitigate conditions hazardous to health.

[4]Specifically, participants were told that "We would like to offer you a debit card with 100 pesos, as a thank you for answering our questions."

[5]IMECA refers to the Metropolitan Air Quality Index (Índice Metropolitano de la Calidad del Aire). IMECA is publicized hourly in Mexico City as an indicator of pollution exposure risk. A graphic with Spanish versions of the alerts is depicted in Figure A.4.

typical pollutant-specific conditions for that month of the year and appropriate avoidance measures. As an example, the reminder for November reads: *"Levels of particulate matter are typically elevated during the month of November. To protect yourself from particulate matter, avoid being outdoors from 10am to 2pm. Physical activity increases the harmful effects of air pollution."* The reminders group was enrolled in the reminders service at no cost. Both the alerts and reminders services were provided for a full calendar year from the time of the baseline survey. This timeline can be seen in Appendix Figure A.1.

Finally, all participants were provided with information on air pollution trends and appropriate avoidance measures during the baseline survey. After obtaining measures of pollution knowledge at baseline and prior to the WTP module, surveyors provided air quality information along with a series of graphics, which can be viewed in Appendix Figures A.5, A.6, & A.7. The information included time of day and months of year with highest air pollution, common health effects of pollution exposure, characteristics of high-risk individuals, and appropriate avoidance behaviors for both particulate matter and ozone. Besides providing valuable health information, ensuring that all participants possessed this information at baseline allows us to isolate the effect of timely and specific pollution alerts and frequent reminders from the potential effect of first time exposure to general air pollution risk information.

2.1.2 Willingness to Pay

We employ a version of the BDM mechanism similar to the titration-based BDM procedure in Mazar et al. (2014) to elicit willingness to pay for the alerts service. The BDM mechanism is similar to a second-price auction in which the second-price is an unknown, randomly generated price.[6] Participants were asked to state the maximum amount that they would be willing to pay for the alerts service, and then a random price was generated using the surveyor's tablet. If the random price was greater than the stated WTP, the respondent could not obtain the alerts service. However, if the random price fell below the stated WTP, the respondent would be charged the randomly determined price and would be enrolled in the service.

Using the surveyor's tablet, we generated the random price as follows. First, a random number,

[6] Under general assumptions, such as expected utility maximization, the BDM mechanism will elicit participants' true WTP when transactions are implemented immediately (Horowitz, 2006). "True" WTP is the highest price at which the participant would purchase the alerts service at a known price.

X, was generated between 0 and WTP inclusive. If the participant was assigned to the alert service treatment group, the price was calculated using the formula $Price = min[WTP - X, compensation\ value]$ where *compensation value* refers to one's assignment of 100 or 150 peso compensation. For security purposes, the compensation value was used as an upper limit to ensure that surveyors never collected cash from participants. If the participant was assigned to the alert service control, the price was calculated using the formula $Price = WTP + X + 1$. This design ensures that the price falls above WTP for participants who were not assigned to the alerts treatment and that the price falls below WTP for participants assigned to the alerts treatment while also randomly varying the revealed price.

We included two sentences in the description of the BDM module to avoid experimenter demand effects. First, immediately after the enumerator explained that she will ask the maximum value that the participant is willing to pay for a 12-month subscription to the SMS alerts service, the enumerator stated "It doesn't matter if it is a large or small amount." Second, as the last sentence of the BDM description, the enumerator stated "Remember, you do not have any obligation to acquire the service."

2.2 Sample Selection, Data, and Experimental Validity

Our sampling methodology aimed to produce a representative sample of households from areas of Mexico City with lower educational achievement. Beginning with the full set of *Áreas Geoestadisticas Básicas* (AGEBs) within Mexico City containing residential households in the 2010 census, we restricted the list to AGEBs with an average education level below the median. We further restricted the sample by excluding AGEBs that were involved in prior data collection and, for safety, those AGEBs located in a *colonia* with a homicide rate above the 70th percentile.[7] The remaining AGEBs were ordered randomly and surveyed in order. The day prior to surveying an AGEB, an advance team visited the AGEB to distribute invitations to all of the first 500 households encountered starting in the Northwestern-most block of the AGEB and moving to the Southeast. Each survey team visited one AGEB each day and attempted to interview each of the 500 households that had received invitations. Our sample contains 1,869 households surveyed at baseline across 118 AGEBs.

[7] In rare cases AGEBs were additionally excluded – due to safety concerns – by a majority vote of the field team.

Study participants were surveyed at baseline and in a follow-up survey approximately five months after the baseline. The baseline was conducted in person at participating households between June 18 and August 1, 2019. The follow-up consisted of two rounds of telephone surveys conducted from November 23 to December 24, 2019. The two rounds were conducted roughly two weeks apart, with an average of 15.5 days between follow-up responses. Appendix Figure A.1 depicts the data collection timeline.

The baseline survey collected a robust set of household and respondent demographic characteristics including age, gender, level of education, type of work, and monthly income for each household member. It collected household health information including whether any members were sick or hospitalized in the last month or had diagnoses of chronic health issues which may increase risk of air pollution exposure. In addition to demographic information, the baseline survey collected respondent perceptions about the general severity of local air pollution and specific beliefs regarding air quality conditions in the prior days. Finally, it elicited respondent beliefs about the effectiveness of various pollution avoidance measures, whether the respondent had engaged in any practices to mitigate pollution exposure in the past, and the frequency with which he or she typically seeks out air quality information. Household and respondent summary statistics at baseline are provided in Table 1 and figure 1 shows the frequency that participants searched for air quality information at baseline. The follow-up survey captured information on air pollution knowledge, sources of air pollution information, and avoidance behaviors.

Appendix Table A.1 displays the balance in 18 household and participant characteristics across the control group and the four treatment groups. Importantly, we find only two characteristics with significant differences between the control group and the alerts treatment group. Compared to the control group, we find that participants in the alerts treatment group are less likely to have experienced a high pollution day in the four days prior to the baseline survey and are less likely to report using a smartphone application to monitor air quality. The mask treatment group differs significantly from the control group in three characteristics (number of household members, age of participant, and the household health index). The compensation treatment group differs from the control group in five characteristics (gender of participant, completion of post-secondary school, experienced a high pollution day in the four days prior to the baseline survey, had used a mask with filter, took precautions in recent contingencies), but there are no significant differences in

income variables. The reminder treatment group differs from the control group in one characteristic (missing income variable).

During the study, 47.2% of households responded to at least one of the follow-up surveys, and 24.3% responded to both. Appendix Table A.2 shows that response to at least one followup survey is not correlated with WTP for the SMS alert service, the mask treatment, the alert treatment or the reminder treatment. However, households in the compensation treatment were 4.8% less likely to participate in at least one follow-up survey. Looking at the follow-up survey rounds separately, there is no correlation between WTP or any of the treatments and response in the first round. However, WTP for alerts is positively associated – and the compensation treatment is negatively associated – with response in the second round.

3 Empirical Methods

In this section, we outline the empirical methods that we use to (1) recover the demand curve for the alerts service, (2) study the predictors of WTP, and (3) estimate treatment effects from our experimental treatment arms.

First, we generate the inverse demand curve for the alerts service by inverting the empirical cumulative distribution of WTP in our sample. Specifically, we order observations by increasing WTP and, for each unique value of WTP in our sample, we calculate the share of observations with WTP greater than the current value. WTP is then plotted against this share, producing a graph of inverse demand.

Second, to study the predictors of willingness to pay for the alerts service, we estimate the following specification by OLS:

$$WTP_i = \alpha + \theta \mathbf{Z}_i + \lambda \mathbf{Surveyor}_i + \epsilon_i, \tag{1}$$

where WTP_i is the willingness to pay of respondent i. $\mathbf{Z}_i$ is the set of predictors of interest, $\mathbf{Surveyor}_i$ are surveyor fixed effects and ϵ_i is the idiosyncratic error term. We estimate equation 1 for different sets of covariates: income, demographics, health-related variables, and beliefs and behaviors related to air pollution and mitigation. For a final regression we select the most relevant

predictors by including all covariates in a LASSO regression and then estimating the pecification 1 by OLS including the predictors which survive LASSO in the first stage. Though estimates of θ from equation 1 should not be interpreted as causal, they are informative of the correlates of WTP for our sample.

Third, we estimate treatment effects on WTP for alerts at baseline and on knowledge and avoidance behavior outcomes at follow-up using the following regression equation estimated via OLS:

$$y_i = \alpha + \beta_A T_i^{Alerts} + \beta_M T_i^{Mask} + \beta_R T_i^{Reminders} + \beta_{HC} T_i^{HighComp} + \theta \mathbf{X}_i + \lambda \mathbf{Surveyor}_i + \epsilon_i, \quad (2)$$

where y_i is the outcome of interest for respondent i; T_i^j is an indicator variable equal to 1 if individual i is assigned to treatment group j for each of the alerts, mask, reminders, and high compensation treatments; $\mathbf{X}_i$ is a vector of baseline controls; $\mathbf{Surveyor}_i$ are baseline surveyor fixed effects; and ϵ_i is the individual error term. Participants are informed of the alerts and reminders treatments *after* eliciting WTP for the alerts service in the baseline survey, while the mask and high compensation treatments are revealed before; therefore, for the WTP outcome, the alerts and reminder treatment indicators serve only as a placebo check. For each outcome, the set of baseline covariates, $\mathbf{X}_i$, included in the regression, is chosen by LASSO double selection. Each treatment indicator (T_i^j) and the outcome (y_i) is regressed independently, via LASSO, on a set of controls collected in the baseline survey. We force inclusion of surveyor fixed effects in each LASSO regression. $\mathbf{X}_i$ is the union of the LASSO-selected covariates from all four first stage regressions. In addition to specification (2), for willingness to pay, we test the interaction of the mask and compensation treatments by including an interaction term:

$$y_i = \alpha + \beta_M T_i^M + \beta_{HC} T_i^{HC} + \beta_{M,C} T_i^M \times T_i^{HC} + \beta_a T_i^A + \beta_r T_i^R + \theta \mathbf{X}_i + \lambda \mathbf{Surveyor}_i + \epsilon_i. \quad (3)$$

4 Willingness to Pay for Air Quality Alerts

4.1 WTP for Air Pollution Alerts

In the pure control group, 72% of respondents reported a positive WTP, 11% of respondents reported a WTP of 0 (i.e., they would accept the alert service if it were free), and 17% of respondents indicated a negative WTP by reporting that they would not accept the alerts service even if it were free of charge.[8] Although the alert service could be canceled at any time, respondents could have a negative WTP (refuse the alert service if it were free) if the non-monetary costs of the air pollution alerts outweighed the benefits. One possibility is that the alerts could cause respondents stress by alerting them to high pollution days and reminding them of the negative health impacts of air pollution when they believe they or their household members cannot engage in effective avoidance behavior. Alternatively, a negative WTP could reflect that the information in the alerts has no value to the respondent and that the respondent would be inconvenienced by receiving alerts. For all analysis, we impute a WTP of 0 for those respondents who indicate that they would not accept the alerts service even if it were free.

Figure 2 plots the inverse demand curve for air pollution alerts based on elicited WTP. Among control group respondents, the mean and median WTP were 54 ($2.83) and 10 pesos ($0.52 USD), respectively. For the full sample of respondents, the mean WTP was 53 pesos ($2.77), and the median was 15 pesos ($0.79). As a benchmark for comparison, each SMS sent incurred a cost of $0.05 USD, implying that the marginal cost of the median user in our sample was $6.45 USD for the 12-month subscription.[9]

4.2 Predictors of WTP for Air Pollution Alerts

Table 2 presents coefficient estimates for the predictors of willingness to pay for the alerts service estimated according to equation 1.[10] The predictors of WTP can be divided into four categories: income, demographics, health, and air pollution beliefs and avoidance behaviors. We include three

[8] In the full sample, 74% of respondents reported a positive WTP, 10% of respondents reported a WTP of 0, and 16% of respondents indicated a negative WTP.

[9] However, if the SMS air quality alert service were scaled up to all residents of Mexico City, the lowest-cost contract (or method of service provision) would likely include a high fixed cost and a marginal cost per user near 0.

[10] Note that the sample size of Table 2 (1,797) decreases relative to the full sample (1,869) due to both non-response to the WTP module (we observe 1,814 responses) and trimming of outliers above the 99th percentile of WTP. Table A.4 reproduces the result of Table 2 with no trimming.

indicator variables for income level as well as one for income not reported. The omitted category is *not working*. Demographics variables include the log of the number of household members, respondent age and gender, an indicator for head of household, and indicator variables for education levels. The omitted category for education level is *completed less than secondary school*. Health variables include a health index and an indicator for not having health insurance. The health index is constructed using principal component analysis of the following variables: (1) a household member has been sick in the last month, (2) a household member has a chronic issue exacerbated by air pollution exposure, (3) a household member has been hospitalized in the last month, (4) a household has senior members (over 65), (5) a respondent has had a cough in the last month, (6) a respondent reports having bad or very bad health in general. We multiply the index by negative 1 so that it is increasing in household health. Finally, the set of air pollution variables include an indicator for whether there was high ozone in the last four days, an indicator for whether the respondent reports that there was high pollution in the last four days, an indicator for whether the respondent reports that a mask protects against air pollution, an indicator for whether the respondent had previously used a mask with a filter, an indicator for whether the respondent had engaged in avoidance behavior during recent contingencies, and an indicator for whether the respondent uses an app to monitor air quality.

In column 1, we include all four sets of covariates in a single regression with WTP for alerts service as the dependent variable. In column 2, we utilize LASSO in a first stage to select the most important predictors and then estimate equation 1 including only the predictors selected in the first stage.

The results in columns (1) and (2) are consistent and very similar. Male, younger, and higher-income respondents have greater willingness to pay.[11] This implies that WTP for air quality alerts may increase over time with economic growth and as younger generations who are more concerned about air quality comprise a larger share of the population of Mexico City.

Also, reporting that there was high pollution in recent days is positively correlated with willingness to pay for air pollution alerts. *Reporting* there was high pollution in the days before the baseline survey is a strong predictor of WTP, but actually experiencing a high pollution (ozone)

[11] We also report coefficient estimates for WTP regressed on each group of covariates separately in Appendix Table A.3. Results are largely the same, however, *no insurance* is significant when health variables alone are included.

day in the days prior to the survey is not correlated with WTP. No household experienced a day with high levels of particulate matter in the days before baseline, but 56% saw at least one day of high ozone. This implies that respondents' *perceptions* of recent pollution levels are correlated with WTP for SMS alerts, but actual recent pollution levels are *not*. Air quality may be more salient for individuals with a stronger preference for clean air or who generally experience more pollution, leading to a higher willingness to pay for air quality alerts and a higher likelihood of perceiving that a recent day had high pollution.[12]

We can rule out an additional, specific channel through which perceptions of high pollution days, actual high pollution days, and WTP for air pollution alerts could be related. Perceptions of recent high pollution days could be correct, and recent days with high ozone could lead to negative health impacts that increase WTP for air quality information. High ozone, while not visible to the eye, could be perceived due to shortness of breath, coughing, and a sore or scratchy throat. However, we can rule out this specific channel by the fact that a high ozone day does not itself predict WTP.

4.3 Treatment Effects on WTP for Air Pollution Alerts

In this section, we present estimates of the mask and compensation treatment effects on willingness to pay for the alerts service. The mask treatment was designed to test whether protective items and timely information on pollution levels are complements or substitutes. A positive treatment effect of the N95 mask would suggest that the mask and the alert service are complements; the value of accurate and timely information on pollution levels is higher when households have access to the means to effectively engage in protective measures. The N95 mask is most effective at lowering exposure when used on days with high pollution. Therefore, information on which days have high levels of air pollution may be more valuable for households that have an N95 mask. A negative treatment effect of the mask would indicate that the mask and the alert service are substitutes; the value of accurate and timely information on pollution levels is lower when households have protective items available. One possible explanation is that households rely on simple rules of

[12] Average levels of particulate matter over the prior 12 months are correlated with reporting that there was high pollution (both particulate matter and ozone) on the days prior to the survey. In contrast, average levels of ozone over the prior 12 months are negatively correlated with reporting that there was high pollution (both particulate matter and ozone) on the days prior to the survey. These differential effects could be partially due to the fact that ozone is more difficult to observe than particulate matter.

thumb or develop routines to determine when to engage in different types of avoidance behavior. For example, households who receive an N95 mask may prefer to wear the mask every day during months that tend to have high levels of particulate matter rather than stay indoors on specific days with high levels of particulate matter. In this case, the value of timely air pollution information is lower for households who receive an N95 mask. The compensation treatment was included to test whether there is an anchoring effect of the compensation amount on WTP and/or cash on hand is a binding constraint for willingness to pay. A positive treatment effect would indicate an anchoring effect or that participants' reported WTP are limited by the immediate availability of funds.

Treatment effect estimates for the impact of the mask and compensation treatments on WTP for SMS air quality alerts are presented in Table 3.[13] Column (1) displays estimates of equation 2. The sign of the mask coefficient is positive, but it is not statistically significant. The cost of the provided masks was 78.01 pesos (approximately $4 USD). In 2019, the daily minimum wage in Mexico was 102.68 Mexican Pesos, so for a minimum-wage worker, purchasing an N95 mask would cost 76% of a day's wage. We find a significant positive impact of the compensation treatment. Increasing the baseline compensation from 100 to 150 pesos resulted in an average increase in WTP of 8.2 pesos over the control group mean of 44.7 pesos (an 18% increase) suggesting anchoring at the compensation amount or a binding cash-on-hand constraint.

Column (2) displays estimates of equation 3 to test for possible interactions of the Mask and Compensation treatment effects.[14] The interaction term is insignificant, and the estimated mask and compensation treatment effects are consistent with those presented in column (1).

5 Treatment Effects on Air Pollution Information and Avoidance Behavior

In this section, we report treatment effect estimates of the four treatment arms on outcomes related to knowledge of air pollution conditions and air pollution avoidance behaviors, as measured during

[13] While the treatment effect estimates presented in Table 3 reflect conditioning on LASSO selected covariates and trimming of observations above the 99th percentile of WTP, unconditional estimates and estimates with no trimming can be found, respectively, in Appendix Tables A.5 and A.6.

[14] In addition to testing for complementary between treatment arms, Muralidharan et al. (2020) highlight the importance of reporting fully interacted specifications for cross-randomized experimental designs to mitigate risk of incorrect inference when interactions may be non-zero. Here we observe no substantial change to estimates of the magnitude or significance levels relative to the un-interacted specification.

follow-up phone surveys roughly five months after the baseline. Since the follow-up survey was conducted in two rounds to maximize response, for households that responded to both follow-up surveys, both responses are included in the analysis and standard errors are clustered by household to address correlation of responses.

The first set of outcomes, presented in Table 4, relate to participant knowledge of air quality at followup.[15] Columns (1)-(3) display treatment effects on self-reports of how respondents learned that there was high pollution during the two weeks prior to the phone survey.[16] SMS alerts, television, and "perception" (i.e., seeing it, smelling it, feeling it, etc.) are the most frequent modes of information acquisition reported by participants at follow-up. Control group means for each are indicated in Table 4.

We observe a large, significant effect of the alerts treatment on reporting having learned about high pollution from SMS alerts (column (1)), as well as a substitution away from receiving pollution information from television (column (2)). There is no discernible effect of the alerts treatment on reports of simply "perceiving" pollution (column (3)).[17]

Column (4) presents treatment effect estimates for reporting whether there was a high pollution day in the past week. This outcome is an indicator variable which takes a value of 1 if the respondent reported that there was a high pollution day in the week prior to the followup survey. Here, we again observe a significant effect of the alerts treatment. Specifically, we observe a 10-percentage point increase in reporting that there was a high pollution day on a control mean of 38%. Since 93.5% of observations experienced a high pollution day in the week prior to the follow-up survey (47.8% high PM and 91.6% high ozone), an average increase in the likelihood of reporting there was a high pollution day does not necessarily reflect an increase in accurate information. As we show in the following two columns, this effect represents a general increase in the awareness or salience of air pollution among members of the alerts treatment group and not an improvement in the precision of air pollution knowledge.

We observe no increase in precision of identifying which specific days had high pollution. The

[15] Comparable estimates which do not condition on baseline covariates can be found in Appendix Table A.7. Results are largely consistent.

[16] These regressions are unconditional; the value is imputed as 0 for each information source if the respondent reported that they did not have a high pollution day in the past two weeks regardless of actual pollution levels.

[17] As few or no respondents indicated receiving information via radio, newspaper, online, or a government application, we therefore exclude these outcomes from the regression analysis.

outcome of Column (5) is the percent of days from the past week for which the respondent correctly identifies whether or not there was high pollution. In this column the sample size decreases slightly owing to the fact that we omit observations for which the outcome is undefined (47 respondents expressed there was at least one high pollution day, but in fact had none, so that the denominator of the outcome would be zero for these observations). Lack of improvement on this outcome suggests either that alerts service members generally recall receiving an alert, but have difficulty remembering the exact days the alert(s) were received, or that the alerts intervention has raised the general salience of air pollution without a meaningful impact on precise information that would allow avoidance behavior to reduce exposure. Column (6) shows that the alert treatment does not increase the likelihood that a respondent correctly identifies whether there was high pollution on the survey day and the day prior to the survey. Restricting the focus to these two days allows us to rule out inaccurate recall and provides additional evidence that the alerts treatment increased the general salience of air pollution but did not increase the accuracy of air pollution information.

The reminders treatment has no effect on the modes of learning about air pollution (columns (1)-(3)), nor on precise pollution knowledge (columns (4)-(5)). Column (4) implies that, compared to the SMS treatment, the information provided in the reminders treatment was not frequent or salient enough to increase the salience of air pollution (column (4)). Additionally, we observe no effect of the mask or compensation treatments on information outcomes.

Table 5 reports treatment effects on outcomes related to air pollution avoidance and mitigation measures at the time of follow-up.[18] Columns (1) - (4) display estimates from equation 2, where the outcome is an indicator equal to 1 if the respondent reports performing the specified behavior on the most recent perceived high pollution day. Respondents were asked first if they did something different (column 1) and if so, were asked *compared to a normal day, what did you do differently on the last high pollution day?*[19] We observe a significant impact of the alerts service on reporting a change in behavior and, specifically, on staying indoors with the windows closed.

Finally, column (5) of Table 5 indicates a significant impact of the mask treatment on reporting

[18] Comparable estimates which do not condition on baseline covariates can be found in Appendix Table A.8. Results are largely consistent.

[19] Specific avoidance options were read to respondents; however, enumerators could indicate multiple behaviors which applied as categorized by the same list of avoidance behaviors asked one-by-one at the time of the baseline survey.

having made use of a mask with filter in the past two weeks prior to follow-up. The magnitude of the effect (6.7%) suggests a large improvement over the control mean of 2.8%. However, we cannot strictly attribute this effect to an improvement in mask usage that would positively influence health outcomes. Similar to the outcome of correct knowledge on days of air pollution in Table 4, in column (6) we observe no effect of the mask treatment on the percentage of days for which a filter mask was used correctly (i.e., utilized when there were dangerous levels of PM). Thus, while the evidence suggests that the provision of a filter mask and the provision of the alerts service influence a change in avoidance behaviors and awareness of air pollution, it is not clear whether this translates to behavioral changes that could significantly lower air pollution exposure enough to improve health outcomes.

6 Conclusion

We conduct a randomized controlled trial in Mexico City to determine WTP for SMS air quality alerts and to study the effects of air quality, reminders, and a reusable N95 mask on air pollution information and avoidance behavior. We find that the perception of recent high pollution days is positively correlated with WTP for the air quality alerts but actually experiencing a recent high pollution day is not. We find that SMS alerts increase the salience of air quality and avoidance behavior, but are unlikely to lead to substantial decreases in exposure to air pollution. Households in the alert treatment are more likely to report receiving air pollution information via SMS, to report that there was a high pollution day during the past week, and to report staying indoors on the most recent perceived high pollution day. However, households in the alert treatment are no more likely to be able to correctly identify recent high pollution days. Similarly, households that received an N95 mask are more likely to report using a mask with a filter in the past two weeks, but they are no more likely to report using a mask with a filter on the specific days with particulate pollution. Taken together, our results illustrate the limitations of information treatments in overcoming perceptions to effectively reduce exposure to air pollution and lower health risks.

Our results suggest that, although alerts increase the general salience of air pollution, air pollution alerts are not conveying as much information as intended. In cities with a long history of high air pollution, policies that exclusively rely on air quality information provided through information

communication technologies to affect behavior changes that reduce the negative health impacts of high pollution days may not be effective. While information can be provided at low cost, more paternalistic policies may be necessary to reduce the population's exposure to air pollution. These findings are consistent with Stieb et al. (1996), which document that Canadian smog advisories had limited impacts on information and behavior change. In another context, these findings are also consistent with recent research demonstrating the limited impact of information nudges on behavior changes that mitigate health risks during the Covid-19 pandemic (Barari et al. (2021) and Sanders et al. (2021)), particularly in contexts in which baseline awareness is high (Blackman and Hoffmann, 2021).

References

Aragón, Fernando M., Juan Jose Miranda, and Paulina Oliva (2017), "Particulate matter and labor supply: The role of caregiving and non-linearities." *Journal of Environmental Economics and Management*, 86, 295–309, URL https://www.sciencedirect.com/science/article/pii/S0095069617301225. Special issue on environmental economics in developing countries.

Barari, Soubhik, Stefano Caria, Antonio Davola, Paolo Falco, Thiemo Fetzer, Stefano Fiorin, Lukas Hense, Andriy Ivchenko, Jon Jachimowicz, Gary King, Gordon Kraft-Todd, Alice Ledda, Mary MacLennan, Lucian Mutoi, Claudio Pagani, Elena Reutskaja, Christopher Roth, and Federico Raimondi Slepoi (2021), "Evaluating covid-19 public health messaging in italy: Self-reported compliance and growing mental health concerns." Working paper, URL https://bit.ly/2UfpoW3.

Barwick, Panle Jia, Shanjun Li, Liguo Lin, and Eric Zou (2020), "From fog to smog: the value of pollution information." Working Paper 26541, National Bureau of Economic Research, URL http://www.nber.org/papers/w26541.

Becker, Gordon M., Morris H. Degroot, and Jacob Marschak (1964), "Measuring utility by a single-response sequential method." *Behavioral Science*, 9, 226–232, URL https://onlinelibrary.wiley.com/doi/abs/10.1002/bs.3830090304.

Bell, Michelle L., Jonathan M. Samet, and Francesca Dominici (2004), "Time-Series Studies of Particulate Matter." *Annual Review of Public Health*, 25, 247–280, URL https://doi.org/10.1146/annurev.publhealth.25.102802.124329. PMID: 15015920.

Bharadwaj, Prashant, Matthew Gibson, Joshua Graff Zivin, and Christopher A Neilson (2017), "Gray matters: Fetal pollution exposure and human capital formation." *Journal of the Association of Environmental and Resource Economists*, 4, 505–542, URL https://www.journals.uchicago.edu/doi/abs/10.1086/691591.

Blackman, Allen and Bridget Hoffmann (2021), "Diminishing returns: Nudging covid-19 prevention among colombian young adults." Working Paper 1217, Inter-American Development Bank, URL https://publications.iadb.org/en/diminishing-returns-nudging-covid-19-prevention-among-colombian-young-adults.

Chang, Tom, Joshua Graff Zivin, Tal Gross, and Matthew Neidell (2016), "Particulate pollution and the productivity of pear packers." *American Economic Journal: Economic Policy*, 8, 141–69, URL https://www.aeaweb.org/articles?id=10.1257/pol.20150085.

Chang, Tom Y., Joshua Graff Zivin, Tal Gross, and Matthew Neidell (2019), "The effect of pollution on worker productivity: Evidence from call center workers in china." *American Economic Journal: Applied Economics*, 11, 151–72, URL https://www.aeaweb.org/articles?id=10.1257/app.20160436.

Chay, Kenneth Y. and Michael Greenstone (2003), "The Impact of Air Pollution on Infant Mortality: Evidence from Geographic Variation in Pollution Shocks Induced by a Recession*." *The Quarterly Journal of Economics*, 118, 1121–1167, URL https://doi.org/10.1162/00335530360698513.

Currie, Janet and Matthew Neidell (2005), "Air Pollution and Infant Health: What Can We Learn from California's Recent Experience?*." *The Quarterly Journal of Economics*, 120, 1003–1030, URL https://doi.org/10.1093/qje/120.3.1003.

Delmas, Magali A. and Aanchal Kohli (2020), "Can apps make air pollution visible? learning about health impacts through engagement with air quality information." *Journal of Business Ethics*, 161, 279–302, URL https://link.springer.com/article/10.1007/s10551-019-04215-7#citeas.

Graff Zivin, Joshua and Matthew Neidell (2009), "Days of haze: Environmental information disclosure and intertemporal avoidance behavior." *Journal of Environmental Economics and Management*, 58, 119–128, URL https://www.sciencedirect.com/science/article/pii/S0095069609000370.

Graff Zivin, Joshua and Matthew Neidell (2012), "The impact of pollution on worker productivity." *American Economic Review*, 102, 3652–73, URL https://www.aeaweb.org/articles?id=10.1257/aer.102.7.3652.

Hanna, Rema and Paulina Oliva (2015), "The effect of pollution on labor supply: Evidence from a natural experiment in mexico city." *Journal of Public Economics*, 122, 68–79, URL https://www.sciencedirect.com/science/article/pii/S0047272714002096.

Horowitz, John K. (2006), "The becker-degroot-marschak mechanism is not necessarily incentive compatible, even for non-random goods." *Economics Letters*, 93, 6–11, URL https://www.sciencedirect.com/science/article/pii/S0165176506001133.

Janke, Katharina (2014), "Air pollution, avoidance behaviour and children's respiratory health: Evidence from england." *Journal of Health Economics*, 38, 23–42, URL https://www.sciencedirect.com/science/article/pii/S0167629614000940.

Lavy, Victor, Avraham Ebenstein, and Sefi Roth (2014), "The Impact of Short Term Exposure to Ambient Air Pollution on Cognitive Performance and Human Capital Formation." NBER Working Papers 20648, National Bureau of Economic Research, Inc, URL https://ideas.repec.org/p/nbr/nberwo/20648.html.

Mazar, Nina, Botond Koszegi, and Dan Ariely (2014), "True context-dependent preferences? the causes of market-dependent valuations." *Journal of Behavioral Decision Making*, 27, 200–208, URL https://onlinelibrary.wiley.com/doi/abs/10.1002/bdm.1794.

Muralidharan, Karthik, Mauricio Romero, and Kaspar Wüthrich (2020), "Factorial designs, model selection, and (incorrect) inference in randomized experiments." CESifo Working Paper Series 8137, CESifo, URL https://EconPapers.repec.org/RePEc:ces:ceswps:_8137.

Neidell, Matthew (2009), "Information, avoidance behavior, and health: The effect of ozone on asthma hospitalizations." *Journal of Human Resources*, 44, 450–478, URL https://www.jstor.org/stable/20648904.

Noonan, Douglas (2014), "Smoggy with a chance of altruism: The effects of ozone alerts on outdoor recreation and driving in atlanta." *Policy Studies Journal*, 42, URL Smoggywithachanceofaltruism:Theeffectsofozonealertsonoutdoorrecreationanddrivinginatlanta.

Saberian, Soodeh, Anthony Heyes, and Nicholas Rivers (2017), "Alerts work! air quality warnings and cycling." *Resource and Energy Economics*, 49, 165–185, URL https://www.sciencedirect.com/science/article/pii/S0928765516300707.

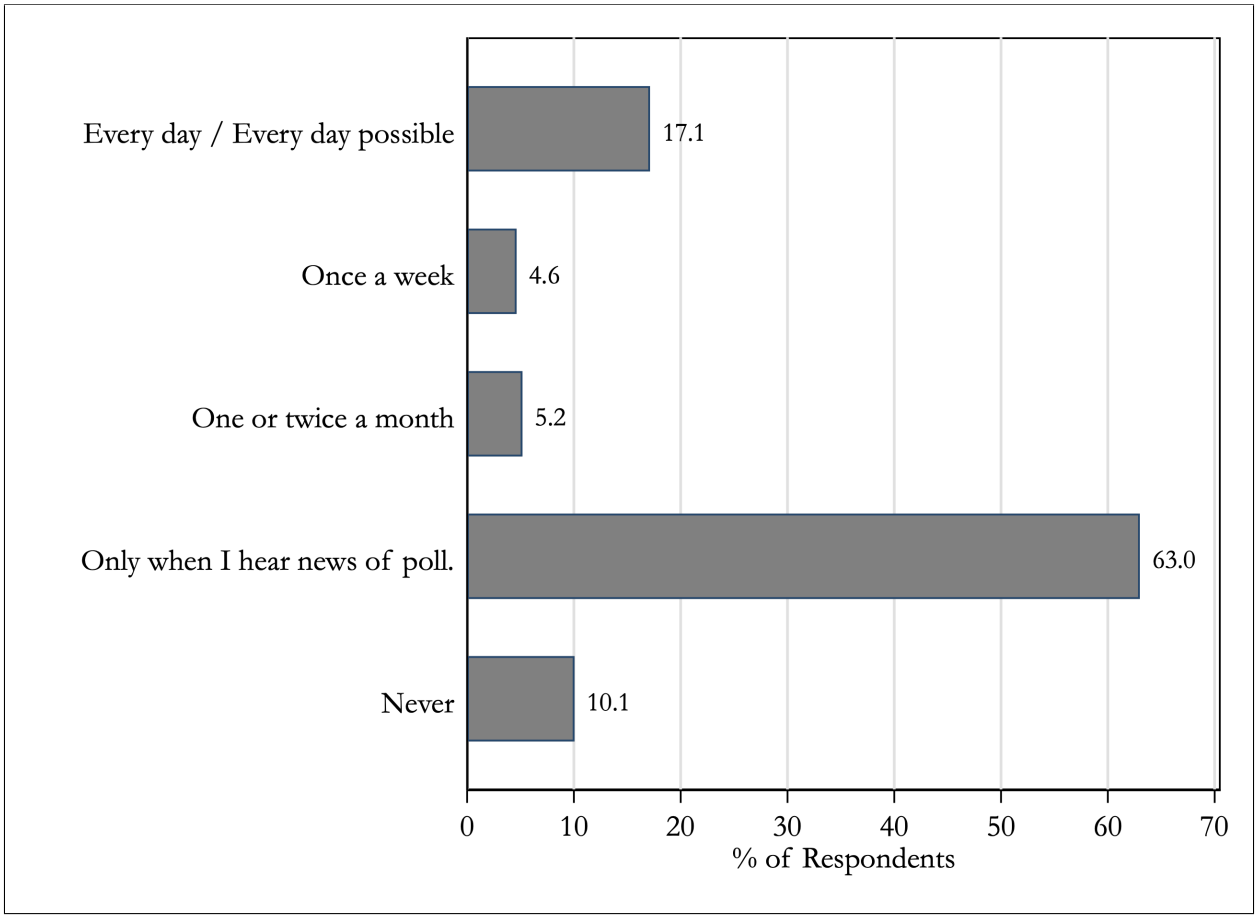
Sanders, Michael, Emma Stockdale, Susannah Hume, and Peter John (2021), "Loss aversion fails to replicate in the coronavirus pandemic: Evidence from an online experiment." *Economics Letters*, 199, 109433, URL https://www.sciencedirect.com/science/article/pii/S0165176520302706.

Semenza, Jan, Daniel Wilson, Jeremy Parra, Brian Bontempo, Melissa Hart, David Sailor, and Linda George (2008), "Public perception and behavior change in relationship to hot weather and air pollution." *Environmental research*, 107, 401–411, URL https://pubmed.ncbi.nlm.nih.gov/18466894/.

Skov, Torsten, Torben Cordtz, Lilli Kirkeskov Jensen, Peter Saugman, Kirsten Schmidt, and Peter Theilade (1991), "Modifications of health behaviour in response to air pollution notifications in copenhagen." *Social Science & Medicine*, 33, 621–626, URL https://www.sciencedirect.com/science/article/pii/0277953691902207.

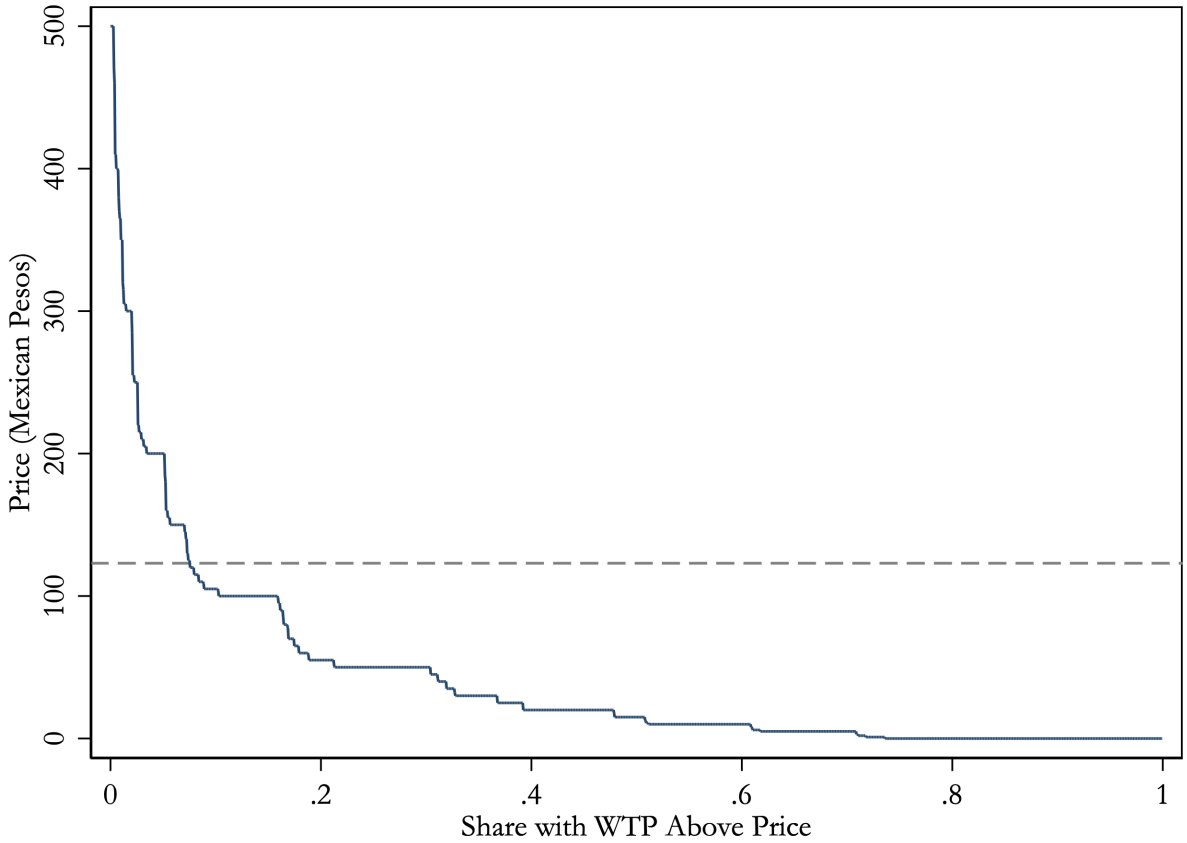
Stieb, DM, J Paola, and K Neuman (1996), "Do smog advisories work? results of an evaluation of the canadian smog advisory program." *Canadian journal of public health = Revue canadienne de sante publique*, 87, 166—169, URL http://europepmc.org/abstract/MED/8771917.

Figure 1: Frequency of Seeking Air Quality Information



Notes: This figure plots the percentage of study participants who indicated the given response at baseline to the question: *"How often do you look for air quality information?"*

Figure 2: Inverse Demand for SMS Air Quality Alerts



Notes: This figure plots prices for the air pollution alerts service against the share of individuals who expressed a willingness to pay for the alerts service above the given price. The marginal cost for the median alerts service user in our sample is roughly 123 Pesos or 6.45 USD (indicated by the dashed line), however, we estimate that if the service was scaled to the full population, marginal cost would be near 0.

Table 1: Baseline Summary Statistics

	Mean (1)	Standard Dev (2)
Household Demographics:		
# of HH Members	3.97	1.77
# Seniors (Over 65)	0.30	0.58
Respondent Demographics:		
Age	42.50	15.28
Gender: Male	0.35	0.48
Head of Household	0.54	0.50
Level of Education:		
Did Not Complete Secondary	0.19	0.39
Secondary School Complete	0.38	0.48
Post-Secondary Degree Complete	0.43	0.50
Income:		
Not Working	0.45	0.50
0 - 2,000 Pesos	0.12	0.32
2,000 - 6,000 Pesos	0.23	0.42
Above 6,000 Pesos	0.13	0.33
Working, but Income Unreported	0.07	0.26
Respondent & Household Health:		
Subjective Health: Bad/Very Bad	0.13	0.34
Cough / Diff. Breathing Last Month	0.24	0.43
Respondent was Sick (Past Month)	0.25	0.43
Respondent has Chronic Health Issue	0.42	0.49
A HH Member was Sick (Past Month)	0.61	0.49
A HH Member has a Chronic Health Issue	0.75	0.43
A HH Member Hospitalized (Past Month)	0.20	0.40
No Insurance	0.19	0.39
Beliefs on Pollution & Avoidance Measures:		
Had High Poll. (Ozone) in Last 4 Days	0.48	0.50
Reports High Pol. in Last 4 Days	0.56	0.50
Mask Effective Against Pollution	0.46	0.50
Avoidance Behaviors:		
Has Used Mask with Filter	0.32	0.46
Took Precautions in Recent Contingencies	0.70	0.46
Uses App to Monitor Air Quality	0.09	0.29

This table presents summary statistics from the baseline survey on respondent and household characterstics, as well as, respondent beliefs on pollution and baseline avoidance behaviors. The number of observations is 1869 for all variables.

Table 2: Predictors of Willingness To Pay

	Dependent Variable: WTP for Alerts Service	
	(1)	(2)
Income: 0 - 2,000 Pesos	-4.952	-4.834
	(4.653)	(4.666)
Income: 2,000 - 6,000 Pesos	-1.466	-1.066
	(4.170)	(4.188)
Income: Above 6,000 Pesos	12.93**	13.41**
	(6.418)	(6.465)
Income: Missing	0.601	0.969
	(6.357)	(6.425)
Log # of HH Members	2.802	
	(3.875)	
Age	-0.503****	-0.472****
	(0.127)	(0.103)
Gender: Male	11.75***	12.00***
	(4.083)	(4.085)
Head of Household	2.872	
	(3.553)	
Educ: Secondary School Complete	-1.694	
	(4.692)	
Educ: Post-Secondary Complete	-0.429	
	(4.869)	
Household Health Index	-0.464	
	(1.149)	
No Insurance	7.138	7.054
	(4.670)	(4.653)
Had High Poll. (Ozone) in Last 4 Days	-1.900	
	(3.295)	
Reports High Poll. in Last 4 Days	9.707***	9.785***
	(3.438)	(3.329)
Mask Effective Against Pollution	-0.0837	
	(3.303)	
Has Used Mask with Filter	2.140	2.314
	(3.530)	(3.578)
Took Precautions in Contingencies	3.411	3.764
	(4.131)	(3.978)
Uses App to Monitor Air Quality	7.414	7.444
	(7.020)	(7.007)
LASSO Selected Covariates	No	Yes
Control Mean	44.7	44.7
Observations (N)	1797	1797

Robust standard errors are reported in parentheses. WTP is in Mexican Pesos. Outliers are dropped above the 99th percentile of WTP. *Log # HH Members*, *Age*, and the *Houeshold Health Index* are continuous variables, while the remainder are indicator variables. The *Household Health Index* is increasing in improved health and is generated using PCA on 6 variables: 1) a household member has been sick in the last month, (2) a household member has a chronic issue exacerbated by air pollution exposure, (3) a household member has been hospitalized in the last month, (4) a household has senior members (over 65), (5) a respondent has had a cough or difficulty breathing in the last month, (6) a respondent reports having bad or very bad health in general. The omitted categories for Income and Education are, respectively, *Not Working* and *Less than Secondary School Completed*. Column 2 reports coefficients from OLS regression on a subset of independent variables selected by LASSO in a first stage. *Middle Income* is dropped by LASSO, but included in the second stage to complete the set of income variables. Regressions (and LASSO) are conditional on surveyor fixed effects. The *Control Mean* reflects the mean of willinness to pay for the pure control group. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table 3: Treatment Effects on Willingness to Pay for Alerts Service

	Dependent Variable: WTP	
	(1)	(2)
Mask	2.961	4.306
	(3.156)	(3.647)
Compensation	8.299**	10.55**
	(3.564)	(5.090)
Mask x Compensation		-4.476
		(6.947)
Control Group Mean	44.70	44.70
Observations (N)	1797	1797

Robust standard errors are reported in parentheses. WTP is in Mexican Pesos. Outliers are dropped above the 99th percentile of WTP and for continuous control variables. Both regressions are conditional on a set of control variables determined by LASSO double selection in a first stage. Regressions (and LASSO) are also conditional on surveyor fixed effects. Alert and Reminder treatment indicators are included in both regressions, but should not impact WTP since assigned after WTP is reported (these coefficients are insignificant as expected). *Control Mean* reflects the mean of WTP for those assigned to no treatment group. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table 4: Followup Treatment Effects: Information on Air Quality

	Knew of Last High Poll. Day From					
	SMS Alert	Television	Perception	Reports there was High Poll. in Past Week	% Days Correctly Identifies High Poll. (Past Week)	Correct Whether High Poll. Today/Yesterday
	(1)	(2)	(3)	(4)	(5)	(6)
Alert	0.144****	-0.0415***	0.000500	0.101****	0.0114	-0.0257
	(0.0183)	(0.0154)	(0.0289)	(0.0285)	(0.0162)	(0.0250)
Mask	-0.00851	0.00105	0.0387	0.0106	-0.0265	-0.0145
	(0.0184)	(0.0157)	(0.0297)	(0.0288)	(0.0164)	(0.0255)
Reminder	0.0151	-0.0155	-0.00518	0.0147	0.00255	-0.0158
	(0.0184)	(0.0155)	(0.0300)	(0.0293)	(0.0170)	(0.0262)
Compensation	0.0203	-0.00907	-0.0256	-0.0158	-0.0172	-0.0427
	(0.0199)	(0.0167)	(0.0313)	(0.0309)	(0.0171)	(0.0270)
Control Group Mean	0.019	0.085	0.377	0.377	0.160	0.387
Unique Households	873	873	873	873	852	873
Observations (N)	1329	1329	1329	1329	1282	1329

Regressions are based on stacked data from two rounds of follpowup surveys. Standard errors, clustered by respondent, are reported in parentheses. Outliers are dropped above the 99th percentile for continuous control variables. Regressions are conditional on surveyor fixed effects and control variables determined by LASSO double selection. *Control Mean* reflects the mean of the dependent variable for those assigned to no treatment group. The dependent variables of Columns 1-3 are dummies taking a 1 if the respondent reports they were aware of the last high pollution day due to SMS, television, or their own perception, respectively. The dependent variable of Column 4 is a dummy equal to 1 if the respondent reported there was a high pollution day in the week before their follpowup survey. The dependent variable of Column 5 is the percent of days in the week before followup for which there was high pollution and the respondent correctly indicates there was high pollution. This regression omits observations for which the outcome would be undefined (i.e., where the respondent expressed there was a high pollution day, but there in fact was none). The dependent variable of Column 6 is a dummy equal to 1 if the respondent was *correct* in indicating whether there was high pollution the day of and the day before the followup survey. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table 5: Followup Treatment Effects: Avoidance Behaviors

	On Last Perceived High Pollution Day Reports					
	Doing Something Different (1)	Staying In With Windows Closed (2)	Using Basic Mask or Scarf (3)	Avoiding Outdoor Activity (4)	Reports Used Filter Mask (Past 2 Weeks) (5)	% High PM Days Uses Filter Mask (Past 2 Week) (6)
Alert	0.0748***	0.0681****	-0.0000187	0.00513	0.0190	0.00531
	(0.0234)	(0.0197)	(0.0124)	(0.0114)	(0.0157)	(0.00669)
Mask	0.0182	0.0118	-0.00199	-0.0151	0.0671****	-0.00130
	(0.0235)	(0.0197)	(0.0120)	(0.0112)	(0.0158)	(0.00731)
Reminder	-0.0368	-0.0210	-0.0142	-0.00130	-0.0197	-0.00110
	(0.0236)	(0.0193)	(0.0127)	(0.0118)	(0.0159)	(0.00767)
Compensation	-0.0291	-0.0109	-0.00393	-0.0133	-0.0133	-0.00378
	(0.0250)	(0.0213)	(0.0137)	(0.0115)	(0.0172)	(0.00850)
Control Group Mean	0.132	0.075	0.047	0.019	0.028	0.018
Unique Households	873	871	871	871	873	568
Observations (N)	1329	1326	1326	1326	1329	757

Regressions are based on stacked data from two rounds of midline surveys. Standard errors, clustered by respondent, are reported in parentheses. Outliers are dropped above the 99th percentile for continuous control variables. Regressions are conditional on surveyor fixed effects and control variables determined by LASSO double selection. *Control Mean* reflects the mean of the dependent variable for those assigned no treatment group. The dependent variables of Columns 1-4 are dummies taking a 1 if the respondent reports doing the indicated avoidance behavior on the last day for which (they believe) there was high pollution. The dependent variable of Column 5 is a dummy taking a 1 if the respondent indicates they used a mask with filter within the previous 2 weeks. The dependent variable of Column 6 is the percent of days, for which there was high PM, that the respondent reports using a filter mask in the 2 weeks before midline . This final regression is conditional on having at least 1 high PM day. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Appendix: Supplementary Figures & Tables

Figure A.1: Timeline of Baseline and Follow-up Surveys

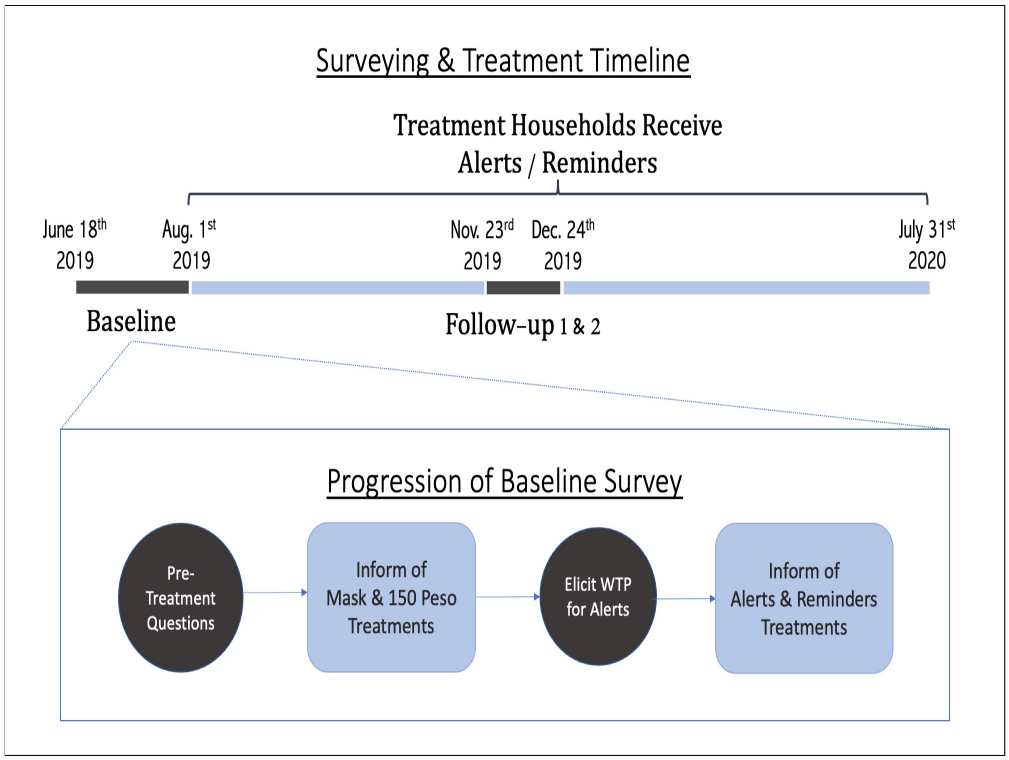


Figure A.2: Experimental Design

Households Assigned to Treatment Branches

	Control	Mask	150 Peso	Mask & 150 Peso	Total
Control	162	165	69	70	466
Alert	162	166	70	70	468
Reminder	164	164	69	71	468
Alert & Reminder	164	163	70	70	467
Total	652	658	278	281	N = 1,869

Figure A.3: Treatment Arms

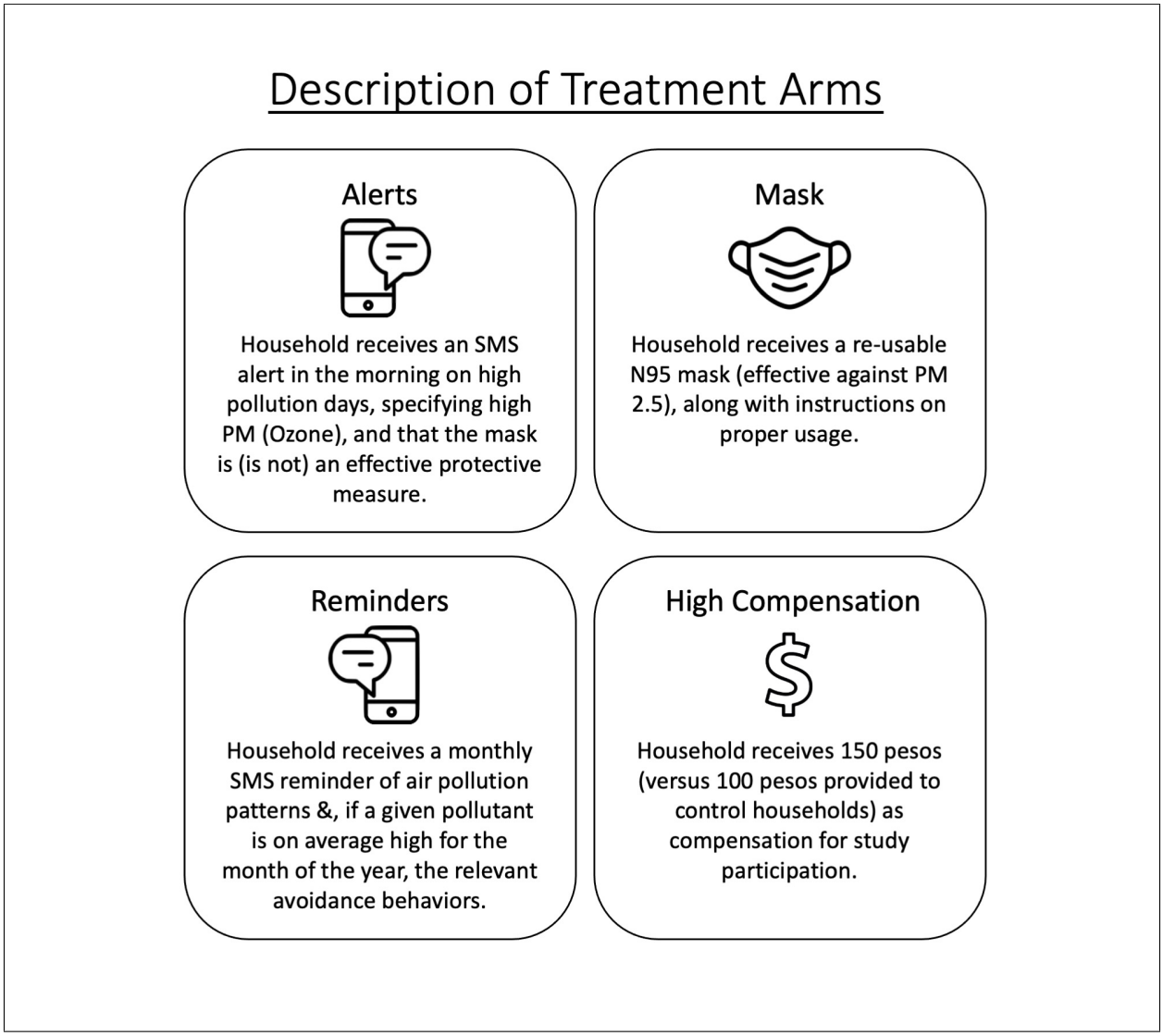


Figure A.4: Messages received by the Alerts Treatment Group.

"**SMS PM Warning:** Suspended particles near your house are high and likely will remain high for the rest of the day. Take precautions. Remember: the mask DOES protect against suspended particles. **SMS Ozone Warning:** It is forecasted that the IMECA, and likely ozone, will be high near your house today. Take precautions. Remember: the mask DOES NOT protect against ozone."

Figure A.5: Pollution timing information provided to all at baseline.

"**Air pollution patterns.** *At what times are pollution levels high?* Ozone: 2pm-6pm, Particles: 10am-2pm. *During which parts of the year are pollution levels high?* Ozone: April & May, Particles: November to February."

Figure A.6: Information on pollution risk provided to all at baseline.

"**Negative impacts of air pollution on health.** *The most common effects are:* cough, head and chest aches, eye irritation, asthma attacks, lung issues. *Increases risk of:* heart attack, stroke, early death. *Individuals most affected by pollution are:* active people, children (when outside), the elderly, persons with lung or heart disease."

Figure A.7: Information on pollution mitigation provided to all at baseline.

"**Protect yourself from air pollution.** Limit duration of outdoor activities. Avoid streets and highways with heavy traffic. Use an N95 certified mask to protect yourself from particles."

Table A.1: Balance at Baseline

	Mean & StDev.	Difference: Treat vs. Control			
	Pure Control	Mask	Comp.	Alert	Reminder
Variable	(1)	(2)	(3)	(4)	(5)
Income: 0 - 2,000 Pesos	0.130	0.005	-0.011	-0.009	-0.012
	(0.337)	{0.753}	{0.507}	{0.566}	{0.439}
Income: 2,000 - 6,000 Pesos	0.222	0.001	0.026	-0.001	0.001
	(0.417)	{0.975}	{0.226}	{0.949}	{0.952}
Income: Above 6,000 Pesos	0.105	0.006	-0.009	-0.003	0.020
	(0.307)	{0.701}	{0.572}	{0.832}	{0.195}
Income: Missing	0.062	0.008	0.009	-0.000	-0.020*
	(0.241)	{0.495}	{0.480}	{0.983}	{0.094}
Log # of HH Members	1.250	-0.053**	0.019	0.017	-0.005
	(0.491)	{0.016}	{0.426}	{0.434}	{0.805}
Age	42.877	2.094***	0.497	-0.289	-0.305
	(15.263)	{0.003}	{0.520}	{0.683}	{0.670}
Gender: Male	0.370	0.019	-0.059**	-0.033	0.023
	(0.484)	{0.397}	{0.013}	{0.134}	{0.295}
Head of Household	0.556	0.020	-0.006	0.011	-0.007
	(0.498)	{0.371}	{0.798}	{0.617}	{0.772}
Educ: Secondary School Complete	0.364	-0.020	-0.000	-0.007	-0.012
	(0.483)	{0.379}	{0.988}	{0.742}	{0.595}
Educ: Post-Secondary Complete	0.426	0.016	-0.054**	0.002	0.011
	(0.496)	{0.495}	{0.029}	{0.927}	{0.637}
Household Health Index	0.086	-0.097*	0.020	0.065	-0.004
	(1.121)	{0.099}	{0.757}	{0.270}	{0.943}
No Insurance	0.136	0.022	0.006	0.004	-0.018
	(0.344)	{0.218}	{0.761}	{0.840}	{0.309}
Had High Poll. (Ozone) in Last 4 Days	0.500	0.038	0.047*	-0.058**	-0.033
	(0.502)	{0.102}	{0.064}	{0.012}	{0.154}
Reports High Pol. in Last 4 Days	0.580	0.007	-0.025	-0.013	-0.007
	(0.495)	{0.746}	{0.329}	{0.575}	{0.758}
Mask Effective Against Pollution	0.420	-0.008	0.022	-0.000	0.001
	(0.495)	{0.744}	{0.390}	{0.986}	{0.957}
Has Used Mask with Filter	0.290	0.024	-0.039*	-0.022	0.015
	(0.455)	{0.252}	{0.088}	{0.305}	{0.469}
Took Precautions in Recent Contingencies	0.673	-0.017	0.039*	-0.002	0.008
	(0.471)	{0.432}	{0.087}	{0.911}	{0.718}
Uses App to Monitor Air Quality	0.080	0.002	0.011	-0.024*	0.014
	(0.273)	{0.909}	{0.452}	{0.073}	{0.300}
Test of Joint Significance F(18,1827)		1.41	1.81	0.95	0.60
p-value		{ 0.12 }	{ 0.02 }	{ 0.52 }	{ 0.90 }
Treat Group Obs.		939	559	936	934
Observations	162	1,869	1,869	1,869	1,869

This table presents sample means and standard deviations (in parentheses) of variables at baseline for the pure control group (1) and reports the difference in mean between each treatment and its *respective* control group (2)-(5). P-values for tests of difference in means are presented in brackets. Stars indicate a statistically significant difference at .1 (*), .05 (**), and .01 (***) levels of significance. The F-statistics reported for each treatment are for the overall test of joint significance of all controls in a regression of the treatment dummy on the 18 baseline control variables. Both reported difference in means and F-statistics are conditional on surveyor fixed effects.

Table A.2: Followup Survey Attrition

	Followup Non-Response		
	Round 1 (1)	Round 2 (2)	Either Round (3)
WTP for Alerts	-0.000214	0.000307**	-0.000174
	(0.000169)	(0.000154)	(0.000170)
Alert Treatment	0.00784	0.0276	0.0229
	(0.0233)	(0.0219)	(0.0237)
Mask Treatment	-0.00476	-0.0123	-0.0140
	(0.0233)	(0.0219)	(0.0237)
Reminder Treatment	-0.0364	-0.0151	-0.0326
	(0.0233)	(0.0220)	(0.0237)
Compensation Treatment	-0.0184	-0.0634***	-0.0479*
	(0.0255)	(0.0244)	(0.0259)
Control Group Mean	0.62	0.72	0.54
Observations (N)	1797	1797	1797

The dependent variable in this table is an indicator equal to 1 if the houeshold did not respond to the indicated round of the followup surveys. Robust standard errors are reported in parentheses. WTP for the alerts service is in Mexican Pesos. Outliers are dropped above the 99th percentile of WTP. Regressions are conditional on surveryor fixed effects. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table A.3: Predictors of Willingness To Pay

	Dependent Variable: WTP for Alerts Service					
	(1)	(2)	(3)	(4)	(5)	(6)
Income: 0 - 2,000 Pesos	-4.808				-4.952	-4.834
	(4.484)				(4.653)	(4.666)
Income: 2,000 - 6,000 Pesos	2.291				-1.466	-1.066
	(4.092)				(4.170)	(4.188)
Income: Above 6,000 Pesos	18.83***				12.93**	13.41**
	(6.424)				(6.418)	(6.465)
Income: Missing	3.356				0.601	0.969
	(6.577)				(6.357)	(6.425)
Log # of HH Members		3.373			2.802	
		(3.738)			(3.875)	
Age		-0.524****			-0.503****	-0.472****
		(0.121)			(0.127)	(0.103)
Gender: Male		13.99****			11.75***	12.00***
		(3.724)			(4.083)	(4.085)
Head of Household		3.836			2.872	
		(3.615)			(3.553)	
Educ: Secondary School Complete		-1.376			-1.694	
		(4.639)			(4.692)	
Educ: Post-Secondary Complete		0.851			-0.429	
		(4.676)			(4.869)	
Household Health Index			-0.479		-0.464	
			(1.129)		(1.149)	
No Insurance			10.09**		7.138	7.054
			(4.670)		(4.670)	(4.653)
Had High Poll. (Ozone) in Last 4 Days				-0.906	-1.900	
				(3.281)	(3.295)	
Reports High Poll. in Last 4 Days				7.881**	9.707***	9.785***
				(3.308)	(3.438)	(3.329)
Mask Effective Against Pollution				0.647	-0.0837	
				(3.242)	(3.303)	
Has Used Mask with Filter				5.203	2.140	2.314
				(3.614)	(3.530)	(3.578)
Took Precautions in Contingencies				0.730	3.411	3.764
				(3.726)	(4.131)	(3.978)
Uses App to Monitor Air Quality				13.50*	7.414	7.444
				(7.058)	(7.020)	(7.007)
LASSO Selected Covariates	No	No	No	No	No	Yes
Control Mean	44.7	44.7	44.7	44.7	44.7	44.7
Observations (N)	1797	1797	1797	1797	1797	1797

Robust standard errors are reported in parentheses. WTP is in Mexican Pesos. Outliers are dropped above the 99th percentile of WTP. *Log # HH Members*, *Age*, and the *Houeshold Health Index* are continuous variables, while the remainder are indicator variables. The *Household Health Index* is increasing in improved health and is generated using PCA on 6 variables: 1) a household member has been sick in the last month, (2) a household member has a chronic issue exacerbated by air pollution exposure, (3) a household member has been hospitalized in the last month, (4) a household has senior members (over 65), (5) a respondent has had a cough or difficulty breathing in the last month, (6) a respondent reports having bad or very bad health in general. The omitted categories for Income and Education are, respectively, *Not Working* and *Less than Secondary School Completed*. Column 6 reports coefficients from OLS regression on a subset of independent variables selected by LASSO in a first stage. *Middle Income* is dropped by LASSO, but included in the second stage to complete the set of income variables. All regressions (and LASSO) are conditional on surveyor fixed effects. Columns 1, 5 & 6 also control for *Income Not Reported*. The *Control Mean* reflects the mean of willinness to pay for the pure control group. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table A.4: Predictors of Willingness To Pay (Results with no Trimming)

	Dependent Variable: WTP for Alerts Service					
	(1)	(2)	(3)	(4)	(5)	(6)
Income: 0 - 2,000 Pesos	-15.77**				-14.96*	-14.24*
	(7.623)				(8.283)	(7.979)
Income: 2,000 - 6,000 Pesos	29.11*				23.49	24.31
	(16.32)				(15.51)	(14.96)
Income: Above 6,000 Pesos	9.388				-4.973	-3.057
	(7.887)				(11.34)	(10.68)
Income: Missing	-2.994				-9.778	-8.995
	(7.715)				(8.468)	(8.135)
Log # of HH Members		1.814			1.200	
		(7.757)			(8.359)	
Age		-0.190			-0.0487	
		(0.318)			(0.358)	
Gender: Male		31.62***			32.25***	32.37***
		(10.16)			(11.29)	(11.71)
Head of Household		4.960			2.937	
		(7.174)			(7.423)	
Educ: Secondary School Complete		12.95			13.19	
		(11.57)			(11.47)	
Educ: Post-Secondary Complete		9.195			10.06	
		(10.48)			(11.43)	
Household Health Index			2.078		3.846	
			(2.593)		(3.446)	
No Insurance			2.622		-3.643	
			(8.866)		(9.631)	
Had High Poll. (Ozone) in Last 4 Days				-1.393	-2.519	
				(8.355)	(8.540)	
Reports High Poll. in Last 4 Days				21.43**	25.77***	23.44***
				(8.385)	(9.596)	(8.430)
Mask Effective Against Pollution				1.873	3.513	
				(8.858)	(8.570)	
Has Used Mask with Filter				15.39	12.15	11.38
				(11.44)	(12.74)	(11.84)
Took Precautions in Contingencies				7.835	16.05*	16.27*
				(6.706)	(8.893)	(8.321)
Uses App to Monitor Air Quality				32.56	24.42	25.43
				(29.13)	(29.04)	(28.27)
LASSO Selected Covariates	No	No	No	No	No	Yes
Control Mean	54.14	54.14	54.14	54.14	54.14	54.14
Observations (N)	1814	1814	1814	1814	1814	1814

Robust standard errors are reported in parentheses. WTP is in Mexican Pesos. *Log # HH Members*, *Age*, and the *Houeshold Health Index* are continuous variables, while the remainder are indicator variables. The *Household Health Index* is increasing in improved health and is generated using PCA on 6 variables: 1) a household member has been sick in the last month, (2) a household member has a chronic issue exacerbated by air pollution exposure, (3) a household member has been hospitalized in the last month, (4) a household has senior members (over 65), (5) a respondent has had a cough or difficulty breathing in the last month, (6) a respondent reports having bad or very bad health in general. The omitted categories for Income and Education are, respectively, *Not Working* and *Less than Secondary School Completed*. Column 6 reports coefficients from OLS regression on a subset of independent variables selected by LASSO in a first stage. *Middle Income* is dropped by LASSO, but included in the second stage to complete the set of income variables. All regressions (and LASSO) are conditional on surveyor fixed effects. Columns 1, 5 & 6 also control for *Income Not Reported*. The *Control Mean* reflects the mean of willinness to pay for pure control group. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table A.5: Treatment Effects on WTP for Alerts (No Control Covariates)

	Dependent Variable: WTP	
	(1)	(2)
Mask	1.991	2.621
	(3.203)	(3.707)
Compensation	6.917*	7.977
	(3.582)	(5.187)
Mask x Compensation		-2.112
		(7.121)
Control Group Mean	44.7	44.7
Observations (N)	1797	1797

Robust standard errors are reported in parentheses. WTP is in Mexican Pesos. Outliers are dropped above the 99th percentile of WTP. Both regressions are conditional on surveyor fixed effects, but include no other control covariates. Alert and Reminder treatment indicators are included in both regressions, but should not impact WTP since assigned after WTP is reported (these coefficients are insignificant as expected). *Control Mean* reflects the mean of WTP for those assigned to no treatment group. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table A.6: Treatment Effects on WTP for Alerts (Results with no Trimming)

	Dependent Variable: WTP	
	(1)	(2)
Mask	-2.066	-1.859
	(8.790)	(12.90)
Compensation	-3.124	-2.776
	(6.754)	(10.61)
Mask x Compensation		-0.693
		(16.78)
Control Group Mean	54.14	54.14
Observations (N)	1814	1814

Robust standard errors are reported in parentheses. WTP is in Mexican Pesos. Both regressions are conditional on a set of control variables determined by LASSO double selection in a first stage. Regressions (and LASSO) are also conditional on surveyor fixed effects. Alert and Reminder treatment indicators are included in both regressions, but should not impact WTP since assigned after WTP is reported (these coefficients are insignificant as expected). *Control Mean* reflects the mean of WTP for those assigned to no treatment group. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table A.7: Followup Treatment Effects: Information on Air Quality (No Control Covariates)

	Knew of Last High Poll. Day From					
	SMS Alert	Television	Perception	Reports there was High Poll. in Past Week	% Days Correctly Identifies High Poll. (Past Week)	Correct Whether High Poll. Today/Yesterday
	(1)	(2)	(3)	(4)	(5)	(6)
Alert	0.143****	-0.0417***	0.0111	0.107****	0.0133	-0.0205
	(0.0181)	(0.0155)	(0.0293)	(0.0295)	(0.0159)	(0.0250)
Mask	-0.0124	-0.000875	0.0460	0.0224	-0.0216	-0.0204
	(0.0177)	(0.0155)	(0.0296)	(0.0295)	(0.0162)	(0.0253)
Reminder	0.0166	-0.0131	-0.000445	0.0230	0.00349	-0.0165
	(0.0186)	(0.0157)	(0.0302)	(0.0303)	(0.0169)	(0.0258)
Compensation	0.0233	-0.00454	-0.0189	0.00137	-0.0141	-0.0441*
	(0.0195)	(0.0165)	(0.0320)	(0.0319)	(0.0170)	(0.0264)
Control Group Mean	0.019	0.085	0.377	0.377	0.160	0.387
Unique Households	873	873	873	873	852	873
Observations (N)	1329	1329	1329	1329	1282	1329

Regressions are based on stacked data from two rounds of followup surveys. Standard errors, clustered by respondent, are reported in parentheses. Regressions are conditional on surveyor fixed effects but no other control variables. *Control Mean* reflects the mean of the dependent variable for those assigned to no treatment group. The dependent variables of Columns 1-3 are dummies taking a 1 if the respondent reports they were aware of the last high pollution day due to SMS, television, or their own perception, respectively. The dependent variable of Column 4 is a dummy equal to 1 if the respondent reported there was a high pollution day in the week before their follpowup survey. The dependent variable of Column 5 is the percent of days in the week before followup for which there was high pollution and the respondent correctly indicates there was high pollution. This regression omits observations for which the outcome would be undefined (i.e., where the respondent expressed there was a high pollution day, but there in fact was none). The dependent variable of Column 6 is a dummy equal to 1 if the respondent was *correct* in indicating whether there was high pollution the day of and the day before the followup survey. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table A.8: Followup Treatment Effects: Avoidance Behaviors (No Control Covariates)

	On Last Perceived High Pollution Day Reports					
	Doing Something Different (1)	Staying In With Windows Closed (2)	Using Basic Mask or Scarf (3)	Avoiding Outdoor Activity (4)	Reports Used Filter Mask (Past 2 Weeks) (5)	% High PM Days Uses Filter Mask (Past 2 Week) (6)
Alert	0.0686***	0.0658****	-0.000980	0.00155	0.0199	0.00187
	(0.0239)	(0.0199)	(0.0124)	(0.0111)	(0.0157)	(0.00631)
Mask	0.0161	0.0111	-0.00460	-0.0116	0.0722****	-0.00119
	(0.0239)	(0.0198)	(0.0123)	(0.0110)	(0.0158)	(0.00749)
Reminder	-0.0315	-0.0192	-0.0145	0.000308	-0.0142	0.000222
	(0.0241)	(0.0197)	(0.0125)	(0.0116)	(0.0163)	(0.00738)
Compensation	-0.0207	-0.000612	-0.00102	-0.0178	-0.0147	-0.00259
	(0.0257)	(0.0220)	(0.0134)	(0.0108)	(0.0167)	(0.00808)
Control Group Mean	0.132	0.075	0.047	0.019	0.028	0.018
Unique Households	873	871	871	871	873	568
Observations (N)	1329	1326	1326	1326	1329	757

Regressions are based on stacked data from two rounds of midline surveys. Standard errors, clustered by respondent, are reported in parentheses. Regressions are conditional on surveyor fixed effects but no other control variables. *Control Mean* reflects the mean of the dependent variable for those assigned no treatment group. The dependent variables of Columns 1-4 are dummies taking a 1 if the respondent reports doing the indicated avoidance behavior on the last day for which (they believe) there was high pollution. The dependent variable of Column 5 is a dummy taking a 1 if the respondent indicates they used a mask with filter within the previous 2 weeks. The dependent variable of Column 6 is the percent of days, for which there was high PM, that the respondent reports using a filter mask in the 2 weeks before midline . This final regression is conditional on having at least 1 high PM day. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$