Multidimensional Impacts of Financial Education in Schools: Experimental Evidence from Brazil

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Abstract

Many countries have recently focused on national financial education strategies for youth, with Brazil being a notable case study due to its low financial literacy, high household debt, and educational challenges. While studies on the effects of school-based programs on financial literacy and behavior have grown, knowledge about their impacts on academic outcomes, student interest, engagement, and non-cognitive traits remains sparse. Our paper fills part of this gap, relying on rich data from a large-scale randomized controlled trial in the state of Goiás, Brazil[1]. The findings suggest positive effects on student financial literacy, program-specific mathematics skills, and the perceived relevance of math. However, no discernible impacts were observed on reported financial behaviors nor on downstream educational outcomes. An interesting and surprising result was the negative effects of the program on non-cognitive dimensions.

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[1] The experiment studied in this paper is registered in the American Economic Association's registry for randomized controlled trials. Register: AEARCTR-0010377.

1 Introduction

In the past decades, several countries around the world have adopted or planned national financial education strategies[2], a trend significantly heightened post the 2008 financial crisis. As attendance in adult financial education workshops is generally low (Bruhn et al., 2014), recent strategic focus has tilted towards youth. The rationale for adopting financial education programs in schools is compelling, with advocates emphasizing that such programs harness the learning capacities of students and instill good financial behaviors and habits at an early stage. As argued by Lusardi et al. (2010), Bruhn et al. (2016), Brown et al. (2016), and Frisancho (2023), these early-formed financial attitudes and habits can prove advantageous, contributing positively to educational attainment and employment prospects in adulthood(Bruhn et al., 2022; Horn et al., 2022).

Additionally, these programs have the potential to foster patience and the ability to delay gratification (Carlin and Robinson, 2012; Alan and Ertac, 2018; Luhrmann et al., 2018; Frisancho, 2020), traits identified as important determinants of academic and socioeconomic outcomes (Mischel et al., 1989; Duckworth and Seligman, 2005; Sutter et al., 2013). In contrast, there are concerns that the inclusion of new content in students' curriculum could harm their academic performance in core subjects or even that the focus on financial topics might encourage them to value work over studies, even leading to school dropout.

Bjorvatn et al. (2020), in fact, find negative treatment effects of a youth entrepreneurship program in Tanzania on student achievement and retention. Bruhn et al. (2016) and Frisancho (2020), assessing the impacts of school-based financial education programs in Brazil and Peru, respectively, find that treated students are indeed more likely to work, but this does not seem to affect their school performance. While the literature on the impacts of these programs on financial knowledge and behavior has grown at a surprising pace in recent years(Kaiser et al., 2022), the exploration of the effects of school-based financial education on relevant dimensions such as non-cognitive traits and both student interest and engagement with school is even more sparse. This highlights the need for further research in these pertinent areas.

Our paper fills part of this literature gap. Relying on rich survey and administrative data from a large-scale randomized controlled trial (RCT) that took place in Brazil in 2021, we investigate the impacts of a financial education program integrated into the mathematics curriculum of 9th-grade students on their academic performance, financial knowledge and behavior, and on measures of non-cognitive development

[2] OECD (2015). National Strategies for Financial Education. OECD/INFE Policy Handbook.

and interest in the studies.

Our findings reveal that students who participated in the program displayed markedly improved performance in the financial knowledge and applied mathematics test, with an increase of approximately 0.15 of a standard deviation (SD). Treated students also performed better in the state's official standardized test in math skills encompassed by the course (henceforth "program-specific skills") and conveyed their belief that the mathematical knowledge acquired was beneficial for aiding their families. Importantly, we observed some negative repercussions of the program on certain non-cognitive dimensions, such as measures of growth mindset, neuroticism, and openness to experience. Further research, using data from the second year of the intervention (2022)[3], will elucidate whether these effects are sustained or merely transient, potentially attributable to the exceptional circumstances of the first year of intervention, which coincided with the coronavirus pandemic, or "news effects" attributed to the implementation of a new curriculum.

Brazil is actually an interesting case to study in depth the impacts of financial education in schools. On the one hand, the country has low levels of financial literacy[4] and high household indebtedness[5]. At the same time, like much of Latin America and other developing countries, Brazil has high levels of school dropout, especially in upper-secondary education (Acosta et al., 2019). Importantly to our setup, one of the main perceived reasons for school dropout is the lack of interest in school and school-related activities (Barros et al., 2017; Soares et al., 2015; da Gama Torres et al., 2013)[6].

In such a context, which relates to the reality of other developing and emerging economies, more than the impacts on financial knowledge and behavior, it is essential to know the effects of school-based financial education on the academic performance and motivation of students. There are some channels through which these programs, most notably the "*Aprendendo a Lidar com Dinheiro*" (ALD or "Learning How to Deal with Money", in free translation) that we evaluate, can positively affect students' outcomes.

Designed to align with the new guidelines of the National Core Curriculum (*Base Nacional Comum Curricular*, in Portuguese, or simply BNCC) and integrated into mathematics classes, the program leverages teachers' prior pedagogical training in active learning methodologies. This approach holds the potential to render classroom sessions more engaging and comprehensible for students by providing direct and day-to-day applications of the concepts studied in the discipline.

[3]This analysis should be available soon after the Department of Education makes relevant administrative data available.
[4]OECD (2020). PISA 2018 Results (Volume IV): Are Students Smart about Money?. PISA, OECD Publishing, Paris.
[5]Household Indebtedness Indicator, Central Bank of Brazil
[6]Annual National Household Survey (PNAD-C), Brazilian Institute of Geography and Statistics

The program's relevance could be particularly significant when considering the familial contexts of the students, most of whom come from middle to low-income households[7]. In Brazil, it's commonplace for such families to include self-employed individuals and micro-entrepreneurs, who may find enhanced relevance and applicability in the content delivered at school. This perception is corroborated by the findings of Bruhn et al. (2016), who documented the spillover of financial knowledge to families resulting from a school-based program implemented in Brazil between 2010 and 2011. Similarly, Foley et al. (2014) demonstrated how a parent's positive valuation of education significantly influences a student's decision to either persist with their studies or drop out.

Besides the direct effects on students' engagement and knowledge, financial education programs have the potential to affect school outcomes and interest in the studies through impacts on non-cognitive traits. In an interesting experiment in Turkey, Alan and Ertac (2018) find that children who were exposed to a school program that encourages forward-looking behavior, with a focus on saving habits, made significantly more patient inter-temporal choices in time preference elicitation tasks, result persistent even three years later. Moreover, a striking finding was that even one year after the intervention, treated students were about 10 percentage points less likely to receive a low "behavior mark" in the school record.

Luhrmann et al. (2018) find results in the same manner for a financial education program in German high schools, with treated students making more time-consistent choices. In a similar approach, Frisancho (2020) investigates the impacts of a school-based program in Peru, targeting 9th, 10th and 11th grades. The author identifies a sizeable positive effect on students' self-control, although the likelihood of passing grades is not affected.

Given the existing evidence, our paper makes two substantial contributions to the literature. Firstly, it provides a more comprehensive and integrated evaluation of the educational impacts of incorporating financial education into the school curriculum for upper-secondary students. As previously noted, much of the literature on youth financial education concentrates on the effects on financial literacy and behavior, as exemplified in the comprehensive meta-analysis of such programs by Kaiser and Menkhoff (2020). While recent studies like those by Alan and Ertac (2018) and Luhrmann et al. (2018) have begun to shed light on the impacts on school outcomes and select non-cognitive dimensions, their scope tends to be narrowly focused on a relatively confined set of dimensions. Our research, however, examines a more expansive set of

[7] This program has been deployed in Brazilian public schools, which are largely attended by students from less advantaged backgrounds.

non-cognitive dimensions. This provides a richer analysis of the interplay between these effects, academic outcomes, and aspects of student motivation and engagement.

Second, considering the low performance of Brazilian students in mathematics (Sassaki et al., 2018) and the little attractiveness of school (Barros et al., 2017), aspects that have been the focus of recent debates and policy efforts in the country as discussed below, our paper brings evidence that the integration of more applied content in core subjects has the potential to improve school outcomes.

The paper proceeds as follows. The second section presents more details about the intervention and the timeline of the study. It also discusses the sampling and randomization methodologies and the empirical strategy. Section 3 describes the survey instruments, and brings information on baseline statistics and take-up and attrition. Section 4 presents the main results, while the fifth concludes.

2 Experimental Design

2.1 Intervention Outline

The program "Learning How to Deal with Money" was conceived by the BEI Institute and offers a financial education course integrated into the mathematics curriculum, along with support material, targeted at 9th grade students. It relies on a project-based learning (PBL) approach, and for this, it also involves pedagogical training for teachers and school coordinators on active learning methodologies.

The program is in accordance with the BNCC (from 2018), and it can be seen as a proposal of an innovative way of teaching mathematics while developing increasingly demanded skills, within the context of recent efforts to modernize upper-secondary school in Brazil and make it more appealing. The initiative aims to increase student engagement and interest in math classes, and in studies in general. At the same time, it also seeks to develop financial literacy and awareness in students, as well as a forward-looking attitude, potentially affecting positively their academic results and valuation of school.

In 2019, in partnership with the Goiás Secretary of Education, the intervention was implemented in a pilot version in 85 public schools of the state. In 2020, due to the restrictions imposed by the outbreak of the new coronavirus pandemic and the closure of schools in the country, the program was adopted in a reduced and remote format, only for teachers, in the same schools as the pilot.

In 2021, with the advance of vaccination and the expectation of resumption of face-to-face classes, the ALD was adopted in its full version, with pedagogical training for mathematics teachers and a 6-month course for 9th grade students, in a new sample of public schools of Goiás (which does not include the control and treatment schools from the previous years). The program allocation was such that an experimental impact evaluation could be jointly conducted.

Hence, the estimation of the causal effects of the intervention on several cognitive, non-cognitive and behavioral dimensions made use of a randomized controlled trial setting. We chose to allocate the program at the school level, in order to mitigate the risk of spillovers (Glennerster and Takavarasha, 2014). In following subsections, the sampling and randomization strategies are presented.

The program began to be implemented after the draw in May 2021, with the completion of the teachers training, followed by the application of the methodologies in the classroom and by the development of the activities from the students book. In that year, classes in the Goiás educational system were resumed in a hybrid format in the first semester and in-person in the second. Thus, the baseline questionnaires for students were applied remotely in March 2021, prior to the draw. This allowed for greater engagement of the control group and the use of baseline data in the school pairing.

In November 2021, at the end of Brazilian school year, a new set of questionnaires was applied remotely in the same schools, and together with a specific exam in mathematics and financial literacy prepared for face-to-face application to students, makes up the follow-up of 2021. Section 3 presents more details on the instruments and the figure below summarizes the timeline described here.

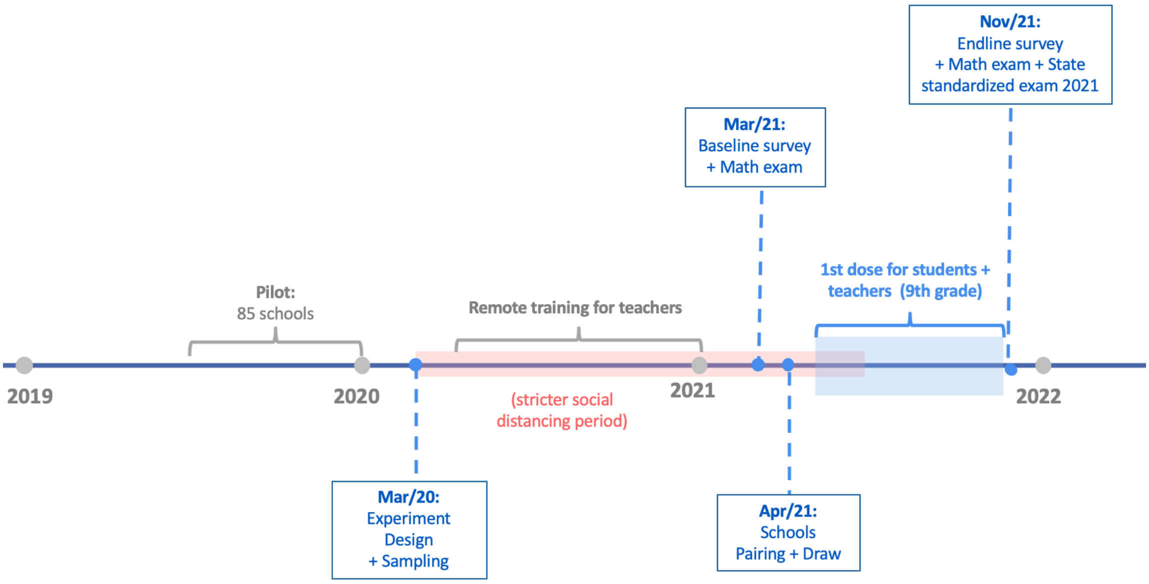
2.2 Sample Selection

190 public schools of Goiás were selected to compose the sample of the study. This selection was made through a stratified draw, where eligible units were randomly chosen from groups of similar schools to compose the sample.

Schools in Goiás educational system can either offer only high school or both upper primary and secondary education, in which case they are called hybrid schools. Due to our goal of evaluating the impacts of the intervention on young people initiating their financial decisions and in their transition to high school, the program was offered only to hybrid schools. By the beginning of 2021, 432 hybrid schools had not received any form of the program, nor were in the control group of the pilot evaluation, making up our target population.

These 432 schools were then divided into 127 groups of similar characteristics (the strata), which were defined according to the following approach: for each of the 40 regions of the Goiás educational system,

Figure 1: Study Timeline



Elaborated by the authors.

schools were divided into smaller groups according to the performance in mathematics of their 9th grade students in the last standardized state exam (SAEGO) available. For larger regional areas, schools were divided into quartiles of that region's mathematics score distribution, while for smaller areas, they were either divided into two strata (according to the median math score) or not divided at all (when there were only four or less hybrid schools left in the region).

The option for this approach was based on the characteristics of the program, which was implemented within the mathematics curriculum, and on fair representativeness results found.

Once the strata were defined, some tests were carried out to ensure that the selection by a stratified draw would result in a representative sample of the target population. This assessment was based on distribution analyses and on Kolmogorov-Smirnov tests of the following dimensions: schools' scores in mathematics and literacy in the 2018 and 2019 SAEGO; performance of the schools in the national assessment of education (IDEB) from 2015 and 2017; and the total enrollment in the schools and in their 9th grade. Appendix A.1 details the representativeness tests.

The sampling was based on generating a random number for each school and selecting those within each strata with a number less than or equal to the 47th percentile in that strata - the idea is that 47% of 432 would give us about 200 schools, our initial target sample. Due to the shift of some schools to a full-time curriculum (in which case, they were not allowed to receive the program) and the closure of the 9th grade on other participants), our first sample of 200 schools[8] was reduced to 190, with no serious loss of statistical power.

2.3 Pairwise Randomization

The allocation of the program among sampled schools made use of a pairwise randomization in a public draw broadcast live on the YouTube channel of the Goiás Secretary of Education, on April 27, 2021. For this purpose, upon the completion of the baseline survey, its data was processed and used to divide the sample into pairs of similar schools. This approach was chosen to mitigate the risk of imbalances in relevant dimensions between treatment and control groups.

Three pairing approaches were tested in terms of the probability of registering imbalances in sets of school-level variables related to: i) the selection of respondents (such as the access of students to internet and the percentage of completed surveys); ii) the performance of students (accounting for their scores in cognitive and non-cognitive outcomes); and iii) the faculty engagement and performance. For each of the proposed pair-matching approach, one hundred randomizations were simulated, and for each resulting draw, a dummy for the assigned group was regressed on the aforementioned sets of variables. Testing the significance of these groups of variables allowed an assessment on whether there were potential selection problems in the pairing approaches. Appendix A.2 presents more details on the variables used and on the approaches.

The chosen pair-matching was the one that recorded the least imbalance in the set of variables related to selection. It consisted of building three principal factors, one for each mentioned set of variables and then aggregating the three into a single principal factor. Schools were then paired according to their proximity in terms of this factor.

Finally, the randomization was publicly streamed and involved 96 sequential draws: one for each pair of schools, allocating them to Group A or B, then a final draw, assigning treatment to one of the groups.

[8]In fact, the first sample was of 201 schools and due to reorganization in schools, a new sample of 200 was selected. Appendix A.1 also details this process.

2.4 Empirical Strategy

Based on the random assignment, the impact of the financial education course on the different students outcomes is measured as the difference in averages between treatment and control groups, following the intention-to-treat (ITT) ordinary least squares (OLS) regression:

$$y_{isp}^{follow} = \alpha + \beta T_{sp} + \sum \gamma_p d_p + \delta X_{isp}^{base} + \lambda y_{isp}^{base} + \epsilon_{isp}$$

Here, y_{isp}^{f} corresponds to a cognitive, non-cognitive or engagement outcome of student i in school s from the pair p in the follow-up, whereas the regressor y_{isp}^{base} corresponds to the baseline value of the outcome. This inclusion follows McKenzie (2012), according to which the implementation of an analysis of covariance (ANCOVA) in the estimation improves considerably the power.

The impact of the treatment is given by β, the coefficient of the treatment dummy T_{sp}, which equals one if student i was in a school s from the pair p randomly assigned to receive the program, and zero otherwise. The specification also includes a set of dummies d_p for the fixed-effects of the pairs, and a set of controls from the baseline survey, X_{isp}^{base}. The choice of which controls would be included followed a machine learning approach to variable selection, specifically the post-lasso regression of Belloni et al. (2014). Due to the large number of variables explored in the baseline survey, this approach was chosen to avoid *ad hoc* choices of controls. Standard errors were clustered at the school-pair level, following de Chaisemartin and Ramirez-Cuellar (2022).

In addition, the Romano-Wolf correction was implemented for outcomes that are part of a family of outcomes (or block of questions), aiming to correct for the familywise error rate (FWER) when testing for multiple hypotheses simultaneously (Romano and Wolf, 2005). Robustness checks were carried out to assess the sensitivity of the results to the exclusion of controls. Those are discussed in the Results section and Appendix.

3 Data and Summary Statistics

3.1 Survey Instruments

A baseline survey was applied to students in the beginning of the academic year (March) and a follow-up by its end (November). The questionnaires were applied online through the official system of the Goiás

Secretary of Education, due to the high adherence rate recorded in the first collection, in the midst of the Covid-19 pandemic when this was the only option. For the endline collection, a mathematics and financial literacy exam was also applied in person in the classroom.

In addition to our own surveys and exams, our research also counted with access to administrative data from the Secretary of Education on transcript grades, school attendance, and student performance in the standardized state exam - annual official assessment of competences in mathematics and Portuguese literacy, following the state curriculum guidelines.

The baseline survey contained questions not only related to the investigated outcomes, but also about students' school background, their race, gender, and socioeconomic condition. The studied outcomes can be divided into four large groups: cognitive dimensions; non-cognitive development; engagement and interest in mathematics and school; financial behavior and attitudes.

Cognitive Dimensions: The program covered basic financial knowledge (such as the concepts of simple and compound interest, risk diversification and inflation) and mathematical skills, which were assessed through a specific exam. This test was applied remotely in the baseline and in the classroom in the follow-up collection. Noteworthy is the fact that the test was crafted by specialists who were not directly involved in the program, assuring an unbiased measurement of the acquired skills. This assessment tool was a compilation of questions from various sources, including the PISA Financial Literacy (provided by the OECD), standard questions adapted from the literature on financial literacy (Lusardi and Mitchell, 2011), and mathematics questions prepared by the pedagogical consultant. Although the exact questions varied in each collection[9], they covered the same skills and were designed so as to maintain the same level of difficulty.

Microdata from SAEGO was used to assess the proficiency in mathematics, and administrative records were used to evaluate the impacts of the program on school grades and passing rates.

Non-Cognitive Dimensions: For the assessment of students' non-cognitive development, the baseline and endline surveys made use of validated questionnaires from the psychology literature. Blocks of questions were adapted and translated to assess students' growth mindset, following the methodology of Dweck (2006); their grit and perseverance (Duckworth et al., 2007); and their internal locus of control development, following the scale of Rotter (1966).

[9]It is worth mentioning that the baseline exam was not as extensive as in the follow-up, not including for instance PISA-OECD questions.

Additionally, partnering with the Ayrton Senna Institute [10], we use a socioemotional survey instrument already validated in public schools of the country to assess the big five personality traits (engaging with others, amity, self-management, negative-emotion regulation, open-mindedness), and some constructs that compose them (such as focus, persistence and enthusiasm) (Primi et al., 2016, 2021).

Interest and Engagement: Since one of the main objectives of the program is to make mathematics content and school more attractive to young people and more applied to their everyday lives, it is extremely relevant to analyze the impacts of the intervention on measures of interest and involvement of students with mathematics classes and studies in general. Therefore, there were some blocks of questions in the baseline and follow-up surveys designed to assess these aspects.

In one of them, we asked students how important they thought it was to finish the 9th grade and high school (answers being "it is not important", "it is not that important", "it is very important", "it is extremely important"). A block of questions also sought to assess study habits and practices in mathematics (for example, how relevant students think it is to practice exercises, study in groups, plan study days, among other practices for their school results).

Another section of the questionnaire asked students how much they agreed with statements about the importance of mathematics in their lives, such as "what I learn in math at school is important for me to fulfill my dreams", "what I learn in math at school is important for me to help my family", "only students who like math should take those classes at school", and others.

Financial Behavior and Attitudes: To evaluate the program's impacts on the financial attitudes and habits of these young people, who still do not have a very active financial life, we based our study on financial education interventions for the same age group. Notably, we adopted questions from the financial autonomy index developed by Bruhn et al. (2016), in partnership with CAEd [11], and applied in their study. According to the authors, the index aggregates a series of questions measuring whether students feel empowered, confident and capable of making independent financial decisions.

3.2 Baseline Summary Statistics

The tables below present pre-program student-level characteristics in the control and treatment groups. We applied the Romano-Wolf correction (Romano and Wolf, 2005) to assess the balance in socioeconomic,

[10]That has the legal rights of the SENNA, the national socioemotional assessment instrument.
[11]Centro de Políticas Públicas e Avaliação da Educação, from Universidade Federal de Juiz de Fora

educational, financial literacy and behavior, and non-cognitive dimensions. There are no relevant differences in the baseline aforementioned characteristics.

Figure 2: Balance: Baseline Socioeconomic and Educational Characteristics

			Control		Treatment				
	Number of schools	Number of respondents	Mean	Standard deviation	Mean	Standard deviation	Difference in means (T-C)	Difference in means test (p-value)	Difference in means test (RW-corrected p-value)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Student background characteristics									
Male	190	9,859	0.46		0.45		-0.01	0.447	0.996
Age	190	13,489	15.11	1.07	15.16	1.06	0.06	0.125	0.936
White	190	9,859	0.29		0.26		-0.02	0.106	0.916
Brown	190	9,859	0.5		0.5		0.0	0.898	0.996
Black	190	9,859	0.1		0.12		0.01	0.043	0.698
Socioeconomic index	190	9,765	-0.01	0.97	0.01	1.03	0.02	0.156	0.955
Panel B: Student educational characteristics									
Public school only	190	9,859	0.73		0.69		-0.03	0.479	0.996
Never failed	190	9,859	0.84		0.83		-0.02	0.321	0.993
Afternoon shift	190	10,276	0.55		0.56		0.01	0.683	0.996
Math grade (2019)	186	9,671	7.13	1.22	7.03	1.25	-0.1	0.487	0.996
Math grade (2020)	187	11,724	7.21	1.16	7.04	1.2	-0.17	0.060	0.788
Believes finishing high school is extremely important	190	9,437	0.81		0.8		-0.01	0.393	0.995
Study strategies (index)	190	9,437	-0.02	0.97	0.02	1.03	0.04	0.051	0.746
Engagement in math (index)	190	9,304	-0.02	1.0	0.02	1.0	0.04	0.104	0.916

Elaborated by the authors.

Figure 3: Balance: Baseline Financial Literacy and Non-Cognitive Dimensions

			Control		Treatment				
	Number of schools	Number of respondents	Mean	Standard deviation	Mean	Standard deviation	Difference in means (T-C)	Difference in means test (p-value)	Difference in means test (RW-corrected p-value)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel C: Financial education characteristics									
Financial literacy test score (perc.)	190	10,046	0.61	0.21	0.61	0.21	0.0	0.293	0.993
Simple interest question	190	9,032	0.25		0.25		0.0	0.653	0.996
Compound interest question	190	9,032	0.33		0.32		0.0	0.736	0.996
Inflation question	190	9,032	0.21		0.19		-0.01	0.194	0.971
Risk question	190	9,032	0.3		0.31		0.0	0.385	0.995
Financial behavior (index)	190	9,032	0.02	0.98	-0.02	1.01	-0.04	0.161	0.955
Panel D: Non-cognitive characteristics									
Growth mindset (index)	190	9,437	-0.02	1.0	0.02	1.0	0.03	0.018	0.289
Grit (index)	190	9,304	0.02	1.02	-0.02	0.98	-0.04	0.199	0.971
Internal locus of control (index)	190	9,168	0.02	1.0	-0.02	1.0	-0.05	0.291	0.993
Self-management (*Senna* index)	190	10,052	0.03	1.03	-0.03	0.96	-0.06	0.127	0.936
Negative-emotion regulation (*Senna* index)	190	10,052	0.03	1.03	-0.03	0.97	-0.06	0.029	0.572
Open-mindedness (*Senna* index)	190	10,052	0.0	0.99	0.0	1.01	0.01	0.565	0.996
Amity (*Senna* index)	190	10,052	0.03	1.0	-0.03	1.0	-0.06	0.096	0.908
Engaging with others (*Senna* index)	190	10,052	0.0	1.0	0.0	1.0	-0.01	0.889	0.996

Elaborated by the authors.

3.3 Program Take-up, Implementation, and Attrition

The implementation of the "Learning How to Deal with Money" program faced various challenges and required consistent and diligent coordination. Initial implementation was particularly demanding, primarily due to the restrictions and uncertainty caused by the COVID-19 pandemic. Yet, through diligent planning and flexible adaptability, the program navigated these circumstances successfully.

A robust daily monitoring and coordination routine was established between the BEI Institute and multiple offices of the Goiás Secretary of Education (henceforth "SEDUC-GO"). This allowed for the efficient monitoring of the program's progression, promptly addressing any emerging issues, and keeping all involved parties informed about the project's status. Official SEDUC-GO channels were used for communication, ensuring a streamlined, efficient flow of information. To minimize potential confounding effects, a thorough monitoring of third-party programs in the Goiás educational system was conducted. This vigilance helped in ensuring that the activities of other initiatives did not interfere with our sample, thereby maintaining the validity and reliability of the study's results.

Field data collection was another crucial aspect of the study's implementation. This process involved daily engagement and mobilization of respondents, facilitated by a well-coordinated effort from our team. The close collaboration with schools and teachers also played an essential role in this successful data collection process. In terms of survey administration, a cost-effective and secure method was implemented, leveraging the power of technology. Online surveys were designed for student and teacher participants, with a secure ID authentication process using administrative data and SEDUC-GO's internal system. This approach helped ensure data integrity and protected the privacy of the respondents.

Regarding participant attrition, a factor commonly encountered in longitudinal studies, the overall attrition rate was 25.4% among students. We did not encounter any significant attrition-related issues, and the rate of attrition did not pose any substantial challenges to the implementation of the program. Crucially, our study did not show evidence of differential attrition, meaning that treatment status did not affect participation rates.

Figure 4: Differential Attrition Test

	Control (1)	Treatment (2)	Difference (T-C) (3)	Difference test (p-value) (4)
Panel A: Students				
Baseline respondents	5,853	6,031		
Attritors	1,556	1,461		
Attrition rate	0.266	0.242	-0.024	0.616

Elaborated by the authors.

4 Results

4.1 Cognitive Dimensions

One of the first aspects we examined was the effect of the financial education program on cognitive dimensions, specifically financial education and applied mathematics knowledge. The analysis shows that the program increased students' knowledge in these areas by 0.15 standard deviations, an effect size that is substantively meaningful and aligns with prior literature. This effect size is similar to the results of other studies that evaluated the impact of financial education programs on students' financial knowledge (Lusardi and Mitchell, 2011).

	FinEdu/Math test (std.)		
	(1)	(2)	(3)
Treatment	0.1280	0.1373*	0.1516*
	(0.0811)	(0.0767)	(0.0843)
Pair FE?	Yes	Yes	Yes
Baseline dep. variable?	No	Yes	
Lasso selection?	No	No	Yes
Clustered SE's?	Yes	Yes	Yes
Observations	5,013	5,013	5,012
R^2	0.10745	0.22360	0.34083

Table 1: Results: Financial Education/Applied Math Test Score (Std.)

We then turned to the SAEGO math proficiency results. The SAEGO exam assesses a broad range of math skills, many of which go beyond the scope of the financial education program. In this analysis, no statistically significant effects were detected. However, the point estimates were consistently positive, suggesting a potentially positive impact that is not detectable with our current sample size.

	SAEGO math proficiency (std.)		
	(1)	(2)	(3)
Treatment	0.0553	0.0621	0.0697
	(0.0551)	(0.0554)	(0.0483)
Pair FE?	Yes	Yes	Yes
Baseline dep. variable?	No	Yes	
Lasso selection?	No	No	Yes
Clustered SE's?	Yes	Yes	Yes
Observations	5,322	5,322	5,321
R^2	0.15043	0.39769	0.48493

Table 2: Results: Math Proficiency (SAEGO Exam) (Std.)

To delve deeper, we subdivided the SAEGO exam into two conceptual areas: questions that covered math skills addressed directly by the program (henceforth, "program-specific skills") and those that assessed math knowledge outside of this scope. To assess whether the program had a differential impact on these two areas, we utilized a difference-in-differences (DiD) approach:

$$score_{i,e,s,p} = \beta_0 + \beta_1 D_e + \beta_2 T_{i,s} + \beta_3 (D_e \times T_{i,s}) + \gamma_p + \epsilon_{i,e,s,p}$$

In this regression, $score_{i,e}$ denotes the score of student i on exam e, D_e is a dummy variable that takes the value 1 if the exam score is related to program-specific skills and 0 otherwise, $T_{i,s}$ denotes school-level treatment assignment (1 for treatment and 0 for control), and γ_p are matched-pair fixed effects. The interaction term $D_e \times T_{i,s}$ allows us to identify the differential impact of the treatment on program-specific skills compared to other skills.

Results from this specification showed a positive impact of the financial education program on program-specific math skills, with a statistically significant increase of 0.06 standard deviations. This finding is intriguing as it indicates that the program may have a concentrated effect on math skills directly related to its content.

For example, elementary school math curriculum often covers topics like arithmetic, basic geometry, and data representation, which are not directly related to financial education. The program, on the other hand, may focus on concepts like compound interest, risk diversification, and financial decision-making, which are not typically covered in elementary school. The presence of the program effect in this targeted area suggests the curriculum is achieving its intended aim of improving financial education and applied math skills.

	DiD-type model (1)
D_e	0.0000
	(0.0228)
$T_{i,s}$	0.0134
	(0.0493)
$D_e \times T_{i,s}$	0.0624*
	(0.0316)
Observations	10,642
R^2	0.11346

Table 3: Results: Program-Specific Math Skills (SAEGO) (Std.)

Moving downstream to educational outcomes like math grades and the probability of passing the school year, we found positive but non-significant effects. While the program did not significantly affect these broader educational outcomes, this is in line with existing literature that finds mixed effects of financial education programs on academic performance (?). It's also important to note that these are distal outcomes, and the program's impact may become more apparent over a longer time span.

To sum up, our findings indicate that the financial education program is achieving its objective of enhancing students' financial and applied math knowledge. However, the program's impact on broader math proficiency and academic performance is less clear and warrants further exploration.

	Math grade (std.) (1)	Passed the school year (dummy) (2)
treatment	0.0117 (0.0650)	0.0015 (0.0014)
Mean in control group	0.0000	0.9980
Effect size (% mean)		0.002
Pair FE?	Yes	Yes
Lasso selection?	Yes	Yes
Clustered SE's?	Yes	Yes
Observations	3,908	5,476
R^2	0.59794	0.02777

Table 4: Results: "Downstream" Educational Outcomes

4.2 Non-Cognitive Dimensions

In addition to the analysis of cognitive dimensions, our study also explored various non-cognitive dimensions, including growth mindset, grit, internal locus of control, and an array of socioemotional skills as proposed by the Senna Institute scale.

Growth mindset, as conceptualized by Carol Dweck (Dweck, 2006), is the belief that abilities are not fixed, but can be developed over time. Grit, as defined by Angela Duckworth (Duckworth et al., 2007), reflects resilience and perseverance in the pursuit of long-term goals. The internal locus of control, a psychological construct, refers to the degree to which individuals perceive that they have control over the events that influence their lives (Rotter, 1966).

The Senna Institute scale outlines several socioemotional skills. Self-management, mirroring the conscientiousness construct, assesses qualities such as determination, organization, and persistence. Engaging with others, associated with extraversion, considers aspects like social initiative, assertiveness, and enthusiasm. Amity, related to agreeableness, comprises facets of compassion, respect, and trust. Negative-emotion regulation, which corresponds to neuroticism, includes stress modulation, self-confidence, and frustration tolerance. Lastly, open-mindedness, connected to openness to experiences, embodies curiosity to learn, creative imagination, and artistic interest.

Figure 5: Senna Socio-Emotional Dimensions

Upon analyzing the program's effects on these non-cognitive dimensions, we discovered intriguing trends. Our analysis revealed that the program had no discernible effects on grit or the internal locus of control. At the same time, small but significant negative effect was detected on growth mindset, showing a reduction of -0.05 standard deviations. This suggests that as students' financial literacy and applied mathematical skills improved, their perception about the potential for growth in these areas seemed to become more fixed. The reasons for this are not clear-cut and further investigations, particularly into the second year of the intervention, may shed more light on this phenomenon.

	Growth mindset (index, std.) (1)	Grit (index, std.) (2)	Internal LoC (index, std.) (3)
treatment	0.0578*	0.0462	-0.0268
	(0.0328)	(0.0372)	(0.0478)
Pair FE?	Yes	Yes	Yes
Lasso selection?	Yes	Yes	Yes
Clustered SE's?	Yes	Yes	Yes
Observations	4,642	4,604	4,599
R^2	0.15882	0.33786	0.17217

Table 5: Results: Grit, Locus of Control, Growth Mindset (index, std.)

In terms of socioemotional skills, a somewhat unexpected trend emerged. The program generally had a negative effect, with statistically significant declines observed in negative-emotion regulation and open-mindedness, each decreasing by over -0.06 standard deviations. This finding offers a valuable contribution to the existing literature. It underscores the potential trade-off that school-based financial education programs might entail, where the often-publicized cognitive gains could come at the expense of socioemotional skills.

Socioemotional skills play an important role in students' academic and personal development. They support effective learning, enable interpersonal relationships, and foster resilience in the face of adversity. These skills are often associated with a range of positive outcomes, including improved academic performance, successful transition into adulthood and improved labor market outcomes (Heckman et al., 2006).

	Negative-emotion regulation (1)	Self-management (2)	Amity (3)	Engaging with others (4)	Open-mindedness (5)
treatment	-0.0600*	-0.0527	-0.0569	-0.0193	-0.0663*
	(0.0343)	(0.0417)	(0.0422)	(0.0271)	(0.0305)
Pair FE?	Yes	Yes	Yes	Yes	Yes
Lasso selection?	Yes	Yes	Yes	Yes	Yes
Clustered SE's?	Yes	Yes	Yes	Yes	Yes
RW correction?	Yes	Yes	Yes	Yes	Yes
Observations	4,724	4,724	4,723	4,724	4,724
R^2	0.40042	0.45221	0.28107	0.36020	0.32007

Table 6: Results: Socio-emotional Skills (Senna Instrument)

The observed negative effects raise important considerations for education policy. Although our program succeeded in enhancing financial literacy and applied mathematical skills, it appears to have unintentionally impinged upon students' socioemotional capacities. These effects could be short-lived, perhaps attributable to the stress induced by the novel program structure and its increased learning demands, or the ongoing COVID-19 pandemic. However, without more comprehensive investigation, these are speculative conjectures at best.

In conclusion, while our program shows promise in advancing cognitive skills, its impact on non-cognitive aspects, particularly socioemotional dimensions, calls for further exploration. This study underscores the need for a more holistic understanding of the effects of financial education programs on student development, considering both cognitive and non-cognitive outcomes. Future research should seek to as-certain the nature, persistence, and mechanisms underlying these effects, as these are critical in guiding policy decisions about integrating financial education in schools.

4.3 School Interest and Engagement

Understanding students' interest in math and engagement in school is crucial, particularly in a developing country's context where student dropout rates are high, and academic performance often lags behind international standards. To shed light on these aspects, we used a series of survey questions designed to measure student engagement and their interest in mathematics. Seven questions such as "What I learn in Mathematics at school interests me," "What I learn in Mathematics at school is important for me to achieve my dreams," "What I learn in Mathematics at school is important for me to help my family," and "I consider Mathematics to be one of the most important things that school teaches," allowed us to create an index for these variables[12].

The index was constructed through Principal Component Analysis (PCA), a statistical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. This transformation is defined in such a way that the first principal component has the largest possible variance (that is, accounts for as much of the variability in the data as possible), and each succeeding component, in turn, has the highest variance possible under the constraint that it is orthogonal to the preceding components. The resulting vectors are an uncorrelated orthogonal basis set[13].

Our analysis indicates that while we did not find a statistically significant overall impact of the program on student interest and engagement (according to the PCA index), when we disaggregated the effect to individual question-level, a unique result emerged. Specifically, we found a robust and statistically significant effect of 0.11 standard deviations on the question: "What I learn in Mathematics at school is important for me to help my family." This result held true across all tested specifications, even after correcting for the family-wise error rate through Romano-Wolf correction.

[12] These were measured on a Likert scale, a popular psychometric approach to measuring attitudes or perceptions.

[13] Principal Component Analysis (PCA) is a statistical procedure that is commonly used in social sciences to extract the main variables from a dataset with many variables while retaining as much of the original information as possible. In simpler terms, imagine having a large survey with many questions. Some of these questions might be closely related to each other, leading to redundancy in your data. PCA allows you to condense this information into a smaller set of 'components' that still holds the most critical parts of the original data. These new components are uncorrelated, meaning that each provides unique information, removing any redundancy. After this index was created, it was standardized using the control group's mean and standard deviation. This standardization step allows us to interpret the effects in terms of standard deviations, a common measure that enables comparison across different studies and contexts.

This result is insightful on several fronts. First, it underscores the importance of context in understanding the impact of financial education programs. In a country like Brazil, where familial ties and responsibilities often play a prominent role, the ability of mathematics to empower students to support their families can be a powerful motivator. This also sheds light on potential levers for enhancing student engagement and interest in the subject. By drawing clear connections between mathematical skills and their real-world applicability, especially in a context directly relevant to the student's life (like helping their families), programs like "Learning How to Deal with Money" can increase student interest and engagement.

It also opens up an interesting avenue of research for future studies. While traditionally, much of the focus of educational interventions is on academic performance outcomes, our findings highlight the importance of considering students' perceptions, interests, and motivations. As we continue to understand the multi-dimensional impacts of such interventions, these insights can help design more effective and holistic educational programs.

	Perceived relevance of math (std.)		
	(1)	(2)	(3)
Treatment	0.0039	0.0098	0.0213
	(0.0808)	(0.0701)	(0.0690)
Pair FE?	Yes	Yes	Yes
Baseline dep. variable?	No	Yes	
Lasso selection?	No	No	Yes
Clustered SE's?	Yes	Yes	Yes
Observations	4,619	4,619	4,619
R^2	0.04118	0.18835	0.20600

Table 7: Results: Interest in Math (index, std.)

	Q109 (1)	Q110 (2)	Q111 (3)	Q112 (4)	Q113 (5)	Q114 (6)	Q115 (7)
treatment	-0.0397	0.0216	0.1102***	0.0026	-0.0077	-0.0353	0.0680
	(0.0515)	(0.0513)	(0.0513)	(0.0553)	(0.0556)	(0.0438)	(0.0583)
Mean in control group	3.08	3.00	3.00	3.00	2.18	2.80	1.97
Effect size (% mean)	-0.013	0.007	0.0367	0.001	-0.004	-0.013	0.035
Pair FE?	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lasso selection?	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE's?	Yes	Yes	Yes	Yes	Yes	Yes	Yes
RW correction?	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,619	4,619	4,619	4,619	4,619	4,619	4,619
R^2	0.15685	0.16747	0.15766	0.13756	0.08373	0.12931	0.15243

Table 8: Interest in Math (survey questions)

4.4 Financial Attitudes, Behavior and Habits

We now turn our attention to evaluating the impact of the program on students' financial behavior and habits. Our evaluation comprised a set of questions to assess behavioral changes, such as seeking help with financial matters, prudent buying decisions, paying attention to economic news, suggesting saving money for emergencies at home, and striving to save for personal enjoyment.

Despite the broad array of behaviors we attempted to impact, we found no substantial evidence that the "Learning How to Deal with Money" program influenced these behaviors over the course of the six-month intervention. This result aligns with previous literature which shows that ingrained behaviors, particularly financial habits, can be challenging to alter in the short term (**??**).

Notably, the program did yield a significant result in one specific area: students reported being more frequently asked for help with finance and money-related matters by their peers. The potential mechanisms behind this result are varied. It is possible that the program's financial education components boosted students' confidence and ability to converse about financial matters, thus making them a resource for their peers. Alternatively, the increased incidence of peer consultations could be due to a greater awareness and curiosity about financial matters within the student community, sparked by the program's activities.

However, in all other areas of financial behavior and habits examined, we did not find significant changes. It should be noted, though, that the lack of immediate effects on financial behaviors does not necessarily imply the program's inefficacy in shaping such habits. Behaviors are often deeply ingrained and take a considerable time to change, especially considering the complexity of the skills the program attempted to inculcate over a relatively short period.

	Financial behavior and habits (index, std.)		
	(1)	(2)	(3)
Treatment	0.0205	0.0050	-0.0039
	(0.0469)	(0.0387)	(0.0371)
Pair FE?	Yes	Yes	Yes
Baseline dep. variable?	No	Yes	
Lasso selection?	No	No	Yes
Clustered SE's?	Yes	Yes	Yes
Observations	4,577	4,577	4,577
R^2	0.02664	0.22109	0.24015

Table 9: Results: Financial Attitudes, Behavior and Habits (index, std.)

These results underscore the importance of long-term assessments of financial education interventions. Behavioral changes may not be apparent immediately post-intervention, but they may manifest over a more extended period as students mature and have more opportunities to apply their learned skills in real-life financial situations. Indeed, as highlighted by Bruhn et al. (2022), long-term follow-up studies of financial education interventions reveal that effects on financial behavior can take years to materialize. As we plan to continue the intervention into a second year, it will be insightful to investigate the stability of these results and whether delayed effects will emerge in financial behavior and habits. This will be a valuable contribution to the literature on the effectiveness of financial education interventions in schools, particularly regarding their ability to foster enduring behavioral changes (Bruhn et al., 2016).

In summary, while the program showed some promise in promoting students to become peer resources for financial matters, the impact on broader financial behavior and habits was limited. However, as behavioral change is a long-term endeavor, further investigation is warranted to assess the program's impact over an extended period. The lessons gleaned from such longitudinal studies would be instrumental in refining the design and implementation of similar financial education initiatives in the future.

5 Conclusion

This paper undertook a comprehensive examination of the ”Learning How to Deal with Money” program, a school-based financial education initiative implemented in public schools in Rio de Janeiro, Brazil. The study's primary objective was to evaluate the program's impacts across a wide array of cognitive and non-cognitive dimensions, as well as on students' interest in school, engagement, financial behaviors, and habits.

One of the paper's central contributions is to the burgeoning literature on the impacts of financial education in schools, especially in developing countries. We found evidence suggesting that the program improved financial education and applied math scores by 0.15 standard deviations, particularly in those areas directly addressed by the curriculum. This result aligns with the previous literature that has generally found positive effects of financial education on financial knowledge and mathematics-related abilities.

However, our analysis also pointed to a novel, perhaps unexpected, finding: that the benefits of financial education might come at a cost to certain socio-emotional skills. We observed statistically significant negative impacts on students' growth mindset and certain socio-emotional skills, particularly those related to negative-emotion regulation and open-mindedness. This underlines the critical need for a more nuanced understanding of the full spectrum of effects that such interventions can have, beyond their primary educational objectives.

Regarding school engagement and interest, we found robust evidence that students deem what they learn in math as more relevant for helping their families, an encouraging result given the socio-economic context of Brazil. However, we did not observe any discernable effect on an overall index of school interest and engagement, suggesting that the intervention did not influence students' general perception of school.

On the aspect of financial behaviors and habits, the evidence was rather mixed. While the program did not appear to impact most financial behaviors and habits over the short term, it did lead to an increase in students being sought out for financial advice by their peers. This underscores the value of patience in expecting behavioral change, particularly given the short duration of the intervention.

Looking ahead, our findings call for further research into several critical areas. A crucial next step is to investigate the longer-term effects of the intervention, particularly in terms of financial behaviors and habits, which may take more time to manifest. Also, understanding the negative effects on socio-emotional skills warrants further investigation, as does the exploration of potential mechanisms behind these observed impacts.

In summary, this paper offers a balanced perspective on the impacts of school-based financial education, highlighting both its benefits and potential trade-offs. The lessons learned here underscore the complexity of educational interventions and the need for rigorous, multi-dimensional evaluations to fully understand their impacts.

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A Appendix

A.1 Sampling Strategy

As presented in the text, the sample selection made use of a stratified draw based on what we have been calling similarity units. These were defined using the following approach: for each regional section of the state educational system with a reasonable number of hybrid schools (eight or more), four similarity units were formed based on the distribution of the 2019 SAEGO mathematics scores in that region (the first unit then corresponds to schools who were in the first math quartile, the second to schools with performance between the 25th and the 50th percentile of the distribution, and so on). As the number of schools in each region varies considerably, some similarity units were with 9 schools, while others had only two. In smaller regional sections (fifteen out of the forty), schools were divided into just two groups (below or above the median score) or were not grouped at all (this was the case of three regions with less than four hybrid schools).

Once the similarity units were defined, sampling tests were performed to assess the representativeness of this approach. In particular, the following process was repeated twenty times and, for each resulting sample, it was tested how representative of the hybrid schools it was: a random number was assigned to each school and, within each similarity unit, schools with a number less than or equal to the 47th percentile were selected.

The representativeness assessment was based on the analysis of the distributions (tables below) of the following variables: mathematics and literacy scores in the 2018 and 2019 SAEGO; the performance of schools in the IDEB from 2015 and 2017; the number of students enrolled in the 9th grade and the total enrollment in the schools. Additionally, Kolmogorov-Smirnov tests were performed to assess the similarity in the distribution of each of the variables in the resulting samples and in the set of the other hybrid schools. Of the twenty resulting samples, in only three of them did any of the variables present a distribution statistically different from the rest of the hybrid schools.

This was considered a good result and the methodology applied again (21st stratified draw) to define the official sample of 201 schools. Kolmogorov-Smirnov tests suggested that the distribution of relevant variables in the sample was similar to the rest of the population. After the sampling, however, the Education Secretary informed us that 5 schools out of the 201 were undergoing reorganization and, therefore, would not be able to participate in the study.

Due to the proximity of the baseline, the solution adopted was again a stratified random selection of 4 new schools from the similarity units with the highest number of schools (twelve). The choice of 4 units out of these 12 was also made from a draw. Once the groups were defined, within each one, the school outside from the original sample and with the lowest value for the previously assigned random number (from the mentioned 21st draw) was selected.

A.2 Pair-Matching

Three sets of variables were used to define and test the school pairing approach:

<u>The Selection Set (variables at the school level)</u>

- percentage of students with internet access at home;
- percentage of students that answered the baseline survey;
- percentage of teachers who answered the baseline survey;
- percentage of students with available academic records.

<u>The Students Set (variables at the school average level)</u>

- five principal factors[14] aggregating students' answers to the baseline socioemotional section. As presented in Section 5, this block of the questionnaire corresponds to the SENNA instrument, applied in several municipalities and states throughout Brazil. The SENNA Institute is responsible for calculating the socioemotional traits scores, based on its own methodology and parameters. As at the time of the draw, the official results were not yet available, the principal component analysis was chosen to partially represent this relevant dimension in the pairing process;
- three principal factors[15] aggregating information on the socioeconomic level of the students;
- percentage of correct answers in each of the four basic financial literacy questions (on inflation, simple and compound interest, and risk diversification);
- the mean, the 25th and 75th percentiles of the 2020 mathematics grade distribution (from academic records).

[14]From a principal component analysis (PCA), statistical technique used to aggregate information from several variables.
[15]From a principal component analysis.

The Teachers Set (variables at the school average level)

- a principal factor aggregating information on the socioeconomic level of the teachers;
- a principal factor aggregating answers to questions regarding external locus of control;
- a principal factor aggregating answers on grit and perseverance;
- a principal factor aggregating answers on self-efficacy;
- a principal factor aggregating answers on their motivation and commitment with the profession;
- the percentage of correct answers in each of the four basic financial literacy questions (on inflation, simple and compound interest, and risk diversification).

The first tested pairing model was based on a principal factor component (PCA) aggregating the following characteristics of the schools at the beginning of 2020[16]:

- dropout, failure and passing rates from 2017, 2018 and 2019;
- mathematics and literacy mean scores in 2017, 2018 and 2019 SAEGO;
- school management index[17] from 2017, 2018 and 2019;
- total enrollment in school (2019) and in the 9th grade (2020);
- the socioeconomic level of the school in 2015 (latest available year at the time), computed by INEP.

In this model, the values for each year were considered as observations (pooled analysis).

The second tested model adopted the following approach: using the selection set aforementioned, a principal factor component was generated along with four groups (quartiles) based on its distribution. The variables from the teachers and students sets were used to create another principal factor aggregating important information on these dimensions. Then, within each selection group, schools were paired for proximity in this second aggregated factor. That is, schools were first grouped based on the availability of information, then paired with similar ones in terms of student and faculty characteristics.

The third model was the chosen one and is based on the following approach: initially, three principal factors were created, being one for each aforementioned set; then, these factors were used to generate a

[16]This model would be used in the impact evaluation of that year if the pandemic had not occurred.
[17]Calculated annually by the Brazilian National Institute of Educational Studies and Research (INEP).

new one aggregating information from schools in all the proposed dimensions. The pairing was made for proximity in terms of this more aggregate factor.

The models were assessed based on the probability of registering imbalances in the three proposed dimensions (selection, students and teachers). For this, by proposed model, one hundred randomizations were simulated and, for each resulting draw, the assigned groups of the schools were regressed on the three sets of variables, seeking to evaluate potential selection problems in the pairing.

The table below summarizes the results, showing by model, in how many draws (out of one hundred), the variables of each dimension showed joint statistical significance. The 2nd and 3rd model presented a total number quite similar (29 and 30, respectively). However, as the latter presented a smaller number of imbalances in the selection dimension (relative to the availability of information), it was the chosen.

A.2.1 Results: Non-Cognitive Dimensions

	Negative-emotion regulation (Senna index, std.)		
	(1)	(2)	(3)
Treatment	-0.1044**	-0.0682**	-0.0600*
	(0.0405)	(0.0341)	(0.0343)
Pair FE?	Yes	Yes	Yes
Baseline dep. variable?	No	Yes	
Lasso selection?	No	No	Yes
Clustered SE's?	Yes	Yes	Yes
Observations	4,724	4,724	4,724
R^2	0.02493	0.35521	0.40042

Table 10: Results: Negative-Emotion Regulation (index, std.)

	Open-mindedness (Senna index, std.)		
	(1)	(2)	(3)
Treatment	-0.0931**	-0.0759**	-0.0663**
	(0.0426)	(0.0302)	(0.0305)
Pair FE?	Yes	Yes	Yes
Baseline dep. variable?	No	Yes	
Lasso selection?	No	No	Yes
Clustered SE's?	Yes	Yes	Yes
Observations	4,724	4,724	4,724
R^2	0.02614	0.31009	0.32007

Table 11: Results: Open-mindedness (index, std.)

	Self-management (Senna index, std.)		
	(1)	(2)	(3)
Treatment	-0.1162**	-0.0697	-0.0527
	(0.0509)	(0.0426)	(0.0417)
Pair FE?	Yes	Yes	Yes
Baseline dep. variable?	No	Yes	
Lasso selection?	No	No	Yes
Clustered SE's?	Yes	Yes	Yes
Observations	4,724	4,724	4,724
R^2	0.03836	0.42196	0.45221

Table 12: Results: Self-Management (index, std.)

	Engaging with others (Senna index, std.)		
	(1)	(2)	(3)
Treatment	-0.0394	-0.0337	-0.0193
	(0.0344)	(0.0280)	(0.0271)
Pair FE?	Yes	Yes	Yes
Baseline dep. variable?	No	Yes	
Lasso selection?	No	No	Yes
Clustered SE's?	Yes	Yes	Yes
Observations	4,724	4,724	4,724
R^2	0.03617	0.34291	0.36020

Table 13: Results: Engaging With Others (index, std.)

	Amity (Senna index, std.)		
	(1)	(2)	(3)
Treatment	-0.1076**	-0.0699	-0.0569
	(0.0486)	(0.0444)	(0.0422)
Pair FE?	Yes	Yes	Yes
Baseline dep. variable?	No	Yes	
Lasso selection?	No	No	Yes
Clustered SE's?	Yes	Yes	Yes
Observations	4,724	4,724	4,723
R^2	0.05421	0.25452	0.28107

Table 14: Results: Amity (index, std.)