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Online teaching, procrastination and student achievement☆

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ABSTRACT

Despite growing consensus in the public debate that self-discipline is key to succeeding in an online learning environment, the evidence available is very limited. We investigate the role of procrastination as a moderator of the impact of online teaching on student performance. We take advantage of the forced transition from traditional class-based to online teaching induced by the COVID-19 pandemic and adopt a difference-in-differences strategy using administrative data of four cohorts of students enrolled in an Italian University. We find that online teaching has reduced student performance by about 1.4 credits per semester on average (0.11 Standard Deviations). However, this aggregate effect masks great heterogeneity as the negative influence on performance varies significantly according to student tendency to procrastinate with online teaching being particularly detrimental for students affected by present-bias problems. The total negative effect for procrastinators amounts to more than 18% of the workload for a semester, so implying a potential delay of approximately two semesters in the expected date of graduation for students following an online as opposed to a face-to-face five-year Degree course.

1. Introduction

In recent years, new styles of education have emerged alongside traditional face-to-face teaching, mainly thanks to technological improvements. Higher education institutions are now able to choose whether to have their students learn via traditional face-to-face teaching, electronic and online media (online teaching) or a combination of both (blended teaching). Nonetheless, not much is known about which system is the most effective under which circumstances.

The Covid-19 pandemic, with the subsequent closure of schools and universities and the massive transition to online teaching, has made these issues even more pressing. Online delivery has made the provision of education to a large mass of individuals possible and many actors have discovered how it can be an important tool in sustaining skill development. Even though there are concerns that online learning may have been a sub-optimal substitute for face-to-face instruction, the forced shift induced by the pandemic is likely to have persistent effects and online and blended teaching are expected to become much more widespread than before the pandemic. Consequently, it is very important not only to understand whether online teaching is as effective as class-based learning, but also to be able to recognize factors that might hinder or inhibit learning in an online environment in order to understand how teaching activities should be organized in the future.

From a theoretical point of view, distance learning has both benefits and drawbacks compared with face-to-face teaching (Figlio et al., 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, the possibility for students to attend classes when they prefer,

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so avoiding overcrowded classrooms, and being able to review 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 & Iloanya, 2016). Last, but not least, distance learning allows both teachers and students to reduce mobility costs and commuting time. On the other hand, disadvantages include the lack of in-person peer contact, more difficult interaction between teachers and students and technology-related hindrances, such as slow or unreliable internet, the cost of connection and insufficient technological skills (Alvarez, 2020; Mathew & Iloanya, 2016; Lynch, 2020). In addition, the lack of a structured environment with a set routine might induce students, especially those with 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 by analyzing the impact of the shift from face-to-face to online teaching during the first wave of the COVID-19 pandemic. Thanks to the richness of our data, we study whether online teaching exacerbates problems deriving from present-biased preferences. Indeed, a number of papers highlight how study activities might be more difficult in a less structured setting without routine interaction with peers and instructors (Banerjee & Duflo, 2014; Figlio et al., 2013; McPherson & Bacow, 2015)[1] Thus, students who tend to procrastinate costly activities, like studying, may perform worse when there is less feedback and commitments become less binding.

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 in exams taken both before and after the transition to online teaching. This allows us to estimate the overall effect on student performance of the shift from face-to-face 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 unaffected) in the exams taken in the first semester, so identifying 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). Even though the pandemic posed additional problems, besides those deriving from the transition to online teaching, which might also have affected student performance, we provide evidence that these aspects are likely to have played a minor role in our setting. Most importantly, given our focus on the role of procrastination, any pandemic-induced confounding factor should not have a different effect according to the degree of students' present-biasedness.

To investigate the role of procrastination in shaping online learning results, we 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), considers how students actually behaved during their enrolling at our university of reference. All students who apply to enroll at the university considered in our study are notified of the admission decision at the same time (through the university official website) and have seven weekdays in which to complete the enrollment procedure (requiring the payment of an initial fee and the filling in of a number of forms). Accomplishing the enrollment procedure generates an immediate cost which students with a tendency to procrastinate might tend to postpone, but accomplishing the procedure at the last moment may be particularly risky as students might end up by being excluded from their chosen degree program due to some unexpected event (illness, bad working of the internet connection etc.). Therefore, with the support of results from our previous research (De Paola & Scoppa, 2015), which showed that students who take longer to accomplish the enrolment procedure are also more likely to self-assess as procrastinators, we assume that procrastinating the completion of this administrative task is predictive of a general tendency to procrastinate.

In line with findings emerging from the recent literature on the topic, our estimation results show that pandemic-induced online teaching has significantly reduced the number of credits acquired over a semester. We also find that student's tendency to procrastinate is an important moderator of this effect and online teaching is particularly detrimental for students affected by present-bias problems. With online teaching, non-procrastinators reduce their performance by about 2 credits per semester while the performance of students with present-bias problems is further reduced by about 1.2 credits. The total effect for procrastinators amounts to more than 18% of a semester workload, so implying a potential delay of approximately two semesters in the time necessary to graduate from an online versus a face-to-face five-year degree course. A similar negative effect is also found when we consider as an outcome variable an overall measure of student performance which takes into account the grades students obtained at exams. Our results are robust to the inclusion of student fixed effects and several control variables for individual and local characteristics. Furthermore, we find that procrastination exerts a negative effect on a student's probability of passing an exam and on the grade obtained.

Although we compare online and face-to-face teaching over a period characterized by a health emergency which could have had an effect on student performance above and beyond the simple change in teaching style, we show that the estimated effect does not seem to depend on the severity of the health emergency or on the quality of internet connections. Indeed, the university considered is located in the south of Italy, an area that has experienced low rates of contagion and death, especially in the first wave of the pandemic.[2] Moreover, the heterogeneity shown by our findings supports the idea that the worsening of student 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 conditions than their colleagues or that instructors were less compassionate with them at exams.

Our research contributes to the literature investigating the impact of online teaching on student performance. Although relatively new to Italy, online university courses were already widespread in the United States and in many other advanced countries before the pandemic crisis. Nonetheless, a number of identification challenges has meant that the literature that tries to identify the causal impact of different teaching methods is rather limited in quantity. 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 showed negative effects of online compared to face-to-face classes. Similar results are found also by Bettinger et al. (2017) and Xu and Jaggars (2013), who considered quite large populations of students and dealt with selection problems by adopting an instrumental variable strategy.

This literature has recently been enriched by several papers examining the impact of the closure of schools and universities and the

[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) showed that procrastination is a predictor of dropping out or failing to complete an online course.

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

consequent switch to remote learning due to the spread of the 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) highlighted a considerably negative impact, particularly for younger students and students from families of low socioeconomic status.[3]

As regards university students, Orlov et al. (2021) compared student performance in standard assessments in spring 2020 to student performance in the same courses in either autumn or spring 2019. They found that during the pandemic there was a decline in total scores and that prior online teaching experience and teaching methods that encouraged active engagement helped to mitigate the effect. Likewise, by using data on a randomized controlled trial comparing online and in-person classes, Kofoed et al. (2021) found that online education led to a lowering of students' final grades, especially with students of below median academic ability. Negative effects were also found by Altindag et al. (2021), who relied on data from a large US public university instead. They also showed 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 the erroneous conclusion that online teaching is better than face-to-face teaching. On the other hand, Binelli et al. (2021) found evidence of a positive effect for students enrolled at a public university located in the North of Italy, probably due to a greater effort made by students in studying activities during the lockdown period.

Our contribution to this literature is twofold. First, we offer new evidence for Italy,[4] a country where the higher education system before the pandemic was mostly traditional and the web and technology were mainly just used as support for face-to-face classes (to share course information and/or additional teaching materials with students).[5] The timing of the transition to online learning for the university considered in this study, coinciding with the beginning of the second semester, just as for many other universities in Italy and in other countries worldwide, allows us to apply a difference-in-differences identification strategy. A similar identification strategy was used by Orlov et al. (2021), but while they only considered 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 moderates the effects of online teaching.[6] 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 feel more involved, 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 impact 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 examines the role of students' tendency to procrastinate. Section 6 looks at the effects of synchronous and asynchronous online teaching. Section 7 offers some concluding remarks.

2. Data

We use very rich administrative data from the University of Calabria, a large public university located in the South of Italy.[7] Our administrative dataset covers four cohorts of students (who 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, province of residence).

Since it was reformed in 2001, the Italian University system has been organized into three main levels: First Level degrees (3 years' legal duration), Second Level degrees or Master's degrees (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 (involving the acquiring of 120 more credits). In some degrees, such as Law and Architecture, the First and the Second Level degrees are coupled together within a degree course lasting 5 years ("Laurea a Ciclo Unico"). After having completed their Master's degree, students can apply to enroll on a Ph.D course. We focus our analysis on students enrolled at First Level degree, Master's degree and a 5 years degree levels.[8]

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 h of teaching and to 108 and 162 nominal hours of study. An exam is passed if evaluated as deserving a mark of at least 18 (the minimum mark) and the maximum grade a student can get is 30 *cum laude*. There is no penalty 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 to 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

[3] Similar evidence emerges from Zierer (2021) and Spitzer and Musslick (2021), who also highlighted highly heterogenous effects. 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) took advantage of the fact that, in the Netherlands, national examinations for primary school pupils take place twice a year and that, in 2020, these tests took place just before and after the first national wide lockdown. Using a difference-in-differences model, they show that, in comparison with the 3 previous years, there was a substantial learning loss in 2020, which was concentrated among students from disadvantaged background. Similar results are found by Maldonado and De Witte (2020), who studied the effects of school closures by using data on standardised tests in the last year of primary education in Flemish schools in Belgium. Evidence for Italian students attending primary and lower secondary schools was provided by Borgonovi and Ferrara (2022), Bazoli et al. (2022) and Contini et al. (2021) and showed a negative impact especially for mathematical skills and for lower-secondary school students.

[4] European student outcomes tend to receive less consideration than the outcomes for U.S. and Canadian students. Since European universities tend to rely much more heavily on high-stakes, end-of-semester testing and exhibit significant institutional/structural differences (larger classes, less student supervision, 3-year degree programmes, few to no general education courses), studying the effect of online teaching in this setting proves important.

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

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

[7] Currently about 25,000 students are enrolled in the 107 degree courses offered by the University of Calabria.

[8] We disregard PhD students as their work is more research driven and there are no standardized measures of performance available.

Table 1
Descriptive statistics.

Variables	Obs.	Mean	Std. Dev.	Min	Max
University related variables					
Credits	96,361	16.851	12.739	0	48
Performance	96,361	48.527	38.014	0	150
Online Teaching	96,361	0.175	0.380	0	1
Master's Degree	96,361	0.250	0.433	0	1
5 Years Degree	96,361	0.124	0.330	0	1
II Semester	96,361	0.493	0.500	0	1
Cohort 2016	96,361	0.359	0.480	0	1
Cohort 2017	96,361	0.308	0.462	0	1
Cohort 2018	96,361	0.215	0.411	0	1
Cohort 2019	96,361	0.119	0.323	0	1
Year:2020	96,361	0.355	0.478	0	1
First Year	96,361	0.354	0.478	0	1
Second Year	96,361	0.213	0.410	0	1
Third Year	96,361	0.134	0.340	0	1
Fourth Year	96,361	0.050	0.217	0	1
First Year Master's Degree	96,361	0.122	0.327	0	1
Second Year Master's Degree	96,361	0.085	0.279	0	1
Procrastination	29,868	1.426	1.546	0	6
Procrastination1	36,810	1.157	1.500	0	6
Demographic characteristics					
Female	96,361	0.566	0.496	0	1
Age	96,361	22.977	4.310	18	71
High School Grade	96,361	85.176	10.982	60	100
Lyceum	96,361	0.543	0.498	0	1
Immigrant	96,361	0.032	0.176	0	1
Same Province	96,361	0.530	0.499	0	1
Different Province and Region	96,361	0.028	0.165	0	1
COVID-19 and technology related variables					
Red Zone	93,656	0.108	0.311	0	1
% Households speed 100–1000 Mbps	94,687	0.678	0.248	0	0.995

Notes: Administrative Data from University of Calabria.

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 by 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 course attended and on whether he/she has completed the program or has dropped-out of university studies.

In most cases, students have to take compulsory courses as a part of their degree courses and they cannot choose which exams to take (this is always the case in the first year and is often the case in subsequent years). Our main measure of performance consists of the credits acquired in passed exams while the choosing not to take a compulsory course exam or failing an exam have the same measurable effect. Furthermore, for each cohort we compare all the enrolled students on each degree course at the beginning of the academic year, so we have no problems of sample selection.

Table 1 presents some descriptive statistics. Our sample includes 23,283 students for a total of 96,361 observations.[9] 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 only acquire 17 credits on average over a semester.[10] This is typical of the Italian university system where students often take much more time than expected to complete their academic career.[11]

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, the sum of the grades at exams passed in each semester was considered (this variable is called *Performance*).[12] To begin with, grades were weighted in terms of credits associated with each examination: the weight was 1 if the exam was worth 9 credits (the typical exam), 2/3 if the exam was worth 6 credits, and so on. In this way, both the number of examinations passed by students and the grades obtained were considered (for example, 3 exams of 9 credits passed with a grade of 20 (20+20+20) are equivalent to 2 exams of 9 credits passed with 30 (30+30)).[13] *Performance* ranges from 0 to 150 and is 48.5 on average in our sample.

About 17.5% of the observations in our dataset 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. 75% of observations refer to students enrolled in a First Level Degree or a 5 Years Degree (about 35% of observations refer to first-year students, 21% to second-year students and 18% to students attending subsequent years), while the remaining 25% regard students enrolled on a Master's Degree.

As regards the demographic characteristics of the sample, students are on average 22.9 years old and about 57% of observations regard women. Students obtained an average *High School Grade* of 85 and 54% of them attended a Lyceum.[14] 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 within the same region (only about 3% come from other Italian regions).

High School Grade is a measure of predetermined abilities that many analyses have shown to be highly correlated to academic performance (see, among others, De Paola & Scoppa 2015). Thus, we used it with the aim of verifying whether students enrolled in different years have comparable abilities and we found supportive evidence. High school grade does not show a clear pattern over time: for students who enrolled in 2016, the average high school grade was 85.08; it was 84.29 in 2017

[9] Table A1 in Appendix A presents descriptive statistics at student level.

[10] The data at hand do not specify whether students do not earn credits because they failed exams or they did not sit them.

[11] Garibaldi et al. (2012) reported that the mean effective duration of a university programme for a sample of graduates 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 programme (*Fuori Corso*). Brunello and Winter-Ebmer (2003) find that 31% of students in Italy expected to complete their programme at least one year later than the required time. See also Aina et al. (2011).

[12] We computed *Performance* as follows: $Performance = \sum_{j=1}^{n} c_j * Grade_j$ where $c_j \in \{\frac{2}{3}, 1, \frac{4}{3}\}$ and n are the number of exams passed. Each exam (j) confers 6, 9 or 12 credits. The grade obtained at each exam is weighted by the number of credits assigned to the exam (2/3 for an exam worth 6 credits, 1 for an exam worth 9 credits, 4/3 for an exam worth 12 credits). For each student, *Performance* was computed as the sum of the of the weighted grades at passed exams in each semester.

[13] De Paola et al. (2012) used a similar measure to evaluate the impact of monetary incentives on student performance.

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

and 84.70 and 85.12 in 2018 and 2019, respectively. Since high school grade ranges from 60 to 100, the small variations observed over time are unlikely to reflect different abilities across cohorts. Analogous evidence on the similarity of the cohorts emerges when considering the percentage of females enrolled and the share of students who frequented a Lyceum. Again, we found that there is not a clear trend. The share of females was respectively of 56.3%, 53.8%, 55.6% and 56.6% in the four years considered in our analysis. The share of students from a Lyceum for each cohort was 56.1%, 51.1%, 52.4% and 51.5%.

As shown in Appendix A of the paper, the number of credits acquired by students tended to increase over time before the pandemic. Considering that there is no similar trend in the indicators of students predetermined ability, the increase in the number of credits is possibly a consequence either of grade inflation or better teaching as resources obtained by Italian universities from central government over recent years have been increasingly based on student performance.[15]

Data at hand allowed 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 all notified of the admission decision at the same time[16] (through the university official website) and students have seven weekdays to complete the enrollment procedures.[17] These procedures require a series of activities (filling in a number of forms and the payment of a small fee)[18] 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 the case of any unexpected event (illness, bank strikes, bad functioning of the university website, etc.). Considering these aspects, we assume that individuals with a tendency to procrastinate are likely to complete the task toward the end of the seven days or just before the deadline. Therefore, we considered the number of days a student takes to accomplish the enrollment procedure after admission notification as a proxy of individual procrastination. More precisely, we built a variable *Procrastination* with 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.

Unfortunately, this variable was not available for students enrolled on master's degrees and for some first level degrees. Furthermore, we decided not to consider students who enrolled after the deadline.[19] Due to these restrictions, the sample we considered to investigate the role of procrastination as a mediating variable became smaller with a total number of 29,868 observations.

A number of degree programmes have also made pre-enrolment procedures available, that is, they have allowed students to enroll earlier (to apply in April/May/June and enroll in July). As our measure *Procrastination* excluded students who have used the pre-enrolment procedures, we built an alternative measure *Procrastination1,* which overlaps with *Procrastination* for values from 0 to 6, but assigns the value of 0 (the lowest value of procrastination), instead of a missing value, to students who enrolled through the pre-enrollment procedures (thus reaching a sample of 36,810 observations).

On average, students complete 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 completing the enrolment procedure on the second or third-day, about 6% of students enrolling on the fourth day and about 12.5% waiting until the last three days before the deadline.

Procrastination behaves consistently with what was found by the existing literature as it is negatively correlated with the number of credits acquired ($\rho=-0.070$, p-value 0.000). Furthermore, similarly to results found by De Paola and Scoppa (2015), for the cohorts of students considered in this study, it was found that our measure of procrastination correlated negatively with student performance at high school as measured through their *High School Grade* ($\rho=-0.073$, p-value 0.000). This negative correlation with a pre-determined performance reassures us that we were not classifying as procrastinators students who delayed enrolling because they were waiting for decisions from other universities and, consequently, were not sufficiently motivated when they ended up being enrolled on a degree program that differed from their first choice.[20]

Finally, we also observed proxies of the geographical spread of COVID-19 and the quality of internet connections at municipal level. As regards the severity of the health emergency, *Red Zone* is a dummy variable which takes the value of 1 for municipalities that were classified as "Red Zones"[21] from March until September 2020 (that is, during the second semester of the academic year 2019/20).[22] About 11% of our sample students come from a municipality that was classified as Red Zone. As regards the quality of internet connections, we used the "Broadband Map" provided by the Italian Authority for Communications,[23] which reports, 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 the share of households served with a quite high speed, that is, in the range 100–1000 Mbps (67.8%) as an indicator of the quality of internet connections in the municipality where each student is resident.

3. Methodology

The academic year at the University of Calabria consists of two

[15] This is further confirmed by the reduction in the share of inactive students (i.e. students who acquire zero credits over a given academic year) which was 14.4% in the academic year 2016/2017 and became 13.4% and 11.3%, respectively, in each subsequent academic year up to 2018/2019.

[16] The admission date is different from the general one for some specific degree programmes. We consider these dates to determine our procrastination variables.

[17] A similar measure was used by Reuben et al. (2015), who considered students' behavior when applying to a master in business administration. Alternative measures of procrastination rely on surveys which ask subjects about their tendency to delay the accomplishment of a task (Mischel et al., 1989, Wong, 2008) or consider student behavior in handing in term papers (Solomon and Rothblum, 1984; Dewitte and Schouwenburg, 2002; Howell et al., 2006).

[18] The enrolment procedure requirs 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.

[19] Students who did not complete their enrolment process were excluded and places left vacant were filled either with students with a rank lower than that initially required or by re-opening the application procedure. Given this procedure, a number of degree course places that were assigned to students after the first selection process 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 different degree course from their first choice or might have other unobservable differences with respect to regularly enrolled students.

[20] De Paola and Scoppa (2015) also showed that this measure of procrastination does not catch factors that might be related to family economic conditions. They showed statistically insignificant correlations between procrastination and different measures of family background, such as family income, parents' education and employment status. Unfortunately, this information is not available for the cohorts of students we consider here.

[21] 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.

[22] Due to data availability, the variable is computed only for students from Calabria, the region where the vast majority of students in our sample reside.

[23] Available at the following link: https://maps.agcom.it/

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 are traditionally classroom-based. However, in the academic year 2019/2020, the COVID-19 pandemic forced a shift from traditional to online teaching to respond to the diffusion of the virus and the University of Calabria was forced to cancel all physical face-to-face classes and to deliver the teaching activities of the second semester (starting from March) online. 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, record lectures and post assignments and grade them digitally rather than by hand. After one week (in some cases two weeks), the lectures of the second semester started online. Therefore, during the first semester students attended face-to-face lectures and sat in-person exams while, in the second semester, both lectures and exams were held online. We took advantage of this change in the educational system to study the effect of the introduction of online learning on student performance. We applied a sort of difference-in-differences strategy comparing the difference between the performance in the exams taken during the second semester of the academic year 2019/20 and that in the exams taken during the second semester of previous academic years (from 2016/17 to 2018/19) with the difference between the performance in the exams taken during the first semester of 2019/20 and that in the exams taken during the first semester of previous academic years. The latter difference identifies pre-treatment differences as, for a given cohort and course year, it compares the pre-treatment (first semester) performance of two different types of students (one affected and the other unaffected by the health emergency). 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 tried to catch with our COVID-19 health problems and technology related controls).

We decided to focus on the second semester 2019–20 because all courses were taught entirely online during that semester, thus allowing a clear identification strategy. On the other hand, starting from the first semester of the academic year 2020–21 (second wave of the pandemic), like most universities throughout the world, the University of Calabria experimented with mixed forms of teaching according to the evolution of the pandemic (with face-to-face classes for some weeks, occasional closures for some weeks and then asking students to rotate between face-to-face classes and online teaching since the number of available seats in classrooms was halved to guarantee social distancing). In addition, starting from the second wave of the pandemic, each degree program at the university had some degree of freedom in deciding whether lectures were to be face-to-face or online. Moreover, students could also choose whether to attend classes in person or online. Both these factors would create a problem for our identification purposes.

We are confident that the validity of our analysis is not affected by a change in grading policies. First of all, the university adopted very strict protocols to monitor online exams during the COVID-19 pandemic (perhaps because the pandemic did not hit the region where the university is located very hard). Students taking exams remotely had to access a virtual environment ("Lockdown Browser" or "Safexam-browser") in order to have their activity monitored. 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.

Secondly, as is shown in Section 5, our main results are based on the different impact of online teaching on procrastinators and non-procrastinators and it is highly implausible that any change in grading policies affected these two categories of students differently.

In our analysis, we estimated the following model:

$$Y_{ijt} = \beta_0 + \beta_1 OnlineTeaching_{jt} + \beta_2 Year2020_{jt} + \beta_3 II\ Semester_{jt} + \beta_4 X_i + \mu_i + \lambda_t + \delta_i + \varepsilon_{ijt} \quad (1)$$

where Y_{ijt} is our outcome variable representing the performance of a student i (in terms of number of credits acquired or comprehensive academic performance) during the semester j of the academic year t; $OnlineTeaching_{jt}$ is a dummy equal to one for the second semester of the academic year 2019/20 in which courses were taught online; $Year2020_{jt}$ is a dummy variable that takes the value of 1 for the academic year 2019/20 and 0 otherwise; $II\ Semester_{jt}$ is a dummy variable that takes the value of 1 for the second semester and 0 otherwise (notice that $OnlineTeaching_{jt}$ corresponds to the interaction term between $Year2020_{jt}$ and $II\ Semester_{jt}$); 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 vector of dummies to control for the type of degree (*First Level, Master's degree* or *5 year degree*) or for each degree course (86 categories); ε_{ijt} is an error term. In some specifications, we also controlled for student fixed effects.

Our parameter of interest is β_1 which represents the change in student 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 had a negative effect on student 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 difference in performance between the two semesters, for example in terms of difficulty, the time available and number of exams.

As shown in the Appendix of the paper, where the parallel trend assumption was tested, student performance in the academic years before 2019/20 (control group) provides an appropriate counterfactual condition of the trend for the academic year 2019/20 (treated group). It was found that students earned a higher number of credits on average in the second semester and that, from 2017 to 2019, there was a positive trend for both semesters while the trend became negative for the second semester in 2020.

We started by estimating this model to study the aggregate effect of online teaching on student performance. Since the pandemic presented other problems which might also have affected student performance besides those deriving from the transition to online teaching, it cannot be excluded that, even though we tried to consider these changes through a large set of controls, our estimates of β_1 might also catch these other emergency-related factors.

These problems should not be relevant when, through a triple difference-in-differences model, we investigated the differential effect produced by the shift to online teaching on students with different attitudes toward procrastination. Indeed, even though the pandemic produced a general change in both their educational and living environments, there is no reason to believe that this change was different for more present-biased students. Consequently, we augmented equation [1] by including among the controls the indicator of procrastination and the interaction terms between this variable and $OnlineTeaching_{jt}$, $Year2020_{jt}$ and $II\ Semester_{jt}$ in order to study whether the effect of online teaching varies as a consequence of student present-biased preferences. More precisely, we estimated the following model:

$$Y_{ijt} = \beta_0 + \beta_1 OnlineTeaching_{jt} + \beta_2 Year2020_{jt} + \beta_3 II\ Semester_{jt} + \beta_4 X_i + \beta_5 OnlineTeaching_{jt} * Procrastination_i + \beta_6 Year2020_{jt} * Procrastination_i + \beta_7 II\ Semester_{jt} * Procrastination_i + \beta_8 Procrastination_i + \mu_i + \lambda_t + \delta_i + \varepsilon_{ijt} \quad (2)$$

Table 2
The impact of online teaching on student performance. Dependent variable: Number of credits.

	(1)	(2)	(3)	(4)	(5)
Online Teaching	−1.436***	−1.442***	−1.430***	−1.409***	−1.487***
	(0.124)	(0.124)	(0.124)	(0.143)	(0.126)
II Semester	8.335***	8.326***	8.304***	8.178***	8.359***
	(0.078)	(0.078)	(0.078)	(0.089)	(0.079)
Year:2020	0.488***	0.447***	0.431***	−0.022	0.499***
	(0.141)	(0.138)	(0.138)	(0.151)	(0.139)
Female		1.473***	−0.240*		−0.342***
		(0.112)	(0.123)		(0.125)
Age		−0.208***	−0.298***		−0.299***
		(0.018)	(0.019)		(0.019)
High School Grade		0.207***	0.263***		0.268***
		(0.005)	(0.005)		(0.005)
Lyceum		0.894***	1.920***		1.936***
		(0.113)	(0.109)		(0.110)
Immigrant		−1.463***	−1.101***		−0.649
		(0.347)	(0.341)		(0.397)
Red Zone					−0.398**
					(0.167)
% Households speed 100–1000 Mbps					0.415**
					(0.206)
Cohort dummies	YES	YES	YES	NO	YES
Year of Degree dummies	YES	YES	YES	YES	YES
Prov. Res. Dummies	NO	YES	YES	NO	YES
Course of study FE	NO	NO	YES	NO	YES
Student FE	NO	NO	NO	YES	NO
Observations	96,361	96,361	96,361	96,361	93,386
Adjusted R^2	0.145	0.194	0.246	0.452	0.248

Notes: OLS estimates. The dependent variable is *Credits*. Standard errors (corrected for heteroskedasticity and allowing 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 3
The impact of online teaching on student comprehensive performance.

	(1)	(2)	(3)	(4)	(5)
Online Teaching	−3.221***	−3.242***	−3.200***	−3.140***	−3.354***
	(0.360)	(0.359)	(0.359)	(0.412)	(0.364)
II Semester	23.890***	23.857***	23.784***	23.452***	23.951***
	(0.225)	(0.225)	(0.225)	(0.258)	(0.228)
Year:2020	1.127***	0.986**	0.924**	−0.213	1.123***
	(0.410)	(0.401)	(0.398)	(0.436)	(0.402)
Student Characteristics	NO	YES	YES	NO	YES
Cohort dummies	YES	YES	YES	NO	YES
Year of degree dummies	YES	YES	YES	YES	YES
Prov. Res. Dummies	NO	YES	YES	NO	YES
Course of study FE	NO	NO	YES	NO	YES
Covid-19 Severity	NO	NO	NO	NO	YES
Internet quality	NO	NO	NO	NO	YES
Student FE	NO	NO	NO	YES	NO
Observations	96,361	96,361	96,361	96,361	93,386
Adjusted R^2	0.149	0.210	0.272	0.486	0.274

Notes: OLS estimates. The dependent variable is *Performance*. Standard errors (corrected for heteroskedasticity.

4. The impact of online teaching on student performance

The impact of online teaching on student performance was evaluated by estimating several specifications of equation [1] on the whole sample of students. Table 2 reports our OLS estimates, using the number of credits acquired in a semester as a dependent variable. In all the specifications, standard errors were corrected for heteroskedasticity and allowed for clustering at student level. In column (1), we have only controlled for treatment year, semester and dummies for cohort and year of degree program. It was found that online teaching significantly reduced the number of credits acquired over a semester by 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 (acquiring 0.49 credits more) than their colleagues (from different cohorts) who were enrolled in the same year of each degree program in previous academic years. Nonetheless, they performed significantly worse when forced to switch to online teaching. We also noted 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 had more time to prepare for the examinations, given that the examination period includes the summer break, (August) or because the exams in the second semester are, on average, less difficult.

In column (2) of Table 2, we have estimated a specification which controls for some individual characteristics (Female, Age, High School Grade, Lyceum, Immigrant) that typically affect student academic performance and, in column (3), a dummy has been included for each degree program (86 categories). By taking these characteristics as constant, it was found that online teaching had almost the same negative effect (−1.44) found in the previous specification. In column (4), student fixed effects have been included and the effect of online teaching does

Table 4
The impact of online teaching by student tendency to procrastinate. Dependent variable: number of credits.

	(1)	(2)	(3)	(4)	(5)	(6)
Online Teaching	−1.773***	−1.774***	−1.784***	−1.687***	−1.694***	−1.721***
	(0.293)	(0.293)	(0.296)	(0.242)	(0.242)	(0.244)
Online Teaching *Procrastination	−0.532***	−0.539***	−0.561***			
	(0.143)	(0.143)	(0.144)			
Procrastination	−0.520***	−0.382***	−0.407***			
	(0.077)	(0.075)	(0.076)			
II semester	8.108***	8.098***	8.069***	9.049***	9.040***	9.035***
	(0.202)	(0.202)	(0.204)	(0.172)	(0.171)	(0.173)
Year 2020	0.448	0.378	0.261	0.294	0.215	0.140
	(0.322)	(0.315)	(0.311)	(0.266)	(0.261)	(0.258)
II semester*Procrastination	−0.009	−0.006	0.028			
	(0.100)	(0.100)	(0.102)			
Year 2020*Procrastination	0.044	0.058	0.062			
	(0.108)	(0.105)	(0.102)			
Online Teaching *Procrastination1				−0.552***	−0.556***	−0.570***
				(0.133)	(0.133)	(0.134)
Procrastination1				−0.385***	−0.227***	−0.279***
				(0.072)	(0.070)	(0.071)
II semester*Procrastination1				−0.314***	−0.312***	−0.287***
				(0.094)	(0.094)	(0.095)
Year 2020*Procrastination1				−0.013	0.011	0.006
				(0.101)	(0.098)	(0.095)
Students' characteristics	NO	YES	YES	NO	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
Covid-19 Severity	NO	NO	YES	NO	NO	YES
Internet Quality	NO	NO	YES	NO	NO	YES
Observations	29,868	29,868	29,265	36,810	36,810	36,158
Adjusted R^2	0.130	0.178	0.240	0.138	0.190	0.249

Notes: OLS estimates. The dependent variable is *Credits*. Standard errors (corrected for heteroskedasticity and allowing 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.

not vary.

The switch to online teaching considered in this paper happened because of the spread of the coronavirus virus and, even though we used data from a university located in the south of Italy, where the effects of the first contagion wave were relatively limited, our estimates might have also captured the effects of other changes. In order to try to control for some of these changes, two control variables have been added for the severity of the health emergency and the quality of the internet connection, column (5), and it is shown that the effect of online teaching remains more or less of the same magnitude and statistical significance. Furthermore, our results proved robust when two other controls were used for the severity of the health emergency (both linearly and interacted with *Online Teaching*), namely the percentage of students who know people who contracted COVID-19 for each municipality and the variation in the 2020 mortality rate compared with the 2015–2019 mortality rate at the municipality level, and when two other controls were applied for potential technology issues at the municipality level, namely the ADSL download speed and the share of households not served by cable internet (results are not reported, but are available upon request).

As regards our control variables, we found that students endowed with a higher level of ability (using the type of high school and the high school grade as proxies) acquired on average a higher number of credits while older students performed worse. A negative effect also emerged for immigrants, possibly because of their difficulties with the Italian language. Students from municipalities classified as *Red Zone* tended to perform worse, ceteris paribus, while performance improved as the share of households with an internet download speed in the 100–1000 Mbps range (a relatively high speed[24]) increased in the municipality where the student was resident. Importantly, the coefficient of *Online Teaching* always remained negative and statistically significant.

In Table 3, the same specifications reported in Table 2 have been replicated by using *Performance* as an outcome variable in order to consider both the number of examinations passed by students (the quantitative aspect) and the grades obtained (the qualitative aspect).[25] Again, there is evidence of a negative effect on student performance of the switch to online teaching: the transition from face-to-face to online teaching reduced *Performance* by 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. and allowing 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.

On the whole, our results point to a negative effect of pandemic-induced online teaching. This effect, however, may mask important heterogeneity if some categories of students suffered more when the teaching style required more commitment and self-discipline. In the following Section, we will investigate this in greater depth by analyzing whether the effect of online teaching is heterogeneous due to differing student attitudes towards procrastination.

5. Online teaching and present-biased students

Self-control and present-bias problems, which are typical of studying activities, might be accentuated by online teaching since students prone to procrastination tend to suffer from the lack of commitment deriving

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

[25] The Average Grade obtained by students might have been an alternative dependent variable. However, since we used administrative data on students' careers, we only observed grades for exams passed by students while we did not observe grades for failed examinations. Therefore, we chose not to use a sample selected on the basis of the dependent variable since this would have led to estimation bias.

Table 5
The impact of online teaching on present-biased students. Alternative measures of procrastination.

	(1)	(2)	(3)	(4)	(5)	(6)
Online Teaching	−2.110***	−2.121***	−2.141***	−1.979***	−1.993***	−2.028***
	(0.290)	(0.289)	(0.292)	(0.240)	(0.240)	(0.242)
Online Teaching* D_Procrastination	−1.166***	−1.160***	−1.201***			
	(0.450)	(0.450)	(0.454)			
D_Procrastination	−1.343***	−0.839***	−0.802***			
	(0.256)	(0.250)	(0.236)			
Online Teaching *D_Procrastination1				−1.303***	−1.293***	−1.317***
				(0.420)	(0.420)	(0.423)
D_Procrastination1				−0.879***	−0.338	−0.403*
				(0.240)	(0.234)	(0.224)
Student characteristics	NO	YES	YES	NO	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
Covid-19 Severity	NO	NO	YES	NO	NO	YES
Internet Quality	NO	NO	YES	NO	NO	YES
Observations	29,868	29,868	29,265	36,810	36,810	36,158
Adjusted R^2	0.129	0.177	0.239	0.137	0.189	0.248

Notes: OLS estimates. The dependent variable is *Credits*. Standard errors (corrected for heteroskedasticity and allowing 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 6
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***	−4.108***	−3.810***	−3.830***	−3.865***
	(0.831)	(0.829)	(0.837)	(0.682)	(0.681)	(0.686)
Online Teaching *Procrastination	−1.648***	−1.670***	−1.724***			
	(0.408)	(0.406)	(0.410)			
Procrastination	−1.626***	−1.177***	−1.174***			
	(0.232)	(0.223)	(0.224)			
Online Teaching *Procrastination1				−1.726***	−1.741***	−1.772***
				(0.378)	(0.377)	(0.380)
Procrastination1				−1.212***	−0.715***	−0.862***
				(0.217)	(0.209)	(0.208)
Students' characteristics	NO	YES	YES	NO	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
Covid-19 Severity	NO	NO	YES	NO	NO	YES
Internet Quality	NO	NO	YES	NO	NO	YES
Observations	29,868	29,868	29,265	36,810	36,810	36,158
Adjusted R^2	0.130	0.196	0.272	0.137	0.207	0.280

Notes: OLS estimates. The dependent variable is *Performance*. Standard errors (corrected for heteroskedasticity and allowing 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.

from in-class comparison with instructors and peers and may be distracted by the availability of Facebook, Instagram, YouTube, chats, and so on, on their computers or mobile phones.[26] These factors might induce them to postpone studying and even attendance at recorded lectures .[27]

Thanks to the richness of our data, including a measure of procrastination based on the enrolment behavior of first-year students, we were able to study whether the switch to online teaching is especially detrimental for some students with present-biased attitudes. Our findings are reported in Table 4.[28] In the first three columns, *Procrastination* has been considered as an indicator of present biased attitudes while, in columns (4)-(6), we have relied on our alternative measure, *Procrastination1*. We have run the same regressions as in columns (1)-(2)-(5) of Table 2, adding to the independent variables our measure of procrastination and the interaction terms of *Procrastination* with *Online Teaching, II Semester* and *Year 2020* (see Eq. (2)).

Since this sample was smaller than the sample considered in Section 4, we first estimated exactly the same regressions as in Table 2 to evaluate the impact of online teaching on this sample, without including the heterogeneity by procrastination level. We found that *Online Teaching* attracted a coefficient of about −2.45, considerably larger than our previous estimate (estimates are not reported), mainly because this sample did not include Master's degree students, for whom online teaching had very limited negative effects.

Column (1) shows that *Procrastination* negatively correlates with student performance in terms of the number of credits acquired in the semester. A delay of one day in the enrollment procedure is associated with a reduction of 0.39 credits in the traditional context of face-to-face teaching. More importantly, our estimates show that online teaching reduces the number of credits acquired in a semester by 1.77 for students

[26] In a randomized experiment, Carter et al. (2017) showed that even the use of computers and tablets in the classroom can be deleterious for student performance.

[27] For instance, the availability of online lecture recordings can foster procrastination by allowing students greater flexibility in the timing of their studies (Chai, 2014).

[28] Descriptive statistics for the samples of students used in this analysis are reported in Tables A4 and A5 in Appendix A of the paper.

Table 7
The impact of online teaching. heterogeneity according to procrastination, lyceum, high school grade and nationality. Dependent variable: number of credits.

	(1)	(2)	(3)	(4)
Online Teaching	−1.674***	−1.667***	2.691*	2.599
	(0.243)	(0.320)	(1.619)	(1.631)
Online Teaching*Procrastination1	−0.556***	−0.548***	−0.567***	−0.562***
	(0.133)	(0.133)	(0.132)	(0.131)
Procrastination1	−0.280***	−0.276***	−0.311***	−0.315***
	(0.070)	(0.070)	(0.069)	(0.069)
Online Teaching* Immigrant	0.321			0.292
	(1.379)			(1.370)
Online Teaching*Lyceum		0.030		0.116
		(0.392)		(0.390)
Online Teaching*High School Grade			−0.050***	−0.050***
			(0.018)	(0.018)
Student characteristics	YES	YES	YES	YES
Cohort dummies	YES	YES	YES	YES
Year of Degree dummies	YES	YES	YES	YES
Prov. Res. Dummies	YES	YES	YES	YES
Course of study FE	YES	YES	YES	YES
Observations	36,810	36,810	36,810	36,810
Adjusted R^2	0.248	0.248	0.252	0.252

Notes: OLS estimates. The dependent variable is Credits. Standard errors (corrected for heteroskedasticity and allowing 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.

who do not procrastinate. However, for students who procrastinate the negative effect of online teaching increases: the interaction term *Online Teaching*Procrastination* is in fact negative and statistically significant at the 1 percent level and the magnitude of the effect of online teaching increases by 0.54 for each day of delay in the enrollment procedure. For example, a student who enrolled with a delay of 4 days has a negative effect of online teaching of −3.92. Results do not change much across the different specifications.

Very similar results were found when using our alternative measure of procrastination, *Procrastination1* (columns 4–6).

In Table 5, we have replicated the same specifications reported in Table 4, but, instead of considering a continuous measure of procrastination, we have used a dummy variable *D_Procrastination* (equal to one for values of *Procrastination* above or equal to 2 and zero otherwise) and interacted *Online Teaching, II Semester* and *Year 2020* with this binary indicator. In column (2), where we have included a rather ample set of controls, we found that students who tend to procrastinate acquire a significantly lower number of credits (−3.28=−2.12–1.16) with online teaching than students who do not procrastinate (−2.12). Similar results were found when we included the full set of controls by adding dummies for each different degree program and the indicators of Covid-19 severity and internet quality (column 3) and when we also included students who used the pre-enrollment procedure among non-procrastinators by using the dummy *D_Procrastination1* (columns 4–6).

Overall, we found that student level of procrastination is an important moderator of the negative effect of online teaching on the number of credits acquired. The students who suffered most were those affected by present-bias problems: non-procrastinators reduced their performance by about 2 credits per semester with online teaching while the performance of students affected by present-bias problems was further reduced by about 1.2 credits. The total effect for procrastinators amounted to more than 18% of the semester workload, so indicating a potential delay of approximately two semesters in the expected time of graduation from an online versus a face-to-face five-year degree program.

In Table 6, we have replicated the specifications reported in Table 4 by considering our comprehensive measure of performance as an alternative outcome variable. Again, we found 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 who followed the pre-enrolment procedure) is negative and statistically significant, so pointing to a further reduction of about 1.7 in *Performance* for each unitary increase in the tendency to procrastinate. Results were robust when we used the dummies *D_Procrastination* and *D_Procrastination1* as in Table 5 (results available upon request).

One may wonder whether our results were driven by a differentiated impact of the shift to online teaching brought about by students' different socioeconomic backgrounds. As discussed above, De Paola and Scoppa (2015) showed no significant correlation between this measure of procrastination and family background. In order to further show that this is not the case, we investigated whether the impact of online teaching is related to two indicators of socioeconomic conditions: having an immigrant background and having attended a Lyceum (students from wealthier families in Italy typically attend this academic-oriented type of High School while those from a poorer background tend to enroll in vocational schools [see, for example, Contini & Scagni, 2011]).[29] In order to maximize the number of observations considered in the analysis, we used the *Procrastination1* indicator, but results do not change much if *Procrastination* is considered. As is shown in column (1) of Table 7, where we have added interaction terms between the dummy variable *Immigrant* and *OnlineTeaching, Year2020* and *II Semester* to our controls, the effect of online teaching continues to be particularly negative for students with a tendency to procrastinate and the magnitude of the effect remains very similar to that reported in Table 4. This did not change much even when we included interaction terms between the dummy variable *Lyceum* and *OnlineTeaching, Year2020* and *II Semester* (column 2). In Column (3), we have investigated whether the differentiated effect due to the individual tendency to procrastinate is driven by differences related to individual ability by including the interaction term *High School Grade* and *OnlineTeaching* (together with the interaction terms *High School Grade* Year2020* and *High School Grade* II Semester)*. We found that students endowed with higher abilities are less negatively affected by the shift to online teaching. However, results concerning our main variable of interest do not vary and the coefficient on the interaction term *Online Teaching*Procrastination1* remains of almost the same magnitude as in Table 4. Finally, in column (4) all the interaction terms included in previous columns have been added together. Again, our results are robust to this new specification.

[29] Unfortunately, we have no alternative measures of socio-economic background for the cohorts of students considered in this study.

Table 8
The impact of online teaching by student tendency to procrastinate. Dependent variable: pass.

	(1)	(2)	(3)	(4)	(5)	(6)
Online Teaching	−0.039***	−0.032***	−0.041***	−0.031***	−0.027***	−0.033***
	(0.011)	(0.011)	(0.011)	(0.009)	(0.009)	(0.009)
Online Teaching *Procrastination	−0.020***	−0.019***	−0.016***			
	(0.006)	(0.006)	(0.006)			
Procrastination	−0.016***	−0.011***	−0.014***			
	(0.003)	(0.003)	(0.003)			
Online Teaching *Procrastination1				−0.023***	−0.021***	−0.018***
				(0.006)	(0.006)	(0.005)
Procrastination1				−0.023***	−0.017***	−0.016***
				(0.003)	(0.002)	(0.002)
Students' characteristics	NO	YES	YES	NO	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
Covid-19 Severity	NO	NO	YES	NO	NO	YES
Internet Quality	NO	NO	YES	NO	NO	YES
Observations	45,635	45,635	44,746	57,434	57,434	56,461
Adjusted R^2	0.019	0.043	0.080	0.021	0.050	0.088

Notes: OLS estimates. The dependent variable is *Pass*. Only first-year students. Observations at student-exam level. Standard errors (corrected for heteroskedasticity and allowing 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 9
The impact of online teaching by student tendency to procrastinate. Dependent variable: grade.

	(1)	(2)	(3)	(4)	(5)	(6)
Online Teaching	−0.095	0.045	−0.156	−0.181	−0.105	−0.251*
	(0.169)	(0.168)	(0.164)	(0.138)	(0.137)	(0.134)
Online Teaching *Procrastination	−0.296***	−0.274***	−0.212**			
	(0.087)	(0.086)	(0.084)			
Procrastination	−0.337***	−0.246***	−0.241***			
	(0.043)	(0.039)	(0.039)			
Online Teaching *Procrastination1				−0.270***	−0.225***	−0.172**
				(0.082)	(0.081)	(0.079)
Procrastination1				−0.386***	−0.275***	−0.254***
				(0.040)	(0.037)	(0.037)
Students' characteristics	NO	YES	YES	NO	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
Covid-19 Severity	NO	NO	YES	NO	NO	YES
Internet Quality	NO	NO	YES	NO	NO	YES
Observations	45,635	45,635	44,746	57,434	57,434	56,461
Adjusted R^2	0.012	0.059	0.114	0.013	0.066	0.120

Notes: OLS estimates. The dependent variable is *Grade*. Only first-year students. Observations at student-exam level. Standard errors (corrected for heteroskedasticity and allowing 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.

5.1. Using alternative measures of academic performance

In this section, we study how procrastination influences the effect online teaching has on student probability of passing a given exam and on the grade obtained at each exam (average effects independently of attitudes to procrastination are presented in Tables B1 and B2 of Appendix B).

In order to investigate this issue, we used student-course level observations and restricted the analysis to first-year students who have to attend compulsory courses and have almost no possibility to choose their first-year study plan. In this way, it was possible to determine the structure of courses for each student and to recover the exams that he/she should have passed, but did not (in addition to the observed exams passed). For each student, we created one observation for each exam in his/her university study plan. The alternative of using all the administrative data provided by the university regarding all passed exams would have posed serious self-selection problems as students might have failed a number of exams which are not observable since students have a number of optional courses to choose after their first academic year. Using these data, we 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 for failed exams (the minimum pass mark is 18, results are robust if we use different values lower than 18).[30]

In Table 8, we report estimates of a Linear Probability model in which the dependent variable is *Pass* and, in Table 9, *Grade* has been considered as the dependent variable. The data further support the role of procrastination as a moderator of the impact online teaching has on student performance. We found that students with stronger tendencies towards procrastination are significantly less likely to pass a given exam and tend to obtain lower grades: with online instead of face-to-face teaching, for each unitary increment in the indicator of

[30] 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.

Table 10
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)
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	YES	YES	YES	YES	YES	YES
Course of study FE	YES	YES	YES	YES	YES	YES
Observations	139,738	139,738	139,738	139,738	44,250	44,250
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 first-year 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.

procrastination, the probability of passing the exam diminishes by about 2 additional percentage points and the grade obtained is reduced by about 0.27 points.

6. Synchronous and asynchronous online teaching

By using data at the exam level, we investigated whether synchronous and asynchronous online teaching have been equally effective and whether these different methods have produced differentiated effects on students with a tendency to procrastinate.

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

On the one hand, present-biased students might suffer less when teaching is organized through synchronous sessions since these require more structure, allow less flexibility and self-organization and have greater resemblance to the face-to-face classroom environment. On the other hand, 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 lost time.

In order to investigate this issue, we used data from a survey carried out by the University of Calabria, which asked students about the type of teaching methods used by their instructors for their online classes, given that instructors were free to choose their preferred method to deliver their lectures. In our sample, about 33% of courses were delivered through synchronous online classes, 47% were organized through synchronous classes but also gave students the possibility to follow asynchronously thanks to recorded videos of the online teaching classes. The remaining 20% of courses were delivered through pre-recorded videos.

Using the information on teaching methods, we built two dummy variables *Synchronous* and *Synchronous with Recorded Videos* (the reference category in our regressions will be *Pre-Recorded Videos*) and the interaction terms between these variables and the dummy variable *Online Teaching*. We included these variables among our regressors and alternatively considered the probability of passing the exam and the grade obtained as outcome variables. Results are reported in Table 10.

In columns (1) and (2), both the *Online Teaching*Synchronous with Recorded Videos* and *Online Teaching*Synchronous* interactions have been included and, therefore, *Online Teaching* refers to (asynchronous) *Pre-Recorded Videos*. We found that all three methods of online teaching have negative effects on students' performance. However, the magnitude of the effect is largest (–6.1 p.p.= –3.5–2.6) for the *Synchronous with Recorded Videos* method, intermediate for *Pre-Recorded Videos* (–3.5 p.p.) and lowest for only *Synchronous* lectures (–2.3 p.p.= –3.5 + 1.2). Similar results also emerge when considering the Grade obtained at exams as an outcome variable (column 2).

The same regressions have been run in columns (3) and (4), but all the courses for which recorded teaching classes were made available have been considered as the reference category (that is, we combined *Synchronous with Recorded Videos* with *Pre-Recorded Videos)*. Again, we found that the negative effects of online teaching are more pronounced when classes are delivered or made available 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 presented through synchronous online classes is higher than for those made available asynchronously (column 3). 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 considered the *Grade* obtained at exams as an outcome variable (column 4), we found that the shift to online teaching produces a negative effect exclusively when the presentation method involves the availability of recorded videos, while *Synchronous* online teaching does not produce a negative effect when compared to traditional classes.

In columns (5) and (6), we have analyzed whether the effects of synchronous and asynchronous delivery modes differ according to the attitude of students to procrastinate. With this aim, we have included the interaction terms *Online Teaching*Procrastination* and *Online Teaching*Synchronous*Procrastination* among regressors. Our results show that online teaching negatively affects students with a tendency to procrastinate, especially when the course is presented via synchronous online classes. The interaction term *Online Teaching*Procrastination* is not statistically significant, 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 student probability of passing exams (column 5). A similar pattern is also found for *Grade* (column 6).

All in all, our results show that the effects of synchronous and asynchronous presentation methods are similar for students with a tendency to procrastinate and, if anything, we find suggestive evidence of larger negative effects for synchronous online teaching. Nonetheless, it is worthwhile noting 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 instructor choice, which might correlate with some unobservable characteristics of students or instructors that affect academic performance. Such a bias should not, however, be related to students' tendency to procrastinate, indeed, the students considered in this analysis were first year students who had to attend compulsory courses and instructors were unlikely to select their teaching method according to the procrastination problems of some of their students. Students following courses with video recorded classes had an average procrastination of 0.95 while those following synchronous online classes had an average procrastination of 1.17. This difference, although statistically significant, vanished when we controlled for degree program fixed effects and this supports the idea that the online teaching method is not related to students' tendency to procrastinate.

7. Concluding remarks

In this paper, we have investigated the impact that the switch from traditional classroom learning to online teaching, due to the COVID-19 pandemic, produced on student performance and the heterogeneity of the effect due to the differing levels of tendency students have towards procrastination. Our investigation is important in order to understand better the challenges deriving from online teaching, especially for students with a tendency to delay tasks because they may be the students who are most in need of the commitment of weekly lectures etc. to structure their study efforts. 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 so as to understand the pros and cons of remote learning better.

We took advantage of a very rich administrative dataset which provided information on the careers of four cohorts of students enrolled at a large public university located in the south of Italy. Our identification strategy relied 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, teaching and exams took place face-to-face, just as in previous years. Thus, when comparing the performance of students of two different cohort-year-of-study pairs (one affected by the health emergency and the other unaffected) in the exams taken in the first semester, we identified a pre-treatment difference, while the difference in performance in the exams taken in the second semester, in addition to any pre-treatment gap, included 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 complemented 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 found evidence of a negative impact of online teaching on student performance: online teaching reduced the number of credits acquired over a semester by about 1.4, a significant effect that corresponds to about 0.11 SD of the dependent variable. A negative effect was also found when considering an overall measure of student performance that also considered the grades obtained by students at exams. This result is robust and had a similar magnitude when we controlled for our proxies of local incidence of the COVID-19 health emergency and the quality of internet connections.

A key result that we found 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 there is a lack of face-to-face interactions with instructors and peers. Our evidence confirms the negative effects of procrastination on online learning envisaged by many authors, but supported with little evidence.

We then analyzed whether the presentation method has some effects on procrastinators and we give some suggestive evidence that synchronous classes tend to have worse effects than asynchronous classes for procrastinators: whereas the former method is more similar to face-to-face classrooms, the latter probably allows students who miss lectures and do not study at foreseen times to catch-up later.

Future research might be aimed at understanding whether the results obtained by these students could have been improved through programmes which supported them in their dealing with self-organization problems. A similar attempt was made by Hardt et al. (2020), who used a randomized experiment to investigate the impact of a program offering remote peer mentoring on a sample of German university students who switched to online teaching due to the COVID-19 pandemic. On average, the effects on student performance were not statistically significant, but this does not exclude the possibility that better targeted programmes might represent a valuable instrument in improving the effectiveness of online teaching.

8. Appendix A. descriptive statistics and methodology

8.1. Descriptive statistics at student level

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	23,283	15.531	9.801	0	45.750
Performance	23,283	44.953	29.896	0	158.333
Online Teaching	23,283	0.213	0.184	0	0.5
Master's Degree	23,283	0.253	0.435	0	1
5 Year Degree	23,283	0.121	0.326	0	1
II Semester	23,283	0.481	0.091	0	0.5
Cohort 2016	23,283	0.238	0.426	0	1
Cohort 2017	23,283	0.262	0.440	0	1
Cohort 2018	23,283	0.250	0.433	0	1
Cohort 2019	23,283	0.250	0.433	0	1
Year:2020	23,283	0.439	0.367	0	1
First Year	23,283	0.467	0.382	0	1
Second Year	23,283	0.169	0.200	0	0.5
Third Year	23,283	0.085	0.140	0	0.5
Fourth Year	23,283	0.026	0.078	0	0.5
First Year Master	23,283	0.151	0.294	0	1
Second Year Master	23,283	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	23,283	0.556	0.497	0	1
Age	23,283	22.834	4.490	18	70
High School Grade	23,283	84.789	11.230	60	100
Lyceum	23,283	0.527	0.499	0	1
Immigrant	23,283	0.033	0.178	0	1
Some Province	23,283	0.539	0.498	0	1
Different Province and Region	23,283	0.027	0.163	0	1
COVID-19 and technology related variables					
Red Zone	22,651	0.109	0.312	0	1
% Households: speed 100–1000 Mbps	22,907	0.680	0.245	0	0.995

Notes: Administrative Data from University of Calabria.

8.2. Common trend assumption

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

Fig. A1 plots the average number of credits for each academic year by semester. It shows that students earned a higher number of credits in the second semester on average and that there was a positive trend for both semesters from 2017 to 2019 while, in 2020, the trend became negative for the second semester.

Our sample included three pre-treatment periods so, in Table A2, we conducted a standard test of the validity of the common trend assumption in order to verify whether credits earned by students in the first and second semester changed in a similar way over time. We restricted the analysis to the pre-treatment periods, that is the academic years from 2016/17 to 2018/19, and regressed 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 leaved the 2016/17 academic year as a reference category. In column (1), we have not included control variables while, in column (2), we have added controls for university related variables, 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 and, thus, we may be confident that the common trend assumption is fulfilled. As a further check, we estimated the effect of two placebo (or fake) online teaching treatments: in column (3), we have restricted the sample to the academic years from 2016/17 to 2018/19 and created a placebo online teaching treatment by interacting the dummy for the second semester with the dummy for the year 2019 while, in column (4), we have also

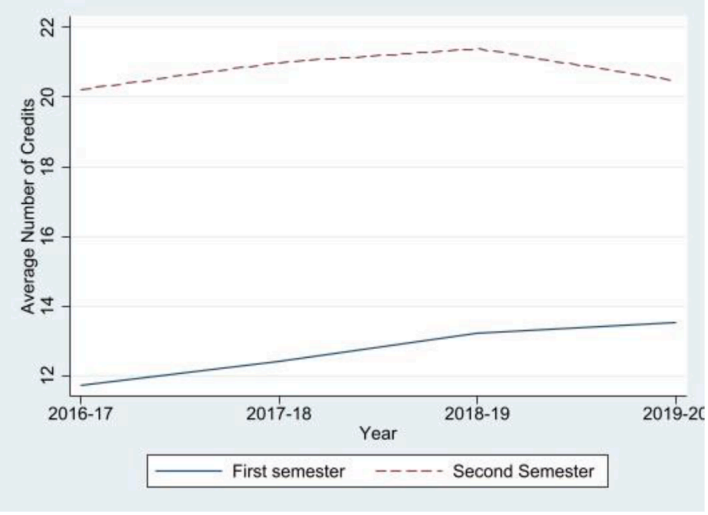

Fig. A1. Average number of credits earned in each semester in the academic years from 2016/17 to 2019/20.

Table A2
Test of the common trend assumption. dependent variable: number of credits.

	(1)	(2)	(3)	(4)
II Semester	8.495***	8.485***	8.488***	8.487***
	(0.225)	(1.094)	(0.709)	(1.094)
Year:2018	0.669***	−0.910		10.624***
	(0.161)	(1.660)		(3.578)
Year:2019	1.478***	−1.836	−0.019	
	(0.155)	(3.156)	(0.436)	
Year:2018*II Semester	0.105	0.004		
	(0.279)	(0.927)		
Year:2019*II Semester	−0.310	−0.393		
	(0.267)	(1.091)		
Placebo Online Teaching 2019			−0.395	
			(0.561)	
Placebo Online Teaching 2018				0.002
				(0.927)
Year dummies	NO	YES	YES	YES
Cohort dummies	NO	YES	YES	YES
Student characteristics	NO	YES	YES	YES
Prov. Res. Dummies	NO	YES	YES	YES
Course of study FE	NO	YES	YES	YES
Observations	62,158	62,158	62,158	32,782
Adjusted R^2	0.108	0.266	0.266	0.272

Notes: OLS estimates. The dependent variable is *Credits*. Standard errors (corrected for heteroskedasticity and allowing 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.

Fig. A2. Performance obtained in academic years from 2016/17 to 2019/20 by semester.

dropped the 2018/19 academic year and created our placebo treatment as the interaction variable between the second semester dummy and the dummy for the year 2018. None of our placebo treatments carries statistical significance and this suggests that our common trend assumption is valid.

In Fig. A2 and Table A3, we report a graphical and econometric test of the common trend assumption using *Performance*.

Table A3
Test of the common trend assumption. Dependent variable: performance.

	(1)	(2)	(3)	(4)
II Semester	24.477***	24.440***	24.400***	24.445***
	(0.672)	(3.248)	(2.070)	(3.249)
Year:2018	1.944***	−2.718		34.131***
	(0.480)	(5.324)		(9.196)
Year:2019	4.538***	−5.419	0.055	
	(0.463)	(10.094)	(1.318)	
Year:2018*II Semester	0.278	−0.060		
	(0.833)	(2.764)		
Year:2019*II Semester	−1.105	−1.358		
	(0.799)	(3.299)		
Placebo Online Teaching 2019			−1.319	
			(1.710)	
Placebo Online Teaching 2018				−0.066
				(2.763)
Year dummies	NO	YES	YES	YES
Cohort dummies	NO	YES	YES	YES
Student characteristics	NO	YES	YES	YES
Prov. Res. Dummies	NO	YES	YES	YES
Course of study FE	NO	YES	YES	YES
Observations	62,158	62,158	62,158	32,782
Adjusted R^2	0.100	0.291	0.291	0.300

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.

8.3. Descriptive statistics: subsample procrastination

In Table A4, we report the descriptive statistics in the subsample of students for which we measure *Procrastination*.

Table A4
Descriptive statistics: subsample procrastination.

Variables	Obs.	Mean	Std. Dev.	Min	Max
University related variables					
Credits	29,868	17.391	12.621	0	48
Performance	29,868	49.327	37.361	0	150
Online Teaching	29,868	0.188	0.390	0	1
Master's Degree	29,868	0.000	0.000	0	0
5 Year Degree	29,868	0.182	0.386	0	1
II Semester	29,868	0.494	0.500	0	1
Cohort 2016	29,868	0.529	0.499	0	1
Cohort 2017	29,868	0.042	0.202	0	1
Cohort 2018	29,868	0.275	0.446	0	1
Cohort 2019	29,868	0.154	0.361	0	1
Year:2020	29,868	0.382	0.486	0	1
First Year	29,868	0.484	0.500	0	1
Second Year	29,868	0.277	0.448	0	1
Third Year	29,868	0.146	0.353	0	1
Fourth Year	29,868	0.093	0.291	0	1
First Year Master	29,868	0.000	0.000	0	0
Second Year Master	29,868	0.000	0.000	0	0
Procrastination	29,868	1.426	1.546	0	6
Procrastination1	29,868	1.426	1.546	0	6
Demographic characteristics					
Female	29,868	0.608	0.488	0	1
Age	29,868	21.676	3.703	18	71
High School Grade	29,868	86.735	10.698	60	100
Lyceum	29,868	0.509	0.500	0	1
Immigrant	29,868	0.026	0.158	0	1
Some Province	29,868	0.538	0.499	0	1
Different Province and Region	29,868	0.018	0.134	0	1
COVID-19 and technology related variables					
Red Zone	29,318	0.111	0.314	0	1
% Households: speed 100–1000 Mbps	29,608	0.681	0.244	0	0.995

Notes: Administrative Data from University of Calabria.

Table A5
Descriptive statistics: subsample procrastination1.

Variables	Obs.	Mean	Std. Dev.	Min	Max
University related variables					
Credits	36,810	17.584	12.699	0	48
Performance	36,810	49.790	37.572	0	150
Online Teaching	36,810	0.196	0.397	0	1
Master's Degree	36,810	0.000	0.000	0	0
5 Year Degree	36,810	0.163	0.369	0	1
II Semester	36,810	0.494	0.500	0	1
Cohort 2016	36,810	0.483	0.500	0	1
Cohort 2017	36,810	0.060	0.238	0	1
Cohort 2018	36,810	0.297	0.457	0	1
Cohort 2019	36,810	0.160	0.367	0	1
Year:2020	36,810	0.398	0.489	0	1
First Year	36,810	0.493	0.500	0	1
Second Year	36,810	0.282	0.450	0	1
Third Year	36,810	0.140	0.347	0	1
Fourth Year	36,810	0.086	0.280	0	1
First Year Master	36,810	0.000	0.000	0	0
Second Year Master	36,810	0.000	0.000	0	0
Procrastination	29,868	1.426	1.546	0	6
Procrastination1	36,810	1.157	1.500	0	6
Demographic characteristics					
Female	36,810	0.563	0.496	0	1
Age	36,810	21.515	3.442	18	71
High School Grade	36,810	86.992	10.650	60	100
Lyceum	36,810	0.534	0.499	0	1
Immigrant	36,810	0.024	0.153	0	1
Some Province	36,810	0.531	0.499	0	1
Different Province and Region	36,810	0.016	0.126	0	1
COVID-19 and technology related variables					
Red Zone	36,215	0.107	0.310	0	1
% Households: speed 100–1000 Mbps	36,542	0.682	0.242	0	0.995

Notes: Administrative Data from University of Calabria.

8.4. Descriptive statistics: subsample procrastination1

In Table A5, we report the descriptive statistics in the subsample of students for which we measure *Procrastination1*.

9. Appendix B. additional analyses

9.1. Pass and grade

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 in each exam, we have stacked data at the student-exam level. We have restricted our analysis to all students enrolled in the first year of a First level Degree because they have to attend mostly compulsory courses and have almost no possibility of choosing their first-year study plan.

In Table B1, we report estimates of a linear probability model in which the dependent variable is *Pass* and, in Table B2, *Grade* is considered as the dependent variable. We found that switching from face-to-face to online teaching significantly reduces the probability of passing a given exam by about 3.2–3.5 percentage points and also lowers the grade obtained of about 0.2–0.3 points.

Table B1
The impact of online teaching on the probability of passing an exam.

	(1)	(2)	(3)	(4)	(5)
Online Teaching	−0.033***	−0.035***	−0.032***	−0.035***	−0.035***
	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)
Year dummies	YES	NO	NO	NO	NO
Cohort dummies	NO	YES	YES	YES	YES
Student characteristics	NO	NO	YES	YES	YES
Prov. Res. Dummies	NO	NO	NO	YES	YES
Course of study FE	NO	NO	NO	YES	YES
Covid-19 & Internet	NO	NO	NO	NO	YES
Observations	143,355	143,355	143,355	143,355	139,360
Adjusted R^2	0.007	0.008	0.032	0.079	0.079

Notes: Linear Probability Model. The dependent variable is *Pass*. Sample: Only first-year students. Observations at student-exam level. Standard errors (corrected for heteroskedasticity and allowing 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 B2
The impact of online teaching on the grade obtained at exams.

	(1)	(2)	(3)	(4)	(5)
Online Teaching	−0.263***	−0.254***	−0.218***	−0.298***	−0.308***
	(0.082)	(0.082)	(0.082)	(0.080)	(0.081)
Year dummies	YES	NO	NO	NO	NO
Cohort dummies	NO	YES	YES	YES	YES
Student characteristics	NO	NO	YES	YES	YES
Prov. Res. Dummies	NO	NO	NO	YES	YES
Course of study FE	NO	NO	NO	YES	YES
Covid-19 & Internet	NO	NO	NO	NO	YES
Observations	143,355	143,355	143,355	143,355	139,360
Adjusted R^2	0.003	0.010	0.049	0.108	0.109

Notes: OLS estimates. The dependent variable is *Grade*. Sample: Only first-year students. Observations at student-exam level. Standard errors (corrected for heteroskedasticity and allowing 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.

Data availability

Data will be made available on request.

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