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ABSTRACT

Online Teaching, Procrastination and Students' Achievement: Evidence from COVID-19 Induced Remote Learning*

The COVID-19 pandemic forced schools and universities to transit from traditional class-based teaching to online learning. This paper investigates the impact produced by this shift on students' performance. We use administrative data of four cohorts of students enrolled in an Italian University and adopt a difference-in-differences strategy exploiting the fact that the transition to online teaching has taken place at the beginning of the second semester, while classes were face-to-face in the first semester. We compare students' performance in the second semester of 2020 with their performance in the first semester and contrast this difference with the difference between second and first semester in the previous academic years. Controlling for a number of variables proxying for COVID-19 incidence and internet connections' quality, we find that online teaching has reduced students' performance of about 1.4 credits per semester (0.11 Standard Deviations). Freshmen are those who suffer more, while almost no negative effect is found for Master's Degree students. Since the need for self-discipline in an online environment could cause students' low achievements, we study the role of procrastination and show that online teaching has been particularly detrimental for students affected by present-bias problems.

JEL Classification: I21, I23, I28, D90, L86

Keywords: online teaching, students' performance, COVID-19, procrastination

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1. Introduction

The COVID-19 pandemic forced many governments worldwide to close several social and economic activities and to implement restrictive measures and protocols to reduce social gatherings and promote social distancing. In an attempt to protect both learners and educators from the infection and decelerate the transmission of the virus, on March 2020 schools at all levels and universities were forced to close down and to look for alternative teaching and learning approaches. Nearly 200 countries shut down schools, with over 90% of the worldwide population of students facing a disruption to their education (UNESCO, 2020).

To fulfill the educational needs of students during this health emergency, educational institutions shifted away from traditional face-to-face teaching to online delivery. This shift is likely to have produced effects that are a matter of concern for both public authorities and stakeholders. A crucial question, also for its implications on how teaching activities should be organized in the future, is whether online teaching has been as effective as class-based learning. Although this question has been a matter of debate well before the COVID-19 pandemic, when a number of universities and colleges began to offer online education, the health emergency has made it more pressing.

From a theoretical point of view, distance learning has both benefits and drawbacks compared with face-to-face teaching (Figlio, Rush and Yin, 2013). The advantages of distance learning include the lower costs deriving from the fact that the same lesson can be followed by a large number of students, and the possibility for students to attend classes when they prefer, avoiding too crowded classrooms and reviewing lessons in order to understand aspects that were not immediately clear. Other benefits for students include access to the latest information, sharing of content, and communication (Mathew and Iloanya, 2016) and, last but not least, distance learning allows both teachers and students to reduce mobility costs and commuting time. On the contrary, disadvantages include the lack of in-person peer interactions, more difficult interactions between teachers and students, and technology-related hindrances, such as slow or unreliable internet, cost of connection, insufficient technological skills (Alvarez, 2020; Mathew and Iloanya, 2016; Lynch, 2020). In addition, the lack of a structured environment with a set routine might induce students, especially those characterized by present-biased preferences, to skip assignments and postpone activities requiring effort.

Given the interplay between these positive and negative aspects, the understanding of how online teaching affects the achievements of students is an empirical matter. In this paper, we focus on tertiary education and address this issue analyzing the impact of the shift from face-to-face to online teaching during the first wave of the COVID-19 pandemic. Even if the pandemic posed additional problems besides those deriving from the transition to online teaching, which might also have affected students' performance, we provide evidence that in our setting these aspects are likely to have played a minor role.

We use very rich administrative data, from a medium sized Italian public university, with information on the academic careers of four cohorts of students. Thanks to the structure of examination sessions, we are able to observe the performance of students at exams taken both before and after the transition to online teaching. This allows us to estimate the overall effect on students' performance of the shift from in-person to online teaching by applying a difference-in-differences identification strategy: we compare the academic performance of students of different cohorts (some affected by the health emergency and others not affected) in the exams taken in the first semester, which identifies a pre-treatment difference, with the difference in performance in the exams taken in the second semester, which includes the effect produced by the transition to distance learning (and other possible changes related to the emergency).

In line with results emerging from the recent literature on the topic, controlling for student characteristics and Degree Course dummies, we find that pandemic-induced online teaching significantly reduced the number of credits acquired over a semester of about 1.4, an effect corresponding to about 0.11 Standard Deviations (SD) of the dependent variable. Most importantly, the estimated effect does not seem to depend on the severity of the health emergency or on the quality of internet connections. A negative effect is also found when considering as outcome variable an overall measure of students' performance taking into account also grades obtained by students at exams. Our results are robust to the inclusion of student fixed effects and several control variables for individual and local characteristics.

Since our data cover the universe of enrolled students, we are able to check whether the estimated effect of online teaching is heterogeneous for more and less experienced students. Freshmen, used to a structured high school environment, may find it more difficult to adapt to the self-discipline required by the organization of university studying activities, especially in an online environment that makes it much more essential. Indeed, we find that effects are particularly detrimental for freshmen and less experienced students while almost no effect is found on Master's Degree students.

A number of papers highlight how study activities might be more difficult in a less structured setting without routine interactions with peers and instructors (Banerjee and Duflo, 2014; Figlio, Rush, and Yin, 2013; McPherson and Bacow, 2015)[1]. Thus, online teaching might exacerbate problems deriving from present biased preferences. Thanks to the richness of our data, we are able to exploit a measure of students' tendency to procrastinate based on their behavior during the enrollment process. This measure, already used by De Paola and Scoppa (2015), has been shown to be a strong predictor of student's academic success. We find results in line with our expectation, with remote learning producing a large negative impact mainly on students with a tendency to procrastinate.

The heterogeneity shown by our findings supports the idea that the worsening of students' academic performance observed in our setting is mainly driven by the change in teaching and learning practices, since it would be difficult to argue that procrastinators were more negatively affected by health

[1] Present-biased preferences have been shown to produce negative consequences on human capital investment decisions (Ariely and Wertenbroch, 2002; De Paola and Scoppa, 2015; Mischel et al., 1989; Wong, 2008). Doherty (2006) shows that procrastination is a predictor of dropping out or failing to complete an online course.

conditions or that instructors were less compassionate with them at exams. Most importantly, these heterogenous effects should be carefully taken into account when evaluating the strengths and weaknesses of different teaching methods; this at the aim of being more effective and avoiding to leave behind some groups of students (often the most fragile).

Our research contributes to the literature investigating the impact of online teaching on students' performance. Although relatively new to Italy, online university courses were widespread in the United States and in many advanced countries also before the pandemic crisis. Nonetheless, the literature trying to identify a causal impact of different teaching methods is quite small because of several identification challenges. Some papers rely on small-scale experiments where students are randomly assigned to alternative teaching systems (face-to-face, online and blended) (Alpert et al. 2016, Bowen et al. 2014, Coates et al. 2004, Cacault et al., 2021; Figlio et al. 2013, Joyce et al. 2015) and show negative effects of online compared to face-to-face classes. Similar results are found also by Bettinger at al. (2017) and Xu and Jaggars (2013) who consider quite large populations of students and deal with selection problems adopting an instrumental variable strategy.

This literature has been recently enriched by a number of works examining the impact of the closure of schools and universities and the consequent switch to remote learning due to the spread of coronavirus disease. In a review of papers studying the effect of COVID-19-related school closures in Spring 2020 on the achievement of students attending primary and secondary schools, Hammerstein et al. (2021) highlight a considerably negative effect specifically for younger students and students from families with low socioeconomic status.[2] While some of the papers dealing with this topic only offer suggestive evidence and do not try to distinguish the impact of online teaching from other confounders, other works try to identify a causal effect. For instance, Engzell et al. (2021) take advantage of the fact that the Netherlands national examinations for primary school pupils take place twice a year and in 2020 these tests took place just before and after the first national wide lockdown. Using a difference-in-differences model, they show a substantial learning loss in 2020 compared to the 3 previous years, which is concentrated among students from disadvantaged background. Similar results are found by Maldonado and De Witte (2020) who study the effects of school closures using data on standardised tests in the last year of primary school in Flemish schools in Belgium.[3]

As regards university students, Orlov et al. (2021) compare students' performance on standard assessments in Spring 2020 to students' performance in the same courses in either Fall or Spring 2019. They find that during the pandemic there was a decline of total scores and that prior online teaching

[2] Similar evidence emerges from Zierer (2021) and Spitzer and Musslick (2021), who also highlight highly heterogenous effects.

[3] Clark et al. (2020) base their analysis on three Chinese middle schools which administered different educational practices during the COVID-19 lockdown, and apply a difference-in-differences approach to estimate the impact of online teaching compared to a situation where students were left without educational support from schools. They find that online learning during lockdown improved student performance of 0.22 of a standard deviation, compared to that of students who received no learning support from their schools. The beneficial effect was mainly concentrated among low achievers and the positive impact was higher when recorded online lessons came from higher-quality teachers.

experience and teaching methods that encouraged active engagement helped to mitigate the effect. Likewise, Kofoed et al. (2021), using data on a randomized controlled trial comparing online and in-person classes, find that online education lowered students' final grades, especially for students with below median academic ability. Negative effects are also found by Altingad et al. (2021) who instead rely on data from a large US public university. They also show that instructor-specific factors, such as leniency in grading due to a more compassionate approach towards students in response to the difficulties caused by the pandemic, play an important role and might lead to erroneously conclude that online teaching is better than face-to-face teaching. Binelli et al. (2021) instead find evidence of a positive effect for students enrolled at a public university located in the North of Italy, probably due to a larger effort provided by students in studying activities during the lockdown period.

Our contribution to this literature is twofold. First, we offer new evidence for Italy, a country where the higher education system before the pandemic has been mostly traditional and web and technology have been mainly used only as a support to face-to-face classes (to share course information and/or additional teaching materials with students).[4] The timing of the transition to online learning for the university considered in this study, as for many other universities in Italy and in other countries worldwide, which has coincided with the beginning of the second semester, allows us to apply a difference-in-differences identification strategy. A similar identification strategy has been used by Orlov et al. (2021). While they only consider seven intermediate-level economics courses, we are able to rely on a very large dataset including hundreds of courses in several academic areas (Scientific, Humanities, Social Sciences) offered by an entire large public university.

Second, compared with the few papers that similarly to our study rely on large populations of students, we are able to offer evidence of the role played by procrastination. The tendency to put off action until some later time is a well-known detrimental attitude to academic achievement. Despite several authors envisaged the potential negative consequences of procrastination on online learning, to the best of our knowledge there are no papers offering empirical evidence on how procrastination mediates the effects of online teaching.[5] Our evidence suggests that, when comparing face-to-face with online teaching, students' present-biased preferences should be taken into account and online teaching should be supported by tools that allow students with a tendency to procrastinate to have a stronger commitment, thus attenuating the larger negative impact on their performance.

The remainder of the paper is structured as follows. In Section 2 we describe the data and in Section 3 the methodology used. In Section 4 we present and discuss our main results on the role of pandemic induced online teaching on the number of credits acquired in a semester and on a comprehensive measure of performance that takes into account grades awarded to students. Section 5

[4] Online courses are provided by private online universities that are often perceived as providers of a lower quality education.

[5] The relationship between procrastination and performance in online learning has been instead investigated by the educational literature, see for instance Elvers, Polzella and Graetz (2003); Romano et al. (2005); Tuckman (2007).

examines the interplay between online teaching and students' tendency to procrastinate. Section 6 offers some concluding remarks.

2. Data

We use very rich administrative data from the University of Calabria, a middle-sized public university located in the South of Italy.[6] Our administrative dataset covers four cohorts of students (enrolled in the academic years from 2016/17 to 2019/20) and contains detailed information on students' academic career (exams passed and credits earned, grades, field of study, date of enrolment) and demographic characteristics (gender, age, type of High School, High School Grade, region of residence).

Since the 2001 reform, the Italian University system is organized into three main levels: First Level Degrees (3 years of legal duration), Second Level Degrees or Master's Degree (2 further years) and Ph.D. Degrees. In order to gain a First Level Degree, students have to acquire a total of 180 credits. Students who have acquired a First Level Degree can undertake a Master's Degree (acquiring 120 more credits). In some Degrees, such as Law and Architecture, the First and the Second Level Degrees are coupled together with a Degree lasting 5 years ("Laurea a Ciclo Unico"). After having accomplished their Master's Degree, students can apply to enroll for a Ph.D. We focus our analysis on students enrolled at First Level Degree, Master's Degree and a 5 years Degree.[7]

During an academic year, students are supposed to take a number of courses that confer 6, 9 or 12 credits each, for a total of about 60 credits per academic year. Most of the courses attended by students are worth 6 and 9 credits corresponding to, respectively, 42 and 63 hours of teaching and to 108 and 162 nominal hours of study. An exam is passed if evaluated with a mark of at least 18 (the minimum mark) and the maximum grade a student can get is 30 *cum laude*. There is no penalization if the student does not sit an exam or fails it. Furthermore, each exam can be taken as many times as a student wants and there are no restrictions on the time a student has to graduate.

Our dataset contains exam-level information for each student enrolled at the university of Calabria from the academic year 2016/17 to 2019/20. We only have information on passed exams. We organize these data at student-semester level: for each academic year, we have two observations for each student, one corresponding to the first semester and the other to the second semester. Each student's career is observed from the year of enrolment until the second semester of the academic year 2019/20 (when data at hand were made available from the university). We end up with an unbalanced panel, where the number of observations for each student depends on his/her year of enrolment, on the type of Degree attended and on whether he/she has accomplished the program or has dropped-out from university studies.

[6] Currently about 25,000 students are enrolled in the 107 Degree Courses offered by the University of Calabria.
[7] We disregard PhD students as their work is more research driven and there are no standardized measures of performance available.

Table 1 presents some descriptive statistics. Our sample includes 23,283 students for a total of 96,361 observations.[8] Although students are expected to earn 60 credits per academic year and finish their First Level Degree in three years, the students in our sample acquire on average only 17 credits over a semester.[9] This is typical of the Italian university system where students take much more time than expected to complete their academic career. [10]

To obtain a comprehensive measure of academic performance including both a "quantity" (number of credits earned) and a "quality" (grades obtained at the examinations) dimension, we consider the sum of the grades at exams passed in each semester (we call this variable *Performance*).[11] Preliminarily, grades are weighted in terms of credits associated with each examination: the weight is 1 if the exam is worth 9 credits (the typical exam), the weight is (2/3) if the exam is worth 6 credits, and so on. In this way, we take into account both the number of examinations passed by students and the grades obtained (for example, 3 exams passed with a grade of 20 are equivalent to 2 exams passed with 30). *Performance* ranges from 0 to 150 and is on average 48 in our sample.

About 17.5% of the observations correspond to the performance of students in the second semester of the academic year 2019/20 (*Online Teaching*), that is the semester affected by the shift to online teaching. About 75% of observations belong to students enrolled in a First Level Degree or a 5 Years Degree (about 35% of observations refer to freshmen, 21% to sophomores and 18% to students attending the following years), while the remaining 25% pertain to students enrolled in a Master's Degree.

As regards sample's demographic characteristics, students are on average 22.9 years old and about 57% of observations are women. Students obtained an average *High School Grade* of 85 and 54% of them have attended a Lyceum.[12] Only 3.2% of observations correspond to foreign students; 53% are from the same province in which the University is located, while the vast majority of the remaining students are from other provinces but within the same regional area (only about 3% of them come from other regions).

Data at hand allow us to build a measure of students' tendency to procrastinate based on their behavior during the enrollment process. This measure, already used in De Paola and Scoppa (2015), exploits the fact that students applying for admission are notified of the admission decision all at the

[8] Table A1 in Appendix A reports descriptive statistics at student level.

[9] The data at hand does not specify whether students do not earn credits because they fail the exams or they do not sit them.

[10] Garibaldi et al. (2012) report that in a sample of graduates the mean effective duration of a university program was 7.41, whereas the legal duration was 4.39 years. About 41% of students were enrolled for more than the legal length of their university program (*Fuori Corso*). Brunello and Winter-Ebmer (2003) find that 31% of students in Italy expect to complete their program at least one year later than the required time. See also Aina, Baici and Casalone (2011).

[11] De Paola, Scoppa and Nisticò (2012) use a similar measure to evaluate the impact of monetary incentives on students' performance.

[12] In Italy, after lower secondary school pupils choose between a 'more academically oriented track' (*Lyceum*), or a more labor market-oriented track (Technical or Vocational). Students coming from more educated families typically choose a Lyceum, while those from poorer socio-economic backgrounds tend to enrol at technical or vocational schools.

same time[13] (through the university official website) and students have seven weekdays to accomplish the enrollment procedures.[14] These procedures require a series of activities (filling in a number of forms and the payment of a small fee)[15] representing an immediate cost for students. However, postponing them until just before the deadline exposes students to the risk of being excluded from the Degree Program in case of any unexpected event (illness, bank or transportation strikes, etc.). Considering these aspects, we assume that individuals with a tendency to procrastinate are likely to accomplish the task toward the end of the seven days or just before the deadline.[16] Therefore, we consider the number of days a student takes to accomplish the enrollment procedure after admission notification as a proxy of individual procrastination. More precisely, we build a variable *Procrastination* taking values from 0, for students who accomplished their enrolment procedure on the first day after the notification of admission, to 6, for students accomplishing the procedure on the last admissible day.[17]

A number of Degree Programs have made available also pre-enrolment procedures. As our measure *Procrastination* excludes students who have used the pre-enrolment procedures, we build an alternative measure *Procrastination1,* which overlaps with *Procrastination* for values going from 0 to 6, but assigns the value of 0 (the lowest value of procrastination), instead of a missing value, also to students who enrolled through the pre-enrollment procedures (thus reaching a sample of 36810 observations).

Students on average accomplish their enrolment procedure 1.43 days after notification of admission (1.16 days when considering *Procrastination1*). However, there is quite a large degree of variability, with about 40.5% of students enrolling immediately after notification, 41% of students who accomplish the enrolment procedure on the second or third-day, about 6% of students who enroll on the fourth day and about 12.5% who wait until the last three days before the deadline.

[13] The admission date is different from the general one for some specific Degree Programs. We take into account these dates to determine our procrastination variables.

[14] A similar measure is used by Reuben et al. (2009) who consider students' behavior when applying to an MBA. Alternative measures of procrastination rely on surveys asking subjects about their tendency delay the accomplishment of a task (Mischel et al., 1989, Wong, 2008) or consider students' behavior in handing in term papers (Solomon and Rothblum, 1984; Dewitte and Schouwenburg, 2002; Howell et al., 2006).

[15] The enrolment procedure required students to make a deposit of a small part of their university fees (320 euros) through a payment at a Bank or a Post Office.

[16] To assess whether this measure of procrastination is a good proxy of individual tendency to procrastinate, De Paola and Scoppa (2015) have conducted a survey from which it emerges that students who take more days to accomplish the enrolment procedures are also more likely to describe themselves as individuals with a tendency to procrastinate.

[17] Students who did not complete their enrolment process were excluded and places left vacant were filled either with students with a rank lower than required in the first stage or by re-opening the application procedure. Given this procedure, a number of places on Degree courses, that were assigned to students after the first selection, ended up vacant after the conclusion of the first stage of enrolment. We exclude these students from our analysis and only consider students whose enrolment was completed within the first deadline. Students enrolled later may have ended up on a Degree course different from that representing their first choice or might have other unobservable differences with respect to regularly enrolled students. Due to these restrictions our sample becomes smaller with a total number of observations equal to 29,868.

Our measures of procrastination behave consistently with what found by the existing literature: we find a strong negative relationship between *High School Grade* and procrastination; male students are more likely to procrastinate.

Table 1. Descriptive Statistics

Variables	Obs	Mean	Std. Dev.	Min	Max
University related variables					
Credits	96361	16.851	12.739	0	48
Performance	96361	48.527	38.014	0	150
Online Teaching	96361	0.175	0.380	0	1
Master's Degree	96361	0.250	0.433	0	1
5 Years Degree	96361	0.124	0.330	0	1
II Semester	96361	0.493	0.500	0	1
Cohort 2016	96361	0.359	0.480	0	1
Cohort 2017	96361	0.308	0.462	0	1
Cohort 2018	96361	0.215	0.411	0	1
Cohort 2019	96361	0.119	0.323	0	1
Year:2020	96361	0.355	0.478	0	1
Freshman	96361	0.354	0.478	0	1
Sophomore	96361	0.213	0.410	0	1
Third Year	96361	0.134	0.340	0	1
Fourth Year	96361	0.050	0.217	0	1
First Year Master's Degree	96361	0.122	0.327	0	1
Second Year Master's Degree	96361	0.085	0.279	0	1
Procrastination	29868	1.426	1.546	0	6
Procrastination1	36810	1.157	1.500	0	6
Demographic characteristics					
Female	96361	0.566	0.496	0	1
Age	96361	22.977	4.310	18	71
High School Grade	96361	85.176	10.982	60	100
Lyceum	96361	0.543	0.498	0	1
Immigrant	96361	0.032	0.176	0	1
Some Province	96361	0.530	0.499	0	1
Different Province and Region	96361	0.028	0.165	0	1
COVID-19 and technology related variables					
Red Zone	93656	0.108	0.311	0	1
% Knowing Infected People	84821	0.104	0.106	0	0.5
Excess Mortality 2020	94797	1.022	0.166	0.550	1.579
% Households speed 100-1000 Mbps	94687	0.678	0.248	0	0.995
Average of ADSL download speed	94531	9.782	2.074	1.021	16.027
% Households not served by wireline	94687	0.093	0.092	0	1

Notes: Administrative Data from University of Calabria

Finally, we also observe a number of proxies of the geographical spread of the COVID-19 and of the quality of internet connections at municipal level. We collect three indicators of the severity of the health emergency. The first is *Red Zone*, a dummy variable taking the value of 1 for municipalities that have been classified as "Red Zone"[18] from March until September 2020 (that is, during the second

[18] A Red Zone is an area with high number of Covid-19 cases. In a Red Zone, individuals have to observe particularly restrictive measures aimed at reducing the spread of the virus.

semester of the academic year 2019/20).[19] About 11% of the sample students come from a municipality that has been classified as Red Zone.

The second indicator is the percentage of students knowing people affected by COVID-19. Data are taken from Carrieri et al. (2021), who, in April 2020, have submitted a survey to about 10,000 students, enrolled at the same university used in the present study, asking if they know someone (relatives, friends or themselves) who tested positive for the diagnosis of COVID-19. About 12.8% of survey respondents answered "Yes". For each town of residence of survey students, we compute the variable *% Knowing Infected People* as the ratio of people resident in the town knowing someone affected by COVID-19 to the total number of respondents coming from the same town. We use this variable as a proxy of the intensity of the health emergency: towns with a value of the variable of 0 are considered as less affected by the coronavirus (about 27% in our sample) while higher values of the variable indicate a stronger intensity of the emergency. The variable is on average 0.11.

Finally, we compute *Excess Mortality 2020* using an indicator provided by ISTAT of the variation in the 2020 mortality rate compared with the 2015-2019 mortality rate, at the municipality level. We use the ratio between the mortality in 2020 and the average mortality in previous years (*Excess Mortality 2020*) and therefore values greater than 1 indicate an increase in the mortality rate in 2020 while values smaller than 1 indicate a decrease. On average *Excess Mortality 2020* is 1.02.

As regards the quality of internet connections, we use the "Broadband Map" provided by the Italian Authority for Communications[20] reporting, for each municipality, several indicators of the quality of internet connections (ADSL number served, ADSL download speed, households served with speed (theoretically expected) in the ranges [0-2; 2-30; 30-100; 100-200; 200-500; 500-1000] Mbps, and we compute three indicators of the quality of internet connections in the municipality where each student is resident: the ADSL download speed (on average 9.78); the share of households not served by wireline network (9.3%) and the share of households served with a quite high speed, that is, in the range 100-1000 Mbps (67.8%).

3. Methodology

The academic year at the University of Calabria consists of two semesters: the first semester starts at the beginning of October with lectures until December and an examination period of about two months (January and February); the second semester begins with teaching activities in March until May and is followed by an examination period in June, July and September.

Teaching activities in both semesters were traditionally classroom-based. However, in the academic year 2019/2020, the COVID-19 pandemic has forced a shift from traditional to online teaching

[19] Due to data availability, the variable is computed only for students coming from Calabria, the region where the vast majority of students in our sample reside.
[20] Available at the following link: https://maps.agcom.it/

to respond to the diffusion of the contagion: the University of Calabria was forced to cancel all physical class meetings and to deliver online the overall teaching activities of the second semester (starting from March). The University quickly provided guidance to instructors on how to use the tools designated to implement remote teaching solutions, such as the available platform, the way to do lectures in streaming, to recording lectures, posting assignments online and grading them digitally rather than by hand. After one week (in some cases two weeks), the lectures of the second semester started online.

Therefore, while during the first semester students attended face-to-face lectures and sat in-person exams, in the second semester both lectures and exams were held online.[21]

We take advantage of this change in the educational system to study the effect of the introduction of online learning on students' performance. We apply a sort of difference-in-differences strategy comparing the difference between the performance at the exams taken during the second semester of the academic year 2019/20 and at the exams taken during the second semester of previous academic years (from 2016/17 to 2018/19) with the difference between the performance at the exams taken during the first semester of 2019/20 and that at the exams taken during the first semester of previous academic years. The latter difference identifies pre-treatment differences as, for a given cohort and year of course, it compares the pre-treatment (first semester) performance of two different types of students (one affected by the health emergency and the other not affected). The first difference, looking at the performance in the exams taken in the second semester, includes the impact produced by the shift to online teaching (plus any possible emergency related effect that we try to catch with our COVID-19 health problems and technology related controls).

More formally, we estimate the following model:

[1]

$$Y_{ijt} = \beta_0 + \beta_1 OnlineTeaching_{jt} + \beta_2 Year2020_{jt} + \beta_3 II\ Semester_{jt} + \beta_4 X_i + \mu_i + \lambda_t + \delta_i + \varepsilon_{ijt}$$

where Y_{ijt} is our outcome variable representing the performance of student i (in terms of number of credits acquired or comprehensive academic performance) during the semester j of the academic year t; $OnlineTeaching$ is a dummy equal to one for the second semester of the academic year 2019/20 in which courses were taught online; $Year2020$ is a dummy variable taking the value of 1 for the academic year 2019/20 and 0 otherwise; $II\ Semester$ is a dummy variable taking the value of 1 if the performance refers to the second semester and 0 otherwise (notice that $OnlineTeaching$ corresponds to the interaction term between $Year2020$ and $II\ Semester$); X_i is the vector of individual control variables; μ_i is a vector of cohort dummies; λ_t is a vector of dummies for the year of the Degree program; δ_i is a

[21] The University has adopted very strict protocols to monitor online exams during the COVID-19 pandemic. Students taking exams remotely had access to a virtual environment ("Lockdown Browser" or "Safexambrowser") to monitor their activity. Students had to turn on their smartphone camera, so that further checks could be made. After that, the teacher was required to inspect the students' rooms and closely monitor their behavior during the examination. Microphones had to be maintained active and students performing oral exams might be required to share their screen.

vector of dummies to control for the type of Degree (*First Level*, *Master's Degree* or 5 years *Degree*) or for each Degree Course (86 categories); ε_{ijt} is an error term. In some specifications we also control for student fixed effects.

Our parameter of interest is β_1. It represents the change in students' academic performance due to online teaching. A positive value of the coefficient indicates that students took advantage of this change while a negative coefficient indicates that online teaching has deteriorated students' performance. β_2 allows us to isolate cohort effects as it compares academic performance in the year 2020 (first semester) with the performance of the previous years (first semester). Finally, β_3 captures the differences in performance between the two semesters, for example in terms of difficulty, time available and number of exams.

3.1. Common Trend Assumption

The estimation of a causal effect by a difference-in-differences method assumes that, in absence of treatment, the difference between control and treatment groups would be constant over time, that is, that the two groups would have had parallel trends. In our setting, this means that the performance of the academic years before 2019/20 (control group) should provide the appropriate counterfactual of the trend for the academic year 2019/20 (treated group), that is, the performance of students if they had not been interested by the shift to online teaching induced by the pandemic.

Figure 1 plots the average number of credits for each academic year by semester. It shows that in the second semester students earn on average a higher number of credits and that from 2017 to 2019 there is a positive trend for both semesters while in 2020 the trend becomes negative for the second semester.

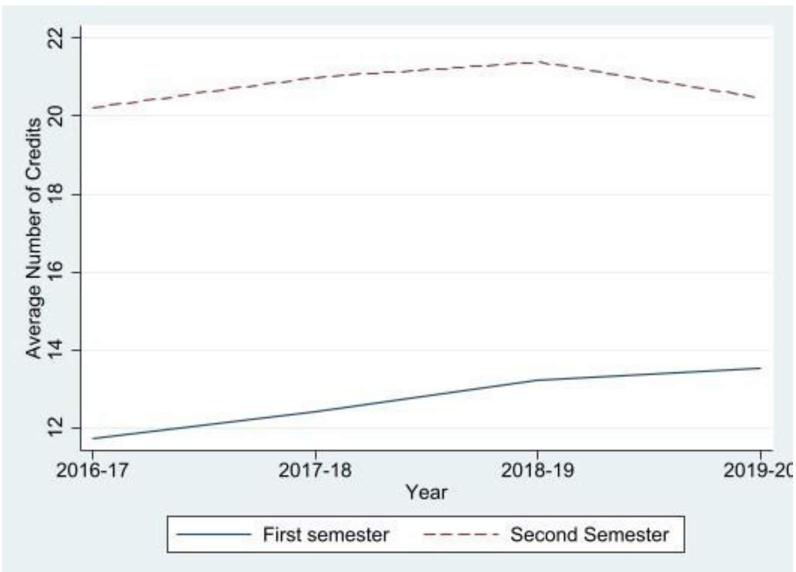

Figure 1: Average number of Credits earned in each semester in the academic years from 2016/17 to 2019/20

Our sample includes three pre-treatment periods thus in Table 2 we conduct a standard test of the validity of the common trend assumption verifying if credits earned by students in the first and second semester have changed in a similar way over time: we restrict the analysis to the pre-treatment periods, that is the academic years from 2016/17 to 2018/19, and regress our dependent variable *Credits* on the dummy for the second semester, dummies for the academic year and interaction variables between the academic year and the *II Semester* dummy. We leave the academic year 2016/17 as reference category. In column (1) we do not include control variables; in column (2) we add controls for university related variables; in column (3) we add demographic characteristics and course of study fixed effects. The estimated coefficients of the interaction variables between the academic year and the second semester are never statistically significant thus we may be confident that the common trend assumption is fulfilled. As a further check, we estimate the effect of two fake online teaching treatments: in column (4) we restrict the sample to the academic years from 2016/17 to 2018/19 and create a fake online teaching treatment by interacting the dummy for the second semester with the dummy for the year 2019; in column (5) we further drop the academic year 2018/19 and create our fake treatment as the interaction variable between the second semester dummy and the dummy for the year 2018. None of our fake treatments carries statistical significance, suggesting the validity of our common trend assumption.

These results remain qualitatively unchanged when we consider the comprehensive measure of performance as outcome variable (see Figure A1 and Table A2 in the Appendix A of the paper).

Table 2: Test of the Common Trend Assumption. Dependent variable: Number of Credits

	(1)	(2)	(3)	(4)	(5)
II Semester	8.495***	8.489***	8.486***	8.488***	8.487***
	(0.225)	(0.215)	(0.205)	(0.709)	(1.094)
Year:2018	0.669***	-1.660***	-0.581***		10.628***
	(0.161)	(0.211)	(0.215)		(3.578)
Year:2019	1.478***	-3.139***	-1.180***	-0.019	
	(0.155)	(0.295)	(0.318)	(0.436)	
Year:2018*II Semester	0.105	0.029	0.004		
	(0.279)	(0.266)	(0.254)		
Year:2019*II Semester	-0.310	-0.390	-0.391		
	(0.267)	(0.254)	(0.243)		
Fake Online Teaching 2019				-0.395	
				(0.561)	
Fake Online Teaching 2018					0.002
					(0.927)
University var.	NO	YES	YES	YES	YES
Demographic Characteristics	NO	NO	YES	YES	YES
Course of study FE	NO	NO	YES	YES	YES
Observations	62158	62158	62158	62158	32782
Adjusted R^2	0.108	0.200	0.265	0.266	0.272

Notes: OLS estimates. The dependent variable is *Credits*. Standard errors (corrected for heteroskedasticity and allowed for clustering at student level) are reported in parentheses. The symbols ***, **, * indicate that the coefficients are statistically significant at the 1, 5 and 10 percent level, respectively.

4. The Impact of Online Teaching on Students' Performance

In this Section we evaluate the impact of online teaching on students' performance estimating several specifications of equation [1]. Table 3 reports our OLS estimates, using as dependent variable the number of credits acquired in a semester. In all the specifications, standard errors are corrected for heteroskedasticity and allowed for clustering at student level. In column (1) we only control for treatment year, semester and dummies for cohort and year of Degree program. We find that online teaching significantly reduced the number of credits acquired over a semester of about 1.43 (t-stat=–11.5), an effect that corresponds to about 0.11 SD of the dependent variable.

The variable *Year 2020* shows evidence of a positive pre-treatment difference: in the first semester of the academic year 2019/20, students performed significantly better than their colleagues (from different cohorts) who in the previous academic years were enrolled at the same year of each Degree program: they acquired 0.49 credits more, maybe because endowed with slightly higher abilities. Nonetheless, they perform significantly worse when forced to switch to online teaching. We also notice that the dummy *II Semester* is positive and statistically significant with students acquiring about 8 credits more in the second semester than in the first one, possibly because they have more time to prepare for the examinations as the examination period includes the summer break (August) or because the type of exams in the second semester is, on average, less hard.

Table 3. The Impact of Online Teaching on Students' Performance. Dependent variable: Number of Credits

	(1)	(2)	(3)	(4)
Online Teaching	-1.436***	-1.442***	-1.430***	-1.409***
	(0.124)	(0.124)	(0.407)	(0.143)
II Semester	8.335***	8.326***	8.304***	8.178***
	(0.078)	(0.078)	(0.552)	(0.089)
Year:2020	0.488***	0.447***	0.431	-0.022
	(0.141)	(0.138)	(0.288)	(0.151)
Female		1.473***	-0.240	
		(0.112)	(0.177)	
Age		-0.208***	-0.298***	
		(0.018)	(0.034)	
High School Grade		0.207***	0.263***	
		(0.005)	(0.017)	
Lyceum		0.894***	1.920***	
		(0.113)	(0.196)	
Immigrant		-1.463***	-1.101**	
		(0.347)	(0.442)	
Cohort dummies	YES	YES	YES	YES
Year of degree dummies	YES	YES	YES	YES
Prov. Res. Dummies	NO	YES	YES	NO
Course of study FE	NO	NO	YES	NO
Student FE	NO	NO	NO	YES
Observations	96361	96361	96361	96361
Adjusted R^2	0.145	0.194	0.246	0.452

Notes: OLS estimates. The dependent variable is *Credits*. Standard errors (corrected for heteroskedasticity and allowed for clustering at student level) are reported in parentheses. The symbols ***, **, * indicate that the coefficients are statistically significant at the 1, 5 and 10 percent level, respectively.

In column (2) of Table 3 we estimate a specification controlling for some individual characteristics (Female, Age, High School Grade, Lyceum, Immigrant) that typically affect students' academic performance. Taking as constant these characteristics, we find that online teaching had almost the same negative effect (-1.44) found in the previous specification. In column (3) we include a dummy for each Degree program (86 categories) and in column (4) we include student fixed effects. The effect of online teaching remains more or less of the same magnitude and statistical significance.

As regards our control variables, we find that students endowed with a higher level of abilities (using the type of High School and the High School Grade as proxies) acquire on average a higher number of credits while older students have a worse performance. A negative effect emerges also for immigrants, possibly because of their difficulties with the Italian language.

In Table 4 we replicate the same specifications reported in Table 3 using as outcome variable *Performance* in order to consider both the number of examinations passed by students (the quantitative side) and the grades obtained (the qualitative side).[22] Again we find evidence of a negative effect of the switch to online teaching on students' performance: the transition from face-to-face to online teaching reduces the *Performance* of about 3.2 points, an effect that corresponds to about 0.08 SD of the dependent variable. The size and statistical significance of the effect is very similar across different specifications.

Table 4. The Impact of Online Teaching on Students' Comprehensive Performance

	(1)	(2)	(3)	(4)
Online Teaching	-3.221***	-3.242***	-3.200**	-3.140***
	(0.360)	(0.359)	(1.219)	(0.412)
II Semester	23.890***	23.857***	23.784***	23.452***
	(0.225)	(0.225)	(1.617)	(0.258)
Year:2020	1.127***	0.986**	0.924	-0.213
	(0.410)	(0.401)	(0.851)	(0.436)
Student Characteristics	YES	YES	YES	YES
Cohort dummies	YES	YES	YES	YES
Year of degree dummies	YES	YES	YES	YES
Prov. Res. Dummies	NO	YES	YES	NO
Course of study FE	NO	NO	YES	NO
Student FE	NO	NO	NO	YES
Observations	96361	96361	96361	96361
Adjusted R^2	0.149	0.210	0.272	0.486

Notes: OLS estimates. The dependent variable is *Performance*. Standard errors (corrected for heteroskedasticity and allowed for clustering at student level) are reported in parentheses. The symbols ***, **, * indicate that the coefficients are statistically significant at the 1, 5 and 10 percent level, respectively.

Using the number of credits acquired over a semester we have also created a variable indicating whether or not the student has been inactive over the semester, that is, whether or not the student has acquired zero credits. About 20 percent of our observations correspond to students being inactive in a

[22] An alternative dependent variable would be the Average Grade obtained by students. However, since we use administrative data on students' careers we observe only grades for exams passed by students while we do not observe grades for failed examinations. Therefore, we have chosen of not using a sample selected on the basis of the dependent variable since this leads to estimation biases.

given semester. Estimating a Linear Probability Model we find that the switching to online teaching induced by the coronavirus pandemic has on average little effect on the probability of being inactive. Results are presented in Table B1 of Appendix B.

We have also studied the effect of the switch to online teaching on the student's probability of passing a given exam and on the grade obtained at each exam. In order to investigate this issue, we have used student-course level observations and restricted the analysis to freshmen who have to attend mostly compulsory courses having almost no possibility to choose their first year study plan. In this way we are able to determine for each student the structure of courses and to recover the exams that he/she should have passed but did not (in addition to the exams passed that we observe). We find that switching from face-to-face to online teaching significantly reduces the probability of passing a given exam of about 3.2-3.5 percentage points and also lowers the grade obtained of about 0.25 points. Results are reported in Tables B2 and B3 of Appendix B.

On the whole, our results point to a negative effect of pandemic induced online teaching. An important question is whether this evidence reflects the impact of the shift from traditional face-to-face to online teaching or is driven by some factors that occurred at the same time of online teaching and that might have affected students' performance, in particular by the simultaneous health emergency due to the spread of coronavirus pandemic and by the quality of internet connections.

To tackle this issue, in the following Section we analyze whether the effect of online teaching is heterogeneous according to some measures representing, at the municipal level, the harshness of the coronavirus pandemic and the quality of internet connections.

4.1. COVID-19 health related problems and technological hindrances

In this section, we investigate whether the negative effect that the switch to online teaching had on students' performance is due, at least partially, to the contextual health emergency and to the quality of internet connections.

In Table 5 we include among our control variables the three indicators of the severity of the health emergency separately: if the estimated negative impact of online teaching on students' performance found in Table 3 is driven by the health emergency and its implications – for example in terms of worrying for personal or relatives' health or reduced social interactions – then the inclusion of these indicators should at least reduce the magnitude of the estimated coefficient. If that is not the case, we are more confident that online teaching has an effect on performance over and above the one induced by the health emergency that has caused the change in the teaching methods.

We find (column 1 of Table 5) that students coming from municipalities classified as *Red Zone* tend to obtain a worse performance (-0.395 credits, *t*-stat=-2.37), ceteris paribus. However, the impact of online teaching is not affected when we control for this variable: the estimated negative effect of online teaching remains of almost the same magnitude and statistical significance. Similar effects are found when controlling for the severity of the health emergency using *% Knowing Infected People* and *Excess Mortality 2020* (columns 2 and 3). These variables have no direct effect on students' academic performance and the coefficient on *Online Teaching* is not affected at all. It is worth to point out that almost all (98%) the students considered in our study are from Calabria region, a geographical area that was affected by the COVID-19 pandemic with much lower intensity than other Italian regions.[23]

We obtain similar results both when we include in the set of controls all of our three measures of COVID-19 severity and when, in order to avoid problems of multicollinearity, we use a synthetic measure of COVID-19 incidence computed as the first component of a Principal Component Analysis (PCA). In both cases, our controls (with the exception of *Red Zone*) have no direct effect on the academic performance of students and, more importantly, the impact of online teaching is not affected (results not reported and available upon request).

Including our indicators of the severity of the health emergency among controls allows us to check whether the estimated effect attributed to the switch to online teaching holds given the spread of the simultaneous health emergency. However, looking at the average effect might still confound the interpretation of the result if the effect is indeed larger the more severe the spread of the pandemic. Thus, in column (4) of Table 5, we investigate if the effect of online teaching is heterogeneous according to the severity of the health emergency by including among regressors the interaction variables between *Red Zone* and *Online Teaching*, *II Semester* and *Year 2020*, respectively. We find that the estimated effect of online teaching remains negative, statistically significant and of a similar magnitude and the interaction variable (*Online Teaching*Red Zone*) is not statistically significant. Qualitatively the same results are found when we interact *Online Teaching* with the other two indicators or the synthetic PCA measure (results not reported).

[23] In Calabria the total number of Covid-19 infections (from February to December 2020) was equal to 23,908 (about 1.27% of the population) and the Covid-19 related deaths in 2020 were 472 (about 25 per 100,000 inhabitants). In the same period in Lombardia, the Covid-19 cases were 478,897 (4.8% of the population) and the deaths were 25,123 (about 252 per 100,000 inhabitants). In Italy as all, 3.56% were infected in 2020 and there were 125 deaths per 100,000 inhabitants.

Table 5. Impact of Online Teaching, COVID-19 and Internet Connections. Dependent variable: Number of Credits

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Online Teaching	-1.485***	-1.446***	-1.460***	-1.460***	-1.459***	-1.558***	-1.450***
	(0.408)	(0.408)	(0.410)	(0.406)	(0.410)	(0.563)	(0.407)
Red Zone	-0.395**			-0.124			-0.461***
	(0.167)			(0.207)			(0.165)
% Knowing Infected People		0.501					0.545
		(0.550)					(0.562)
Excess Mortality 2020			0.312				0.350
			(0.299)				(0.340)
Online Teaching* Red Zone				-0.216			
				(0.394)			
% Households with speed 100-1000 Mbps					0.414**	0.266	0.295
					(0.193)	(0.251)	(0.286)
Online Teaching* % Households with speed 100-1000 Mbps						0.147	
						(0.423)	
Average of ADSL download speed							0.054*
							(0.029)
% Households not served by wireline							-0.641
							(0.783)
Student Characteristics	YES	YES	YES	YES	YES	YES	YES
Cohort dummies	YES	YES	YES	YES	YES	YES	YES
Year of degree dummies	YES	YES	YES	YES	YES	YES	YES
Prov. Res. Dummies	YES	YES	YES	YES	YES	YES	YES
Course of study FE	YES	YES	YES	YES	YES	YES	YES
Observations	93656	84821	94797	93656	94687	94687	84087
Adjusted R^2	0.248	0.247	0.247	0.248	0.247	0.247	0.247

Notes: OLS estimates. The dependent variable is *Credits*. Standard errors (corrected for heteroskedasticity and allowed for clustering at student level) are reported in parentheses. The symbols ***, **, * indicate that the coefficients are statistically significant at the 1, 5 and 10 percent level, respectively. In column 4 we include among controls also the interaction variables between *Red Zone* and *II Semester* and *Red Zone* and *Year 2020*. In column 6 we include among controls also the interaction variables between *% Households with speed 100-1000 Mbps* and *II Semester* and *% Households with speed 100-1000 Mbps* and *Year 2020*.

Another possible confounding factor in the comparison of online versus face-to-face teaching is that online teaching requires a good technological endowment; therefore, a poor performance may be due not to the effectiveness of remote teaching per se but also to technological issues such as slow or unreliable internet connections. To check this possibility, in column (5) of Table 5 we include among regressors, as an indicator of the quality of internet connections, the share of households served with speed in range 100-1000 Mbps (a relatively high speed[24]) in the municipality where the student is resident. The coefficient of *Online Teaching* remains negative and statistically significant. This holds true also when we interact the indicator of the quality of internet connections with *Online Teaching* (column 6). The positive coefficient of the interaction term *Online Teaching*% Households with speed 100-1000 Mbps* in column (6) suggests a lower magnitude of the negative impact of online teaching

[24] In comparison to the share of households with speed in range 0-100.

when internet connections are relatively better, however the difference is small and statistically insignificant. Similar results are found if we build a dummy variable taking the value of one for students living in an area where this share is above the median and zero otherwise and when using as alternative measures of quality of internet connections the *Average of ADSL download speed* at the municipal level (demeaned) and *% Households not served by wireline*. In all cases, the interaction term between the indicator of quality of internet connections and *Online Teaching* is statistically not significant and the coefficient of *Online Teaching* remains negative and statistically significant (results not reported).

Finally, in column (7) we estimate the same specification as in Table 3, column 3, and include the full set of controls for COVID-19 health related problems and quality of internet connections. Our results are confirmed.

In Table 6 we report the same specifications of Table 5 using as dependent variable *Performance*. Results are again very similar.

Table 6. Impact of Online Teaching, COVID-19 Severity and Internet Connections. Dependent variable: Performance

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Online Teaching	-3.350***	-3.243**	-3.290***	-3.299***	-3.290***	-3.448**	-3.244***
	(1.224)	(1.234)	(1.232)	(1.210)	(1.232)	(1.669)	(1.230)
Red Zone	-1.413***			-0.367			-1.668***
	(0.508)			(0.602)			(0.501)
% Knowing Infected People		1.599					1.833
		(1.589)					(1.622)
Excess Mortality 2020			0.650				0.806
			(0.891)				(1.019)
Online Teaching* Red Zone				-0.433			
				(1.156)			
% Households with speed 100-1000 Mbps					1.147*	0.658	0.854
					(0.594)	(0.744)	(0.857)
Online Teaching* % Households with speed 100-1000 Mbps						0.235	
						(1.235)	
Average of ADSL download speed							0.095
							(0.084)
% Households not served by wireline							-1.640
							(2.393)
Student Characteristics	YES	YES	YES	YES	YES	YES	YES
Cohort dummies	YES	YES	YES	YES	YES	YES	YES
Year of degree dummies	YES	YES	YES	YES	YES	YES	YES
Prov. Res. Dummies	YES	YES	YES	YES	YES	YES	YES
Course of study FE	YES	YES	YES	YES	YES	YES	YES
Observations	93656	84821	94797	93656	94687	94687	84087
Adjusted R^2	0.274	0.273	0.273	0.274	0.273	0.273	0.274

Notes: OLS estimates. The dependent variable is *Performance*. Standard errors (corrected for heteroskedasticity and allowed for clustering at student level) are reported in parentheses. The symbols ***, **, * indicate that the coefficients are statistically significant at the 1, 5 and 10 percent level, respectively. In column 4 we include among controls also the interaction variables between *Red Zone* and *II Semester* and *Red Zone* and *Year 2020*. In column 6 we include among controls also the interaction variables between *% Households with speed 100-1000 Mbps* and *II Semester* and *% Households with speed 100-1000 Mbps* and *Year 2020*.

4.2. Beginners vs Experienced Students

In the previous analyses we pooled together all the cohorts and years of Degree programs. The estimates in Section 4.1 suggest that our estimated effect is driven by the different teaching and learning method rather than by the simultaneous health emergency.

However, our aggregate data may hide important heterogeneity. In fact, while there is no particular reason to assume that the spread of coronavirus pandemic may have affected differently students depending on their year of study (controlling for age), the change in the teaching method and, in turn, in the learning process – characterized by more diluted interactions with instructors and peers – could have affected more students that are in their first years as they have less experience with the organization of university studying especially due to the autonomy and self-discipline that characterizes it as compared with high school studying.

In order to investigate heterogeneity along this dimension, in Table 7 we look at the effects separately for each year of course of both the First Level and 5 Years Degrees and the Master's Degree.

In the first three columns we consider only students enrolled in either a First Level Degree or 5 Years Degree. In all specifications we control for individual characteristics and Course of study dummies as in column (3) of Table 3. We find that freshmen students (column 1) have earned almost 2 credits less after the switch to online teaching, corresponding to about 0.15 SD (*t*-stat=-8.8). The magnitude of the effect is pretty larger than the average effect estimated in Table 3. In column (2) we focus on second year students. We find a negative effect of online teaching of about 1.72 credits. Finally, in column (3) we restrict our attention to students in their third year and find that the effect is still negative and statistically significant but even smaller (-1.14 credits).

In the last two columns we focus on students attending a Master's Degree. We find that online teaching has a negative but very small impact on first year students enrolled in a Master's Degree as compared with freshman students while it has no negative effect on second year Master's students: the coefficient is positive but far from being significant.

Our results are robust if we restrict the analysis and compare the cohorts affected by the change in teaching method with only the cohorts enrolled in the previous academic year (estimates not reported) thus comparing more similar students. Likewise, our results hold if we include among our controls the set of variables related to COVID-19 and technology (estimates not reported).

Table 7. The Impact of Online Teaching by Year of Degree program. Dependent variable: Number of credits

	First Level and 5 Years Degrees			Master's Degree	
	First	Second	Third	First	Second
	(1)	(2)	(3)	(4)	(5)
Online Teaching	-1.962***	-1.724***	-1.144***	-0.924**	0.681
	(0.223)	(0.265)	(0.340)	(0.379)	(0.498)
II Semester	8.129***	8.184***	8.508***	8.760***	8.146***
	(0.113)	(0.154)	(0.237)	(0.188)	(0.277)
Female	-0.429***	-0.220	-0.591*	-0.018	0.108
	(0.160)	(0.220)	(0.308)	(0.245)	(0.298)
Age	-0.270***	-0.149***	-0.329***	-0.706***	-0.515***
	(0.021)	(0.033)	(0.049)	(0.039)	(0.049)
High School Grade	0.364***	0.321***	0.297***	0.101***	0.048***
	(0.006)	(0.009)	(0.013)	(0.011)	(0.014)
Lyceum	2.697***	1.978***	2.239***	-0.011	0.823***
	(0.141)	(0.190)	(0.270)	(0.222)	(0.277)
Immigrant	-0.506	-0.784	-3.260***	-0.554	0.641
	(0.427)	(0.642)	(0.941)	(0.854)	(0.947)
Cohort dummies	YES	YES	YES	YES	YES
Prov. Res. Dummies	YES	YES	YES	YES	YES
Course of study FE	YES	YES	YES	YES	YES
Observations	34080	20546	12892	11717	8185
Adjusted R^2	0.290	0.237	0.203	0.247	0.198

Notes: OLS estimates. The dependent variable is *Credits*. We control for individual characteristics and Course of study dummies as in column (3) of Table 3. Standard errors (corrected for heteroskedasticity and allowed for clustering at student level) are reported in parentheses. The symbols ***, **, * indicate that the coefficients are statistically significant at the 1, 5 and 10 percent level, respectively.

Table 8 shows that when considering *Performance* as outcome variable the impact of online teaching becomes smaller in magnitude as the student becomes more experienced with university studying and the estimated effect of online teaching for students attending a Master's Degree program is not statistically significant.

Table 8. The Impact of Online Teaching by Year of Degree program. Dependent variable: Performance

	First Level and 5 Years Degrees			Master's Degree	
	First	Second	Third	First	Second
	(1)	(2)	(3)	(4)	(5)
Online Teaching	-4.385***	-3.911***	-2.184**	-1.899	2.268
	(0.625)	(0.749)	(0.992)	(1.165)	(1.547)
Student characteristics	YES	YES	YES	YES	YES
Cohort dummies	YES	YES	YES	YES	YES
Prov. Res. Dummies	YES	YES	YES	YES	YES
Course of study FE	YES	YES	YES	YES	YES
Observations	34080	20546	12892	11717	8185
Adjusted R^2	0.317	0.267	0.232	0.253	0.199

Notes: OLS estimates. The dependent variable is *Performance*. We control for individual characteristics and Course of study dummies as in column (3) of Table 3. Standard errors (corrected for heteroskedasticity and allowed for clustering at student level) are reported in parentheses. The symbols ***, **, * indicate that the coefficients are statistically significant at the 1, 5 and 10 percent level, respectively.

We have also performed a number of other heterogeneity analyses along students' characteristics in terms of gender, ability, nationality and commuting.[25] We present our results in Table 9. In each specification, we run the same regression as in Table 3 column (3) and include among regressors the interaction variables between the variable of interest and *Online Teaching*, *II Semester* and *Year 2020*, respectively, but for the sake of brevity, we report only the coefficient of the interaction variable with *Online Teaching*. We find a slightly stronger negative effect for female students, for students with a lower high school grade, for students who have attended a more vocational school track, for immigrant students and for students who are not commuters. However, the differences between these groups of students are never statistically significant.[26] This is consistent with results found by Orlov et al. (2021) showing that students' characteristics, including gender, race, and immigrant background, had no significant association with the decline in students' performance in the pandemic semester.

Table 9. The Impact of Online Teaching. Heterogeneity according to Gender, Lyceum, High School Grade, Nationality. Dependent variable: Number of credits

	(1)	(2)	(3)	(4)	(5)
Online Teaching	-1.280***	-1.658***	-1.319***	-1.400***	-1.518***
	(0.440)	(0.459)	(0.445)	(0.410)	(0.435)
Online Teaching*Female	-0.276				
	(0.581)				
Online Teaching*Lyceum		0.432			
		(0.381)			
Online Teaching*Abv Avg High School Grade			-0.278		
			(0.453)		
Online Teaching*Immigrant				-1.231	
				(0.985)	
Online Teaching*Commuter					0.399
					(0.331)
Full set of interaction variables	YES	YES	YES	YES	YES
Student's characteristics	YES	YES	YES	YES	YES
Cohort dummies	YES	YES	YES	YES	YES
Year of degree dummies	YES	YES	YES	YES	YES
Prov. Res. Dummies	YES	YES	YES	YES	YES
Course of study FE	YES	YES	YES	YES	YES
Observations	96361	96361	96361	96361	96361
Adjusted R^2	0.246	0.246	0.234	0.246	0.246

Notes: OLS estimates. The dependent variable is *Credits*. Standard errors (corrected for heteroskedasticity and allowed for clustering at student level) are reported in parentheses. The symbols ***, **, * indicate that the coefficients are statistically significant at the 1, 5 and 10 percent level, respectively.

All in all, our results suggest that online teaching has exerted a strong and negative impact for younger students while the effect becomes gradually weaker as students become more experienced and

[25] In order to create our indicator of commuting, we use data provided by ISTAT (Italian National Institute of Statistics) available at https://www.istat.it/it/archivio/157423 to compute the distance in kilometers from the place of residence and the place where the University is located. We define as *Commuter* a student which is resident in a place distant more than 0 and less than 35 kilometers (results hold if we restrict to 25) from the University. Students resident in a more distant place, typically rent a room close to the University to save on commuting time thus they are assigned the value 0 similar to students resident in the same place where the University is located.
[26] Similar results are found when considering as outcome variable *Performance* (not reported).

reduces to zero for Master's Degree students. It is likely that students with more academic experience have acquired abilities and developed a method of study that allow them to better tackle the lack of face-to-face teaching. Instead, younger students, especially those who have just started their university studies, may suffer more from the absence of physical attendance and peer interactions as they represent a sort of link with their previous studying experience.

5. Online Teaching and Present Biased Students

Self-control and present-bias problems, that are typical of studying activities, might be accentuated by online teaching since students prone to procrastinate tend to lack the commitments deriving from in class comparison with instructors and peers and can distract themselves by the availability on their computers of Facebook, Instagram, YouTube, chats, and so on.[27] These factors can induce them to postpone studying and even lectures' attendance when these are recorded.[28]

Thanks to the richness of our data, including a measure of procrastination based on the enrolment behavior of freshmen, we may study whether the switch to online teaching is detrimental especially for some students characterized by present biased attitudes. Our findings are reported in Table 10. In the first three columns we consider as indicator of present biased attitudes *Procrastination* while in columns (4)-(6) we rely on our alternative measure *Procrastination1*. We run the same regressions as in Table 3 columns (1)-(3) adding among independent variables our measure of procrastination and the interaction terms of *Procrastination* with *Online Teaching*, *II Semester* and *Year 2020.*

Column (1) shows that *Procrastination* negatively correlates with students' performance in terms of the number of credits acquired in the semester. One day of delay in the enrollment procedure is associated with a reduction of 0.39 credits in the traditional face-to-face teaching. More importantly, our estimates show that online teaching reduces the number of credits acquired in a semester of 1.77 for students who do not procrastinate. However, for students who procrastinate the negative effect of online teaching widens: the interaction term *Online Teaching*Procrastination* is in fact negative and statistically significant at the 1 percent level: the magnitude of the effect of online teaching increases of 0.54 for each day of delay in the enrollment procedure. For example, a student enrolling with 4 days of delay has a negative effect of online teaching of -3.92. Results do not change much across the different specifications.

Very similar results are found also when using our alternative measure of procrastination, *Procrastination1* (columns 4-6). Furthermore, our results are robust to the inclusion of our controls for COVID-19 and variables measuring the quality of internet connections at municipal level (results not reported).

[27] Carter, Greenberg, and Walker (2017) in a randomized experiment show that even the use of computers and tablets in the classroom can be deleterious for students' performance.
[28] For instance, the availability of online lecture recording can foster procrastination by allowing students greater flexibility in timing their study (Chai, 2014).

Table 10. The Impact of Online Teaching according to Student Tendency to Procrastinate. Dependent Variable: Number of credits

	(1)	(2)	(3)	(4)	(5)	(6)
Online Teaching	-1.774***	-1.774***	-1.748***	-1.693***	-1.694***	-1.673***
	(0.293)	(0.293)	(0.293)	(0.242)	(0.242)	(0.242)
Online Teaching *Procrastination	-0.538***	-0.539***	-0.540***			
	(0.143)	(0.143)	(0.143)			
Procrastination	-0.387***	-0.382***	-0.399***			
	(0.075)	(0.075)	(0.076)			
II semester	8.098***	8.098***	8.071***	9.040***	9.040***	9.015***
	(0.202)	(0.202)	(0.202)	(0.171)	(0.171)	(0.171)
Year 2020	0.398	0.378	0.297	0.225	0.215	0.155
	(0.315)	(0.315)	(0.309)	(0.261)	(0.261)	(0.256)
II semester*Procrastination	-0.006	-0.006	-0.005			
	(0.100)	(0.100)	(0.100)			
Year 2020*Procrastination	0.048	0.058	0.056			
	(0.105)	(0.105)	(0.101)			
Online Teaching *Procrastination1				-0.555***	-0.556***	-0.554***
				(0.133)	(0.133)	(0.133)
Procrastination1				-0.233***	-0.227***	-0.274***
				(0.070)	(0.070)	(0.070)
II semester*Procrastination1				-0.311***	-0.312***	-0.312***
				(0.094)	(0.094)	(0.094)
Year 2020*Procrastination1				0.004	0.011	0.004
				(0.098)	(0.098)	(0.094)
Students' characteristics	YES	YES	YES	YES	YES	YES
Cohort dummies	YES	YES	YES	YES	YES	YES
Year of degree dummies	YES	YES	YES	YES	YES	YES
Prov. Res. Dummies	NO	YES	YES	NO	YES	YES
Course of study FE	NO	NO	YES	NO	NO	YES
Observations	29868	29868	29868	36810	36810	36810
Adjusted R^2	0.177	0.178	0.238	0.189	0.190	0.248

Notes: OLS estimates. The dependent variable is *Credits*. Standard errors (corrected for heteroskedasticity and allowed for clustering at student level) are reported in parentheses. The symbols ***, **, * indicate that the coefficients are statistically significant at the 1, 5 and 10 percent level, respectively.

In Table 11, instead of considering a continuous measure of procrastination, we use a dummy variable *D_Procrastination* (equal to one for values of *Procrastination* equal or higher than 2) and zero otherwise. By including the full set of controls (column 2), we find that with online teaching students who tend to procrastinate acquire a significantly lower number of credits (-3.28=-2.12-1.16) compared with students who do not procrastinate (-2.12). Similar results are found when we include dummies for each different Degree program (column 3) and when we include among non-procrastinators also students who have used the pre-enrollment procedure by using the dummy *D_Procrastination1* (columns 4-6).

Table 11. The Impact of Online Teaching on Present Biased Students. Alternative Measures of Procrastination

	(1)	(2)	(3)	(4)	(5)	(6)
Online Teaching	-2.121***	-2.121***	-2.097***	-1.993***	-1.993***	-1.974***
	(0.289)	(0.289)	(0.701)	(0.240)	(0.240)	(0.575)
Online Teaching* D_Procrastination	-1.157**	-1.160***	-1.159*			
	(0.450)	(0.450)	(0.634)			
D_Procrastination	-0.868***	-0.839***	-0.817***			
	(0.250)	(0.250)	(0.249)			
Online Teaching *D_Procrastination1				-1.290**	-1.293***	-1.284*
				(0.420)	(0.420)	(0.621)
D_Procrastination1				-0.371	-0.338	-0.425
				(0.234)	(0.234)	(0.323)
Students' characteristics	YES	YES	YES	YES	YES	YES
Cohort dummies	YES	YES	YES	YES	YES	YES
Year of degree dummies	YES	YES	YES	YES	YES	YES
Prov. Res. Dummies	NO	YES	YES	NO	YES	YES
Course of study FE	NO	NO	YES	NO	NO	YES
Observations	29868	29868	29868	36810	36810	36810
Adjusted R^2	0.176	0.177	0.237	0.188	0.189	0.247

Notes: OLS estimates. The dependent variable is *Credits*. Standard errors (corrected for heteroskedasticity and allowed for clustering at student level) are reported in parentheses. The symbols ***, **, * indicate that the coefficients are statistically significant at the 1, 5 and 10 percent level, respectively.

In Table 12 we replicate the same specifications reported in Table 10 considering as an alternative outcome variable our comprehensive measure of performance. We find again that the impact of online teaching is worse for students who procrastinate: the interaction between *Online Teaching* and procrastination (both without – columns 1 to 3 – and with – columns 4 to 6 – the inclusion of students following the pre-enrolment procedure) is negative and statistically significant pointing to a further reduction of about 1.7 in the *Performance* for each unitary increase in the tendency to procrastinate.

Table 12. The Impact of Online Teaching according to Student Tendency to Procrastinate. Dependent Variable: Performance

	(1)	(2)	(3)	(4)	(5)	(6)
Online Teaching	-4.124***	-4.126***	-4.043***	-3.828***	-3.830***	-3.763***
	(0.829)	(0.829)	(0.828)	(0.681)	(0.681)	(0.680)
Online Teaching *Procrastination	-1.667***	-1.670***	-1.669***			
	(0.407)	(0.406)	(0.406)			
Procrastination	-1.188***	-1.177***	-1.173***			
	(0.223)	(0.223)	(0.222)			
Online Teaching *Procrastination1				-1.739***	-1.741***	-1.732***
				(0.377)	(0.377)	(0.377)
Procrastination1				-0.731***	-0.715***	-0.865***
				(0.209)	(0.209)	(0.206)
Students' characteristics	YES	YES	YES	YES	YES	YES
Cohort dummies	YES	YES	YES	YES	YES	YES
Year of degree dummies	YES	YES	YES	YES	YES	YES
Prov. Res. Dummies	NO	YES	YES	NO	YES	YES
Course of study FE	NO	NO	YES	NO	NO	YES
Observations	29868	29868	29868	36810	36810	36810
Adjusted R^2	0.194	0.196	0.270	0.206	0.207	0.278

Notes: OLS estimates. The dependent variable is *Performance*. Standard errors (corrected for heteroskedasticity and allowed for clustering at student level) are reported in parentheses. The symbols ***, **, * indicate that the coefficients are statistically significant at the 1, 5 and 10 percent level, respectively.

We have also investigated whether synchronous and asynchronous online teaching has been equally effective and whether these different methods have produced differentiated effects on students with a tendency to procrastinate.[29] These students might suffer less when teaching is organized through synchronous sessions, since these require more structure, allow less space for flexibility and self-organization and have a higher resemblance to face-to-face classroom. On the other hand, it could be that if synchronous classes are not enough to keep procrastinating students committed, then the availability of video recorded classes might help them to catch up and make up for the lost time.

At the aim of investigating this issue we use data from a survey undertaken by the University of Calabria and asking students about the type of teaching methods used by their instructors for their online classes. We match this information with our dataset organized at the student-course level. As shown in Table B4 in the Appendix B of the paper, we find that the negative effect of online teaching is larger for courses in which classes were delivered asynchronously through pre-recorded videos or synchronously but with the availability of recorded videos, while smaller effects emerge for synchronous online teaching. As regards procrastination, our results show that the effects of synchronous and asynchronous delivery methods are similar for students with a tendency to procrastinate, if anything we find suggestive evidence of larger negative effects for synchronous online teaching. Nonetheless, it is worthwhile to notice that this evidence is only suggestive and has to be taken with caution, as it could be biased by endogeneity issues deriving from the fact that the teaching method is not randomly assigned but is the result of instructors' choices and could be correlated to some unobservable characteristics of students or instructors affecting the academic performance.

6. Concluding Remarks

In this paper we investigate the impact that the switching from traditional classroom learning to online teaching, due to COVID-19 pandemic, produced on students' performance. Our investigation is important both to document the effects produced by the pandemic on the accumulation of human capital and to better understand the challenges deriving from online teaching. As the adoption of online learning is likely to persist post-pandemic and to become an integral component of education, it is relevant to provide evidence on its effects and to better understand the pros and cons of remote learning.

We take advantage of a very rich administrative dataset providing information on the careers of four cohorts of students enrolled at a medium sized public university located in the South of Italy. Our identification strategy relies on the fact that the switch to online courses and online exams happened in the second semester of the academic year 2019/20, while in the first semester of the same academic year

[29] In synchronous online teaching, even if physically distant, instructor and students can communicate in real time, while this is not possible with asynchronous online teaching, which in the University we consider was mainly based on pre-recorded videos and presentations.

teaching and exams were held, as in the previous years, face-to-face. Thus, when comparing the performance of students of two different cohort-year-of-study pairs (one affected by the health emergency and the other not affected) in the exams taken in the first semester we identify a pre-treatment difference, while the difference in performance in the exams taken in the second semester, in addition to any pre-treatment gap, includes the effect produced by the transition to distance learning. The estimated impact represents the overall effect produced by the transition from face-to-face to online teaching and in principle by the different living conditions that students experienced during the second semester of 2020. Thus, we complement our difference-in-differences approach by controlling for a rich set of socio-demographic characteristics and also for local health conditions and technology-related variables.

We find evidence of a negative impact of online teaching on students' performance: online teaching significantly reduced the number of credits acquired over a semester of about 1.40, an effect that corresponds to about 0.11 SD of the dependent variable. A negative effect is also found when considering an overall measure of students' performance that also considers the grades obtained by students at exams. This result is robust and has a similar magnitude when we control for our proxies for the local incidence of the COVID-19 health emergency and for the quality of internet connections. In addition, the impact of online teaching is negative independently of these conditions.

We find also that online teaching has produced a strong and negative impact mainly for freshmen and less experienced students while almost no effect is found for Master's Degree students.

A key result that we find is that students with a stronger tendency to procrastinate are more negatively affected by the shift to online teaching, maybe because it becomes more difficult for them to commit to studying activities when face-to-face interactions with instructors and peers are missing. Our evidence confirms the negative effects of procrastination on online learning envisaged by many authors but supported with little evidence. We also offer suggestive evidence that the delivery method does not seem to play a role in shaping these effects as they are similar both when teaching is organized through synchronous classes and when it is delivered through asynchronous classes.

Future research pointed towards the understanding of whether the results obtained by these students can be improved through programs aimed at supporting them to deal with self-organization problems would be particularly relevant. A similar attempt has been carried out by Hardt et al. (2020) who use a randomized experiment to investigate the impact of a program offering remote peer mentoring at a sample of German university students that switched to online teaching due to the COVID-19 pandemic. On average the effects on students' performance are not statistically significant, but this does not exclude that better targeted programs might represent a valuable instrument to improve the effectiveness of online teaching.

APPENDIX A. Descriptive Statistics and Methodology

In Table A1 we report the descriptive statistics of our sample at student level.

Table A1. Descriptive Statistics at student level

Variables	Obs	Mean	Std. Dev.	Min	Max
University related variables					
Credits	23283	15.531	9.801	0	45.750
Performance	23283	44.953	29.896	0	158.333
Online Teaching	23283	0.213	0.184	0	0.5
Master's Degree	23283	0.253	0.435	0	1
5 Year Degree	23283	0.121	0.326	0	1
II Semester	23283	0.481	0.091	0	0.5
Cohort 2016	23283	0.238	0.426	0	1
Cohort 2017	23283	0.262	0.440	0	1
Cohort 2018	23283	0.250	0.433	0	1
Cohort 2019	23283	0.250	0.433	0	1
Year:2020	23283	0.439	0.367	0	1
Freshman	23283	0.467	0.382	0	1
Sophomore	23283	0.169	0.200	0	0.5
Third Year	23283	0.085	0.140	0	0.5
Fourth Year	23283	0.026	0.078	0	0.5
First Year Master	23283	0.151	0.294	0	1
Second Year Master	23283	0.074	0.165	0	0.5
Procrastination	7337	1.361	1.577	0	6
Procrastination1	9201	1.085	1.510	0	6
Demographic characteristics					
Female	23283	0.556	0.497	0	1
Age	23283	22.834	4.490	18	70
High School Grade	23283	84.789	11.230	60	100
Lyceum	23283	0.527	0.499	0	1
Immigrant	23283	0.033	0.178	0	1
Some Province	23283	0.539	0.498	0	1
Different Province and Region	23283	0.027	0.163	0	1
COVID-19 and technology related variables					
Red Zone	22651	0.109	0.312	0	1
% Knowing Infected People	20524	0.104	0.106	0	0.5
Excess Mortality 2020	22931	1.023	0.165	0.550	1.579
ADSL download speed	22870	9.767	2.071	1.021	16.027
% Households not served by wireline	22907	0.092	0.091	0	1
% Households: speed 100-1000 Mbps	22907	0.680	0.245	0	0.995

Notes: Administrative Data from University of Calabria.

In Figure A1 and Table A2 we report a graphical and econometric test of the common trend assumption using *Performance*.

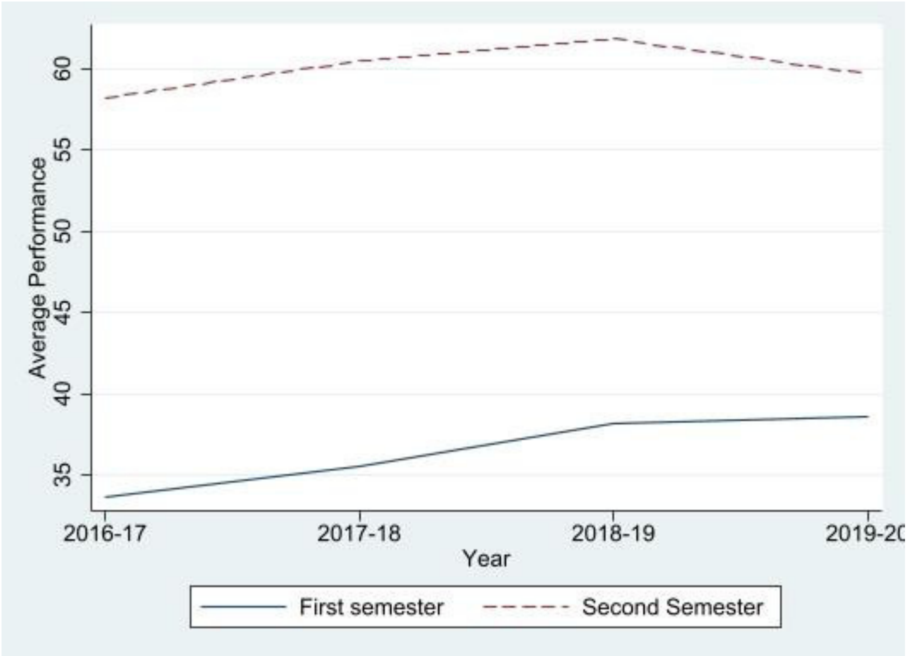

Figure A1: Performance obtained in academic years from 2016/17 to 2019/20 by semester

Table A2: Test of the Common Trend Assumption. Dependent variable: Performance

	(1)	(2)	(3)	(4)	(5)
II Semester	24.546***	24.521***	24.510***	24.513***	24.514***
	(0.676)	(0.640)	(0.603)	(2.083)	(3.267)
Year:2018	1.928***	-2.984***	0.081		34.279***
	(0.481)	(0.633)	(0.643)		(9.191)
Year:2019	4.526***	-5.338***	0.158	0.001	
	(0.464)	(0.897)	(0.964)	(1.326)	
Year:2018*II Semester	0.345	0.087	0.003		
	(0.837)	(0.789)	(0.746)		
Year:2019*II Semester	-0.897	-1.145	-1.149		
	(0.804)	(0.758)	(0.717)		
Fake Online Teaching 2019				-1.157	
				(1.742)	
Fake Online Teaching 2018					-0.002
					(2.779)
University var.	NO	YES	YES	YES	YES
Demographic Characteristics	NO	NO	YES	YES	YES
Course of study FE	NO	NO	YES	YES	YES
Observations	62158	62158	62158	62158	32782
Adjusted R^2	0.100	0.211	0.288	0.290	0.299

Notes: OLS Estimates. The dependent variable is *Performance*. Standard errors (corrected for heteroskedasticity) are reported in parentheses. The symbols ***, **, * indicate that the coefficients are statistically significant at the 1, 5 and 10 percent level, respectively.

APPENDIX B. Additional Analyses

In Table B1 we estimate a Linear Probability Model to look at the impact of *Online Teaching* on the probability of being inactive in a semester, that is on the probability of having obtained zero credits in that semester. In column (1) we find an aggregate null result. However, columns (2) and (3) show that the switch to online teaching significantly increased the probability of being inactive for freshmen and sophomores. Instead, students enrolled in a Master's Degree are marginally less likely to be inactive with online teaching (columns 5 and 6).

Table B1. The Impact of Online Teaching Overall and by Year of Degree program. Dependent variable: Inactive

	All	**First Level and 5 Years Degrees**			**Master's Degree**	
		First	Second	Third	First	Second
	(1)	(2)	(3)	(4)	(5)	(6)
Online Teaching	0.003	0.019***	0.043***	0.005	-0.017	-0.020*
	(0.004)	(0.007)	(0.008)	(0.009)	(0.011)	(0.011)
II Semester	-0.081***	-0.078***	-0.082***	-0.040***	-0.099***	-0.046***
	(0.002)	(0.003)	(0.005)	(0.006)	(0.005)	(0.006)
Female	-0.046***	-0.051***	-0.072***	-0.045***	-0.021***	-0.029***
	(0.003)	(0.006)	(0.007)	(0.007)	(0.008)	(0.007)
Age	0.009***	0.010***	0.003***	0.006***	0.019***	0.012***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
High School Grade	-0.006***	-0.010***	-0.006***	-0.004***	-0.001***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lyceum	-0.033***	-0.050***	-0.029***	-0.023***	-0.002	0.001
	(0.003)	(0.006)	(0.007)	(0.007)	(0.008)	(0.007)
Cohort dummies	YES	YES	YES	YES	YES	YES
Prov. Res. Dummies	YES	YES	YES	YES	YES	YES
Course of study FE	YES	YES	YES	YES	YES	YES
Observations	96361	34080	20546	12892	11717	8185
Adjusted R^2	0.093	0.109	0.054	0.037	0.075	0.038

Notes: Linear Probability Model. The dependent variable is *Inactive*. The coefficients report marginal effects at the mean of the independent variables. Standard errors (corrected for heteroskedasticity and allowed for clustering at student level) are reported in parentheses. The symbols ***, **, * indicate that the coefficients are statistically significant at the 1, 5 and 10 percent level, respectively.

To examine the effect of the switch to online teaching on the student's probability of passing a given exam and on the grade obtained at each exam, we have stacked data at the student-exam level. We have restricted our analysis to all students enrolled at the first year of a First level Degree because they have to attend mostly compulsory courses having almost no possibility to choose their first year study plan. For each student, we have created one observation for each exam belonging to his/her university study plan. The alternative of using all the administrative data provided by the University covering all passed exams poses serious self-selection problems as students might have failed a number of exams which we are not able to observe since students after their first academic year have a number of optional courses to choose.

Using these data, we have created the variable *Pass* which is a dummy equal to one when the student passes a given exam, and zero otherwise and the variable *Grade* which corresponds to the grade obtained for passed exams and is set to 12 (the minimum passing line is 18, results are robust if we use different values lower than 18) for failed exams. The mean value of *Pass* is 0.595 and its standard deviation is 0.49. The mean value of *Grade* is 20.26 and its standard deviation is 7.38.

In Table B2 we report estimates of a linear probability model in which the dependent variable is *Pass* and in Table B3 we consider *Grade* as the dependent variable. We find that switching from face-to-face to online teaching significantly reduces the probability of passing a given exam of about 3.2-3.5 percentage points and also lowers the grade obtained of about 0.25 points.

Table B2. The Impact of Online Teaching on the Probability of Passing an Exam.

	(1)	(2)	(3)	(4)
Online Teaching	-0.033***	-0.035***	-0.032***	-0.035***
	(0.006)	(0.006)	(0.005)	(0.005)
Year dummies	YES	NO	NO	NO
Cohort dummies	NO	YES	YES	YES
Student characteristics	NO	NO	YES	YES
Prov. Res. Dummies	NO	NO	NO	YES
Course of study FE	NO	NO	NO	YES
Observations	143355	143355	143355	143355
Adjusted R^2	0.007	0.008	0.032	0.079

Notes: Linear Probability Model. The dependent variable is *Pass*. Sample: Only freshmen students. Observations at student-exam level. Standard errors (corrected for heteroskedasticity and allowed for clustering at student level) are reported in parentheses. The symbols ***, **, * indicate that the coefficients are statistically significant at the 1, 5 and 10 percent level, respectively.

Table B3. The Impact of Online Teaching on the Grade Obtained at Exams.

	(1)	(2)	(3)	(4)
Online Teaching	-0.263***	-0.254***	-0.218***	-0.298***
	(0.082)	(0.082)	(0.082)	(0.080)
Year dummies	YES	NO	NO	NO
Cohort dummies	NO	YES	YES	YES
Student characteristics	NO	NO	YES	YES
Prov. Res. Dummies	NO	NO	NO	YES
Course of study FE	NO	NO	NO	YES
Observations	143355	143355	143355	143355
Adjusted R^2	0.003	0.010	0.049	0.108

Notes: OLS estimates. The dependent variable is *Grade*. Sample: Only freshmen students. Observations at student-exam level. Standard errors (corrected for heteroskedasticity and allowed for clustering at student level) are reported in parentheses. The symbols ***, **, * indicate that the coefficients are statistically significant at the 1, 5 and 10 percent level, respectively.

We have used these data also to investigate whether synchronous and asynchronous online teaching produce similar effects on students' performance. In order to run this analysis, we have exploited a survey undertaken by the University of Calabria to understand how the switch to remote learning was perceived by students. Among the questions included in the survey, there was one asking students about the type of teaching methods used by their instructors to deliver their online courses. In the sample used in our analysis, about 33% of courses were delivered through synchronous online classes, 47% were organized through synchronous classes but also gave students the possibility to attended asynchronously thanks to the recorded videos of the online teaching classes. The remaining 20% of courses were delivered through pre-recorded videos.

Using these information, we have built two dummy variables *Synchronous* and *Synchronous with Recorded Videos* and the interaction terms between these variables and the dummy variable *Online Teaching*. We include these variables among our regressors and consider as outcome variables alternatively the probability of passing the exam and the grade obtained. Results are reported in Table B4 (specification with the full set of controls).

In columns (1) and (2) we include both the interactions *Online Teaching*Synchronous with Recorded Videos* and *Online Teaching*Synchronous* and therefore *Online Teaching* refers to pre-recorded videos. We find that all three methods of online teaching have negative effects on students' performance. However, the magnitude of the effect is larger (-6.1 p.p.= -3.5-2.6) for the *Synchronous with Recorded Videos* method, intermediate for video-recorded lectures (-3.5 p.p.) and lower for only *Synchronous* lectures (-2.3 p.p.= -3.5+1.2). Similar results emerge also when considering as outcome variable the *Grade* obtained at exams (column 2).

In columns (3) and (4) we run the same estimates but consider as reference category all the courses for which were made available recorded teaching classes (*Synchronous with Recorded Videos* combined with *Asynchronous* pre-recorded videos*).* Again, we find that the negative effects of online teaching are more pronounced when classes are delivered asynchronously (-5.4 p.p.). The interaction term *Online Teaching*Synchronous* is positive and statistically significant at the 1% level, implying that the probability of passing the exams of courses delivered through synchronous online classes is higher compared to those delivered asynchronously. The effect of the shift to *Synchronous* online teaching is however still negative (-2.4 p. p.= -5.4+3.0). On the other hand, when we consider as outcome variable the *Grade* obtained at exams (column 4), we find that the shift to online teaching produces a negative effect exclusively when the delivery method implies the availability of recorded videos, while *Synchronous* online teaching does not produce a negative effect compared to traditional classes.

In columns (5) and (6) we analyze whether the effects of synchronous and asynchronous delivery modes are differentiated according to tendency of students to procrastinate. To this aim we include among regressors the interaction terms *Online Teaching*Procrastination* and *Online Teaching*Synchronous*Procrastination*. Our results show that online teaching negatively affects students with a tendency to procrastinate especially when the delivery mode is with synchronous online classes. The interaction term *Online Teaching*Procrastination* is negative but statistically insignificant, while the term *Online Teaching*Synchronous*Procrastination* is negative and statistically significant at the 10% level, suggesting a relatively worse impact of synchronous online teaching on students' probability of passing the exams (column 5). A similar pattern is found also for *Grade* (column 6).

Table B4. The Impact of Synchronous and Asynchronous Delivery on Student Performance.

	(1) Pass	(2) Grade	(3) Pass	(4) Grade	(5) Pass	(6) Grade
Online Teaching	-0.035***	-0.799***	-0.054***	-0.725***	-0.059***	-0.611***
	(0.010)	(0.152)	(0.007)	(0.098)	(0.013)	(0.195)
Online Teaching*Synchronous with Recorded Videos	-0.026**	0.104				
	(0.011)	(0.164)				
Online Teaching*Synchronous	0.012	0.820***	0.030***	0.747***	0.038**	0.965***
	(0.011)	(0.175)	(0.009)	(0.131)	(0.016)	(0.249)
Online Teaching*Procrastination					-0.008	-0.131
					(0.007)	(0.106)
Online Teaching*Synchronous*Procrastination					-0.015*	-0.203
					(0.009)	(0.132)
Procrastination					-0.013***	-0.245***
					(0.003)	(0.038)
Observations	139738	139738	139738	139738	44250	44250
Adjusted R^2	0.078	0.108	0.078	0.108	0.077	0.110

Notes: OLS estimates. The dependent variable is *Pass* in columns 1, 3, 5 and *Grade* in columns 2, 4, 6. Sample: Only freshmen students. Observations at student-exam level. Standard errors (corrected for heteroskedasticity and allowed for clustering at student level) are reported in parentheses. The symbols ***, **, * indicate that the coefficients are statistically significant at the 1, 5 and 10 percent level, respectively.

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