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Estimating causal effects of extended school closures on non-cognitive factors: evidence from TIMSS and PISA

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Abstract: This study investigates the causal impact of prolonged school closures during the COVID-19 pandemic on non-cognitive predictors of mathematics achievement and the strength of their association with student performance. Drawing on data from TIMSS (2015, 2019, 2023) and PISA (2022), we apply difference-in-differences (DiD) models across two research designs: successive cross-sections of 4th-grade cohorts and a pseudo-panel following a cohort from primary to secondary school. Our findings indicate that, although school closures did not significantly affect the level of students' self-beliefs, they did reduce the strength of the association between negative attitudes and achievement—particularly among girls and in OECD countries. The results highlight the nuanced effects of distance learning on mathematics outcomes, contributing to the literature on the role of affective-motivational factors in education.

Keywords: Mathematics achievement, non-cognitive factors, distance learning, school closures, TIMSS, PISA, gender differences, math anxiety, self-efficacy

JEL codes: I21, I24, C21, C23, C83

Introduction

1.1. Non-cognitive predictors of mathematics achievement

It is well established in the research that scores on mathematics assessments reflect not only students' academic achievement but also, to a significant extent, environmental predictors such as family socioeconomic status (Bradley & Corwyn, 2002; Sirin, 2005) and school socioeconomic status (Kim et al., 2019; Perry & Mcconney, 2010). There is also the other group of crucial predictors of academic achievement: non-cognitive factors, such as intrinsic motivation, attitude towards subject and self-related beliefs (Lee & Stankov, 2018; Lee, 2009; Marsh et al., 2005). Numerous studies highlight that they are particularly important in relation to achievement in mathematics (Habók et al., 2020; Pipere & Mieriņa, 2017b) and unlike environmental factors, are considered significantly changeable through effective teaching and targeted interventions (Lee & Shute, 2010a).

According to meta analyses, the most crucial non-cognitive factors in relation to mathematics achievement are: engagement and motivation, self-concept, math anxiety, and attitude towards mathematics (Hattie, 2008). Another study confirms that especially important for the success in this subject are self-related beliefs, which include general attitude towards mathematics, self-confidence, self-efficacy and math anxiety (Lee & Stankov, 2018b). While self-efficacy is defined as the belief in one's ability to achieve desired outcomes (Bandura, 1997), math anxiety is characterized by difficult physiological and emotional responses when an individual engages in a mathematical task (Ashcraft, 2002; Hembree, 1990). Results from large-scale assessments indicate that mathematics achievement is as strongly correlated with mathematics anxiety as with parents' level of education, an indicator of socioeconomic status (Lee & Stankov, 2018a). The correlation between mathematics achievement and mathematics self-efficacy is even stronger, highlighting the important role of non-cognitive predictors. Self-related beliefs are also highly intercorrelated. For instance, mathematics anxiety has been found to exhibit a strong negative correlation with both enjoyment of learning mathematics and confidence in mathematics among school-aged children (Hembree, 1990).

Gender has been one of the most extensively studied factors in relation to non-cognitive predictors and mathematics. While there is little or no difference between girls and boys in mathematics performance (Else-Quest et al., 2010), boys report more positive attitudes towards learning mathematics and science (Else-Quest et al., 2010), and girls report lower self-confidence and greater mathematics anxiety (Devine et al., 2012; Jacobs et al., 2002). Although even in the earlier grades boys often rate themselves higher in mathematics than girls do (Dowker et al., 2012), most studies suggest that gender differences are developing just at adolescence (Dowker et al., 2016; Wu et al., 2012). Several studies have explored the role of gender in the relationship between mathematics anxiety and achievement, yielding mixed findings. Some research suggests that mathematics anxiety is more negatively associated with performance in males than in females (Hembree, 1990). In contrast, other studies report no significant gender differences in the strength of this relationship (Wu et al., 2012), while yet others indicate that mathematics anxiety is more strongly related to basic mathematics performance in males and to applied mathematics performance in females (Miller & Bichsel, 2004). These diverse findings underscore the need for further research to better understand the factors that influence gender differences in both self-related beliefs and their association with mathematics performance (Dowker et al., 2016).

1.2. Distance learning during COVID-19

Globally schools have been closed for an average of 5.5 months (22 weeks) since the beginning of the pandemic in 2020, but there is considerable variation across regions and countries (*UNESCO*, 2023). Those school closures and rapid shifts to remote learning have led to substantial learning losses across various domains, educational levels and countries (Betthäuser et al., 2023; Engzell et al., 2020). The educational loss is estimated to be equivalent to roughly a one-half of a school year, while every week that schools were closed makes the loss increase by almost 1 percent of a standard deviation (H. Patrinos et al., 2023). Moreover, the learning loss can be translated into economic loss, which amounts to almost one percentage point reduction in global GDP growth (Jakubowski et al., 2023). The consequences are believed to be especially harmful in developing countries, where remote learning has faced numerous challenges including limited internet access and lack of dedicated study spaces (Lichand et al., 2021).

The losses in the results from mathematics and science are assessed to be significantly larger than from humanities (Di Pietro, 2023). Decline in mathematics is estimated at 14 percent of a standard deviation, roughly equal to seven months of learning (Jakubowski et al., 2025). Interestingly, it is not clear to state whether remote learning also increased math anxiety and its impact on math achievement, although students experienced negative feelings during lockdown, such as being anxious, stressed, overwhelmed, tired, and depressed (Al-Maskari et al., 2021; Camacho-Zuñiga et al., 2021). Some studies proved the significant growth of math anxiety (Li et al., 2023; Lichand et al., 2021b), but the impact was estimated on small samples and appears to be influenced by various factors such as the quality of the Internet (Lanius et al., 2022). Simultaneously, high math anxious students reported significantly lower levels during distance learning, while no significant changes were observed for moderate and low math anxious students (Doz & Doz, 2022). According to another study conducted during the pandemic, students prefer in-person learning to distance learning, but in this preferred mode they experience statistically significant higher math learning and evaluation anxiety, which is induced by the teacher's explanations and by having to perform difficult tasks (Pirrone et al., 2022).

Moreover, the pre-pandemic research indicates that online learning of mathematics can influence positively on students' attitudes towards this subject, especially in the group of students with a weaker mathematical background (A. Luna et al., 2022). In examined statistics classes, there were reported statistically significant decreases in anxiety and increases in attitudes by online students. It can be an encouragement to use online materials and techniques to reduce anxiety (DeVaney, 2010). The possible explanation of this phenomenon is that during distance learning students can learn at their own pace, revisiting electronic resources such as instructional videos and online materials as needed (Edwards & Rule, 2013). Moreover, many online games and quizzes give immediate results to students and the possibility to improve the achievement, which is difficult to achieve in face-to-face teaching (Yeung et al., 2021). Nevertheless some distance learning approaches may also lead to passive learning if they lack sufficient opportunities for active participation and in-depth discussion, which are supportive for deep understanding of mathematics concepts (A. Luna et al., 2022).

1.3. The current research

The presented research, including studies based on large-scale assessments, indicates that longer durations of school closures are associated with greater learning losses in mathematics (H. Patrinos et al., 2023; Jakubowski et al., 2023; Lichand et al., 2021). However, comparatively little is known about how these extended periods of distance learning have affected non-cognitive factors such as attitudes toward mathematics, self-efficacy, and the extent to which these factors explain the strength of association between non-cognitive traits and mathematics achievement (Habók et al., 2020). The present study aims to examine the impact of prolonged school closures on students' attitudes toward mathematics, as well as on the strength of the relationship between selected non-cognitive factors and mathematics achievement. Accordingly, the following research questions are addressed:

1) To what extent did prolonged time of distance learning affect the levels of non-cognitive predictors of mathematics achievement among successive cohorts of fourth-grade

students (TIMSS 2015, 2019, 2023) and within a single student cohort (TIMSS 2015 and PISA 2022)?

2) What impact did extended school closures have on the strength of the association between non-cognitive factors and mathematics achievement in both successive cohorts of fourth-grade students (TIMSS 2015, 2019, 2023) and a single cohort observed longitudinally (TIMSS 2015 and PISA 2022)?
3) Are there significant gender differences in the outcomes related to questions (1) and (2)?

2. Data & Methodology

Large-scale assessments, such as TIMSS and PISA, are designed to provide information about both math achievement and a wide range of external factors, including environmental indicators and variables that measure mathematics self-efficacy and anxiety (PISA), confidence in mathematics and enjoyment of learning this subject (TIMSS). Large scale assessments thus facilitate not only cross-country comparisons, but also using quasi-experimental methods for estimating causal effects of educational policies such as regression discontinuity design (Shen & Konstantopoulos, 2019; Luyten, 2006) and differences in differences approach (Pedraja-Chaparro et al., 2015; Lavrijsen & Nicaise, 2015; Jakubowski, 2010; Hanushek & Wößmann, 2006).

2.1. Large Scale Assessments: TIMSS, PISA

According to research questions, we utilize data on mathematics achievement and non-cognitive factors from two large-scale international assessments: TIMSS (4th grade) and PISA (15-year-olds). Two separate analyses are conducted: among successive cohorts of fourth-grade students (TIMSS 2015, 2019, 2023), denoted as “Analysis 1”, and approximately within a single student cohort (TIMSS 2015, PISA 2022), denoted as “Analysis 2”.

Waves of TIMSS included in Analysis 1 provide information on two latent variables representing non-cognitive constructs: confidence in mathematics and enjoyment of learning mathematics. On average, enjoyment of learning mathematics accounts for 3.7% of the country-level variance in mathematics achievement, whereas confidence in mathematics demonstrates substantially greater explanatory power, accounting for 16.6% of the variance. When both variables are included in a multiple regression model, they jointly explain approximately 17.6% of the variance in mathematics achievement. Due to their high combined explanatory strength, the highest among all non-cognitive variables considered, these two constructs are retained for use in subsequent modeling. Analysis 2 adopts a pseudo-panel design, treating data from TIMSS 2015 (4th grade, the average age is 10) and PISA 2022 (15-year-olds) as longitudinally comparable cohorts. Such an approach has already been applied in articles measuring the effect of early tracking on achievement in secondary education (Lavrijsen & Nicaise, 2015; Hanushek & Wößmann, 2006). The time gap between TIMSS 2015 and PISA 2022 amounts to 7 years, which is close to the age difference between the participants of TIMSS and PISA. We assume that they are representations of almost the same birth cohorts and they are taken from roughly the same populations.

To ensure comparability between TIMSS and PISA, it is necessary to harmonize the data across both assessments. According to mathematics achievement, both large-scale studies report individual-level performance using plausible values. While TIMSS provides five plausible values and PISA 2023 provides ten, the methodologies employed for constructing plausible values and estimating average scores at the population are broadly comparable. In terms of non-cognitive factors, TIMSS 2015 includes two latent constructs measuring students' confidence in mathematics and enjoyment of learning mathematics, whereas PISA 2022 includes a single construct focused on mathematics anxiety. To facilitate comparison between the two assessments, a composite variable is generated to represent negative attitudes toward mathematics. This variable is derived from four conceptually aligned items selected from each assessment, as detailed in Table 1. All items are rated on a four-point Likert scale and were reverse-coded where necessary to ensure that higher scores consistently reflect more negative attitudes toward mathematics. The observations with missing values in examined variables are excluded from the analysis.

The *negative attitude* variable is constructed as the standardized sum of selected items. This standardized variable is constructed consistently across all TIMSS waves included in Analysis 1 and serves as a common measure of negative attitudes toward mathematics in all analyses. In the 2023 wave of TIMSS, however, the question represented by Item 2 was excluded from the questionnaire, therefore, the negative attitude score for that wave is computed using the remaining three items.

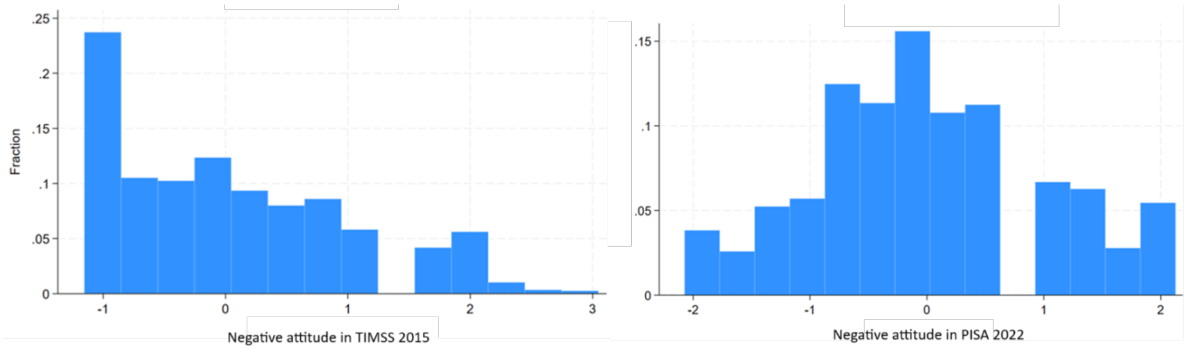
Table 1. Items included in the calculation of negative attitude variable

Item	TIMSS 2015, 2019	PISA 2022

$Item_1$	Mathematics is one of my favourite subjects.	Mathematics is one of my favourite subjects.
$Item_2$	Mathematics makes me nervous.	I get very nervous doing mathematics problems.
$Item_3$	Mathematics is easy for me. (reversed)	Mathematics is harder for me than any other subject.
$Item_4$	Mathematics makes me confused.	I feel helpless when doing a mathematics problem.

The histograms presented in Figure 1 indicate a significantly more positive attitude toward mathematics among elementary school students, which is consistent with research findings. As the difficulty of math learning increases with higher grade levels, the attitude towards this subject deteriorates with age (Wu et al., 2012; Mata et al., 2012; Olmez & Ozel, 2012).

Figure 1. Histogram of negative attitude in: a. TIMSS 2015, b. PISA 2022



To address the second research question, two indicators of the association strength between non-cognitive factors and mathematics achievement are estimated: (1) the proportion of variance in mathematics achievement explained by non-cognitive factors, expressed as the coefficient of determination ($R^2{}_{t,i}$); and (2) the regression coefficients representing the slopes of achievement regressed on non-cognitive predictors. While the $R^2{}_{t,i}$ values serve as the primary measure in subsequent analyses- reflecting the extent to which variation in mathematics achievement is accounted for by the model in each country and assessment wave- the regression slopes are utilized as part of robustness check. In Analysis 1, for each country $i \in \{1,2,\ldots,39\}$ and wave $t \in \{TIMSS\ 2015, TIMSS\ 2019, TIMSS\ 2023\}$, the association metrics ($R^2{}_{t,i}$, $a_{t,i}$, $b_{t,i}$) are estimated from linear regression models of the following form

$$Achievement_{t,i,j} = \mathrm{a}_{t,i} * \text{confidence}_{t,i,j} + \mathrm{b}_{t,i} * \text{enjoyment}_{t,i,j} + \varepsilon_{t,i} ,$$

where j indexes students within each country and waves. In Analysis 2, the association between mathematics achievement and the composite *negative attitude* variable is estimated using simple linear regression models, separately for each country $i \in \{1,2,\ldots,36\}$ and wave $t \in \{TIMSS\ 2015, PISA\ 2022\}$, as described by the following equation:

$$Achievement_{t,i,j} = \mathrm{a}_{t,i} * \text{negative attitude}_{t,i,j} + \varepsilon_{t,i}.$$

The resulting coefficients of determination and regression slopes are used to evaluate the impact of extended school closures on the relationship between non-cognitive factors and mathematics achievement.

2.2. Difference in differences

To measure effects of longer time of distance learning, countries are categorized into intervention and control groups based on the duration of full school closures, measured in weeks, as reported by UNESCO (UNESCO, 2025, February). According to UNESCO, full school closures are defined as "government-mandated closures of educational institutions affecting most or all of the student population." Countries that experienced school closures lasting 14 weeks or more, the median duration in the UNESCO dataset, are assigned to the intervention group, while those with shorter closures are placed in the control group. Detailed information regarding the countries included in the analyses, such as OECD membership, duration of school closures, and inclusion in each analysis, is provided in Table 2.

Table 2. Information about countries included in control and intervention group.

Weeks of fully schools closure									
13 or less (control group)					14 or more (intervention group)				
Country	*Weeks*	*Analysis 1*	*Analysis 2*	*OECD*	*Country*	*Weeks*	*Analysis 1*	*Analysis 2*	*OECD*
Australia	0	x	x	x	**Chile**	14	x	x	x
Sweden	0	x	x	x	**Germany**	14	x	x	x
USA	0	x	x	x	**Morocco**	17	x		
Japan	3	x	x	x	**United Arab Emirates**	18	x	x	
Singapore	4	x	x		**Morocco**	17	x	x	

Norway	5	x	x	x
France	7	x	x	x
Denmark	8	x	x	x
Finland	8	x	x	x
Croatia	8		x	
New Zealand	8	x	x	x
Oman	8	x		
Armenia	9	x		
Kazakhstan	9	x	x	
Spain	10	x	x	x
Lithuania	10	x	x	x
Slovakia	10	x	x	x
Republic of Korea	11	x	x	x
Netherlands	12	x	x	
Portugal	12	x	x	x
Canada	13	x	x	x
Cyprus	13	x		
Italy	13	x	x	x
	N	22	26	16

Bulgaria	18	x	x	
Georgia	19	x	x	
Indonesia	20		x	
Czechia	20	x	x	x
Hungary	20	x	x	x
Slovenia	21		x	x
Ireland	22	x	x	x
Iran	22	x		
Qatar	25	x	x	
Poland	26	x	x	x
Serbia	28	x	x	
Turkey	28	x	x	x
Bahrain	34	x		
Saudi Arabia	50	x	x	
Kuwait	62	x		
	N	17	16	8

With the intervention and control groups defined, the first research question is examined using a difference-in-differences (DiD) approach applied to repeated cross-sectional data, as large-scale assessments involve distinct samples of individuals across countries and time points. To estimate the causal effect of prolonged school closures on non-cognitive predictors, the DiD method compares changes in the outcome variable between treatment and control groups before and after the intervention (Collischon, 2022). The DiD estimator reflects the difference in these changes over time and can be expressed in the following regression specification:

$$y_{i,c,t} = \beta_c + \beta_t + \delta * D_{c,t} + \varepsilon_{\mathrm{i,c,t}} ,$$

where $y_{i,c,t}$ denotes the observed level of the non-cognitive factor for individual $i$in country c at time t; β_c and β_{t} represent country and time fixed effects, respectively; $D_{c,t}$ is a binary treatment indicator for whether country c experienced prolonged school closures at time t; δ is the DiD estimator capturing the treatment effect and $\varepsilon_{\mathrm{i,c,t}}$ is the error term.

The second research question aims to assess the impact of prolonged school closures on the strength of association between non-cognitive factors and mathematics achievement at the country level. This association is operationalized using two statistical indicators: the coefficient of determination (R^2) and the slope of the regression line, which is used as the robustness check. While Analysis 1 investigates changes across countries in successive cohorts of 4th-grade students, Analysis 2 seeks to identify within-cohort changes as students progress from primary to secondary education. This longitudinal approach has been previously employed in studies evaluating the effects of early tracking on academic outcomes in secondary education (Lavrijsen & Nicaise, 2015; Hanushek & Wößmann, 2006). To estimate the causal effect of extended distance learning, a difference-in-differences (DiD) approach is applied to panel data using the following regression specification:

$$y_{c,t} = \beta_t + \delta * D_{c,t} + \varepsilon_{\mathrm{c,t}},$$

where $y_{c,t}$ represents the observed strength of the association between non-cognitive factors and mathematics achievement in country c at time t; β_t denotes the time fixed effect; $D_{c,t}$ is a binary treatment indicator equal to 1 if country c experienced prolonged school closures at time t; δ is the DiD estimator reflecting the treatment effect and $\varepsilon_{\mathrm{c,t}}$ is the error term.

To address the third research question concerning gender differences, the analyses are replicated separately for male and female students. The average treatment effects are then estimated independently within each group, and their statistical significance is verified across genders.

For the difference-in-differences (DiD) estimator to yield a causal interpretation, several key assumptions must be satisfied. Foremost among these is the parallel trends assumption, which assumes that, in the absence of the treatment, the mean outcome would have evolved similarly over time for both the treatment and control groups. This assumption underlies the credibility of DiD estimates by asserting that any observed divergence in outcomes post-treatment can be attributed to the intervention, rather than to pre-existing differences in trends. However, it is important to acknowledge that the parallel trends assumption is in fact untestable, as it concerns the counterfactual evolution of the untreated group. Its plausibility is typically assessed by examining pre-treatment trends in the outcome variable for both groups. This validation is feasible in Analysis 1, where data are available for two pre-treatment periods: TIMSS 2015 and TIMSS 2019. By contrast, in Analysis 2, the assessment is more challenging due to the availability of only two time points: TIMSS 2015 and PISA 2022. Despite this limitation, TIMSS 2015 is employed as a baseline reference in both analyses, while TIMSS 2023 and PISA 2022 are closely aligned in terms of timing. Furthermore, both analyses utilize a consistently defined and constructed measure of students' negative attitudes toward mathematics. If the parallel trends assumption is met across TIMSS 2015, 2019, and 2023, it is reasonable to extend this assumption to the TIMSS 2015–PISA 2022 comparison as well (Rothbard et al., 2023).

Second, the Stable Unit Treatment Value Assumption (SUTVA) must be satisfied. This assumption requires that the treatment administered to one unit does not influence the outcomes of other units. That is, no spillover effects between the treatment and control groups should occur. In the context of this study, the likelihood of such spillover effects is minimal, as the units of analysis are distinct national student populations. Lastly, the assumption of no anticipation effects must also be held. This condition is met in the present study, as the onset of the COVID-19 pandemic, and the corresponding duration of school closures, could not have been anticipated by the affected countries or their education systems.

3. Results

3.1. Analysis 1: TIMSS 2015, TIMSS 2019, TIMSS 2023

Although the parallel trends assumption is satisfied across all estimated models, the average treatment effect on the treated (ATET) of prolonged school closures on both the levels of non-cognitive factors (confidence in mathematics and enjoyment of learning mathematics) as well as on the strength of the association between these factors combined and mathematics achievement, is not statistically significant within the successive cohorts of 4th-grade students. Comparable results are observed when the analysis is conducted using the composite variable representing negative attitudes toward mathematics. Detailed results are presented in Table 3.

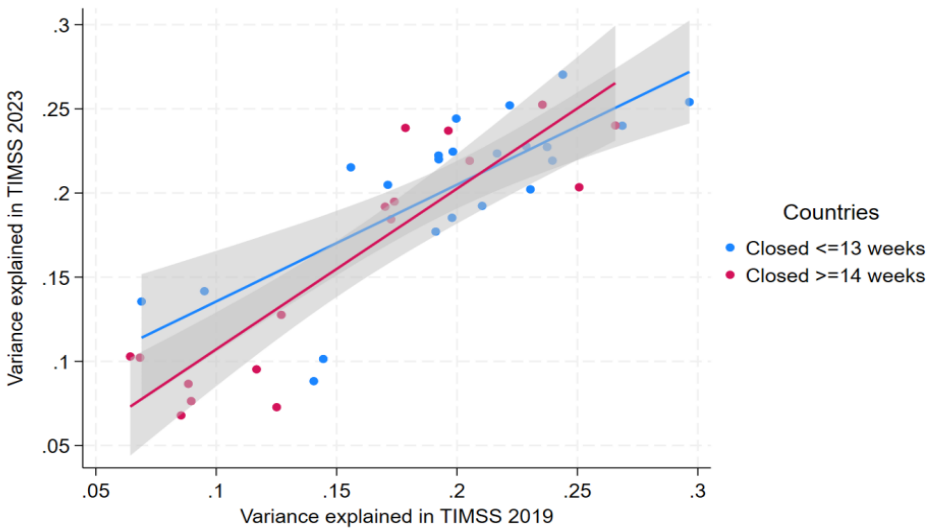
Table 3. Estimates from difference-in-differences model in Analysis 1

	Average Treatment Effect on Treated			Parallel Lines Assumption	
	Coefficient	t	P>|t|	F(1, n)	P>F
Non-cognitive factors					
R. Question 1 (*confidence*)	-.0415187	-0.44	0.661	0.03	0.8708

R. Question 2 (*enjoyment*)	.1355201	1.28	0.210	0.71	0.4031
R. Question 2	-.0083189	-0.91	0.368	2.06	0.1596
Negative attitude					
R. Question 1	-.0294157	-0.77	0.444	0.03	0.8654
R. Question 2	-.0063439	-0.69	0.494	2.06	0.1596

The relationships between coefficients of determinations calculated for TIMSS 2019 and 2023 in both the intervention and control group are illustrated in Figure 2. It also visualises that there are no significant differences between two fitted lines, which represent treatment and control groups.

Figure 2. The relationship between variance explained in TIMSS 2019 and TIMSS 2023 in control and intervention group



Similarly, the average treatment effects on the treated (ATET) are not statistically significant when the analysis is disaggregated by gender and restricted to OECD, while in all cases the parallel trends assumption is verified. In summary, the findings suggest that extended school closures had no statistically significant impact on the levels or effects of non-cognitive factors, and no gender-based differences were observed within the successive cohorts of 4th-grade students.

3.2. Analysis 2: TIMSS 2015, PISA 2022

In this section, we aim to test the hypothesis that prolonged school closures reduce both the level of negative attitudes toward mathematics and the strength of their association with mathematics achievement. As shown in Table 4, across all countries, negative attitudes account for an average of 13.8% of the variance in mathematics achievement in PISA 2022 and 12.5% in TIMSS. On average, a one standard deviation increase in negative attitude is associated with a decrease of approximately 28 points in TIMSS and 32 points in PISA mathematics achievement scores.

Table 4. Basic summary statistics of association measures for all countries and OECD

Strength of association	TIMSS 2015		PISA 2022	
	Mean	Std. dev.	Mean	Std. dev.
All countries				
Explained variance (R2)	.12532	.0370628	.138818	.0549042
Regression slope	-27.68036	4.672475	-31.98161	7.492783
OECD countries				
Explained variance (R2)	.1358817	.0322581	.1595291	.049414
Regression slope	-27.69027	4.653316	-34.56494	6.12468

Two countries, Netherland and Indonesia, were excluded from the analysis on the basis of the "two standard deviation" rule for outliers in the coefficient of determination (R2). Finally 34 countries are included in the model, of which 15 experienced longer time of distance learning. According to the methodological section, the parallel lines assumption for all estimated models is believed to be met as it is met for Analysis 1 (Table 3). There is no statistical significant effect of extended time of school closures on reported negative attitude towards mathematics (coef.=-0.022; p-value=0.750). Similarly for girls (coef.=0.146; p-value=0.126), boys (coef.=0.075; p-value=0.448) and within OECD countries (coef.=0.104; p-value=0.296).

Table 5 reports estimates from six difference-in-differences models assessing the impact of prolonged school closures on changes in the variance in mathematics achievement explained by negative attitudes (R^2) between 2015 and 2022. For the full sample, the treatment effect is statistically significant, indicating a reduction of 4.7 percentage points across all countries and 5.7 points within OECD countries, approximately one standard deviation in PISA 2022 (see

Table 4). The effect is stronger among girls (5.5– 6.8 percentage points) and statistically significant within both all countries and within OECD, while for boys the effect is not significant at all in the full sample.

Table 5. Estimates from difference-in-differences models on explained variance

ATET (1 vs 0)	Students		Girls		Boys	
	All	OECD	All	OECD	All	OECD
Coefficient	**-.0467867**	**-.0574859**	**-.0547053**	**-.067713**	-.0373109	**-.0521352**
Robust std. err.	-.0131931	.020277	.01774796	.0187665	.0191176	.0243051
t	-2.73	-2.84	-3.13	-3.61	-1.95	-2.15
P>|t|	0.010	0.009	0.004	0.001	0.060	0.043
N (treatm.)	15	8	15	8	15	8
N (contr.)	19	16	19	16	19	16

Note: Bolded font means that the estimate is statistically significant for p<0.05.

Figure 3 illustrates the effect of prolonged school closures. The horizontal axis shows the variance in mathematics achievement explained by negative attitudes in Grade 4 (TIMSS 2015), while the vertical axis shows the same measure in upper secondary school (PISA 2022). The regression line for countries with longer closures lies noticeably below that of other countries, suggesting that extended distance learning may weaken the impact of negative attitudes on achievement over time. This effect is even more pronounced among OECD countries.

Figure 3 The relationship between variance explained in TIMSS 2015 and PISA 2022 in: a. full sample, b. OECD countries

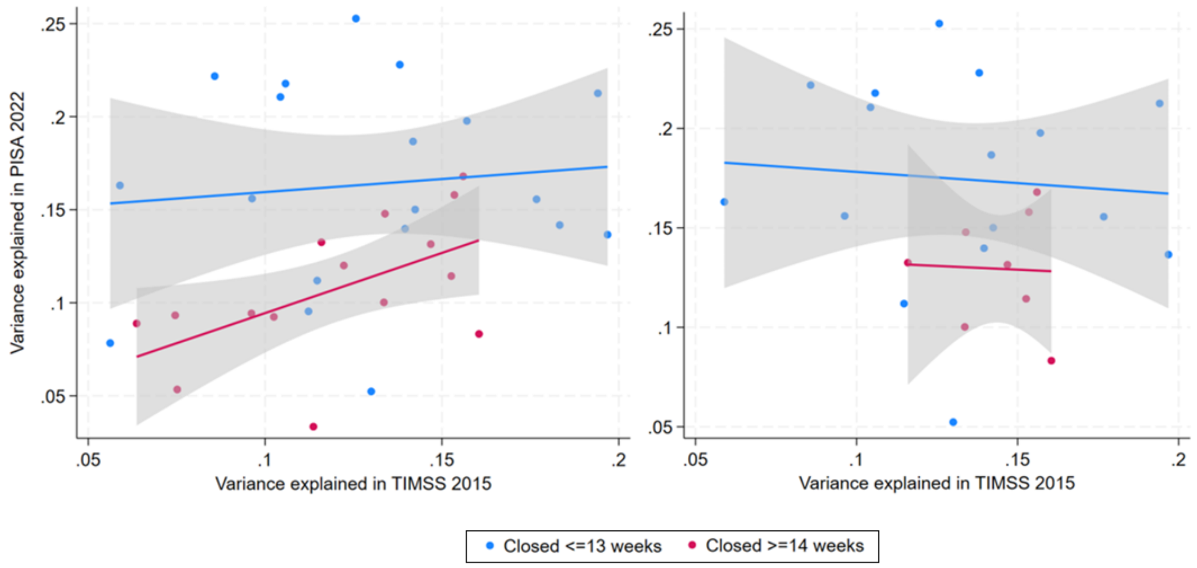
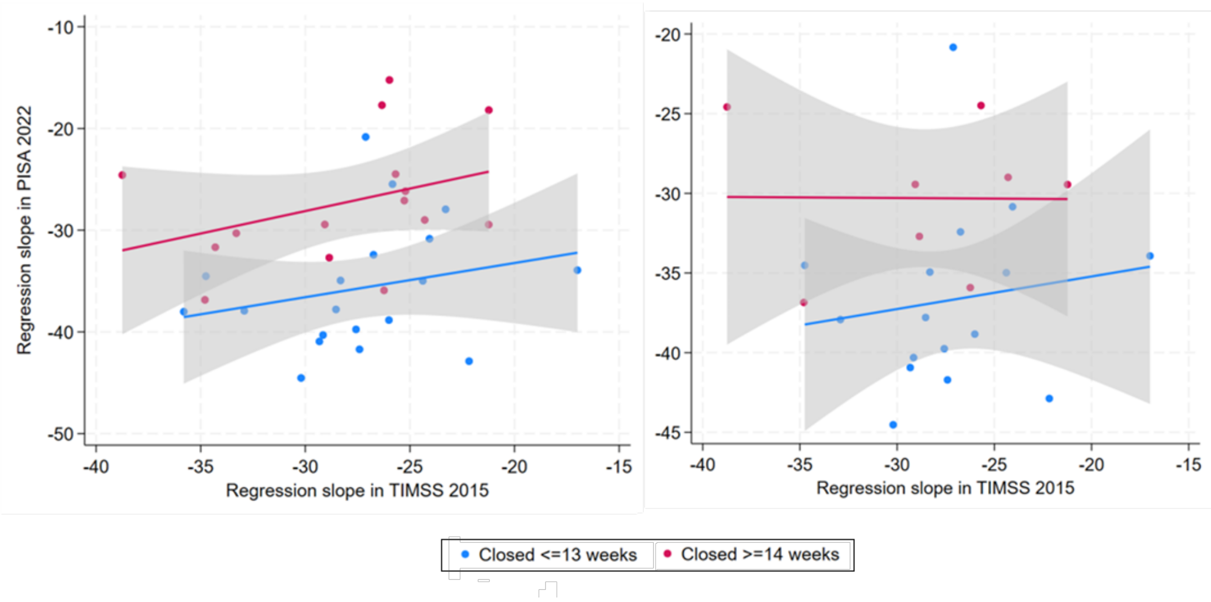


Figure 4. The relationship between regression slopes in TIMSS 2015 and PISA 2022 in: a. full sample, b. OECD countries



In order to verify the reliability and consistency of findings, the robustness check is conducted and the results are shown in Table 6, while the visualization is presented in Picture 3. We use the regression slope, instead of the explained variance (R^2), as the measure of association between math achievement and negative attitude. For the full sample we also get statistically significant ATETs, which equals between 1.2 and 1.3 standard deviation (Table 3). The effects for both association measures point in the same direction: longer time of school closures results in smaller explained variance and flatter regression slope. Although the estimates for girls and boys are almost the same, the effect for boys is not statistically significant in OECD countries, which can be treated as the sign of consistency with the results presented in Table 5.

Table 6. Estimates from difference-in-differences models on regression slope

ATET (1 vs 0)	Students		Girls		Boys	
	All	OECD	All	OECD	All	OECD
Coefficient	**9.09811**	**7.779386**	**9.076885**	**8.496416**	**9.309006**	7.910181
Robust std. err.	2.289336	3.043466	2.188043	2.570154	2.768887	3.986647
t	3.97	2.56	4.15	3.31	3.36	1.98
P>|t|	0.000	0.018	0.000	0.003	0.002	0.059

Note: Bolded font means that the estimate is statistically significant for $p<0.05$.

4. Discussion and conclusions

This study examines whether extended periods of distance learning in certain countries led to a decline in the levels of non-cognitive predictors and weakened their association with mathematics achievement. No statistically significant effects were observed within successive cohorts of 4th-grade students. To assess potential impacts within a single cohort, we applied a difference-in-differences framework using data on non-cognitive factors and mathematics achievement from TIMSS 2015 (elementary level) and PISA 2022 (secondary level). The results indicate that, in countries with prolonged school closures, the association between negative attitudes toward mathematics and achievement in secondary school is significantly weaker, despite no marked change in the overall level of negative attitudes. This effect, robust across two measures of association and consistent within OECD countries, amounts to a reduction of approximately 4.7 percentage points in explained variance, equivalent to about one standard deviation in PISA 2022. According to the prior evidence indicating higher levels of mathematics anxiety among girls (Devine et al., 2012), the attenuation of the association is particularly pronounced in this group, with a reduction of 5.5 percentage points. These findings underscore the broader educational implications of COVID-19-related school disruptions, highlighting the importance of non-cognitive outcomes alongside academic performance.

These findings offer important insights for mathematics education. First, distance learning appears to attenuate the strength of the association between negative attitudes toward mathematics, including mathematics anxiety, and achievement outcomes. This is particularly relevant given the well-documented detrimental effects of such attitudes in mathematics education (Lee & Stankov, 2018a). Second, although substantial learning losses in mathematics achievement have been widely reported, with each additional week of school closure exacerbating the decline (H. Patrinos et al., 2023), the extended period of distance learning may also yield positive outcomes. Specifically, it appears to weaken the association between negative attitudes and achievement without significantly altering the overall level of negative attitudes themselves. This observation corresponds with previous research demonstrating that online learning environments can lead to reductions in anxiety and improvements in attitudes among students (A. Luna et al., 2022). However, further empirical investigation is needed to fully understand the effects of distance learning on mathematics anxiety and attitudinal dispositions.

Moreover, the observed reduction in the strength of this association is more pronounced among female students. Given the well-established gender differences in mathematics-related attitudes and self-perceptions (Devine et al., 2012; Jacobs et al., 2002), this finding is of particular significance. Although further research is warranted, the current analysis, when considered alongside prior evidence, reinforces the importance of non-cognitive predictors in understanding mathematics learning processes and in evaluating the broader educational implications of distance learning. A more detailed understanding of these factors may inform interventions aimed at mitigating the development of negative attitudes toward mathematics, which are known to intensify with age and contribute to gender disparities in mathematics performance (Dowker et al., 2016; Wu et al., 2012).

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