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Breathe Easy, There's an App for That: Using Information and Communication Technology to Avoid Air Pollution in Bogotá

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Abstract: Ambient air pollution is a leading cause of death in developing countries. In theory, using smartphone apps, text messages, and other personal information and communication technologies to disseminate real-time information about such pollution can boost avoidance behavior like wearing face masks and closing windows. Yet evidence on their effectiveness is limited. We conduct a randomized controlled trial to evaluate the impact of training university students in Bogotá, Colombia to use a newly available municipal government smartphone app that displays real-time information on air quality. The training increased participants' acquisition of information about air quality, their knowledge about avoidance behavior, and their actual avoidance behavior. It also enhanced their concern about other environmental issues. These effects were moderated by participants' characteristics. For example, the training was generally less effective among job holders.

Keywords: air pollution; Colombia; information; randomized controlled trial; experiment; smartphone application

JEL codes : Q53, Q56, Q58, I15

1. INTRODUCTION

A product of decades of industrialization, urbanization, and motorization, chronic severe air pollution is now a global phenomenon. Today, 90 percent of the world's people live in places that do not meet World Health Organization air quality standards (WHO 2021). The consequences for human health have been grave. Each year, air pollution causes 5 to 9 million premature deaths and many more cases of bronchitis, asthma, and other cardiopulmonary illnesses (World Bank/IHME 2016; GBD 2021; Vorha et al. 2021). The global south is the epicenter of this problem, accounting for more than 90 percent of the mortality and morbidity attributed to air pollution (World Bank/IHME 2016). Although indoor air pollution from the use of biomass fuels is a major contributor, most deaths and illnesses are caused by ambient pollution (Landrigan et al. 2018). Moreover, in most developing countries, ambient air pollution is getting worse. A recent study predicted that absent aggressive interventions, the number of deaths from such pollution will increase by 50 percent by 2050 (Lelieveld et al. 2015).

Unfortunately, a variety of structural and institutional factors limit the effectiveness of regulatory initiatives aimed at controlling ambient air pollution in developing countries (Blackman 2010). Therefore, perhaps the most practical and cost-effective strategy for reducing illness and death caused by air pollution in the short to medium term is to reduce exposure, particularly that of vulnerable individuals. In practice, that entails encouraging people to avoid outdoor activities, close windows, and engage in other avoidance behaviors on days when air pollution is severe. And that, in turn, requires disseminating timely and accurate information about air quality, along with recommendations about how to avoid exposure. Information and communication technologies (ICTs) are a logical means of providing such information.

Recently, smartphone apps that display real-time information on air quality have become available. For example, the U.S. Environmental Protection Agency's AirNow app provides historical, real-time, and predicted data for most cities in the United States. Sameer, Air Quality China, and AirRater provide similar data for cities in India, China, and Australia. And apps like AirVisual and IQAir compile this information for cities around the world. However, the extent to which these apps actually affect avoidance behavior, environmental attitudes, and other outcomes is not clear: to our knowledge, a rigorous evaluation of an air quality smartphone app has yet to appear.

Here, we report on a randomized controlled trial aimed at evaluating the effect of training university students in Bogotá, Colombia—a city with chronic severe air pollution—to use Aire Bogotá, an air quality smartphone app developed by the municipal government. We randomly assigned a sample of 578 students to either a control group or a treatment group that received an information session—on air pollution, avoidance behaviors, and the Aire Bogotá app—along with an invitation to participate in a six-week interactive email campaign designed to habituate them to using the app. A baseline survey, which was administered in person in March 2020 just before the information session, and an endline survey, which was administered remotely three months later, collected information on sociodemographic characteristics and a range of behavioral and attitudinal outcomes. Both surveys were administered in proctored sessions capped at 30 participants. We find that the training boosted participants' acquisition of information about air quality, their knowledge about avoidance behavior, and their actual avoidance behavior. It also enhanced their concern about other environmental issues. Finally, we find that the effects of the training were moderated by participants' characteristics; for several outcomes, the training was less effective among participants who were job holders.

Our study makes three contributions to the emerging literature on the use of ICTs to disseminate information on air quality. First, to our knowledge, it is the first rigorous study of an air quality smartphone app and is among only a handful of studies examining 'personal' air quality ICTs that provide information tailored to specific subgroups or individuals (e.g., text messages and portable air quality monitors). The lion's share of air quality ICT studies focus on radio, television, newspapers, webpages and other 'impersonal' mechanisms offering the same content to all users. Personal ICTs hold particular promise because they can provide information on air quality at specific times and/or locations—data that can be used to plan avoidance behavior. Second, as far as we know, ours is only the third study of an air quality ICT to use experimental methods. Finally, to our knowledge, it is only the third such study to focus on the global south, where the problem we study is most urgent.

Studies of impersonal ICTs tend to focus on air quality alerts disseminated through conventional electronic and print media and mostly find that they boost avoidance behavior. For example, researchers have found that air quality alerts reduce attendance at zoos and botanical gardens in Southern California (Ziven and Neidell 2009), lower attendance at baseball games in South Korea (Yoo 2021), cut the use of outdoor recreation facilities by the elderly and other sensitive groups in Atlanta (Noonan 2014), reduce the use of bicycles by 14–35 percent in Australia (Saberian et al. 2017), and double online queries for face masks with filters in China (Liu et al. 2017). In addition, two recent studies conclude that over the past two decades, the rollout of automated real-time air quality monitoring and disclosure systems across cities in China has boosted indicators of avoidance behaviors including purchases of air purifiers and online searchers for face masks (Barwick et al. 2019; Greenstone et al. 2019). The evidence on the effects of impersonal informational mechanisms is not uniformly positive, however. For example, Semenza et al. (2008) and Steib et al. (1996) find that air quality alerts in Canada, Texas, and Oregon have little effect on self-reported avoidance behavior. All of these studies of impersonal air quality ICTs are quasi-experimental; none use randomized controlled trials.

The literature on personal ICTs is far more limited, and the results are mixed. On one hand, Araban et al. (2017) find that a bundled intervention consisting of daily text messages on air quality, motivational interviewing, and printed educational materials boosted avoidance behavior in a sample of pregnant women in Tehran. Hanna et al. (2021) report that in Mexico City, SMS air quality alerts tailored to recipients' locations increased the probability that recipients stayed indoors with windows closed on perceived high-pollution days. And Oltra et al. (2017) find that in Barcelona, individual air quality monitors increased awareness of and motivation for avoidance behaviors more than impersonal information dissemination mechanisms. On the other hand, however, Lyons et al. (2016) find that AirAware, a targeted personal air pollution information system in the United Kingdom that delivers texts, emails, and voicemail messages to high-risk persons, increased emergency-room admissions for respiratory conditions (which they attribute to the system's having exacerbated participants' anxiety about air pollution). And Haddad and de Nazelle (2018) report that in the United Kingdom, individual air pollution monitors and smartphone apps did not affect travel-related behaviors or attitudes in a group of pilot testers. Among these studies of personal air quality ICTs, both Araban et al. (2017) and Hanna et al. (2021) use randomized controlled trials, Lyons et al. (2016) rely on quasi-experimental methods, and Oltra et al. (2017) and Haddad and de Nazelle (2018) use small-sample focus groups.

The remainder of the paper is organized as follows. The next section provides background information on air quality in Bogotá and on the smartphone app we study. The third section discusses our experimental design and data. The fourth section presents our regression models. The fifth section reviews our results, and the last section sums up and concludes.

2. BACKGROUND

2.1. Air quality in Bogotá

Air quality in Bogotá regularly fails to meet World Health Organization standards by a considerable margin (Figure 1). Fine particulate matter alone is estimated to cause more than 1,600 premature mortalities per year in the city (Blackman et al. 2021). Vehicles are the source of 81 percent of combustion emissions of fine particulates in Bogotá, and trucks account for 60 percent of vehicular emissions (SDA 2020). Episodes of severe air pollution occur most frequently in February and March and to a lesser extent in January, April, November, and December, when thermal inversions trap air pollution at ground level. Air quality is markedly worse than average in the southwestern part of the city. The air quality monitoring network in Bogotá (Red de Monitoreo de Calidad del Aire de Bogotá, RMCAB) consists of 13 stations that provide hourly data on six air pollutants and seven weather variables.

[Insert Figure 1 here]

2.2 The Aire Bogotá app

Created by the municipal environmental agency (Secretaría Distrital del Ambiente) and launched in January 2020, Aire Bogotá is a free interactive smartphone app that provides a range of information on air quality in the city. Perhaps most important, it displays either real-time concentrations or a color coded air quality index called the IBOCA (*Índici Bogotano de Calidad del Aire y Riesgo en Salud*) for three pollutants—fine particulates, coarse particulates, and ozone—at the city's 13 air quality monitoring stations, with interpolated information for points in between, such as health clinics, public transit stations, and museums. In addition, the app provides historical data on air quality for the past seven days, predictions for the coming 48 hours, and health recommendations based on the index. Figure 2 compiles four screenshots illustrating the app's capabilities: real-time data on air quality at the monitoring stations (Panel

A), real-time data at points of interest selected by the user (here, health clinics) (Panel B), historical air quality data (Panel C), and air quality predictions (Panel D).

[Insert Figure 2 here]

3. EXPERIMENTAL DESIGN AND DATA

We used a preregistered experimental design to assess the effects of training university students to use of the Aire Bogotá app on their acquisition of air quality information, knowledge about avoidance behavior, actual avoidance behavior, dissemination of air quality and environmental information, and attitudes about the environment.

3.1 Sample

Our sample comprised students 18 years of age or older studying at universities in Bogotá. We focused on university students for two reasons. First, we expected virtually all to have smartphones, to be comfortable with and habituated to using digital technologies, and to have easy access to Wi-Fi networks that would enable them to use the Aire Bogotá app at no cost. And second, we expected them to have relatively flexible schedules that would lower the costs of avoidance behaviors, such as limiting outdoor activities and adjusting travel on severe air pollution days.

We used print and digital social media to recruit a convenience sample of students. A total of 665 students at 24 universities participated in our baseline sessions, and 578 participated in our endline sessions, implying an overall attrition rate of 13 percent. Attrition is balanced across the treatment and control groups (Table A1). In our final sample of 578 students, the treatment group comprised 244 participants (42 percent), and the control group, 334 participants (58 percent). Although randomization was designed to assign roughly half of the sample to each group, actual assignment percentages differ because randomization was at the session level.

3.2. Timeline

Our experiment proceeded as follows (Figure 3). The Aire Bogotá app was launched in January 2020. In February, we recruited our sample. Between March 2 and March 14, we conducted 30 in-person baseline sessions with a total of 665 participants. At each baseline session, we first administered our baseline survey and then conducted either a treatment or a control (placebo) information session (described below). Participants were randomly assigned to treatment and control groups at the baseline session level. Of the 30 baseline sessions, 14 sessions with a total of 272 participants featured the treatment materials, and 16 sessions with 393 participants featured the control materials. In the six weeks following their baseline session, participants engaged in an interactive email campaign (also described below). Finally, between May 11 and June 19, we conducted 46 remote endline sessions with 578 participants.

[Insert Figure 3 here]

Our experiment coincided with the beginning of the Covid-19 pandemic in Bogotá. The first case in the city was reported on March 6, 2020; most universities closed March 16; and a national lockdown began on March 20. Our planned baseline sessions were nearly completed when the Rosario Experimental and Behavioral Economics Lab, which hosted them, was shuttered on March 16. By that date, we had completed baseline surveys for 665 participants representing 89 percent of our planned baseline sample of 750 participants. We discuss other potential effects of the pandemic on our study in Section 3.5 and Section 6.

3.3. Treatments

We administered a bundled treatment that amounted to a training in the use of the Aire Bogotá app. It had three components: (i) information on the Aire Bogotá app, (ii) information meant to motivate use of the app, including on air pollution, its health effects, and how to minimize them by engaging in avoidance behaviors, and (iii) a six-week interactive email campaign aimed at reinforcing the first two elements. We employed a bundled treatment instead of simply providing information on the Aire Bogotá app to increase the probability that treated participants would regularly use the app—the same general strategy used by Araban et al. (2017). One disadvantage of this strategy is that we are not able to disentangle the effects on our outcomes of the three components of our treatment. For example, we are not able to identify the effect of simply making the Aire Bogotá app freely available for download.[1] However, we

[1] Had we focused only on encouraging use of the Aire Bogotá app, without providing any information about its potential benefits, we could have used a randomized promotion (encouragement) design to identify its effects. That

believe that our experimental design addresses a policy-relevant question: what is the effect of training in the use of a personal ICT for air pollution?

Participants assigned to the treatment group attended an in-person information session lasting approximately 20 minutes (Appendix 1) that covered the following topics:

- *Air quality in Bogotá* regularly fails to meet international standards and is worse than that in most Latin American cities.
- *Effects of air pollution on human health* include a variety of short- and long-term illnesses and, in Bogotá, approximately 2,000 deaths per year, 14 percent of all deaths in the city.
- *Basic information on air pollution,* including the most important types, temporal variation over the course of the year and the day, and spatial variation within Bogotá.
- *Avoidance behavior* to reduce health risks from air pollution: wearing an N95 mask, limiting outdoor physical activity, and closing windows when and where air quality is particularly poor, seeing a doctor promptly when experiencing cardiorespiratory symptoms, and avoiding tobacco products.
- *Aire Bogotá app* download and installation instructions, the main types of information it provides, and its functionality.
- *Using Aire Bogotá app* to reduce exposure by determining when and where to engage in avoidance behavior.
- *Email campaign*: an offer to participate in a six-week interactive email campaign, for which the Aire Bogotá app would be needed.

The purpose of the interactive email campaign was to train participants to use the Aire Bogotá app, to habituate them to using it, and to reinforce the informational treatment. Participants received six email messages, one per week, during the six weeks following the baseline session (Appendix 1). Each contained a brief bullet-point summary of selected key points from the baseline information session about the health effects of air pollution and

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is, we could have used assignment to the treatment as an instrument for use of the app because the exclusion restriction would plausibly have been satisfied: the treatment likely would only have affected outcomes (avoidance behavior, environmental attitudes, etc.) through the app. But our bundled treatment, which combines encouragement to use the app with motivational information, likely had direct effects on our outcomes.

avoidance behavior. In addition, each email included a question about air quality at a specific time and location in Bogotá: for example, “What was the IBOCA for PM2.5 at the Barrios Unidos air quality monitoring station on March 21 at 9:00 pm?” To answer these questions, participants needed to query the Aire Bogotá app and submit and answer using a SurveyCTO link within 24 hours of receiving the email.

Participants assigned to the control group received a placebo information session on art history, an offer to participate in a six-week placebo email campaign for which they would need a free app called DailyArt, and instructions on how to download, install, and use the app. The purpose was to minimize differential attrition by ensuring that participants in the control group had an opportunity to earn compensation comparable to those in the treatment group. Compensation is discussed in Section 3.5.

3.4. Outcomes

In our baseline and endline surveys, we collected information about six sets of outcomes (Table 1). The first set concerned the acquisition of air quality information. Respondents indicated whether they had installed Aire Bogotá app on an electronic device (*installed app*), whether they had used the Aire Bogotá app to search for air quality information (*info searched app*), and whether they had used other means to do that (*info searched other*). At baseline—that is, before the treatment was administered—only 3 percent of our participants had installed the Aire Bogotá app on an electronic device and only 2 percent had used the app to search for air quality information in the previous two weeks (Table 1). Nevertheless, during this time 37 percent had sought information on air quality from another source.

[Insert Table 1 here]

The second set of outcomes concerned knowledge about air pollution and avoidance behaviors. Respondents indicated whether they knew that their own behavior could reduce the health risks from air pollution (*know*) and whether they knew that specific behaviors could reduce those risks, including restricting outdoor activities (*know outdoors*), changing their travel mode or route (*know travel*), wearing a mask with a filter (*know mask*), closing windows *(know windows*), smoking tobacco products less (*know smoking*), using an air purifier (*know air* *purifier*), and wearing a simple scarf over their face and/or applying creams or medicines (*know other*). At baseline, 90 percent of participants knew that changing their own behavior could have health benefits. Participants' knowledge about specific avoidance behaviors ranged from a low of 22 percent for restricting outdoor activity to a high of 56 percent for wearing a mask with a filter.

The third set of outcomes concerned avoidance behaviors. Respondents reported whether they had changed any behavior specifically because of poor air quality in the previous two weeks (*behavior*), and if so, what specific type of behavior they had changed (*behavior outdoors*, *behavior travel, behavior mask, behavior windows, behavior smoking*, *behavior air purifier*, *behavior others*). At baseline, few participants—only 13 percent—reported engaging in any type of avoidance behavior because of poor air quality in the two weeks before the baseline session. The most common avoidance behaviors were restricting outdoor activity (7 percent) and changing travel mode or route (5 percent).

The fourth and fifth sets of outcomes concerned the dissemination of information about the environment. The fourth set had to do with providing warnings about air quality. Respondents reported whether they had warned anyone about poor air quality in the previous two weeks (*aq warn anyone*), and if so, whom they had warned, including family members (*aq warn family*), peers (*aq warn peers*), and teachers and/or health care workers (*aq warn others*). At baseline, almost a third of participants reported having warned someone about poor air quality in the previous two weeks. Among the specific groups of people warned, perhaps not surprisingly, the most common were immediate family members (27 percent) and peers (23 percent).

The fifth set of outcomes concerned discussing environmental issues more broadly. Respondents reported whether they had discussed environmental issues with anyone in the previous two weeks (*enviro. discuss anyone*), and if so, whom they had discussed it with (*enviro. discuss family*, *enviro. discuss peers*, *enviro. discuss others*). The purpose of this fifth set of outcomes, along with some of those in the sixth category of outcomes, was to shed light on whether our bundled treatment had spillover effects on environmental issues beyond air pollution. At baseline, almost two-thirds of participants said they had discussed environmental issues with others in the previous two weeks. Here, too, the most common interactions were with immediate family members (43 percent) and peers (55 percent).

The last set of outcomes had to do with respondents' attitudes about various environmental issues. Using a five-point Likert scale, respondents indicated their level of concern about air quality in the long run (*concern aq long run*), water pollution (*concern water pollution*), and hazardous waste (*concern waste*). In addition, they responded to a question that aimed to elicit their general attitudes about environmental issues: whether it is necessary to pollute to foster economic growth (*concern trade off growth*). At baseline, Likert-scale measures of concern ranged from 2.7 for water pollution and hazardous waste to 3.2 for the long-term effects of air pollution. And more than two-thirds of participants believed that pollution was a necessary trade-off for fostering economic growth.

3.5. Logistics

Study participants were compensated: they received COP 30,000 (US $9.25) for attending the baseline survey and information session, COP 40,000 (US $12.30) for attending the endline survey session, and COP 6,000 (US $1.85) for each email question answered correctly.[2] By attending the baseline and endline sessions and answering every email question correctly, participants could earn a maximum of COP 142,000 (US $43.78). Payments for baseline sessions were made in cash immediately after the session. Payments for correct responses to questions in the email campaign and for the endline session were made using money transfer smartphone applications.

To reduce inattention and to ensure adherence to study protocols, both the baseline and the endline sessions were conducted in proctored group meetings with a maximum of 30 participants. Baseline sessions were conducted in person at the Rosario Experimental and Behavioral Economics Lab in Bogotá's city center. Because of Covid-19 social distancing requirements, endline sessions were conducted online using a web conferencing platform (Zoom). Both in-person baseline and remote endline sessions were proctored by at least two members of the study team, who checked identification to verify that participants were the university students who had been invited; obtained consent; introduced, explained, and monitored engagement with the surveys; answered procedural questions; and, following completion of the baseline survey, presented the informational treatments. Administered using SurveyCTO online software, the baseline and endline surveys elicited information on the

[2] USD amounts assume 3243 COP per USD, the exchange rate in January 2020.

outcomes described above and on sociodemographic characteristics (Table 1). An average of 22 students participated in each baseline session and an average of 13 students participated in each endline session.

3.6. Sociodemographic characteristics

Study participants' sociodemographic characteristics may moderate the effect of our treatment. At baseline, just over a third of the students in our sample came from homes in the lowest or second-lowest *estratos*—socioeconomic categories used by Colombian municipal governments (Table 1).[3] Slightly more than half were male, 83 percent lived with their immediate family, and just under a quarter held full- or part-time jobs in addition to attending university (Table 1). Twenty-two percent smoked tobacco products, just under a fifth had a cardiopulmonary condition that could be exacerbated by air pollution, and 55 percent had an immediate family member with such a condition. A significant share lived with household members vulnerable to the effects of air pollution: 14 percent lived with children younger than five, and 30 percent lived with adults older than 60. Almost a third exercised outdoors at least some days of the week. Forty-two percent lived in the southwestern part of Bogotá, which, as noted above, has the city's most severe air pollution.

Although participants were randomly assigned to either the treatment or the control group at the baseline information session level, it is useful to check for balance on their observable characteristics. Only one covariate—*estrato 1&2*—is (weakly) correlated with treatment assignment (Table A2). To control for residual correlations, we include participant characteristics as covariates in the regressions used to generate treatment effect estimates and analyze treatment effect heterogeneity (see Equations 1 and 2, below).

3.7. Noncompliance

Study participants exhibited two types of noncompliance. The first concerned installation of the Aire Bogotá app and was two-sided. Of the 244 participants in the treatment group, 2 percent never installed the app, and another 15 percent installed it at some point during the experiment but had uninstalled it by the time of the endline survey (Table 2). Of the 334

[3] *Estratos* are used to charge differential fees and taxes for public services and to allocate various benefits (DANE 2020). The six *estratos* are 1 (low-low), 2 (low), 3 (medium-low), 4 (medium), 5 (medium-high), and 6 (high).

participants in the control group, 4 percent had the app installed at the time of the endline survey, and 12 percent had installed it at some point before the endline but had since uninstalled it.

[Insert Table 2 here]

The second type of noncompliance concerned treated participants' engagement in the six-week interactive email campaign and was, by definition, one-sided. On average, treated participants did not respond to 2.4 (40 percent) of the six emails they were sent. And on average, 7 percent of treated participants' responses were incorrect. In the next section, we discuss the implications of both types of noncompliance for the consistency of our treatment effect estimates.

4. ESTIMATIONS

We estimate intent-to-treat (ITT) effects using ordinary least squares (OLS) to fit regressions of the form

$$Y = \beta_1 treated + \beta_2 y + \beta_3 x' + \epsilon \qquad (1)$$

where *Y* is the outcome at endline, *treated* is a binary indicator of whether a participant received the treatment information session, *y* is the outcome at baseline, *x* is a vector of covariates, β is a parameter or vector of parameters, and ϵ is an error term. The elements of *x* are *estrato 1&2, male, education mother, live with immediate family, employed, health self, health family, smoke, no. hh members <5, no. hh members >60, exercise outdoors,* and three region fixed effects (Table 1). We cluster standard errors at the baseline survey session level. Our estimated treatment effect is given by β_1. For robustness, in the Appendix we report results from simplified regressions that omit the vector of participants' characteristics variables.

As noted in the previous section, our study participants exhibited two types of noncompliance, one of which was two-sided. Not all the participants in the treatment group were fully treated (not all installed the Aire Bogotá app on an electronic device and kept it installed for the duration of the experiment, and not all fully participated in the email campaign) and some of the participants in the control group were partly treated (some had installed the app on an electronic device). Although the scope of this noncompliance was not extreme—for example, only 2 percent of the treatment group never installed the app and only 4 percent of the control group had it installed at baseline—the implication of noncompliance in each group is that our treatment effect estimates are likely to be biased downward (Gertler et al. 2016). Hence our ITT effect estimates can be considered lower bounds on true effects.

To evaluate treatment effect heterogeneity, we use OLS to fit regressions of the form

$$Y = \beta_1 treated + \beta_2 treated \times x' + \beta_3 y + \beta_4 x' + \epsilon \quad (2)$$

Here, too, we cluster standard errors at the baseline survey session level.

5. RESULTS

5.1. Main effects

Our bundled treatment led to substantial changes in four of our six categories of outcomes: acquisition of air quality information, avoidance behavior, avoidance knowledge, and attitudes. Regarding the acquisition of air quality information, the treatment led to very large increases in use of the Aire Bogotá app to gather information on air quality but had no discernible effect on the use of other means to do that. Specifically, it led to an 84 percentage point increase in the probability of having the Aire Bogotá app installed (2,556 percent increase over a baseline level of 3 percent) and a 29 percentage point increase in the probability of using it to search for air quality information (1,873 percent increase over a baseline level of 2 percent) (Table 3).

[Insert Table 3 here]

The treatment had substantial effects on participants' knowledge about avoidance behaviors. It led to a 3 percentage point increase in the probability of knowing that changing one's behavior can reduce the adverse health effects of air pollution (3 percent increase over a baseline level of 90 percent) (Table 4). As for knowing that specific behaviors can reduce such health effects, the treatment spurred a 20 percentage point increase in the probability of knowing about restricting outdoor activities (92 percent increase over a baseline level of 22 percent), a 16 percentage point increase in the probability of knowing about wearing a mask with a filter (28 percent increase over a baseline level of 56 percent), a 31 percentage point increase in the probability of knowing about closing windows (106 percent increase over a baseline level of 30 percent), and a 9 percentage point increase in the probability of knowing that smoking less can reduce health effects (28 percent increase over a baseline level of 33 percent at baseline).

[Insert Table 4 here]

What might explain variation in the economic and statistical significance of estimated treatment effects related to knowledge about avoidance behavior? In general, we observe large significant effects for avoidance behaviors that were specifically discussed in the treatment information session and for which baseline levels of awareness were relatively low (restricting outdoor activity and closing windows), and we observe smaller or statistically insignificant effects for behaviors that either (i) were not specifically mentioned in the treatment information session (changing travel, using an air purifier, and the behaviors grouped in the *other* category—using a simple face covering and taking medicines), or (ii) were specifically discussed in the baseline treatment session but for which baseline levels of awareness were relatively high (knowing about any avoidance behavior, wearing a mask with a filter, and not using tobacco products).

The treatment also had substantial effects on participants' actual avoidance behavior. It led to a 9 percentage point increase in the probability of changing any behavior as a result of poor air quality (68 percent increase over a baseline level of 13 percent). Specifically, the treatment spurred a 5 percentage point increase in the probability of wearing a mask with a filter (241 percent increase over a baseline level of 2 percent) and a 7 percentage point increase in the probability of closing windows (215 percent increase over a baseline level of 3 percent) (Table 4).[4] We are not able to discern effects on other avoidance behaviors, including restricting outdoor

[4] Masks with a filter were in short supply in Bogotá during our experiment because of increased demand associated with the Covid-19 pandemic (Semana 2021). Nevertheless, we believe our estimated treatment effect for wearing a mask with a filter is plausible. Even though it is large in percentage terms (230 percent), baseline rates of wearing a mask with a filter were quite low (2 percent). Therefore, our estimated effect only implies that the treatment caused a dozen members of our 244-person treatment group to begin wearing such masks because of poor air quality. That said, given the shortage of masks with filters, we cannot rule out the possibility that some treated participants who reported starting to use such masks during the course of the experiment had in mind masks without filters.

activities, changing a travel mode or route, wearing a simple face covering, smoking less, using an air purifier, or adjusting medications. We discuss potential bias in these results due to self-reporting and the effects of the Covid-19 pandemic in Section 6.

What might explain variation in the magnitudes of estimated treatment effects related to avoidance behavior? Ceiling effects are unlikely to be the explanation: baseline levels of all our specific avoidance behaviors (wearing masks, closing windows, etc.) were less than 10 percent. Rather, we hypothesize that the explanation may have to do with the unobserved financial and/or psychological costs associated with the behavior. Treatment effects for behaviors for which one would expect such costs to be substantial (changing travel, limiting outdoor activities, using an air purifier, and reducing the use of tobacco products) are not statistically significant, whereas treatment effects for behaviors for which one would expect these costs to be lower (wearing a mask with a filter and closing windows) are significant.

In terms of magnitude, the effect of our bundled treatment on the probability of changing any behavior as a result of poor air quality—a 69 percent increase—is comparable to effects reported in the literature of other personal ICTs on similar outcomes (Table A7). Araban et al. (2017) find that a bundled intervention, including text messages, boosted a self-reported Likert-scale measure of a group of avoidance behaviors by 81 percent, and Hanna et al. (2021) find that text messages increased the probability of "having done something different in the past week" by 62 percent. However, the effects of our treatment on the probability of closing windows—a 237 percent increase—is considerably larger than the only similar treatment effect reported in the literature of which we are aware: Hanna et al. (2021) find that text messages increased the probability of staying home with closed windows by 88 percent. The discrepancy may be at least partly attributable to the fact that Hanna et al. (2021) measure the effect of an ICT on both closing windows and staying home, whereas we measure the effect only on closing windows. Although we are not able to discern an effect of our treatment on restricting outdoor activities, other studies have found significant (albeit somewhat modest) effects of impersonal air quality alerts ranging from 6 to 35 percent.

Our treatment had only weak effects on participants' warnings about air quality and discussions about environmental issues (Table 5). At most, all such effects were significant at only the 10 percent level. As for warnings, the treatment led to an 8 percentage point increase in the probability of warning someone about poor air quality (24 percent increase over a baseline level of 32 percent). Specifically, it spurred an 8 percentage point increase in the probability of warning family members (30 percent increase over a baseline level of 27 percent). As for effects on environmental discussions, the treatment spurred a 6 percentage point increase in the probability of having discussed an environmental issue with anyone (10 percent increase over a baseline level of 65 percent) (Table 5). Specifically, it led to an 8 percentage point increase in the probability of having had such discussions with family members (19 percent increase over a baseline level of 43 percent). We hypothesize that we find (weakly) significant effects of our treatment on warnings and discussions with family members and not with peers or others because the costs of communicating with family were relatively low: recall that 83 percent of our participants live with their families. In addition, at least in the case of warnings, the perceived benefits may have been higher.

[Insert Table 5 here]

Finally, our bundled treatment had significant effects on participants' attitudes about the environment, including their attitudes about environmental problems other than air pollution (Table 6). It boosted concern about hazardous waste, increasing by 0.19 the self-reported [0–4] Likert-scale level of concern (7 percent increase over a baseline level of 2.7). The treatment had a weak effect on the level of concern about water pollution, raising it by 0.14 (5 percent increase over a baseline level of 2.8). Somewhat counterintuitively, the treatment did not have a discernible effect on the level of concern about the effect of air pollution on health, perhaps because the average Likert-scale level was quite high at baseline (3.2). Finally, the treatment cut by 8 percentage points the probability of believing that pollution was a necessary trade-off for fostering economic growth (13 percent reduction from a baseline level of 67 percent).

[Insert Table 6 here]

For all six categories of outcome variables, simplified main effects regressions that omit participants' characteristic covariates generate results that are qualitatively identical to those summarized above (Tables A3–A6).

5.2. Treatment effect heterogeneity

To make the analysis of treatment effect heterogeneity tractable, we limit it to one representative outcomes in each of our six categories of outcomes (Table 7). For example, for the "Avoidance Behavior" category, rather than analyzing treatment effect heterogeneity for all eight outcomes, we focus on *behavior*, an indicator of whether the participant changed any behavior in the previous two weeks as a result of poor air quality. We find that all but one treatment effect for these six representative outcomes are moderated by participants' characteristics. Moreover, for three, we find our treatment was less effective in changing outcomes among participants who were job holders. Although our heterogeneity results generally comport with intuition, our explanations for these effects are necessarily speculative—they amount to hypotheses that provide fodder for follow-on study.

[Insert Table 7 here]

For the category "acquisition of air quality information," we focus on *info searched app*, an indicator of whether the participant used the Aire Bogotá app to search for air quality information in the previous two weeks. We find that our treatment was more effective in spurring use of the Aire Bogotá app among participants who at baseline exercised outdoors frequently and was less effective among participants who at baseline were jobholders, and who were male (Table 7). Participants who at baseline exercised outdoors frequently may have been more affected by our treatment because they were more exposed to outdoor air pollution and therefore benefited more from using the app and/or because air pollution was a more salient issue for them. Job holders may have been less affected because they had less control over their travel behavior and immediate environment and, as a result, fewer opportunities for avoidance behavior (e.g., delaying travel and closing windows). The reason that males were less affected by the treatment is not clear.

For the category, "avoidance knowledge", we focus on *know*, an indicator of whether participants know that changing any type of behavior can reduce adverse effects of air pollution. Recall that at baseline, 90 percent of participants knew this. Hence, ceiling effects likely come into play. We find that our bundled treatment was less effective in boosting awareness about avoidance behavior for participants whose mothers attended college (Table 7). The explanation may be that, for whatever reason, ceiling effects were slightly less binding for this subgroup—they were slightly less likely to be aware of the health benefits of avoidance behavior at baseline (89 percent versus 91 percent for participants whose mothers did not attend college).

For the category "avoidance behavior," we focus on *behavior,* an indicator of whether the participant changed any behavior because of poor air quality in the previous two weeks. We find that our treatment was less effective in changing this outcome among participants who were job holders and those whose mothers had attended college (Table 7). Job holders may have been less affected for the reason noted above—they had fewer opportunities for avoidance behavior. We hypothesize that here, mother's education picks up the effect of socioeconomic status. Participants with higher socioeconomic status may have been less affected because they had better access to health care and were therefore less risk averse. In Bogotá, poor households mainly rely on public health facilities not private ones, and as a result do not have access to health care on a par with richer households (Garcia-Subirats 2014).

For the category "air quality warnings," we focus on *aq warn anyone*, an indicator of whether the participant warned anyone about poor air quality in the previous two weeks. We find that our treatment was less effective among those who were job holders and those living in households with persons over the age of 60 (Table 7). Job holders may have been less affected because their propensity to warn others was correlated with their own ability to engage in avoidance behavior. The reason the treatment was less effective among participants living with elderly people may have to do with the Covid-19 pandemic. Although we are not aware of any age-specific data on mobility during the pandemic, anecdotally, elderly residents of Bogotá were more likely to stay at home than younger ones, and thus participants living with people over 60 would have less cause to warn others about air quality.

For the category "environmental discussions," we focus on *enviro. discuss anyone*, an indicator of whether the participant discussed environmental issues with anyone in the previous two weeks. We find that our treatment was more effective in motivating discussions among participants who lived with immediate family members (Table 7). Such participants may have been more affected because they were more apt to have such discussions with family members than with others.

Finally, for the category "attitudes," we focus on *concern aq long run,* a five-point Likert-scale level of concern about air quality. None of the interaction terms are statistically significant (Table 7).

6. DISCUSSION

We conducted a randomized controlled trial with university students in Bogotá to evaluate the effect on a range of outcomes of training in the use of a smartphone app that provides information on air quality. We found that the training boosted the acquisition of information about air quality, knowledge about avoidance behavior, and adoption of some avoidance behaviors—specifically, wearing a mask with a filter and closing windows during severe air pollution episodes. It also enhanced concern about other environmental issues—namely water pollution and hazardous waste—and reduced concerns about potential trade-offs between environmental protection and economic growth. It had only weak effects on providing warnings about air quality to others and discussing environmental issues with others. Finally, we found that the effects of the training were moderated by participants' characteristics; for several outcomes it was less effective among those who were job holders.

Our study has a number of limitations. First, for reasons discussed above, we relied on a bundled treatment comprising (i) information on the Aire Bogotá app, (ii) information on air pollution, its health effects, and how to minimize them through avoidance behaviors, and (iii) a six-week interactive email campaign aimed reinforcing the first two elements. We are not able to disentangle the effects of individual components of this treatment.

Second, our outcome data are self-reported and could be biased upward if respondents tended to provide answers that conform to perceived social norms (Zerbe and Paulhus 1987; Fisher 1993). This bias, in turn, could affect our treatment effect estimates if it was correlated with our treatment—that is, if our bundled treatment created additional incentives for participants to overreport compliance. Unfortunately, we are not able to test for such bias because we do not observe actual outcomes. However, two factors provide reassurance. First, we find statistically significant effects for some outcomes but not others. If self-reporting bias were driving our results, we would expect to see more consistently significant treatment effects. For example, among our behavior outcomes, we are able to discern significant effects for wearing a mask and closing windows but not for other avoidance behaviors that were specifically recommended in our treatment materials, including limiting outdoor activities during severe air pollution episodes and not smoking. In addition, although we are not aware of any evidence on bias of self-reports about pollution avoidance behavior, studies of self-report bias for other types of avoidance behavior have concluded that it is not large.[5] Replicating a version of our experiment with observable outcomes, such as travel data from smartphone geolocators, would help clarify the issue.

Third, in principle, the overlap between Covid-19 pandemic and our experiment could bias our results. Our difference-in-differences empirical design controls for cross-cutting factors that affect both treatment and control groups in the same way.[6] The pandemic definitely affected both groups. Nevertheless, our results could be biased upward if it had differential effects on those groups—either making positive changes in outcomes more likely in the treatment group or less likely in the control group. That might happen if, for example, our bundled treatment led participants to perceive a positive link between exposure to air pollution and susceptibility to Covid-19, thereby creating additional incentives for them to undertake avoidance behavior, warn others about severe air pollution, etc.

Unfortunately, we have no way of testing for such perceptions or bias using our survey data. Here, too, however, several factors provide some reassurance. Our treatment materials were designed well before the pandemic began and made no reference to Covid-19, a potential link between air pollution and Covid-19, or even a link between air pollution and an infectious disease. In addition, one of the two statistically significant effects of our treatment on avoidance behavior does not comport with the hypothesis of bias induced by the pandemic. We find that our treatment increased the probability that participants had closed windows as a result of air pollution in the previous two weeks. Covid-19 mitigation guidance would recommend the opposite: keeping windows open. Finally, we find it improbable that the positive spillover effects

[5] Three studies of bias in self-reports about avoidance behaviors intended to slow the spread of Covid-19, including mask wearing and social distancing—each using a different method to detect deviations between actual and self-reported behaviors (list experiments, cross-wise models, and analysis of smartphone location data)—concluded that these deviations are quite small or negligible (Jensen 2020; Gollwitzer et al. 2020; Larsen et al. 2020).

[6] For example, by restricting economic activity—and in particular motor vehicle use—the Colombian lockdown improved air quality in Bogotá: on average, concentrations of fine particulates fell by more than a third in the first several months of the lockdown, when our experiment was implemented (Blackman et al. 2021). In addition, the lockdown caused people to remain indoors. Both the improvement in air quality and the decline in outdoor activities should have reduced our participants' incentives to learn about avoidance behavior, to undertake such behavior, to warn others about air pollution, etc. But unless these factors affected our treatment and control participants differently—and we see no reason to expect they did—they would not bias our results.

of our treatment for concern about environmental issues other than air pollution arose from concerns about Covid-19. Notwithstanding these factors, we acknowledge that it is possible for our treatment effect estimates to have been biased because of the Covid-19 pandemic. Replicating our experiment after the pandemic has subsided would help clarify the issue.

Our findings have several policy implications. First, they add to the growing evidence that ICTs providing real-time information on air quality can help reduce exposure to pollution. More specifically, they suggest that training in the use of smartphone apps may be an effective means of reducing exposure in developing countries, where air pollution has the most severe effects on human health and where prospects for reducing emissions in the short to medium term are arguably most limited. Third, they provide some evidence that training in the use of air quality ICTs can have spillover effects on people's attitudes about other types of pollution and environmental quality in general.

Our study highlights several directions for future research. First, it would be useful to determine whether and how our results generalize to other geographic settings and how place-based factors moderate treatment effects. For example, would a similar training generate substantial effects in a city with only moderately severe air pollution? In addition, it would be helpful to disentangle the individual effects of our bundled treatment. Would the release of a smartphone app like Aire Bogotá have significant benefits absent training? And would training be effective absent an interactive email campaign? Third, it would be useful to compare the effectiveness of personal ICTs like the Aire Bogotá app with impersonal ones like air quality alerts disseminated through conventional media. Fourth, it would be instructive to study the use of ICTs like Aire Bogotá in different subpopulations—particularly those who are most vulnerable to the effects of air pollution and for whom personal ICTs may have the greatest benefits. Finally, as noted above, it would be useful to replicate some version of our experiment to test for any self-reporting and pandemic-related biases.

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Table 1. Variables and means at baseline

Variable	Units	Definition	N obs.	Mean
TREATMENT				
treated	0/1	received treatment information session	578	0.42
OUTCOMES				
Acquisition Air Q. Info.				
installed app	0/1	installed app on smartphone	578	0.03
info. searched app	0/1	searched for info. on air quality past 2 weeks using app	577	0.02
info. searched other	0/1	searched for info. on air quality past 2 weeks using other source	577	0.37
Avoidance Knowledge				
know	0/1	knows own behavior can reduce adverse health effects air pollution	576	0.90
know outdoors	0/1	knows restricting outdoor activity can reduce adverse health effects	576	0.22
know travel	0/1	knows changing travel mode or route can reduce ad. health effects	576	0.46
know mask	0/1	knows wearing mask w/ filter can reduce adverse health effects	576	0.56
know windows	0/1	knows closing windows can reduce adverse health effects	576	0.30
know smoking	0/1	knows smoking less can reduce adverse health effects	576	0.33
know air purifier	0/1	knows using air purifier can reduce adverse health effects	576	0.23
know other	0/1	knows wearing scarf & medicines can reduce ad. health effects	576	0.48
Avoidance Behavior				
behavior	0/1	changed behavior due to poor air quality past 2 weeks	578	0.13
behavior outdoors	0/1	restricted outdoor activity due to poor air quality past 2 weeks	578	0.07
behavior travel	0/1	changed travel mode or route due to poor air quality past 2 weeks	578	0.05
behavior mask	0/1	wore mask w/ filter due to poor air quality past 2 weeks	578	0.02
behavior windows	0/1	closed windows due to poor air quality past 2 weeks	578	0.03
behavior smoking	0/1	smoke less due to poor air quality past 2 weeks	578	0.01
behavior air purifier	0/1	used air purifier due to poor air quality past 2 weeks	578	0.00
behavior other	0/1	used scarf or medicines due to poor air quality past 2 weeks	578	0.05
Air Quality Warnings				
aq warn anyone	0/1	warned anyone about poor air quality past 2 weeks)	577	0.32
aq warn family	0/1	warned family members about poor air quality past 2 weeks	577	0.27
aq warn peers	0/1	warned peers about poor air quality past 2 weeks	577	0.23
aq warn others	0/1	warned teachers or h. care workers about poor air q. past 2 weeks	577	0.03
Enviro. Discussions				
enviro. discuss anyone	0/1	with anyone discussed enviro. issues past 2 weeks	577	0.65
enviro. discuss im. family	0/1	with family members discussed enviro. issues past 2 weeks	577	0.43
enviro. discuss peers	0/1	with peers discussed enviro. issues past 2 weeks	577	0.55
enviro. discuss others	0/1	with teachers or h. care wkrs. discussed env. issues past 2 weeks	577	0.13
Attitudes				
concern aq long run	[0-4]	level of concern about effect air quality on health in long-run	578	3.19
concern water pollution	[0-4]	level of concern about water pollution	577	2.75
concern waste	[0-4]	level of concern about hazardous waste	576	2.74
concern tradeoff growth	0/1	believe pollution is needed to foster economic growth	574	0.67
COVARIATES				
estratos 1&2	0/1	family home in estrato 1 or 2[a]	568	0.35
male	0/1	male	577	0.51
education mother	0/1	mother's attended college or graduate school	568	0.35
live with immediate family	0/1	live with immediate family	572	0.83
employed	0/1	hold paid job in addition to studying	570	0.23
health self	0/1	has cardiopulmonary condition[b]	578	0.18
health family	0/1	member imm. family has cardiopulmonary condition[b]	577	0.55
smoke	0/1	smoke tobacco products	575	0.22
no. hh members <5	0/1	household members <5 years old	578	0.14
no. hh members >60	0/1	household members >60 years old	578	0.30
exercise outdoors	0/1	exercise outdoors at least some days of the week	578	0.32
region 1	0/1	north (A18)	572	0.40
region 2	0/1	outside Bogotá[c]	572	0.05
region 3	0/1	southeast[c]	572	0.13
region 4	0/1	southwest[c]	572	0.42

[a]*Estratos* are socioeconomic categories used by Colombian municipal governments to charge differential fees and taxes for public services and to allocate various benefits (DANE 2020). The six *estratos* are 1 (low-low), 2 (low), 3 (medium-low), 4 (medium), 5 (medium-high), and 6 (high).
[b]Conditions are asthma, chronic bronchitis, lung or throat cancer, heart disease, chronic obstructive pulmonary disease, pneumonia, high blood pressure, or other cardiopulmonary condition.
[c]The *localidades* (municipal administrative units) that correspond to each region are: *region 1*, southwest: Bosa, Ciudad Bolivar, Fontibon, Kennedy, Puent Aranda, Rafael Uribe, Usme, Tunjelito; *region 2*, outside Bogotá; *region 3*, southeast: Antonio Nariao, La Candaleria, Los Martires, San Cristobal, Sante Fe; *region 4*, north: Barios Unidos, Chapinero, Engativa, Suba, Teusquillo, Usaquen.

Table 2. Treatment assignment noncompliance (%)

	Control group (n=334)	Treatment group (n=244)	*Total* (n=578)
Aire Bogotá app installed at endline?			
Yes	4	83	37
At one time but no longer	12	15	13
Never	84	2	49
Total	100	100	100
Treatment email campaign (n = 6)			
Email questions without responses	n/a	40	n/a
Participants not responding to 3 or more questions	n/a	41	n/a
Email questions with incorrect responses	n/a	7	n/a
Participants with 3 or more incorrect responses	n/a	4	n/a

Table 3. Intention-to-treat effect estimates:
Acquisition of air quality information (s.e.)

	installed app	*info. searched app*	*info. searched other*
treated	0.840***	0.292***	0.051
	(0.024)	(0.034)	(0.040)
Baseline mean	0.03	0.02	0.37
% change	2556.48	1872.55	13.61
N obs.	542	541	541
R2	0.712	0.239	0.127
F	213.8	19.2	11.3

The dependent variable is listed in the top row. Independent variables are *treated*, the baseline dependent variable, and the following covariates: *estratos 1&2, male, education mother, live with immediate family, employed, health self, health family, smoke, no. hh members <5, no. hh members >60, exercise outdoors*, and three region fixed effects. Standard errors are clustered at baseline survey session level. The baseline mean is for the entire sample.

Table 4. Intention-to-treat effect estimates:
Knowledge and behaviors

Panel A: Knowledge								
	know	*know outdoors*	*know travel*	*know mask*	*know windows*	*know smoking*	*know air purifier*	*know other*
treated	0.027**	0.204***	0.022	0.159***	0.312***	0.092**	0.018	-0.012
	(0.012)	(0.046)	(0.033)	(0.038)	(0.035)	(0.038)	(0.030)	(0.051)
Baseline mean	0.90	0.22	0.46	0.56	0.30	0.33	0.23	0.48
% change	3.00	92.40	4.84	28.32	105.58	27.68	7.89	-2.52
N obs.	540	540	540	540	540	540	540	540
R2	0.046	0.125	0.092	0.098	0.168	0.222	0.144	0.095
F	2.1	7.7	14.2	9.0	20.4	30.8	9.9	18.2
Panel A: Behavior								
	behavior	*behavior outdoors*	*behavior travel*	*behavior mask*	*behavior windows*	*behavior smoking*	*behavior air purifier*	*behavior other*
treated	0.089**	0.048	0.023	0.046**	0.071***	0.008	0.014	0.034
	(0.033)	(0.036)	(0.016)	(0.018)	(0.022)	(0.010)	(0.010)	(0.022)
Baseline mean	0.13	0.07	0.05	0.02	0.03	0.01	0.00	0.05
% change	67.78	68.20	44.01	240.56	215.18	63.82	817.93	68.62
N obs.	542	542	542	542	542	542	542	542
R2	0.081	0.077	0.029	0.051	0.073	0.073	0.180	0.036
F	3.4	3.9	3.2	6.0	3.3	2.5	.	2.3

The dependent variable is listed in the top row of each panel. Independent variables are *treated*, the baseline dependent variable and the following covariates: *estratos 1&2, male, education mother, live with immediate family, employed, health self, health family, smoke, no. hh members <5, no. hh members >60, exercise outdoors,* and three region fixed effects. Standard errors are clustered at baseline survey session-level. The baseline mean is for the entire sample

Table 5. Intention-to-treat effect estimates: Warnings and discussions

Panel A: Warnings about air quality				
	aq warn anyone	*aq warn family*	*aq warn peers*	*aq warn others*
treated	0.078*	0.080*	0.018	0.008
	(0.042)	(0.042)	(0.026)	(0.011)
Baseline mean	0.32	0.27	0.23	0.03
% change	24.33	30.35	7.81	23.90
N obs.	541	541	541	541
R2	0.103	0.116	0.086	0.045
F	13.0	14.4	10.4	1.1

Panel B: Discussions about the environment				
	env. disc. anyone	*env. disc. imm. fam.*	*env. disc. peers*	*env. disc. others*
treated	0.062*	0.079*	0.056	0.002
	(0.035)	(0.039)	(0.035)	(0.022)
Baseline mean	0.65	0.43	0.55	0.13
% change	9.64	18.48	10.22	1.56
N obs.	541	541	541	541
R2	0.088	0.131	0.109	0.083
F	10.3	15.0	12.7	2.8

The dependent variable is listed in the top row of each panel. Independent variables are *treated*, the baseline dependent variable and the following covariates: *estratos 1&2, male, education mother, live with immediate family, employed, health self, health family, smoke, no. hh members <5, no. hh members >60, exercise outdoors*, and three region fixed effects. Standard errors are clustered at baseline survey session level. The baseline mean is for the entire sample

Table 6. Intention-to-treat effect estimates: Attitudes

	concern aq long run	*concern wat. poln.*	*concern waste*	*concern t.o. gr.*
treated	0.005	0.138*	0.186**	-0.084**
	(0.072)	(0.069)	(0.085)	(0.035)
Baseline mean	3.19	2.75	2.74	0.67
% change	0.15	5.04	6.78	-12.47
N obs.	542	541	541	539
R2	0.148	0.361	0.307	0.266
F	8.3	42.5	35.6	27.5

The dependent variable is listed in the top row. Independent variables are *treated*, the baseline dependent variable and the following covariates: *estratos 1&2, male, education mother, live with immediate family, employed, health self, health family, smoke, no. hh members <5, no. hh members >60, exercise outdoors,* and three region fixed effects. Standard errors are clustered at baseline survey session level. The baseline mean is for the entire sample.

Table 7. Intention to treat effect heterogeneity (s.e.)

	info searched app	*know*	*behavior*	*aq warn anyone*	*env. disc. anyone*	*concern aq priority*
treated×estrado	0.051	-0.013	0.061	0.015	0.006	-0.008
	(0.081)	(0.025)	(0.073)	(0.056)	(0.103)	(0.226)
treated×male	-0.108*	0.032	0.021	-0.075	-0.096	0.038
	(0.057)	(0.038)	(0.079)	(0.069)	(0.099)	(0.199)
treated×education mother	-0.058	-0.053*	-0.165**	-0.133	0.007	-0.060
	(0.063)	(0.028)	(0.065)	(0.090)	(0.101)	(0.203)
treated×live w imm. family	0.053	0.021	-0.038	-0.019	0.208*	-0.366
	(0.088)	(0.039)	(0.080)	(0.101)	(0.108)	(0.274)
treated×employed	-0.201**	-0.025	-0.187**	-0.143*	-0.073	-0.127
	(0.074)	(0.046)	(0.090)	(0.082)	(0.093)	(0.160)
treated×health self	0.095	0.038	0.122	0.147	-0.000	0.108
	(0.094)	(0.028)	(0.081)	(0.087)	(0.119)	(0.189)
treated×health family	-0.002	0.010	-0.087	-0.048	0.117	-0.109
	(0.060)	(0.027)	(0.061)	(0.063)	(0.078)	(0.147)
treated×smoke	0.006	-0.050	0.065	0.024	0.006	-0.253
	(0.055)	(0.043)	(0.069)	(0.088)	(0.103)	(0.151)
treated×no. hh members <5	0.108	0.022	0.045	0.034	0.127	0.074
	(0.072)	(0.032)	(0.066)	(0.099)	(0.119)	(0.204)
treated×no. hh members >60	-0.025	-0.008	0.138	-0.116*	0.124	0.186
	(0.063)	(0.045)	(0.092)	(0.059)	(0.089)	(0.209)
treated×exercise outdoors	0.182***	0.046	-0.007	0.071	-0.005	-0.105
	(0.065)	(0.033)	(0.059)	(0.088)	(0.110)	(0.122)
N obs.	541	540	542	541	541	542
R2	0.3	0.1	0.1	0.1	0.1	0.2
F	219.7	16.5	120.6	404.8	57.1	23.6

The dependent variable is listed in the top row. Independent variables are *treated*, the baseline dependent variable and the following covariates: *estratos 1&2, male, education mother, live with immediate family, employed, health self, health family, smoke, no. hh members <5, no. hh members >60, exercise outdoors,* and three region fixed effects. Standard errors are clustered at baseline survey session level.

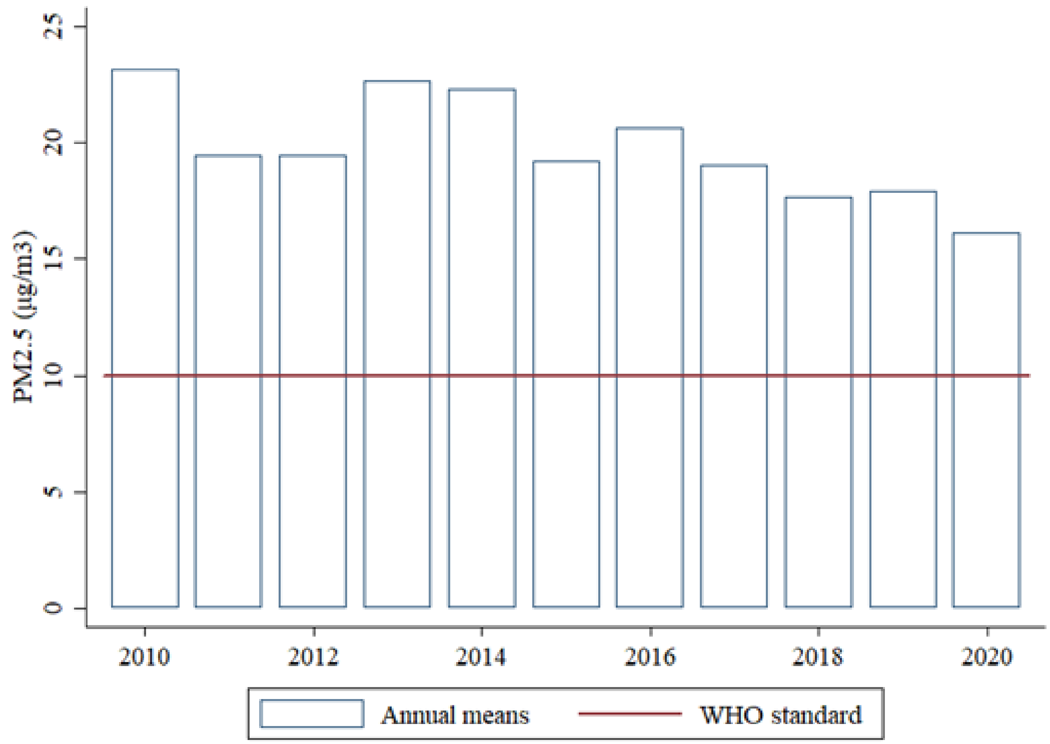
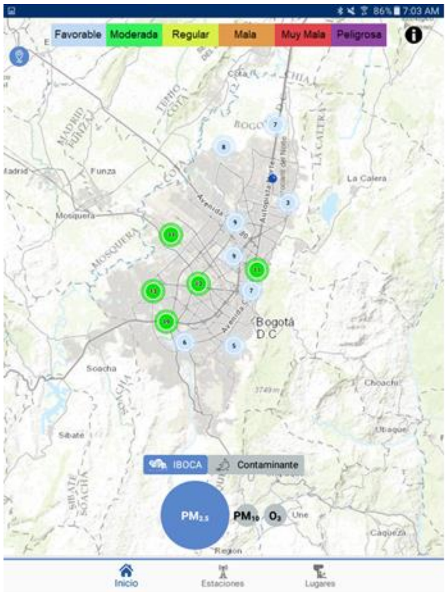
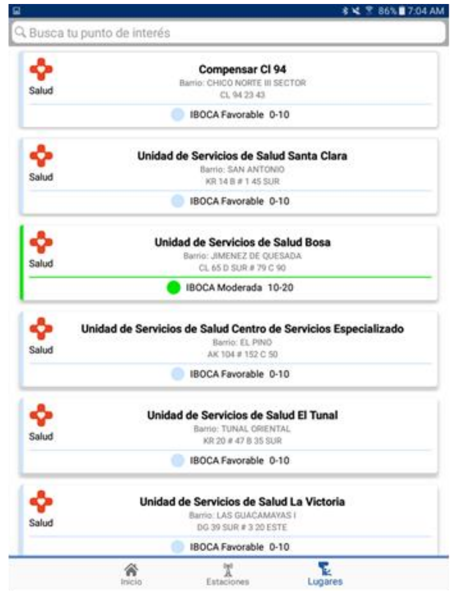


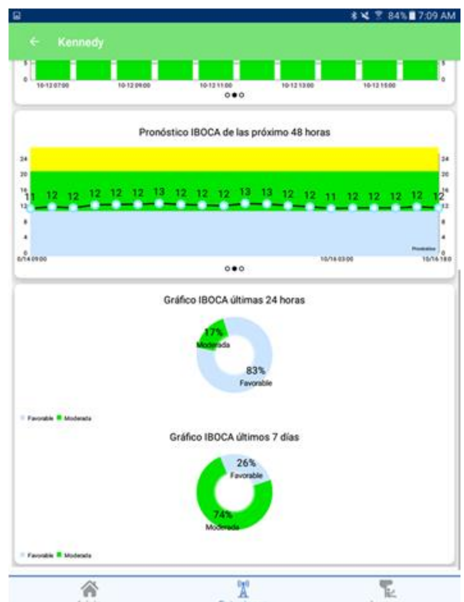
Figure 1. Average annual ambient concentration of fine particulate matter (PM2.5) in Bogotá 2010–2020 and World Health Organization (WHO) standard



Panel A



Panel B



Panel C

Panel D

Figure 2. Aire Bogotá smartphone app screenshots: fine particulate matter (PM2.5) air quality index at Bogotá's 13 monitoring stations (Panel A), air quality data at points of interest selected by user (here, health clinics) (Panel B), historical air quality data (Panel C), and air quality predictions (Panel D).

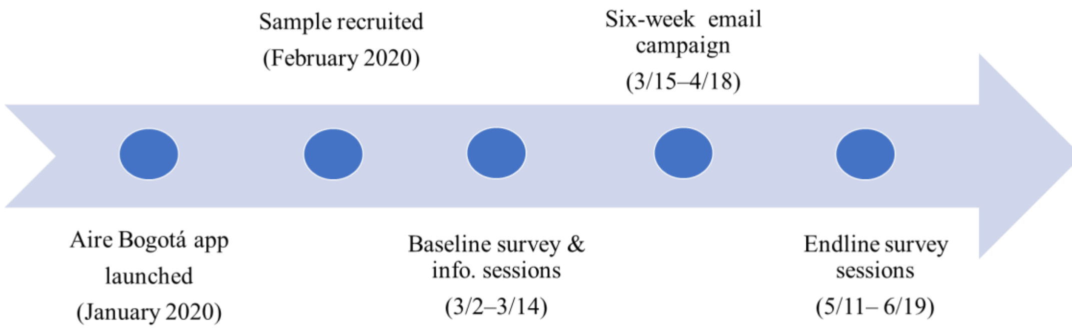


Figure 3. Timeline of experiment

Table A1. Testing for attrition bias: probit regression results; dependent variable is probability that baseline participant did not take endline survey and was dropped from sample; marginal effect (s.e.)

Variable		
treated	0.0106	-0.0003
	(0.0277)	(0.0245)
Controls	no	yes
N obs.	661	613
Chi-squared	0.148	126.921

For model with controls, independent variables are: *estratos 1&2, male, education mother, live with immediate family, employed, health self, health family, smoke, no. hh members <5, no. hh members >60, exercise outdoors,* and three region fixed effects.

Table A2. Covariate balance: probit regression results; dependent variable is probability of assignment to treatment group; marginal effects (s.e.)

Variable	
estratos 1&2	-0.102*
	(0.053)
male	0.044
	(0.049)
education mother	0.045
	(0.053)
live with immediate family	-0.053
	(0.058)
employed	0.088*
	(0.053)
health self	-0.006
	(0.049)
health family	-0.021
	(0.040)
smoke	-0.048
	(0.057)
no. hh members <5	0.018
	(0.071)
no. hh members >60	0.048
	(0.050)
exercise outdoors	0.025
	(0.038)
region 1	0.001
	(0.112)
region 3	0.056
	(0.128)
region 4	0.015
	(0.103)
N obs.	542
Joint significance[a]	0.092

[a]Probability-value of test that all covariates are jointly significant predictors of treatment.
*** p<0.01, ** p<0.05, * p<0.1.

Table A3. Intention-to-treat effect estimates: Acquisition of air quality information (s.e.)

	installed app	*info. searched days*	*info. searched app*	*info. searched other*
treated	0.834***	0.330**	0.275***	0.024
	(0.023)	(0.130)	(0.031)	(0.037)
N obs.	578	577	577	577
R2	0.687	0.071	0.161	0.067
F	679.1	13.9	49.3	19.1

The dependent variable is listed in the top row. Independent variables are *treated* and the baseline dependent variable. Standard errors are clustered at baseline survey session-level.

Table A4. Intention-to-treat effect estimates:
Knowledge and behaviors

Panel A: Knowledge								
	know	*know outdoors*	*know travel*	*know mask*	*know windows*	*know smoking*	*know air purifier*	*know other*
treated	0.020	0.197***	0.024	0.154***	0.298***	0.086**	0.023	-0.020
	(0.013)	(0.045)	(0.031)	(0.039)	(0.035)	(0.036)	(0.032)	(0.042)
N obs.	576	576	576	576	576	576	576	576
R2	0.006	0.104	0.062	0.088	0.138	0.152	0.113	0.065
F	2.0	24.6	37.1	31.3	65.9	60.9	29.6	14.5
Panel A: Behavior								
	behavior	*behavior outdoors*	*behavior travel*	*behavior mask*	*behavior windows*	*behavior smoking*	*behavior air purifier*	*behavior other*
treated	0.073**	0.035	0.024	0.041**	0.061***	0.003	0.011	0.026
	(0.034)	(0.032)	(0.017)	(0.020)	(0.020)	(0.011)	(0.008)	(0.021)
N obs.	577	577	577	577	577	577	577	577
R2	0.036	0.031	0.003	0.006	0.027	0.008	0.144	0.008
F	10.1	4.5	1.0	2.2	7.5	0.4	.	2.9

The dependent variable is listed in the top row of each panel. Independent variables are *treated* and the baseline dependent variable. Standard errors are clustered at baseline survey session level.

Table A5. Intention-to-treat effect estimates: Warnings and discussions

Panel A: Warnings about air quality				
	aq warn anyone	*aq warn family*	*aq warn peers*	*aq warn others*
treated	0.071*	0.069*	0.022	0.008
	(0.035)	(0.037)	(0.022)	(0.010)
N obs.	577	577	577	577
R2	0.046	0.055	0.034	0.006
F	17.6	15.2	7.3	0.5
Panel B: Discussions about the environment				
	env. disc. anyone	*env. disc. imm. fam.*	*env. disc. peers*	*env. disc. others*
treated	0.032	0.058	0.020	0.001
	(0.034)	(0.036)	(0.034)	(0.020)
N obs.				
R2	577	577	577	577
F	0.051	0.089	0.074	0.068

The dependent variable is listed in the top row of each panel. Independent variables are *treated* and the baseline dependent variable. Standard errors are clustered at baseline survey session level.

Table A6. Intention-to-treat effect estimates: Attitudes

	concern aq long run	*concern wat. poln.*	*concern waste*	*concern t.o. gr.*
treated	0.001	0.103	0.186**	-0.064*
	(0.072)	(0.072)	(0.086)	(0.033)
N obs.	578	577	576	573
R2	0.148	0.338	0.271	0.218
F	39.1	109.0	83.7	70.1

The dependent variable is listed in the top row. Independent variables are *treated* and the baseline dependent variable. Standard errors are clustered at baseline survey session-level.

Table A7. Treatment effect sizes from studies finding that information and communication technologies (ICTs) affect avoidance knowledge and/or behavior

Study	Intervention	Outcome	Units	Effect (% change)
Personal ICTs				
Araban et al. (2017)	Text msgs. + others	Perceived benefit avoidance behavior	LS [4-16]	8
	Text msgs. + others	Perceived barriers avoidance behavior	LS [1-5]	-9
	Text msgs. + others	Self-efficacy[a]	LS [4-16]	31
	Text msgs. + others	Practice[b]	LS [5-20]	81
Hanna et al. (2021)	Text msgs.	Knowledge of high pollution day[c]	(0/1)	26
	Text msgs.	Did something different[c]	(0/1)	62
	Text msgs.	Staying home & closing windows[c]	(0/1)	88
Impersonal ICTs				
Liu et al. (2017)	Air quality alert	On-line queries[d]	no	100
Noonan (2014)	Air quality alert	Exercizing in park	(0/1)	-26
	Air quality alert	Running in park	(0/1)	-17
	Air quality alert	Children in park	(0/1)	-14
	Air quality alert	Elderly in park	(0/1)	-5
Saberian et al. (2017)	Air quality alert	Cycle use	no.	-(14–35)
Yoo (2021)	Air quality alert	Baseball game attendence	no.	-7
Ziven and Neidell (2009)	Air quality alert	Zoo attendance	no.	-13
	Air quality alert	Observatory attendence	no.	-6

LS = Likert scale. [a]Confidence in ability to undertake avoidance behavior; [b]Actual avoidance behavior; [c]In past week; [d]For N95 masks and air filters.

APPENDIX 1

TREATMENT AND CONTROL GROUP INFORMATION SESSIONS

1. Background

As discussed in the main text, immediately after the baseline survey, participants in both the treatment group and the control group attended an information session in which a member of the study team gave a PowerPoint presentation. Toward the end of the information session, all participants were given an opportunity to engage in a six-week email campaign. Those who volunteered to do so received six emails—one per week for the next six weeks. Below, we present English translations of the information session PowerPoint and of the first of the six emails in the campaign (subsequent emails were similar but contained different questions).

2. Treatment group

2.1. Text of PowerPoint slides

Slide 1: Agenda

- Air pollution in Bogotá
- Effects of air pollution on health
- Basic information about air pollution
- Behaviors to avoid exposure to air pollution in Bogotá
- Aire Bogotá smartphone application
- How to use the Aire Bogotá app
- Explanation of email campaign

Slide 2: What is level of air pollution in Bogotá?

- Bogotá is one of the most polluted cities in Latin America

Slide 3: Short-term effects of air pollution on health

- Sore throat
- Bronchitis
- Pneumonia
- Asthma
- Allergic reactions

Slide 4: Long-term effects of air pollution on health

- Accelerated aging of the lungs
- Loss of lung capacity
- Chronic pulmonary illnesses

Slide 5: Deaths and illnesses due to air pollution in Bogotá

- Air pollution causes almost 2,000 deaths per year in Bogotá
- Air pollution in Bogotá raises the mortality rate by 14%

- According to the office of the mayor of Bogotá, in 2019 there were 130,000 medical consults for respiratory problems

Slide 6: What is air pollution?

- Air pollution is a mix of sold particles and gases
- The three most important pollutants are PM2.5 (material smaller than 2.5 microns), PM10 (material smaller than 10 microns), and O_3 (ozone)

Slide 7: Air quality monitoring network of Bogotá

- The monitoring network of Bogotá consists of 13 fixed stations and 1 mobile station

Slide 8: On the same day, air pollution in Bogotá can vary greatly across locations

- In general, air pollution is worse in the southwest and better in the north

Slide 9: On the same day, air pollution in Bogotá can vary a lot from block to block

- In general, pollution is worse close to main roads

Slide 10: Air pollution in Bogotá varies a lot over time: Generally it is worse at noon

Slide 11: Behaviors for avoiding air pollution (1/3)

- The municipal government of Bogotá recommends that inhabitants take the following measures during severe air pollution episodes
- Wear a face mask
- Avoid outdoor exercise

Slide 12: Behaviors for avoiding air pollution (2/3)

- N95 face mask versus normal face mask

Slide 13: Behaviors for avoiding air pollution (3/3)

- See a doctor promptly when experiencing symptoms of exposure to air pollution
- Do not smoke tobacco products
- Close windows and clean with a damp mop

Slide 14: Information available in the Aire Bogotá app

- [Map of air quality index at monitoring stations]

Slide 15: Prerecorded tutorial on the use of the Aire Bogotá app

Slide 16: How one can use information on air pollution to make decisions

- At what time and where to exercise outdoors
- When to wear a mask
- When to close windows
- Choosing travel modes and times

Slide 17: Email example

- [See below]

Slide 18: Confirmation email (to sign up for email campaign)

Slide 19: Inputs needed to sign up

Slide 20: The Aire Bogotá app
- Available in Play store and Appstore

Slide 21: Weekly email process

Slide 22: Practice email
- If you have questions about the dynamic, please raise your hand and a member of the staff will assist you.

Slide 23: Questions
- If you have questions about the material presented, raise your hand
- If in the coming weeks you have another question, please write an email to [email address]

2.2. Text of sample email

Hello << First Name >>,

We are sending you this email from Innovations for Poverty Action to invite you to interact with the AIRE BOGOTÁ app and then answer two questions. This action will not take more than five minutes, and you will receive a monetary compensation of 6,000 COP, paid in May 2020, for correctly answering the question presented in the link in this email. You will have an opportunity to earn a total of (6 weeks × 6000 COP =) 36,000 COP over the course of the 6-week email campaign. You will be paid for all correctly answered questions in May 2020 electronically so that you do not have to go to the University of Rosario or any other public place to receive the payment.

First step:
1. Go to the AIRE BOGOTÁ app (PlayStore and AppStore)
2. Go to the Barrios Unidos station and select the information about the pollutant PM2.5.
3. Then find the PM2.5 concentration level (ug/m^3) at this station.
4. Additionally, find out what voluntary actions the application offers you.

Second step: Go to this link and answer the questions related to the information you just searched for.

[Sample question: Where is the painting from the article that was posted on March 20, 2020 on exhibit?]

The question asked in the questionnaire linked to this email will be available only for a period of 24 hours once this email is received. If you have any questions, please write to [email address]; our service channel will be open on Tuesdays and Wednesdays from 7:00 a.m. to 7:00 p.m.

Information of interest

> Exposure to air pollution is associated with asthma, bronchitis, chronic obstructive pulmonary disease, and other serious cardiopulmonary conditions. These are the same conditions that significantly increase the risk that a case of coronavirus will result in severe illness or death. With the information offered by the Air Bogotá application, you can

- Decide when and where it is best to exercise outdoors.
- When it is necessary to wear an N95 mask.
- When it is necessary to close the windows at home.
- Select the best schedule and means of transportation to get around.

Thank you for taking the time to learn about air quality levels in Bogotá!

3. Control group

3.1. Text of PowerPoint slides

Slide 1: Agenda
- What is art history
- Principal characteristics of the artistic periods
- Explanation of the dynamic of emails

Slide 2: What is art history
- Art history is the study of art objects in their historical development and stylistic contexts; that includes genre, design, format, and style
- The study covers painting, sculpture, architecture, ceramics

Slide 3: Characteristics of artistic periods (1/8)
- Art prehistory: representation of objects, animals, and rituals
- Ancient art: its purpose was to tell stories, decorate objects, depict religious rituals, and display social status
- Medieval art: characterized by grotesque images and brutal landscapes

Slide 4: Characteristics of artistic periods (2/8)

- Renaissance: focus on nature and individualism, thinking of man as independent and self-sufficient

- Mannerism: it arises from the ideals of the Renaissance, but its focus on style and technique exceeded the meaning of the subject
- Baroque: it was characterized by greatness and wealth, marked by an interest in expanding the human intellect

Slide 5: Characteristics of artistic periods (3/8)
- Rococo: it is characterized by its lightness and elegance, focusing on the use of natural shapes, asymmetrical design, and colors
- Neoclassical: it drew on elements of classical antiquity
- Romantic: rejects order, harmony, and rationality; Romantic artists emphasized the individual and the imagination

Slide 6: Characteristics of artistic periods (4/8)
- Realism: inspired a new interest in accurately capturing everyday life
- Art Nouveau: focused on the natural world, characterized by long, sinuous lines and curves
- Impressionism: characterized by short, quick brush strokes and an unfinished sketch feel.

Slide 7: Characteristics of artistic periods (5/8)
- Post-Impressionism: focused on subjective visions and symbolic and personal meanings rather than observations of the outside world
- Fauvism: characterized by the expressive use of intense colors, lines, and brushstrokes
- Expressionism: emerged in response to increasingly conflicting world views and loss of spirituality

Slide 8: Characteristics of artistic periods (6/8)
- Cubism: rejects the concept that art should copy nature
- Surrealism: works of art that defied reason
- Abstract expressionism: used spontaneity and improvisation to create abstract works of art

Slide 9: Characteristics of artistic periods (7/8)
- Op art: artists active in this style used shapes, colors, and patterns to create images that appeared to be moving or blurry.
- Pop art: used everyday objects to create innovative works of art that challenged consumerism and the media.
- Povera art: challenged modernist and contemporary systems by infusing common materials into creations

Slide 10: Characteristics of artistic periods (8/8)
- Minimalism: focused on anonymity, drawing attention to the materiality of the works
- Conceptual art: artists valued ideas about visual components, creating art in the form of ephemeral representations
- Contemporary art: the 1970s marked the beginning of contemporary art, which extends to the present day

Slide 11: Email

- [See below]

Slide 12: DailyArt application

- Available in Play store and Appstore

Slide 13: Confirmation email (to sign up for email campaign)

Slide 14: Inputs needed to sign up

Slide 15: Weekly email process

Slide 16: Practice email

- If you have questions about the dynamic, please raise your hand and a member of the staff will assist you.

Slide 17: Questions

- If you have questions about the material presented, raise your hand
- If in the coming weeks you have another question, please write an email to [email address]

3.2. Text of example email

Hello << First Name >>,

We are sending you this email from Innovations for Poverty Action to invite you to interact with the Daily Art app and then answer one question. This action will not take more than five minutes, and you will receive a monetary compensation of 6,000 COP, paid in May 2020, for correctly answering the question presented in the link in this email. You will have an opportunity to earn a total of (6 weeks × 6000 COP =) 36,000 COP over the course of the 6-week email campaign. You will be paid for all correctly answered questions in May 2020 electronically so that you do not have to go to the University of Rosario or any other public place to receive the payment.

First step: Go to the DailyArt app (PlayStore and AppStore) and see where the painting from the article that was posted on March 20, 2020, is on exhibit.

Second step: Go to this link and answer the question related to the information you just looked up.

The question asked in the questionnaire linked to this email will be available only for a period of 24 hours once this email is received. If you have any questions, please write to [email address]; our service channel will be open on Tuesdays and Wednesdays from 7:00 a.m. to 7:00 p.m.

Thank you for taking the time to learn about art history!