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Remote learning during the Covid-19 pandemic: evidence from a three-level survey of Italian schools*

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Abstract

This paper investigates how Italian upper secondary schools reorganized their teaching and organizational practices during the second wave of the COVID-19 pandemic, and whether these changes influenced learning outcomes. Using novel survey data covering 11,154 students (11th and 13th grade), 3,905 teachers, and 105 school principals, we document limited innovation in school practices, a widespread replication of traditional teaching formats in online settings, and a mismatch between teachers' perceived digital readiness and their actual methodological adjustments. Teacher training was uneven and rarely focused on pedagogical innovation. Regression results suggest that the adoption of innovative teaching methods and appropriate organizational changes are positively associated with students' self-reported learning outcomes. Overall, the findings provide valuable insights for school-level interventions and teacher development policies, particularly in light of the ongoing technological transformation of the education sector.

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1 Introduction

During the COVID-19 pandemic, many countries opted to suspend in-person schooling to minimize contact and mitigate the spread of the virus. In April 2020, at the peak of the pandemic, over 1.6 billion K-12 learners in more than 190 countries were unable to attend school in person. The educational community made considerable efforts to maintain learning activities remotely, and remote learning (RL, hereafter) became the standard mode of instruction in most countries (Schleicher, 2020; Muñoz-Najar et al., 2021). As of October 2021, 32 percent of countries worldwide still had either fully or partially closed schools.

Following China, where the outbreak began, Italy was among the first countries to adopt nationwide school closure measures and was also the first European country to be severely affected by the pandemic.[1] During the first wave of infections, from March 2020 to the end of the school year, in-person teaching was suspended at all educational levels. The second wave, which began across Europe in fall 2020, saw Italian schools remain closed longer than in most other industrialized countries.

While there is increasing consensus that the pandemic resulted in learning losses and widened educational inequalities across students and areas, there is still limited evidence on the mechanisms that may have shaped these outcomes. This paper contributes to filling this gap by investigating the possible drivers of RL effectiveness (or ineffectiveness) during the second lockdown in Italy. In particular, it provides novel evidence on how schools adapted their teaching and organizational practices in a context where remote instruction was no longer an emergency response but a foreseeable alternative to in-person schooling.

The main focuses of this study is on the role played by Italian teachers and school principals in introducing organizational and pedagogical innovations during the pandemic. We concentrate on the *second* lockdown, from September 2020 to June 2021. Unlike the first, this period was marked by a very different institutional setting. RL was anticipated as a likely scenario, and before the start of the 2020–21 school year, the Ministry of Education released the official guidelines for *Didattica Digitale Integrata* or Integrated Digital Teaching (IDT), which laid out general principles for organizing distance learning.[2] These guidelines, however, were not binding and left substantial autonomy to principals and teachers in determining how to organize RL activities.

We exploit the resulting heterogeneity in school-level decisions to examine how

[1]Italy was one of the first countries in the world to implement school closures nationwide from March 4, 2020, as part of measures to contain the spread of COVID-19. It was also one of the countries that maintained the measure longer, especially for upper secondary schools (Camera dei deputati, 2022).

[2]*Decreto Ministeriale n. 89, August 7, 2020, "Adozione delle Linee Guida sulla Didattica digitale integrata."* Note that freedom of teaching is a constitutional principle in Italy, although national curriculum guidelines outline general pedagogical approaches.

different organizational models and teaching practices shaped student outcomes. To this end, we collect data from a unique three-level survey involving principals, teachers, and upper secondary students (a total of 14,447 observations). We focus on upper secondary education because in Italy this level experienced the longest periods of remote instruction.[3]

This rich dataset offers detailed information on how schools reorganized RL, which teaching methodologies were adopted, how stakeholders perceived the effectiveness of remote instruction on cognitive and non-cognitive outcomes, and how interpersonal relationships evolved during RL. To our knowledge, this is the first study in Italy to simultaneously gather large-scale data from all three key stakeholders in each school, enabling a triangulated analysis of the relationship between organizational and pedagogical choices, training practices, and student outcomes.

Despite the richness of the dataset, the study has some limitations. First, the sample shows signs of selection bias: schools from northern regions and general academic tracks are overrepresented, and comparing with the population students characteristics, our school selection includes less dropouts and students repeating grades. This means that our results are more likely to reflect better-resourced and higher-performing institutions. Second, the cross-sectional nature of the data and the lack of valid instruments limit our ability to identify causal effects. The results reflect robust associations, not causal estimates as endogeneity may still arise from unobserved characteristics that are not captured by our data.

Our descriptive analysis shows that teaching during RL remained largely a direct transposition of in-person instruction. In details, compared with the in-person setting, our principals, teachers and students all agree that very few changes have been made either in a) the timetable b) in their teaching methods when conducting synchronous remote-learning activities. Because our sample is biased toward higher-performing schools and students, this finding suggests that the government's support and incentives for adopting organizational and instructional practices suited to the remote-learning context were, most likely, far from adequate.

Interestingly, many teachers perceived their digital competencies for remote schooling as adequate, despite making only minimal methodological adaptations in their teaching. This suggests that in designing future interventions, such overconfidence may represent a potential obstacle that needs to be considered. Our evidence also indicates considerable heterogeneity in both the quantity and, likely, the quality of teacher training on digital skills.

Second, based on students' self-reports, the data confirms that most learners felt they acquired less during remote learning than they would have through in-person instruction. The negative impact of RL was more pronounced among vulnerable

[3] Moreover, the length of in-person schooling during the 2020–21 school year varied significantly across regions and municipalities due to local regulations (Bovini and De Philippis, 2021; Conteduca and Borin, 2022).

students, indicating an increase of pre-existing inequalities.

The regression analysis finds that the use of innovative teaching methodologies and the adoption of flexible school organization models during RL are positively and significantly associated with students' perceived learning, as well as with their overall experience, motivation to continue digital activities post-pandemic, and quality of interaction with peers and teachers. Moreover, the intensity of innovative teaching practices correlates with the quantity of training received by teachers during the pandemic, suggesting the importance of professional development in facilitating pedagogical change.

To test the robustness of our findings, we performed several checks. We re-estimated the main models on high-response schools to address potential non-response bias, and on the full sample including low-response schools. We further included school fixed effects and omitted sampling weights to test sensitivity to model specifications. Finally, we assessed heterogeneity by macro area and school location (urban vs. less densely populated). Results remained robust throughout, with no significant geographical variation.

In sum, this paper contributes to the relatively limited literature on school reorganization during the pandemic by (providing extensive evidence that explore) exploring key mechanisms that may have influenced the effectiveness of remote learning and contributed to the widening of educational inequalities, while also providing a clear picture of what happened, or, more precisely, what did not happen, in Italian schools. The shift to remote learning and the integration of digital technologies required a substantial rethinking of school schedules and teaching methods to ensure instructional effectiveness. Yet, to our knowledge, few studies have systematically analyzed whether and how schools restructured their organization or whether teachers adapted their teaching practices during the second phase of the pandemic. One exception for Italy is (Bertoletti et al., 2023), which focuses on teachers in primary and middle schools during the initial emergency lockdown. Our study expands on this by examining institutional and behavioral mechanisms that shaped RL outcomes in a more stabilized and policy-defined setting.

Our research contributes to two strands of the education literature. First, while the importance of teacher quality for student outcomes is well established (Hanushek, 2011; Chetty et al., 2011; Rivkin et al., 2005; Hanushek and Rivkin, 2012), less is known about how to enhance teacher effectiveness. During the pandemic, part of the challenge appeared to lie in insufficient digital skills, a long-standing issue in Italian schools. We provide novel evidence on the quantity and quality of teacher training during this period and its association with more innovative and effective instructional practices. Second, a growing literature links school management to student achievement (Bloom et al., 2015; Di Liberto et al., 2015; Agasisti et al., 2020). This research highlights the indirect yet crucial role of principals in shaping the school environment and enabling effective teaching (Di Liberto, 2017; Robinson et al., 2008; Grissom and Loeb, 2011). Our principal-level data offer valuable insights into how school leaders organized instruction under challenging and uncertain circumstances.

The remainder of the paper proceeds as follows. Section 2 briefly reviews the literature on the use of ICT in the classroom and the impact of online learning activities during the pandemic on student learning losses. Section 3 describes our survey and the data collection process. Section 4 presents the main descriptive analysis, while Section 5 examines the presence of inequality patterns. Section 6 discusses the results of the regression analysis, while Section 7 heterogeneity and robustness checks. Finally, Section 8 offers a discussion of the findings and outlines potential implications for policymakers.

2 ICT, online learning and pandemic consequences: a review of the literature

This section offers a brief overview of the main recent findings on the role of Information and Communication Technology (ICT) in learning outcomes and the impact of the COVID-19 pandemic and subsequent school closures on students' educational outcomes. We separate the two streams of the literature since the effect of digital technology in schools may differ during school closures compared to standard school years (Carlana and La Ferrara, 2024).

Before the pandemic, various studies explored whether and how ICT technologies could transform teaching and students' learning. Overall, the evidence on the impact of ICT on learning outcomes is mixed, and both pre and post-pandemic studies on Internet-enabled classroom technology identify both positive and negative effects on student performance. On the positive side, ICT may make education more effective, engaging, and accessible. Possible positive impacts include enhanced group activities, immediate feedback, faster note-taking, and easy storage of notes (Carter et al., 2017). Comi et al. (2017) and Rovai (2001) find that increased connectivity outside the classroom fosters communication and collaboration among peers, schools, and families and supports the co-production of knowledge among teachers. Some evidence suggests that learning communities enhance a sense of connectedness, shared knowledge, and common goals, which can reduce dropout rates (DiRamio and Wolverton, 2006). Additionally, "enhanced" textbooks have been found to offer capabilities such as embedded videos and hyperlinks, benefiting both students and teachers with specific educational software for tracking progress (Anderson et al., 2001). More recently, Carlana and La Ferrara (2024) identified a positive effect of a Tutoring Online Program (TOP) both during (2020) and after (2022) the pandemic on the math performance of underprivileged middle school students, with additional effects on aspirations, socio-emotional skills, and psychological well-being.[4]

However, other studies suggest that the use of ICT in class can negatively impact student learning. Carter et al. (2017) find lower exam scores in computer-using groups. Bakia et al. (2013) highlight potential inequalities, with advantages accruing to students with stronger academic backgrounds, self-discipline, and access to technology at home. Additionally, computer use can be a distraction, leading to web-surfing and reduced academic performance, as evidenced by Barak et al. (2006) and research on multitasking with laptops (Fried, 2008; Kraushaar and Novak, 2010; Grace-Martin and Gay, 2001). Moreover, the lack of interaction between learners and instructors, and among learners themselves, can lead to feelings of isolation (Hughes et al., 2007; Xiaojing et al., 2007; McInnerney and Roberts, 2004; Pigliapoco and Bogliolo, 2008).

In contrast to the mixed findings on ICT, there is a broad consensus in the second stream of literature on the pandemic's substantial negative and uneven impact on students' educational outcomes across different countries and school levels.[5] Most studies estimate the effect of the pandemic on student achievement by comparing cohorts of students affected by school closures with those unaffected, controlling for various characteristics such as prior achievement, family background, gender, migrant status, and geographic area of residence.

Many studies highlight the unequal impact of COVID-19 on students. Using an experimental setting in a sample of 551 West Point students Kofoed et al. (2024) find that online education lowered a student's final grade by 0.215 standard deviations, with largest negative effect for academically at-risk students. Interestingly, this study also suggests that not all online learning is detrimental but that online learning that simply reproduce the traditional classroom directly into a virtual environment may worsen learning. Engzell et al. (2021) and Haelermans et al. (2022) find that an 8-week lockdown resulted in significant learning losses in primary schools in the Netherlands, ranging from 0.08 to 0.21 standard deviations in math, spelling, and reading, with losses up to 60% more prominent among students from less-educated households. Similar results are found in Belgium by Maldonado and De Witte (2022) comparing standardized test scores of the students in the last year of primary school in 2020 who were affected by school closures with previous cohorts. They find a decrease in mathematics and language scores by 0.17 and 0.19 standard deviations, respectively. In Switzerland, Tomasik et al. (2021) report that secondary school pupils were mainly unaffected, whereas primary school students experienced a learning slowdown of approximately 0.2 SD during an 8-week closure. In Norway, Skar et al. (2022) observed a 0.24 SD decrease in reading performance among first-grade students during the 2019/20 school year compared to their peers

[4]These effects are identified only during the school closure periods.

[5]For more on this, see the surveys by Hammerstein et al. (2021); Storey and Zhang (2021); Di Pietro (2023).

before the pandemic. Further, school closures seem to have exacerbated already existing inequalities, with heterogeneous effects on achievement based on student and family characteristics. Pupils from low socio-economic backgrounds, those with lower prior achievement, minorities, students with poorer home learning environments, and those experiencing more extended school closures were most affected (Asakawa et al., 2021; Contini et al., 2021, 2023; Grewenig et al., 2021; Halloran et al., 2021; Strunk et al., 2023; Di Pietro et al., 2020; Engzell et al., 2021).

Evidence on Italian students is no exception. Contini et al. (2021) estimated the effects on primary school children, finding a negative impact on mathematics achievement (-0.19 SD). Learning losses were more significant among children of low-educated parents, particularly for the best-performing students (up to -0.51 SD) and for girls (-0.29 SD). Bazoli et al. (2022) found significant learning losses in reading and mathematics, especially severe in mathematics, among Italian students in grades 5, 8, and 13. Borgonovi and Ferrara (2023) reported an 85% reduction in expected yearly learning gain in mathematics and a 40% reduction in reading for lower secondary students, with smaller but still significant losses for primary students. Contini et al. (2023), found that the pandemic harmed upper secondary school students' performance in mathematics and reading (approximately 0.4 SD in both subjects). Finally, unlike the previous studies, Alderighi et al. (2023) use a different outcome variable, a measure of hidden drop-outs: these are students who formally completed secondary school but did not acquire a level of competencies and skills that can be considered sufficient in standardized test results. Alderighi et al. (2023) used standardized test results to measure hidden drop-outs, finding an 8.6% increase in students not reaching minimum competency levels, particularly among those with lower prior achievement, from poorer families, and emotionally disrupted during assessments.

3 The three-level survey

To construct our dataset, we conducted a three-level survey, administering different questionnaires to upper secondary students (11th and 13th graders), their teachers, and the principals of each participating institution.

Sampling was conducted by randomly selecting 5% of schools within each Italian macro-area (NUTS 1), stratified by school type to account for the different educational tracks students enter from grade 9 onwards, and to reflect geographical disparities in educational outcomes. A substantial body of evidence shows that school location is a key determinant of student achievement in Italy, with students in Northern regions consistently outperforming those in the South (Bratti et al., 2007; Cipollone et al., 2010; Di Liberto, 2008). Furthermore, the Italian upper secondary education system is organized into three main tracks general/academic (*Licei*), technical (*Istituti Tecnici*), and vocational (*Istituti Professionali*), and this tracking is closely linked to social stratification. Students in general tracks tend to perform better academically and come from more advantaged socio-economic backgrounds than their peers in vocational pathways (Brunello and Checchi, 2007).

Data collection took place between March and June 2021. Schools were first contacted via email with an introductory letter describing the project, followed by a phone call to the principal. In case of refusal, we randomly selected a substitute school with similar characteristics. This occurred in 38% of cases and substitutions never exceeded three rounds (27.5% first substitution, 7.8% second, and 2.9% third).

Upon acceptance, schools were responsible for distributing the questionnaire links to their teachers and to students in the 11th and 13th grades, and participation was voluntary. Given the exceptional circumstances of the pandemic we anticipated challenges in achieving high participation rates, particularly among more disadvantaged schools and individuals.

To encourage participation, the protocol included two reminder messages sent to schools, inviting them to redistribute the questionnaire link to students and teachers. In addition, students were offered an incentive: 500 Amazon vouchers (each worth €20) were raffled among those who completed the questionnaire.

Despite these efforts, response rates remained low in some schools, particularly among students. The average student response rate is similar for 11th-grade (29.3%) and 13th-grade students (30.7%). The average teacher response rate is higher, at 55.7%.[6] In 16 schools, the principal did not respond, although students and teachers did. In our analysis we excluded all schools in which fewer than 15 students and 8 teachers completed the survey.

Overall, the final sample size is still substantial: we retain data on 10,730 students (6,596 in 11th grade and 4,134 in 13th grade), 3,612 teachers, and 105 principals. To the best of our knowledge, this level of coverage and triangulation is unique in the Italian context. However, selection bias remains a concern. To assess its extent, we compare the characteristics of our sample with those of the overall population. For this purpose, we merged our survey data with the administrative dataset "*La scuola in chiaro*", provided by the Italian Ministry of Education (MIUR), which contains detailed information on school and student-level characteristics.

Table 1 clearly illustrates the challenges encountered in engaging schools from southern regions in the project, and how our sample overrepresents schools located in northern Italy and those following the more academic track.

[6] We use administrative data to compute student response rates for 11th and 13th graders at the school level, while teacher response rates are estimated based on the OECD's Education at a Glance 2021 student–teacher ratio of 10.93 for Italian upper secondary schools.

Table 1. Selection: by area and school type

	Sample		Population	
	N. of schools	% of schools	N. of schools	% of schools
North	83	50.9	1931	36.9
Center	24	14.7	1007	19.2
South	56	34.4	2299	43.9
Lyceum	69	42.3	2063	39.4
Technical institute	56	34.4	1827	34.9
Vocational School	38	23.3	1347	25.7
Total	163	100	5237	100

Notes: Macro-areas include the following regions. *North*: Emilia-Romagna, Friuli-Venezia Giulia, Liguria, Lombardy, Piedmont, Veneto, and Trentino. *Center*: Lazio, Marche, Tuscany, and Umbria. *South*: Abruzzo, Apulia, Basilicata, Calabria, Campania, Molise, Sicily, and Sardinia.

Table 2. Selection: by students characteristics

Sample data	Mean	Standard Deviation	Min	Max	Obs.
Outgoing students	0.017	0.014	0	0.065	155
Incoming students	0.010	0.018	0	0.13	157
Dropout	0.0038	0.0084	0	0.060	155
Grade retention	0.0049	0.010	0	0.063	159
Population data	Mean	Standard Deviation	Min	Max	Obs.
Outgoing students	0.019	0.032	0	0.56	5448
Incoming students	0.017	0.048	0	0.75	5747
Dropout	0.0057	0.016	0	0.24	5448
Grade retention	0.0087	0.024	0	0.53	5722

Notes: All variables are expressed as a proportion of the total number of students. *Incoming students* are those who enrolled after previously attending a different school; *Outgoing students* are those who left the school to enroll elsewhere.

Table 2 presents differences in grade retention, dropout rates, and student mobility (i.e., transfers in and out of schools). Our sample includes fewer dropouts and lower retention rates than the population average. Table 3 reports the same statistics disaggregated by school track: Lyceum, Technical, and Vocational. Here too, the shares of dropouts and grade retention confirm the presence of a selection pattern favoring higher-performing schools also within each school type.

Table 3. Selection: by students characteristics and school type

	Lyceum		Technical		Vocational	
	Sample	Population	Sample	Population	Sample	Population
Outgoing students	0.016	0.015	0.016	0.017	0.019	0.018
	(0.013)	(0.014)	(0.013)	(0.018)	(0.015)	(0.021)
Incoming students	0.0071	0.0059	0.0097	0.0093	0.014	0.011
	(0.019)	(0.0099)	(0.012)	(0.015)	(0.024)	(0.017)
Dropout	0.0016	0.0030	0.0036	0.0047	0.0065	0.0100
	(0.0041)	(0.0072)	(0.0072)	(0.011)	(0.012)	(0.019)
Grade retention	0.0011	0.0029	0.0049	0.0068	0.0098	0.016
	(0.0025)	(0.0072)	(0.0092)	(0.014)	(0.015)	(0.028)

Notes: All variables are expressed as a proportion of the total number of students. *Incoming students* are those who enrolled after previously attending a different school; *Outgoing students* are those who left the school to enroll elsewhere.

Table 4. Selection: by students characteristics and macro-area

	North		Center		South	
	Sample	Population	Sample	Population	Sample	Population
Outgoing students	0.018	0.017	0.017	0.018	0.014	0.015
	(0.013)	(0.018)	(0.015)	(0.017)	(0.014)	(0.016)
Incoming students	0.0075	0.0065	0.015	0.0094	0.0096	0.0095
	(0.0086)	(0.0098)	(0.024)	(0.015)	(0.022)	(0.016)
Dropout	0.0056	0.0052	0.0014	0.0048	0.0037	0.0056
	(0.010)	(0.011)	(0.0033)	(0.012)	(0.0085)	(0.014)
Grade retention	0.0042	0.0043	0.0041	0.0081	0.0069	0.0098
	(0.0088)	(0.0094)	(0.0085)	(0.018)	(0.014)	(0.022)

Notes: All variables are expressed as a proportion of the total number of students. *Incoming students* are those who enrolled after previously attending a different school; *Outgoing students* are those who left the school to enroll elsewhere.

Finally, Table 4 investigates whether our sample differs from the population in terms of student characteristics across macro-areas. For schools located in the North, we do not find clear signs of selection bias favoring academically stronger students: the sample and the population display very similar rates of dropouts and grade retention. However, positive selection re-emerges in schools located in the Center and, even more markedly, in the South and Islands. We account for this selection issue when interpreting the subsequent analyses.

4 Comparing Perspectives on Remote Learning

In this section, we present the main findings on what happened in Italian schools during the second lockdown, drawing on the perspectives of principals, teachers, and students who completed the questionnaire. This allows us to compare their perceptions regarding three core aspects of remote learning (RL) implementation during the second COVID-19 wave: the school timetable, teaching methodologies, and the training received.[7]

4.1 The principals' perspective

The COVID-19 pandemic significantly increased the organizational burden on principals, affecting their ability to coordinate teaching and learning. During the first wave (March–June 2020), schools implemented what has been widely defined as Emergency Remote Teaching, as the shift to online learning came unexpectedly and with minimal preparation (Bertoletti et al., 2023). The Italian Ministry of Education issued only a few emergency rules: remote learning was optional, written assessments were suspended, including the INVALSI tests, and grade retention was cancelled for the 2019–20 school year (Contini et al., 2023). As a result, schools were left to self-organize with substantial autonomy.

In contrast, during the second lockdown, the Government introduced clearer national guidelines through the Integrated Digital Teaching (IDT) framework and issued protocols to support both in-person and remote instruction. Schools were required to submit an IDT plan (*Piano per la Didattica Digitale Integrata*) in consultation with teaching staff. Upper secondary schools were granted flexibility to: a) adjust schedules, b) reduce lesson durations, c) consolidate subjects, and d) adopt other forms of organizational adaptation. The only strict requirement was to guarantee at least 20 hours per week of synchronous instruction for full class groups, with the possibility of adding small-group and asynchronous activities.[8]

Although these guidelines encouraged the adoption of ICT-based teaching and organizational flexibility, most schools made very limited changes. According to our principals, 65% of schools retained their pre-pandemic timetables, 26% reduced synchronous hours proportionally across subjects, and only 8% implemented more substantial adjustments, typically prioritizing core subjects such as Italian, mathematics, and foreign languages. These more significant changes were more frequently reported in vocational schools, which faced additional challenges in adapting lab activities and work-based learning (*PCTO*) to an online format.

[7] This analysis summarizes more detailed findings presented in a report published by Fondazione Agnelli. Readers interested in further evidence and descriptive statistics may consult the full report at the following link: `https://www.fondazioneagnelli.it/wp-content/uploads/2021/07/Ricerca_La-DaD-as-2020-21_una-fotografia.pdf`.

[8] Decree of the Minister of Education No. 39/2020, with guidelines published in August 2020.

Additionally, while 62% of schools reduced lesson durations, over 30% continued to use 60-minute formats. About 23% of schools made no adjustments at all, replicating both the weekly schedule and 60-minute lesson format. These findings suggest that, despite the flexibility offered by national policy, many schools struggled or decided not to reconfigure their schedules effectively.

The IDT guidelines also encouraged the adoption of teaching practices different from in-person instruction, promoting more inclusive and interactive approaches aligned with international research on ICT-based learning (see Section 2).[9] Yet, 62% of principals reported that frontal teaching remained the predominant method used.

Principals also stress the teachers' lack of expertise on ICT-skills. They estimated that at least one in four teachers needed support with ICT tools for assessment (72%), classroom instruction (69%), interdisciplinary teaching (61%), and software use (40%). Existing evidence supports this perception suggesting that prior policies had not adequately equipped Italian teachers with the digital skills required to respond to the RL challenge (Bussu et al., 2023).

This perceived skills gap raises the question of whether schools provided adequate training to support teachers. In Italy, schools enjoy autonomy in organizing inservice training, which is planned during collegial meetings (*Collegio dei docenti*). Principals are legally responsible for promoting professional development, but financial resources are centrally allocated based on staff size. This allocation mechanism disadvantages smaller schools, particularly those in rural or southern areas, which are more likely to serve vulnerable student populations. Collaborative training across schools can mitigate these constraints but requires substantial coordination and strategic planning. Even before the pandemic, this combination of centralized and limited funding and decentralized implementation risked exacerbating inequalities in training quantity and quality across schools.

According to principals, during the pandemic, training efforts were mostly focused on software use, and between 20% and 40% of schools offered no training on digital pedagogy or assessment practices.

[9] The IDT guidelines are available at: https://www.miur.gov.it/documents/20182/0/ALL.+A+_+Linee_Guida_DDI_.pdf/f0eeb0b4-bb7e-1d8e-4809-a359a8a7512f

Table 5. Teachers' training: use of external or internal resources

The principals' perspective	No training	External	Internal	Total
Use of software/platforms for teaching purposes	1.03	9.28	89.69	100.0
Innovative methodologies for inclusion	36.08	23.71	40.21	100.0
Innovative teaching and learning	22.68	29.90	47.42	100.0
Tools/methodologies for new forms of assessment	41.24	20.62	38.14	100.0
The teachers' perspective				
	No training	External	Internal	Total
Use of software/platforms for teaching purposes	2.19	6.80	91.01	100.0
Innovative methodologies for inclusion	27.39	19.44	53.17	100.0
Innovative teaching and learning	14.98	29.12	55.90	100.0
Tools/methodologies for new forms of assessment	31.91	25.13	42.96	100.0

Notes: The Table shows the share of teachers who received digital training, as reported by principals and teachers, distinguishing between training delivered internally and by external providers.

As shown in Table 5, most of the training was delivered using internal resources, such as digital teams or designated expert teachers. This, again, raises concerns about consistency and quality across schools. The absence of national standards may have contributed to increasing inequalities in student outcomes.

Finally, principals' responses reveal regional disparities in additional funding beyond state funding during the second lockdown: schools in wealthier regions received more external resources, while those in the South lagged behind (See Figure A1, in Appendix). However, as seen above, our Southern sample is positively selected toward better-performing schools, which may bias both the perceived learning and funding results.

4.2 The teachers' perspective

The teacher questionnaire aimed to gather information on how teachers adapted their practices during remote learning, the type and focus of the training they received, and their perceptions of the effectiveness of the strategies adopted. In the following, we compare their responses to those of principals, focusing on key dimensions of the school response to the second lockdown.

The sample includes teachers across all subject areas, with 75% teaching core subjects: 33% teach mathematics or science, 27% humanities, and 15% foreign languages. By school track, 46% work in lyceums, 31% in technical institutes, and 23% in vocational schools. Nearly half (46%) are class coordinators, suggesting a likely positive selection of more motivated teachers. Furthermore, 4.4% are digital animators or members of innovation teams introduced by the 2015 National Plan for Digital Education (Law 107) to address Italy's long-standing ICT gap. In 2011, only 30% of Italian eighth-graders used ICT in science classes, compared to an OECD average of 48% (Avvisati et al., 2013). One structural barrier is identified in the ageing teaching workforce: in 2019, 58% of Italian primary, 53% of lower-secondary, and 62% of upper-secondary teachers were over 50, compared with OECD averages of 33%, 36%, and 40% respectively (OECD, 2021). Older teachers are also less likely to undertake training or adopt pedagogical innovations (OECD, 2023).

Teachers largely confirmed the principals' reports of organizational continuity. A significant majority (85%) considered the pre-pandemic timetable suitable for remote learning and supported its online replication. Only 6.4% found the synchronous workload excessive, primarily among those teaching laboratory-based subjects that are inherently difficult to translate online.

A similarly conservative attitude emerged with respect to methodological adjustments, further supporting principals' accounts of limited pedagogical innovation. Synchronous teaching during remote learning largely consisted of a direct transposition of in-person instruction, relying primarily on video lectures and teacher-led explanations (63%) and homework assignments (58%). In contrast, more interactive and student-centered strategies—such as student self-assessment (25%), peer evaluation (22%), and project-based learning (19%)—were rarely adopted, despite being encouraged by national guidelines.

Further, teachers widely acknowledged that RL disrupted school relationships, particularly those involving students, teachers, and families (see Appendix Figure A2). They reported student fatigue, reduced concentration, and diminished social interaction. These findings are consistent with experimental evidence from U.S. college students showing that replicating traditional classroom formats online can harm learning and negatively affect concentration and relationships with teachers and peers (Kofoed et al., 2024).

Similar to principals, we asked teachers about the training they received. Around 80% reported training on software use, especially during the first lockdown, but only about 50% received support on pedagogical or assessment methods. This largely mirrors the principals' accounts and suggests that training during the pandemic was heavily skewed towards technical rather than instructional dimensions.

The mismatch between recommended practices and actual teaching strategies raises the issue of teacher digital skills. Here, the perceptions of principals and teachers diverge. Principals emphasized significant skills gaps among their staff, while 85% of teachers felt their digital and teaching skills were adequate for remote learning. Thus, a divergence emerges between teachers' self-assessed competence and their actual practices. This may reflect overconfidence, consistent with known self-perception biases, or the interpretation of remote learning merely as a digital extension of in-person teaching, where the emphasis was on mastering software tools rather than rethinking pedagogy. Another possible explanation concerns the nature of the training provided: low-quality training may have increased teachers' confidence without meaningfully affecting their teaching practices. These interpretations should be regarded as preliminary, and further research is needed to assess the validity of these explanations.

4.3 The students perspective

The students perspective fully confirms that both the daily timetable and the teaching approaches were almost exact online replicas of their regular in-person schedules. The students' responses concerning classroom activities pertain to one of four subjects covered in class: Italian, Mathematics, English, and another significant subject relevant to their particular course of study. During the survey, students were randomly assigned one of these four subjects. Students' evidence does not identify significant differences across subjects on the use of different activities in class.

On the former, almost all (91%) students stated they spent between five and six hours per day engaged in synchronous video activities, following a subject distribution that mirrored their pre-pandemic timetables. On teaching methodologies, nine out of ten students reported that their teachers primarily used three activities during RL: video lessons, assessments, and homework. In contrast, more interactive or student-centered activities, such as independent or group research activities (both online and offline), educational games, apps, and interactive exercises were rarely used. Similarly, only 10% of students were asked to produce their own learning materials, and the use of supplementary educational content remained limited (See also A3 in Appendix).

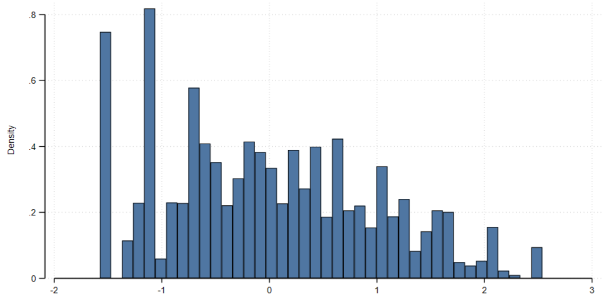
To assess the degree of innovation in online teaching, we extract a latent factor from students' reports on innovative practices implemented during remote learning. Factor analysis is a statistical technique used to reduce data complexity by identifying latent constructs that explain the patterns of association among observed variables. We employ the Principal Component Factor (PCF) method to extract latent factors from a set of observed indicators. PCF is particularly useful in exploratory settings, as it allows researchers to reduce the dimensionality of the explanatory variables while preserving the underlying structure of the data. By summarizing the information contained in a set of correlated variables, this approach helps mitigate multicollinearity issues and improves the interpretability of the analysis. In our case, we retain and use the first factor as a composite measure in the subsequent empirical analysis.

The index is based on students' reports of how often they engaged in the following practices and tools during synchronous online activities: discussions on non-school topics; online and offline research or lab activities; sending recorded content; digital games or interactive exercises; use of school platforms; other video content; and student-produced digital content.[10] The PCF model yielded an eigenvalue of 2.34,

[10] More details in Figure A3.

explaining 30% of the total variance, and the index showed good internal consistency, with a Cronbach's alpha of 0.64.

Figure 1. The distribution of the innovative teaching index



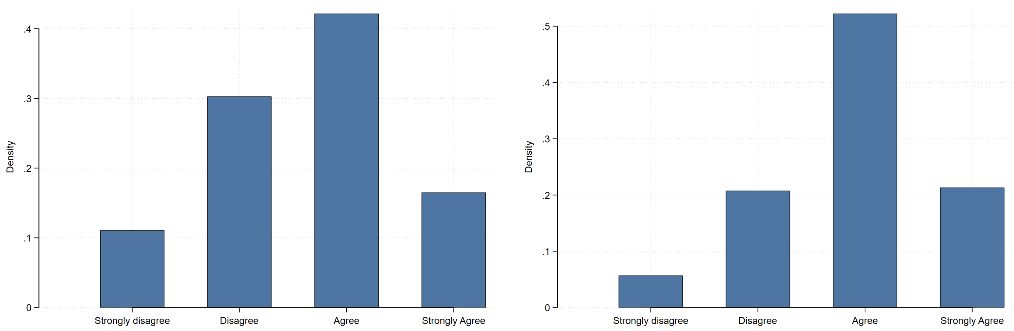
Notes: The innovation index is constructed with factor analysis using the answers on innovative teaching methodologies adopted in class.

Figure 1 shows that the distribution of the index is slightly right-skewed, indicating a concentration of students with lower levels of exposure to innovative practices, and reveals substantial heterogeneity across students.

We then focus on the main outcome variable of our analysis. In this study we cannot rely on objective measures of students' cognitive skills, such as the standardized tests provided by the National Institute for the Evaluation of the Education System (INVALSI).[11] Unlike primary and lower secondary school levels, in 2021 Italian upper secondary students did not take these tests, and we rely on students' perceived learning during remote learning, measured through their level of agreement with the statement: "I learned about as much as I would have by going to school". Following other studies, we ask students to compare their actual learning during RL with the counterfactual scenario of regular in-person schooling (Aucejo et al., 2020). While an in-depth discussion of the educational psychology literature is beyond the scope of this paper, we note that comparative items of this type are more robust to typical systematic perception bias than questions assessing absolute levels of learning and have been shown to correlate reasonably well with objective indicators of learning outcomes when formal testing is unavailable (Kruger and Dunning, 1999; Goffin and Olson, 2011; Kuncel et al., 2005; Aucejo et al., 2020).

[11]INVALSI is an independent national public agency responsible for implementing standardized testing procedures. These tests are compulsory for all students in selected grades and are administered annually to assess proficiency in three subjects: Italian language, mathematics, and English.

Figure 2. Remote versus in-presence school: the students' learning perception



(a) I learned as much as I would have in presence

(b) I got similar grades at school

Notes: In Panel (a), students answer how much they agree to the following statement: "During RL, I learned about as much as I would have by going to school". In panel (b) they answer how much they agree with the statement: "The grades that I get are similar to those I would get in presence." All answers relate to all the school activities offered from September onward.

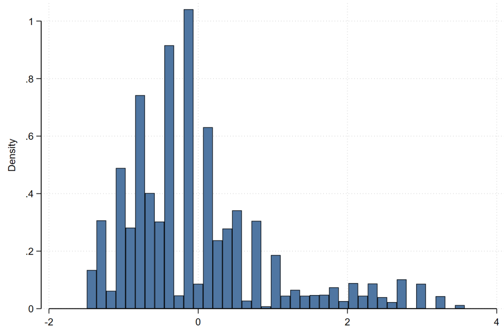
As shown in Figure 2 (Panel a), 43% of students disagreed with the statement, suggesting a perceived learning loss; the remaining 57% perceived no substantial difference. We also ask students to compare their actual grades during RL with the counterfactual scenario of regular in-person schooling. Panel (b) shows that in this case about two-thirds of students believed their grades were similar to what they would have received during in-person schooling. These findings suggest that assessments during the pandemic were likely more lenient, or that students had greater opportunities to cheat, as 70% of them reported it was easier to copy or receive hints during online assessments. Finally, consistent with teachers' reports, students perceived remote learning as more cognitively demanding than in-person instruction. Approximately 65% reported increased fatigue, and 73% found it harder to concentrate. Only one in four students found it easier to interact with teachers or request clarification during online lessons. The lack of in-class social interaction was frequently cited as a major limitation of remote learning. In addition, 61% of students reported difficulties in coping with frequent organisational changes, such as shifts between online and in-person formats and timetable adjustments, introduced by national and local authorities.

5 Pandemic, remote learning and students inequality patterns

We now turn to the patterns of inequality emerging from the data. To capture key dimensions of student vulnerability, we again rely on a principal component factor model to construct two indices: a deprivation index, which serves as a proxy for socioeconomic background, and a self-efficacy index, which captures various non-cognitive attitudes and aspects of student motivation.

The deprivation index is constructed from five student-reported items: satisfaction with their primary device; difficulty finding a quiet place to study; internet connection problems; use of a shared device; and whether device sharing hindered participation in lessons. The first factor yielded an eigenvalue of 1.96, explaining 39% of the total variance, and the resulting index exhibited a Cronbach's alpha of 0.52.

Figure 3. The distribution of the deprivation index



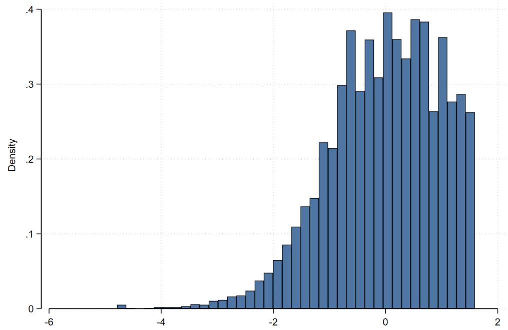
Notes: The deprivation index is constructed with factor analysis using the students answers on: satisfaction with their primary device; difficulty finding a quiet place to study; internet connection problems; use of a shared device; and whether device sharing hindered participation in lessons.

Figure 3 shows its distribution. This pattern reflects both the sample's bias toward more advantaged students and, possibly, the impact of policy interventions, such as the distribution of digital device, implemented to mitigate digital inequality during the second lockdown (Contini et al., 2023).

The self-efficacy Index is based on nine items (see Table 6) concerning students' school engagement, perseverance, and beliefs about the value of education, dimensions widely recognized as predictors of academic success (Buchholz et al., 2022; Zhou, 2016).[12]

[12] Several items were drawn from OECD-PISA instruments. Questions 3 and 4 refer to work mastery; questions 5 and 7 to perseverance; and questions 8 and 9 to how students value school outcomes (Buchholz et al., 2022).

Figure 4. The distribution of the self-efficacy index



Notes: The self-efficacy index is constructed with factor analysis using answers to the nine questions reported in Table 6.

Figure 4 displays the distribution of the index. As in the case of the deprivation index, the evidence points to a positive selection in our sample, while also revealing substantial heterogeneity among respondents.

Table 6 presents an initial analysis of inequality patterns within our student sample. We stratified the sample based on the median value of the deprivation index and subsequently report the results for the nine constituent items of the self-efficacy index. As expected, students from more disadvantaged backgrounds report significantly lower levels of motivation and school engagement across most dimensions.

Table 6. Students perceptions by high/low values of the deprivation index

	Low deprivation	High deprivation	Difference
Q1 - I enjoy receiving good grades	3.723	3.649	0.074***
Q2 - Trying hard at school is important	3.429	3.414	0.015
Q3 - I continue working on tasks until everything is perfect	3.435	3.356	0.079***
Q4 - Part of the enjoyment I get from doing things is when I improve on my past performance	3.375	3.353	0.022
Q5 - If I am not good at something, I keep trying until I master it	3.154	3.098	0.057***
Q6 - My goal is to avoid doing worse than my peers	2.398	2.471	-0.073***
Q7 - I enjoy exploring topics in as much depth as possible	2.642	2.636	0.006
Q8 - Trying hard at school will help me get a good job	3.082	3.055	0.027
Q9 - Trying hard at school will help me get into a good college	3.265	3.205	0.060***
Index - Perception of self-efficacy	2.546	2.454	0.092***

Notes: Students had to indicate how much they agreed with each statement using the following scale: 1-Strongly disagree, 2-Disagree, 3-Agree, 4-Strongly Agree. Students are categorized as experiencing low deprivation if their deprivation index score falls below the median of the distribution. Conversely, students with scores exceeding the median are classified as experiencing high deprivation. The t-test of equal means reported with significance levels identified by * 10%, ** 5%, *** 1%.

We then examine how perceived learning outcomes vary across different student socio-economic subgroups. Table 7 compares students' perceptions of learning loss and grading consistency for different deprivation levels. Students from higher socio-economic backgrounds (low deprivation) are significantly more likely to report having learned as much and to perceive grade continuity across learning modalities.

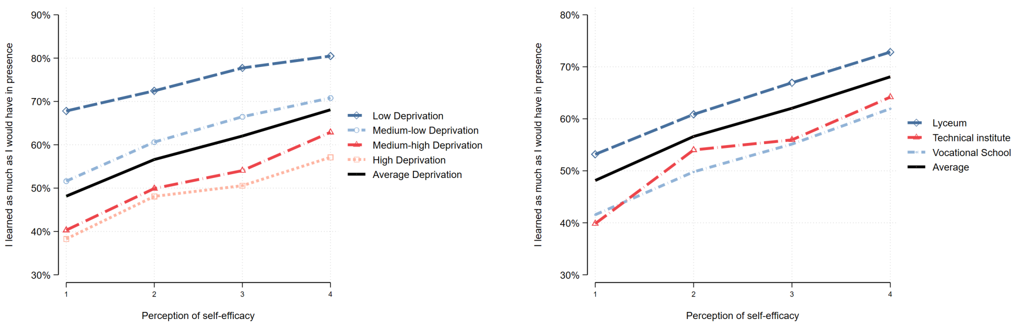
Table 7. Different learning perceptions by socio-economic background

	Low deprivation	High deprivation	Difference
I learned as much as I would have in presence	2.816	2.475	0.341***
I got similar grades as I would have in presence	3.001	2.790	0.211***

Notes: Students had to indicate how much they agreed with each statement using the following scale: 1-Strongly disagree, 2-Disagree, 3-Agree, 4-Strongly Agree. The low-high cutoff of the deprivation index is identified by the median of the distribution. The t-test of equal means reported with significance levels identified by * 10%, ** 5%, *** 1%.

Figure 5 (panel a) illustrates this pattern by showing perceived learning loss across deprivation and self-efficacy indices quartiles. Students with less resources for remote learning and lower self-efficacy report greater learning losses.

Figure 5. Inequality patterns



Notes: In the Y axis measures the % of students who agreed or strongly agreed with the statement: "During RL, I learned about as much as I would have by going to school". In panel (a) both the SES index and the self-efficacy indexes are divided into quartiles. The different colored dashed lines identify the different SES quartiles, while the black continuous line identifies the average. In panel (b) the self-efficacy index is divided into quartiles. The different colored dashed lines identify the different types of schools the students attend, while the black continuous line identifies the average. All answers relate to all the school activities offered from September onward.

We then replicate this analysis by replacing the deprivation index with school track (Lyceum, Technical, Vocational). Figure 5 Panel (b) shows that students attending Lyceums reported smaller learning losses, consistent with existing evidence on social stratification in the Italian school system. Overall, the evidence confirms the cumulative disadvantage faced by more vulnerable students during remote learning.

6 Results

To further investigate the relationship between school outcomes during RL we will employ a simple cross-section OLS model. Our main focus is on the role of teaching practices adopted during online syncronous activities, but we also include in our analysis the many covariates we have collected in our three-level survey to isolate the partial correlation between $TEACH_{ij}$ and a list of additional important determinants. The regression model takes the form:

$$Y_{ij} = \alpha + \beta TEACH_{ij} + \gamma X_{ij} + \delta Z_j + v_{ij} \tag{1}$$

where Y_{ij} represent an outcome variable of student i attending school j, X_{ij} and Z_j are vectors of individual student controls and school controls, respectively; and the variable $TEACH_{ij}$ represents the teachers' innovation index. Moreover, to take into account the area fixed characteristics, including the differences in the length of in-person schooling across the different areas during the second lockdown, all models always adds area dummies at the NUTS3 level.[13] Finally, since students' responses to different classroom activities refer to one of four specific subjects, we also include dummy variables for the different subjects.

Table 8 presents the results obtained using our most important dependent variable, which reflects student agreement with the statement, "During RL, I learned about as much as I would have by going to school." This variable is a dummy equal to one for students who agree or strongly agree with this statement. Estimates are obtained using a Linear Probability Model, with standard errors clustered at the school level.[14] To account for the oversampling of specific areas, the analysis applies sampling weights to align the sample distribution with the population proportions.

Column 1 presents the results of the most parsimonious specification, which includes only our main variable of interest, $TEACH_{ij}$, the teaching innovation index constructed from student responses about specific teaching methodologies adopted during the prolonged period of online learning. We then expand the model to further explore the relationship between perceived learning loss during RL, incorporating additional variables from our survey that may have influenced students' RL experiences. Models 2 and 3 add student-level characteristics, including the deprivation index and students' perceived self-efficacy. Model 4 further introduces a dummy

[13] To account for the oversampling of specific areas, we replicate the analysis using sampling weights that reflect population proportions. The results remain robust and are available upon request.

[14] We use LPM for its robustness as observed by Angrist and Pischke (2009). However, the use of a Logit estimator yields the same results.

variable identifying 11th-grade students, the type of school attended, school size, and grade retention. The latter is derived from *La scuola in chiaro* dataset and measures the percentage of students in the school who repeated the academic year.

Models 5 and 6 incorporate two variables derived from the principals' survey. For the first, we use a PCF model to identify schools that made no organizational changes to their timetable compared to in-person schooling during the RL periods. The PCF model is based on three items: (i) whether there was a need to revise the weekly timetable and subject weight, (ii) the average number of hours students spent daily in online learning, and (iii) whether the school reduced the standard 60-minute lesson duration in the RL timetable.[15] Model 6 adds a variable measuring additional school funding, calculated as the mean of five binary indicators capturing whether the school received support from each of the following sources: regional and local authorities, third-sector organizations, private sector, religious entities, and families. A higher index value indicates broader financial support from external sources (see Figure A1).

Except for school size, most variables are statistically significant and display the expected signs. Student deprivation and grade retention are negatively associated with perceived learning during RL, while self-efficacy and motivation show the expected positive relationship. Compared to 13th graders, younger students reported higher perceived learning during RL. It is likely that the uncertainty surrounding the final year of upper secondary education and the upcoming high-stakes national exam (esame di maturità) negatively affected 13th graders' perceptions. Using Lyceum as the reference category the coefficients for technical and vocational schools are negative.

When additional variables from the principals' survey are included (Models 5 and 6), the sample size decreases, as principals in some school did not participate, although students and teachers from those schools responded. Despite the reduced sample, the signs and statistical significance of the key variables remain stable. The variable capturing the absence of organizational innovations during synchronous teaching is negatively associated with students' perceived learning, while the presence of additional funding is positively correlated. Notably, the teaching innovation index consistently shows a positive association with students' perceived performance during remote learning.

Table 9 further investigates these relationships using an ordered logit model that exploits the ranking nature of our dependent variable.[16] Table 9 shows the marginal

[15]The first factor's eigenvalue is 1.18, explaining 39% of the total variance, with a Cronbach's alpha of 0.18. This index displays weaker internal consistency relative to the others used in the analisys.

[16]The ordered logit model is estimated using Stata's feologit function Baetschmann et al. (2020). This model assumes independent and identically distributed error terms. We employed the efficient blow-up and cluster estimator for model fitting. In this estimation, we do not include variables at the principal school level, as the estimator accounts for school fixed effects.

Table 8. Perception of learning during RL

Dep. var.: *I learned as much as I would have in presence (yes=1)*						
	(1)	(2)	(3)	(4)	(5)	(6)
Innovation index	.045***	.044***	.034***	.038***	.04***	.04***
	(.0065)	(.0059)	(.0053)	(.0054)	(.006)	(.0061)
Deprivation index		-.089***	-.086***	-.083***	-.087***	-.087***
		(.0057)	(.0055)	(.0055)	(.0057)	(.0057)
Perception of self-efficacy			.065***	.065***	.065***	.065***
			(.0054)	(.0055)	(.0063)	(.0063)
Grade retention (%)				-2.7***	-2.4***	-2**
				(.86)	(.79)	(.83)
Grade 11				.063***	.079***	.079***
				(.014)	(.015)	(.015)
Technical institute				-.078***	-.056***	-.056***
				(.027)	(.018)	(.018)
Vocational School				-.095***	-.1***	-.11***
				(.019)	(.023)	(.022)
School size				-.00088	.0032	.0028
				(.0039)	(.0024)	(.0022)
No organizational changes					-.012	-.018*
					(.01)	(.01)
Additional school funds						.044*
						(.025)
Observations	9360	9345	9320	9297	7506	7506
Adjusted R^2	0.025	0.057	0.073	0.083	0.087	0.087
Number of schools	87	87	87	87	71	71

Notes: The dependent variable measures the learning loss during RL as perceived by students. Standard errors in parentheses are clustered at the school level. Estimates include fixed effects for NUTS3 areas and control for subject-specific variation through subject dummies. * p<0.10, ** p<0.05, *** p<0.01.

effects for the different degrees of agreement or disagreement of the dependent variable, along with standard errors for three main covariates: the teachers' innovation Index, the deprivation index, and the self-efficacy index. The regression includes all the additional controls of model 4 in Table 8 with standard errors clustered at the school level.

Table 9. Perception of learning during RL: ordinal logit

Dep. var.: *I learned as much as I would have in presence*	Innovation index	Deprivation index	Perception of self-efficacy
Strongly disagree	-.016***	.037***	-.032***
	(.0025)	(.0025)	(.0028)
Disagree	-.022***	.053***	-.045***
	(.0035)	(.0035)	(.004)
Agree	.016***	-.039***	.033***
	(.0026)	(.0026)	(.0029)
Strongly disagree	.022***	-.051***	.044***
	(.0034)	(.0034)	(.0038)
Observations	9297		
Number of schools	87		
Log likelihood	-1.1e+06		
Pseudo R2	.051		

Notes: Additional controls include grade retention, a dummy for 11th graders, school size, types of school and subject dummies. See notes on Table 8 for details on the dependent variable. Standard errors in parentheses are clustered at the school level. * p<0.10, ** p<0.05, *** p<0.01.

Our dependent variable reflects students' agreement with the statement "During RL, I learned about as much as I would have by going to school" on a 4-point Likert Scale, with choices: Strongly Disagree, Disagree, Agree, or Strongly Agree. Results in column one indicate that a one-unit increase in the teaching innovation index decreases the probability of being in the "strongly disagree" category by 2 percentage points while increasing the probability of "strongly agree" by 2.7 percentage points, on average, holding other factors constant. Similar trends are observed for the self-efficacy index and the deprivation index, with the latter showing the expected opposite signs.

Table 10 presents the results when using alternative students outcome variables while including the same set of control variables as model 6 of Table 8. The survey gathered students' assessments of their overall online learning experience, including their interactions with teachers and classmates. We expect that these perceptions are influenced by the implementation of online teaching, thus correlating with our measure of innovative teaching and other covariates.

The first new dependent variable, *Student RL Engagement*, is a dummy equal to one for students who agree or strongly agree with the statement: "Teachers had us experience new teaching methods during online learning, which I greatly appreciated." The second variable, *Wish for RL to continue*, is similarly calculated based on the statement: "I would like the use of digital platforms and learning apps to continue once we return to school after the COVID emergency."[17] The third

[17] As above, these variables describe students' agreement on a 4-Point Likert Scale: Strongly Disagree, Disagree, Agree, or Strongly Agree.

outcome variable, RL Efficacy (Model 3), aims to capture whether students perceived it as easier to interact with teachers during remote learning compared to in-person instruction. To assess the validity of the latent construct underlying RL Efficacy, we estimate a PCF model using responses to the following items: (1) intervening during online lessons is easier than during face-to-face schooling; (2) teamwork activities are easier online; and (3) getting in touch with teachers is easier in remote settings than in person.[18]

Table 10. Alternative students' outcome variables

	(1) Student RL Engagement	(2) Wish for RL to continue	(3) RL efficacy
Innovation index	0.122***	0.036***	0.099***
	(0.007)	(0.007)	(0.012)
Deprivation index	-0.066***	-0.057***	-0.132***
	(0.006)	(0.005)	(0.016)
Grade retention (%)	-0.202	0.380	-5.391**
	(0.853)	(0.609)	(2.210)
Grade 11	0.076***	0.052***	0.210***
	(0.017)	(0.015)	(0.037)
Technical institute	0.070***	0.061***	0.313***
	(0.023)	(0.016)	(0.054)
Vocational School	0.112***	0.016	0.347***
	(0.024)	(0.022)	(0.060)
School size	-0.004	0.003	0.002
	(0.002)	(0.002)	(0.006)
No organizational changes	-0.019	-0.026***	0.016
	(0.013)	(0.008)	(0.022)
Additional school funds	0.046*	-0.028	0.106**
	(0.024)	(0.021)	(0.046)
Observations	7528	7528	7528
Adjusted R^2	0.113	0.028	0.080
Number of schools	71	71	71

Notes: Additional controls include grade retention, a dummy for 11th graders, school size, and types of school and subject dummies, the absence of changes in the school organization during the RL periods, and the additional school funds received. See notes on Table 8 for details on the dependent variable. Standard errors in parentheses are clustered at the school level. Estimates include fixed effects for NUTS3 areas and control for subject-specific variation through subject dummies. * p<0.10, ** p<0.05, *** p<0.01.

Overall, the results in Table 10 confirm that teaching methodologies deemed more suitable and effective for online learning are consistently positively correlated not only with perceived student learning but also with a better RL experience, a desire to continue using online activities post-pandemic, and the perception of

[18] The first factor has an eigenvalue of 1.77 , explains 59% of the total variance, with a Cronbach's alpha of 0.65.

greater effectiveness in specific activities and interactions.

Finally, given its policy relevance, we investigate the relationship between our main variable of interest, $TEACH_{ij}$, which captures the extent of innovative teaching methodologies adopted during RL, and a set of key factors likely to influence it. Among these, training in digital skills emerges as especially relevant, as it likely shaped teachers' capacity and willingness to implement effective instructional practices during RL.

Our analysis considers two distinct measures of training, derived from separate survey sources. The first is constructed from the principals' survey and reflects school leaders' perceptions of teachers' training needs during the second lockdown (see Figure 5). Higher values of this variable indicate a greater perceived need for ICT-related instructional support among teaching staff. The second measure is based on self-reported data from the teacher survey. Teachers were asked to indicate whether they received training in various ICT-related areas during the pandemic. For each respondent, we compute the average percentage of items for which they reported receiving no training during the lockdown period. For both variables, the expected sign is negative, implying that either a greater perceived need for training (first measure) or a lower level of training received (second measure) is associated with lower levels of teaching innovation during RL.

Table 11. Teachers' training and innovative teaching methodologies

Dep. Var: *Innovative teaching index*	(1)	(2)
No digiskills training (Teachers' survey)		-0.631*
		(0.333)
Teachers low digiskills (School principals' survey)	0.0498	
	(0.0468)	
Observations	7521	7521
Adjusted R^2	0.124	0.124
Number of schools	71	71

Notes: The dependent variable is the innovative teaching index as described in Figure 6. Additional controls include grade retention, a dummy for 11th graders, school size, and types of school and subject dummies, the absence of changes in the school organization during the RL periods, and the additional school funds received. Standard errors in parentheses are clustered at the school level. Estimates include fixed effects for NUTS3 areas and control for subject-specific variation through subject dummies. * p<0.10, ** p<0.05, *** p<0.01.

Table 11 introduces the innovative teaching index as the dependent variable. Models 1 and 2 report only the coefficients for the two alternative teacher training variables; the full set of controls is listed in the notes to Table 11. In model 1, using principals' perceptions of teachers' digital training needs, the coefficient is not significant. In model 2, the intensity of training received as perceived by teachers during RL shows the expected negative and significant coefficient.

7 Robustness and extensions

In this section, we assess the robustness of the main results by using alternative sample selections and model specifications. All additional results are reported in the Appendix.

First, we test the sensitivity of our findings to the exclusion of schools with low response rates. Table A1 re-estimates the main regression models, this time including 12 additional schools with fewer than 15 student or 8 teacher responses. The results remain consistent across samples and model specifications.

Next, to address potential non-response bias, we re-run the models on a subsample of schools with high student response rates. We define "high response" as above the sample median value of 0.20. Table A2 presents results for 56 schools in models 1 to 4, and 45 schools in models 5 and 6 (where organizational variables from the principals' questionnaire are included). Even within this more selective subsample, the estimated coefficients remain broadly consistent with the main results, although we observe some loss of statistical significance due to the smaller sample size.

Third, Table A3 reports results from specifications including school-level fixed effects to account for unobserved heterogeneity. Student-level variables remain stable and consistent with the main analysis. We also re-estimate the models without applying sampling weights and confirm that the results are robust to the choice of weighting scheme.[19]

Overall, the findings are broadly consistent across different specifications and sample restrictions. While some school-level variables lose statistical significance, mainly due to reduced statistical power, the direction and magnitude of the estimated coefficient remain stable, supporting the robustness of our conclusions.

We further investigate whether the results vary by geographical context. Specifically, we test for heterogeneity by macro-area (North vs. Centre and South) and by urban–rural classification based on Istat definitions.[20] Schools in "Densely populated areas" are coded as urban (urban = 1), while those in "Intermediate density" or "Rural areas" are classified as non-urban. Only two schools in our sample fall into the rural category, which is expected given the concentration of upper secondary schools in more urbanized areas.

Comparisons across macro-areas and between urban and non-urban schools do not reveal significant differences. Moreover, both the regional and the urban–rural analyses involve sample size reductions, and the regional subsamples, particularly those from the Centre and South, are affected by substantial selection bias. For these reasons, we do not include these results in the Appendix.

As a final step, and to account for urban–rural heterogeneity without further

[19] These results are available upon request.

[20] See https://www.istat.it/classificazione/principali-statistiche-geografiche-sui-comuni/

reducing the sample size, we extended the models by including interaction terms between the urban school dummy, the Teaching Innovation Index, and organizational change variables. Results in Table A4 confirm that innovative teaching practices remain positively associated with students' perceived learning, with a slightly stronger effect in urban schools. Conversely, the absence of organizational changes is associated with lower perceived learning, independently of school location. Overall, these results offer only a very preliminary insight into territorial heterogeneity. Given the potential policy relevance of geographic disparities in school response and capacity, this dimension should be systematically explored in future research.

8 Final discussion

This study offers new evidence on how upper secondary schools in Italy responded to the COVID-19 crisis. In particular, we examine the second lockdown (Sept 2020–June 2021), when the Ministry issued non-binding guidelines on remote learning, covering minimum online hours, digital tools, and assessment, and leaving principals and teachers broad discretion in implementation.

Our evidence is based on a rich three-level dataset. Our results indicate that, even during the second lockdown, when remote instruction had shifted from an emergency response to a foreseeable alternative to in-person schooling, remote learning activities were implemented with minimal pedagogical and organizational innovation. Synchronous instruction largely mirrored traditional in-person practices, despite national guidelines encouraging more innovative and flexible approaches.

Importantly, this pattern is observed in a sample biased toward higher-performing schools and students, suggesting that the broader education system may have encountered even greater difficulties. It also points to the limited effectiveness of government efforts to promote and support the adoption of context-appropriate teaching practices during the emergency. Most of the training focused on technical aspects, rather than providing support for pedagogical approaches to online teaching, and was often delivered using internal school resources.

From the students' perspective, this replication of in-person teaching in a digital format was cognitively demanding and often ineffective. Student learning, concentration, and engagement were widely reported as challenges, particularly among those from disadvantaged backgrounds or with low self-efficacy. The inequality patterns observed are consistent with prior evidence on the unequal impact of school closures. Regression results indicate that innovative teaching practices and more flexible school organization were positively associated with student-reported engagement and perceived learning. Furthermore, teacher training is positively correlated with the adoption of innovative methods, underscoring the importance of high-quality professional development.

While not reported in detail here, our survey responses also suggest that both school principals and teachers were optimistic about the long-term effects of the pandemic on digital competence and the integration of technology into teaching practices. However, Italian schools seems to have largely reverted to traditional methods.

These findings raise several policy considerations. First, the limited pedagogical adaptation observed during remote learning calls into question the effectiveness of previous digital education initiatives, including the 2015 National Plan for Digital Education (Law 107), in addressing Italy's longstanding ICT gaps.

Second, the analysis raises questions about the effectiveness of how teacher training was delivered during the crisis, a model that has not enabled widespread innovation of traditional practices. These findings suggest that simply giving schools autonomy over training may not be effective unless it is matched by adequate resources, structured guidance, and a clear framework for identifying and closing competency gaps. When such autonomy is paired with per-capita funding but lacks centrally defined quality standards and robust support, decentralization may end up reinforcing, rather than narrowing, the disparities that already exist.

Our evidence is primarily descriptive, and it highlights several mechanisms that call for future research. These include the heterogeneous teachers' training quality, the persistence of traditional instructional models despite the availability of digital tools, and likely overconfidence among teachers regarding their digital competencies. More granular data on teacher characteristics and the specific content and delivery of training would support a better understanding of what works, for whom, and under what conditions. In addition, future research should investigate geographical disparities in teachers' digital skills, as well as in the quality and quantity of training opportunities, both across regions and between urban and rural areas.

In sum, this study offers a useful framework for understanding how education systems can better adapt to ongoing technological change. As digital transformation accelerates, driven also by the rapid diffusion of artificial intelligence, equipping teachers with the skills needed to integrate innovative practices into everyday teaching becomes a crucial policy lever, not only for improving student outcomes but also for reducing educational inequalities.

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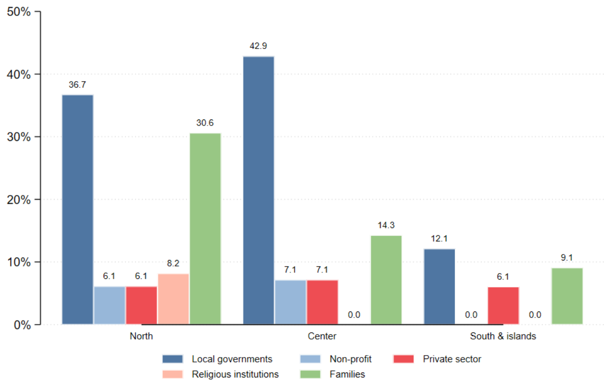
A Appendix

A.1 Additional Figures

Figure A1. External schools' funds received during the second lockdown



Notes: *This chart analyzes the distribution of financial support for schools across three different areas: North, Centre, and South Islands. Data are based on the principals' answers on the level of support their schools received during the lockdown in addition to the state funding from the local governments, the third sector, the private sector, religious organizations, and families.*

Figure A2. RL and dimensions of the relationship among school actors

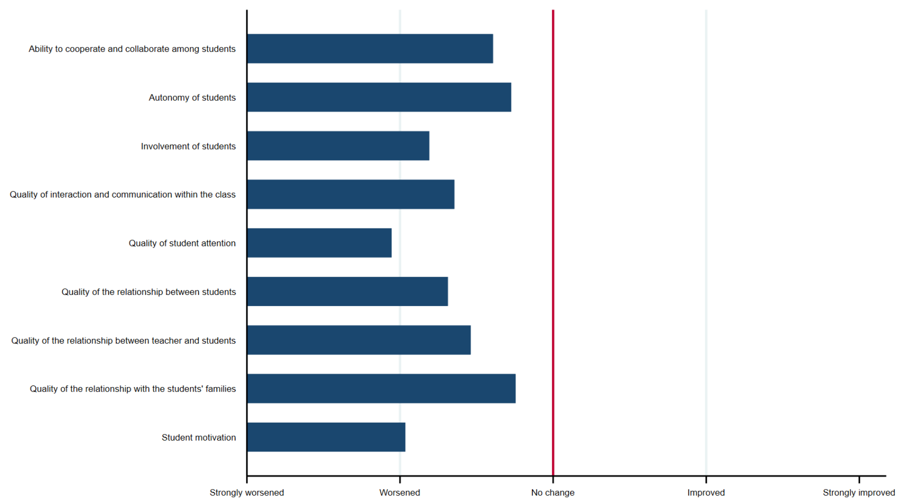
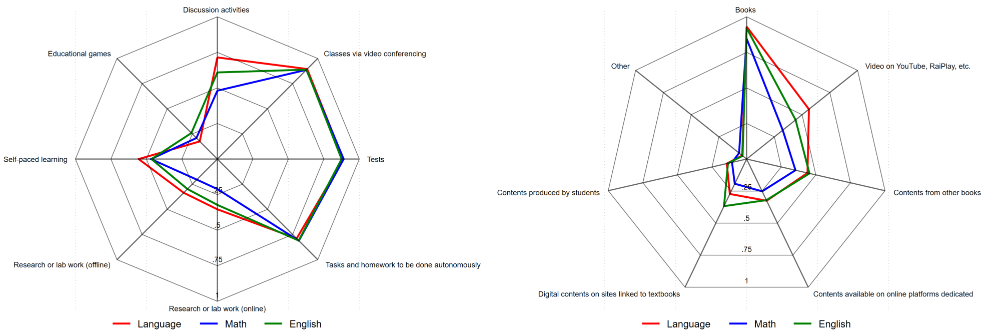


Figure A3. Teaching activities and additional learning materials: students perspectives



(a) Teaching activities

(b) Additional learning materials

Notes: *we show the spider plot depicting the frequency of teacher methodologies during RL from the student perspective. The greater the distance from the center on a particular axis, the higher the average probability that teachers employ that specific practice.Panel a) depicts the teaching activities while Panel b)illustrates the additional learning material*

A.2 Additional Tables

Table A1. Perception of learning during RL: without removing low response schools

Dep. var.: *I learned as much as I would have in presence (yes=1)*						
	(1)	(2)	(3)	(4)	(5)	(6)
Innovation index	0.043***	0.043***	0.032***	0.036***	0.039***	0.039***
	(0.007)	(0.006)	(0.005)	(0.005)	(0.006)	(0.006)
Deprivation index		-0.089***	-0.086***	-0.084***	-0.087***	-0.086***
		(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Perception of self-efficacy			0.066***	0.065***	0.065***	0.065***
			(0.005)	(0.006)	(0.006)	(0.006)
Grade retention (%)				-2.568***	-2.568***	-2.185***
				(0.875)	(0.778)	(0.814)
Grade 11				0.060***	0.077***	0.077***
				(0.014)	(0.015)	(0.015)
Technical institute				-0.079***	-0.056***	-0.056***
				(0.026)	(0.018)	(0.018)
Vocational School				-0.091***	-0.102***	-0.108***
				(0.019)	(0.023)	(0.023)
School size				-0.001	0.002	0.002
				(0.004)	(0.002)	(0.002)
No organizational changes					-0.010	-0.015
					(0.010)	(0.011)
Additional school funds						0.043*
						(0.023)
Observations	9517	9502	9476	9446	7631	7631
Adjusted R^2	0.025	0.058	0.074	0.083	0.087	0.087
Number of schools	99	99	99	99	79	79

Notes: *The dependent variable measures the learning loss during RL as perceived by students. Standard errors in parentheses are clustered at the school level. Estimates include fixed effects for NUTS3 areas and control for subject-specific variation through subject dummies. * p<0.10, ** p<0.05, *** p<0.01.*

Table A2. Perception of learning during RL: only schools with high response rate

Dep. var.: *I learned as much as I would have in presence (yes=1)*						
	(1)	(2)	(3)	(4)	(5)	(6)
Innovation index	0.050***	0.049***	0.039***	0.042***	0.043***	0.043***
	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Deprivation index		-0.089***	-0.086***	-0.083***	-0.091***	-0.091***
		(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Perception of self-efficacy			0.064***	0.062***	0.061***	0.061***
			(0.005)	(0.006)	(0.006)	(0.006)
Grade retention (%)				-3.259***	-2.580***	-2.447**
				(1.009)	(0.839)	(0.929)
Grade 11				0.073***	0.085***	0.085***
				(0.014)	(0.017)	(0.017)
Technical institute				-0.067**	-0.039*	-0.038*
				(0.030)	(0.022)	(0.022)
Vocational School				-0.074***	-0.071***	-0.074***
				(0.018)	(0.021)	(0.022)
School size				-0.003	0.001	0.001
				(0.004)	(0.002)	(0.002)
No organizational changes					-0.012	-0.015
					(0.008)	(0.010)
Additional school funds						0.013
						(0.023)
Observations	8074	8061	8039	8016	6503	6503
Adjusted R^2	0.028	0.059	0.075	0.084	0.086	0.086
Number of schools	56	56	56	55	45	45

Notes: *The dependent variable measures the learning loss during RL as perceived by students. Standard errors in parentheses are clustered at the school level. Estimates include fixed effects for NUTS3 areas and control for subject-specific variation through subject dummies.* * p<0.10, ** p<0.05, *** p<0.01.*

Table A3. Perception of learning during RL: adding school fixed effects

Dep. var.: *I learned as much as I would have in presence (yes=1)*				
	(1)	(2)	(3)	(4)
Innovation index	.048***	.047***	.037***	.039***
	(.0066)	(.006)	(.0054)	(.0055)
Deprivation index		-.087***	-.084***	-.083***
		(.0056)	(.0056)	(.0055)
Perception of self-efficacy			.066***	.063***
			(.0054)	(.0055)
Grade 11				.068***
				(.015)
Observations	9357	9342	9317	9317
Adjusted R^2	0.035	0.065	0.082	0.086
Number of schools	87	87	87	87
School FE	yes	yes	yes	yes

Notes: *The dependent variable measures the learning loss during RL as perceived by students. Standard errors in parentheses are clustered at the school level. * p<0.10, ** p<0.05, *** p<0.01.*

Table A4. Perception of learning during RL: interaction with urban areas

Dep. var.: *I learned as much as I would have in presence (yes=1)*	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Innovation index	0.034***	0.037***	0.029***	0.030***	0.030***	0.030***	0.030***
	(0.008)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)
Deprivation index		-0.089***	-0.086***	-0.083***	-0.087***	-0.087***	-0.086***
		(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Perception of self-efficacy			0.065***	0.065***	0.065***	0.065***	0.065***
			(0.005)	(0.006)	(0.006)	(0.006)	(0.006)
Urban	-0.004	-0.002	-0.006	0.028	-0.010	-0.013	-0.004
	(0.026)	(0.027)	(0.027)	(0.022)	(0.026)	(0.024)	(0.023)
Urban × Innovation index	0.021*	0.015	0.010	0.015	0.023*	0.022*	0.022*
	(0.012)	(0.011)	(0.011)	(0.011)	(0.012)	(0.012)	(0.012)
Grade retention (%)				-3.004***	-2.387***	-1.972**	-2.405**
				(0.919)	(0.832)	(0.864)	(0.925)
Grade 11				0.063***	0.079***	0.079***	0.079***
				(0.015)	(0.015)	(0.015)	(0.015)
Technical institute				-0.078***	-0.057***	-0.056***	-0.057***
				(0.027)	(0.018)	(0.018)	(0.018)
Vocational School				-0.101***	-0.100***	-0.105***	-0.106***
				(0.019)	(0.023)	(0.022)	(0.022)
School size				-0.001	0.003	0.003	0.004
				(0.004)	(0.002)	(0.002)	(0.003)
No organizational changes					-0.013	-0.020*	-0.036**
					(0.012)	(0.011)	(0.017)
Additional school funds						0.043*	0.033
						(0.024)	(0.029)
Urban × No org. changes							0.042
							(0.032)
Observations	9360	9345	9320	9297	7506	7506	7506
Adjusted R^2	0.025	0.057	0.073	0.083	0.087	0.088	0.088
Number of schools	87	87	87	87	71	71	71

Notes: *The dependent variable measures the learning loss during RL as perceived by students. Standard errors in parentheses are clustered at the school level. Estimates include fixed effects for NUTS3 areas and control for subject-specific variation through subject dummies.* * *p<0.10, ** p<0.05, *** p<0.01.*