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# The Impact of the COVID-19 Pandemic on Teaching Outcomes in Higher Education

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# The impact of the COVID-19 pandemic on teaching outcomes in higher education*

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**Abstract**

The COVID-19 pandemic forced much of the world to adapt suddenly to severe restrictions. In this study, we attempt to quantify the impact of the pandemic on student performance in higher education. To collect data on important covariates, we conducted a survey among first-year students of Microeconomics at the University of Cologne. In contrast to other studies, we are able to consider a particularly suitable performance measure that was not affected by the COVID-19 restrictions implemented shortly before the start of the summer term 2020. While the average performance improves in the first term affected by the restrictions, this does not apply to students with a low socioeconomic background. Trying to identify more specific channels explaining this finding, interestingly, our data yield no evidence that the average improvement results from the altered teaching formats, suggesting instead that the enhanced performance stems from an increase in available study time.

***JEL Codes***: I24, I230, I310, I240, A220
***Keywords***: COVID-19, Higher Education, Wellbeing, Education and Inequality, Introductory Economics.

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# 1 Introduction

The COVID-19 pandemic has enormous effects on our economy and social life.[1] Partial and full lockdowns and social distancing forced universities to offer nearly their full teaching portfolio in a digital format. Among many other challenges, the pandemic implies less social contacts and forces students to cope with more autonomy due to the new online teaching formats.[2] Survey results of Aucejo et al. (2020) and Jaeger et al. (2021) indicate that the effects on students are multifaceted. Many students lose their jobs or internship opportunities. Moreover, some decrease their weekly study time, while others report an increase. The impact also seems to differ with respect to the socioeconomic background. Given these results and the ongoing debate in politics about the continuation of university closures, it is natural and important to quantify the effect of the pandemic on students' learning outcomes.

In this paper, we evaluate empirically the effect on students who participated in the courses *Principles of Microeconomics* and *Microeconomics for Business* ('Grundzüge der Mikroökonomik' and 'Mikroökonomik für BWL', respectively) in the Bachelor programs at the University of Cologne in Germany since the 2019 summer term. Our outcome of interest is the students' performance in weekly online exercises, which allow them to improve their final exam scores. We complement our data on the students' performance with data from a survey to control for important confounders. Our survey shows that students tend to be more depressed, have worse exmployment opportunities, and are more likely to live with their parents during the pandemic. We find that the students' performance increases on average. Next, we try do identify the channels leading to this outcome. Thus, we are especially interested in the effect online learning had on performance in times of the pandemic. While we find overall no measurable effect, we find the best quartile of students to profit less from high participation in teaching formats during the pandemic. Moreover, we find that students with a low socioeconomic background fared worse during the pandemic.

Our paper contributes to the literature dealing with the impact of the pandemic on students, which can be further divided into two strands. The first one mainly looks at the impact on students in schools, while the second one focuses on higher education. Moreover, we add evidence to the general literature in economics analyzing the impact of online teaching on student outcomes. Studies by Grewenig et al. (2020) and Agostinelli et al. (2020) analyze the effect of the COVID-19 pandemic in terms of school closures on students in schools. They both argue that low-skilled students are particularly negatively affected.

Gonzalez et al. (2020) is one of two other studies so far to measure the impact of the pandemic on students' performance in higher education. In line with our results, they find a positive effect and trace this back to more efficient learning strategies. However, our study extends their analysis, as our survey results, as well as other confounders, allow us to go beyond a simple mean comparison of treatment and control group.[3]

Rodríguez-Planas (2020) analyze the effect of the pandemic on students' performance as well.

[1] See Baldwin and Weder di Mauro (2020) for a book discussing the multifaceted impact of the pandemic.

[2] First studies show that the pandemic leads to psychological distress for university students. See, for instance Cao et al. (2020).

[3] Furthermore, our outcome variable is more objective because Gonzalez et al. (2020) need to normalize their test scores across terms. In contrast, our bonus point questions are identical across terms and thus easily comparable.

Assuming parallel trends of both groups they apply a difference-in-difference approach to calculate differences in performance changes of high-and low-income students. Thus, they rather focus on the analysis of heterogeneous effects. In line with our results, they find a positive overall effect. However, in contrast to their study, we are able to use an objective performance measure, which has not been subject to change during the pandemic.

Moreover, our study complements the one of Aucejo et al. (2020), Rodríguez-Planas (2021) and Jaeger et al. (2021). They issued a survey and find large negative effects for students in terms of experiences and future expectations (i.e., employment opportunities). Our study supplements the survey results with quantitative evidence in terms of impact on students' performance.

The effect of online learning methods in higher education on teaching outcomes has already been studied for a long time in the economic literature. There exist many descriptive studies (see Means et al. (2010) for a meta-analysis), which in their majority suggest a positive relationship between online teaching methods and student outcomes. However, many of these studies do not account for self-selection effects, as a result of which students with characteristics that are particularly important for success in digital learning environments choose to participate in online courses (see Coates et al. (2004)). To overcome this drawback, newer studies use instrumental variable approaches, quasi- or experimental settings to estimate causal effects. Coates et al. (2004), Bettinger et al. (2017) and Xu and Jaggars (2013) all use IV approaches. While the latter two studies suggest negative effects on student outcomes, the study by Coates et al. (2004) finds positive effects. Experimental evidence is provided by Figlio et al. (2013), Joyce et al. (2015), Bowen et al. (2014) and Alpert et al. (2016).[4] Their results are ambiguous as well. Figlio et al. (2013) and Alpert et al. (2016) conclude that live teaching is superior to online formats in terms of student performance, while Joyce et al. (2015) find no significant difference. According to Bowen et al. (2014), hybrid systems have the potential to achieve at least equivalent outcomes. Another recent study is conducted by Cacault et al. (2019). They find that online livestreaming of classes increases the performance of high-achieving students, while the opposite is true for low achievers.

However, it should be noted that our study is not intended to measure the effects of the switch to online formats, but rather to evaluate the success of the newly introduced teaching formats in times of pandemic. Although the pandemic is clearly an exogenous shock, it is not a clean natural experiment that allows researchers to evaluate causal impacts of the newly introduced educational policies in universities around the world. As pointed out by Bacher-Hicks and Goodman (2020), the shock affects the outcome of interest (students' performance) not only via online teaching, because it is likely that the pandemic causes changes in other factors that are equally important in determining student performance as well.[5] Nevertheless, it is possible to measure the impact of the pandemic as a whole and to estimate the effect of online teaching in times of COVID-19. Given the high relevance of the topic, we think it is important to examine the effects of these policies ex-post.

Our study design has three advantages compared to other studies. First, we have an objective outcome measure, as weekly online exercises are identical in the treatment and in the control

[4]The studies by Figlio et al. (2013), Joyce et al. (2015) and Bowen et al. (2014) analyze the impact of online teaching on students in a Microeconomics course, too.

[5]In econometrics this is known as a violation of the so-called exclusion restriction for instruments.

group and are thus easily comparable. Second, in contrast to other studies, we observe the students' performance repeatedly, which allows for a more precise measurement of learning outcomes then, for instance, the performance in the final exam, which is only observed once per term. Third, the high response rate in our survey allows us to control for important confounders as well as the analysis of heterogeneous effects. In contrast to other studies, this allows us to analyze heterogeneities which go beyond differences in performance, but rather focus on differences in the personal background of students.

The structure of the paper is as follows. In the next section, we describe our data and explain the different teaching formats. Section three contains the main analysis as well as the analysis of heterogeneous effects. Section four concludes the analysis.

## 2 Online teaching and data

To understand our research design better, we provide more information in this section about the groups of students we consider and explain the different teaching formats that are applied in the courses.

### 2.1 Students

Both courses are organized by the same lecturers in the University's Department of Economics. The majority of the participants were undergraduate students at the Faculty of Management, Economics and Social Sciences at the University of Cologne. While *Principles of Microeconomics* is a mandatory first year course in the Majors *Economics* and *Social Sciences*, it is also an elective course in the Majors *Mathematics* and *Mathematical Economics* at the Faculty of Mathematics and Natural Sciences. *Microeconomics for Business* is a mandatory first-year course for students of *Business Administration*. Our data set consists of 664 observations, mainly comprising students of Business (66%), Economics (19%) and Social Sciences (14%).[6]

### 2.2 Teaching

While *Principles of Micreconomics* and *Microeconomics for Business* were distinct courses in the terms we are considering, in previous years all students were jointly taught in one course. Since both modules are still organized by the same lecturers, the way of teaching does not differ between the groups. There are minor differences in the focus of contents which, however, do not affect our analysis in this paper.[7] In particular, our measure for the students' learning progress during the term, which will be discussed in more detail in the following subsection, is identical for both groups. Hence, in the following we will treat our data as if all considered students took the same introductory course in Microeconomics and simply refer to it as *Microeconomics*.

The course consists of several complementary teaching formats. As is standard practice for most introductory courses at the University of Cologne, a ninety-minute *lecture* held by the Professor

[6] More details on the students' majors and the University's Bachelor programs can be found in the Appendix.

[7] In all considered terms, the differences are mainly restricted to a differing emphasis on some of the concepts. In particular, note that in every written examination, which accounts for 100% of the final grade, at least 96% of the points to be achieved were awarded for solving the exact same exercises.

is offered twice a week for all students participating in the course. The lectures are conducted as "chalk and talk" teaching and present the concepts covered by the course in a rather abstract and theoretical manner. After the students have seen the material for the first time in the lecture hall, they can review it in voluntary online practice questions that are conducted via the university's online learning platform. Apart from their own learning benefit, there is no explicit incentive for the students to take part in these questions regarding the final grade.

Additionally, students have the opportunity to visit a *tutorial*. Tutorials are ninety-minute sessions taking place once a week in smaller groups. In this teaching format, students work on basic exercises about the material covered in the previous lectures. They work on the exercises on their own or in groups of up to four students, presenting their results to the group. Tutorials are supervised by student teaching assistants, who are more experienced students in at least their second year of studies. They receive detailed teaching instructions directly from a senior lecturer. The prerequisite to get the position is, in addition to a good overall grade point average, a very good exam result in Microeconomics.

After the tutorial, students can participate in *online exercises* on material already covered in other formats. Correct solutions to these exercises are awarded with bonus points for the exam, which can possibly improve the students' final grade. Since the number of correct solutions in this teaching format is our main measure for the students' learning progress, the following section explains these in more detail.

The last teaching format in this course is the *exercise session*, which is a ninety-minute session that usually takes place every second week during the term conducted by PhD candidates at the Department of Economics or senior lecturers. The main purpose of this format is to discuss solutions of the online exercises and generally to review the covered material by solving more sophisticated exercises on the presented concepts.

Due to the pandemic, it was not possible to have any sessions in a lecture hall since March 2020 and therefore the teaching formats were adapted immediately at the start of the summer term in April 2020. While the online review questions as well as the incentivized online exercises were already conducted via the university's online learning platform, the former classroom events moved to digital formats. Live tutorials and exercise sessions were offered via the video conference software Zoom without changing the teaching style in these sessions. On the other hand, the lecture format changed slightly. Instead of the professor talking in front of the students at the university, the lectures were replaced by uploaded and prerecorded video shots in which the professor explained the concepts as he would in a 'real' lecture, but without any interaction with the students. While the content of the lecture remained unchanged in the adaptation to the online teaching format, a stronger emphasis was placed on advising students to read a standard textbook on Intermediate Microeconomics, which had already been recommended in previous semesters, however. Since online exercises were part of the teaching concept already before the pandemic, the general organization of the course as well as the materials remained largely unchanged.

Before and during the restrictions due to the COVID-19 pandemic, all teaching formats, including the incentivized online exercise sessions, were voluntary. As it is common practice in introductory courses at the faculty, the only mandatory appointment for a student to pass the module is the final written examination which constitutes 100% of the final grade. It is not monitored either whether students attend any of the classes during the term.[8]

### 2.3 Outcome measure

Within a teaching project initiated by the Department of Economics at the University of Cologne, voluntary, but incentivized, online exercises have been part of *Microeconomics* since the summer term 2018. During the whole term, once per week, students can hand in solutions to exercise questions via the university's online learning platform.[9] Each exercise covers material that was the subject of the previous lectures and tutorials. Although feedback regarding the achieved points is immediately given by an automated evaluation system after submitting the answers, it is not possible to copy solutions to these exercises from fellow students in the course, as the exercises contain randomized parameters.[10] Depending on the number of correct answers, students receive up to six bonus points, that is, up to six points which are automatically added to the score of the final exam in case the exam is passed.[11]

Since these online exercises have not changed due to the pandemic, the students' achievements in these exercises serve as an objective outcome measure, which ensures comparability between terms that are affected by the adaptation of the teaching formats due to the COVID-19 restrictions and terms before the pandemic. It should be emphasized that using the students' success in the bonus point exercises as the outcome variable has many advantages compared to the perhaps more common approach of using the exam results. While final examinations vary not only regarding the difficulty and the choice of content between terms, they also differ regarding the date the exam takes place and therefore are subject to possibly severe differences in the students' time to prepare for the examination.[12] In addition, the format of the exam changed from a pen-and-paper to an online format. This made participation during the pandemic much easier compared to before, which, together with the fact that failing the exam no longer had any consequences[13], led to many more people sitting the exam compared to the previous semester. Thus we likely would have a selection bias in the exam result data. Since the online exercises

[8] In fact, it is explicitly communicated that attendance is not mandatory in any of the classes. Although in higher years, in some courses, it is at least implicitly expected from students to participate actively in classes, this is not the case in first-year courses of undergraduate programs considered here.

[9] In total there are twelve sets of exercise questions such that students can hand in solutions each week, starting in the second week of the term.

[10] In one of the exercises, for example, students had to derive the optimal supply function of a firm, but for each student the firm faced a slightly different cost function.

[11] If a student solves all questions in a week's exercise correctly, one point is added to his bonus point account. Partially correct answers are awarded with a fraction of the bonus point. At the end of the term, bonus points are converted to additional exam points according to a scale that is published at the beginning of the semester. The distribution of points for each question as well as the scale remains unchanged across terms. In summer term 2019 and winter term 2019/20, a total number of ninety points could be achieved in the final exam, while only sixty points could be achieved in the following summer term 2020 and winter term 2020/21. This means that the percentage of the maximum number of exam points increased during the pandemic. However, it seems plausible that from the students' point of view the incentive to work on the exercises was not affected by this change, since usually students are not aware of the total number of points in the exam and even less aware of a change over time. Furthermore, the only relevant grade for the GPA is the final grade, for which the scale from achieved exam points to the final grade changes between terms and is not published in any term.

[12] At first, this might not be considered too much of a major problem when comparing the number of days between the exam and the lecture; however, at least in our anecdotal experience at the University of Cologne, in some terms the majority of the students have to take several exams in a short period, while in other terms students have no other exam to prepare in a few weeks.

[13] Usually, students can only fail an exam thrice before being expelled. This rule was suspended during the pandemic.

have to be solved during the term given a fixed (and, between terms, identical) syllabus, our outcome measure is not subject to any such differences.

Throughout our analysis, the terms before the pandemic serve as a control group, while the following terms serve as a treatment group. In order to make sure that our results are not affected by any seasonal effects, in the main part we restrict our analysis to a comparison of the summer terms, which are the summer term 2019 as the control group and the summer term 2020 as the treatment group.[14]

## 2.4 Survey

To be able to control for important confounders that may have influenced the performance of students, we conducted a survey. This survey was sent to all students from the summer term 2019, winter term 2019/2020 and summer term 2020. In total, we sent an invitation to $2,068$ students and received 664 replies. This yields a response rate of 32.1%. The survey is designed to control for attendance in different teaching formats, exchange with fellow students, socioeconomic status, and changes in psychological wellbeing.[15] As our main analysis is restricted to both summer terms, the following description and summary statistics exclude data from the winter term 19/20.

Since attendance is not mandatory in any classes at the University of Cologne, we ask students to provide information about the frequency of their attendance in lectures, exercise sessions and tutorials.[16] Moreover, since a stronger emphasis was placed during the pandemic to read an additional standard textbook, we used the survey to ask students about the use of additional literature and online resources. Table 1 shows summary statistics for the aforementioned questions. For lectures, exercise sessions and tutorials, we do not see a large difference in terms of average attendance. However, we observe that students on average nearly doubled the use of a textbook as an additional resource.

It is well known in the literature that peer effects play an important role in academic success (Sacerdote, 2011). Learning groups are a specific channel via which peer effects may occur. We also collected information about whether students were part of a learning group, whether they perceived it as difficult to form one, and about the frequency of exchange within this group. Additionally, we asked about the frequency of general informal exchange with fellow students. The percentage of students who were part of a permanent learning group is four percent lower in the summer term 2020, compared to the summer term 2019. Moreover, nearly five percent of the students perceived it as more difficult to form a learning group in the summer term 2020. However, when students were part of a learning group, the frequency of their meetings did not seem to change. We observe the same for informal exchange (see Table 2).[17]

Table 2 shows summary statistics for two more survey items. We asked students about their

[14] The summer term 2019 took place from April 01 until July 17, 2019, while the summer term 2020 started on April 20, and ended on July 17, 2020.

[15] The whole survey can be found in the Appendix.

[16] All questions on frequency use a five-item Likert scale, which means that questions can be answered with *never, rarely, often, very often* and *always* (see Robinson (2014)).

[17] We have no information about particular groups that were formed. Thus, we are not able to estimate any kind of peer effects. As we asked students about the frequency of their meetings and assumed that the selection process was the same across terms, we may overcome associated endogeneity problems and are able to estimate whether the effectiveness of group meetings may change. However, this is not the main objective of our analysis.

| | Mean | Std.Dev. | P25 | P75 | N |
|---|---|---|---|---|---|
| **Summer Term 2019** | | | | | |
| Attendance lecture | 3.41 | 1.36 | 2 | 5 | 228 |
| Attendance exercise | 3.36 | 1.31 | 2 | 5 | 228 |
| Attendance tutorial | 3.32 | 1.40 | 2 | 5 | 228 |
| Intensity using book | 1.44 | 0.78 | 1 | 2 | 228 |
| Online resources | 2.28 | 1.05 | 1 | 3 | 227 |
| **Summer Term 2020** | | | | | |
| Attendance lecture | 3.38 | 1.47 | 2 | 5 | 256 |
| Attendance exercise | 3.22 | 1.46 | 2 | 5 | 256 |
| Attendance tutorial | 3.27 | 1.50 | 2 | 5 | 256 |
| Intensity using book | 2.61 | 1.33 | 2 | 4 | 256 |
| Online resources | 2.25 | 1.09 | 1 | 3 | 256 |

Table 1: Summary statistics for attendance-related questions

| | Mean | Std.Dev. | P25 | P75 | N |
|---|---|---|---|---|---|
| **Summer Term 2019** | | | | | |
| Engagement for studies | 3.61 | 0.95 | 3 | 4 | 228 |
| Cancel studies thoughts | 1.87 | 1.16 | 1 | 2 | 228 |
| Exchange with peers | 4.16 | 0.86 | 4 | 5 | 228 |
| Intensity learning group | 3.89 | 0.95 | 3 | 5 | 61 |
| **Summer Term 2020** | | | | | |
| Engagement for studies | 3.57 | 0.98 | 3 | 4 | 256 |
| Cancel studies thoughts | 1.90 | 1.24 | 1 | 2 | 256 |
| Exchange with peers | 4.12 | 0.96 | 4 | 5 | 256 |
| Intensity learning group | 3.69 | 0.90 | 3 | 4 | 58 |

Table 2: Summary statistics for engagement and exchange

subjective perception of effort spent for studying as well as about the frequency of thoughts spent on canceling their studies. We observe no significant difference for either of the survey items across terms.

It is well-known that the socioeconomic background is an important determinant of academic success in higher education (Jury et al., 2017). Social economic status only plays a role in our main analysis in case there is an imbalance between treatment and control group.[18] Table 3 shows that this is not the case. We measure socioeconomic background by the highest educational achievement of at least one parent. Table 3 shows the results. We see that in both terms roughly $60-70\%$ have at least one parent with a university degree, while only roughly 5% of the students have parents without a university diploma or vocational training. Even though this is not important for the main part, it allows us to check for heterogeneous effects.

Many studies show that the pandemic and especially the social distancing has an influence on psychological wellbeing. In case the students' performance decreases during the pandemic, one may think of a decrease in subjective wellbeing as a potential channel. To account for changes in mental state, we conducted the positive and negative affection schedule (PANAS), as well

[18]Additionally, the GPA in university entrance exams is typically strongly correlated with social economic status.

| | Summer 2019 | | Summer 2020 | |
|---|---|---|---|---|
| Parents' level of education | Absolute value | in % | Absolute value | in % |
| University diploma | 137 | 60 | 173 | 68 |
| Vocational training | 79 | 35 | 66 | 26 |
| None | 11 | 5 | 16 | 6 |
| Sum | 227 | - | 255 | - |

Table 3: Survey results on SES

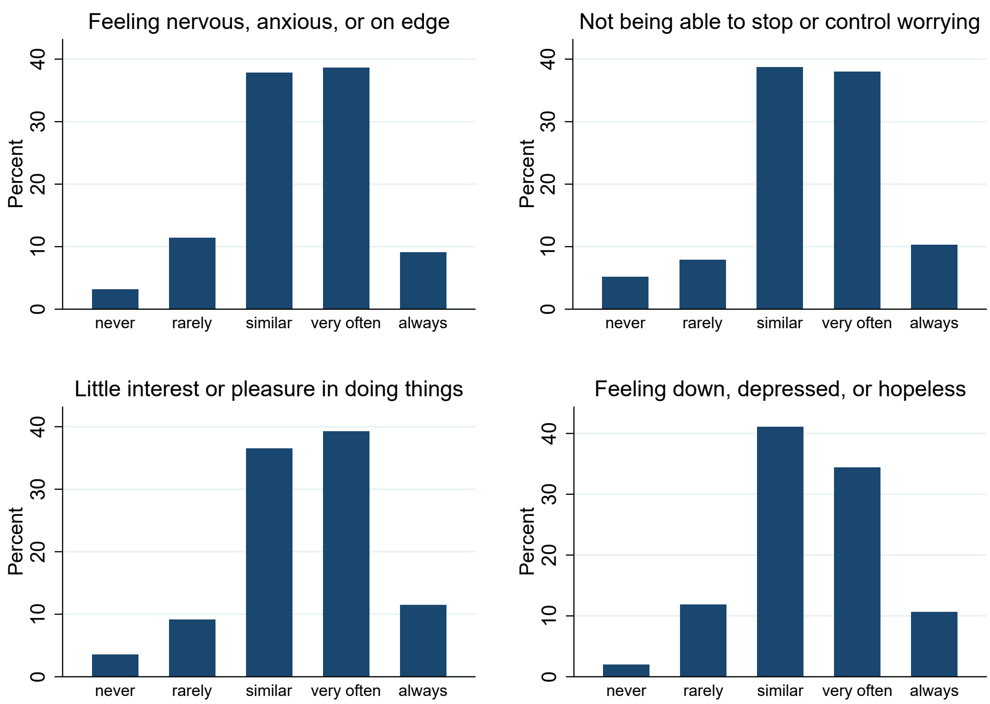


Figure 1: PHQ-4 summary for students of the summer term 2020.

as the PHQ-4 questionnaire.[19] However, we lack status-quo inquiries of the students before the pandemic started and it is difficult to measure psychological wellbeing retrospectively (see Kahnemann and Krueger (2006)). To tackle this problem, we adapt this framework, asking instead for the relative change in the frequency of certain feelings and thoughts compared to before the pandemic started.[20]

Figure 1 represents the relative frequency of feelings or thoughts described in each of the four questions of the PHQ-4 compared to the point in time before the pandemic started. We see that roughly 50% of the students of the summer term 2020 feel more nervous or anxious. The same

[19]See Breyer and Bluemke (2016) for details on the PANAS questionnaire and Löwe et al. (2010) for details on the PHQ-4 questionnaire. Both papers show the respective German versions. While the PANAS questionnaire tries to measure subjective wellbeing in terms of the emotional state, the PHQ-4 questionnaire measures the level of depressiveness.

[20]We are aware that this comes with measurement errors. However, we believe that this is the best we can do under the given circumstances. We still ask these questions to the students of the control group and check that the distribution of answers is not much different compared to the answers of the treatment group. This justifies the assumption that the counterfactual of the treatment group would have been the baseline score, i.e., assuming that the average psychological wellbeing of students of both cohorts would have been the same without the rise of the pandemic.

pattern can be observed for worrying, interest or pleasure in doing things, and feeling depressive in a more narrow sense. This can be seen as suggestive evidence that the pandemic in general caused an increase in depressiveness.

## 3 Effects of the pandemic

As a baseline model, we estimate the overall effect of the pandemic on learning outcomes. We use a simple linear-regression model of the following form:

$$y_i = \beta_0 + \beta_1 \mathbb{I}_{C,i} + \gamma \mathbf{x_i} + \varepsilon_i. \tag{1}$$

Here, $y_i$ denotes the share of online exercises student $i \in N$ solved correctly, $\mathbb{I}_{C,i}$ is a dummy for whether these points were achieved in times of the pandemic, $\mathbf{x_i}$ are exogenous controls, and $\varepsilon_i$ denotes the error term. The results can be found in Table 4.

| | (1)<br>Points (share) | (2)<br>Points (share) | (3)<br>Points (share) |
|---|---|---|---|
| COVID-19 | 0.079$^{**}$ | 0.068$^{**}$ | 0.057$^{*}$ |
| | (0.034) | (0.032) | (0.031) |
| High-school GPA | | 0.203$^{***}$ | 0.145$^{***}$ |
| | | (0.027) | (0.027) |
| Advanced math in school | | -0.001 | 0.001 |
| | | (0.032) | (0.031) |
| Parents w/ college | | | -0.025 |
| | | | (0.033) |
| Male | | | 0.039 |
| | | | (0.030) |
| Economics$^{\ddagger}$ | | | -0.243$^{***}$ |
| | | | (0.063) |
| Social science$^{\ddagger}$ | | | -0.187$^{***}$ |
| | | | (0.047) |
| Other$^{\ddagger}$ | | | -0.505$^{***}$ |
| | | | (0.073) |
| Constant | 0.588$^{***}$ | -0.014 | 0.213$^{**}$ |
| | (0.024) | (0.085) | (0.090) |
| Observations | 438 | 438 | 438 |
| Adjusted $R^2$ | 0.010 | 0.118 | 0.213 |

Robust standard errrors in parentheses. $^{*}$ $p < .1$, $^{**}$ $p < .05$, $^{***}$ $p < .01$
$^{\ddagger}$ Reference category is business studies

Table 4: Baseline model: OLS results

Just including the COVID-19-dummy, we find a sizable and significant positive effect on learning outcomes, suggesting that overall students performed roughly 8% better during the pandemic compared to the previous summer term. However, this model has almost no explanatory power, as suggested by the very low adjusted $R^2$. As soon as we control for students' GPA[21] or whether they took an advanced mathematics class in high school, the effect shrinks to 6.8%. This suggests

[21] The German grade scale goes from 1, being the best, to 5, being the worst. However, for a more intuitive interpretation and to make it more easily comparable with international grading scales, we have converted it to the US GPA scale from 0 to 4. Hence, now a better grade is associated with a higher number.

that the positive effect is partially driven by a difference in student-body composition in terms of ability. In particular, the GPA is a very good predictor for student performance, as the significant better fit also suggests. The regression presented in the third column includes further control variables such as gender, choice of major,[22] as well as socioeconomic background, proxied by whether at least one of their parents has a college degree. The point estimate for the effect of the pandemic shrinks a little further, and is now only weakly significant, but the additional variables lead to a much better model fit. Interestingly, neither gender nor the socio economic status control (i.e. college degree of parents) has a significant effect on the performance.

It is possible that these linear regression models are misspecified, as the outcome variable $y$ is a share, and as such bounded between 0 and 1. Yet, in the first two regressions, all predicted values fall into the respective range and in the last model 98.74% of the predictions do. Nevertheless, we repeat the regressions presented here using a GLM with a logit link and the binomial family, as suggested by Papke and Wooldridge (1996), in a robustness check. The GLM estimation results are qualitatively the same, suggesting that the boundedness of $y$ is not a serious source of bias, which can be seen in Table 9 in the appendix.

### 3.1 The effect of online teaching in times of the pandemic

The baseline results suggest that, overall, the pandemic has a small positive effect on students' performance. However, it is unclear which channels are responsible for these results, as many aspects of the students' lives changed simultaneously. As noted before, besides the switch to online learning, the psychological wellbeing of students has especially changed, but also their employment situation and whether they live on their own or with their parents. All of these factors are not only outcomes of the pandemic, but also very likely affect students' performance. Furthermore, as noted in Section 2.2 above, a significant share of students does not attend lectures or other teaching events. It stands to reason that those students cannot possibly be affected by the switch to online teaching, but of course the attendance measure itself could be impacted by the pandemic. To try first to isolate the effect of different intensities of attendance in online teaching formats in times of the pandemic, we estimate the following model:

$$y_i = \beta_0 + \beta_1 \mathbb{I}_{C,i} + \beta_2 \text{attend}_i + \beta_3 \text{attend}_i \times \mathbb{I}_{C,i} + \gamma \mathbf{x_i} + \varepsilon_i. \tag{2}$$

The model now includes an interaction term between attendance (*attend*) and the pandemic-dummy. We want to estimate the success of online teaching formats in times of the pandemic by estimating how different levels of participation affect the total bonus points scored. We argue that only those who actually attended the teaching units can possibly be affected by the switch to online teaching, while other channels should work more universally.

Note that it is possible that attendance is in itself affected by the pandemic. For another, the sorting into high and low attendance is not at all random; rather it is likely that better students are also more likely to attend. This gives rise to the possibility that selection effects matter here, i.e., that only the better students attended during the pandemic, thereby biasing our estimate. To make sure this is not the case, we first plot the attendance measures by

[22] In the German university system, students have to decide on their major and minor when applying for admission, and their studies almost exclusively consist of courses of that major and minor.

GPA, where we find no systematic difference between terms (see Figures 6-9 in the Appendix). Second, we also estimate a regression with attendance as the dependent variable, where the pandemic term has an insignificant effect, both statistically and economically, on attendance. Therefore, the interaction term should give us a proper measure of how much attendance in online teaching formats during the pandemic mattered compared to classical formats before the pandemic started.

As mentioned before, we measure three dimensions to attendance: Whether students attended the lecture or watched the lecture videos, whether they attended the (online) exercise sessions and whether they attended the (online) tutorials. Yet, including them all in a regression would be unwise, for two reasons: First, this would presumably result in collinearity because a student's attendance in different parts of the module is likely to be highly correlated.[23] Second, including all three measures, each of which has five parameter values, would lead to a total of 12 interaction terms, making the model very unwieldy and lowering the degrees of freedom. Instead, we use principle component analysis (PCA) to construct a single variable, which retains most of the original variables' variance, the results of which can be found in Table 10 in the Appendix. Using the loading of the first component as weights, we calculate a linear combination of the three attendance measures, which does capture about 73% of their variance[24] and is therefore used as the attendance measure from here on. Intuitively, this is very similar to just adding all three attendance measures together, since the weights are almost identical, and then normalizing the sum. To check whether this measure is indeed a valid control, we regressed the attendance measure on the COVID-dummy, the results of which suggest there is no evidence to assume attendance was affected by COVID (see Table 8)[25].

Using this, we estimate the model in Equation (2), while controlling for other possible outcomes of the pandemic, the results of which are shown in Table 5. It seems we have controlled for all available explanatory variables that might be considered as an outcome of the pandemic, as the coefficient estimates for the COVID dummy are all very close to zero, and far from statistical significance[26]. As one would expect and hope, higher attendance does lead to better teaching outcomes. Specifically, a 1% higher attendance does lead to about 0.4% more points, *ceteris paribus*. The interaction effect between attendance and the pandemic-dummy on the other side is positive in all specifications, but never statistically significant and also very small. The point estimates range between 0.01 and 0.07, implying that the effect of 1% higher attendance is only about 0.06% percentage points more effective during the pandemic compared to offline teaching before the pandemic, which is very close to a null result, especially given the statistical uncertainty.

It therefore seems likely that the enhanced performance of students in the first COVID term had different causes. One likely reason is students having more time on their hands to study,

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[23] This is indeed the case; the correlation between attending the lecture and attending the exercise/the tutorial are 0.58 and 0.54, respectively. The correlation between attending the exercise and attending the tutorial is 0.67.

[24] The first component is also the only one with an absolute eigenvalue above one, satisfying the Kaiser criterion. The linear combination is then scaled such that all values lie between zero and one, allowing for an easier interpretation.

[25] A similar conclusion can also be drawn from the fact that the correlation between COVID and Attendance is only -0.0235, with an associated $p$-value of 0.6235.

[26] To make sure the inclusion of attendance is not the reason the COVID term is no longer significant we also estimated Equation (2) without the interaction term. The results can be seen in Table 11 in the Appendix and indeed confirm that the inclusion of attendance does not qualitatively change the estimates.

| | (1) Points (share) | (2) Points (share) | (3) Points (share) | (4) Points (share) | (5) Points (share) |
|---|---|---|---|---|---|
| Attendance | 0.456*** | 0.450*** | 0.421*** | 0.404*** | 0.398*** |
| | (0.074) | (0.075) | (0.074) | (0.074) | (0.073) |
| COVID-19 | 0.064 | 0.096 | 0.098 | 0.086 | 0.083 |
| | (0.070) | (0.071) | (0.070) | (0.071) | (0.071) |
| COVID-19 × Attendance | 0.023 | 0.003 | 0.007 | 0.010 | 0.009 |
| | (0.098) | (0.098) | (0.096) | (0.095) | (0.097) |
| High-school GPA | 0.104*** | 0.109*** | 0.114*** | 0.099*** | 0.099*** |
| | (0.024) | (0.024) | (0.024) | (0.025) | (0.025) |
| Economics‡ | -0.242*** | -0.255*** | -0.223*** | -0.214*** | -0.230*** |
| | (0.058) | (0.055) | (0.056) | (0.058) | (0.059) |
| Social science‡ | -0.131*** | -0.143*** | -0.141*** | -0.137*** | -0.142*** |
| | (0.045) | (0.045) | (0.044) | (0.045) | (0.045) |
| Other‡ | -0.462*** | -0.469*** | -0.470*** | -0.480*** | -0.489*** |
| | (0.077) | (0.079) | (0.079) | (0.077) | (0.078) |
| Change in neg. affection | | 0.003 | | | |
| | | (0.048) | | | |
| Change in pos. affection | | 0.125*** | 0.089*** | 0.094*** | 0.092*** |
| | | (0.043) | (0.033) | (0.034) | (0.034) |
| PHQ4 | | 0.010 | | | |
| | | (0.010) | | | |
| High interaction | | | 0.078*** | 0.086*** | 0.083*** |
| | | | (0.028) | (0.027) | (0.027) |
| Part-time job | | | | -0.076*** | -0.080*** |
| | | | | (0.028) | (0.029) |
| Parents w/ college | | | | -0.005 | |
| | | | | (0.030) | |
| Gender | | | | 0.021 | |
| | | | | (0.028) | |
| Adv. math in school | | | | 0.022 | |
| | | | | (0.027) | |
| Living alone§ | | | | | -0.061 |
| | | | | | (0.043) |
| Shared flat§ | | | | | -0.005 |
| | | | | | (0.029) |
| Constant | 0.062 | 0.054 | 0.021 | 0.096 | 0.142 |
| | (0.084) | (0.083) | (0.084) | (0.097) | (0.091) |
| Observations | 438 | 438 | 438 | 438 | 438 |
| Adjusted $R^2$ | 0.356 | 0.366 | 0.376 | 0.383 | 0.387 |

Robust standard errrors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$
‡ Reference category is business studies, § Reference category is living with parents

Table 5: The effect of online teaching: OLS results

since many popular spare time activities, such as partying, team sports, or going to the cinema could not take place during the pandemic. We will explore this hypothesis in more detail later. However, it is substantiated by the fact that having a part-time job does indeed have a negative effect on performance. In terms of psychological wellbeing, only the change in positive affection seems to affect a student's performance. This is interesting, as we found a significant change during the pandemic in all three measures, although this might be due to multi-collinearity, as unsurprisingly all three measures are highly correlated. To circumvent this issue, we only include the change of positive affection in the following regressions, as it has the highest explanatory power of these three measures.[27] It is also possible that the pandemic could have affected how much students interact with each other. We therefore control for this with a dummy indicating whether a student reported to have talked *often* or *very often* about the content of the course with others (*High interaction*). Indeed, this seems to matter. Students who talked a lot with others about Microeconomics received about 8% more points than those who did not. The domestic situation, however, does not seem to matter much. All other controls behave as one would expect from the baseline model (Equation (1)). It should also be noted that even just including attendance increases the fit of the model significantly, while all other controls improve the adjusted $R^2$ only marginally.

There are several reasons to believe, however, that the results from Table 5 do not capture all of the effects online learning had on teaching outcomes in times of the pandemic. First, as many more students sat the exam in the COVID term than before, it is possible they were more incentivized to work on the bonus-point exercises, causing the better performance. We do not think that this is a serious issue, however. It seems unlikely that students already decided at the start of the term not to take part in the exam, since the exam is the only possibility to receive credit points for the course. It therefore seems reasonable to assume that all students who started working on the online exercises had the intention to take the exam.[28] To make sure this is the case we re-estimated the model from Equation (2), controlling for whether a student participated the exam, which results in qualitatively similar estimates (see Table 12 in the Appendix). We do not include this variable in our main estimations, however, as it is possibly endogenous, since students may decide whether to take the exam depending on how many bonus points they achieved. Second, it seems likely that people in different performance quantiles are affected differently. To examine this conjecture, we utilize quantile regressions in the next section.

### 3.2 Quantile regression

We perform quantile regressions in order to provide a richer characterization of the relationship between teaching outcomes and relevant regressors. The results in Section 3.1 indicate that the sudden switch to online teaching at the beginning of the pandemic did not affect teaching outcomes on average when controlling for the relevant confounders. While this is a valuable insight with respect to the effect on the conditional mean of teaching outcomes, we use quantile regression to provide a more comprehensive picture about the conditional distribution of the outcome variable. In contrast to the least squares procedure for estimating the conditional mean of the dependent variable, quantile regression estimates conditional quantiles, using a *least absolute deviations* estimation. The quantile regression estimator for the $q$th quantile solves the minimization problem

$$\underset{\boldsymbol{\beta}_q}{\text{Min}} \sum_{i:y_i \geq \boldsymbol{\beta}'\boldsymbol{x}_i^*} q|y_i - \boldsymbol{\beta}_q'\boldsymbol{x}_i^*| + \sum_{i:y_i < \boldsymbol{\beta}'\boldsymbol{x}_i^*} (1-q)|y_i - \boldsymbol{\beta}_q'\boldsymbol{x}_i^*|, \tag{3}$$

[27] We believe this to be a valid strategy to deal with multi-collinearity, since we only want to control for possible psychological effects of the pandemic, not explain them.

[28] A concern might be that students changed their mind on taking the exam during the term due to epidemiological developments. In Figure 3 we plot the share of students trying to solve an exercise on the number of the exercise over the whole term and see no significant difference between the terms.

where $y_i$ denotes the dependent variable, $\boldsymbol{\beta}_q$ is the coefficient vector for the $q$th quantile and $\boldsymbol{x}_i^*$ is a vector comprising the pandemic dummy variable $\mathbb{I}_{C,i}$, the attendance variable $\text{attend}_i$, the interaction term $\text{attend}_i \times \mathbb{I}_{C,i}$ and other relevant covariates $\boldsymbol{x}_i$ (cf. Equation (2) in Section 3.1).

Evaluating the conditional distribution of teaching outcomes at various quantiles has an additional advantage in our case. The distribution of the dependent variable is bimodal, with peaks at zero and at the upper end of the distribution. This leads us to believe that the conditional mean fails to capture the full pattern in the data. Although students were not obliged to participate, excluding students who did not solve any of the online excercises correctly (e.g., $y_i = 0$) does not provide a valid solution, since the non-participating share could be affected by the pandemic. Using quantile regression to evaluate the conditional distribution at different points prevents the peak at $y_i = 0$ from blurring the effects at the higher quantiles.

In Table 6, we report OLS estimates next to the results for the quantile regressions at the $0.25, 0.5$ and 0.75 quantiles. In this specification, we include the most relevant control variables in the regressions, as stipulated in the previous section[29] (cf. Columns (4) and (5) of Table 5). The OLS regression estimates mirror the results in Section 3.1. Higher attendance, a better high-school GPA and interaction with fellow students lead to better teaching outcomes, while having a part-time job affects the teaching outcomes negatively, *ceteris paribus*. The coefficient of the average positive affection is positive and significant at the 5 percent level. As expected from the previous section, the effect of the pandemic and the interaction effect between attendance and the pandemic dummy are statistically insignificant.

Turning to the coefficients of the quantile regression, the results reveal important differences across different stages of the conditional distribution of teaching outcomes. The coefficient of the pandemic dummy changes from negative to positive when moving from the 0.25 to the median quantile, although the estimated standard errors are twice as high. On the other hand, the estimate for the 0.75 quantile is positive and of considerably higher magnitude. One possibility is that students in the upper end of the conditional distribution could particularly focus on their studies during the pandemic and thus successfully accomplish the online exercises. While higher attendance has a strong and positive impact on all considered conditional quantiles, the effect is most eminent at the lower end of the conditional distribution, indicating that weaker students benefit most from attending classes. Although the point estimate of 0.34 for the 75% quantile is considerably smaller than for the 25% quantile (0.64), the interaction effect between attendance and the pandemic dummy displays a significant negative effect for the 75% quantile, while the estimates for the median and 25% quantile are positive, but insignificant. We observe that the regression at the higher quantile attaches great weight to the most active students in the course,[30] and we suspect that these students were particularly affected by the sudden change in teaching format and the resulting adaptation to a completely altered teaching environment.

The results shown in Figure 2 substantiate these conjectures. The figure displays the estimates of

[29] The variables that are statistically insignificant and, in addition, are not of particular interest in this analysis are not included.

[30] As reported in Section 2.4, we ask students about the frequency of their attendance in lectures, exercise sessions and tutorials. The mean of the attendance variables corresponds to 2.61 for students in the lowest performance quartile and equals 4.18 for students in the highest quartile. The attendance-related questions use a five-item Likert scale (see Section 2.4 for more details).

| | (1) Points (share) | (2) 75% Quantile | (3) Median | (4) 25% Quantile |
|---|---|---|---|---|
| Attendance | 0.403*** | 0.343*** | 0.387*** | 0.658*** |
| | (0.073) | (0.047) | (0.070) | (0.129) |
| COVID-19 | 0.079 | 0.211*** | 0.051 | -0.051 |
| | (0.071) | (0.049) | (0.095) | (0.120) |
| COVID-19 × Attendance | 0.019 | -0.205*** | 0.003 | 0.109 |
| | (0.096) | (0.058) | (0.109) | (0.154) |
| Change in positive affection | 0.091*** | 0.041*** | 0.049 | 0.050 |
| | (0.034) | (0.016) | (0.031) | (0.040) |
| High-school GPA | 0.102*** | 0.025 | 0.097*** | 0.126*** |
| | (0.025) | (0.017) | (0.026) | (0.030) |
| High interaction | 0.084*** | 0.033*** | 0.067*** | 0.054 |
| | (0.027) | (0.012) | (0.025) | (0.042) |
| Part-time job | -0.077*** | -0.026** | -0.052* | -0.121*** |
| | (0.028) | (0.012) | (0.029) | (0.042) |
| Economics‡ | -0.219*** | -0.111 | -0.384*** | -0.221*** |
| | (0.058) | (0.073) | (0.116) | (0.046) |
| Social science‡ | -0.138*** | -0.088** | -0.172*** | -0.176*** |
| | (0.045) | (0.037) | (0.062) | (0.066) |
| Other‡ | -0.477*** | -0.671*** | -0.559*** | -0.402* |
| | (0.076) | (0.191) | (0.069) | (0.234) |
| Constant | 0.110 | 0.557*** | 0.212** | -0.205 |
| | (0.089) | (0.068) | (0.099) | (0.138) |
| Observations | 438 | 438 | 438 | 438 |

Robust standard errrors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$
‡ Reference category is business studies

Table 6: The effect of online teaching: Quantile regression results

the quantile regression for several of the covariates across the different quantiles. For comparison purposes, the respective OLS estimates are included as dashed lines. The figure illustrates a positive coefficient for attendance across all conditional quantiles, which peaks around the 20% quantile and considerably exceeds the OLS coefficient at this point. The positive effect gradually decreases for higher quantiles, reaffirming the relevance of attendance for weaker students. The quantile regression coefficient of the pandemic dummy changes from negative to positive above the median quantile and reaches the maximum around the 80% quantile, while, interestingly, the interaction effect between attendance and the pandemic acts vice versa and changes from positive to negative above the median quantile. As mentioned above, we suspect that the quantile regression coefficients at the lower quantiles are somewhat blurred by the large number of zero observations. As a consequence, the coefficients are estimated with large uncertainty at the lower quantiles, displayed by the wide confidence bands. On the other hand, the confidence bands tighten at the higher quantiles. The better teaching outcomes in the summer term of 2020 are reflected in the positive coefficient for the pandemic dummy beyond the median quantile, while the altered teaching environment seems adversely to affect the performance of students in the higher quantiles. As mentioned above, the students in the higher quantiles are also the most active students and hence mostly affected by the pandemic.

The quantile regression coefficients of the control variables displayed in the second row of Figure 2 feature the same signs as the coefficients of the conditional mean regression, but differ in

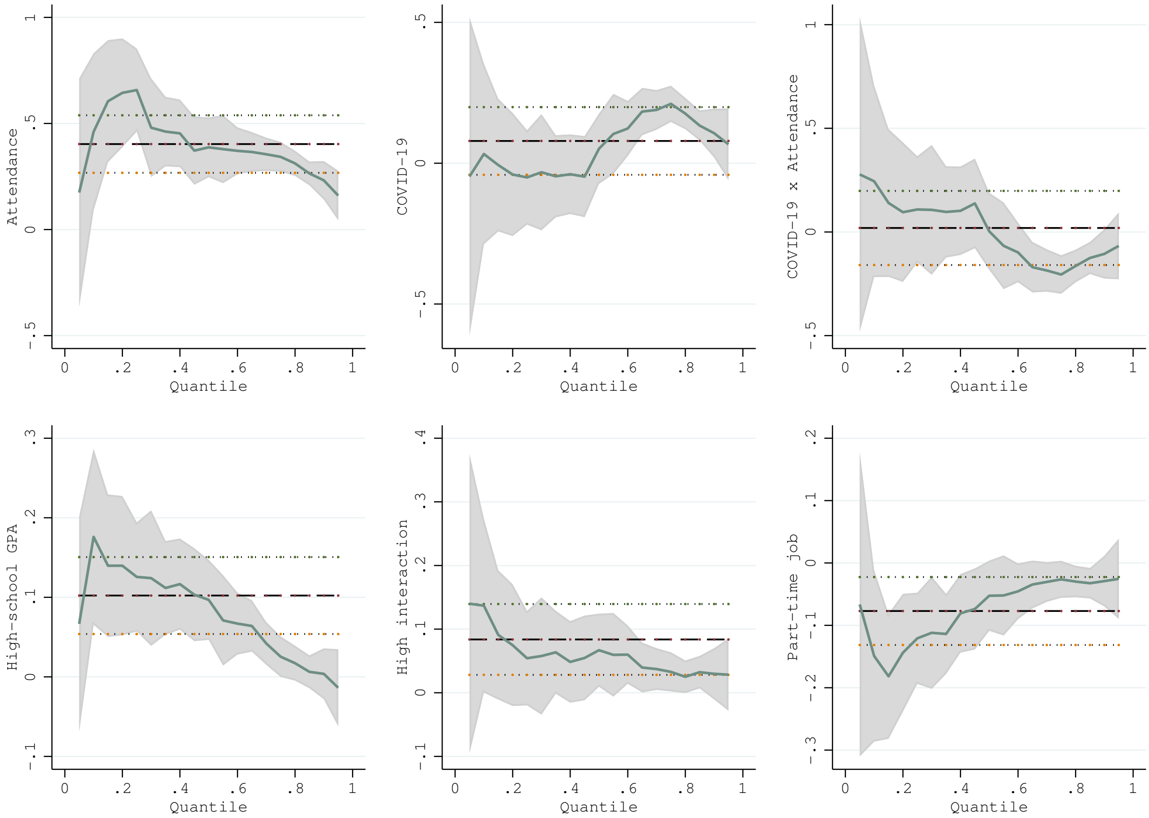



Figure 2: Quantile regression

magnitude along the conditional distribution. Interestingly, the positive effect of high school GPA and the negative effect of having a part-time job are most pronounced at lower quantiles and diminish in size when moving towards the upper end of the conditional distribution. However, the coefficients for these covariates are likewise estimated with large uncertainty at the lower end of the conditional distribution. The pattern for high interaction with fellow students looks similar, with the maximal coefficient at the lower end and a decreasing tendency when moving to the upper part of the conditional distribution.

While the effect sizes for attendance, high-school GPA, high interaction and part-time job decrease when moving towards the upper part of the conditional distribution, the pandemic and the interaction between the pandemic and attendance seem to have the largest impact on the best performing students. Although teaching outcomes improved in general during the summer term of 2020, the results of the quantile regression indeed indicate an adverse effect of the interaction between the pandemic and attendance on teaching outcomes for good students.

| | (1) Points (share) | (2) Points (share) | (3) Points (share) | (4) Points (share) | (5) Points (share) | (6) Points (share) |
|---|---|---|---|---|---|---|
| COVID-19 | 0.086 | 0.044 | 0.112*** | 0.163*** | 0.053 | 0.106*** |
| | (0.148) | (0.036) | (0.040) | (0.043) | (0.035) | (0.032) |
| COVID-19 × High-school GPA | 0.001 | | | | | |
| | (0.046) | | | | | |
| COVID-19 × Part-time Job | | 0.084 | | | | |
| | | (0.055) | | | | |
| COVID-19 × High interaction | | | -0.055 | | | |
| | | | (0.052) | | | |
| COVID-19 × Living alone | | | | -0.048 | | |
| | | | | (0.085) | | |
| COVID-19 × Shared flat | | | | -0.161*** | | |
| | | | | (0.059) | | |
| COVID-19 × Parents w/ college | | | | | 0.099* | |
| | | | | | (0.058) | |
| COVID-19 × Financial aid | | | | | | -0.109 |
| | | | | | | (0.069) |
| High-school GPA | 0.096*** | 0.094*** | 0.097*** | 0.099*** | 0.094*** | 0.093*** |
| | (0.031) | (0.026) | (0.025) | (0.026) | (0.025) | (0.025) |
| Attendance | 0.404*** | 0.400*** | 0.404*** | 0.400*** | 0.405*** | 0.406*** |
| | (0.054) | (0.054) | (0.054) | (0.054) | (0.054) | (0.054) |
| Change in positive affection | 0.091*** | 0.089*** | 0.094*** | 0.097*** | 0.094*** | 0.090*** |
| | (0.033) | (0.033) | (0.033) | (0.033) | (0.033) | (0.033) |
| High interaction | 0.084*** | 0.087*** | 0.111*** | 0.080*** | 0.084*** | 0.082*** |
| | (0.028) | (0.028) | (0.038) | (0.027) | (0.027) | (0.028) |
| Part-time job | -0.081*** | -0.124*** | -0.082*** | -0.082*** | -0.084*** | -0.086*** |
| | (0.029) | (0.038) | (0.029) | (0.028) | (0.028) | (0.028) |
| Living alone§ | -0.061 | -0.063 | -0.062 | -0.027 | -0.069 | -0.059 |
| | (0.042) | (0.042) | (0.042) | (0.059) | (0.042) | (0.042) |
| Shared flat§ | 0.002 | 0.002 | 0.000 | 0.083** | -0.001 | 0.001 |
| | (0.029) | (0.029) | (0.029) | (0.042) | (0.029) | (0.029) |
| Parents w/ college | 0.008 | 0.004 | 0.009 | 0.012 | -0.039 | 0.006 |
| | (0.032) | (0.032) | (0.032) | (0.032) | (0.041) | (0.031) |
| Financial aid | -0.048 | -0.041 | -0.051 | -0.053 | -0.048 | 0.006 |
| | (0.037) | (0.037) | (0.037) | (0.036) | (0.037) | (0.049) |
| Observations | 438 | 438 | 438 | 438 | 438 | 438 |

Robust standard errrors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$, § Reference category is living with parents
All regressions were estimated with a constant and subject-dummies, which were omitted in this table for brevity.

Table 7: Heterogeneous effects: OLS results

### 3.3 Other channels

In this section we try to further disentangle the relationship between the pandemic and learning outcomes. To do so, we first examine whether the pandemic changed the relationships between performance and its other determinants, and, second, how these determinants changed due to the pandemic. To see how the relationship between performance and its other determinants changes, we extend the approach laid out in Equation (2). Specifically, we are now interested in how our controls for SES, having a part-time job and the living situation affect learning outcomes differently during the pandemic compared to before. The results of these estimations are reported in Table 7. As we can see, the pandemic affected different students heterogeneously. In particular, students who receive financial aid or have no parents with a university degree fared worse during the pandemic than those with a higher socioeconomic status. This is very much in line with previous findings, as discussed before. We can speculate that this might be because these students do not have the same access to resources aiding them in the switch to online learning, which is what similar studies in schools have found. Related to this finding, living in shared accommodation negatively affected performance during the pandemic, while having no large effect in general. This makes sense intuitively, as especially during the lockdown it is very likely that most flatmates were also at home and hence negatively affected each other's study environment. On the other hand, we find no heterogeneous effects for ability, proxied by the High School GPA. A part-time job seemed to be less detrimental during the pandemic term, while interacting a lot with other students was less beneficial, although neither of those effects are statistically significant.

Overall, this supports our hypothesis that the switch to online learning was only one of many relevant channels. And it seems likely that, besides affecting the relationship between determinants, the pandemic also affected these determinants themselves. We find three determinants particularly interesting: the positive affection measure, whether they had a part-time job and their living situation. Also, to see whether the models in Section 3.1 are well specified, we consider whether attendance is affected by the pandemic. To see how the COVID-19 pandemic affected the likelihood of a student living in shared accommodation and whether they had a part-time job, we estimate a probit model and calculate the average marginal effects, reported in Columns 1 and 2 of Table 8. As we can see, students were much less likely to have a part-time job during the pandemic term compared to the previous summer term. This is fairly intuitive, as students often work in restaurants, bars, hotels, etc., which were closed during most of the term. And because they were less likely to have a job and did not have to go to the university, it makes sense they were less likely to live in a shared flat. Considering the results from Table 7, this suggests that the COVID-19 pandemic indirectly affects performance positively because students are more likely to live with their parents and less likely to have a part-time job, which could explain the overall positive effect of the pandemic we saw before. On the other hand, as can be seen from the OLS-estimates reported in Column (3) of Table 8, the pandemic negatively affected the psychological wellbeing, especially of male students, which in turn would negatively impact their performance. Lastly, from the OLS estimates reported in Column (4) of Table 8, we see that attendance was not significantly affected by the pandemic overall, suggesting that the interaction between attendance and COVID can be interpreted as the effect of online teaching in times of the pandemic.

| | (1) Part-time job | (2) Shared flat | (3) Positive affection | (4) Attendance |
|---|---|---|---|---|
| COVID-19 | -0.151*** | -0.125*** | -0.303*** | -0.046 |
| | (0.046) | (0.046) | (0.040) | (0.029) |
| High-school GPA | -0.166*** | -0.039 | -0.056 | 0.086*** |
| | (0.040) | (0.041) | (0.039) | (0.025) |
| Gender | -0.000 | -0.018 | -0.091** | 0.075*** |
| | (0.046) | (0.045) | (0.040) | (0.028) |
| Parents w/ college | 0.035 | -0.180*** | -0.062 | -0.015 |
| | (0.049) | (0.046) | (0.040) | (0.029) |
| Economics‡ | 0.033 | 0.027 | 0.116 | -0.007 |
| | (0.087) | (0.087) | (0.094) | (0.053) |
| Social science‡ | 0.058 | 0.143** | 0.110*** | -0.120*** |
| | (0.069) | (0.069) | (0.039) | (0.038) |
| Other‡ | -0.078 | -0.029 | 0.098 | -0.100 |
| | (0.139) | (0.140) | (0.083) | (0.086) |
| Part-time job | | 0.125*** | 0.016 | -0.040 |
| | | (0.045) | (0.043) | (0.029) |
| Constant | | | 0.194 | 0.355*** |
| | | | (0.140) | (0.085) |
| Observations | 438 | 438 | 438 | 438 |
| Adjusted $R^2$ | | | 0.144 | 0.071 |

Robust standard errrors in parentheses. $^{*}$ $p < .1$, $^{**}$ $p < .05$, $^{***}$ $p < .01$
‡ Reference category is business studies

Table 8: Other dependent variables: OLS results / Probit avg. marginal effects

# 4 Conclusion

In this paper, we study the effects of the COVID-19 pandemic on teaching outcomes in higher education, using data on students' performance in weekly exercises within the courses Principles of Microeconomics and Microeconomics for Business in the Bachelor programs at the University of Cologne. Moreover, we issued a survey to collect data on personal characteristics to be able to control for important confounders, as well as for the analysis of heterogeneous effects.

In line with Gonzalez et al. (2020), we find that students' performance increases on average. In terms of channels, online teaching in times of the pandemic does not seem to affect performance on average. Cacault et al. (2019) find that high-skilled students benefit more from online teaching compared to low-skilled students; our quantile regressions show the opposite in times of the pandemic. Likely that is because, in our data, student attendance is positively correlated with performance. Thus, low-skilled students are less likely to be affected by the switch to online teaching, simply because they were less likely to attend in the first place. Instead, the data suggest that the better performance may be due to an increased availability of study time, as fewer students are employed in part-time jobs, and social contacts are reduced overall, the latter also because the students are less likely to live in a shared flat. This is in line with the survey results of Aucejo et al. (2020), where some students report an increase of their time studying during the pandemic, highlighting an additional channel potentially responsible for positive effects. Gonzalez et al. (2020) argue that student performance increases because they were able to learn more continuously, and hence more efficiently, in times of COVID confinement.

The positive effect of the pandemic is negated for low-SES students, likely because they lack the resources to use online learning efficiently and are in general more affected by the negative consequences in terms of employment opportunities.[31]

For future research, it is important to identify the exact channels responsible for the change of performance in times of the pandemic. Moreover, to increase external validity of our results, other researchers may replicate this study with data from other institutions and other subjects. Lastly, many studies show that students' psychological wellbeing decreases during the pandemic. It is still unclear, however, to which extent online teaching formats are responsible, and to which extent this is due to the other restrictions stemming from the pandemic.

Our results imply that the many disadvantages of university closures discussed in the media do not necessarily carry over to student performance. This supports the ongoing closures of universities for the sake of national health. However, universities should increase their efforts to support low-SES students, either through financial aid or other targeted support programs.

[31] See, for instance, Berkes et al. (2020).

## References


Agostinelli, F., Doepke, M., Sorrenti, G., and Zilibotti, F. (2020), When the Great Equalizer Shuts Down: Schools, Peers, and Parents in Pandemic Times, Working Paper 28264, National Bureau of Economic Research.

Alpert, W. T., Couch, K. A., and Harmon, O. R. (2016), A Randomized Assessment of Online Learning, *American Economic Review* **106** (5): 378–82.

Aucejo, E. M., French, J., Ugalde Araya, M. P., and Zafar, B. (2020), The Impact of COVID-19 on Student Experiences and Expectations: Evidence from a Survey, NBER Working Paper No. 27392, National Bureau of Economic Research.

Bacher-Hicks, A. and Goodman, J. (2020), The Covid-19 Pandemic Is A Lousy Natural Experiment for Estimating the Effects of Education Policy Changes, Working paper.

Baldwin, R. and Weder di Mauro, B. (2020), Economics in the Time of COVID-19, VOX CEPR Press.

Berkes, J., Peter, F., and Spieß, K. (2020), Wegfall von Studi-Jobs könnte Bildungsungleichheiten verstärken, *DIW aktuell* **44**.

Bettinger, E. P., Fox, L., Loeb, S., and Taylor, E. S. (2017), Virtual Classrooms: How Online College Courses Affect Student Success, *American Economic Review* **107** (9): 2855–75.

Bowen, W. G., Chingos, M. M., Lack, K. A., and Nygren, T. I. (2014), Interactive Learning Online at Public Universities: Evidence from a Six-Campus Randomized Trial, *Journal of Policy Analysis and Management* **33** (1): 94–111.

Breyer, B. and Bluemke, M. (2016), 'Deutsche Version der Positive and Negative Affect Schedule PANAS (GESIS Panel)', Zusammenstellung sozialwissenschaftlicher Items und Skalen (ZIS).

Cacault, M. P., Hildebrand, C., Laurent-Lucchetti, J., and Pellizzari, M. (2019), Distance Learning in Higher Education: Evidence from a Randomized Experiment, CEPR Discussion Paper 13666.

Cao, W., Fang, Z., Hou, G., Han, M., Xu, X., Dong, J., and Zheng, J. (2020), The Psychological Impact of the COVID-19 Epidemic on College Students in China, *Psychiatry Research* **287**: 112934.

Coates, D., Humphreys, B. R., Kane, J., and Vachris, M. A. (2004), "No Significant Distance" Between Face-To-Face and Online Instruction: Evidence from Principles of Economics, *Economics of Education Review* **23** (5): 533–546.

Figlio, D., Rush, M., and Yin, L. (2013), Is It Live or Is It Internet? Experimental Estimates of the Effects of Online Instruction on Student Learning, *Journal of Labor Economics* **31** (4): 763–784.

Gonzalez, T., de la Rubia, M. A., Hincz, K. P., Comas-Lopez, M., Subirats, L., Fort, S., and Sacha, G. M. (2020), Influence of COVID-19 Confinement on Students' Performance in Higher Education, *PLOS ONE* **15** (10): 1–23.

Grewenig, E., Lergetporer, P., Werner, K., Woessmann, L., and Zierow, L. (2020), COVID-19 and Educational Inequality: How School Closures Affect Low-and High-Achieving Students, IZA Discussion Paper 13820, Institute of Labor Economics (IZA), Bonn.

Jaeger, D. A., Arellano-Bover, J., Karbownik, K., Martínez-Matute, M., Nunley, J., and Seals, R. A. (2021), The Global COVID-19 Student Survey: First Wave Results, IZA Discussion Paper 14419, Institute of Labor Economics (IZA), Bonn.

Joyce, T., Crockett, S., Jaeger, D. A., Altindag, O., and O'Connell, S. D. (2015), Does Classroom Time Matter?, *Economics of Education Review* **46**: 64–77.

Jury, M., Smeding, A., Stephens, N. M., Nelson, J. E., Aelenei, C., and Darnon, C. (2017), The Experience of Low-SES Students in Higher Education: Psychological Barriers to Success and Interventions to Reduce Social-Class Inequality, *Journal of Social Issues* **73** (1): 23–41.

Kahnemann, D. and Krueger, A. B. (2006), Developments in the Measurement of Subjective Well-Being, *Journal of Economic Perspectives* **20** (1): 3–24.

Löwe, B., Wahl, I., Rose, M., Spitzer, C., Glaesmer, H., Wingenfeld, K., Schneider, A., and Brähler, E. (2010), A 4-item Measure of Depression and Anxiety: Validation and Standardization of the Patient Health Questionnaire-4 (PHQ-4) in the General Population, *Journal of Affective Disorders* **122** (1): 86–95.

Means, B., Toyama, Y., Murphy, R., Bakia, M., and Jones, K. (2010), Evaluation of Evidence-Based Practices in Online Learning: A Meta-Analysis and Review of Online Learning Studies, U.S. Department of Education, Washington, D.C.

Papke, L. and Wooldridge, J. (1996), Econometric Methods for Fractional Response Variables With an Application to 401 (k) Plan Participation Rates, *Journal of Applied Econometrics* **11** (6): 619–632.

Robinson, J. (2014), Likert Scale, *in* A. C. Michalos, ed., 'Encyclopedia of Quality of Life and Well-Being Research', Springer Netherlands, Dordrecht, pp. 3620–3621.

Rodríguez-Planas, N. (2020), Hitting Where It Hurts Most: COVID-19 and Low-Income Urban College Students, IZA Discussion Paper 13644, Institute of Labor Economics (IZA), Bonn.

Rodríguez-Planas, N. (2021), COVID-19 and College Academic Performance: A Longitudinal Analysis, IZA Discussion Paper 14113, Institute of Labor Economics (IZA), Bonn.

Sacerdote, B. (2011), Chapter 4 - Peer Effects in Education: How Might They Work, How Big Are They and How Much Do We Know Thus Far?, *in* E. A. Hanushek, S. Machin, and L. Woessmann, eds, 'Handbook of the Economics of Education', Vol. 3 of *Handbook of the Economics of Education*, Elsevier, pp. 249–277.

Xu, D. and Jaggars, S. S. (2013), The Impact of Online Learning on Students' Course Outcomes: Evidence from a Large Community and Technical College System, *Economics of Education Review* **37**: 46–57.

# Appendix A

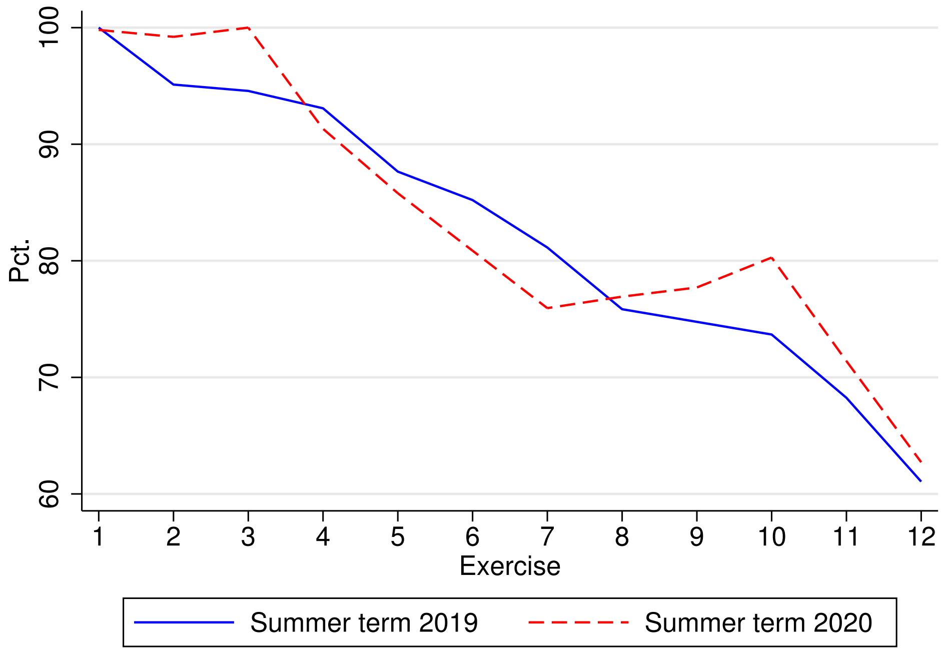



Figure 3: Share of participants taking part in each exercise by term

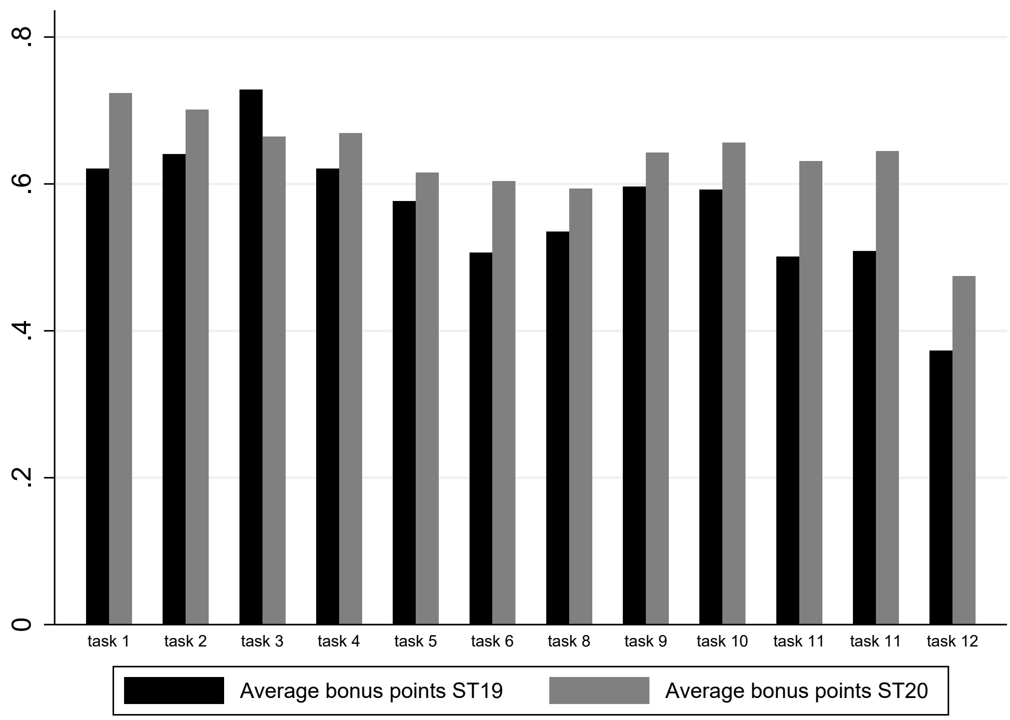



Figure 4: Term comparison: Average bonus points per assignment

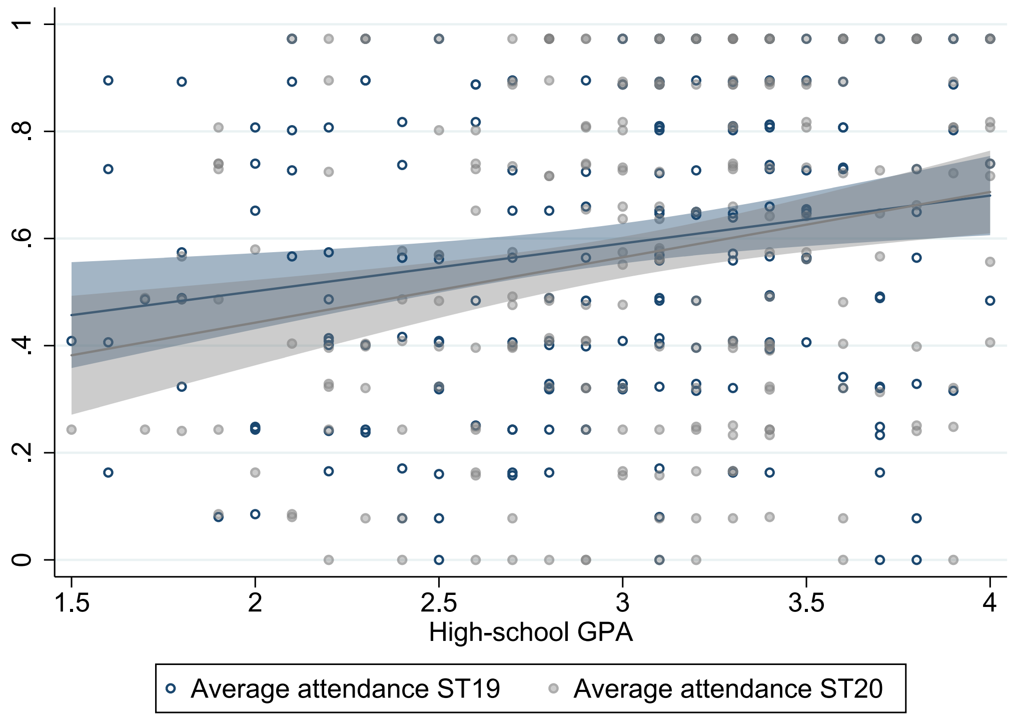
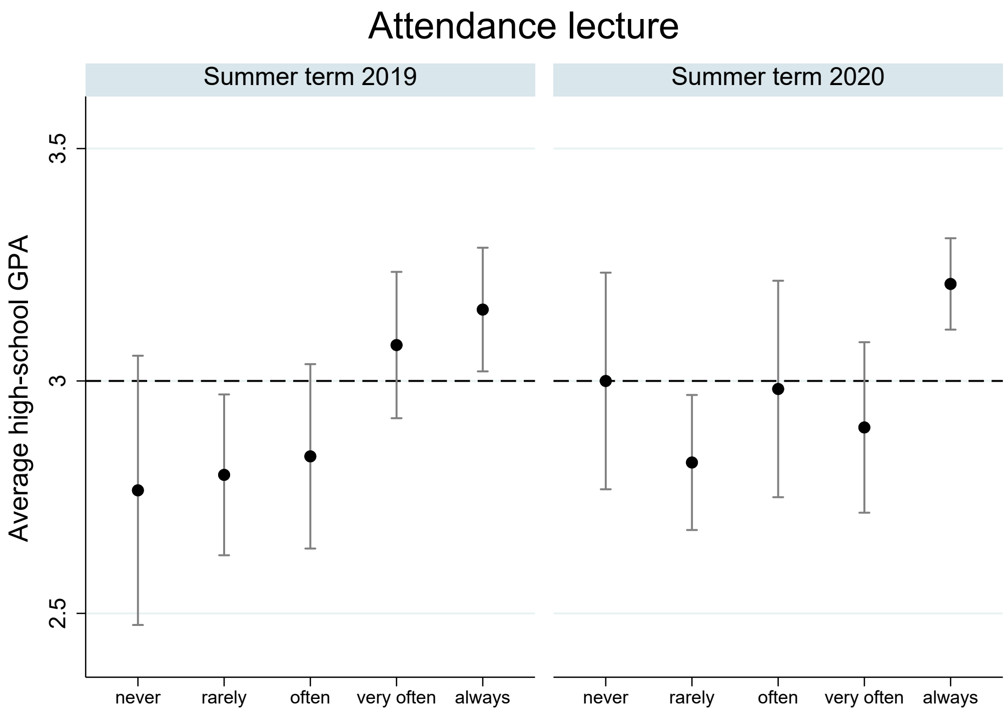



Figure 5: Average performance conditional on high-school GPA by term




*Note*: This figure shows high-school GPA averages conditional on the frequency of attendance of this event. Additionally, 95% confidence intervals are shown.

Figure 6: Term comparison: Average high-school GPA per participation in a lecture

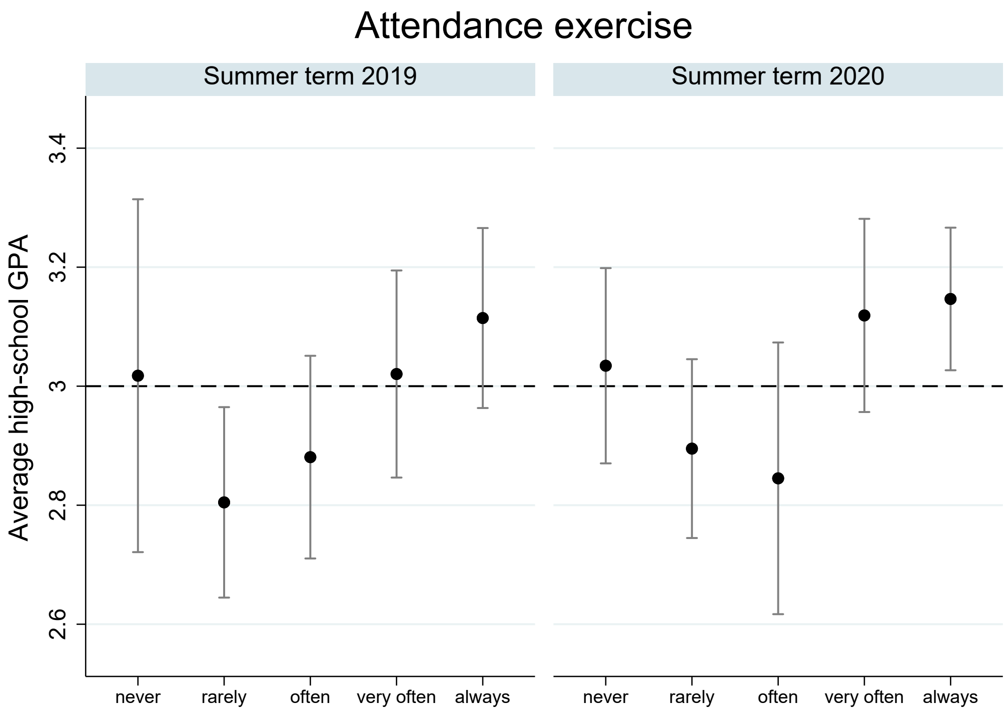



Figure 7: Term comparison: Average high-school GPA per participation in an exercise session

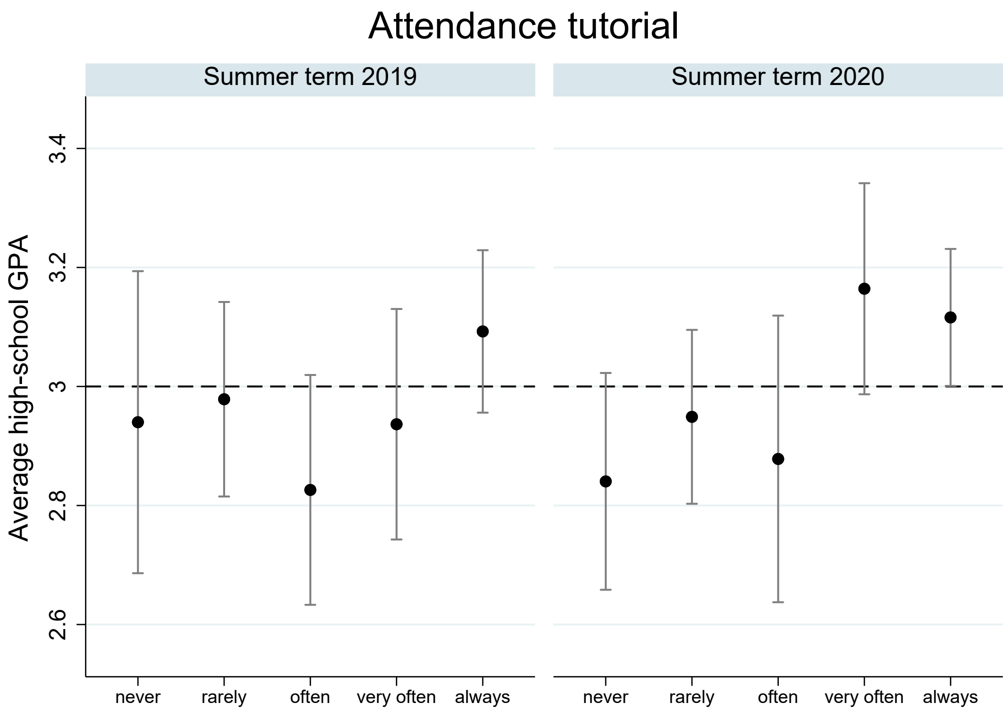



Figure 8: Term comparison: Average high-school GPA per participation in a tutorial

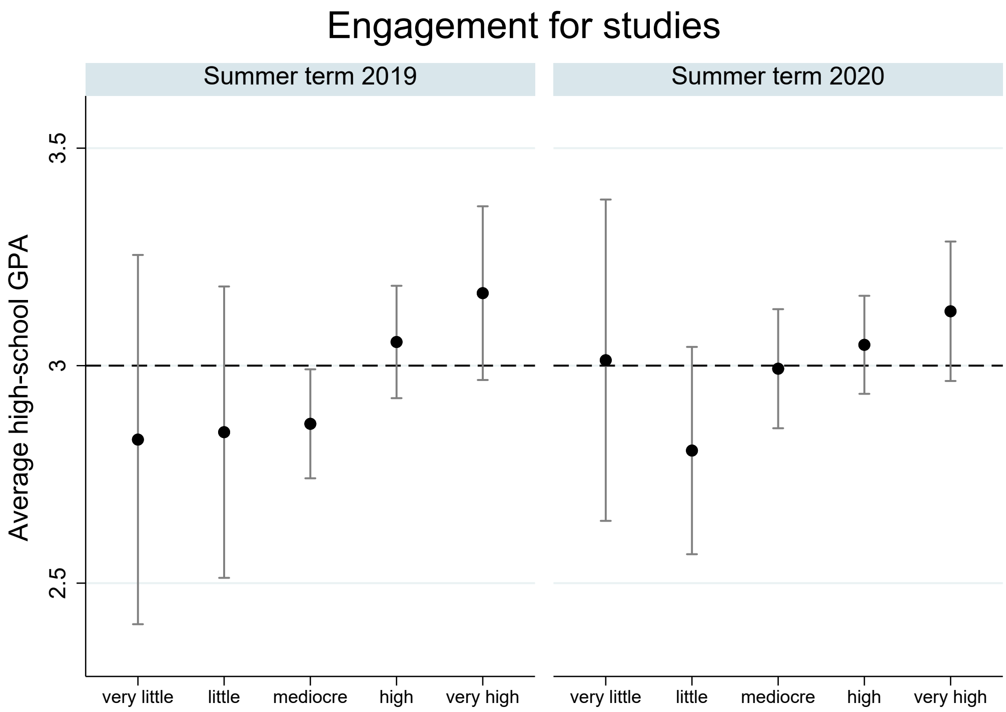



Figure 9: Term comparison: Average high-school GPA per overall engagement in the university

| | (1) | (2) | (3) |
|---|---|---|---|
| COVID-19 | 0.078** | 0.067** | 0.058* |
| | (0.033) | (0.031) | (0.031) |
| High-school GPA | | 0.195*** | 0.137*** |
| | | (0.025) | (0.024) |
| Advanced math in school | | 0.001 | 0.003 |
| | | (0.032) | (0.031) |
| Parents w/ college | | | -0.024 |
| | | | (0.032) |
| Male | | | 0.040 |
| | | | (0.030) |
| Economics‡ | | | -0.239*** |
| | | | (0.064) |
| Social science‡ | | | -0.181*** |
| | | | (0.047) |
| Other‡ | | | -0.538*** |
| | | | (0.086) |
| Observations | 438 | 438 | 438 |
| *BIC* | . | . | . |

Robust standard errrors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$
‡ Reference category is business studies

Table 9: Baseline model: GLM results

| Component | Eigenvalue | Difference | Proportion | Cumulative |
|---|---|---|---|---|
| Component 1 | 2.19212 | 1.70705 | 0.7307 | 0.7307 |
| Component 2 | .485071 | .162259 | 0.1617 | 0.8924 |
| Component 3 | .322811 | . | 0.1076 | 1.0000 |

Table 10: Attendance: PCA results

| | (1) Points (share) | (2) Points (share) | (3) Points (share) | (4) Points (share) | (5) Points (share) |
|---|---|---|---|---|---|
| Attendance | 0.469*** | 0.451*** | 0.425*** | 0.410*** | 0.403*** |
| | (0.053) | (0.054) | (0.054) | (0.056) | (0.054) |
| COVID-19 | 0.077*** | 0.098*** | 0.102*** | 0.092*** | 0.088*** |
| | (0.028) | (0.031) | (0.029) | (0.029) | (0.030) |
| High-school GPA | 0.104*** | 0.109*** | 0.114*** | 0.099*** | 0.099*** |
| | (0.025) | (0.024) | (0.024) | (0.026) | (0.025) |
| Economics‡ | -0.241*** | -0.255*** | -0.223*** | -0.214*** | -0.230*** |
| | (0.058) | (0.055) | (0.056) | (0.058) | (0.059) |
| Social science‡ | -0.131*** | -0.143*** | -0.141*** | -0.136*** | -0.142*** |
| | (0.045) | (0.045) | (0.044) | (0.045) | (0.045) |
| Other‡ | -0.461*** | -0.469*** | -0.470*** | -0.480*** | -0.488*** |
| | (0.077) | (0.079) | (0.079) | (0.077) | (0.078) |
| Change in neg. affection | | 0.003 | | | |
| | | (0.048) | | | |
| Change in pos. affection | | 0.125*** | 0.089*** | 0.094*** | 0.093*** |
| | | (0.043) | (0.033) | (0.034) | (0.033) |
| PHQ4 | | 0.010 | | | |
| | | (0.010) | | | |
| High interaction | | | 0.078*** | 0.086*** | 0.083*** |
| | | | (0.027) | (0.027) | (0.027) |
| Part-time job | | | | -0.076*** | -0.080*** |
| | | | | (0.028) | (0.029) |
| Parents w/ college | | | | -0.005 | |
| | | | | (0.030) | |
| Gender | | | | 0.021 | |
| | | | | (0.028) | |
| Adv. math in school | | | | 0.023 | |
| | | | | (0.028) | |
| Living alone§ | | | | | -0.062 |
| | | | | | (0.042) |
| Shared flat§ | | | | | -0.005 |
| | | | | | (0.029) |
| Constant | 0.054 | 0.053 | 0.019 | 0.092 | 0.139 |
| | (0.082) | (0.080) | (0.082) | (0.095) | (0.090) |
| Observations | 438 | 438 | 438 | 438 | 438 |
| Adjusted $R^2$ | 0.357 | 0.367 | 0.377 | 0.384 | 0.388 |

Robust standard errrors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$
‡ Reference category is business studies, § Reference category is living with parents

Table 11: The effect of Attendance: OLS results

| | (1)<br>Points (share) | (2)<br>Points (share) | (3)<br>Points (share) | (4)<br>Points (share) | (5)<br>Points (share) |
|---|---|---|---|---|---|
| Attendance | 0.326*** | 0.320*** | 0.291*** | 0.280*** | 0.280*** |
| | (0.062) | (0.062) | (0.061) | (0.061) | (0.060) |
| COVID-19 | -0.037 | -0.004 | -0.003 | -0.011 | -0.010 |
| | (0.062) | (0.063) | (0.062) | (0.062) | (0.061) |
| COVID-19 × Attendance | 0.079 | 0.059 | 0.063 | 0.067 | 0.064 |
| | (0.083) | (0.083) | (0.081) | (0.080) | (0.081) |
| Sat exam | 0.381*** | 0.379*** | 0.380*** | 0.372*** | 0.370*** |
| | (0.043) | (0.042) | (0.042) | (0.043) | (0.042) |
| High-school GPA | 0.085*** | 0.091*** | 0.095*** | 0.087*** | 0.086*** |
| | (0.023) | (0.023) | (0.023) | (0.024) | (0.023) |
| Economics‡ | -0.172*** | -0.185*** | -0.154*** | -0.149** | -0.160*** |
| | (0.058) | (0.056) | (0.057) | (0.058) | (0.059) |
| Social science‡ | -0.127*** | -0.139*** | -0.137*** | -0.136*** | -0.139*** |
| | (0.041) | (0.040) | (0.039) | (0.040) | (0.040) |
| Other‡ | -0.284*** | -0.294*** | -0.292*** | -0.301*** | -0.308*** |
| | (0.052) | (0.052) | (0.054) | (0.056) | (0.055) |
| Change in neg. affection | | 0.010 | | | |
| | | (0.042) | | | |
| Change in pos. affection | | 0.117*** | 0.088*** | 0.091*** | 0.089*** |
| | | (0.041) | (0.033) | (0.034) | (0.033) |
| PHQ4 | | 0.007 | | | |
| | | (0.008) | | | |
| High interaction | | | 0.077*** | 0.082*** | 0.081*** |
| | | | (0.024) | (0.024) | (0.024) |
| Part-time job | | | | -0.048* | -0.051** |
| | | | | (0.026) | (0.026) |
| Parents w/ college | | | | -0.002 | |
| | | | | (0.027) | |
| Gender | | | | 0.016 | |
| | | | | (0.025) | |
| Adv. math in school | | | | 0.006 | |
| | | | | (0.024) | |
| Living alone§ | | | | | -0.036 |
| | | | | | (0.037) |
| Shared flat§ | | | | | 0.005 |
| | | | | | (0.026) |
| Constant | -0.095 | -0.103 | -0.135* | -0.084 | -0.060 |
| | (0.078) | (0.076) | (0.076) | (0.087) | (0.086) |
| Observations | 438 | 438 | 438 | 438 | 438 |
| Adjusted $R^2$ | 0.496 | 0.505 | 0.516 | 0.516 | 0.519 |

Robust standard errrors in parentheses. $^{*}$ $p < .1$, $^{**}$ $p < .05$, $^{***}$ $p < .01$
‡ Reference category is business studies, § Reference category is living with parents

Table 12: Controlling for participation in exam: OLS results