Behavioral Insights for Better Public Communication in Health Crisis*

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Abstract

Amidst the COVID-19 pandemic, effective public communication became of utmost importance. This is especially true for the time after the easing of lockdowns, which meant an increased emphasis on personal responsibility and adoption of self-care measures. We conducted an experiment that tested three behavioral tools for communication —framing, population targeting, and social norms— to assess behavioral biases that pose a barrier to effective communication efforts and provide useful information for governments to use in crisis situations. In order to measure the effectiveness of the various communication features, we relied on an Attitudes Scale developed and tested for this purpose.

Keywords: Behavioral biases; crisis communication; COVID-19; framing; population targeting; social norms; Attitudes Scale.

JEL: D91; D90; I12; D83; C91.

Ideas conductuales para mejorar la comunicación pública en las crisis sanitarias

Resumen

En medio de la pandemia de COVID-19, la comunicación pública efectiva se volvió de suma importancia. Esto es especialmente cierto para el tiempo posterior a la relajación de los bloqueos, lo que significó un mayor énfasis en la responsabilidad personal y la adopción de medidas de autocuidado. Se llevó a cabo un experimento que probó tres herramientas conductuales para la comunicación —encuadre, focalización de mensajes y normas sociales— a fin de evaluar los sesgos conductuales que representan una barrera para los esfuerzos de comunicación efectivos y brindan información útil para que los gobiernos la utilicen en situaciones de crisis. Para evaluar la efectividad de las diversas medidas de comunicación, nos basamos en una escala de actitudes desarrollada y probada para este propósito.

Palabras clave: sesgos conductuales; comunicación de crisis; COVID-19; encuadre; población destinataria; normas sociales; escala de actitudes.

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Introduction

The COVID-19 pandemic took both Public Health Systems and the whole State apparatus by surprise. The initial response to the upcoming health crisis, given the ubiquitous uncertainty about the nature of the pandemic, saw the rise of strict lockdown measures all over the world. This restrictive measure eventually started to prove costly, and their effectiveness in the developing world wore down due to widespread defiance of lockdowns, with many informal workers unable to provide for their families and limited public assistance (Andia et al., 2022; Busso et al., 2020; Denegri et al., 2022; Delaporte & Peña, 2020). Particularly, Colombia had one of the longest and strictest lockdowns in 2020, starting with national lockdowns in March until early September, when these measures were delegated to subnational governments.

The subsequent dismantling of lockdown measures meant a new challenge for governments: To effectively communicate the dangers of contracting the novel coronavirus and to convey the importance of adopting the appropriate self-care measures. The pandemic proved to be the biggest crisis management challenge of the 21st century, and a chance to appreciate just how determinant and consequential an effective crisis communication can be.

Behavioral science literature highlights many cognitive barriers individuals will face when assessing their optimal level of self-care in these situations (Metcalf & Haushofer, 2020; Kalichman & Eaton, 2020) and during in vaccination process (Hortal,2022). Moreover, it provides useful tools for addressing such issues (Van Bavel, et al. 2020; Lunn et. al, 2020).

In this article, three of these tools are tested: Framing —gain vs loss—, Population Targeting —evoking group identity or not—, and Social Norms —descriptive vs prescriptive—. Based on the BASIC —Behavior, Analysis, Strategies, Intervention, Change— model, from OECD (2019), the target behaviors were identified, assessed, and an experiment was designed to test the behavioral response. The target behaviors are those related to self-care measures for COVID-19 prevention: Use of masks, social distancing, and handwashing.

The related behavioral barriers to fulfilling what is thought of as an "appropriate level of self-care" come in all sorts; this is documented, among others, in Martínez et al. (2020) and Tantia & Perez (n. d.). The early literature about outstanding behavioral barriers can be classified into three general kinds: belief formation, the building of preferences, and information processing.

First, those related to belief formation, such as optimism bias, by which individuals would rate their chances of catching COVID at a lower level than their peers (Soofi et al., 2020), and overconfidence bias, shown in the individuals' self-perceived ability to evade contagion despite lacking in care, which feeds back over time when people don't contract the virus, leading to an inevitable scenario of irresponsible behavior and/or illness (Egan, et al., 2020; Kalichman & Eaton, 2020). The targeting of messages to allude to group identity could help individuals assess the risk of contagion upon receiving a message because they are better able to imagine themselves in harm's way. This has been tested, among others by Alsan, et. al. (2021), with mixed results.

The second is the building of preferences. In particular, great concern has been shown by the potential of social norms -as it relates to preference setting, to hinder the effectiveness of safety measures communication. In particular, the discussion centered on the prevalence of either prescriptive or descriptive social norms in shaping preventive behavior (Metcalf & Haushofer, 2020; Tantia & Perez, n. d.). If prescriptive social norms prevail —that is, people's behavior is guided by what ought to be done—, then we should expect individuals to naturally adhere to the guidelines, and communications should therefore focus on the right way to approach self-care. On the other hand, if descriptive norms are the drivers of said behaviors, then the above-average behavior would theoretically see itself reinforced over time, whether that is taking proper care or not. This is referenced as "herd behavior" (Soofi et al., 2020).

A more nuanced approach would suggest that descriptive norms-driven behavior responds further to the nearer and more specific context —the closer peers—, rather than to the whole population. What this entails for public communication, is that relatable examples of people adopting the appropriate self-care measures constitute a more effective communication strategy, and that, theoretically, a successful enforcement of said measures could loop back into a more favorable self-motivated adoption.

Other relevant behavioral biases related to how preferences are built include short-termism (Martínez et al., 2020), status quo bias (Lunn, et.al 2020), delayed discounting (Halilova et al. 2022) and loss-aversion (Kluwe, et al., 2021).

Lastly, as it relates to information processing, the early literature showed the importance of the framing effect in public messaging. Whether messages relating to the compliance of COVID safety guidelines and their effects on an individual level are presented as a loss or a gain, seems to be relevant for how seriously people take these guidelines. However, there is a standing discussion on the contexts in which each of these is more effective. Van Bavel et al., (2020) argue that loss framing is particularly effective at dealing with overconfidence, by having a proportionally larger effect on risk perception. Notwithstanding, they also warn about the limited effectiveness of the loss framing when individuals perceive they don't have the means to deal with the threat and could even be counterproductive. A meta-analysis run by Gallagher & Updegraff (2012) indicates that the gain framing is better at promoting preventive behaviors, like those necessary to deal with COVID-19.

Additionally, in the Colombian context, Gantiva et al. (2021) found that the gain framing increased the individuals' self-reported intention to adopt self-care measures, and those kinds of messages were also found to be more impactful, while loss-framed messages increased risk perception. As to what framing entails in messaging, Celis (2022) highlights that the particular features to fiddle with are the types of content, word selection, shape and, tone, which can together turn a gain perception into a loss one and vice-versa.

Following these findings, the theoretical frames available and the potential for instant implementation in public communication, the framing, population targeting, and social norms strategies were chosen for the experiment. Moreover, in the design of messages, further recommendations were followed to maximize the effects —simple, coherent, clear and bright colors, few texts, and use of prominence, as per (Tagliaferri et al., 2020)—, and applied to all equally, to not distort the comparisons.

Whereas early experiments have rightly chosen the above behavioral biases as a focus for research, there is a common limitation in most behavioral experiments of this kind: They don't measure behavior. Because it is a near impossible feat to track individuals and observe their actual self-care behaviors, researchers have opted for self-reported intentions and an evaluation by the treated of the messages received; behavioral economics itself provides the basis for why this might not be a right proxy for behavior: intention-action gap.

To assess this limitation, we turned to the social psychology literature and borrowed the "Attitudes Scale" measurement tool, which measures individuals' attitudes in three different aspects: Cognitive, Emotional, and Behavioral (Hair et al., 2019). Moreover, the responses by individuals are not binomial and allow for a more meaningful evaluation of the treatment effects.

Experiment

Methodological notes

The experiment was conducted, in chronological order, as such: (i) Preliminary survey; (ii) Baseline survey; and (iii) Treatment and end-line survey.

The experiment was set out in two different interventions, both of which followed a quasi-experimental between-subjects design. That meant each individual produced an initial and final measurement and was exposed to a single treatment. This design allowed for an appropriate comparison of individuals with others similar to them, and both the effects of a particular treatment on a group and the difference between treatments to be evaluated. As such, a causal effect was able to be estimated.

Also, unlike a within-subjects design, the between-subjects design prevents the learning effect, which would undermine the attempt to measure the effect of a particular treatment. Moreover, it also ensures a shorter survey time, which could affect the quality of responses. The statistical noise generated by the comparison between groups was reduced through stratification and randomization of the sample.

Preliminary survey

The preliminary survey consisted of several questions which aimed to reveal the outstanding issues relating to the adoption of different COVID-related safety measures. The sample is unrelated to that of the other survey, in order to avoid any potential biases. This was an attempt to ground the international literature, which does not always reflect the distinct dynamics of issues in the developing world. Among the findings, we encountered vulnerable populations having particular difficulties adhering to the safety guidelines, as expected by Perez (n. d.). An outstanding importance of peers and family in determining beliefs and preferences was found, as well as distinct personal distance preferences, which were always hypothesized to be culture-specific. Moreover, individuals tend to underestimate risk exposure in trusted environments, that is, people find their close relatives to be a less likely source of contagion than a stranger.

Interventions: Sample

All surveys were collected online, and the target population was that of the city of Barranquilla, Colombia. The survey was advertised on Facebook, from the official account of Universidad del Norte, and was further shared among the University's community, which is quite diverse. Furthermore, the survey collected data on location and age and eliminated from the sample those outside the Barranquilla Metropolitan area and those under 18. As an incentive to conduct the follow-up survey and treatment, people were informed in the advertisement of a lottery upon completion of the experiment, which awarded four random prizes.

The sub-samples from both interventions were extracted from the same survey, which was segmented into two: (i) Vulnerable population, according to "the socioeconomic stratum", belongs to "*estrato*"[1] 1 and 2. (ii) The rest: "*estrato*" 3, 4, 5 and 6.[2]

This segmentation was done following the results of the preliminary survey, the literature on specific issues for vulnerable populations, and the "*estrato*" index as per Uribe-Mallarino (2008). While the socioeconomic stratum is formally dictated by the government upon a geographic area for urban development, tax collection, and subsidy purposes, people self-identifying in one of these categories has been shown to drive behavior, based on group identity. The total sample for the baseline survey was 1114.

Dependent Variable

The bottom line target of the study is the actual behavior. Since it cannot be measured directly, as mentioned, we have chosen an Attitudes Scale as a proxy measure of behavior. This consists of a questionnaire containing several assertions about situations relating to COVID-19 preventive knowledge, emotions, and behavior, to which the respondents answer the extent of their agreement with the assertion. There are five categories, ranging from totally agree, to totally

1 "Estrato' is a sui-generis concept in Colombia, which alludes to the classification of residential units' location used to cross-subsidize public utilities, running from 1 (most vulnerable) to 6 (wealthiest). To avoid confusion, "estrato" is used instead of the literal translation strata, a separate statistical concept.

2 For simplicity, the subsample of low-"estrato" is abbreviated as LE, and the subsample of higher as HE.

disagree. If the assertion is favorable to or in line with self-care measures, totally agree grants a score of 5, and totally disagree a score of 1. If the assertion is unfavorable to or out of line with self-care measures, totally agrees grants a score of 1, and totally disagrees a score of 5. Answers in between follow the same logic.

Each experiment has a different set of queues (21 (HE) and 25 (LE)). The outcome of the questionnaire is a score, which can be stated as the sum of all scores for individual queues- or on average. As mentioned, the Attitudes Scale has three components, and there is a corresponding score for each, as each of them relates to certain assertions.

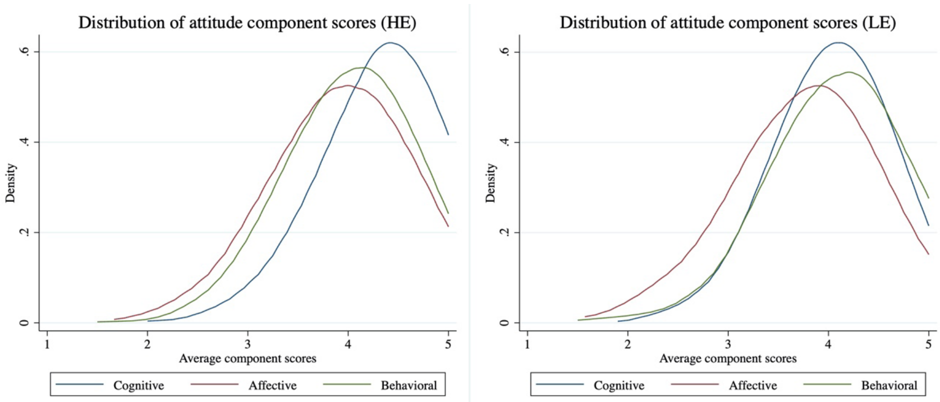
For the HE subsamples, the overall average score was 4.1, while the average scores for the cognitive, affective and behavioral components were 4.32, 3.93 and 4.03, respectively. For the LE subsample, the overall average score was 3.975, while the average scores for the cognitive, affective and behavioral components were 4.04, 3.76 and 4.08, respectively.

The Affective component appears to be the biggest issue, as it has the lowest average score. Moreover, it has the largest variance, meaning it depends more on other individual characteristics. The Cognitive and Behavioral components drive up the average in both subsamples, and the cognitive component has the most cohesive set of answers – and has the smallest variance.

In all, the evidence points to a relatively lesser problem in terms of information and prospective behavior, and more on the emotional and affective response, which would hinder appropriate reaction to exposure of COVID-related situations.

A visual representation of the distribution of component scores further illustrates these trends.

Figure 1. Distribution of initial component scores



Source: Own elaboration with experimental data.

Independent Variables

The independent variables are the different treatments applied to the subsamples. The "HE" experiment sample is subject to either positive framing or negative framing, descriptive norms or prescriptive norms. Meanwhile, the "LE" experiment sample is subject to either positive framing or negative framing, or population targeting or no particular population targeting of the message. Each group is then subject to only 1 of 4 available treatments (8 in total) and is to be compared to its behavioral tool counterpart[3].

There are various visual elements used to correctly convey the message in the intended way and differentiate them, without changing the background message. As Figure A.1 shows, the framing treatments in the HE subsamples differ in many respects, like the color – red for negative and green for positive, and the wording of the message with the negative highlighting the losses coming from bad behavior and the positive highlighting the gains from good behavior, respectively depicted. Meanwhile, the difference between the descriptive and prescriptive norms is shown in two ways. First, it shows two different contexts, one, a real-world scenario that was happening at the time (Paris in lockdown), and the other, a hypothetical one depicting a lockdown situation at home. Secondly, the message compliments the image, as the descriptive tells a story of the consequences of bad behavior, while the prescriptive highlights what are the normative consequences of engaging in bad behavior[4].

For the LE subsample, the treatments are intertwined to maximize the sample size available for cross-comparisons. The negative framing ones are orange and carry a loss-framed message, while the positive ones are blue and carry a gain-framed message. The targeting is comprised of a depiction of a common circumstance for the targeted group, which is an informal street market.

Control Variables

From the preliminary survey, several variables were identified as to having a possible relationship with the level of preventive behavior: (1) Whether the person or a relative had contracted COVID earlier; (2) Whether a person's relative has deceased of COVID; Whether there is someone older than 65 years old in the household; (4) Whether there is someone with a comorbidity in the household; (5) Gender; (6) Age; (7) Educational attainment, which was broken down into two dummies for Undergraduate or Technical education and for Masters or above; and (8) the "*Estrato*" of the residence, which was broken into a dummy for each subsample, either from "*Estrato*" 1 or 2 for LE, and is either Middle Class (3 and 4) or Upper Class (5 and 6).

Moreover, in the "LE" experiment, further controls were included: (9) Employment status; (10) Income in relation to the mini wage; and (11) Household seize.

3 The images containing each of the treatments are attached in the appendix.

4 *Whether intentional or not, there is always an inherent framing, so it was decided to go for the negative framing in the norms treatment.*

Results

Baseline Analysis

A difference in means test was applied to the average scale score of each subsample to test the possible effects of each variable. From the ones independently significant, altogether, linear models were estimated (Model 2). Additional models were also estimated, with every variable available (Model 3), and only with the variables whose estimate showed a significance of at least 10%.

Despite the preliminary process of identification, the control variables only explain 12-13% of the variation in average scores. This result was unexpected, and further research is necessary in order to account for and explain the variability in individuals' preventive behavior against COVID-19.

The only variables that were similarly significant across both subsamples were [*QD5*] identifying as a woman and the age [*QD6*]. Both women and older people tended to score better, and so, are assumed to engage in stricter measures for COVID-19 prevention. This is consistent with the literature, as women and older people tend to show less overconfidence effect.

Table 1. Estimates for initial scores in HE subsamples

	Model 1 b/se	Model 2 b/se	Model 3 b/se
Relative deceased ~d	0.104**	0.102**	0.102**
	(0.04)	(0.04)	(0.04)
Woman	0.162***	0.163***	0.167***
	(0.04)	(0.04)	(0.04)
Age	0.007***	0.006***	0.007***
	(0.00)	(0.00)	(0.00)
Master	0.112*	0.159**	0.168**
	(0.04)	(0.06)	(0.06)
>65 yr old is hous~d		0.030	0.023
		(0.04)	(0.04)
Technical or Under~d		0.058	0.055
		(0.04)	(0.04)
Contracted Covid, ~e			-0.057
			(0.04)
Comorbidity in hou~d			0.029
			(0.04)
Upper class			-0.063
			(0.04)
constant	3.653***	3.622***	3.643***
	(0.05)	(0.05)	(0.07)
R-sqr	0.120	0.122	0.128
dfres	727	725	722
BIC	979.9	991.0	1005.7

* p<0.05, ** p<0.01, *** p<0.001

Source: Own elaboration with experimental data.

Notably, people from "*estrato*" 3 to 6 seem to care more about whether a relative had deceased of COVID when deciding their level of self-care than those of "*estrato*" 1 and 2. Meanwhile, the latter seems more concerned about having a vulnerable member in the household than the former.

The comorbidity in households displaces the effect of having a +65-year-old in the household, as they were closely associated all throughout the pandemic. The variable is also multi-collinear for values of age > 65. Results for educational attainment are not robust and vary substantially with "*estrato*" and age. They were estimated using only two dummies for Technical or Bachelor and Masters or over, as there were only three observations with maximum Primary studies.

Conflicting hypotheses could be made for the effect of having contracted COVID previously, with one argument laying out the recognition of the true —and otherwise abstract— cost of contracting it, while the counter-argument states that both surviving and the belief of immunity provides a boost to the overconfidence effect.

Table 2. Estimates for initial scores in LE subsample

	Model 1 b/se	Model 2 b/se	Model 3 b/se
Comorbidity in hou~d	0.123* (0.05)	0.109* (0.05)	0.116* (0.06)
Woman	0.248*** (0.05)	0.247*** (0.05)	0.242*** (0.05)
Age	0.006* (0.00)	0.006* (0.00)	0.005* (0.00)
Technical or Under~d	0.106* (0.05)	0.107* (0.05)	0.123* (0.05)
Master	0.212 (0.12)	0.218 (0.12)	0.247 (0.13)
Stratum 2	0.124* (0.05)	0.120* (0.05)	0.120* (0.05)
>65 yr old is hous~d		0.057 (0.05)	0.061 (0.05)
Contracted Covid, ~e			-0.054 (0.06)
Relative deceased ~d			0.035 (0.06)
Employed			-0.040 (0.06)
Big household			-0.020 (0.06)
constant	3.442*** (0.09)	3.436*** (0.09)	3.470*** (0.11)
R-sqr	0.135	0.138	0.142
dfres	375	374	370
BIC	556.9	561.7	583.4

* p<0.05, ** p<0.01, *** p<0.001

Source: Own elaboration with experimental data.

The biggest overarching conclusion from these initial results is that there lies a big gap in understanding what drives preventing behavior related to COVID. Having considered up to 10 different characteristics of individuals, from education and socioeconomic status to their personal contact with the disease, we were only able to explain 15% of the variability in the scale scores.

Sample Checks

From the baseline analysis sample of 1114[5], only 52 % went on to answer the second survey. That left the total sample of the treated to be 587 individuals, distributed as indicated in Table 3. This massive dropout of participants led to the need to test for possible attrition bias in the sample.

Table 3. Sample size by treatment group

Treatment group	Frequency	Percent
HE - Loss framing	88	7.92
HE - Gain framing	85	7.65
HE - Descriptive norm	80	7.2
HE - Prescriptive norm	87	7.83
LE - Negative Framing & No-targetting	57	5.13
LE - Negative Framing & Targetting	60	5.4
LE - Positive Framing & No-targetting	76	6.84
LE - Positive Framing & Targetting	54	4.86
Subtotal	587	52.83
HE - Control	395	35.55
LE - Control	129	11.61
Total	**1.111**	

Source: Own elaboration with experimental data.

The initial scores between those who left the sample – here coined “control”- and the treated are not significantly different from each other, for any either subsample. Some characteristics, nonetheless, are different. Those who left the study tended to be older – by 7 years for HE and 3 for LE, people who had contracted COVID before and those who held a master’s degree were more likely to drop out in HE, as well as those in “*estrato*” 2 for LE. As per the control parameters estimated ahead, these differences proved not to be relevant. Differences among the different treatment groups are also explored. No initial scores or characteristics were significantly different.

5 The final figure for treatment analysis was 1111, as 3 individuals were treated but their specific treatment wasn’t recorded and had to be dropped.

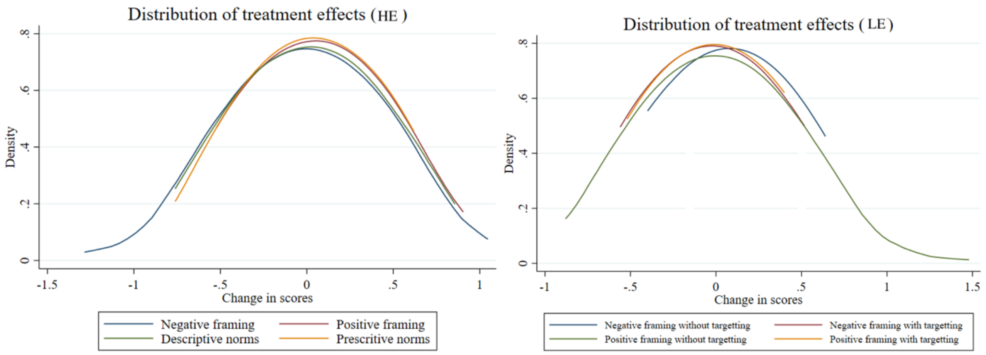
Additionally, further checks were performed on the time taken for the survey and the effect of prior COVID-19 surveys. Having completed 1 or more COVID-related surveys before had no effect on the scores, or on the score changes after treatment. The time taken was also uncorrelated with the scores, but only for the LE subsample. For HE, the time taken was positively associated with both the baseline and end-line survey, with the latter having a larger coefficient[6]. As such, the time taken in both was tested together against the change in scores, and there is no significant relation between the time taken in the treatment with the change in scores (even if estimated coefficient is negative). This means that the lack of an effect cannot be attributed to poor attention to the treatment, as measured by the time taken.

Treatment Analysis

The treatments saw mostly positive changes in the average scores, as expected. However, particular outcomes stand out. Firstly, as shown in Figure 2 describing the distribution of the change in scores, all treatments have both negative and positive effects, with very widespread effects. Despite some natural and possible deviations that might lead some individuals to score worse in the second survey, after a treatment that had the conceptual backing to produce positive effects –or at the very least null–, it was surprising that there was the utmost of half of the individuals who scored less after the treatment.

Secondly, despite the rest of the treatments having average positive effects, the targeting of community-specific elements for communication with vulnerable individuals, and the negative framing for middle-upper class, both had negative average effects.

Figure 2. Distribution of treatment effects by treatment type and subsample



Source: Own elaboration with experimental data.

6 These tests were performed using a cap of 30 minutes for the survey to be completed, as any time longer than that is not reasonable. Indeed, the test yielded significant results only when this cap was introduced.

Interestingly, the effects of the treatment have different spreads. The negative framing for the HE has a more prolonged tail in the negative side of effects (positive also longer, but less so), meaning that the reaction to a message with this characteristic, whether negative or positive, is expected to be greater. For LE, the positive framing without targeting seemed to have the widest variance, signaling both the importance of the public that receives the message, and whether the message is tailored to them or not. It is hypothesized that no targeting makes the message less clear, and susceptible to a wider range of interpretations.

Moreover, while they all seem to peak in density around 0 and/or above, some effect distributions are shifted more to the left or the right, indicating larger or reduced average effects. In the end, the large variance would prove the biggest hindrance to consistently finding significant results.

Testing the aggregate effects, we find that the treatments for the HE subsample are associated with a 0.027, significant at a 10% level, while the treatments for LE were not significantly different from zero. Nonetheless, testing for heterogeneous effects, we found that those who did the worst in the before treatment (less than average score), saw an increased and significantly positive (1%) change in scores after the treatment, as indicated in Table 4.

Table 4. Mean aggregate change in scores

	Obs	Mean	Std. err.	Std. dev.	t	Ho: mean = 0	[95% conf.	interval]
Higher "*estrato*"								
Δ in score	337	0.0274	0.0148	0.2724	1.847	Pr(T > t) = 0.0656	-0.00178	0.05660
Δ in score (below avg. scores)	152	0.0620	0.0250	0.3077	2.485	Pr(T > t) = 0.0140	0.01271	0.11135
Lower "*estrato*"								
Δ in score	247	0.0136	0.0162	0.2545	0.840	Pr(T > t) = 0.4017	-0.01829	0.04550
Δ in score (below avg. scores)	118	0.0661	0.0246	0.2675	2.684	Pr(T > t) = 0.0083	0.01733	0.11487

Source: Own elaboration with experimental data.

By looking at the disaggregated effects by treatment type, we can more easily identify the biggest contributors to aggregate effects, evaluate the individual treatment effects, and start comparing the relative size of their effects[7]. This is shown in Figure 3, and further detailed in tables A.1 and A.2 in the Appendix.

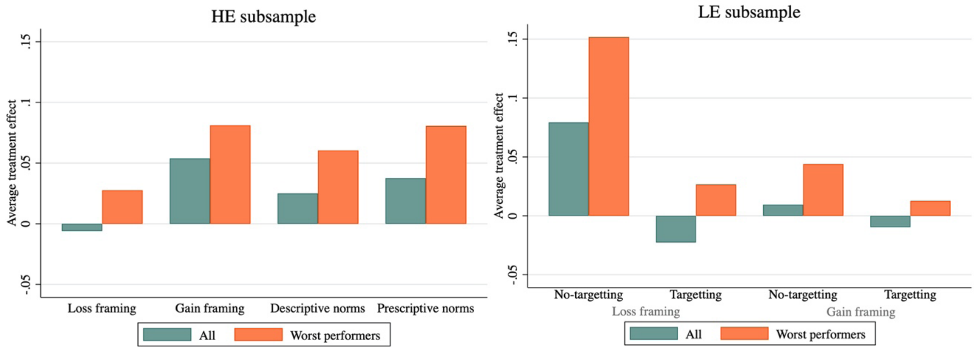
The positive framing seems to have the largest average effect of all for the HE subsamples, while for LE, the negative framing without targeting seems to have the biggest effect. Moreover, the treatments that involved targeting had an overall negative average effect. These 2 were the only individual treatments with an overall significant average effect (tables A.1 and A.2), and both of these results were unexpected and contradict some of the literature. Other studies

7 Treatments across subsamples are not comparable, as they are applied to individuals who are systematically and by definition different in meaningful characteristics, and the measurement instrument that yields the final score is comprised of different elements.

have found the loss framing to be more effective at inducing preventive behavior, such as that against COVID, and the foremost drawback was a possible adverse effect when people expect not to be able to comply given their characteristics, which is less probable for the people above "*estrato*" 3 (HE). Furthermore, the targeting is hypothesized to convey the message better, and the message itself is hypothesized to have a positive effect, as such, treatments involving images that targeted group identity were expected to have a larger effect than those that didn't.

We also evaluate whether there are differential effects for those who had the worst scores, given that they have the most to be gained from in terms of improving their behavior. This seems to be in fact the case. Not only do all the effects grow in size towards a positive average value, but all of the effects that were negative become positive. This tells us that, indeed, those who indicated they engage in the least preferable behaviors, do gain the most from treatments involving messaging, across the board. However, only the average effects for the prescriptive norms treatment ceases to be non-significantly different from zero (Table A.1).

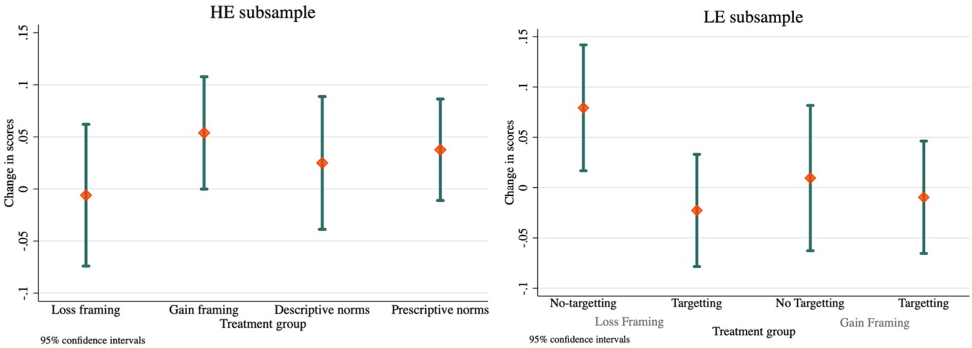
Figure 3. Average disaggregated effects by treatment



Source: Own elaboration with experimental data.

In order to assess the behavioral questions: "*Which framing is better inducing preventive behavior for COVID? Are individuals more motivated to change behavior by the way their peers act, or by being reminded of descriptive norms? Are individuals more likely to amend behavior when the message received has queues that reference their particular identity?*", we evaluate the statistical difference of the respective treatment pairs.

Figure 4. Confidence intervals for treatment effects



Source: Own elaboration with experimental data.

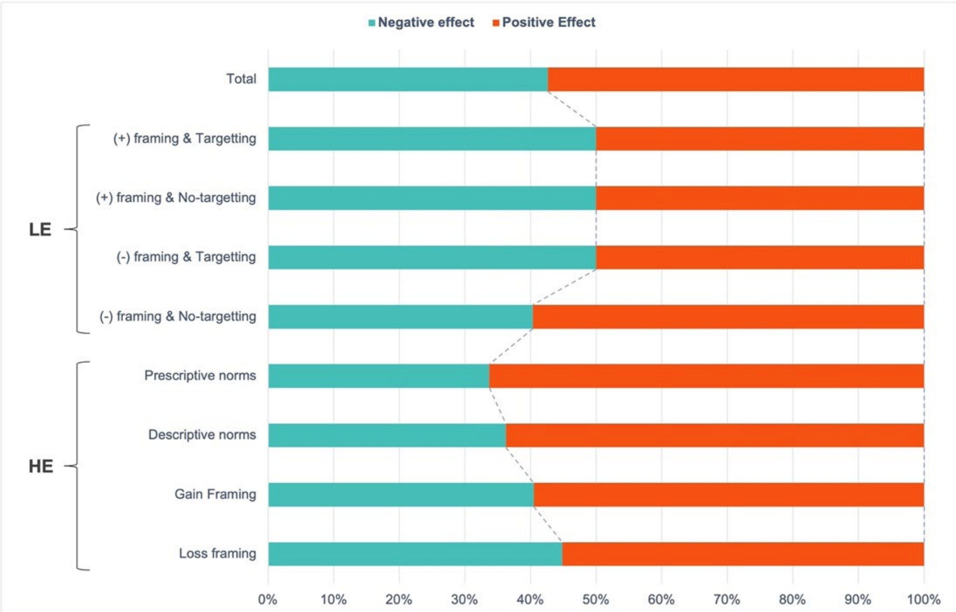
Despite being significantly above zero, the treatment effects of positive framing are not statistically different from the negative framing at a 95% significance level. None of the other treatments were significantly different from their pair, except from those who engaged in targeting versus those who didn't, in favor of no-targeting –at a 10% level. The controls were added for further control, on top of the randomization, and still no significant differences were found.

While the treatments do generate positive effects and, under some conditions, generate average effects that are significantly different from zero, we found scarce evidence in this experiment to conclude that behavioral treatment produces better effects than its respective pair. The lack of significant differences can be largely attributed to the wide variance of changes in scores, something to be discussed later on. Moreover, one significant difference was found, pointed in a counterintuitive direction, as no targeting produced statistically higher effects on scores. There are many caveats and explanations for this, and they will be explored in the discussion section.

If we theorize that there are particular and identifiable reasons that make an individual react either positively or negatively to messages urging them to take care regarding COVID-19, then we can segment the sample into those two groups and analyze them separately.

As shown in Figure 5, at least half of the individuals in any particular treatment saw positive effects. The two treatments with the most positive effects were the two images that convey messages related to social norms. This could be thought of as the kinds of messages that generate the least resistance" overall. However, it still remains a question why there are up to half of individuals in some treatments reacting adversely to it, such that, in many cases, average effects do not differ from 0.

Figure 5. Share of negative and positive effects

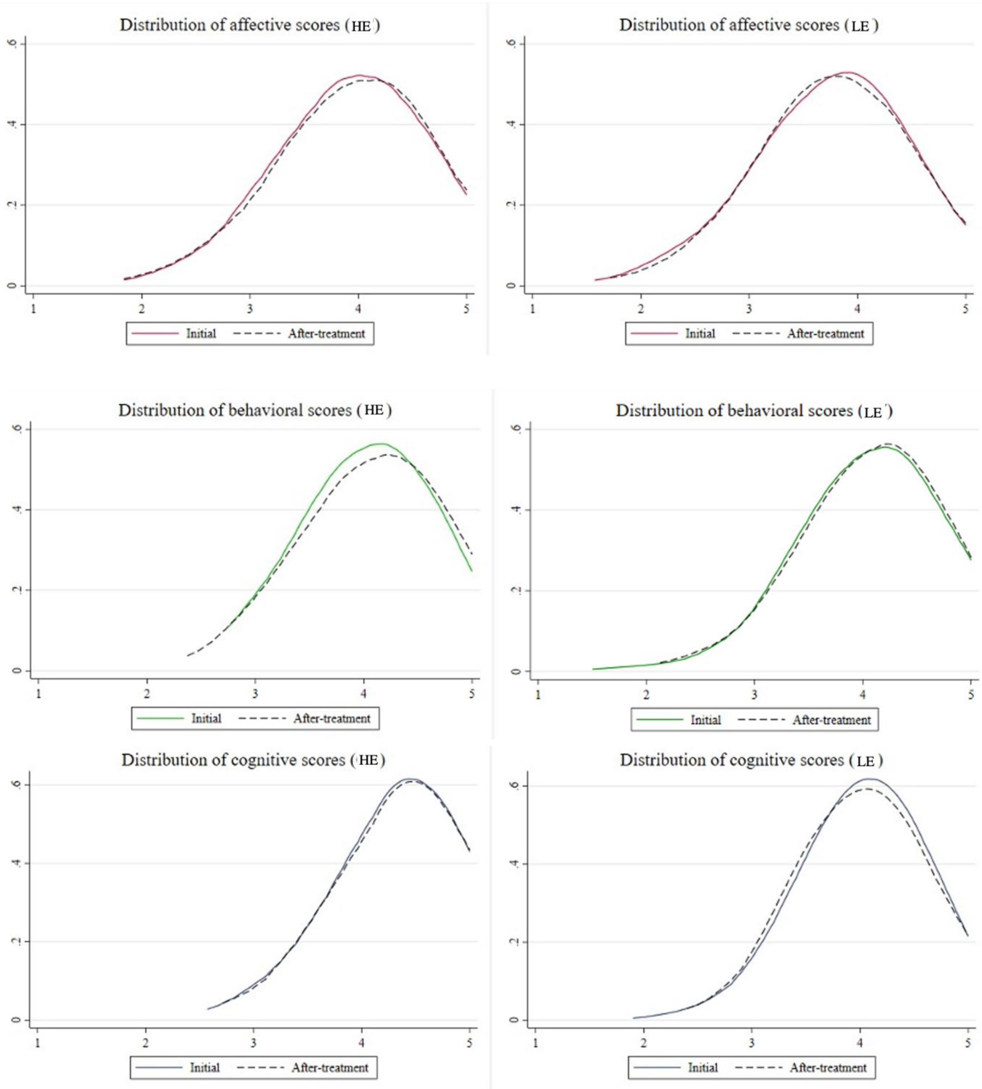


Source: Own elaboration with experimental data.

We looked at different elements that might affect the likelihood of obtaining positive results. As shown in Table A.4, for the subsample LE, the likelihood of getting a positive effect is inversely and significantly associated with the initial scores. However, for HE, they are not. Furthermore, we found that positive results are associated with having household members with comorbidities, with increased age, and being upper class, for HE, and associated with having contracted COVID-19 previously for LE, but with a significance slightly below standard level.

Finally, evaluating the treatment effects by components, in order to disentangle the different reasons why an individual might decide to alter their behavior, we find that changes in scores were not uniform across the different components —cognitive, affective, and behavioral— (Figure 6). The differences are also seen across samples, within components. Furthermore, it is also evident that the difference in the distribution before and after treatments (the effect) tends to vary along the distribution line, signaling the previously stressed heterogeneous effects for those who initially scored low.

Figure 6. Change in distribution of scores by components



Source: Own elaboration with experimental data.

Evaluating the size and statistical significance of these differences in component scores, we find that the treatments, in the aggregate, only significantly affect the behavioral component in the HE subsample, and are effective in the LE subsample (Figures A.5 and A.6). Visibly, both effects changed the distribution differently. For the behavioral effect on the HE subsample, all of the distribution seems to shift right-wards (Figure 6), and the average effect size increases by 0,03 when restricting the sample to below-average score. Meanwhile, the affective effect on the LE subsample seems to have concentrated a lot more on the left-hand tail of the distribution, hence the effect size increased by 0,06 and the significance level increased more, as well.

A closer look into the significant effects of these components shows the heterogeneity of effects by treatment[8]. The loss framing has a negative (yet not significant) effect on behavioral component scores for HE, while the gain framing has a positive and significant effect at 10%, with a considerable 0.13 points difference between them. When it comes to social norms, both have positive effects, but only the effect of prescriptive norms is significant (at 1%) and is 0.10 points larger than those of descriptive norms.

On the other hand, for LE, the effect on the affective component by type of framing shows that both have an overwhelmingly significant and positive incidence. Negative framing has the largest effect of the two, with a 0.14 average points difference after treatment. For targeting, as per the earlier results, while both effects are positive and significant, no targeting displayed a larger size effect – 0.137 vs 0.079 with targeting. The effects when targeting was applied seemed to have also been more variable, and therefore less significant, but that may be due to a smaller sample in this treatment[9].

Discussion

The prominence of behavioral studies is growing. The pandemic allowed a scenario in which multiple institutions such as the IDB, Kantar Public, and the Behavioral Insights Team in the UK, among others, have furthered the understanding of the incidence of behavioral economics in public policies. The European Commission is studying Countering COVID-19 misinformation through targeted behavioral interventions. At this moment, experiments like the ones presented in this article are on the rise, and there is an ever-growing consensus that adopting the behavioral framework in the design of policies can aim to reduce implementation gaps by shifting behaviors more effectively.

OECD (2017) showed some experiences with a wide range of results relevant to health policy, much like those presented in this paper. Nevertheless, the use of these tools is farther reaching: We can also find applications for public service delivery, taxes, telecommunications, education,

8 Here, only the effects on the individuals who scored below average pre-treatment are evaluated. The overall effects are more variable and lower in average size and are thus not significant. Notably, some treatments seem to affect those with lower initial scores proportionately more than others.

9 Despite randomization, the share of individuals with below-average scores was much higher for those who went on to be treated with a non-targeted message.

etc. There are even upcoming comprehensive frameworks to deploy these, such as the one laid out by Khadzhyradieva et al. (2019), who show the conditions for the implementation of Behavioral Insights in public policy. Likewise, as a consensus is built around the use of nudges, larger and better experiments are carried out, such as Milkman et al. (2022), who demonstrate the incidence of text-based reminders in vaccination in a 680,000-person Megastudy. In Colombia, an important paper was written by Blackman and Hoffmann (2022) about the differences between private and public benefits in boosting concern about Covid 19.

Given the positive results on several interventions, and the strength of the knowledge field, how can we improve its implementation and the results? Maybe international institutions can guide the studies and support it, and every policymaker should know the behavioral tool kit in order to select, in the context, the appropriate combination of strategy —plans, programs— and behavioral components. There is still much to do to advance this research: To further appeal to policy-makers, it is important to be able to link lab results to real-world policy outcomes.

However, much effort was made into crafting a measurement that captured as closely the actual change in behavior after being exposed to these messages, we are still not able to extrapolate into how much “x” amount of points differences in the test scores translates into a measure of the behavior, nor how that shapes the contagion patterns, in order to gauge whether these interventions represent a considerable dent in the speed of spread of the disease. For that, we would have had to conduct the same survey across different geographical units, controlling for potential sources of endogeneity, and then establish a link between the effectiveness of the behavioral tools, as measured by the Attitudes scale, and the prevention of lives lost, as well as the equivalent opportunity cost saved from not engaging in further lockdowns, among other ways of accounting the benefits.

Nonetheless, from these results, we can confidently assert that behavioral tools are, at the very least, a much more useful complementary tool in the midst of a health crisis that involves changing individual behaviors voluntarily. Due to their low cost, being often times a simple matter of integrating the analysis into existing communication strategies, behavioral tools should always play a role in these kinds of health crises, such as the hopefully fading COVID-19 pandemic.

Another limitation of the study is the conclusiveness of some of the results, given many instances where differences were not significant. There is no ex-ant reason to believe that a non-significant result indicates something is wrong, but we identified three reasons why some results might be underestimated. First, while higher initial scores of those who dropped out were not significantly different from those who stayed, the unaccounted-for determinants of scores could have affected the decision not to continue the study and might have affected the distribution of post-treatment results in a way that reduced the estimations.

Second, is the likely attenuation bias following a measurement error of the attitude scale. The instrument presents an inherent trade-off, by which more questions theoretically increase accuracy, but can induce information overload on participants who might start making random errors in their own assessment of their opinions, feelings, and behaviors. Lastly, the existence of heterogeneous effects, as demonstrated by the robustly higher scores and the likelihood of positive effects for those who had initially lower scores.

Conclusions

Coming into the study, we were able to make use of preliminary data from a survey by the IADB's Behavioral Economic Group, which would logically have led us to be able to identify the main drivers of COVID-related preventive behaviors. However, the fact that control variables only explain 12-13% of the variation in average scores shows there is still much research to be done to properly identify determinants of preventive behavior. This result was unexpected, and further research is necessary to account for and explain the variability in individuals' preventive behavior against COVID-19. Variables like identifying as a woman and age tended to score better, and so, are assumed to engage in stricter measures for COVID-19 prevention. This is consistent with the literature, as women and older people tend to show less of an overconfidence effect.

Considering the low cost of behavioral public policy and the possible efficacy of its interventions, the article provides information for public health experts who are interested in using behavioral insights with communication tools. In this paper, the tested treatments generated positive effects and, under some conditions, generated average effects significantly different from zero. We found evidence in this experiment that indicates that certain behavioral treatments can produce better effects than their respective pair, but the evidence is very contextual. The conclusions of the research can be linked to future real-world policy initiatives or interventions already in place.

The treatments saw mostly positive changes in the average scores. However, particular outcomes stand out. Firstly, all treatments have both negative and positive effects, with very widespread effects, after a treatment that had the conceptual backing to produce positive effects —or at the very least null—, it was surprising that there was the utmost of half of the individuals who scored less after the treatment. Secondly, despite the rest of the treatments having average positive effects, the targeting of community-specific elements for communication with vulnerable individuals, and the negative framing for middle-upper class, both had negative average effects.

Between the respective treatment pairs, for the middle-high income group, the positive framing and the prescriptive norms outperformed their counterparts, while for the low-income group, the negative framing and no targeting were found to have larger average effects. Nonetheless, the level of statistical significance of these differences tended to be low, partially attributable to limitations of the sample size, the large unaccounted-for variability, and likely attenuation biases.

We found that positive results are associated with having household members with comorbidities, with increased age, and being upper class, for individuals self-identified as upper and middle class, and associated with having contracted COVID previously for vulnerable populations.

Evaluating the treatment effects by components, in order to disentangle the different reasons why an individual might decide to alter its behavior, we find that changes in scores were not uniform across the different components — cognitive, affective, and behavioral. For the subsample of middle-and-upper-income individuals, the biggest effect was on the behavioral component, and for the lower-income individuals, the biggest effect was on the affective component. This could be researched in further experiments to evaluate consistency and robustness. As per earlier results, positive framing, prescriptive norms, and no targeting performed better than their counterparts.

Lastly, we consistently found that individuals with lower scores in the baseline tended to have the biggest improvements post-treatment. This has a very clear policy implication. Were the findings the contrary, then the prospects for communication as an effective policy for correcting undesirable health behaviors would be bleak. This is a strong suggestion that the behavioral tools employed are effective at changing the "undesired" behaviors. When thinking of aggregate results in the field the evidence overwhelmingly supports the use of behaviorally informed messaging in health crisis.

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Appendix

Figure A.1. Treatment images for HE subsample

Negative Framing

Positive framing

Descriptive norm

Prescriptive norm

Source: Own elaboration.

Figure A.2. Treatment images for LE subsample

Source: Own elaboration.

Table A.1. Disaggregated effects by treatment for HE subsample

	Obs	Mean	Std. err.	Std. dev.	t	Ho: mean = 0	[95% conf. interval]	
Negative framing								
Δ in score	87	-0.0060	0.0342	0.3193	-0.176	Pr(|T| > |t|) = 0,8608	0.07406	0.06202
Δ in score (below avg. scores)	38	0.0276	0.0637	0.3925	0.433	Pr(|T| > |t|) = 0,6675	-0.10143	0.15657
Positive framing								
Δ in score	84	0.0539	0.0271	0.2486	1.986	Pr(|T| > |t|) = 0,0504	-0.00009	0.10780
Δ in score (below avg. scores)	37	0.0811	0.0459	0.2792	1.766	Pr(|T| > |t|) = 0,0858	-0.01201	0.17418
Descriptive norms								
Δ in score	80	0.0250	0.0320	0.2866	0.780	Pr(|T| > |t|) = 0,4376	-0.03878	0.08878
Δ in score (below avg. scores)	41	0.0604	0.0514	0.3289	1.176	Pr(|T| > |t|) = 0,2466	-0.04341	0.16420
Prescriptive norms								
Δ in score	86	0.0377	0.0245	0.2272	1.537	Pr(|T| > |t|) = 0,1280	-0.01105	0.08635
Δ in score (below avg. scores)	36	0.0807	0.0333	0.1997	2.424	Pr(|T| > |t|) = 0,0207	0.01311	0.14826

Source: Own elaboration.

Table A.2. Disaggregated effects by treatment for LE subsample

	Obs	Mean	Std. err.	Std. dev.	t	Ho: mean = 0	[95% conf. interval]	
Negative framing & no targetting								
Δ in score	57	0.0793	0.0312	0.2359	2.538	Pr(|T| > |t|) = 0.0139	0.01672	0.14188
Δ in score (below avg. scores)	34	0.1518	0.0442	0.2577	3.434	Pr(|T| > |t|) = 0.0016	0.06185	0.24168
Negative framing & targetting								
Δ in score	60	-0.0227	0.0279	0.2159	-0.813	Pr(|T| > |t|) = 0.4193	-0.07844	0.03310
Δ in score (below avg. scores)	21	0.0267	0.0313	0.1433	0.853	Pr(|T| > |t|) = 0.4039	-0.03856	0.09189
Positive framing & no targetting								
Δ in score	76	0.0095	0.0363	0.3162	0.261	Pr(|T| > |t|) = 0.7946	-0.06277	0.08172
Δ in score (below avg. scores)	41	0.0439	0.0532	0.3408	0.825	Pr(|T| > |t|) = 0.4143	-0.06367	0.15147
Positive framing & targetting								
Δ in score	54	-0.0096	0.0278	0.2045	-0.346	Pr(|T| > |t|) = 0.7307	-0.06546	0.04620
Δ in score (below avg. scores)	22	0.0127	0.0405	0.1902	0.314	Pr(|T| > |t|) = 0.7567	-0.07160	0.09705

Source: Own elaboration.

Table A.3. Share of positive and negative results

	Treatment group								
	CCEN	**CCEP**	**CCND**	**CCNP**	**PVENGEN**	**PVENVUL**	**PVEPGEN**	**PVEPVUL**	**Total**
Negative effect	39 44,83%	34 40,48%	29 36,25%	29 33,72%	23 40,35%	30 50%	38 50%	27 50%	249 42,64%
Positive effect	48 55,17%	50 59,52%	51 63,75%	57 66,28%	34 59,65%	30 50%	38 50%	27 50%	335 57,36%
Total	87 100%	84 100%	80 100%	86 100%	57 100%	60 100%	76 100%	54 100%	584 100%

Source: Own elaboration.

Table A.4. Regression tables: Likelihood of positive results given initial score

```
Probit regression                                       Number of obs =    337
                                                        LR chi2(1)    =   0.92
                                                        Prob > chi2   = 0.3363
Log likelihood = -224.71238                             Pseudo R2     = 0.0021
```

positive	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
CCprom	.1365486	.1421309	0.96	0.337	-.1420229	.41512
_cons	-.2794107	.5888871	-0.47	0.635	-1.433608	.8747868

```
Probit regression                                       Number of obs =    247
                                                        LR chi2(1)    =   7.23
                                                        Prob > chi2   = 0.0072
Log likelihood = -167.3495                              Pseudo R2     = 0.0211
```

positive	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
PVprom	-.4314038	.1631323	-2.64	0.008	-.7511373	-.1116703
_cons	1.773229	.6556818	2.70	0.007	.488116	3.058341

Table A.5. Disaggregated effects by component for HE subsample

	Obs	Mean	Std. err.	Std. dev.	t	Ho: mean = 0	[95% conf.	interval]
Affective								
Δ in score	337	0.0242	0.0232	0.4259	1.045	pr(T > t) = 0.2970	-0.02140	0.06987
Δ in score (below avg. scores)	152	0.0461	0.0335	0.4128	1.375	Pr(T> t)= 0.1711	-0.02010	0.11221
Behavioral								
Δ in score	337	0.0408	0.0213	0.3912	1.915	pra- > t)= 0.0564	-0.00111	0.08271
Δ in score (below avg. scores)	152	0.0789	0.0352	0.4334	2.246	pr(T > t)= 0.0262	0.00949	0.14841
Cognitive								
Δ in score	337	0.0148	0.0183	0.3364	0.810	pr(T > t)= 0.4187	-0.02121	0.05088
Δ in score (below avg. scores)	152	0.0564	0.0317	0.3909	1.779	pr(T > t)= 0.0773	-0.00625	0.11903

Source: Own elaboration.

Table A.6. Disaggregated effects by component for LE subsample

	Obs	Mean	Std. err.	Std. dev.	t	Ho: mean = 0	[95% conf. interval]	
Affective								
Δ in score	247	0.0544	0.0229	0.3595	2.377	pr(T > t) = 0.0182	0.00931	0.09943
Δ in score (below avg. scores)	118	0.1162	0.0328	0.3568	3.538	Pr(T > t) = 0.0006	0.05117	0.18128
Behavioral								
Δ in score	247	0.0046	0.0228	0.3575	0.200	pra- > t)= 0.8415	-0.04025	0.04936
Δ in score (below avg. scores)	118	0.0551	0.0339	0.3678	1.627	pr(T > t)= o. 1065	-0.01198	0.12214
Cognitive								
Δ in score	247	-o. 0077	0.0205	0.3221	0.840	pr(T > t)= 0.4017	-0.04805	0.03267
Δ in score (below avg. scores)	118	0.0398	0.0327	0.3555	1.217	pr(T > t)= 0.0083	-0.02497	0.10464

Table A.7. Sample statistics

	Variable	***#***	***Overall***	***HE***	***LE***
1	**Person or a relative contracted COVID earlier**		*74%*	*76%*	*68%*
2	**Has relative deceased of COVID**		*69%*	*68%*	*70%*
3	**Someone older than 65 years old in the household**		*40%*	*44%*	*34%*
4	**Someone with a comorbidity in the household**		*69%*	*71%*	*65%*
5	**Gender (Woman)**		*65%*	*66%*	*62%*
6	**Age**		*32,98*		
7	**Educational attainment**				
	High School	326	*29%*		
	Technical or Undergraduate	622	*56%*		
	Marter or More	163	*14%*		
8	**Estrato**				
	I	160	*14%*		
	II	222	*20%*		
	III	253	*23%*		
	IV	250	*22%*		
	V	111	*10%*		
	VI	118	*11%*		

Source: Own elaboration.