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Lelys Dinarte-Díaz
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Lelys Dinarte-Díaz*
Pablo Egana-delSol**
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* World Bank, IZA, CESifo, and HiCN
** Adolfo Ibanez University School of Business, EGAP, MNEW
*** Inter-American Development Bank and Pontificia Universidad Católica de Chile
**** Inter-American Development Bank

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When Emotion Regulation Matters: The Efficacy of Socio-Emotional Learning to Address School-Based Violence in Central America*

Lelys Dinarte-Diaz† Pablo Egana-delSol‡ Claudia Martinez A.§
Cindy Rojas Alvarado ¶

Abstract

After-school programs (ASP) that keep youth protected while engaging them in socio-emotional learning might address school-based violent behaviors. This paper experimentally studies the socio-emotional-learning component of an ASP targeted to teenagers in public schools in the most violent neighborhoods of El Salvador, Honduras, and Guatemala. Participant schools were randomly assigned to different ASP variations, some of them including psychology-based interventions. Results indicate that including psychology-based activities as part of the ASP increases by 23 percentage points the probability that students are well-behaved at school. The effect is driven by the most at-risk students. Using data gathered from task-based games and AI-powered emotion-detection algorithms, this paper shows that improvement in emotion regulation is likely driving the effect. When comparing a psychology-based curriculum aiming to strengthen participants' character and another based on mindfulness principles, results show that the latter improves violent behaviors while reducing school dropout.

JEL classifications: I29, K42, I25, D87
Keywords: After-school programs, Psychology-based interventions, School-based violence, Emotion regulation

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†The World Bank, IZA, CESifo, HiCN. Email: ldinartediaz@worldbank.org

‡Adolfo Ibanez University School of Business, EGAP, MNEW. Email: pablo.egana@uai.cl.

§Corresponding author. Inter-American Development Bank and Pontificia Universidad Católica de Chile, J-PAL. Email: claudiam@iadb.org

¶Inter-American Development Bank. Email: cindyro@iadb.org

1 Introduction

Children living in gang-controlled areas of Latin America are at high risk of being exposed to or engaging in violent activities. These outcomes can affect adolescents' well-being and economic opportunities, including worsening labor market outcomes or increasing involvement in crime (Sviatschi, 2022; Caudillo and Torche, 2014; Monteiro and Rocha, 2017; Heckman et al., 2006). For at-risk individuals, their inability to regulate their emotions can increase the likelihood that they will respond violently to some stimuli (Peterson and Seligman, 2003; Heller et al., 2017).

One strategy to reduce this exposure to and engagement in violence is to limit these students' unstructured time. After-school programs (ASPs) are an attractive approach since they can *protect* children by keeping them occupied and off the streets when they might otherwise be left unsupervised and exposed to external risks; they thereby prevent children's victimization and delinquent behavior (Gottfredson et al., 2004). ASPs may also directly invest in students' human capital. When these programs include a curriculum designed to foster socio-emotional skills and help students control their impulsive responses, they also offer an alternative source of *socio-emotional learning* (SEL) (Taheri and Welsh, 2016; Durlak et al., 2010), which translates into improvements in adolescents' violent behaviors and their ability to regulate their emotions (Dinarte-Diaz and Egana-delSol, 2023).

But whether the ASP SEL component affects adolescents' behaviors and academic outcomes and which ASP curricula (targeting different skills) are more effective are unexplored questions. On the one hand, evidence from the education and crime literature shows that protecting youths through lengthening school days (Berthelon and Kruger, 2011; Jacob and Lefgren, 2003) or providing summer jobs (Heller, 2014) without offering any violence-reduction curriculum can reduce adolescents' violent and criminal behaviors. On the other hand, more recent evidence suggests that programs targeted at adolescents and young adults that include a psychology-based curriculum can reduce violence-related and criminal outcomes (Heller et al., 2017; Blattman et al., 2017; Dinarte-Diaz and

Egana-delSol, 2023; Bhatt et al., 2024) and improve socio-emotional skills (Cook et al., 2014; Barker et al., 2021) and academic outcomes (Cook et al., 2014; Heller et al., 2017).

This paper experimentally evaluates the role SEL plays in the effectiveness of ASPs on violent behaviors and academic performance by conducting a simultaneous randomized control trial (RCT) in three of the most violent countries in the world. Specifically, we make three contributions. First, we experimentally evaluate bundling SEL with ASPs. Second, we evaluate two different SEL curricula which target different skills. Third, we develop methods for directly measuring growth in socio-emotional skills. In combination, this allows us not only to evaluate the effectiveness of offering SEL as part of ASPs, but also to understand how the choice of SEL curriculum may matter in the development of specific socio-emotional skills and later outcomes.

The ASP (and the variations that we explain below) was implemented in public schools in the most violent neighborhoods of El Salvador, Honduras, and Guatemala. The program was targeted at students aged 12 to 19 by the implementing NGO. Within the Central American context, this age range is significant because gangs are most likely to recruit adolescents of this age (International Crisis Group, 2017). All the ASP variations we study were implemented in school facilities after school, two days per week for seven months (between April and October) during the 2019 academic year. Each meeting lasted approximately 1.5 hours; 69% of students attended at least 70% of sessions. On average, each ASP was implemented in groups of 13–15 participants and was run by adult volunteers who had no formal training in social work or psychology, which matters for scalability.

We enrolled 897 students between 12 and 19 years of age from 21 public schools to participate in the study. We conducted a stratified randomization at the country (El Salvador, Honduras, and Guatemala) and school-risk level (high or low risk, proxied by the homicide rate in the school's municipality),[1] and randomly assigned the 21 participating schools (with equal probability)[2] to one of three treatment arms.[3] The first group received

[1]A school was denoted "high risk" if it was located in a municipality with a homicide rate greater than the mean rate at the country level in 2018.

[2]We estimate using wild clusters to correct standard errors, given the small number of schools.

[3]Because of constraints affecting the implementing NGO, we do not have a pure control group (a group

the implementing NGO's ASP (*Clubs*), which includes extracurricular activities such as dance, sports, and art. The instructors of *Clubs* played a limited role as facilitators (they registered participants' attendance, distributed materials, and led the activities). The other two groups were assigned to a variation of the ASP that, in addition to the extracurricular activities of *Clubs*, also contained supplementary activities from a psychology-based curriculum.[4] In these groups, the first half of the session consisted of the activities from the psychology-based curriculum and the second half included extracurricular activities from *Clubs*.

We selected the psychology-based curriculum to test two programs that differ in design and cost. The first, the Character Strengths Development Program (*Virtue*), aims to strengthen participants' character and increase their psychological well-being. It was designed for the Central American context through a consultation process, as documented in Vásquez and Dinarte-Diaz (2021), and inspired by Peterson's (2004) model of character strength and virtue. The curriculum includes 32 training and self-reflection activities distributed across the sessions. It employs an active-learning methodology, which places students at the center of the learning experience and motivates participation in individual and group activities.

The second psychology-based curriculum we study is Calm Classroom® (*Mindful*), a mindfulness-based and relaxation-response program. The program includes 16 standard breathing, stretching, relaxation, and focusing activities. It aims to help participants to develop self-awareness, control of automatic responses, mental concentration, and emotion

that does not receive any intervention) in our experimental design, which limits our ability to measure the pure protection component—that is, the impacts on outcomes of interest of being assigned to *Clubs* relative to receiving no intervention. In designing the RCT, we aimed to address this by selecting similar schools through a propensity score matching approach. However, the result of the matching was that selected schools were not comparable in several student-level baseline characteristics (whether the student was enrolled in the afternoon shift, travel time, household composition (living with both parents or only with the mother), and mother's education) and in most of the outcomes and mechanisms measured at the student level (including behavior at school, perseverance, self-control, risk aversion, and arousal). Therefore, we did not pursue this analysis.

[4]We acknowledge that participating in the *Clubs* can strengthen students' social learning, due to the opportunity to interact with other children, among other channels. In this sense, our hypothesis is that any impact we may find from the SEL component would be driven by the specific activities included in the psychology-based curriculum, beyond the social learning that may come from the participation in the *Clubs*.

regulation. We used the standard curriculum, which is homogeneous across contexts and demographics. Thus, we can think of this curriculum as a blueprint that is cheaper and easier to replicate and scale up than other psychology-based programs, including *Virtue*.

To measure the impacts of the ASPs on students' outcomes and explore potential mechanisms, we collected data before the start of the intervention (baseline) and right after its completion (follow-up). To measure the main outcomes—namely, behavior at school, school dropout, and academic performance (math scores)—we rely on administrative records submitted as printed reports by teachers from the three countries. Data on behavior at school and math grades were collected at baseline and endline, whereas reports on school dropout are available only at endline.

Moreover, we undertook an innovative and exploratory investigation to provide evidence on three potential mechanisms underlying the effects of psychology-based interventions on students' main outcomes—namely, socio-emotional skills, fluid intelligence,[5] and emotion regulation.[6] To gather measures of socio-emotional skills, we used task-based games available in an application developed and used by Danon et al. (2023). We collected measures to proxy for perseverance, self-control, and risk-averse behaviors. To assess emotion regulation, we examined the impact of our intervention on indicators of emotional reactions, which we refer to as *emotion regulation* markers. These markers were estimated using a software platform based on computer vision and AI called Reactiva (Amangeldiyev and Egana-delSol, 2018) and a platform designed to conduct research on behavioral economics in the field.[7] Last, we use a progressive matrices test (similar to a

[5]Fluid intelligence is consistent with Mullainathan and Shafir's (2013) idea of mental bandwidth. The ASPs' psychology-based curriculum may increase concentration capacity and, thus, improve fluid intelligence, which proxies for logical thinking.

[6]The literature defines *emotion regulation* as a mixture of cognitive and emotional processes that affect a person's disposition to act (Salzman and Fusi, 2010). Drawing from Kahneman's (2011) theory of automaticity, which posits that individuals often act automatically and unthinkingly because of habitual responses, we argue that participants in both *Virtue* and *Mindful* may increase their emotion regulation by reducing their automatic emotional reactions to both positive and negative stimuli.

[7]For the former, we leverage a software development kit, developed by a spin-off of MIT's Affective Computing Group (Picard, 1995; McDuff et al., 2015), that measures different features of emotions and has been trained on millions of subjects. Regarding the latter, we construct an online platform with research-related protocols such as the ability to randomly show emotionally laden stimuli and present cognitive tests.

Raven (1936)) test to assess the effect of emotion regulation on fluid intelligence [8].

We document four main results. First, we find that compared to students in *Clubs*, participants in the *Virtue* and *Mindful* curricula (henceforth, psychology-based interventions or curricula) are 23 percentage points (pp) more likely to be well-behaved at school (*p-value*=0.015). This improvement is equivalent to an increase of 36% relative to the share of students in *Clubs* with an above-the-median behavior score. Moreover, we find no statistically significant effects of the SEL component on school dropout and math grades.

Second, we study the differential impacts of the SEL component on behavior at school for different student characteristics using a machine learning approach (Athey and Wager, 2016, 2019; Athey et al., 2019), following Wang (2022) and Carlana et al. (2022). Our results indicate that the most at-risk students are benefiting the most from the ASP's SEL component. That is, the net effect of this ASP component is larger for students with greater exposure to risks (those living in high-homicide urban municipalities or engaging in worse behavior at school at baseline), students likely to have less adult supervision (not living with both parents, living with mothers with more years of education,[9] or enrolled in the afternoon shift at school), students whose demographic characteristics are positively correlated with violent behaviors (male and older students), and students who have lower fluid intelligence and higher alertness or stress at baseline. Therefore, the psychological-based curricula have a positive impact on those who might be more in need of the ASP SEL component.

Third, among the three potential mechanisms we explore, we only find evidence of emotion regulation as a mechanism driving the effects of the SEL component on behavior at school. Our results show that students who participated in the variant of the ASP that included psychology-based interventions reduced their emotion-regulation score (called "valence") by 0.24 standard deviations (sd) relative to students assigned to the variant that includes only a protection component (*p-value*=0.050). This reduction in emotion reg-

[8] We found, through correlation analysis of our study sample, that our progressive matrices tests correlate strongly with math scores. Results available upon request

[9] In Central America, women with higher levels of education are more likely to be employed in formal (non-domestic) full-time jobs, and, thus, their children are more likely to be alone after school.

ulation can be interpreted as saying participants became emotionally and behaviorally calmer and less impulsive. We rule out that the net effects of the SEL component are driven by changes in socio-emotional skills or fluid intelligence. A potential explanation for why these two mechanisms seem not to be at play is that we are estimating average effects from two interventions that, by design, are targeting different skills.[10]

Considering the above, our last result is that the type of curriculum for the SEL component matters. The net SEL component can complement the pure protection component's effectiveness by including either of the psychology-based curricula. Compared to students in *Clubs*, those who participated in *Virtue* or *Mindful* are better behaved at school (23 pp (*p-value*=0.035), and 24pp. (*p-value*=0.020), respectively). When we look at other main outcomes, we find that although the mindfulness curriculum produces a nonsignificant reduction in dropout rates of 4pp relative to *Clubs* (*p-value*=0.12), the observed disparity between the two curricula is noteworthy (*p-value*=0.020).[11]

Despite similar behavioral improvements, the underlying mechanisms of the curricula differ because of their distinct content. The virtue-based curriculum enhances behavior by decreasing risk-taking behaviors (0.25 sd, *p-value*=0.020) and improving emotion regulation (a 0.27 sd decrease in the valence index, *p-value*=0.030). The former effect is consistent with an excess of risk-taking in highly vulnerable and violent contexts, as in the three countries in our study. Meanwhile, the mindfulness-based curriculum affects both behavior and dropout rates by improving emotion regulation, which translates into an increase in logical-thinking (that is, fluid intelligence) scores after the subjects are disrupted by negative stimuli (0.22 sd, *p-value*=0.010). This suggests a heightened resilience in youth, enabling better focus and improved performance on standardized tests such as the Raven's matrices test. These findings highlight the different benefits of both curricular approaches. While both are effective in behavioral enhancement, the mindfulness approach offers additional advantages in reducing dropout rates and enhancing youth

[10] *Mindful* is expected to improve fluid intelligence, self-control, and emotion regulation, whereas *Virtue* is expected to improve perseverance, self-control, risk-taking behaviors, and emotion regulation.

[11] The greater effects of *Mindful* relative to *Virtue* or *Clubs* are not driven by differences in ASP attendance rates. On the contrary, we show that attendance in the *Virtue* ASP was higher compared to the other two ASPs.

resilience and focus, making it a particularly compelling option in educational settings.

This paper contributes to three strands of the literature. The first strand includes studies concerning how school-based programs targeted at adolescents can improve participants' behaviors, academic outcomes, emotion regulation, and socio-emotional skills (Alan and Kubilay, 2024; Dinarte-Diaz and Egana-delSol, 2023; Jackson et al., 2020; de Chaisemartin and Navarrete, 2019; Levine and Zimmerman, 2010; Fleming et al., 2008; Vandell et al., 2007).[12] Some of these studies measure the total effects of programs that mostly just protect students for a certain period. Others measure the effect of combining protection and SEL elements on participants' outcomes. We contribute to this literature by providing experimental evidence of the net SEL component of an ASP. This evidence has important policy implications related to the design of programs targeted at adolescents: since the SEL component provides an impact beyond the protection component, policymakers should invest in including psychology-based curricula in ASPs.

Second, this paper contributes to the growing economics literature on the impacts of psychology-based interventions on outcomes of at-risk adolescents and young adults.[13] Our findings demonstrate the efficacy of psychology-based interventions in highly violent environments, particularly benefiting the most at-risk children. Our study is innovative in comparing different types of psychology-based curricula that aim to decrease bad behavior in teenagers. Our results provide critical information on how to foster good behavior and emotion regulation through school-based interventions that differ in intensity and suitability. Moreover, since the type of curriculum matters, resources should be allocated to the most cost-effective curriculum. Last, we show that these programs can be implemented in a cost-effective manner. These programs are relatively cheap: the average cost per student of the respective ASPs is US$296.5 (US$269.4 for *Clubs*, US$292.5 for *Mindful*,

[12]For meta-analysis of ASPs implemented in high-income countries, see Cappella et al. (2018); Kremer et al. (2015).

[13]For research concerning cognitive behavioral therapy as a particular psychology-based curriculum, which has proven highly effective to improve violent behaviors and academic performance, see Heller et al. (2017) and Cook et al. (2014) for Chicago, Blattman et al. (2017) for Liberia, Barker et al. (2021) for Ghana, and Dinarte-Diaz and Egana-delSol (2023) for El Salvador. From the psychology evidence, evaluations of self-control strategies or grit show positive effects on achievement of academic goals (Duckworth et al., 2016) and perseverance (Santos et al., 2022).

and US$327.6 for *Virtue*), which is only one-seventh[14] the cost of similar programs for at-risk youth in the United States (Heller et al., 2017). Remarkably, our back-of-the-envelope calculation shows a benefit–cost ratio that ranges from 11.3 to 45.2. Hence, from a public policy perspective, this program is worth investing in because it is likely to pay for itself in the short run and can even generate large additional welfare gains in the long run.

Finally, our paper makes an important contribution related to measurement of socio-emotional skills and emotion regulation in the field. Most of the existing evidence on these outcomes has been obtained through self-reported questionnaires. However, self-reported responses always entail the risk of reference or self-reporting bias, an issue that becomes more salient when evaluating programs aimed at improving these outcomes since there is no way to assess the direction of the bias.[15] Recent papers have been using task-based games to avoid bias and obtain more objective measures of outcomes.[16] In addition to such games, we use an AI-powered emotion-detection experimental protocol in the field, which allows us to collect emotion-regulation and fluid-intelligence measures in school contexts with minimal infrastructure.

Unlike in other studies, our interventions take place within the unique violent environments of three Central American countries. During the last decade, these three nations have been among the world's 10 deadliest places for young boys. The mortality rate related to personal violence for adolescents was almost 10 times as high as the global average. Moreover, adolescent boys in Honduras are 1.9 times more likely to die by homicide than from any other cause. In El Salvador and Guatemala, one-third of the deaths of adolescent boys are due to homicide (UNICEF, 2017). In addition, during the last decade, these countries have experienced a 13% average reduction in the educational enrollment

[14] Alternatively, the PPP-adjusted cost of these at-risk programs in the United States would be 3.1 times the cost of the programs under analysis in this study.

[15] For example, Lira et al. (2022) shows that self-reporting questionnaires are prone to reference bias. Moreover, as argued in Egana-delSol (2016a), Egana-delSol (2016b), and Egana-delSol et al. (2023), participants may underreport their skill level because they may have become more aware of their skill level during the intervention and may feel that they have not achieved proficiency. Alternatively, they may overreport their skill level to prove that they have learned something from the intervention.

[16] See Danon et al. (2023). Also, see Kautz et al. (2014) for a discussion of a task-based framework for identifying and measuring noncognitive skills.

rate, with over 18% of students reporting that they dropped out of school because of delinquency.[17] The grave situation in these countries points to the urgent need to find solutions to such violence.

2 Research Design

2.1 Interventions

To experimentally estimate the net impacts of the SEL component of an ASP, beyond the effects of the protection component, on behavioral and academic outcomes, we study three variations of an ASP: a traditional ASP with extracurricular activities (hereafter *Clubs*) and two psychology-based curricula, the Character Strengths Development Program (*Virtue*) and Calm Classroom® (*Mindful*). We describe the structure and curriculum of each of these three variations below.

As noted, in 2019, Glasswing International implemented these three ASP variations in public schools in the most violent neighborhoods of El Salvador, Honduras, and Guatemala.[18] The ASPs targeted students between 12 and 16 years old in the three countries.[19] In Central America, targeting programs at adolescents is important because they are more likely to be forcibly recruited or decide voluntarily to join gangs (Cruz et al., 2016; International Crisis Group, 2017).

The three ASPs were implemented in school facilities after class time, two days per week for seven months in the 2019 academic year. On average, each ASP was implemented in groups of 13–15 participants. The ASPs were run by adult volunteers who had no formal training in social work or psychology.[20] During the sessions, the volunteers

[17] Moreover, in El Salvador, 66% of detained unaccompanied children cited violence on the part of organized criminal groups as their main motivation for seeking asylum in the United States (UNHCR, 2014).

[18] Glasswing International started operations in El Salvador in 2007 and has implemented projects throughout Central America, Mexico, Colombia, and the Caribbean. More information about Glasswing International and its work can be found here: https://glasswing.org/.

[19] As we explain below, the NGO requested that we allow a few students between 17 and 19 years of age to enroll. Yet they represent only 2.45% of our total sample.

[20] Three types of volunteers supported this ASP: community volunteers, who were tutors living in the

supervised the adolescents and protected them from risky contexts for approximately 1.5 hours.

Clubs, which serves as our curriculum of comparison for the SEL component, consists of extracurricular activities including sports, science, and arts.[21] To keep the structure of *Clubs* as close to a pure protection ASP as possible, the instructors of this ASP variation played a restricted role, serving only as supervisors or facilitators who registered participants' attendance, distributed materials, and led the activities. Instructors were not allowed to use any activities from the two curricula we describe below.

The structures of *Virtue* and *Mindful* groups were similar to *Clubs*, but they also contained supplementary activities related to their specific curricular aims. That is, in each of the sessions, students participating in *Virtue* and *Mindful* first received the psychology-based curriculum during the first part of each session (more details below). During the second part of each session, they received the *Clubs* intervention. The number of volunteers, types of facilities, and number of sessions scheduled per week were the same across all ASPs. We argue, therefore, that any difference in the effects of these interventions was driven by variations in the psychology-based curriculum instead of by how the ASP was implemented.

The first psychology-based curriculum we study, *Virtue*, aimed to strengthen participants' character and increase their psychological well-being.[22] In coordination with local experts and psychologists, Glasswing International developed the *Virtue* program, which

community and stood out because of their leadership skills; corporate volunteers, who were associated with a firm involved in a social project with Glasswing; and independent volunteers, who were usually college students involved in social work. Unfortunately, we do not have information on which type of volunteers facilitated each program. Yet we know that each volunteer was in charge of one and only one group; thus, contamination is not a concern.

[21]More details about this ASP can be found here: https://glasswing.org/program/after-school-programs/. The type of extracurricular activity was fixed for each group. For example, if a group were focused on sports, then they were doing the same activity during the academic year—that is, they did not do any science-related activity. Dinarte-Diaz and Egana-delSol (2023) experimentally evaluated a version of this ASP in El Salvador and presents a detailed description of the program. Overall, they find that ASP participants improved their academic performance and behavior at school relative to students in the control group (no ASP).

[22]Evidence from psychology shows that character development can improve peer relations and measures of school grades and engagement (Park et al., 2017).

was inspired by Peterson et al.'s (2004) model of character strengths and virtues.[23] These virtues are perseverance, self-control, perspective, courage, social intelligence, creativity, and hope. The curriculum includes 32 activities distributed across all of the sessions.[24]

The *Virtue* program included both training and self-reflection activities. The training sessions presented concepts, while the reflection sessions invited participants to assess their personal history and environment. To achieve the desired level of reflection, volunteers used an active-learning methodology, which placed the students at the center of the learning experience and motivated participation in individual and group activities. Participants actively practiced their strengths, reflected on how they had applied them in their daily lives, and acquired tools to adopt them easily.[25]

For example, the *Virtue* curriculum included four sessions (one training and three self-reflective) to develop perseverance. In the training session, participants discussed the definition of perseverance and how perseverance can be beneficial to them. Then, the self-reflection sessions included three main activities: The Backpack, My Map, and Fighting for the Puzzle. In The Backpack, participants were invited to think about two goals and to describe what tools they would carry in their backpacks to have ready at hand to achieve these goals. In My Map, participants discussed the path they would take to achieve the goals they defined in the previous activity, the potential obstacles they may face, and how the tools they included in their backpacks would help them overcome obstacles.[26] Finally, in Fighting for the Puzzle, participants had to earn the individual pieces of a puzzle and then complete it. Students had to accomplish some physical tasks such as push-ups in order to obtain each piece of the puzzle. Then, they discussed how achieving the goal (completing the puzzle) required them to exert effort.

The second curriculum we study, *Mindful*, is a mindfulness-based and relaxation-

[23] Vásquez and Dinarte-Diaz (2021) describe how the *Virtue* curriculum was developed. This process includes validation of the most relevant character strengths of the group of students from the three countries in our sample. The program was piloted with a group of adolescents in each country before it was implemented in participant schools in this study.

[24] For details on the structure of the program and sessions, see Appendix Table A1.

[25] The instructor's manual and support materials for *Virtue* are available in Spanish here.

[26] The activity sheets for these two modules can be found in Appendix Figures A1 and A2, respectively.

response program. This curriculum was adapted by the NGO to the Central American context from the program developed by the Luster Learning Institute after the NGO conducted a pilot program among 200 Salvadoran students in 2017.[27] The program included directed meditation to reduce stress and anxiety and to control automatic responses. It also used thought techniques to help participants develop self-awareness, mental concentration, and inner calm. Through a series of activities, *Mindful* provided students with tools to manage their stress more effectively and to regulate their emotions.

The *Mindful* program included 16 breathing, stretching, relaxation, and focusing activities, which were implemented throughout all of the sessions. During each session, the volunteers explained each technique for about three minutes and then demonstrated and led the students in the practices throughout the session. These activities were supplemented with the *Clubs* activities. For example, in the I am Calm activity, students used breathing and consciousness techniques such as deep breathing and sun and butterfly breathing to try to calm themselves. During the Sun Breathing activity, participants were invited to sit comfortably in their chairs with their feet on the floor. Then they were asked to breathe for 10 seconds while being conscious of their breathing. They were instructed to inhale through their noses, stretch their arms above their heads, and then lower their arms slowly after 5 seconds. They repeated this exercise 10 times, after which they inhaled and exhaled for 20 to 30 seconds, opened their eyes, and discussed how they felt.[28]

2.2 Conceptual Framework

Our analysis is organized around the conceptual framework we present in Figure 1, which was preregistered at the AEA RCT Registry. This framework approaches the incipient problem of high incidence of school-based violent behaviors in low- and middle-income countries and how an ASP can help to address it. We expect that the SEL component can affect at least three primary outcomes. By learning new skills and techniques from the

[27] For more details on the original program, visit `www.calmclassroom.com.`

[28] This activity is presented in Figure A3 in the Appendix. A manual covering the complete intervention, including support materials along with the activity schedule for every academic year, is available in Spanish here.

two psychology-based curricula included in the ASP (*Virtue* and *Mindful*), participant students could improve their behavior at school, school dropout, and academic performance, relative to students who attended the protection-based ASP (*Clubs*).[29]

In terms of potential mechanisms, we hypothesize the SEL component could affect the main outcomes through improving socio-emotional skills, fluid intelligence, and emotion regulation. We also hypothesize that because of the focuses of the curricula, the curricula can affect different mechanisms. On the one hand, *Mindful* cultivates a greater consciousness among students, helping them foster attitudes of respect, kindness, and regulation toward themselves and others within their school environment (Keng et al., 2011). Considering the essential elements of *Mindful*, this curriculum is expected to improve self-control, fluid intelligence, and measures of emotion regulation. These hypotheses are consistent with evidence of the positive effects of practicing mindfulness on emotion regulation, the capacity to perform tasks, memory, and attention.[30] On the other hand, following existing empirical evidence (Park et al., 2017; Linley et al., 2007; Shimai et al., 2006), we hypothesize that the *Virtue* ASP increases perseverance and self-control, reduces risk-taking behaviors, and improves emotion-regulation measures. We preregistered these outcomes in the PAP and collected data to measure these dimensions.

2.3 Experimental Design

In January 2019, we identified and recruited 21 public schools to test the SEL component of our ASP.[31] Our selection process took into account four school criteria: i) the school is located in one of the most violent municipalities in El Salvador, Honduras, or Guatemala, ii) it has not participated in a Glasswing intervention in the past five years, iii) it has both the physical and technological infrastructure to implement the ASP, and iv) school

[29] Studies have shown that psychological interventions targeted at adolescents or young adults reduce criminal and violence-related outcomes (Heller et al., 2017; Blattman et al., 2017; Dinarte-Diaz and Egana-delSol, 2023), improve socio-emotional skills (Cook et al., 2014; Barker et al., 2021), and improve academic outcomes (Cook et al., 2014; Heller et al., 2017; Dinarte-Diaz and Egana-delSol, 2023).

[30] See Galla et al. (2020); Kral et al. (2018); Saltzman and Goldin (2008); Zelazo and Lyons (2011); Huppert and Johnson (2010); Van de Weijer-Bergsma et al. (2012); and Meiklejohn et al. (2012).

[31] Figure 3 in the Appendix presents a timeline of the intervention divided into stages.

principals supported the study and intervention. The schools that met these criteria were chosen and randomized across the three interventions described above.

As we depict in Figure 2, we conducted a stratified randomization at the country (El Salvador, Honduras, and Guatemala) and school-risk levels (high or low risk, proxied by the homicide rate in the school's municipality). A school was considered high risk if it was located in a municipality with a homicide rate greater than the mean rate at the country level in 2018. The design includes a total of six strata based on three values for country and two for school-risk level. Then, we randomly assigned the 21 participating schools to the three treatment arms—*Clubs*, *Virtue*, and *Mindful* (7 schools per arm). We used a self-coded randomization procedure in Stata to randomly assign schools to the ASP variations. Then, we informed our implementing partner about the treatment allocation. The NGO distributed materials, trained mentors, and supervised implementation accordingly. Treated schools were aware of their treatment status and the research project's evaluation goals, but the schools were not aware that another treatment group existed.

We test the SEL component by comparing the main outcomes (that is, behavior, school dropout, and academic performance) of students enrolled in schools that were randomly assigned to any psychology-based intervention (either *Virtue* or *Mindful*) to the same outcomes of the students enrolled in schools assigned to *Clubs*.[32] Moreover, we test which curriculum (*Virtue* or *Mindful*) more efficiently improves participants' outcomes by using the experimental variation and comparing the average outcomes of the students who were randomly assigned to *Virtue* with the average outcomes of those assigned to *Mindful*. Both outcomes are then compared to the average outcomes of students allocated to *Clubs*. Last, to study the mechanisms driving these effects, we conduct similar comparisons to those described above but using the variables that measure the potential channels, as specified in our conceptual framework—that is, students' socio-emotional skills, fluid intelligence, and emotion regulation.

[32] In other words, we pooled students assigned to these two treatment arms together and compared them to students assigned to *Clubs*.

2.4 Recruitment of Participants

Between mid-January and February 2019, before collecting baseline data and implementing the ASP, the implementing partner visited the 21 schools in our sample. It advertised the ASP and provided informational brochures and videos in the 21 schools, excluding references to any specific activity related to *Virtue* or *Mindful*. During its visit to any school, the NGO gave consent forms to both students and their parents to confirm their interest in participating in both the intervention and the study.

In March 2019, the NGO and research team returned to the schools to register and enroll children in the ASP. Any child was allowed to self-enroll as long as they and their parent or legal guardian signed a consent form. During the registration process, students used tablets to complete the enrollment form with personal and family information as well as completing the application to participate in a particular type of activity (sports, dance, or arts) at school. More details on the enrollment process are presented in the next section. We recruited and enrolled 897 students between 12 and 19 years of age (341 in *Clubs*, 294 in *Virtue*, and 262 in *Mindful*).

3 Data and Summary Statistics

3.1 Data Collection

In this section, we describe the stages during which we collected information from schools and participants and the procedures we followed. Figure 3 presents a timeline indicating when we collected the data.

Baseline data collection. As mentioned before, during the enrollment process, students interested in participating in the study completed an enrollment form. It includes 21 questions and takes approximately 10 minutes to complete and was completed using tablets (see Table A2). The staff of the NGO oversaw registration. Once registered, each student received a unique identification number, which enabled us to track them through all data sets.

Two weeks after the registration process and before program implementation, enumerators went to schools to collect baseline information on social-emotional skills, fluid intelligence, and emotion regulation. To reduce the risk of fatigue among students, we collected these data over two days. On the first day, we asked students to complete the tasks used to collect data on social-emotional skills on a tablet. On the following day, the students completed the tasks used to collect fluid-intelligence and emotion-regulation data. In each school, we organized several classrooms in which students were scheduled to arrive in groups at specific times. Once the groups arrived, we gave the instructions to them and gave each student a tablet. Enumerators followed up with students who had questions.

Before the intervention commenced, we were given access to students' administrative records, which included behavior at school and academic performance (specifically, math grades). Teachers submitted this information as printed reports for their students enrolled in the school. We collected, digitized, and cleaned all these paper reports for the students registered in the program and enrolled in the participating schools in El Salvador, Guatemala, and Honduras. One field coordinator per country was responsible for checking that the digitized data were consistent. Because of ethical protocol, we were unable to keep the records of students who did not consent to participate in the study.

We collected data on the characteristics of the participant schools from the 2018 Educational Censuses for El Salvador and Guatemala and from a school-level survey conducted by the authors for Honduras. We were able to obtain information on school location, enrollment, equipment available, and infrastructure, among other aspects. Last, we collected data on homicide rates at the municipality level from each country's national police, which we use as a stratification variable.

Short-term follow-up data collection. As presented in the project timeline in Figure 3, the implementation of the ASP and intervention curricula was completed by the end of September 2019. We started short-term follow-up data collection in October 2019, while the students were still enrolled in school and before they took final exams, to maximize our ability to locate them. During this process, we gathered the same data (on social-emotional skills, fluid intelligence, and emotion regulation) and followed identical procedures as at baseline. In addition, we collected teachers' reports on students' behavior at school, academic performance (specifically, math grades), and school dropout in February 2020. We followed the same procedures to digitize and clean all these paper reports in the three countries.

As we reported in our PAP, we planned a midterm data-collection process in July and August 2020 (six months after the intervention ceased) to study whether the impacts found remained stable or changed over time. Unfortunately, we were unable to collect such data at that time because COVID-19 hit and all schools were functioning virtually and were not systematically collecting student data. As of November 2021, we were still unable to conduct fieldwork because of the outbreak. Considering this time gap, it was no longer useful to conduct this follow-up.

Focus groups. To understand other potential mechanisms driving the short-term results and to obtain reports from parents and teachers, we implemented 24 virtual focus groups between February and March 2021. In each country, 4 focus groups were conducted with teachers and 4 with parents. These focus groups were separated by treatment arm so that we could inquire into each treatment effect. Parents and teachers were recruited from the list of participants. For methodological reasons, we recruited between 6 and 8 participants per group.

During these discussions, we gathered information that would allow us to complement the quantitative results from our analysis and to obtain information about potential mechanisms using parents' and teachers' input. For example, we included the following questions: i) "Have parents/teachers observed the same or different behaviors in their child as those identified in the short-term results?"; ii) "How easy/difficult is it for teachers/parents to teach skills such as perseverance, self-control, etc.?"; and iii) "What are the parents'/teachers' perceptions of and expectations for students?" In Appendix 1, we provide further details on the methods used and all the questions included in the qualitative component of our study.

3.2 Data Sources, Instruments, and Outcomes

All the outcomes measured in this paper were selected based on the conceptual framework presented in Section 2.2. A summary of outcomes, data source, and type of outcome is shown in Appendix Table A3.

A. Main Outcomes

We use administrative data provided by schools to measure the three primary outcomes: behavior at school, school dropout, and academic performance (math grades). As described in Section 3.1, we collected data on behavior at school and on math grades at baseline and endline. School-dropout data were collected at endline only.

a. Behavior at school. To proxy for bad behavior at school, we use teachers' reports. Each country has a different way of assessing behavior:

- El Salvador evaluates behavior using a Likert scale that ranges from Good, Very Good, to Excellent.
- Honduras provides an evaluation of behavior using a Likert scale that includes the following four categories: Good Behavior, Very Good Behavior, Excellent Behavior, and Outstanding Behavior.
- Guatemala does not conduct a behavior evaluation, but schools participating in the treatment were requested to evaluate behavior using the same Likert scale as in El Salvador.

Teachers submitted a printed report for each student enrolled in the school, which we subsequently digitized. We transformed the reports into numerical variables on a scale from 1 to 3 for El Salvador and Guatemala, and a scale from 1 to 4 for Honduras. In both cases, a higher value indicates better behavior. To standardize the measure of behavior reports among countries and schools, we define the outcome as a dummy indicator that equals 1 if the student has a behavior score above the median of the school they attend.[33]

[33] In El Salvador and Honduras, teachers were already collecting these data for school reports. In

b. School dropout. We referred to teacher reports to measure whether the participants dropped out and created a dummy indicator that equals 1 if the student abandoned school in 2019.[34] We collected dropout data from 868 students in the follow-up only.

c. Academic performance. We use students' grades as a proxy for academic performance. Since we do not have a standardized test for the three countries, we use math grades because the mathematics curricula in these three countries are similar and, therefore, comparable.[35] In all cases, a higher value indicates better math grades. To standardize the measure of math-grade reports among countries and schools, we define the outcome as a dummy indicator that equals 1 if the student has a behavior score above the median of the school they attend.

A potential concern in using teachers' reports to measure the main outcomes is that this reporting may be affected by teachers' knowing which students are participating in the ASP. We argue that this occurrence is unlikely because we requested the records of all students, without informing the teachers that we were going to use only the data from students participating in the ASP.

B. Mechanisms

According to the conceptual framework and existing evidence summarized in Heller et al. (2017) and Dinarte-Diaz and Egana-delSol (2023), behavioral outcomes correlate in a statistically significant way with skills such as self-control, emotion regulation, persistence, and prudence. For this reason, we collected data to measure proxies for these skills using the SoftGames (to measure socio-emotional skills) and Reactiva (to measure fluid intelligence and emotion regulation) applications.

Social-Emotional Skills

SoftGames was developed and used by Danon et al. (2023). It can be played on a tablet and

Guatemala, we asked teachers to do so for this study. As for 2023, data were collected for school reports in all three countries.

[34] We are able to measure school dropout only for students who i) were not enrolled in the same school (or in any other school in our sample) or ii) reported they were going to abandon the educational system (due to migration to another country, for example).

[35] Teachers in Honduras and Guatemala score performance between 0 and 100, and teachers in El Salvador report math grades with a score between 0 and 10.

includes three task-based games that allowed us to collect information to measure the following three social-emotional skills, which we aggregate to generate a social-emotional-skills index for our estimations.[36]

a. Perseverance. This skill is defined as a continued effort to do or achieve something despite difficulties or obstacles. To proxy for this skill, we estimate a measure of short-term perseverance using the Additions Game [37], similar to the Alan and Ertac Grit Task Alan and Ertac (2019). In this game, participants are given a tablet showing a set of additions that are easy or difficult to solve. After each round, the participants are asked to choose the level of difficulty of the next set. The outcome is measured as a dummy that equals 1 if a participant persists after failing in round 1, a round of high difficulty level as predetermined by the tablet.[38]

b. Self-control. This trait is defined as the tendency to avoid acting suddenly without thinking carefully about the consequences of an action.[39] We estimate this trait using the Go-NoGo task-based game, which measures the player's ability to inhibit an inappropriate response as determined by a Go-NoGo rule [40]. Specifically, the participant is presented with a square on the screen for a very short period. If the square is not black, the participant must touch the screen as quickly as possible (the "Go" stimulus). If the square is black (the "NoGo" stimulus), then the respondent must refrain from responding and touching the screen. A total of 72 trials are presented (48 "Go," 24 "NoGo"). The outcome is the number of times a participant responds correctly to the "NoGo" stimulus. The data are standardized relative to the comparison (*Clubs*) group.

c. Risk-averse behavior. A risk-taking behavior is any consciously or unconsciously con-

[36] The advantages of summary indexes are that they are more robust to overtesting and potentially more powerful than individual-level tests because they reduce random error in each outcome measure (Anderson, 2008). This summary index is a weighted mean of the three standardized skills measured, where the weights are calculated to maximize the amount of information captured in the index using an efficient Generalized Least Squares estimator.

[37] For papers related to the use or validation of this instrument, refer to Sule et al. (2019) and Duckworth and Quinn (2009).

[38] Unlike in Danon et al. (2023), our respondents are more likely to possess the required math ability (one- and two-digit addition).

[39] Alternatively, it is defined as the capacity to regulate attention, emotion, and behavior in the presence of temptation (Duckworth and Gross, 2014).

[40] For papers related to use or validation of this instrument, refer to Bezdjian et al. (2009) and Patton (1995).

trolled behavior with a perceived uncertainty about its benefits or detriment to the well-being of oneself or others (Trimpop, 1994). To measure risk-taking behavior, we used the Balloon Analogue Risk Task (BART)[41]. Participants were asked to maximize the number of points they could earn from pumping a balloon. They earned points for every pump but could lose all of their points if the balloon popped. Risk-taking was measured as the average number of pumps for the balloons that did not pop. We adjusted the values of this variable to reflect a different orientation of risk attitudes, so that risk-taking, reversed, defines the risk-aversion outcome.[42] If originally high scores indicated high risk-taking, reversing them means now lower scores indicate higher risk-taking. Thus, the greater the risk-taking reversed score, the more risk-averse the individual is. The data are also standardized relative to the comparison group for consistency.

Emotion Regulation

This trait is defined as all of the conscious and nonconscious strategies we use to increase, maintain, or decrease one or more components of an emotional response (Gross, 2001). To measure this skill, we use the Reactiva application (Amangeldiyev and Egana-delSol, 2018). This platform synthesizes the pioneering technology developed by MIT's Affective Computing Group (Picard, 1995; McDuff et al., 2015) with a bespoke platform tailored for conducting field research in behavioral economics. Specifically, we used the *affdex* software development kit created by Affectiva, a spin-off of Affective Computing Group. Affectiva's technology analyzes videos captured from the front camera of smartphones or tablets to proxy for emotions. It measures emotional reaction to different emotionally laden stimuli (negative and positive videos) based on face detection, facial-feature extraction, and expression classification. Via the front cameras of tablets, the computer vision algorithm identifies key landmarks on the face. The machine learning algorithm then an-

[41]For papers related to the validation of this instrument, refer to Lejuez et al. (2002).

[42]In Stata, *revrs* is a module to reverse variable value order. Reversing with the *revrs* command in Stata specifically means taking a variable's values and changing their order so the highest becomes the lowest and vice versa, effectively flipping the scale. For example, if a scale originally runs 1 to 5, reversing it would make 1 correspond to 5, 2 to 4, and so on, altering the dataset to reflect the inverse value for each entry. We used it to reverse the order of the risk-taking variable values so that it reflects risk-averse behavior, our outcome of interest.

alyzes pixels to classify facial expressions. The accuracy level of these algorithms (that is, success rate in predicting emotional state) is around 60%–80% (McDuff et al., 2015; Stockli, 2018). Affectiva's metrics indicate when individuals manifest a specific emotion or expression (for example, a smile) along with the degree of confidence.[43]

The Reactiva application, in particular, follows a protocol similar to that of Egana-delSol (2016a), Egana-delSol (2016b), and Egana-delSol et al. (2023) to construct arousal (proxy of alertness and stress) and valence (proxy of emotional self-regulation) indices at the onset of positive and negative stimuli using emotionally laden videos from the Geneva Affective Picture Database (GAPED) (Dan-Glauser, 2011). Valence is a composite emotional metric that measures overall emotional experience. Valence values from 0 to 100 indicate a neutral to positive experience, while values from -100 to 0 indicate a negative to neutral experience. We interpret a reduction of valence, either positive or negative, as a proxy of a decrease in the emotional reaction to a stimulus or, put differently, an increase in emotion regulation.

Arousal is defined as the physiological and psychological state of being awake or reactive to stimuli. Arousal values range from 0 to 100. We interpret a reduction of arousal as a proxy of a decrease in emotional reaction to a stimulus, or, in other words, as an increase in emotion regulation. We present more details about the rationale for using these metrics, our collection procedure for these measures, and how we analyzed them in Appendix 3.

Both outcomes, valence and arousal, were coded by averaging the 10 highest arousal or valence scores recorded with the Reactiva application during the interval in which the student is watching the emotionally laden videos from GAPED (Dan-Glauser, 2011). Based upon the confidence variable provided by Reactiva with each video observation, we keep only measures that are above the 30th percentile of the standardized AI confidence for the group of observations. First, for each country separately, and with respect to the control group's confidence, we standardize the confidence variable in the baseline; second, we trim observations that stem from videos that are below the 30th percentile of detection

[43] See Figure 4 in Appendix 3 for an illustration.

confidence;[44] finally, we standardize the remaining observations relative to the comparison group.

Fluid Intelligence and Fluid Intelligence after Stimuli

Fluid intelligence refers to the capacity to think logically and solve problems in novel situations, independent of acquired knowledge. To collect a proxy for fluid intelligence, we use a tool similar to Raven's Progressive Matrices (Raven, 1936).[45]

This nonverbal assessment tool presents a series of visual puzzles missing a piece, and the individual is required to identify the correct piece from a set of options. Each puzzle is designed to be increasingly complex, requiring more abstract reasoning, pattern recognition, and problem-solving skills, which are key components of fluid intelligence. Before the participant solves each matrix, we randomly show negative and positive stimuli using emotionally laden videos from GAPED (Dan-Glauser, 2011). The outcome is measured by calculating the percentage of correct answers after the positive and negative stimuli; we also calculate the total percentage of correct answers, irrespective of which stimuli were shown before the matrix. Then, these percentages are standardized with respect to the *Clubs* group. Thus, an increase in the score after the negative stimuli can be thought of as an increase in emotion regulation, but also in Mullainathan and Shafir (2013)'s concept of "mental bandwidth," which translates directly into better reasoning.

3.3 Baseline Summary Statistics

Table 1 reports the average characteristics of the participant schools, and Table 2 shows the average characteristics of participant students. In both tables, column (1) exhibits statistics for the total sample, column (2) for the students in *Clubs*, column (3) for any psychology-based intervention, and columns (4) and (5) for the *Virtue* and *Mindful* groups,

[44] To reduce the number of variables and ease the analysis, we only present in our tables the results with trimming at the 30th percentile, but the analyses conducted with these variables trimmed at the 10th, 20th, and 40th percentiles follow those with the variables trimmed at the 30th percentile.

[45] The Progressive Matrices are widely recognized for their ability to assess cognitive ability without being influenced by language and cultural background, making them a valuable tool in the study of fluid intelligence.

respectively. On average, more than half of participating schools are located in very violent communities, and around 71% are in urban areas. The schools are midsized in terms of enrollment (an average of 410 students in grades 1-9). Most schools have their own building (81%), are connected to a water supply (86%), and have computers within the facilities (76%). Finally, around 81% of schools have a food program for students, but less than 50% of schools provide health services.

Moreover, Table 2 shows that, of the total sample of 897 participant students, 49% are girls and the average age is 14 years. The students' average travel time from home to school is 14.5 minutes. On average, 37% of these adolescents are not living with both parents, which is typical for households in these three countries. Only 2% of students report having tried to emigrate to the United States, and 13% report currently working. In terms of the main outcomes, 81% of students have a behavior-report score that is above the school median, and 57% have a math-score report that is higher than the school median.

Regarding mechanisms, 30% of students persisted after failing the first round in the Additions Game, indicating low perseverance. The average student responded correctly to 86% of the "NoGo" stimuli, which indicates high self-control. The average score in the risk-aversion measure was 32 out of 38 points. Thus, students in our sample have a low tendency to take risks. In terms of fluid intelligence, our sample shows that 61% of the time students answered correctly the progressive matrices of the Raven-like test. This result remains similar when measuring the percentage of correct answers after positive (62%) or negative (58%) stimuli. Regarding arousal and valence, we find that students have relatively high arousal at baseline (68 out of 100) and a positive valence index (21 in the range -100 to 100).

3.4 Balance and Attrition

We test whether there are differences across ASP variations by comparing the means of the baseline variables at the school and student levels. We present unadjusted p-values and sharpened two-stage q-values to account for multiple hypothesis testing in Tables A4 and A5 for the school and student characteristics, respectively. Overall, our balance tests indicate that schools assigned to the different ASPs are statistically similar in their average characteristics, except for school location: all schools in the *Mindful* ASP are in urban areas. Moreover, most of the individual and household characteristics are balanced across treatment arms, except students' age, students' course, student's travel time from home to school, and whether students are enrolled in the evening shift.[46] Moreover, some outcomes and mechanisms were imbalanced at baseline, including behavior at school, perseverance, risk-aversion behavior, fluid intelligence, arousal, and valence. We account for these differences by including the characteristics as controls and by using a difference-in-differences approach as the main estimation model, as we describe in the next section.

A potential concern is that our results might be driven by differences in matching rates with administrative data on the main outcomes or in survey response rates for the data on the mechanisms. To test whether there is differential attrition among treatment arms, we create an indicator that takes the value of 1 for students for whom we were not able to collect administrative data on the main outcomes (behavior, school dropout, or math grades) or whom we were unable to contact for collecting mechanism data (social-emotional skills, fluid intelligence, and emotion regulation) at endline. Our estimations indicate an average survey attrition rate of 18% and an average matching rate with administrative data of 99%. These rates are only slightly higher than in previous studies conducted in similar contexts (Dinarte-Diaz and Egana-delSol, 2023). As presented in Appendix Table A6, the estimations indicate that the matching rates with administrative data and attrition rates in the survey are balanced across all treatment arms.

[46] Because of limited infrastructure, and to meet most of the demand for education, schools in El Salvador operate in two shifts, one in the morning and another in the afternoon.

4 Empirical Strategy

4.1 Empirical Methods

Given our randomized experimental design, it is straightforward to measure the intent-to-treat effects of the interventions on the outcomes of interest using Ordinary Least Squares. However, since differences exist in the means of our outcomes of interest measured at baseline, we measure the net effects of the SEL component of the ASP (beyond the effects of the protection component) on our main outcomes using a difference-in-differences approach and estimate the following equation:

$$Y_{ist} = \mu_0 + \mu_1 AnyT_{is} + \mu_2 AnyT_{is} \times Post + \gamma X_{isj} + \pi_j + \varepsilon_{isjt} \tag{1}$$

Here, Y_{ist} is the outcome for student i at school s during period t. $AnyT_{is}$ is a dummy indicating that a student is enrolled in a school that was randomly assigned to treatment *Virtue* or *Mindful*. $Post$ is the post-intervention indicator variable.[47] X_{isj} is a vector of baseline control variables that includes the $Post$ indicator, an indicator for whether the baseline outcome was missing,[48] and the variables that are not balanced between treatment arms at the student level: student's age, course, travel time from home to school, and whether the student is enrolled in the evening shift. π_j captures stratum fixed effects for the six strata—the interaction between country and whether the school is located in a highly violent community. Because of our small number of classrooms, we use wild cluster bootstrap at the classroom level (Cameron et al., 2008) in all our estimations. We also conduct Least Absolute Shrinkage and Selection Operator (LASSO) analysis to identify variables with strong relationships with Y_{ist}, to assess their suitability for inclusion as controls in equation (1) following Bruhn and McKenzie (2009), and to confirm the stability

[47] For the dropout outcome, we estimate the model only with one difference, as we do not have baseline data.

[48] To reduce the number of observations lost because of missing data at baseline, we impute the value of the mean for each outcome at the school level and include an indicator (a dummy) of imputation in all estimations. We do not impute values in follow-up data.

of our estimated coefficients after including the control variables selected by LASSO for each of our main outcomes.

In this model, $\hat{\mu_2}$ captures the *net* SEL component of the ASP—that is, the short-term effect on dropout, behavior at school, and math grades of being assigned to participate in an ASP including a psychological curriculum (*Virtue* or *Mindful*) compared to only being protected (*Clubs*).

To measure the SEL component of each type of psychology-based intervention, we modify specification (1) to capture the effects of each treatment arm (*Virtue* and *Mindful*) relative to *Clubs*. Specifically, instead of including the indicator $AnyT_{is}$, we add two dummies ($Virtue_{is}$ and $Mindful_{is}$) that equal 1 if the student i is enrolled in a school s randomly assigned to *Virtue* or *Mindful*, respectively, and interact these indicators with the $Post$ variable as follows:

$$Y_{ist} = \theta_0 + \theta_1 Virtue_{is} + \theta_2 Mindful_{is} + \theta_3 Virtue_{is} \times Post + \theta_4 Mindful_{is} \times Post + \gamma X_{isj} + \pi_j + \varepsilon_{isjt} \tag{2}$$

All variables are defined as before. In this model, $\hat{\theta_3}$ and $\hat{\theta_4}$ capture the SEL component of each psychology-based curriculum relative to the effects from the *Clubs* ASP. Moreover, we test whether $\hat{\theta_3}$ = $\hat{\theta_4}$ to provide evidence of the differential impacts by type of psychology-based curriculum on the main outcomes of interest.

4.2 Heterogeneity Analysis

For the heterogeneity analysis of the main treatment effect, we use machine learning tools following the recent literature on heterogeneous treatment effects (Athey and Wager, 2019; Davis and Heller, 2017). This approach allows us to capture a high-dimensional combination of covariates that the researcher-specified interactions may miss. To this end, we estimate the first-difference conditional average treatment effect (CATE), using the first-difference causal forest (FDCF) algorithm (Athey and Wager, 2016, 2019; Athey et al., 2019), following Wang (2022). We train 100,000 trees using the honest approach (Athey and Wager, 2016; Athey et al., 2019). We include in the causal forest all the individual and household characteristics available at baseline and other school and neighborhood characteristics we collected.

We also follow Athey and Wager (2019) and Carlana et al. (2022) in using the predictions of the expected treatment effect for each student, given the set of covariates, to categorize participants into two groups, the *"Strong"* and *"Weak"* groups. This classification is achieved by categorizing the CATEs into three tiers: "High," "Medium," and "Low." The *"Strong"* group refers to the subgroup whose CATEs fall within the "High" category (that is, above the 66th percentile) of all CATEs when switching from *Clubs* to the *Mindful* or *Virtue* treatment. In contrast, the *"Weak"* group consists of participants with "Medium" and "Low" CATEs (that is, positioned at or below the 66th percentile). Then, to understand what types of students are more likely to see an increase in the main outcomes due to the interventions, we characterize the groups using a balance test.

5 Results

5.1 Main Results

Table 3 presents the main results of our paper. We show the net impact of the SEL component—beyond the regular protection component—estimated using equation (1) on the primary student outcomes measured using administrative data: an indicator for whether the behavior at school report was above the school median (column (1)), an indicator for whether the students abandoned school during the 2019 academic year (column (2)), and an indicator for whether the math-score report was above the school median (column (3)).

The impact estimates show positive and significant effects on students' behavior at school. Compared to students in *Clubs*, participants in the psychology-based interventions (*Virtue* and *Mindful*) are 23 pp more likely to be better behaved at school. This improvement is equivalent to an increase of 36% relative to the share of students in the ASP's protection component with an above-the-median behavior score. We find no statistically significant effects of the SEL component on school dropout and math grades. These results are robust to the selection of control variables using LASSO (Table A7). Moreover, these estimated impacts align with focus group feedback from parents and teachers, who perceived that program participants improved their behavior at school and tendencies toward violence outside school.

Taken together, these results are consistent with the evidence that adding psychology-based curricula to interventions such as traditional ASPs (in this case, *Clubs*) is essential to increase the impact of the interventions on students' behavior at school (Dinarte-Diaz and Egana-delSol, 2023). Note that these effects are on top of the effects of *Clubs*. Our finding of positive effects from the net SEL component on behavior at school aligns with existing evidence of the positive effects of other socio-emotional-skills curricula used in previous high-quality interventions for adolescents (Vandell et al., 2007; Heller et al., 2017; Dinarte-Diaz and Egana-delSol, 2023). For example, Vandell et al. (2007) find that high-quality ASPs can improve behavior among disadvantaged students in the United States. Similarly, Heller et al. (2017) find that the Becoming A Man program for youth in Chicago reduced violent-crime arrests. In El Salvador, Dinarte-Diaz and Egana-delSol (2023) estimate positive effects on participants' violent behaviors of an ASP that includes components of cognitive behavioral therapy, using teachers' reports of behavior at school and students' self-reports of violent behaviors.

We argue that the finding of no impact of SEL on school dropout or math grades is not surprising since we are evaluating the net effect of the SEL of the ASP, which does not target academic performance directly. It may be expected, however, that some of the skills learned through the psychology-based intervention, such as perseverance, indirectly affect academic performance. Yet the evidence from psychology has found that grit, a measure of perseverance in effort, is only modestly correlated with teacher ratings in math scores ($r \leq 0.25$) (Usher et al., 2019). Moreover, evidence of positive effects of psychology-based interventions on academic performance through perseverance comes from programs based on the concept of mindset (Bettinger et al., 2018) or based on math-specific self-perceptions of perseverance, which capture students' perceived tendency and ability to persevere at challenging math problems (Miele et al., 2022). Thus, we may need either interventions with a stronger focus on math-specific perseverance or different approaches from the ones explored in this study.

5.2 Heterogeneous Effects of the ASP's Socio-Emotional-Learning Component

We study the differential impacts of the SEL component on behavior following the machine-learning approach discussed in Section 4.2. Table 4 presents the first-difference CATE for behavior at school, for the *"Strong"* and *"Weak"* groups, as defined in Section 4.2. Additionally, we characterize the groups using a balance test for the baseline variables. We present the differences shown by the balance tests (column (3)) along with the corresponding p-values adjusted for the Benjamini-Hochberg procedure for multiple-hypothesis testing for that difference across these groups (column (4)).

Overall, the results indicate that the most vulnerable students are benefiting the most from the SEL component—that is, they are overrepresented among students with a higher CATE. For example, the program has a larger impact on male and older students, on those with worse behavior at school before the intervention, and on those enrolled in a higher-level course (which is related to age). Moreover, students with greater exposure to risks are also benefiting more from the intervention. Specifically, students who are enrolled in the afternoon shift (and thus less likely to have adult supervision during the morning), or who are less likely to be working[49] are overrepresented in the Strong CATE group.

Household and school/neighborhood characteristics support the result that the most vulnerable students benefit the most from this intervention. First, the *Strong* group is overrepresented by students living only with their mothers (and underrepresented by students living with both parents), who are less likely to have adult supervision compared to those living with both parents. This result aligns with existing evidence from Chile that the effects of an ASP are larger for children who at baseline spent after-school hours at home alone (Martínez and Perticará, 2020). Second, the average number of years of education

[49]Based on our discussions with the NGO, we interpret this result as follows: if students are working, they are busier (have less unsupervised time) and probably are less exposed to risks. Also, working students attend fewer sessions, which makes them less likely to benefit from the curricula.

of the mother is larger in the *Strong* group relative to the *Weak* group. In Central America, women with higher levels of education are more likely to be employed in formal (non-domestic) full-time jobs and thus their children are more likely to be alone after school. Additionally, the *Strong* group is overrepresented by students attending schools located in urban communities or communities affected by higher crime. These results also point to a larger impact in contexts in which socio-emotional skills or emotion regulation might be more important.

Last, we find statistically significant differences in fluid intelligence and arousal between both groups, which indicate that students with worse scores and higher stress/alertness, as proxied by arousal, at baseline are more likely to be more responsive to the psychology-based interventions (that is, they are in the *Strong* group).[50]

5.3 Mechanisms

We explore three potential mechanisms for the SEL component of the ASP: socio-emotional-skills, fluid-intelligence, and emotion-regulation measures. Table 5 shows the net SEL effects on these potential channels.

We only find evidence of emotion regulation as a mechanism driving the effects of the SEL component. Our results show that students who participated in the variation of the ASP that included a psychology-based intervention reduced their valence score by 0.24 sd relative to students assigned to the variation that includes only a protection component.[51] The program is most likely affecting the capacity to be aware of emotions and be less affected by and impulsive about emotionally laden triggers. We argue that a decrease in valence indicates that participants became emotionally and behaviorally calmer and less impulsive. Such a calming effect is particularly beneficial to individuals who live in a

[50] We observe a larger share of students from El Salvador and Honduras in the *Strong* group relative to the *Weak* group, which may indicate more local capacity of the implementing partner in those two countries relative to Guatemala. This greater capacity may translate into more efficient identification of good volunteers and more trust on the part of the communities, which may increase the overall effectiveness of the intervention.

[51] These results are robust to the inclusion of control variables selected using a Double-LASSO procedure, as we show in Table A8.

violent environment and are prone to violence. These results are consistent with previous estimates of the impact of an ASP based on cognitive behavioral therapy, a well-studied psychology-based curriculum, on valence using biomarkers in El Salvador (Dinarte-Diaz and Egana-delSol, 2023).

We rule out that, in this context, the net effects of the average SEL components are driven by changes in socio-emotional skills or fluid intelligence. A potential explanation of this finding is that we are estimating average effects from two interventions that, by design, are targeting different skills, as discussed in Section 2.2. On the one hand, *Mindful* is expected to improve fluid intelligence, self-control, and emotion regulation. On the other hand, *Virtue* improves perseverance, self-control, risk-taking behaviors, and emotion regulation. Pooling the effects of both curricula may be biasing the average effect on these measures toward zero. We explore this hypothesis in the next section.

In sum, important policy implications regarding the implementation of these interventions arise from these results. Early findings in Davidson et al. (2003) suggested that impulsive aggression and violence are positively associated with lack of emotion regulation. More recent work finds a similar association between maladaptive cognitive-emotion-regulation strategies and violence-related behaviors among adolescents in the United States (Bao et al., 2016). Thus, psychology-based curricula should be incorporated into ASPs to ensure the greatest impacts, particularly for at-risk adolescents.

5.4 Which Curriculum with a Social-Emotional-Learning Component Is More Effective?

As demonstrated previously, the psychology-based ASP improves behavior at school and reduces student valence. To understand which of the two psychology-based curricula is driving these effects, we measure the impacts of each curriculum separately using equation (2). We present the impacts on the main outcomes in Table 6 and the effects on potential mechanisms in Table 7.

We document three main results. First, we find that relative to the pure ASP (*Clubs*), both curricula have similar impacts on behavior at school (23 pp). We are not able to reject the null hypothesis of equality of the two estimated impacts (p-value = 0.868). Thus, the net SEL component can add to the effectiveness of the pure protection component by including either psychology-based curriculum. When we look at other main outcomes, however, we find that the *Mindful* curriculum is more effective at reducing school dropout compared to students in the *Virtue* variation. We find a reduction of 4.0 pp in school dropout relative to the *Clubs* ASP (p-value = 0.120, Table 6) and 5.6 pp (-4.0 pp $-$ 1.6 pp) relative to the *Virtue* ASP (p-value = 0.020, Table 6). The effect relative to the control is sensitive to the controls included, but the difference between the larger effect (*Mindful*) and the *Virtue* effect with respect to the control remains when controls are selected using LASSO (p-value = 0.008, Table A9). The positive effect of a mindfulness-based curriculum on school dropout is consistent with existing evidence of an association between mindfulness and adolescents' intention to drop out of school in the United States (Carsley et al., 2017) and with a meta-analysis showing that interventions implemented in schools promise to improve children's and youths' resilience and academic performance in general (Zenner et al., 2014).

Second, we explore the effects of these two curricula separately on the socio-emotional-skills index and fluid-intelligence and emotion-regulation measures. Moreover, since each curriculum may affect different skills included in the socio-emotional-skills index, we estimate the main effects of each curriculum on these skills separately. We find that the effects of each type of curriculum on behavior at school, relative to the *Clubs* ASP, are driven by effects on different mechanisms. The effects from the *Virtue* ASP may be driven by reduction in risk-taking (0.025sd) and valence (0.27 sd), whereas the effects of the *Mindful* ASP seem to be driven by improvements in fluid intelligence after exposure to negative stimuli (0.22 sd).

Last, we document that the differential impacts of *Mindful*, relative to *Virtue*, on school dropout may be driven by improvements in fluid intelligence after negative stimuli (0.34 sd, p-value = 0.005). In other words, if the mindfulness-based program can increase concentration capacity, measured as a greater score in fluid intelligence, that would increase the mental bandwidth of the individual and reduce their probability of abandoning school.[52]

Overall, these results contribute to the existing body of research that shows the positive effects of mindfulness on an array of behaviors and outcomes of adults (Keng et al., 2011). The main feature of the *Mindful* intervention is that it is low cost, which is an attractive feature of public policy. Based on the impacts estimated from the ASP, an ASP should also include an evidence-based curriculum oriented toward improving student outcomes. We find that the *Mindful* intervention is the best curriculum to add to *Clubs* to help vulnerable youth in poor and highly violent countries.

5.5 ASP Attendance

We first explore the differences in ASP attendance by ASP variation using data obtained from reports from volunteers. Table 8 shows the results from estimating a version of specification (2), which excludes the interactions with the *Post* variable. Column (1) presents the effects on attendance (as a percentage of the total sessions scheduled), column (2) shows the effects on an indicator of whether the student dropped out of the ASP, and column (3) presents the effects on the number of sessions scheduled. We find that, on average, students assigned to *Clubs* attended 61% of the scheduled sessions. The attendance rate was greater for the *Virtue* intervention relative to both *Clubs* and *Mindful* (column (1)). Moreover, students in the *Virtue* ASP are 11 pp less likely to abandon the intervention relative to students assigned to *Clubs* (column (2)). We show that these differences in attendance are not driven by differences in number of sessions scheduled in each type of ASP variation (column (3)). Considering the ASP attendance and dropout results together, we show that the *Virtue* ASP was more attractive to the students assigned to it since they attended a greater share of sessions relative to both *Mindful* and *Clubs* and they were less likely to abandon the intervention relative to *Clubs*.

[52]Overall, these results are robust to the inclusion of control variables selected using a Double-LASSO procedure, as we show in Table A10.

5.6 Cost-Benefit Analysis

Cost estimates provided by Glasswing International indicate that the average cost of a seven-month-long ASP intervention per student is US$296.5. The cost is US$269.4 for *Clubs*, US$292.5 for *Mindful*, and US$327.6 for *Virtue*.[53] Based on the literature that estimates the relationship between human capital interventions and impacts on adult earnings (Holla et al., 2021; Ganimian et al., 2021; Galasso and Wagstaff, 2019) and following the framework of Hendren and Sprung-Keyser (2020) for estimating the marginal value of investments using public funds, we conducted a calculation of the program's approximate benefit–cost ratio.[54]

Our estimates indicate that the present discounted value of earning gains expected to result from ASP-induced improvements in behavior at school and an indirect potential reduction in school dropout yields a benefit–cost ratio that ranges from 11.3 to 45.2. Consequently, this program should be encouraged as a public policy, as the intervention is likely to pay for itself even in the short run and has the potential to generate large additional welfare gains in the long run.

6 Conclusions

This paper provides an experimental evaluation to understand the effect of different ASP curricula implemented in three developing and highly violent countries on adolescent behavior at school, academic performance, socio-emotional skills, and emotion regulation. To our knowledge, this is the first study to use AI technology and task-based games to estimate proxies for the difficult-to-measure competencies of socio-emotional skills and emotion regulation.

To achieve our end, we created exogenous variation by randomly assigning partici-

[53]Similar interventions involving at-risk youths in the Unitedd States (Heller et al., 2017) are 6.8 times more expensive per participant (in nominal terms, or 3.1 times more expensive in PPP terms) than the average of the interventions involved in this study.

[54]For more details of our approach, see Appendix 4 and Table A12.

pant schools to three ASP interventions: one based only on recreational activities such as sports, art, and dancing (*Clubs*) and two psychological interventions based, respectively, on a curriculum that aims to strengthen character and virtues (*Virtue*) and a mindfulness-and-relaxation program (*Mindful*). Every *Virtue* and *Mindful* meeting was immediately followed by *Clubs* activities. By comparing the average outcomes of students enrolled in schools assigned to either of the two psychology-based curricula with students enrolled in schools assigned to *Clubs*, we measure the net socio-emotional-learning channel. We provide evidence that the psychology-based interventions improve students' behavior at school and decrease valence, a proxy for emotion regulation.

We also find policy-relevant heterogeneous effects. First, the psychology-based curriculum has larger effects on students more vulnerable to violence: boys, students older than 14 years, those with bad or average school behavior at baseline, those in urban schools within high-homicide-rate municipalities, and those not living with both of their parents. Second, the type of psychology-based curriculum matters. On average, the *Virtue* curriculum affects student behavior, risk-taking, and emotion regulation (that is, valence). Meanwhile, the *Mindful* curriculum improves behavior at school, decreases school dropout relative to *Virtue*, and increases fluid intelligence after negative stimuli. Therefore, we conclude that *Mindfulness*, which is a standard intervention, is more effective in improving students' outcomes.

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7 Tables and Figures

Table 1: **Mean School Characteristics by Treatment Group**

	(1) Full Sample	(2) *Clubs*	(3) *Virtue* or *Mindful*	(4) *Virtue*	(5) *Mindful*
School characteristics					
School is located in a highly violent community	0.52	0.43	0.57	0.43	0.71
School is in an urban area	0.71	0.57 †	0.79+	0.57	1.00
Total school enrollment (1st to 6th courses)	306.62	269.86	325.00	302.86	347.14
Total school enrollment (7th to 9th courses)	104.29	81.43	115.71	145.00	86.43
School has its own building	0.81	0.71	0.86	0.86	0.86
School is connected to a water supply	0.86	0.86	0.86	0.86	0.86
School has computers	0.76	0.86	0.71	0.71	0.71
School has a health program for students	0.43	0.29	0.50	0.43	0.57
School has a food program for students	0.81	0.71	0.86	0.71	1.00
Observations	21	7	14	7	7

Notes: This table shows descriptive statistics of the available variables at baseline for the sample of participant schools. All information was obtained at the school level. Data were obtained from the Educational Censuses for El Salvador and Guatemala (2018) and self-collected by the authors for Honduras. Column (1) presents the mean characteristics for the full sample of schools and column (2) for the schools assigned to the *Clubs* group. The average characteristics for schools assigned to either of the psychology-based interventions are presented in column (3). Characteristics for schools in each of the interventions (*Virtue* or *Mindful*) are presented in columns (4) and (5), respectively. Total school enrollment refers to the enrollment in the school, not to the ASP or study. "Observations" indicates the number of schools within each group. The symbols representing unadjusted *p*-values in the balance tests for all available variables are as follows: Clubs vs (Mindful + Virtue): *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Clubs vs Mindful: † † † $p<0.01$, †† $p<0.05$, † $p<0.1$. Clubs vs Virtue: §§§ $p<0.01$, §§ $p<0.05$, § $p<0.1$. Mindful vs Virtue: +++ $p<0.01$, ++ $p<0.05$, + $p<0.1$. For more information on balance tests, exact *p*-values, see Table A4 in the Appendix.

Table 2: **Mean Student Characteristics at Baseline by Treatment Group**

	(1) Full Sample	(2) *Clubs*	(3) *Virtue* or *Mindful*	(4) *Virtue*	(5) *Mindful*
Individual Characteristics					
Female	0.49	0.50	0.49	0.52	0.45
Student's age	13.55*	13.87	13.36	13.35	13.36††
Student's course	7.33	7.37	7.30	7.29	7.32†
Student is enrolled in the afternoon shift	0.40***	0.64	0.25	0.08§§§	0.44††
Travel time (minutes from home to school)	14.50**	16.41	13.32++	14.88	11.57††
Student has tried to immigrate to USA	0.02	0.03	0.01	0.01	0.02
Student works	0.13*	0.15	0.11	0.11	0.11
Household Characteristics					
Student's household composition					
Student lives with both parents	0.63	0.62	0.63	0.66	0.60
Student lives only with mother	0.29	0.30	0.28	0.26	0.31
Student lives only with father	0.02	0.01	0.02	0.02	0.02
Student lives with other relatives	0.07	0.06	0.07	0.05	0.08
Student lives with unrelated adult	0.00	0.01	0.00	0.00	0.00
Mother's education level					
Years of education	7.60	7.42	7.71	7.96	7.45
Main Outcomes					
Behavior at school	0.81*	0.86	0.78	0.74§	0.82
Math grades	0.57	0.56	0.57	0.55	0.59
Mechanisms					
SES Index	0.83	0.86	0.81	0.73	0.89
Short-term perseverance	0.30	0.32	0.29	0.29	0.28†
Self-control	0.86	0.85	0.86	0.85	0.88
Risk-aversion	31.88*	32.07	31.76	31.61§§	31.93
Fluid intelligence	0.61	0.62	0.60	0.61	0.59††
Fluid intelligence after negative stimuli	0.58	0.60	0.57	0.59	0.55†††
Fluid intelligence after positive stimuli	0.62	0.63	0.61	0.62	0.60††
Arousal	68.08	66.40	69.08+	65.86	71.99††
Valence	20.94	18.90	22.16++	18.69	25.28††
Observations	897	341	556	294	262

Notes: This table shows average student characteristics and outcomes at baseline for the sample of participants. Column (1) presents mean characteristics for the full sample. Columns (2) and (3) show mean characteristics for the pure-control and *Clubs* groups. Average characteristics for participants assigned to either of the psychology-based interventions are presented in column (4) and for each of the interventions, *Virtue* and *Mindful*, in columns (5) and (6), respectively. A description of individual and household characteristics is presented in Appendix 2. Details on the outcomes and mechanism variables are discussed in Section 3.2. All data on individual and family characteristics and outcomes were collected by the authors during the enrollment phase and baseline data collection using the different instruments as summarized in Table A3. "Observations" indicates the number of students within each group. The symbols representing unadjusted p-values in the balance tests for all available variables are as follows: Clubs vs (Mindful + Virtue): *** p<0.01, ** p<0.05, * p<0.1. Clubs vs Virtue: §§§ p<0.01, §§ p<0.05, § p<0.1. Clubs vs Mindful: † † † p<0.01, †† p<0.05, † p<0.1. Mindful vs Virtue: +++ p<0.01, ++ p<0.05, + p<0.1. For more information on balance tests, exact p-values, and adjusted sharpened two-stage q-values, see Table A5 in the Appendix.

Table 3: **Effects of ASP Social-Emotional Learning on Behavior and Academic Outcomes**
(Intention-to-Treat Estimates)

	Behavior at School (1)	School Dropout (2)	Math Grades (3)
Psychology-based curricula	0.232***	-0.010	-0.017
	(0.078)	(0.023)	(0.076)
	[0.015]	[0.640]	[0.860]
Mean pure club group	0.650	0.037	0.587
MDE	0.068	0.037	0.099
Observations	887	868	855
R-squared	0.076	0.076	0.019

Notes: This table shows the estimated impacts of the ASP's social-emotional learning on behavioral and academic outcomes. *Psychology-based intervention* is a dummy equal to 1 if the student was enrolled in a school that was randomly assigned to the *Virtue* or *Mindful* intervention, and 0 if assigned to *Clubs*. *Mean pure club group* is the mean of the outcome for the group that only participates in *Clubs*, without any extracurricular activity. We present the estimated coefficient $\hat{\mu_2}$ from specification (1). The description of dependent variables is available in Section 3.2. *Behavior at school* is a dummy that equals 1 if the student's behavior report is above the school median. *School dropout* is a dummy variable that equals 1 if a student dropped out of any school in our study in the 2019 academic year. *Math grades* is a dummy that equals 1 if the student's behavior report is above the school median. All outcomes were obtained from administrative data sources (namely, teachers' reports). Sample size in each specification varies according to the number of observations available for each outcome. Estimations include all individual controls for which there is an imbalance at baseline. All regressions include randomization-block (strata) fixed effects. Strata are defined as country and violence level (high or low) of the community in which the school is located. Wild bootstrap standard errors are shown in parentheses, and adjusted p-values are in brackets. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 4: **Conditional Average Treatment Effect (CATE): Behavior at School**

	"Strong" Group (1)	"Weak" Group (2)	Diff. (3)	MHT. *p*-value (4)
ITT behavior at school	0.259	0.212	0.047	
Individual Characteristics				
Female	0.420	0.525	-0.105	0.006
Student's age	13.730	13.475	0.255	0.014
Bad or regular behavior at school at baseline	0.904	0.723	0.181	0.000
Student is enrolled in the afternoon shift	0.573	0.320	0.253	0.000
Student's course	7.659	7.164	0.495	0.000
Travel time (minutes from home to school)	15.181	14.197	0.984	0.349
Student has tried to immigrate to USA	0.031	0.015	0.016	0.214
Student works	0.099	0.144	-0.045	0.068
Household Characteristics				
Student's household composition				
Student lives with both parents	0.519	0.682	-0.163	0.000
Student lives only with mother	0.406	0.231	0.175	0.000
Student lives only with father	0.007	0.022	-0.015	0.068
Student lives only with other relatives	0.075	0.063	0.012	0.572
Mother's education level				
Years of education	8.563	7.116	1.447	0.000
Mechanisms				
SES Index	-0.069	-0.104	0.035	0.627
Fluid Intelligence	-0.207	-0.052	-0.155	0.074
Arousal	0.169	-0.012	0.181	0.028
Valence	0.114	0.070	0.044	0.622
School and Neighborhood Characteristics				
School is urban	0.956	0.569	0.387	0.000
School is located in a highly violent community	0.853	0.145	0.708	0.000
Country				
El Salvador	0.372	0.287	0.085	0.021
Guatemala	0.191	0.632	-0.441	0.000
Honduras	0.437	0.080	0.357	0.000
Observations	293	585		

Notes: "Strong Group" refers to subgroups whose conditional average treatment effect (CATE) is above the 66th percentile of all CATEs when switching from *Clubs* to the *Mindful* or *Virtue* treatment, and equal or below to the 66th percentile for the "Weak group." A positive number in the "Difference" column indicates that the average covariate value for the "Strong" subgroup is higher. *P*-values for the difference between groups are shown in the fourth column (using Benjamini-Hochberg correction for multiple hypothesis testing).

Table 5: **Effects of ASP Social-Emotional Learning on Social-Emotional Skills and Emotion Regulation** *(Intention-to-Treat Estimates)*

	SES Index	Fluid Intelligence	Fluid Intelligence after Negative Stimuli	Fluid Intelligence after Positive Stimuli	Arousal	Valence
	(1)	(2)	(3)	(4)	(5)	(6)
Psychology-based curricula	0.003	-0.037	0.051	-0.027	-0.014	-0.245*
	(0.013)	(0.088)	(0.086)	(0.094)	(0.117)	(0.129)
	[0.845]	[0.700]	[0.600]	[0.830]	[0.910]	[0.050]
Mean pure club group	0.000	0.000	0.000	0.000	0.000	0.000
MDE	0.233	0.219	0.221	0.217	0.233	0.230
Observations	755	733	733	733	622	622
R-squared	0.043	0.045	0.032	0.030	0.034	0.024

Notes: This table shows the estimated impacts of the ASP's social-emotional learning on social-emotional-skills (SES) and emotion-regulation outcomes. *Psychology-based intervention* is a dummy equal to 1 if the student was enrolled in a school that was randomly assigned to the *Virtue* or *Mindful* intervention, and 0 if assigned to *Clubs*. *Mean pure club group* is the mean of the outcome for the group that only participates in *Clubs*, without any extracurricular activity. We present the estimated coefficient $\hat{\mu_2}$ from specification (1). The description of dependent variables is available in Section 3.2. All dependent variables are measured in standard deviations relative to the comparison group. Sample size in each specification varies according to the number of observations available for each outcome. Estimations include all individual controls for which there is an imbalance at baseline. All regressions include randomization-block (strata) fixed effects. Strata are defined as country and violence level (high or low) of the community in which the school is located. Wild bootstrap standard errors are shown in parentheses and adjusted p-values in brackets. $^{***}p < 0.01$, $^{**}p < 0.05$ $^{*}p < 0.1$

Table 6: **Which Curriculum Is the Most Effective? - Behavior at School and Academic Performance**
(Intention-to-Treat Estimates)

		Estimated Coefficient (1)	Standard Error (2)	*P*-value (3)	*P*-value Wild Bootstrap (4)	Mean Clubs Group (5)	P-value *Virtue*=*Mindful* (6)	Observations (7)
Behavior at school	*Virtue*	0.229***	(0.083)	(0.007)	[0.035]	0.650	0.868	887
	Mindful	0.236***	(0.079)	(0.004)	[0.020]			
School dropout	*Virtue*	0.016	(0.029)	(0.573)	[0.640]	0.037	0.020	868
	Mindful	-0.040*	(0.023)	(0.085)	[0.120]			
Math grades	*Virtue*	-0.054	(0.089)	(0.545)	[0.635]	0.587	0.447	855
	Mindful	0.023	(0.090)	(0.802)	[0.840]			

Notes: This table shows the estimated impacts of each type of psychology-based curriculum with a social-emotional-learning component. Descriptions of all dependent variables are available in Section 3.2. *Virtue* and *Mindful* are dummies equal to 1 if the student was enrolled in a school that was randomly assigned to the *Virtue* or *Mindful* intervention, respectively, and 0 if assigned to *Clubs*. In column (1), we present the estimated coefficients of the interaction between the treatment dummies and the *Post* indicator. Clustered standard errors, unadjusted *p*-values, and *p*-values adjusted using a wild bootstrap procedure (adjusted for a small number of clusters) are shown in columns (2), (3), and (4), respectively. *Mean Clubs Group* in column (5) is the mean of the outcome for the group that only participates in *Clubs*, without any extracurricular activity. Column (6) presents the *p*-value for the test for differences between estimated coefficients for *Virtue* and *Mindful* presented in column (1). Sample size in each specification presented in column (6) varies according to the number of observations available for each outcome. Estimations include all individual controls for which there is imbalance at baseline. All regressions include randomization-block (strata) fixed effects. Strata are defined as country and violence level (high or low) of the community in which the school is located. $^{***}p < 0.01,\ ^{**}p < 0.05,\ ^{*}p < 0.1$

Table 7: **Which Curriculum Is the Most Effective? - Social-Emotional Skills and Emotion Regulation**

Intention-to-Treat Estimates

		Estimated Coefficient (1)	Standard Error (2)	*P*-value (3)	*P*-value Wild Bootstrap (4)	Mean Clubs Group (5)	P-value *Virtue=Mindful* (6)	Observations (7)
SES index	*Virtue*	-0.000	(0.014)	(0.996)	[0.995]	0.000	0.381	755
	Mindful	0.007	(0.014)	(0.608)	[0.685]			
Short-term perseverance	*Virtue*	0.004	(0.010)	(0.736)	[0.725]	0.000	0.902	759
	Mindful	0.005	(0.008)	(0.576)	[0.580]			
Self-control	*Virtue*	-0.008	(0.012)	(0.497)	[0.530]	0.000	0.469	776
	Mindful	-0.013	(0.011)	(0.233)	[0.230]			
Risk aversion	*Virtue*	0.025**	(0.012)	(0.032)	[0.020]	0.000	0.066	773
	Mindful	0.004	(0.011)	(0.709)	[0.715]			
Fluid intelligence	*Virtue*	-0.116	(0.080)	(0.152)	[0.210]	0.000	0.244	733
	Mindful	0.037	(0.132)	(0.780)	[0.815]			
Fluid intelligence - after negative stimuli	*Virtue*	-0.119	(0.095)	(0.217)	[0.280]	0.000	0.005	733
	Mindful	0.220**	(0.089)	(0.016)	[0.010]			
Fluid intelligence - after positive stimuli	*Virtue*	-0.068	(0.091)	(0.456)	[0.555]	0.000	0.531	733
	Mindful	0.009	(0.132)	(0.944)	[0.930]			
Arousal	*Virtue*	0.027	(0.111)	(0.811)	[0.845]	0.000	0.617	622
	Mindful	-0.059	(0.171)	(0.731)	[0.720]			
Valence	*Virtue*	-0.270**	(0.106)	(0.013)	[0.030]	0.000	0.792	622
	Mindful	-0.211	(0.219)	(0.338)	[0.360]			

Notes: This table shows the estimated impacts of each type of psychology-based curriculum with a social-emotional-learning component. Descriptions of all dependent variables are available in Section 3.2. *Virtue* and *Mindful* are dummies equal to 1 if the student was enrolled in a school that was randomly assigned to the *Virtue* or *Mindful* intervention, respectively, and 0 if assigned to *Clubs*. In column (1), we present the estimated coefficients of the interaction between the treatment dummies and the *Post* indicator. Clustered standard errors, unadjusted *p*-values, and *p*-values adjusted using a wild bootstrap procedure (adjusted for small number of clusters) are shown in columns (2), (3), and (4), respectively. *Mean Clubs Group* in column (5) is the mean of the outcome for the group that only participates in *Clubs*, without any extracurricular activity. Column (6) presents the *p*-value for the test for differences between estimated coefficients for *Virtue* and *Mindful* presented in column (1). Sample size in each specification presented in column (7) varies according to the number of observations available for each outcome. Estimations include all individual controls for which there is imbalance at baseline. All regressions include randomization-block (strata) fixed effects. Strata are defined as country and violence level (high or low) of the community in which the school is located. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

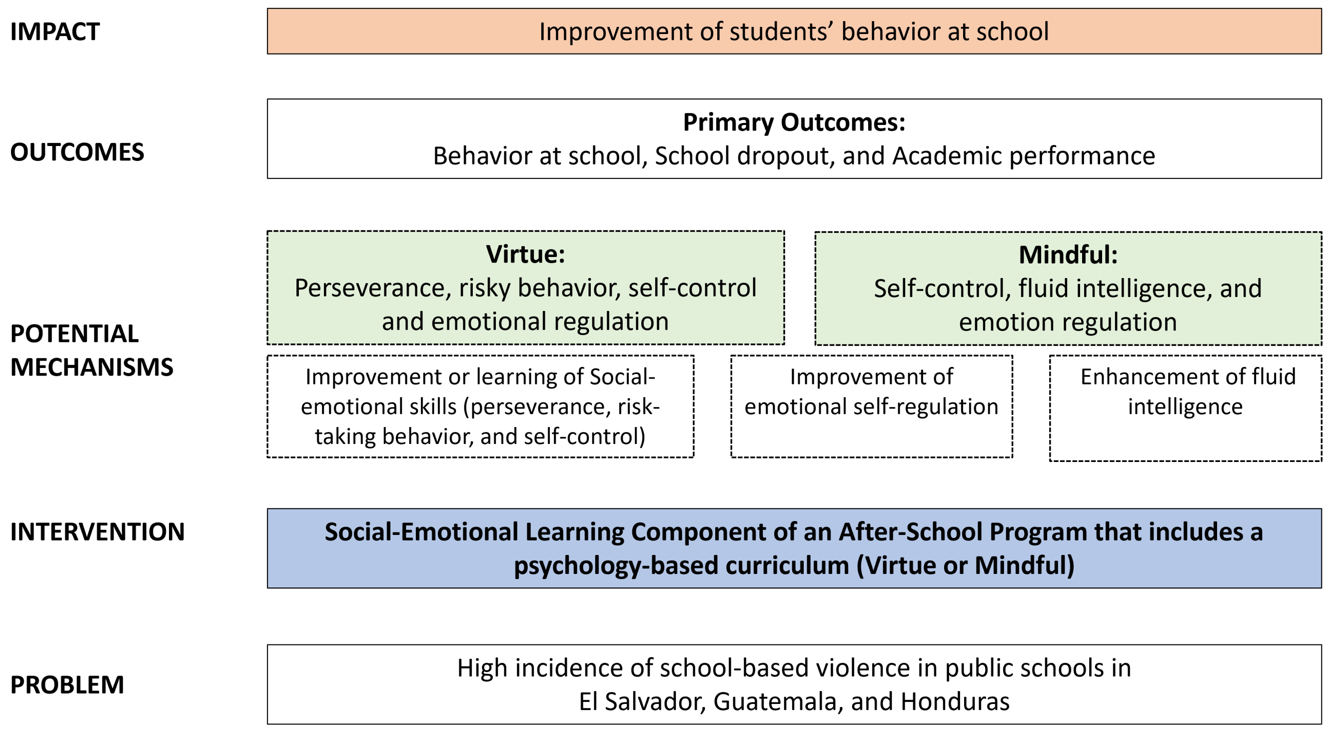
Table 8: **ASP Attendance and Dropout**

	Attendance (as % of sessions) (1)	Dropped the ASP (2)	Sessions scheduled (3)
Virtue	0.195***	-0.110**	0.235
	(0.048)	(0.046)	(3.548)
Mindful	0.064	-0.058	0.034
	(0.043)	(0.040)	(2.871)
Psychology-based curricula	0.131***	-0.084**	0.137
	(0.042)	(0.039)	(2.723)
P-value for *Virtue* = *Mindful*	0.0046	0.1598	0.9542
Mean *Clubs* group	0.6142	0.2258	42.7689
Observations	897	897	897

height

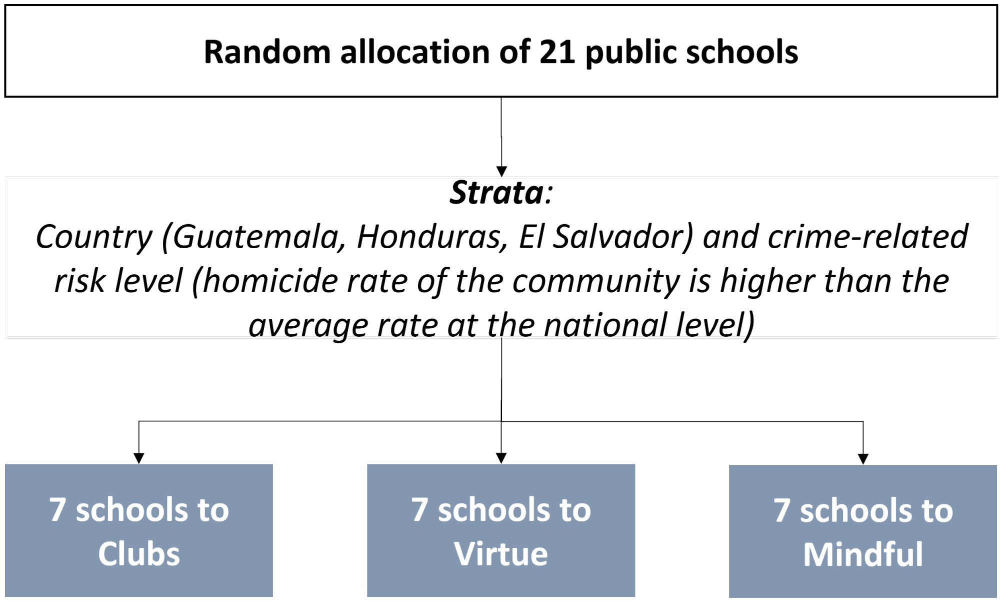
Notes: This table shows the ASP attendance rates. The estimation sample includes all students treated in *Clubs*, *Virtue*, or *Mindful*. It compares the attendance of participants randomly assigned to *Virtue* or *Mindful* to those treated in *Clubs*. Column (1) shows the attendance rate as a percentage of the number of total sessions conducted (column (3)). Column (2) presents the share of students who dropped out of the ASP. "Mean Clubs group" is the mean of the outcome for the group that participated in *Clubs*. The coefficients for both the *Virtue* and *Mindful* groups are derived from a unified regression analysis. Conversely, the coefficient on the broader category of psychology-based curricula is obtained from a distinct regression that employs a dummy variable set to 1 for students who participated in any such curriculum *(Virtue or Mindful)*. All estimations include the relevant control variables at baseline. Bootstrapped standard errors at the course level are in parentheses. $^{***}p < 0.01,\ ^{**}p < 0.05, ^{*}p < 0.1$

Figure 1: **Conceptual Framework**



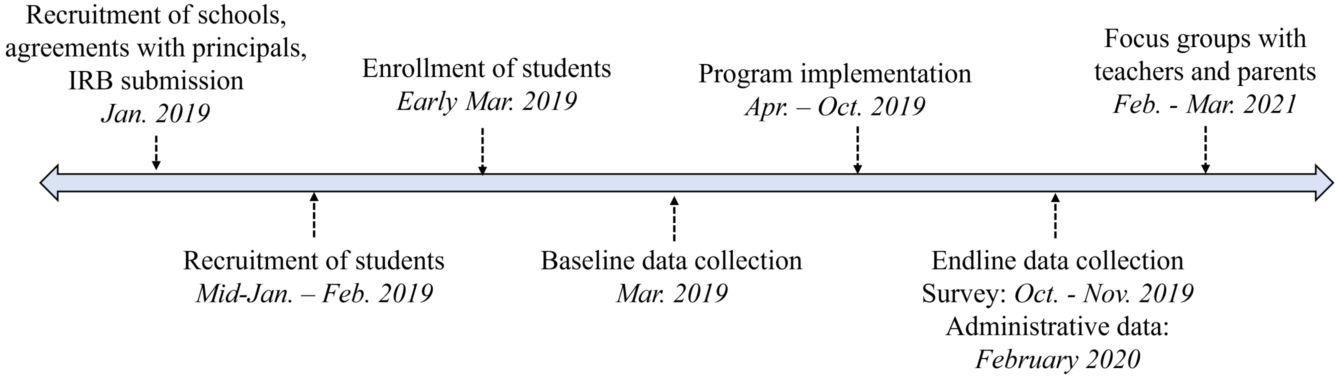
Notes: This diagram shows the conceptual framework for our analysis. For more details about this framework, see Section 2.2.

Figure 2: **Experimental Design**



Notes: This figure summarizes the experimental design that the authors developed to address this project's main research questions.

Figure 3: **Project Timeline**



Notes: This figure shows the timeline of the different activities implemented in the project. In 2019, the academic year for El Salvador and Guatemala spanned from January through November. In contrast, Honduras followed a slightly different schedule, with its school year running from February to November. Additionally, some schools in Honduras chose to extend their academic year into December.

Appendix for Online Publication Only

Appendix 1 Qualitative Study

This appendix provides further information on the methods used in the qualitative component of the study. The main results from this component are presented in the main text.

3.1 Approach and Structure

The qualitative study aims to obtain information to complement the quantitative results through focus group discussions. In these groups, instead of interviewing the students, we invited parents and teachers of students who took part in the study, either in any treatment or in the control group.

For the qualitative study, a narrative interviewing technique was used. It is a semi-structured approach that uses open-ended questions to permit more variation in responses. These focus groups create a natural in-depth discussion that yields specific details on the different components included in the survey instrument.

We organized a total of 24 focus groups between February and March 2021, with 8 focus groups per country. Within each country, we organized 2 focus groups for each treatment (*Virtue*, *Mindful*, *Clubs*) and the schools without ASP, one with teachers and another with parents.

The focus group discussions were virtual and lasted up to 1.5 hours. A local consultant with expertise in qualitative research and knowledge of the interventions conducted the interviews. The NGO recruited participants, obtained their informed consent, and organized the discussions. Then, the consultant conducted the focus groups and produced transcripts from them. Special care was taken to preserve participant anonymity and obtain consent. To maintain trust and safety, it was made clear to all participants that the purpose of the focus groups was to improve the quality of the extracurricular activities implemented in their children's schools by Glasswing International. Only audio of the conversations was recorded; no photos or videos were allowed.

3.2 Sample Distribution

In El Salvador, 30 parents of students enrolled in 10 schools participated in the focus groups (28 mothers and 2 fathers). Each group had between 6 and 8 participants. Similarly, 28 teachers working in 9 participating schools joined the focus groups, 20 being female and the rest male. These teachers taught students in grades four through nine. Each focus group for teachers included 5 to 8 participants.

In Honduras, we recruited 29 parents of students enrolled in eight participating schools; most were mothers. The focus group size was between eight and nine participants. For the focus groups with teachers, we recruited 27 teachers from the same participating schools. The participants were mostly women teaching students in grades four through nine. Each focus group had eight participants, on average.

Last, 23 parents of students who took part in the study joined the focus group discussions from the participating schools in Guatemala. Most of the participants were mothers or other female relatives (aunts or grandmothers); 2 were fathers. Each group included between 5 and 7 participants. The focus groups with teachers included 22 participants from the participating schools; 19 were women, and they taught students in grades four to nine. In each group, more than 6 people participated.

3.3 Instruments

The instruments include two sets of questions, tailored to teachers or parents. In the first set, we asked the following questions, which allowed us to complement or confirm our quantitative results:

- Did you observe changes in your students'/children's behaviors, emotion regulation, or social-emotional skills?
- Did you observe changes in how students used their time at home during the pandemic?
- How easy/difficult is it to teach some skills or academic content? For example, math versus perseverance, or control of impulsive behavior versus reading? How

confident do you feel that you can help your child with each of them?

In the second set of questions, we asked teachers and parents about themselves, aiming at obtaining information on potential mechanisms to explain the quantitative results. We asked the following:

- What are your academic or personal expectations of your students/children?
- How easy/difficult is it to teach some skills or academic content? For example, math versus perseverance, or control of impulsive behavior versus reading? How confident do you feel that you can help your child with each of them?
- Have you felt stressed or more anxious during the past two months?

Appendix 2 Description of Variables and Mechanisms Concerning Student and Household Characteristics

A. Household Characteristics

1. *Student lives with both parents:* dummy variable equals 1 if the student lives with both mother and father and otherwise equals 0
2. *Student lives only with mother:* dummy equals 1 if the student lives only with mother and otherwise equals 0
3. *Student lives only with father:* dummy variable equals 1 if the student lives only with father and otherwise equals 0
4. *Student lives with other relatives:* dummy variable equals 1 if the student lives with a relative (other than father or mother) and otherwise equals 0
5. *Student lives with an unrelated adult:* dummy variable equals 1 if the student lives with an unrelated adult and otherwise equals 0
6. *Mother's years of education:* a numeric variable representing the number of years of education completed by the mother

B. Student Characteristics

1. *Female:* dummy variable equals 1 if the student is female and otherwise equals 0
2. *Student's age:* a numeric variable that indicates the age of the student
3. *Student is enrolled in the afternoon shift:* dummy variable equals 1 if the student is enrolled in the afternoon shift and otherwise equals 0; because infrastructure is limited, schools in El Salvador operate in two shifts, one in the morning and another in the afternoon, to meet most of the demand

4. *Student's course:* a numeric variable that indicates the course the student is enrolled in

5. *Travel time (home to school):* a numeric variable that indicates how long (minutes) it takes the student to walk to school

6. *Student has tried to immigrate to the USA:* dummy variable equals 1 if the student has tried to immigrate to the USA and otherwise equals 0

7. *Student works:* dummy variable equals 1 if the student works and otherwise equals 0

Appendix 3 Measuring Emotions Using an Artificial Intelligence (AI) Algorithm

Why use computer vision to proxy emotional reactions?

Many studies have shown that emotions play a role in economics. For example, they affect decision-making, investment behaviors, and human capital accumulation, among other things (Weber and Johnson, 2009). The main objective of Reactiva is to measure emotional reactions to different emotion-laden stimuli based on AI-powered computer vision in the context of social-program evaluations in the field.

This tool was developed because of the need to proxy the social-emotional dimensions of human capital in a more objective way than through self-reported tests (such as the Grit Test, Locus of Control Test). In particular, through this tool, we can estimate both positive and negative emotional reactions to stimuli based on videos from the GAPED database in the arousal and valence dimensions.

We hypothesize that programs that aim to improve social-emotional skills, such as cognitive behavioral therapy, will tend to reduce the valence and arousal of emotional reactions to negative stimuli while maintaining, or even reducing, reactions to positive stimuli. Moreover, we expect that the effect of negative stimuli will decrease. To test our hypothesis, we added Raven-like matrices after both negative and positive stimuli to observe whether this affected the subjects' capacity to provide the correct responses to these questions, which is a proxy for fluid intelligence. In other words, we expect to observe a decrease in performance in these Raven-like tests after subjects observe a video that induces negative emotion. Unfortunately, there is no evidence on how these metrics of emotional reactions correlate with the self-reported tests of social-emotional skills typically used in the literature.

Moreover, we expect that the effect of the stimulus (that is, the negative video) will decrease after the students attend the program, thereby demonstrating that the students are less sensitive to this kind of shock after the intervention. We argue that this decreased sensitivity should be interpreted as an increase in resilience/capacity to regulate emotion.

Reactiva

Reactiva is a smartphone application we created to collect data and conduct simple experiments in the field. The name of the platform is a play on words regarding the algorithm of the Affectiva application, which was developed by Affectiva and a team of researchers in MIT Media Lab's Affective Computing Group (founded by Rosalind Picard). Affectiva, a company that spun off from this research group, commercializes market-oriented versions of its AI-powered algorithms. Operating since 2009, Affectiva's main focus is "to teach computers to understand human emotions." The advertising sector uses the company's solutions primarily to study individuals' emotional reactions to video advertisements by using a webcam and AI-powered algorithms to recognize and categorize emotions. Based on such observations, this sector can evaluate responses to the same ad among different demographic groups. The company offers its algorithms free of charge for research purposes.

The origins of the use of facial expressions and affective computing to proxy emotions

In 1872, Charles Darwin published a notable work in which he argued that most emotions are universal in the sense that human faces express them in the same way across races and cultures. In his study of human behavior, he explicitly stated that universal facial expressions provide information about a person's cognitive states. These states include boredom, stress, confusion, and others.

More than a century after Darwin conducted his studies, the field of affective computing (also called artificial emotional intelligence, or emotion AI) arose. While this field's core ideas may be traced to Darwin's work and even early philosophical inquiries into emotion, the more modern branch of computer science originated with Rosalind Picard's (1995) paper on affective computing and her book *Affective Computing* (Picard, 1997). Affective computing is the study and development of systems and devices that can recognize, interpret, process, and simulate human affects. It is an interdisciplinary field spanning computer science, psychology, and cognitive science.

The science behind affective computing

Determining or recognizing emotions takes place in three stages: face detection, facial-feature extraction, and expression classification. By using webcams and the front cameras of smartphones and tablets, computer vision algorithms identify key landmarks on the face (for example, the corners of the eyebrows, tip of the nose, corners of the mouth). Machine learning algorithms (classifiers) then analyze pixels in those regions to classify facial expressions. Affectiva uses the Facial Action Coding System, the most common coding system cited in the literature, to classify facial expressions or action units. Combinations of these facial expressions are then mapped to emotions.

We used Affectiva's software development kit (SDK). The SDK is built on Affectiva's industry-leading patented science. The highly accurate classifiers of this kit have been trained and tested using Affectiva's extensive emotion data repository—the world's largest emotion database, which includes analyses of more than 6.5 million faces from 87 countries.

Affectiva identifies 7 emotions and 20 expressions, as well as 13 emojis (not considered here), and it includes classifiers for age and gender. We took advantage of Affectiva's existing SDK because it includes all three phases of the emotion-recognition process, works quickly, and is stable in real time. By using the classic web camera, the kit allowed us to detect facial landmarks on an image automatically. We were also able to take advantage of the SDK's geometric feature-based approach for feature extraction.

An attractive element of the SDK is its ability to measure the distance between landmarks on the face and to select the optimal set of features. The proposed system uses a neural network algorithm for classification, and it recognizes seven facial expressions: anger, disgust, fear, happiness, sadness, surprise, and neutral. The metric values indicate the likelihood a particular emotion is being expressed and the degree to which it is being expressed. Therefore, an intense smile will produce a much higher measure than a subtle one. For our purposes, we looked at the average of the highest 10 measures of the valence and arousal metrics. More details about the management of valence and arousal variables can be found in Section 3.1. Importantly, on an individual level, the program is more likely to misread an input (for example, respondent scratches his face, resulting in a false positive); thus, we ensured that the subjects were observed long enough for the software to capture a sufficiently intense response and interpret its corresponding emotion.

Finally, a recent peer-reviewed validation of Affectiva situates its accuracy between 60% and 80% (Stockli, 2018). The authors of the study argue that the accuracy (in analyzing pictures of prototypical emotions) reveals that Affectiva performs comparably to human judges for negative emotions, while human judges still outperform Affectiva when analyzing positive emotions. This contrasts with the 85% accuracy found previously by the Affective Computing group at MIT (McDuff et al., 2015).

How Affectiva maps facial expressions to emotions

The emotion predictors observe facial expressions as inputs, which are then used to calculate the likelihood of an emotion. Our mapping of facial expressions to emotions builds on the EMFACS mappings developed by Ekman and Friesen (1978). The facial expressions indicate to greater or lesser degrees the likelihood of the corresponding emotion. The following table shows the relationship between facial expressions and emotion predictors.

Table 9: **Facial Expressions and Emotions Predictors**

Emotion	Greater likelihood	Lesser likelihood
Joy	Smiled	Brow Raised Brow Furrowed
Anger	Brow Furrowed Lid Tightened Eye Widen Chin Raised Mouth Opened Lip Sucked	Inner Brow Raised Brow Raised Smiled
Disgust	Nose Wrinkled Upper Lip Raised	Lip Sucked Smiled
Surprise	Inner Brow Raised Brow Raised Eye Widened Jaw Dropped	Brow Furrowed
Fear	Inner Brow Raised Brow Furrowed Eye Widened Lip Stretched	Brow Raised Lip Corner Depressed Jaw Dropped Smiled
Sadness	Inner Brow Raised Brow Furrowed Lip Corner Depressed	Brow Raised Eye Widened Lip Pressed Mouth Opened Lip Sucked Smiled
Contempt	Brow Furrowed Smirked	Smiled

[rgb] 1, 1, 1

Furthermore, the SDK measures valence and engagement as alternative metrics for emotional experience. The kit measures engagement as facial-muscle activation that illustrates the subject's expressiveness, ranging in value from 0 to 100. More specifically, engagement or expressiveness is a weighted sum of the following facial expressions:

- Brows raised
- Brows furrowed
- Nose wrinkled
- Lip corner(s) depressed
- Chin raised
- Lips puckered
- Lips pressed
- Mouth open
- Lips sucked in
- Smile

In addition, valence measures the degree to which an experience and emotion are either positive or negative on a spectrum ranging from -100 to 100. Table 10 provides details regarding how valence is measured.

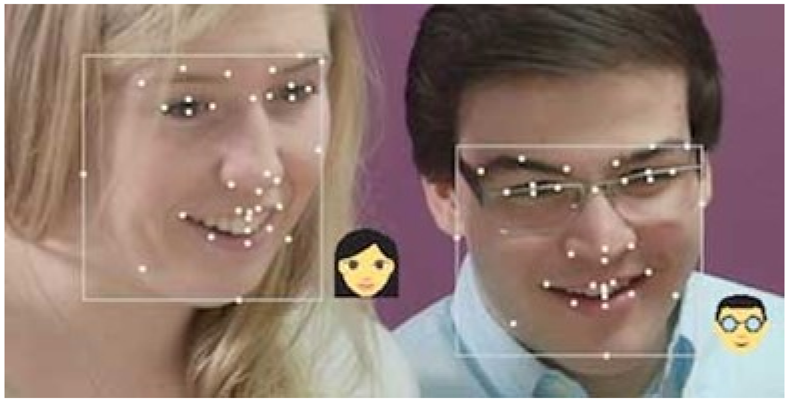
Table 10: **The Relationship between Facial Expressions and Their Valence Measures**

Increase positive likelihood	**Increase negative likelihood**
Smile	Inner-Brow Raise
Cheek Raise	Brow Furrow
	Nose Wrinkle
	Upper-Lip Raise
	Lip-Corner Depression
	Chin Raise
	Lip Press
	Lip Suck

Using the metrics

Emotion and expression metric scores indicate when users show a specific emotion or expression (for example, a smile) along with the degree of confidence. See Figure 4. The metrics can be thought of as detectors: as the emotion or facial expression occurs and intensifies, the score rises from 0 (no expression) to 100 (expression fully present). We also measure a composite emotional metric called valence, which provides feedback on overall experience. Valence values from 0 to 100 indicate a neutral to positive experience, while values from -100 to 0 signify a negative to neutral experience.

Figure 4: **Facial Expressions and Detectors**



Appendix 4 Cost-Effectiveness Analysis

We conduct a cost-effectiveness analysis of the ASP according to the previously documented approaches of Holla et al. (2021); Ganimian et al. (2021); Galasso and Wagstaff (2019) and the framework of Hendren and Sprung-Keyser (2020) by estimating the relationship between (1) human capital interventions and their impacts on adult earnings and (2) the marginal value of investments using public funds. More specifically, we estimate the intervention's cost–benefit ratio by considering its indirect impact on reducing school dropout by improving behavior at school. The complete analysis is summarized in Table A12.

We first use the estimated treatment effects of the intervention on behavior at school in the short run. We calculate the indirect effect of the ASP on dropout by comparing behavior at school and school dropout and the estimated impact of the intervention on behavior at school. Our approximation of this indirect effect is a reduction in dropout of 2 percentage point, which is equivalent to 18 students who complete more than elementary school rather than dropping out of school (see panel A in Table A12). Data on implementation costs by type of intervention were obtained from the NGO's administrative records. On average, the ASP costs US$296.5 per participant, ranging between US$269 for *Clubs* to US$327 for *Virtue*. See more details in panel B in Table A12.

To estimate the ASP's benefits, we discount the cost of the current interventions based on projected increases in income that participants will experience in their future wages because they did not drop out of school. Expected annual wages by education level completed were obtained from El Salvador's 2018 Household Survey (*Encuesta de Hogares y Propositos Multiples*, or EHPM).[55] Using these wages, we estimate the net present value (NPV) of the potential earnings of an individual who has completed elementary school, high school, technical school, or college. For the NPV estimation, we assume that the individuals will work until the age of 55 years and discount the earning inflows at a rate

[55]The average salaries across El Salvador, Honduras, and Guatemala are very similar, so using the data from one country is not grossly different from using another country's data.

of 5% with no increase in salary over time.[56] As we show in panel C in Table A12, estimated NPV ranges from US$35,000 for individuals who complete elementary school only to US$110,000 for those who graduate from college. We estimate that relative to the NPV of those who drop out of elementary school, those who complete at least high school make approximately US$19,000 more in NPV terms, and those who finish college make up to US$75,000 more in NPV terms than those who drop out of elementary school.

Considering that these interventions can reduce the total number of dropouts by 20 students, we estimate the net total of what students will earn if they do not drop out of school and do complete a higher education. Then, assuming that these students could pay an income tax of at least 1% to fund this ASP,[57] and using the total program cost per participant, we estimate that the ASP yields a benefit–cost ratio between 11.3 for students who complete up to high school and 45.2 for those who finish college. In this sense, investing in this program is worthwhile because the intervention is likely to pay for itself even in the short run and has the potential to generate large additional welfare gains over time.

[56] Highly skilled individuals' salaries usually increase at a higher rate than the salaries of less skilled workers. Thus, the assumption of a lack of increase in salary will underestimate the differences in NPV between those who have completed high school or more education and those who have completed only elementary school.

[57] The average income tax rate in El Salvador, Guatemala, and Honduras is 10%.

Appendix Tables and Figures

Table A1: **Structure of the *Virtue* ASP**

Strength	Activity	Type	Goals	Duration
Introduction to Wellness and Character Strengths	1	Formative	Introduce to the participants the theme and methodology that they will be working on throughout the academic year.	60 min
Creativity	2 3 4 5	Formative Reflective Reflective Reflective	Explain what creativity is and why it is important. Come up with a tool to help develop creativity. Come up with a tool to help develop creativity. Assess how creativity can be put into practice in the club.	60 min 15-30 min 15-30 min 15-30 min
Perspective	6 7 8 9	Formative Reflective Reflective Reflective	What is perspective and why is it important? Come up with a tool to help develop perspective. Come up with a tool to help develop perspective. Come up with a tool to help develop perspective.	60 min 15-30 min 15-30 min 15-30 min
Courage	10 11 12 13	Formative Reflective Reflective Reflective	What is courage and why is it important? Come up with a tool to help develop courage. Come up with a tool to help develop courage. Come up with a tool to help develop courage.	60 min 15-30 min 15-30 min 15-30 min
Reflection: Am I putting my character strengths into practice?	14	Formative	Reflect on the importance of practicing character strengths every day.	60 min
Perseverance	15 16 17 18 19	Formative Reflective Reflective Reflective Formative	What is perseverance and why is it important? Set a goal toward which the student will have to work for one month. Come up with a tool to help develop perseverance. Monitor progress. Come up with a tool to help develop perseverance. Monitor progress. Set life goals. Identify what skills students have learned in the club that will help them meet their goals.	60 min 15-30 min 15-30 min 15-30 min 60 min
Self-control	20 21 22 23	Formative Reflective Reflective Reflective	What is self-control and why is it important? Come up with a tool to help develop self-control. Come up with a tool to help develop self-control. Come up with a tool to help develop self-control.	60 min 15-30 min 15-30 min 15-30 min
Social Intelligence	24 25 26 27	Formative Reflective Reflective Reflective	What is social intelligence and why is it important? Come up with a tool to help develop social intelligence. Come up with a tool to help develop social intelligence. Reflect on past events and ask: how empathetic have I been?	60 min 15-30 min 15-30 min 15-30 min
Hope	28 29 30 31	Formative Reflective Reflective Reflective	What is hope and why is it important? Come up with a tool to help develop hope. Come up with a tool to help develop hope. Come up with a tool to help develop hope.	60 min 15-30 min 15-30 min 15-30 min
Closure	32	Formative	Reflect deeply on what one has learned and achieved. Plan the next (personal) steps students will take to continue building their character.	60 min

Table A2: **Registration Form**

Question	Response Options
Full name	
Gender	Male Female
How old are you?	
In what municipality were you born?	
What is your current home address? Please include municipality and community.	
With whom do you live?	With both of my parents Only with my mother Only with my father With my mother and my stepfather With my father and my stepmother With my grandfather and/or grandmother With an aunt or uncle With another person known to my parents Other(s)
Have you traveled to and from the United States?	Yes No
Do you work during your free time? For example, with your family in agriculture, as a store clerk, or on the street, etc.	Yes No
What do you do for work?	
How many minutes does it usually take you to walk to school?	
What is the name of your responsible? Please write the full name.	
What is your responsible's phone number?	
How are you related to your responsible?	Mother Father Uncle/aunt Grandfather/grandmother Stepmother Stepfather Other
What is your mother's education level?	
If your responsible is someone other than your mother, what is your responsible's education level?	
What does your responsible do to earn income?	Has a steady job (works every day) Has his own business Works only sometimes. It depends on whether he gets work Would like to work but has not been able to find a job Is permanently disabled/chronically ill Is retired Other
If your responsible has a stable job, what is his or her occupation?	
If your responsible has his own business, what is is occupation?	
If your responsible works a few times per week, what does he usually do for work?	
If your responsible has a stable job or his own business, how many days or hours does he work per week?	Full day, every day per week Half a day, every day per week Whenever he gets work
Which adult relative is at your house most often when you arrive home from school?	Mother Father Uncle/aunt

Table A3: **Summary of Outcomes, Data Sources, and Instruments or Tasks**

	Source (1)	Game or Instrument (2)	Type of Outcome (3)
Panel A. Outcomes			
Behavior at school	Administrative Records	Teacher's Report	Main
School dropout	Administrative Records	Teacher's Report	Main
Math grades	Administrative Records	Teacher's Report	Main
Panel B. Mechanisms			
Social-emotional-skills index			
Perseverance	SoftGames App	Additions Game	Mechanism
Self-control	SoftGames App	Go-NoGo Task	Mechanism
Risk-taking behavior	SoftGames App	Bartik Analog Risk Task (Balloons Game)	Mechanism
Fluid intelligence	Reactiva App	Raven's Matrices	Mechanism
Emotion regulation			
Arousal	Reactiva App	AI-Based Emotion Detection	Mechanism
Valence	Reactiva App	AI-Based Emotion Detection	Mechanism

Table A4: ***P*-values of Differences between Treatment and Control Group**
School Characteristics

	(1) *Clubs vs Mindful + Virtue*	(2) *Clubs vs Mindful*	(3) *Clubs vs Virtue*	(4) *Mindful vs Virtue*
School Characteristics				
School is located in a highly violent community	0.56	0.32	1.00	0.32
School is in an urban area	0.33	0.06	1.00	0.06
Total school enrollment (1st to 6th courses)	0.62	0.53	0.82	0.73
Total school enrollment (7th to 9th courses)	0.57	0.93	0.43	0.42
School has its own building	0.46	0.55	0.55	1.00
School is connected to a water supply	1.00	1.00	1.00	1.00
School has computers	0.49	0.55	0.55	1.00
School has a health program for students	0.37	0.32	0.61	0.63
School has a food program for students	0.46	0.15	1.00	0.15

Notes: This table shows unadjusted *p*-values of balance tests for all available variables at baseline of Table 1.

Table A5: **Sharpened Two-Stage Q-values and P-values of Differences between Treatment and Control Groups at Baseline**

Individual Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Clubs vs. Mindful + Virtue		*Clubs vs. Mindful*		*Clubs vs. Virtue*		*Mindful vs. Virtue*	
	P-value	Q-value	P-value	Q-value	P-value	Q-value	P-value	Q-value
Individual Characteristics								
Female	0.72	0.57	0.86	0.56	0.75	1.00	0.46	1.00
Student's age	0.07	0.39	0.03	0.11	0.15	1.00	0.25	1.00
Student's course	0.58	0.57	0.05	0.13	0.87	1.00	0.52	1.00
Student is enrolled in the afternoon shift	0.00	0.01	0.03	0.11	0.00	0.00	0.29	1.00
Travel time (minutes from home to school)	0.04	0.39	0.03	0.11	0.21	1.00	0.02	0.32
Student has tried to immigrate to USA	0.19	0.41	0.45	0.43	0.32	1.00	0.82	1.00
Student works	0.07	0.39	0.67	0.44	0.13	1.00	0.45	1.00
Household Characteristics								
Student's household composition								
Student lives with both parents	0.19	0.41	0.16	0.23	0.36	1.00	0.92	1.00
Student lives only with her mother	0.22	0.41	0.29	0.34	0.30	1.00	0.98	1.00
Student lives only with her father	0.26	0.41	0.48	0.43	0.47	1.00	0.79	1.00
Student lives with other relatives	0.50	0.57	0.56	0.43	0.66	1.00	0.80	1.00
Student lives with unrelated adult	0.22	0.41	0.18	0.23	0.26	1.00	0.16	1.00
Mother's education level								
Years of education	0.43	0.57	0.44	0.43	0.37	1.00	0.81	1.00
Main Outcomes								
Behavior at school	0.07	0.39	0.59	0.43	0.08	1.00	0.32	1.00
Math grades	0.85	0.63	0.94	0.75	0.68	1.00	0.78	1.00
Mechanisms								
SES index	0.11	0.41	0.11	0.18	0.11	1.00	0.49	1.00
Perseverance	0.18	0.41	0.08	0.15	0.22	1.00	0.16	1.00
Self-control	0.73	0.57	0.55	0.43	0.62	1.00	0.18	1.00
Risk-aversion	0.05	0.39	0.51	0.43	0.01	0.17	0.48	1.00
Fluid intelligence	0.25	0.41	0.01	0.06	0.72	1.00	0.51	1.00
Fluid intelligence after negative stimuli	0.20	0.41	0.00	0.00	0.96	1.00	0.25	1.00
Fluid Intelligence after positive stimuli	0.34	0.51	0.04	0.12	0.67	1.00	0.60	1.00
Arousal	0.55	0.57	0.01	0.06	0.46	1.00	0.08	1.00
Valence	0.24	0.41	0.01	0.07	0.98	1.00	0.02	0.32

Notes: This table shows adjusted sharpened two-stage q-values and unadjusted p-values of balance tests for all available variables at baseline of Table 2.

Table A6: **Matching Rate with Administrative Data and Survey Attrition**

	Attrition (=1 if no follow-up)			
	Administrative Data		Softgames & Reactiva	
	(1)	(2)	(3)	(4)
Psychology-based intervention	-0.004	-0.038	-0.008	-0.054
Individual Characteristics				
Female		0.005		-0.023
Student's age		0.002		-0.004
Student is enrolled in the afternoon shift		-0.009		0.014
Student's course		0.000		0.013
Travel time (minutes from home to school)		-0.000		0.002
Student has tried to immigrate to USA		0.006		-0.145
Student works		0.002		-0.053
Household Characteristics				
Student's household composition				
Student lives with both parents		-0.006		0.127
Student lives only with mother		-0.002		0.155*
Student lives only with father		-0.002		0.178**
Student lives only with other relatives		-0.002		0.075**
Student lives only with unrelated adult		-0.007		0.197**
Mother's education level				
Years of education		-0.000		0.001
Main Outcomes				
Behavior at school		-0.006		-0.009
Math grades		0.001		0.016
Mechanisms				
SES Index		-0.002		-0.001
Fluid intelligence		0.020		-0.184**
Arousal		0.000		-0.000
Valence		-0.000		-0.001
Observations	879		854	
Interaction with treatment	No	Yes	No	Yes

Notes: This table shows the estimated differences between students assigned to the psychology-based interventions relative to the comparison group on matching rate with administrative data (columns 1 and 2) and SoftGames and Reactiva (columns 3 and 4). The dependent variable *Attrition* is a dummy indicating whether there is information available for a student at endline (short-term follow-up). Model in columns (1) and (3) includes only the indicator of being assigned to the social-emotional-learning component, whereas model 2 (columns 2 and 4) includes interactions between the treatment indicator and all variables available at baseline. All regressions include randomization block (strata) fixed effects. Strata were defined as country and violence level (high or low) of the community where the school is located. Clustered standard errors at the course level are shown in parentheses. $***p < 0.01$, $**p < 0.05$, $*p < 0.1$

Table A7: **Effects of ASP-Emotional Learning on Behavior and Academic Outcomes**
(Intention-to-Treat Estimates, Including Control Variables Selected Using LASSO)

	Behavior at School (1)	School Dropout (2)	Math Grades (3)
Psychology-based curricula	0.241***	-0.010	-0.015
	(0.078)	(0.034)	(0.076)
	[0.002]	[0.795]	[0.865]
Mean pure club group	0.650	0.037	0.587
MDE	0.068	0.037	0.099
Observations	887	868	855
R-squared	0.076	0.076	0.014
LASSO controls selected (n)	4	4	4

Notes: This table shows the estimated impacts of the ASP's social-emotional learning on behavioral and academic outcomes. *Psychology-based intervention* is a dummy equal to 1 if the student was enrolled in a school that was randomly assigned to the *Virtue* or *Mindful* intervention, and 0 if assigned to the *Clubs* group. *Mean pure club group* is the mean of the outcome for the group that only participates in *Clubs*, without any extracurricular activity. We present the estimated coefficient $\hat{\mu_2}$ from specification 1. The description of dependent variables is available in Section 3.2. *Behavior at School* is a dummy that equals 1 if the student's behavior report is above the school median. *School Dropout* is a dummy variable that equals 1 if a student dropped out of any school in our study in the 2019 academic year. *Math grades* is a dummy that equals 1 if the student's behavior report is above the school median.. All outcomes were obtained from administrative data sources (namely, teachers' reports). Sample size in each specification varies according to the number of observations available for each outcome. Estimations include all double-LASSO-selected control variables, and they are specified in Table A11 with an "X." All regressions include randomization block (strata) fixed effects. Strata were defined as country and violence level (high or low) of the community where the school is located. Wild bootstrap standard errors are shown in parentheses, and adjusted p-values are in brackets. $^{***}p < 0.01,\ ^{**}p < 0.05,\ ^{*}p < 0.1$

Table A8: **Effects of ASP Social-Emotional Learning on SES and Emotion Regulation**
(Intention-to-Treat Estimates, Including Control Variables Selected Using LASSO)

	SES Index	Fluid Intelligence	Fluid Intelligence after Negative Stimuli	Fluid Intelligence after Positive Stimuli	Arousal	Valence
	(1)	(2)	(3)	(4)	(5)	(6)
Psychology-based curricula	0.011	-0.037	0.053	-0.026	-0.017	-0.237*
	(0.014)	(0.087)	(0.083)	(0.094)	(0.117)	(0.126)
	[0.845]	[0.690]	[0.635]	[0.805]	[0.885]	[0.050]
Mean pure club group	0.000	0.000	0.000	0.000	0.000	0.000
MDE	0.233	0.219	0.221	0.217	0.233	0.230
Observations	755	733	733	733	622	622
R-squared	0.043	0.045	0.032	0.030	0.034	0.024
LASSO controls selected (n)	6	4	4	4	5	5

Notes: This table shows the estimated impacts of the ASP's social-emotional learning on SES and emotion-regulation outcomes. *Psychology-based intervention* is a dummy equal to 1 if the student was enrolled in a school that was randomly assigned to the *Virtue* or *Mindful* intervention, and 0 if assigned to *Clubs*. *Mean pure club group* is the mean of the outcome for the group that only participates in *Clubs*, without any extracurricular activity. We present the estimated coefficient $\hat{\mu_2}$ from specification 1. The description of dependent variables is available in Section **??**. All dependent variables are measured in standard deviations relative to the comparison group. Sample size in each specification varies according to the number of observations available for each outcome. Estimations include all double-LASSO-selected control variables, and they are specified in Table A11 with an "X." All regressions include randomization block (strata) fixed effects. Strata were defined as country and violence level (high or low) of the community where the school is located. Wild bootstrap standard errors shown in parentheses and adjusted p-values in brackets. $^{***}p < 0.01$, $^{**}p < 0.05$ $^{*}p < 0.1$

Table A9: **Which Curriculum Is the Most Efficient? - Behavior at School and Academic Performance**
(Intention-to-Treat Estimates, Including Control Variables Selected Using LASSO)

		Estimated Coefficient	Standard Error	*P*-value	*P*-value Wild Bootstrap	Mean Clubs Group	P-value *Virtue=Mindful*	LASSO Selected Controls (n)	Observations
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Behavior at school	*Virtue*	0.229***	(0.083)	(0.007)	[0.035]	0.650	0.870	8	887
	Mindful	0.236***	(0.079)	(0.004)	[0.020]				
School dropout	*Virtue*	0.024	(0.031)	(0.445)	[0.465]	0.037	0.008	3	868
	Mindful	-0.039	(0.028)	(0.166)	[0.205]				
Math grades	*Virtue*	-0.054	(0.089)	(0.547)	[0.635]	0.587	0.449	3	855
	Mindful	0.022	(0.090)	(0.804)	[0.840]				

Notes: This table shows the estimated impacts of each type of psychology-based curriculum from the social-emotional-learning component. The descriptions of all dependent variables are available in Section 3.2. *Virtue* and *Mindful* are dummies equal to 1 if the student was enrolled in a school that was randomly assigned to the *Virtue* or *Mindful* intervention, respectively, and 0 if assigned to *Clubs*. In column (1), we present the estimated coefficients of the interaction between the treatment dummies and the *Post* indicator. Clustered standard errors, unadjusted *p*-values, and *p*-values adjusted using a wild bootstrap procedure (adjusted for a small number of clusters) are shown in columns (2), (3), and (4), respectively. *Mean Clubs Group* in column (5) is the mean of the outcome for the group that only participates in *Clubs*, without any extracurricular activity. Column (6) presents the *p*-value for the test for differences between estimated coefficients for *Virtue* and *Mindful* presented in column (1). Sample size in each specification presented in column (6) varies according to the number of observations available for each outcome. Estimations include all double-LASSO-selected control variables, and they are specified in Table A11 with an "E." All regressions include randomization block (strata) fixed effects. Strata were defined as country and violence level (high or low) of the community where the school is located. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table A10: **Which Curriculum Is the Most Efficient? - SES and Emotion Regulation**

(Intention-to-Treat Estimates, Including Control Variables Selected Using LASSO)

		Estimated Coefficient (1)	Standard Error (2)	*P*-value (3)	*P*-value Wild Bootstrap (4)	Mean Clubs Group (5)	P-value *Virtue=Mindful* (6)	LASSO Selected Controls (n) (7)	Observations (8)
SES index	*Virtue*	-0.000	(0.014)	(0.996)	[0.995]	0.000	0.381	3	755
	Mindful	0.007	(0.014)	(0.608)	[0.685]				
Short-term perseverance	*Virtue*	0.004	(0.010)	(0.736)	[0.725]	0.000	0.902	4	759
	Mindful	0.005	(0.008)	(0.576)	[0.580]				
Self-control	*Virtue*	-0.008	(0.012)	(0.497)	[0.530]	0.000	0.469	5	776
	Mindful	-0.013	(0.011)	(0.233)	[0.230]				
Risk aversion	*Virtue*	0.025**	(0.012)	(0.032)	[0.020]	0.000	0.066	3	773
	Mindful	0.004	(0.011)	(0.709)	[0.715]				
Fluid intelligence	*Virtue*	-0.115	(0.080)	(0.154)	[0.210]	0.000	0.235	3	733
	Mindful	0.040	(0.132)	(0.760)	[0.755]				
Fluid intelligence - after negative stimuli	*Virtue*	-0.118	(0.096)	(0.219)	[0.285]	0.000	0.005	3	733
	Mindful	0.222**	(0.089)	(0.014)	[0.010]				
Fluid intelligence - after positive stimuli	*Virtue*	-0.068	(0.091)	(0.459)	[0.555]	0.000	0.516	3	733
	Mindful	0.012	(0.132)	(0.926)	[0.910]				
Arousal	*Virtue*	0.027	(0.111)	(0.811)	[0.845]	0.000	0.615	3	622
	Mindful	-0.059	(0.171)	(0.730)	[0.720]				
Valence	*Virtue*	-0.270**	(0.106)	(0.013)	[0.030]	0.000	0.788	3	622
	Mindful	-0.210	(0.219)	(0.339)	[0.365]				

Notes: This table shows the estimated impacts of each type of psychology-based curriculum from the social-emotional-learning component. The descriptions of all dependent variables are available in Section 3.2. *Virtue* and *Mindful* are dummies equal to 1 if the student was enrolled in a school that was randomly assigned to the *Virtue* or *Mindful* intervention, respectively, and 0 if assigned to *Clubs*. In column (1), we present the estimated coefficients of the interaction between the treatment dummies and the *Post* indicator. Clustered standard errors, unadjusted *p*-values, and *p*-values adjusted using a wild bootstrap procedure (adjusted for a small number of clusters) are shown in columns (2), (3), and (4), respectively. *Mean Clubs Group* in column (5) is the mean of the outcome for the group that only participates in *Clubs*, without any extracurricular activity. Column (6) presents the *p*-value for the test for differences between estimated coefficients for *Virtue* and *Mindful* presented in column (1). Sample size in each specification presented in column (6) varies according to the number of observations available for each outcome. Estimations include all double-LASSO-selected control variables and they are specified in Table A11 with an "E." All regressions include randomization block (strata) fixed effects. Strata were defined as country and violence level (high or low) of the community where the school is located. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table A11: **Double-LASSO-selected Control Variables**

Extended control variable	Behavior at School	School Dropout	Math Grades	SES Index	Short-Term Perseverance	Self-Control	Risk-Aversion	Fluid Intelligence	Fluid Intelligence after Negative Stimuli	Fluid Intelligence after Positive Stimuli	Arousal	Valence
Individual Characteristics												
Female					E							
Student's age	E											
Student's course	E											
Student is enrolled in the afternoon shift	XE	X	X	X				X	X	X	X	X
Travel time (minutes from home to school)	E	E	E	E	E	E	E	E	E	E	E	E
Student has tried to immigrate to USA												
Student works												
Household Characteristics												
Household composition												
Student lives with both parents												
Student lives only with her mother												
Student lives only with her father												
Student lives with other relatives												
Student lives with unrelated adult												
Mother's education												
Years of education												
School Characteristics												
School is located in a highly violent community												
School is in an urban area	XE	XE	XE	XE	E	E	E	E	E	E	XE	XE
Total enrollment (1st to 6th courses)												
Total enrollment (7th to 9th courses)				X		E						
School has its own building				X				X	X	X	X	X
School is connected to a water supply	XE	X	X	X				X	X	X	X	X
School has computers	E					E						
School has health program for students	X	X	X	X				X	X	X	X	X
School has a food program for students	E	E	E	E	E	E	E	E	E	E	E	E

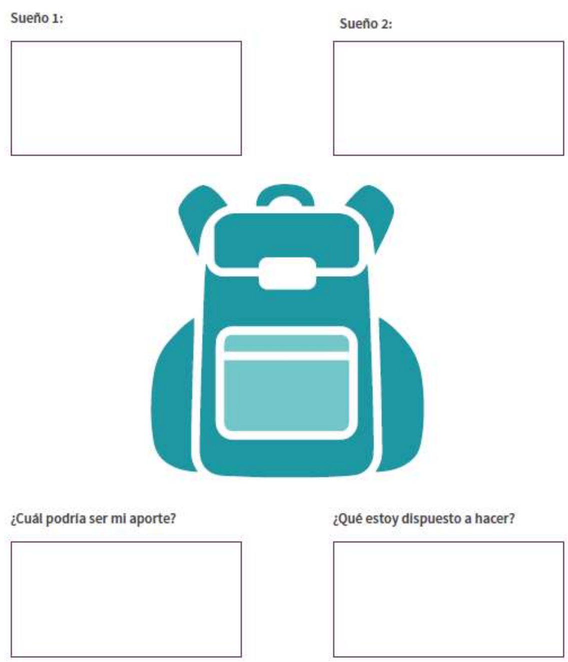
Notes: This table shows all variables from which the double-LASSO selection algorithm could select. "X" denotes variables selected for regressions for Tables A7 and A8, while "E" denotes those selected for the curriculum-efficiency regressions (Tables A9 and A10).

Table A12: **Cost-Benefit Analysis**

Description	Values	Notes and Assumptions
Panel A. Indirect Impacts of the Intervention		
Correlation between behavior at school and school dropout	-0.05	Source: Study data
Intervention effect on behavior at school	0.232	Effect on behavior at school from any psychology-based intervention (Table 3)
Indirect effect of the intervention on dropout	−0.020	Adjusting the effect on bad behavior using correlation with dropout
Reduction in number of potential dropouts	−18	Sample of study (897) × indirect effect on dropout due to the program
Panel B. Costs		
Annual cost per club (US$)		
Clubs	3,232.29	Source: Glasswing costing data
Virtue	3,931.10	
Mindful	3,509.45	
Annual club cost per participant (US$)		
Clubs	269.36	
Virtue	327.60	Annual cost per club divided by an average of
Mindful	292.46	12 participants per club
Average	296.48	
Panel C. Wages		
Annual wage of an individual who completed (US$)		
Elementary school	1,946.52	Source: Households Survey (EHPM) 2018
High school	3,056.88	
Technical school	5,407.68	
College	6,600.96	
NPV of wages of an individual who completed (US$)		
Elementary school	35,070.54	
High school	53,638.63	Assuming that they work until age 55,
Technical school	91,944.35	discount rate 5%, no salary growth
College	109,528.48	
Difference in NPV relative to elementary school education (US$)		
High school	18,568.09	
Technical school	56,873.81	NPV of completing this education level -
College	74,457.94	completing basic education only
Panel D. Intervention Effects on Total Earnings and Taxes		
Total earnings of potential dropouts who stay in school and complete (US$)...		
High school	371,361.8	
Technical school	1137,476.2	
College	1489,158.8	
Taxes paid for those who completed at least (US$)		
High school	3,713.61	
Technical school	11,374.76	Assuming that individuals who might dropout
College	14,891.58	will pay 1% of income tax for this ASP
Benefit–cost ratio for those who complete at least...		
High school	11.3	
Technical school	34.5	Assuming that the government uses tax
College	45.2	dollars to pay for the intervention

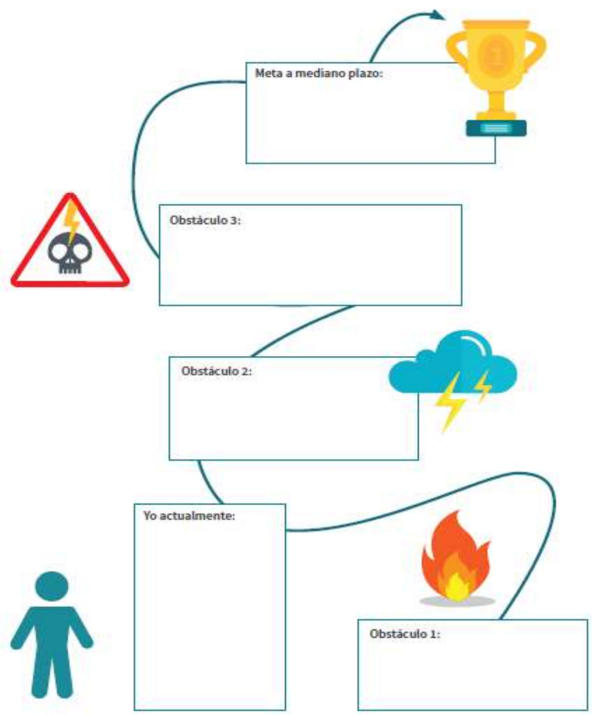
Notes: This table summarizes the assumptions and values used for the cost–benefit analysis of the ASP. More details regarding the analysis are presented in Appendix 4.

Figure A1: **Activity Sheet for the *Virtue* Curriculum—The Backpack**



Notes: This figure shows the activity sheet for The Backpack activity, which involves a reflexive session related to building perseverance in the *Virtue* curriculum.

Figure A2: **Activity Sheet for the *Virtue* Curriculum—My Map**



Notes: This figure shows the activity sheet used for the My Map activity, which involves a reflexive session to help build perseverance in the *Virtue* curriculum.

Figure A3: **Manual for the *Mindful* Curriculum—Sun Breathing Activity**

RESPIRACIÓN DEL SOL **CIERRE**

Vamos a practicar la "Respiración del Sol."

Siéntate derecho y cómodo en tu silla.

Descansa las manos en tu escritorio o sobre tus piernas.

Cierra los ojos.

Siente los pies apoyados en el suelo.

Relaja los hombros hacia atrás y hacia abajo.

Deja todo tu cuerpo quieto.

Siente el aire entrando y saliendo por la nariz.
[Espera 10 segundos]

Ahora, inahala profundamente por la nariz y estira los brazos hacia arriba de tu cabeza bien derechos, con las palmas frente a frente. Espera. Lentamente baja los brazos y exhala.

Inhala estirándote hacia arriba, espera, exhala, bajando los brazos.

Inhala estirándote hacia arriba, espera, exhala, bajando los brazos.

Inhala estirándote hacia arriba, espera, exhala, bajando los brazos.

Ahora, descansa las manos en tu escritorio o sobre tus piernas.

Siente el aire entrando y saliendo por la nariz.
[Espera 20 a 30 segundos]

Ahora, inhala profundamente, espera y exhala lentamente.

Nota cómo te sientes.
[Espera 10 segundos]

Abre los ojos lentamente.

Notes: This figure shows the instructions for the Sun Breathing activity, which involves a breathing and relaxation exercise in the *Mindful* curriculum.