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Debiasing policymakers. The role of behavioral economics training*

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Abstract

Behavioral biases often lead to suboptimal decisions, a vulnerability that extends to policymakers who operate under conditions of fatigue, stress, and time constraints, with significant implications for public welfare. While behavioral economics offers strategies like default adjustments to mitigate decision-making costs, deploying these policy interventions is not always feasible. Thus, enhancing the quality of public policy decision-making is crucial. Evidence suggests that targeted training can boost job performance among policymakers. This study evaluates the impact of a behavioral training course on policy decision-making through a randomized experiment and a survey test that incorporates problem-solving and public policy decision-making tasks among approximately 25,000 participants enrolled in the course. Our findings reveal a significant improvement in the treated group, with responses averaging 0.6 standard deviations better than those in the control group. Given the increasing prevalence of such courses, this paper underscores the potential of behavioral training and advocates for further research through additional experimental studies to study decision-making more precisely and consider potential decay effects.

Keywords: Experimental design, Behavioral economics, Training, Public policy, Government officials.
JEL codes: H83, Z18

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1. Introduction

A vast literature from psychology and economics has shown that individuals tend to have nonstandard preferences (e.g., social preferences), nonstandard beliefs (e.g., overconfidence), and nonstandard decision-making (e.g., framing and limited attention) (DellaVigna, 2009). Policymakers are no exception. Research has consistently shown that policy professionals are susceptible to nonstandard beliefs and decision-making traps. Overconfidence, for example, has been observed in the judgments of physicians, clinical psychologists, lawyers, negotiators, engineers, bankers, and security analysts (Berner and Graber, 2008; Griffin and Tversky, 1992; Kovacs et al., 2020; Lambert et al., 2012; Sandroni and Squintani, 2004; Stark and Sachau, 2016). Policy professionals are further affected by framing outcomes as losses or gains and by confirmation bias (Banuri et al., 2019).

These biases can have real implications. For example, U.S. judges' opinions are significantly influenced by the political composition of judicial panels (Sunstein, 2006), and the temporal order of rulings may affect the outcomes (Danziger et al., 2011). In the case of healthcare, biases are likely to influence diagnosis and make treatment decisions and levels of care dependent on patient characteristics (FitzGerald and Hurst, 2017). In education, teachers' unconscious biases and preferences related to students' gender, race, sexual orientation, socio-economic background, or other aspects of identity can affect learning outcomes and perpetuate inequalities in the classroom (Farfan Bertran et al., 2021).

Becoming aware of our systematic errors may help correct them (Farfan Bertran et al., 2021). There are ways to reduce overconfidence (Brookins et al., 2014) and other biases. Making individuals reflect on their choices and providing information about actual performance and the risks entailed by wrong choices helps. For example, once NBA referees are made aware of their implicit preferences, their favoritism bias disappears (Pope et al., 2018). This is particularly relevant in the context of policymaking, where biased judgment can have significant welfare consequences (Cafferata et al., 2023).

Could training help? A meta-analytic review of management training programs found that those focused on human resources, soft skills, marketing, and finance and accounting, especially when organized by local organizations, tend to result in better firm performance (Busso et al., 2023). In the case of public servants, some types of training have been found to be effective, at least in the short run. Training programs for hospital managers positively affected managerial skills, knowledge, and competencies (Ravaghi et al., 2021). Training police officers in investigation techniques and soft skills increased the satisfaction of crime victims (Banerjee et al., 2012) and reduced some types of crimes (Garcia et al., 2013).

In this paper, we test whether a behavioral economics (BE) online course for public officials affects their problem-solving skills and policy decisions, including fighting the COVID-19 pandemic. This test is independent of exams regarding course material knowledge that take place at the end of each unit and require participants to approve in order to continue with the course.

The experiment took place in the context of the online behavioral course provided by the Inter-American Development Bank (IDB) on its learning platform. We randomized the individuals enrolled in 16 editions of the Spanish-language version of the course into treatment and control groups (about 25,000 individuals.) The control group was asked to solve problems in a six-question questionnaire before starting the course, and the treatment group did so at the end of the course.

Results indicate that the course had a positive effect on improving problem-solving and decision-making over public policy choices. When considering the overall score, treated individuals scored 0.6 standard deviations higher than the control group. Regarding specific questions, the impact was between 0 and an increase of 34 percentage points.

The results are robust to a series of tests that exploit the fact that the control group took the test before and after the course, as well as the rollover nature of the different editions of the course. Regarding mechanisms, we added to the survey a question (not considered in the overall score calculation) covered in the lectures and in-course tests. Participants scored higher on that one than on the other questions (40.8 percentage points), providing partial evidence that the effects happened because of learning.

This study complements nascent but still scant research showing that debiasing training can significantly improve decision-making, with both short-term and long-term effects (Morewedge et al., 2015; Sellier et al., 2019). While previous studies have worked with a dedicated sample of lab or student participants watching a video or a case study, we evaluate the impact of a multi-week-long course designed for policymakers that was imparted over several years. It also complements a literature that evaluates the effectiveness of online learning tools (Cristia and Vlaicu, 2023). Here, we show that online courses can improve learning outcomes and decision-making abilities. Finally, the paper complements the vast literature on behavioral science by showing that training courses could be an additional tool available for better decision-making. This study could serve as the stepping stone to experiments that test problem-solving skills more broadly and generate incentives for further replication studies using the multiple courses on behavioral science available.

2. The Experiment

2.1. The IDB Course on Behavioral Economics

The IDB provides online education aimed at policymakers in Latin America and the Caribbean.[1] In 2020, the IDB launched the first online course in Behavioral Economics offered in Spanish.[2] The course is interactive, self-paced, and applied to public policy design. It is offered at no cost and targets Latin American policymakers. More than 14,000 individuals registered to participate, and by the end of 2023, the number had climbed to more than 25,000. The Portuguese and English versions were launched during the second semester of 2020.

The course is divided into four modules with an approximate workload of 4-5 hours per week. It was designed to be completed within four weeks, but participants are allowed to finish the course in up to six weeks. The first two modules cover the main concepts of the field (main biases and behavioral insights) and explain how these differ from the notions of the standard economic model. For example, module 1 includes ten activities that take between 3 and 30 minutes each to complete. Activity 1 provides an introduction to "How good are we at making decisions?" Activity 2 describes what behavioral science is. Activity 3 provides an overview of the field and applications of behavioral economics.

Activity 4 teaches about examples of non-standard preferences, activity five is about non-standard beliefs, and activity six is about the factors that affect information processing. Activities 7 to 9 deal with the main terms used in the field, how governments use behavioral insights, and the role of behavioral economics in the design and execution of public policies. Activity 10 is the learning assessment for the module. The third module focuses on applied cases in several sectors, with a special focus on tax compliance and health, two areas in which the IDB has built a broader portfolio. Starting with session 3, a specific section on COVID-19 was added. The revised learning guide, with a full description of the contents of the course, is provided in the Online Appendix.

The teaching methodology consists of providing reference materials such as videos, interactive presenta-

[1] By 2020, the IDB offered more than 200 online courses in development effectiveness, integration and trade, project management, social and environmental risks management, water and climate change, and others. The full catalog of courses is available at https://cursos.iadb.org/en/indes/programas?lang=en

[2] For context, the course's first five editions or sessions were launched in Spanish on February 18, March 17, May 19, July 28, and October 6, 2020.

tions, and readings and carrying out activities and exercises using real case examples from Latin America, the Caribbean, and other parts of the world. After each module, participant knowledge is tested. There are five learning assessments or tests during the course: Modules 1 and 2 each contribute 20% to the total assessment. Module 3 consists of two assessments, one for the tax compliance section and one for the health section, each contributing 15%. The learning assessment for Module 4 is weighted at 30%.[3] Although completing each questionnaire is mandatory in order to move on to the next module, passing it is not a prerequisite for advancing in the course. The passing score for each assessment and the overall course is at least 80 percent of the total score, and the final score is calculated based on the weights assigned to each questionnaire. Those who finish the course are awarded a certificate of completion (see example in the Online Appendix), and they can also share digital badges on social media.

2.2. Experiment Design

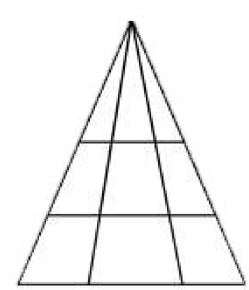
To evaluate the impact of the course, we randomized those who registered for each one of the sessions in Spanish. Once individuals register for a course, they are divided into two groups (treatment and control) and then assigned to virtual classrooms of up to 100 people (each classroom is formed by individuals from the same group: treated or control.)[4]

Before starting the course, students receive a questionnaire with basic demographic questions (country of origin, sex, academic degree, etc.).[5] Those individuals in the control group also receive a survey test that includes five questions (first two sessions) or six questions (beginning with session 3).[6] Everybody received the same survey test at the end of the course.

The questions included in the test were of two types: i) cognitive skills tasks: a cognitive illusion ("triangles"), a computation of compound interest ("lottery"—only in sessions 1 and 2), and an expected value question ("disease"); and ii) public policy questions that tested the individual knowledge of behavioral insights. One of these questions ("teachers' incentives") was explicitly considered in the set of materials provided during the course; therefore, it acts as a validation exercise.

The questions included in the survey (in the order they are presented to the individuals) are the following (right answers in **bold face**):

1. (5 sessions) **Triangles: Reasoning:** "How many triangles are in the figure?"
   (a) 12
   (b) 7
   (c) 15
   (d) **18**
   (e) 10
   (f) I don't want to answer



This cognitive illusion question tested respondents' perception and attention skills. This kind of illusion is often used to evaluate the conscious processing of visual inputs, making it a great test for inattention

[3]In the first two sessions, the learning assessment for Module 3 was weighted at 20%, and Module 4 was weighted at 40%.
[4]The purpose of the classrooms is to provide the opportunity for interaction in virtual chats. These chats are not supervised or monitored.
[5]This information is available only for sessions 1 to 5 for those who chose to complete the questionnaire.
[6]The changes in the questionnaire responded to the introduction of COVID-19 material in the course; one of the original questions was replaced to avoid extending the survey too much.

(Kahneman and Bar-Hillel, 2020; Vandenbroucke et al., 2014). It assessed whether respondents answered the problem more carefully after taking the course.

2. (sessions 1 and 2) **Lottery: Cognitive Reflection:** "You have won a small amount of money playing the lottery. You are offered two options. If you choose the first one, you will receive $170 in cash in 6 months. If you choose the second one, you would get $100 deposited in a bank account right now, and you would accumulate interest at a monthly composite rate of 10%. In this case, you can only withdraw the money after 6 months. What option do you prefer?"
   (a) First option: $170 in cash
   (b) **Second option: $100 in a bank account that accumulates a 10% monthly cumulative interest**

This cognitive reflection question tested respondents' use of "system one" versus "system two." To answer correctly, respondents' "system two," typically associated with solving math problems, would have to override the fast, automatic, and unconscious tendency to choose the most intuitively attractive choice sent by "system one" (Frederick, 2005). We removed this question starting in session three because it had a very high correct response rate, creating a ceiling effect.

3. (sessions 3 to 5) **COVID-19: Behavioral Intervention:** "To successfully comply with hygiene and social distancing guidelines during this pandemic, citizens have the difficult task of overcoming profound behavioral biases and barriers while making decisions. Which of the following strategies is used by behavioral economics to promote good sanitary practices during the pandemic?"
   (a) Provide direct cash transfers to low-income citizens during quarantine
   (b) Assign employees to supermarkets' entrances to control customer flow, keeping the number of customers to the maximum allowed by law
   (c) Control the number of people allowed in public spaces, using characteristics such as age group or gender as allocation rules
   (d) **Send text messages to micro-entrepreneurs stating "[Name], do not risk losing your business. Make sure to comply with the two meters distance rule among your customers"**

This question tested respondents' ability to identify and apply two behavioral concepts, reminders and loss aversion, to the COVID-19 crisis. Only option D is correct. All the other answers are traditional policy tools, regulations, and cash transfers. To answer correctly, respondents needed to understand the difference between traditional and behavioral tools, which is part of the material covered in the course. This question and the following question were included once the pandemic started in an attempt to measure whether the course could improve the quality of public policy-making during a pandemic.

4. (sessions 3 to 5) **COVID-19: Social Distancing:** "Which of the following messages would you consider less effective in a communication campaign to promote the social distancing habit during this pandemic?"
   (a) Stay at home and buy groceries only once a week
   (b) **The WHO recommended social distancing to reduce COVID-19 transmission**
   (c) Your family and country need your help reducing coronavirus spread. Respect social distancing
   (d) When you go out, imagine the length of a bed between you and the person nearest to you

This question also tested respondents' ability to identify and apply several behavioral concepts, heuristics, reference points, simplification, concrete steps, social norms, and reciprocity to improve communications during the pandemic.

5. (5 sessions) **Teachers Incentives:** "Imagine a policymaker seeking to improve students' performance in high school tests. In your opinion, which of the following programs for teachers will be more successful in achieving this goal (suppose that all options can be implemented)?"
   (a) A performance-based incentive program in which bonuses are granted twice a year to the country's best teachers
   (b) A performance-based incentive program in which a bonus is granted at the end of the year to the country's best-performing teachers
   (c) **A performance-based incentive program in which a bonus is granted to all teachers at the beginning of the year, but only the best-performing ones can keep it at the end of the year. All other teachers need to return the bonus**
   (d) An educational system without a performance-based incentive program

This question assessed respondents' ability to remember and recognize a behaviorally-informed policy design and timely micro-incentives for teachers to improve students' performance. Respondents needed to know the evidence on incentives and/or understand the concept of loss aversion (Fryer Jr et al., 2012) to answer correctly. This question was included as part of the materials included in Module 2. Therefore, it works as a validation exercise.

6. (5 sessions) **Disease: Expected Value:** "Imagine that your country is preparing for the outbreak of a rare disease, which is expected to kill 600 people. Two alternative programs have been proposed to fight such diseases. Suppose that the estimated consequences of the programs are as follows:
   Program A: If adopted, 300 people will die for sure
   Program B: If adopted, there is a 40% chance that 600 people will be saved and a 60% chance that no one will be saved
   If you had to choose between these two programs, which one would you choose?"
   (a) **Program A**
   (b) Program B

This question tested whether or not respondents' math and problem-solving skills could override their loss aversion bias. To answer correctly (Program A), respondents needed to know how to perform a simple expected value calculation. However, Program B could be more attractive for some because it framed the scenario with uncertain lives saved instead of certain deaths (adapted from Tversky and Kahneman (1981)).

7. (5 sessions) **Child Anemia: Social Norms and Loss Aversion:** "Childhood anemia in children from 6 to 24 months old is a serious problem among the poorest populations in developing countries, as its symptoms and consequences are not visible. This lack of prominence leads parents to feed their children with fewer micronutrients than they need. To solve this problem, your government is developing the content for a campaign targeted at parents to improve micronutrient intake and reduce anemia in children. Which of the following messages do you think is the most effective? (Select one)"
   (a) "Every day, thousands of children in your community do not receive the micronutrients they need to prevent anemia. Adherence to micronutrient treatments is essential to improve your children's health."
   (b) "Every day, thousands of children in your community do not receive the micronutrients they need to prevent anemia. Disregarding micronutrient treatments worsens your children's health."
   (c) "Every day, thousands of children in your community receive the micronutrients they need to prevent anemia. Adherence to micronutrient treatments is essential to improve your children's health."
   (d) **"Every day, thousands of children in your community receive the micronutrients they need to prevent anemia. Disregarding micronutrient treatments worsens your children's health."**

This question examined respondents' ability to identify and apply several behavioral insights, descriptive social norms, framing, and loss aversion to a communications campaign to reduce anemia in children. Only option D is correct. To answer correctly, respondents needed to have a good understanding of behavioral concepts and enough mastery to apply them.

3. Data

We have collected the data for the 17 first courses in Spanish (Course 10 data are missing due to problems with the platform). A total of 25,189 individuals registered for the courses, and 5,664 finished (22.5%). Table A1 in the Online Appendix describes the number of individuals registered in each session and the share who finished. Registration numbers and finishing rates were higher during the pandemic than later on (which may reflect that people had more time to dedicate to training). Of those who finished the course, 45.4% are women, 53.9% are from the Andean countries, 23.1% are from Mexico and Central America, and 16.7% are from the Southern Cone. As mentioned, the course is freely available on the IDB's online learning platform.

The courses were advertised on IDB social media platforms and other IDB communication channels. Therefore, the potential sample is formed by those who have participated in IDB activities, follow IDB social media, or are affiliated with governments that actively engage with the IDB. Participation is voluntary, so the actual sample is affected by selection: those who know about the course, are interested and motivated, registered, and have completed the course. While it could affect the external validity of some of the results, it should not affect the experiment's internal validity.

Table 1: *Balance Table*

	Control (1)	Treatment (2)	Sample Size (3)
	All students registered		
Female	.49	.009	15181
	(.013)	(.008)	
Academic degree	1.92	.032	9047
	(.026)	(.024)	
Experience in the field	.259	.014	9047
	(.011)	(.009)	
	Students who finished the course		
Female	.502	-.002	4695
	(.02)	(.014)	
Academic degree	1.887	.074	3840
	(.04)	(.036)	
Experience in the field	.293	.02	3840
	(.018)	(.014)	

Notes: Each row shows statistics for a different observable variable we have. Column [1] and Column [2] show the regression coefficient and the standard error in parenthesis corresponding to an OLS regression that includes session fixed effects. Column [2] shows the difference with control group. Standard errors are robust. *** p<0.01, ** p<0.05, * p<0.1.

Table 1 shows that the control and treatment groups are balanced in the few observables available: gender, education, and experience in the field for both the sample of registered individuals and the sample of individuals who finished the course. Gender was recorded in every session of the course. Still, the two other variables were recorded only during the first five sessions, which explains the differences in the number of observations across variables. Responding to these items was voluntary, so a few people did not respond. As such, the balance tables show fewer observations than the total. Because the assignment was randomized at the individual level at the moment of registration, there is no reason to believe there would be any imbalance among those who did not provide the information.

4. Empirical Analysis

Formally, we estimate the following linear regression model

$$y_i^j = \alpha + \beta T + u_i, \tag{1}$$

where y is the dependent variable. The dependent variables are the following: i) a composite variable that sums the total number of right answers (except the one used as validation) z-standardized; ii) the individual responses (right or wrong) to each individual question. T takes the value of one for those individuals in the treatment group; that is, those who filled out the questionnaire only at the end of the course. β measures the average difference of the dependent variable between the treatment and control group. We also include session fixed effects. Standard errors are clustered at the classroom level. The sample for the main analysis includes those individuals who are part of the control group and finished the course (but answered the questionnaire before the course took place) and those in the treatment group (who answered the questionnaire after they finished the course).

Results for the pooled sample in Table 2 show that individuals in the treatment group get 0.6 standard deviations better scores than individuals in the control group (column 1). This number corresponds to about one more answer right than the control group. The effect is not homogenous across questions. While treated individuals answer better in four of the questions, they do equal ("lottery") or marginally worse ("expected value") in two of them. Regarding the lottery question, there may be some ceiling effects, as almost 80% of the individuals in both groups answered it correctly, while in no other question, 55% or more of the control group did. Regarding the computation of expected values, about half of the control and the treatment groups answered correctly. In this case, the course had no effect. Figures 1 and 2 show the distribution of responses for the control and treatment groups. Tables A2 and A3 in the Online Appendix shows the results for the individual courses.

We found no significant heterogeneous effects[7]. Neither gender, academic degree, nor experience in their job at the time of the course had any differential effect. This is important, as it shows that everybody benefited equally from the course.

[7]This analysis exclusively focuses on sessions 1 to 5, as they are the only sessions for which information is available on the variables used for heterogeneity analyses. Nevertheless, the available information pertains solely to individuals who chose to complete the demographic questionnaire.

Table 2: Treatment Effects (all courses pooled)

	Test z-score (1)	Triangles: Reasoning (2)	Disease: Exp Value (3)	Child Anemia: SocNorm & Loss Av (4)	Lottery (5)	COVID-19: Beh Interv (6)	COVID-19: Social Distancing (7)	Teachers Incentives (8)
Treatment	0.600***	0.030**	-0.024*	0.340***	0.012	0.147***	0.290***	0.408***
	(0.027)	(0.012)	(0.014)	(0.014)	(0.032)	(0.014)	(0.014)	(0.014)
Constant	-0.121***	0.429***	0.571***	0.242***	0.717***	0.544***	0.278***	0.442***
	(0.032)	(0.018)	(0.021)	(0.020)	(0.028)	(0.016)	(0.016)	(0.018)
Observations	5655	5655	5655	5655	864	4791	4791	5655
Clusters	247	247	247	247	32	215	215	247
Course FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj R-squared	0.086	0.008	0.005	0.132	0.003	0.038	0.107	0.196

Notes: each row shows the regression coefficients and the standard error in parenthesis corresponding to an OLS regression, including session fixed effects. Standard errors are clustered at the session level. *** p<0.01, ** p<0.05, * p<0.1. Differences in the number of observations across columns because COVID questions were included starting in Session 3 when the Lottery question was eliminated.

Figure 1: *Distribution of Correct Answers*

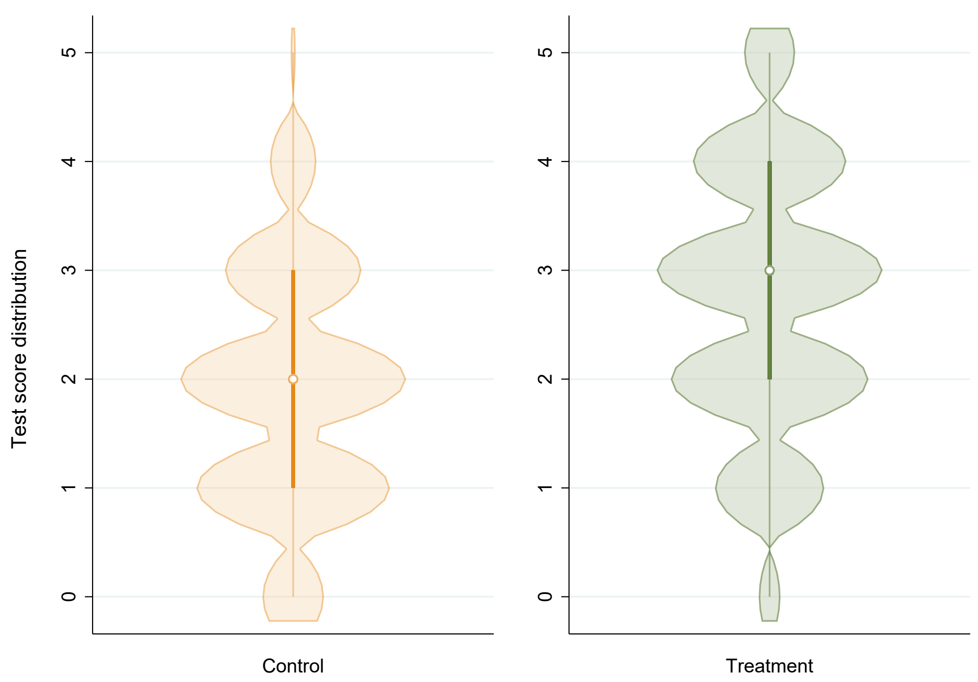
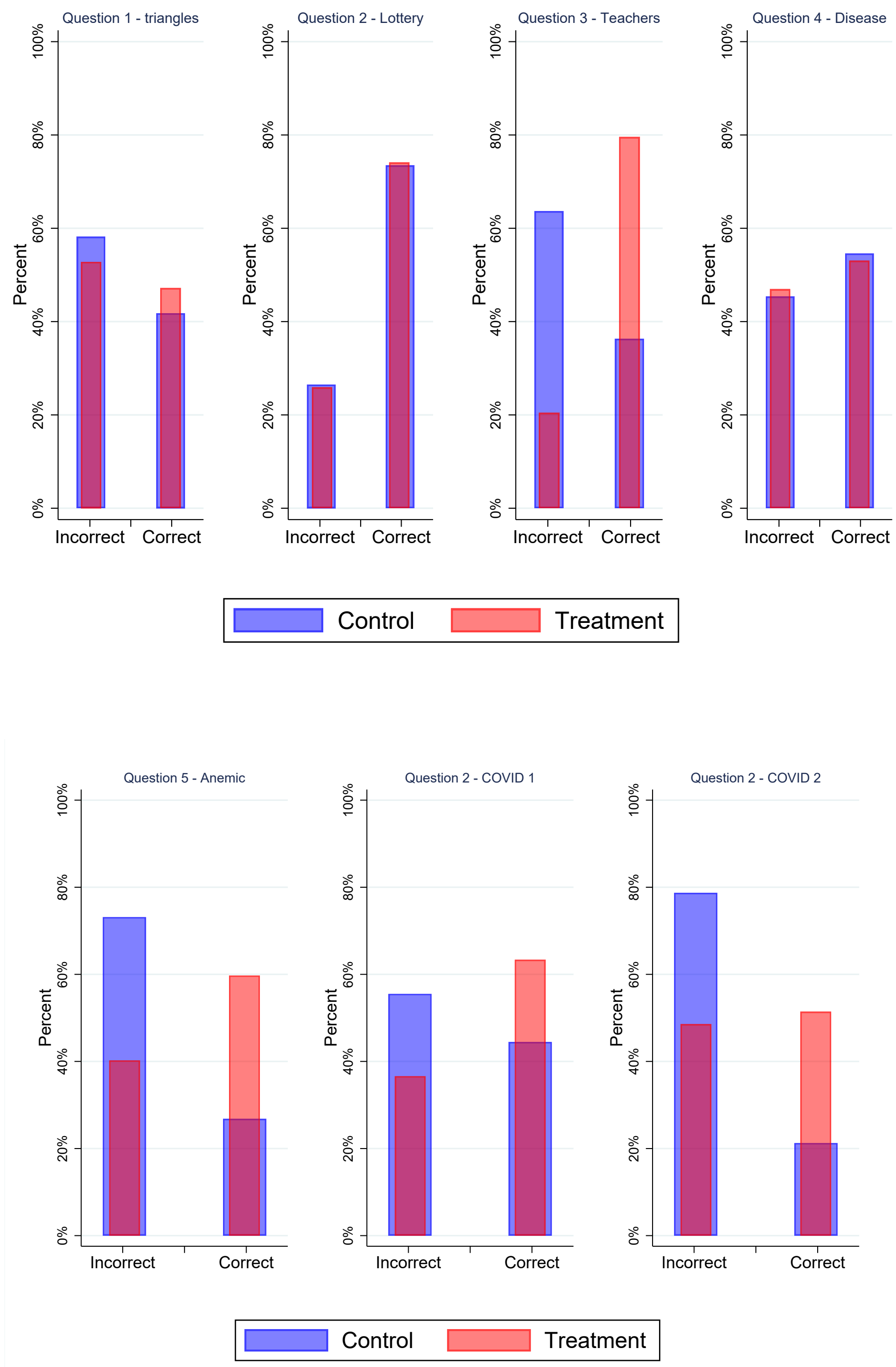


Figure 2: *Correct and Incorrect Answers per Question and Group*



5. Mechanism and Robustness

Can we be sure that the differences between the treatment and control groups come from the course? To provide some evidence in this direction, we have performed three exercises. First, we introduced one question in the test that was also part of the tests within the course. The difference between the control and treatment groups in this question is higher than for any other test questions (see column 8 in Table 2.)

Second, because the individuals in the control group took the questionnaire before and after the course, we can evaluate if the quality of their answers improved. As shown in Table 3, the individuals in the control group scored much higher in the test after taking the course than before the course. In particular, the overall score improves by 0.6 standard deviations.

Table 3: *Control group: Differences between before and after the course (all courses pooled)*

	Test z-score (1)	Triangles: Reasoning (2)	Disease: Exp Value (3)	Child Anemia: SocNorm & Loss Av (4)	Lottery (5)	COVID-19: Beh Interv (6)	COVID-19: Social Distancing (7)	Teachers Incentives (8)
After taking the course	0.616***	0.114***	-0.029***	0.319***	0.036	0.191***	0.253***	0.382***
	(0.020)	(0.008)	(0.010)	(0.014)	(0.029)	(0.011)	(0.011)	(0.014)
Constant	-0.308***	0.424***	0.550***	0.277***	0.719***	0.541***	0.295***	0.447***
	(0.033)	(0.018)	(0.020)	(0.017)	(0.029)	(0.018)	(0.017)	(0.016)
Observations	2933	2933	2933	2933	478	2455	2455	2933
Clusters	124	124	124	124	17	107	107	124
Course FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj R-squared	0.253	0.059	0.003	0.202	0.005	0.110	0.155	0.296

Notes: each row shows the regression coefficients and the standard error in parenthesis corresponding to an OLS regression, including session fixed effects. Standard errors are clustered at the session level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. ifferences in the number of observations across columns because COVID questions were included starting in Session 3 when the Lottery question was eliminated.

Third, one potential issue with the current analysis is that we are comparing individuals who took the survey test at different points; that is, the control takes the test a few weeks earlier than the treatment does. In order to control for that, we exploit the recurring nature of the courses and compare groups of people who took the survey test at approximately the same time, even though they belong to different course sessions (cohorts). That way, we can compare treated individuals in session 1 with control individuals in session 2 (who eventually finished their course), treated in session 2 with controls from session 3, and so on.[8] Results are shown in Table 4. Each column compares the results from the treated in session t with the control group (who then finished their course) in session $t + 1$. The results are very similar to those presented so far. Those who took the course answered between 0.2 and 0.9 standard deviations better than those who had not yet taken and finished the course.

As a final analysis, we ran a robustness exercise by evaluating whether there were any differences between the treatment and the control group after both had taken the course. We present the results in Table 5. As can be observed, differences are small and fluctuate in terms of the sign. The treatment group scored higher than the control group after the course in only 3 of them. Overall, the opposite effect seems to dominate according to the composite score: the control group scored higher than the treatment group. This result could be expected given that the control group had already taken the survey test before the course, which may have led to some learning even though they did not receive feedback.

While this set of exercises does not offer full evidence on the mechanism, they suggest that there seems to be no randomization bias. It does not appear that the treatment was better than the control in answering

[8]For reference, in the first year, the sessions started on February 18, March 17, May 19, July 28, and October 6, 2020

Table 4: *Treatment Effect Across Courses*

	Course 1 T Course 2 C	Course 2 T Course 3 C	Course 3 T Course 4 C	Course 4 T Course 5 C	Course 5 T Course 6 C	Course 6 T Course 7 C	Course 7 T Course 8 C
				Test z-score			
Treatment	0.511***	0.210***	0.562***	0.621***	0.652***	0.857***	0.628***
	(0.097)	(0.053)	(0.061)	(0.060)	(0.161)	(0.096)	(0.181)
Observations	383	665	942	941	582	207	250
Clusters	15	25	35	35	24	8	11
	Course 8 T Course 9 C	**Course 11 T Course 12 C**	**Course 12 T Course 13 C**	**Course 13 T Course 14 C**	**Course 14 T Course 15 C**	**Course 15 T Course 16 C**	**Course 16 T Course 17 C**
				Test z-score			
Treatment	0.525***	0.741***	0.682***	0.460***	0.742***	0.516***	0.312**
	(0.104)	(0.118)	(0.126)	(0.138)	(0.145)	(0.162)	(0.128)
Observations	177	137	193	244	119	218	215
Clusters	9	8	10	13	9	18	19

Notes: each row shows the regression coefficients and the standard error in parenthesis corresponding to an OLS regression. Standard errors are robust. *** p<0.01, ** p<0.05, * p<0.1. Source: Authors' calculations.

Table 5: *Ex-post: Differences between Treatment and Control after course (all courses pooled)*

	Test z-score (1)	Triangles: Reasoning (2)	Disease: Exp Value (3)	Child Anemia: SocNorm & Loss Av (4)	Lottery (5)	COVID-19: Beh Interv (6)	COVID-19: Social Distancing (7)	Teachers Incentives (8)
Treatment	-0.048*	-0.083***	0.006	0.026*	-0.021	-0.045***	0.038**	0.029***
	(0.027)	(0.011)	(0.013)	(0.014)	(0.029)	(0.014)	(0.014)	(0.011)
Constant	0.024	0.563***	0.571***	0.654***	0.760***	0.732***	0.551***	0.844***
	(0.030)	(0.015)	(0.016)	(0.015)	(0.024)	(0.014)	(0.016)	(0.012)
Observations	5655	5655	5655	5655	864	4791	4791	5655
Clusters	247	247	247	247	32	215	215	247
Course FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj R-squared	0.001	0.013	0.005	0.040	0.001	0.017	0.017	0.097

Notes: each row shows the regression coefficients and the standard error in parenthesis corresponding to an OLS regression. Standard errors are robust. *** p<0.01, ** p<0.05, * p<0.1. Source: Authors' calculations.

questions for reasons other than taking the course (e.g., the passage of time). Moreover, people do not seem to be learning about the right answers independently of the course, and there is no selection effect arising from the different cohorts: those who took the course answer better than those in their same cohort but also better than those in future cohorts who take the survey test at approximately the same time.

6. Conclusions

Behavioral biases lead to suboptimal decisions, and policymakers are not exempt from them. These biases tend to have a larger effect when individuals are tired, under high stress, or have limited time to decide. This scenario often describes the environment in which policymakers must make decisions with significant welfare consequences. Behavioral economics has suggested ways to mitigate the cost of certain decisions, such as by changing defaults. However, restricting the policy space is not always feasible, which makes improving policymaking processes critically important.

Training courses for policymakers have been shown to increase job performance effectively. This paper tests whether a behavioral course can improve decisions during cognitive skill tasks and public policy questions. We present suggestive evidence that it can. These results should not be considered definitive but rather as a stepping-stone for more comprehensive evaluations. Future research should include a broader set of questions that thoroughly assess decision-making abilities post-course. Additionally, this study does not evaluate the long-term sustainability of the training effects. Regular testing of policymakers after they complete the course could provide valuable insights into the durability of these gains.

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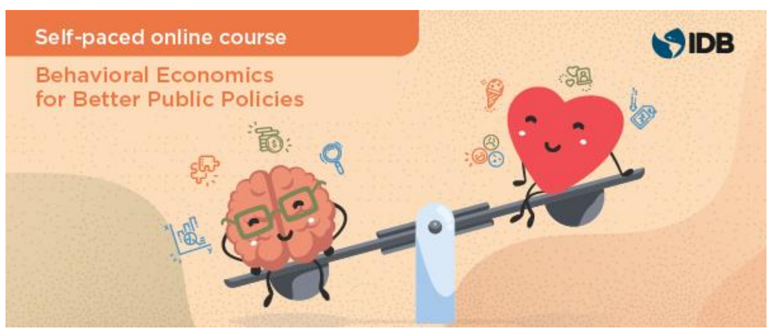
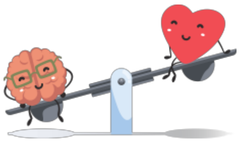
A. Online Appendix

A.1. Course Learning Guide

The course website link in English is: https://indesvirtual.iadb.org/enrol/index.php?id=1960
The full course learning guide is also provided below.

BEHAVIORAL ECONOMICS
FOR BETTER PUBLIC POLICIES
Learning Guide





CONTENTS

In recent years, an increasing number of governments and policymakers have come to realize that in order for public policies to be truly successful, they must consider how individuals behave and make decisions. Based on this premise, this course aims to teach you key concepts of behavioral economics and how they differ from the view of the standard economic model. The course also introduces tools that can help promote a better decision making and presents reviews cases from real interventions in which these nudges were used to improve public policies in Latin American countries and other parts of the world.

TARGETS AND OBJECTIVES

At the end of this course, you will be able to:

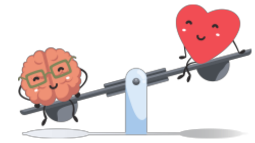
1. **Recognize** the key concepts and main characteristics of behavioral economics.
2. **Identify** cognitive biases and other behavioral barriers to the effectiveness of public policy in Latin America and the Caribbean.
3. **Recognize** behavioral economics tools that can be applied in overcoming barriers relevant to public policies in Latin America and the Caribbean.
4. **Identify** how the implementation of interventions using behavioral economics tools can complement the effectiveness of public policies based on the traditional economic model.

COURSE PACE AND METHODOLOGY

This is self-paced course. This means that you can take the course at your own pace and complete activities according to the schedule suggested for each one. Because it is self-guided, this course does not involve one-on-one interaction with instructors. However, in some activities you will have the opportunity to interact with other active participants.

The course is organized in 4 thematic modules, each with different educational resources, practical activities, and a learning assessment. A new theme will be covered each week, but all modules are interrelated and have been designed to be completed within a period of 3 to 4 hours each.

The course will focus on developing activities that allow students to be the protagonists of their own learning process. The teaching methodology consists of analyzing reference materials such as videos, interactive presentations, and readings, as well as carrying out activities and exercises using real case examples from Latin America and the Caribbean and other parts of the world. The activities proposed for each week may include simulations, reflection, analysis of problem situations or cases, and simulations for decision making, among others. Each teaching resource is applied according to the learning objectives of each module.



Module 1 (4 hours) → Module 2 (3 hours) → Module 3 (6 hours) → Module 4 (3 hours)

"NETIQUETTE" RULES FOR FORUM PARTICIPANTS

1. **Use appropriate language.** Try to avoid slangs (or local idioms) as much as possible. It helps us understand each other better. Also, do not write IN CAPITAL LETTERS! This can be interpreted as if you were shouting.
2. **Watch the tone of your interventions.** Since the written language lacks the support of facial expressions or voice tones, we can easily be misunderstood. We suggest that you read your texts aloud before posting them and avoid using words that may be offensive to others.
3. **Recognize and respect diversity.** Opinions can be different. If you need to express disagreement, do so in a respectful tone, acknowledging the valuable aspects of your fellow course participants. Accept that other people can also have their own perspective and different experiences in the topic.
4. **Be brief.** If your intervention is too long, your fellow participants probably will not have time to read everything you write.
5. **Explain, justify, and argue your opinion.** Avoid posting messages that contain only a few generic words or statements, such as "I agree with you", just for the sake of participating in the forum. Keep in mind that the idea is to contribute to the debate. Therefore, always justify your answers and do not allow them to be loosely interpreted.
6. **Make an inference.** Review the contributions of other participants. Someone else might share your opinion entirely or in part. Besides allowing you to take advantage of third-party contributions, it will also avoid repetition, hence establishing genuine dialogues. When referring to something previously written by another participant, mention the line of your comment, so that other participants will not need to go back in the forum thread to read it.

OBJECTIVES OF THE MODULES

Module 1 - Key concepts

- **1.1** **Compare** the principles of the traditional economic model with those of behavioral economics.
- **1.2** **Identify** the main terms of behavioral economics, such as the dual process theory and major cognitive biases.
- **1.3** **Recognize** the importance of behavioral economics in public policies.

Module 2 - Toolbox

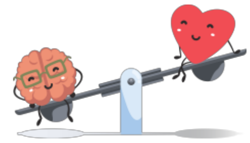
- **2.1** **Review** the main applications of behavioral economics to public policies.
- **2.2** **Recognize** various tools of behavioral economics, with a view to overcoming biases and behavioral barriers and promoting better decision making.

Module 3 - Applied cases

- **3.1** **Identify** behavioral biases and the most relevant tools for the effectiveness of public policies in Latin America and the Caribbean, through cases applied to healthcare and tax compliance.

Module 4 - From theory to practice: an interactive game

- **4.1** **Review** the key concepts of behavioral economics.
- **4.2** **Recognize** how behavioral economics complements the effectiveness of policies based on conventional models.
- **4.3** **Identify** when the tools of behavioral economics can be used in public policies.



ASSESSMENT

Your performance will be assessed on a continuous basis through questionnaires applied at the end of each module and upon completion of all proposed activities. All course activities are mandatory, insofar as each contributes to your learning process. However, while all activities are mandatory, some will not be reflected in your final score.

Activity	Activity module	Weight in score
Learning assessment questionnaire	Module 1	20%
Learning assessment questionnaire	Module 2	20%
Learning assessment questionnaire	Module 3	30%
Learning assessment questionnaire	Module 4	30%

PASS POLICY

The course passing score is at least 80 percent, and the final score will be calculated based on the weights assigned to each learning assessment questionnaire, as shown in the table above. Course grades are Passed/Not Passed, based on the total percentage achieved.

This course includes five learning assessments. Modules 1 and 2 weight 20%. Module 3 has two assessments, one for the tax compliance section and one for the health section, where each weight 15%. Module 4 learning assessment weights 30%. To pass each of these assessments you need to score at least 80 percent of the correct answers. The passing score for the course is at least 80 percent of the total score.

You will have two attempts to answer correctly each question of the learning assessments for Modules 1, 2 and 3 and three attempts to answer correctly each question of the final course assessment (Module 4). The correct answers will appear after you have completed your attempts. If you do not pass any of the assessments, you may move forward in the course modules. In other words, passing a learning assessment is not a prerequisite for advancing in the course.

Learning activities will not be assessed but are mandatory. To successfully complete the course, you must complete all learning activities.

If you do not pass the course you will need to re-enroll to take it again from the beginning, following the required enrollment instructions.

CERTIFICATION

Upon completion of the course, a **pass certificate** will be issued to those who meet the participation conditions, i.e., **a total performance score of at least 80 percent .**

No certificate will be issued to those with a total performance score of less than 80 percent.

DIGITAL BADGES

After completing and passing the course, you will also receive a digital badge that you can share on social media. This badge will be awarded at the end of the course, and instructions on how to access it will be sent to your registered email account.

COURSE POLICIES

As the person responsible for your training process, it is your duty to review and understand each of the policies governing this course. Therefore, we invite you to read the policies on which our courses are based at https://indesvirtual.iadb.org/mod/page/view.php?id=66844&lang=es#

WORK PLAN

The course is designed to be completed within a four-week time period. However, access to the course will be extended by an additional two weeks, to allow you enough time to complete all activities. We suggest that you follow the proposed work plan below, as it will help you organize your study time according to the course activities.

Because it is a self-paced course, you can set your own learning pace and advance in the contents and devote more - or less - hours a week to studying if you so wish. This means that you can complete a certain number of activities and/or modules within a shorter or longer period of time than the one suggested in the work plan. **However, you must complete all activities in one module before moving on to the next. Otherwise, the activities will not be visible for consultation.**

If you fail to complete any of the activities according to the suggested work plan, you will receive automatic notifications from the learning platform. Therefore, we suggest that you check your inbox frequently and make the necessary adjustments to prevent these notifications from going to spam.

Use the checklist below to organize yourself properly and avoid last-minute work.

Welcome to the course (week 1) 4 hours	
Activity	Estimated time
☐Activity 1: Read the welcome description and course objectives ☐Activity 2: Watch the course welcome video ☐Activity 3: Read the learning guide	30 min
Module 1 - Key concepts	
☐Activity 1: Watch the "*How good are we at making decisions? A brief introduction to behavioral economics*" video and answer the proposed questions.	15 min
☐Activity 2: Watch the "*What is behavioral science?*" video	3 min
☐Activity 3: Study the "*The behavioral economics field*" lesson	30 min
☐Activity 4: Study the "*Examples of non-standard preferences*" lesson	20 min
☐Activity 5: Study the "*Examples of non-standard beliefs*" lesson	20 min
☐Activity 6: Study the "*Factors that affect information processing*" lesson	20 min
☐Activity 7: Browse the "*Behavioral Economics: Main terms*" interactive glossary	30 min
☐Activity 8: Watch the "*How can governments use behavioral economics tools?*" video	3 min
☐Activity 9: Study the "*Behavioral economics and public policies*" lesson	30 min
☐Activity 10: Take the learning assessment for Module 1.	30 min
Module 2 - Toolbox (Week 2) 3 hours	
☐Activity 1: Watch the **"***Introduction to the module*" video and answer the proposed questions.	15 min
☐Activity 2: Study the "*Examples of frequently used 'nudges'* lesson	60 min
☐Activity 3: Participate in the *"Is opt-out a better form of consent?"* forum	30 min
☐Activity 4: Browse the *"Behavioral Economics*: *Toolbox*" interactive glossary	30 min
☐Activity 5: Study the "*To conclude, a methodological note*" lesson	15 min
☐Activity 6: Take the learning assessment for Module 2.	30 min

Module 3 - Applied cases (week 3) 6 hours	
☐Activity 1: Read the *"Tax Compliance"* section	10 min
☐Activity 2: Study the *"Beliefs, barriers, and examples of solutions"* lesson	35 min
☐Activity 3: Study the *"Preferences, barriers, and examples of solutions"* lesson	35 min
☐Activity 4: Study the *"Information processing, barriers and nudges"* lesson	30 min
☐Activity 5: Participate in the "*Should we shame tax evaders?"* forum	25 min
☐Activity 6: Read *"Conclusions"*	5 min
☐Activity 7: Browse the *"Takeaways for tax compliance"* interactive summary	15 min
☐Activity 8: Take the learning assessment for the section on tax compliance	25 min
☐Activity 9: Read the "Health" section and watch the video	15 min
☐Activity 10: Study the *"Frequent biases in a patient's decisions"* lesson	40 min
☐Activity 11: Study the *"Nudges to overcome the barriers presented"* lesson	40 min
☐Activity 12: Study the "*Behavioral Economics can help fight COVID-19*" lesson	15 min
☐Activity 13: Participate in the *"The ethics of health nudges* **-** *where is the limit?"* forum	25 min
☐Activity 14: Read *"Conclusions"*	5 min
☐Activity 15: Browse the *"Takeaways on patients' decisions"* interactive summary	15 min
☐Activity 16: Take the learning assessment for the section on health	25 min
Module 4: From theory to practice: An interactive game (week 4) 3 hours	
☐Activity 1: Watch the *"Can behavioral economics help improve vaccination rates?"* video	5 min
☐Activity 2: Participate in the interactive game	120 min
☐Activity 3: Take the learning assessment for Module 4	40 min
☐Activity 4: Watch the **"***Course closing"* video	5 min

CREDITS

This course was developed by IDB's Research Department and the Knowledge, Innovation and Communication Sector, under the coordination of its Behavioral Economics Group. The following IDB staff participated in the preparation of these contents:

- Carlos Scartascini, Nina Rapoport, Ana María Rojas y Cristina Parilli - Research Department
- Florencia Lopez Boo and Nicolás Ajzenman - Social Sector
- Carlos Gerardo Molina and Fernanda Camera - Knowledge, Innovation and Communication Sector

B. Certificate of completion


IDB Inter-American Development Bank

INDES Instituto Interamericano para el Desarrollo Económico y Social

El Banco Interamericano de Desarrollo, a través del
Instituto Interamericano de Desarrollo Económico y Social (INDES),
en coordinación con el Grupo de Economía del Comportamiento del BID

certifican que

ha aprobado el curso

ECONOMÍA DEL COMPORTAMIENTO PARA MEJORES POLÍTICAS PÚBLICAS - EDICIÓN 5

15 de Noviembre de 2020 - 16 HORAS ACREDITADAS

Juan Cristóbal Bonnefoy
INDES Chief

Carlos Scartascini
Líder del Grupo de Economía del Comportamiento del BID

Código de Certificación: XPdAYsufnz
Para verificar el certificado acceder a https://indes.iadb.org/certificates/ e ingresar el código.

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C. Additional Tables

C.1. Analysis at Course Session Level

Table A1: *Number of students in each course session*

Course	Number of students registered	Number of students finished	Percentage finished
Course 1	2453	720	29.35%
Course 2	650	148	22.77%
Course 3	4126	1147	27.80%
Course 4	2712	788	29.06%
Course 5	4257	1041	24.45%
Course 6	381	138	36.22%
Course 7	1142	283	24.78%
Course 8	1023	236	23.07%
Course 9	1535	111	7.23%
Course 10	-	-	-
Course 11	982	168	17.11%
Course 12	635	106	16.69%
Course 13	1552	319	20.55%
Course 14	894	125	13.98%
Course 15	1004	119	11.85%
Course 16	1275	151	11.84%
Course 17	568	64	11.27%
Total	**25189**	**5664**	**100%**

Table A2: *Treatment Effect*

	Course 1	Course 2	Course 3	Course 4	Course 5	Course 6	Course 7	Course 8
Test z-score								
Treatment	0.645***	0.088	0.581***	0.599***	0.672***	0.757**	0.765***	0.459***
	(0.064)	(0.093)	(0.058)	(0.060)	(0.067)	(0.181)	(0.165)	(0.140)
Triangles: Reasoning								
Treatment	0.082**	0.113**	-0.032	-0.010	0.064*	0.035	0.074	-0.018
	(0.034)	(0.045)	(0.028)	(0.031)	(0.032)	(0.023)	(0.047)	(0.050)
Disease: Expected Value								
Treatment	0.083**	0.095	-0.036	-0.033	-0.031	-0.078	0.000	-0.055
	(0.036)	(0.068)	(0.031)	(0.031)	(0.034)	(0.099)	(0.089)	(0.059)
Child Anemia: Social Norm and Loss Aversion								
Treatment	0.454***	-0.087*	0.346***	0.367***	0.320***	0.395***	0.414***	0.318***
	(0.032)	(0.041)	(0.030)	(0.044)	(0.027)	(0.045)	(0.079)	(0.058)
Lottery								
Treatment	0.025	-0.046						
	(0.037)	(0.041)						
COVID-19: Behavioral interventions								
Treatment	0.147***	0.158***	0.192***	0.239**	0.094	0.097		
	(0.028)	(0.034)	(0.027)	(0.069)	(0.068)	(0.060)		
COVID-19: Social Distancing								
Treatment	0.296***	0.290***	0.265***	0.276*	0.384***	0.229**		
	(0.029)	(0.030)	(0.027)	(0.095)	(0.081)	(0.078)		
Teachers Incentives								
Treatment	0.440***	-0.239***	0.452***	0.422***	0.417***	0.603***	0.350***	0.357***
	(0.031)	(0.057)	(0.023)	(0.029)	(0.033)	(0.089)	(0.074)	(0.062)
Observations	717	147	1147	788	1041	138	283	236
Clusters	24	8	42	28	43	4	12	11

Notes: Each row shows the regression coefficients and the standard error in parenthesis corresponding to an OLS regression. Standard errors are robust. *** p<0.01, ** p<0.05, * p<0.1. Source: Authors' calculations.

Table A3: *Treatment Effect*

	Course 9	Course 11	Course 12	Course 13	Course 14	Course 15	Course 16	Course 17
Test z-score								
Treatment	0.722***	0.718***	0.852***	0.484***	0.538***	0.596***	0.382**	0.134
	(0.166)	(0.121)	(0.092)	(0.150)	(0.114)	(0.162)	(0.168)	(0.077)
Triangles: Reasoning								
Treatment	0.116	0.118	-0.049	0.042	-0.089**	0.037	0.100	-0.008
	(0.062)	(0.066)	(0.056)	(0.065)	(0.037)	(0.070)	(0.068)	(0.117)
Disease: Expected Value								
Treatment	-0.116	0.059	-0.091*	-0.097	0.124	-0.020	-0.212***	-0.369***
	(0.078)	(0.064)	(0.042)	(0.058)	(0.100)	(0.097)	(0.065)	(0.060)
Child Anemia: Social Norm and Loss Aversion								
Treatment	0.404***	0.341***	0.541***	0.214***	0.196*	0.389***	0.157*	0.332***
	(0.050)	(0.085)	(0.059)	(0.048)	(0.099)	(0.086)	(0.077)	(0.030)
COVID-19: Behavioral interventions								
Treatment	0.029	0.120**	0.276**	0.111	0.081	0.084	0.146*	-0.025
	(0.105)	(0.046)	(0.103)	(0.067)	(0.056)	(0.093)	(0.069)	(0.121)
COVID-19: Social Distancing								
Treatment	0.422***	0.248***	0.311**	0.315***	0.357***	0.214**	0.254***	0.235
	(0.056)	(0.060)	(0.096)	(0.047)	(0.070)	(0.076)	(0.044)	(0.147)
Teachers Incentives								
Treatment	0.371***	0.330***	0.576***	0.425***	0.350***	0.477***	0.409***	0.389***
	(0.075)	(0.045)	(0.062)	(0.055)	(0.094)	(0.048)	(0.075)	(0.066)
Observations	111	168	106	319	120	119	151	64
Clusters	6	10	6	15	9	10	13	6

Notes: Each row shows the regression coefficients and the standard error in parenthesis corresponding to an OLS regression. Standard errors are robust. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Source: Authors' calculations.