Tutoring in (Online) Higher Education: Experimental Evidence*

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Abstract

Demand for personalized online tutoring in higher education is growing but there is little research on its effectiveness. We conducted an RCT offering remote peer tutoring in micro- and macroeconomics at a German university teaching online due to the Covid-pandemic. Treated students met in small groups, in alternating weeks with and without a more senior student tutor. The treatment improved study behavior and increased contact to other students. Tutored students achieved around 30% more credits and a one grade level better GPA across treated subjects. Our findings suggest that the program reduced outcome inequality. We find no impacts on mental health.

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1 Introduction

A large share of university students never obtain a degree, and those who do often take much longer than the program design would suggest.[1] This issue in higher education is at risk of worsening with more students studying virtually since the literature has largely found online teaching to be less effective than classroom-based teaching (e.g., Figlio et al., 2013; Bettinger et al., 2017). In the recent pandemic, many students struggled to study successfully due to the shift to online teaching (Aucejo et al., 2020; Bird et al., 2020; Kofoed et al., 2021). Students' mental health may also be affected by a lack of interactions when studying online, as suggested by evidence of worse student mental health during the Covid pandemic (e.g., Lai et al., 2020; Son et al., 2020; Browning et al., 2021; Logel et al., 2021).[2] Since three in ten Americans state that they would prefer an online-only learning option even in the absence of the Covid threat (Strada Education Network, 2020), it is important to understand how to improve online learning.

Personalized remote tutoring is a promising way to tackle central problems in (online) higher education and improve student outcomes. In-person tutoring interventions have been shown to be effective across differing settings and for a wide variety of students (Fryer, 2017; de Ree et al., 2021). The experimental literature on tutoring has so far primarily focused on PreK-12 interventions, finding increases in learning outcomes of around 0.37SD on average, a large effect in comparison to other education interventions (Nickow et al., 2020). This remarkable success of tutoring is in contrast to mentoring interventions that have at best shown small improvements in average student performance or improvements only for subgroups of students (e.g., Angrist et al., 2009; Oreopoulos and Petronijevic, 2019).

To date, little is known about whether tutoring is effective in higher education settings. This is why peer tutoring has not been labeled a high-impact practice by the Association of American Colleges and Universities (Kuh, 2008).[3] However, tutoring is one element of highly successful student support programs such as the City University of New York's Accelerated Study in Associate Programs (ASAP, see Scrivener et al., 2015; Sommo et al., 2018; Weiss et al., 2019). Remote tutoring is also a large and

[1] For instance, data from the National Center for Education Statistics show that in the United States, less than 40 percent of a cohort entering four-year institutions obtain a bachelor's degree within four years (Weiss et al., 2019). See also, e.g., `https://nces.ed.gov/programs/digest/d13/tables/dt13_326.10.asp`, last accessed November 17, 2021.

[2] Among the primary correlates of worse mental health of students during the pandemic are loneliness or studying in isolation (e.g., Elmer et al., 2020; Jaeger et al., 2021; Logel et al., 2021).

[3] See also "As Students Dispersed, Tutoring Services Adapted" on *Inside Higher Ed* on March 16, 2021, `https://www.insidehighered.com/news/2021/03/16/face-face-peer-tutoring-decimated-pandemic-universities-turn-new-tools-times-and`, last accessed November 4, 2021.

growing market served by private sector firms. Market analysts estimated the global market size for online tutoring at around USD 150bn in 2020 and it is projected to reach about 280bn by 2026 (Valuates Reports, 2021).[4]

In this paper, we report results of a randomized trial designed to test whether small-group remote peer tutoring affects student outcomes in (online) higher education. Our sample comprises second term students from the core undergraduate program at a large Germany university's *School of Business, Economics, and Society*. Each fall, students enroll in the three-year bachelor's program *Economics and Business Studies*. In each of the first two semesters, students are to pass six courses each worth five credits. Since the second term includes more rigorous courses relative to the first semester, many students struggle in this term.[5]

Our program provided personalized remote tutoring in two economics courses. The program featured small groups of two or three students. These small groups met every week via Zoom, in alternating weeks with and without a more senior student tutor. In these meetings, students discussed problems in micro- and macroeconomics taken from problem sets and past exams that were available to all students. As tutors, we hired students from a more advanced term in the same study program. Thus, this kind of tutoring could be scaled up easily and at modest cost. For instance, including one additional student into the program for a three-month period would cost about €60.

Our results show that the tutoring intervention was highly effective in improving learning outcomes. First, relative to the control group, treated students are more likely to report having studied throughout the term and report being more in contact with other students. Second, treated students earn 30% more credits and obtain a GPA across both tutoring subjects that is better relative to control group students by around one grade level. Studying the students' performance in both tutoring courses' written exams, we find that treated students perform about 30% of a standard deviation better than students in the control group. This is of comparable magnitude than the impacts of tutoring in K-12 education (Nickow et al., 2020). Third, the largest improvements in academic performance occur among students who previously did not perform well. As a result, the program reduced the inequality of academic outcomes among students. Fourth, because of the induced small-group peer interactions, we also hypothesized that the tutoring intervention would improve students' mental health, especially in light of the pandemic setting. However, we find no impacts on any survey outcome related to mental health.

[4]On private K-12 tutoring markets, see Kim et al. (2021).

[5]Administrative data from the year 2018/19 shows that even in regular times, many students underperform relative to the suggested curriculum: after the first semester, only 59 percent of enrolled students have completed courses worth at least 30 credits.

This paper contributes to several literature strands. First, we add to research on the effectiveness of online higher education. Most of this literature has found online teaching to be somewhat less effective than classroom-based teaching (Figlio et al., 2013; Bettinger et al., 2017). A driver of this lower effectiveness seems that students have problems of disorganization when taught online, a culprit that could be well addressed by personalized tutoring (e.g. Banerjee and Duflo, 2014).[6] Delivery-side frictions such as lack of experience in online teaching may however also be important (e.g., Orlov et al., 2021). There is substantially less research on interventions aiming at improving student outcomes within an online environment.[7] Our results show that remote tutoring in small groups substantially raises student outcomes in such an environment. Thus, remote tutoring may prove an effective and efficient way to personalize and improve online education.

Second, we also contribute to the experimental literature on tutoring interventions. Tutoring has been shown to be highly effective in PreK-12 education (Fryer, 2017; de Ree et al., 2021). In a recent review, Nickow et al. (2020) report that tutoring increases learning outcomes by around 0.37SD on average, a large effect in comparison to other education interventions. There is much less evidence on the effectiveness of tutoring in higher education, and the available evidence does not provide a clear picture of the effectiveness of such interventions (see, e.g., Parkinson, 2009; Munley et al., 2010; Paloyo et al., 2016; Pugatch and Wilson, 2018, 2020; Gordanier et al., 2019). However, tutoring is an important part of CUNY's ASAP program that seems highly effective (Scrivener et al., 2015; Sommo et al., 2018; Weiss et al., 2019). We contribute to this literature by providing the first estimates of the effect of a pure tutoring program on student outcomes. We show that remote small-group peer tutoring is similarly effective in higher than in PreK-12 education.

Finally, we contribute to emerging research on effective education policies during the Covid pandemic. Most papers in this literature have focused on primary or secondary education (e.g., Angrist et al., 2021; Bacher-Hicks et al., 2020; Grewenig et al., 2021). The closest paper is Carlana and La Ferrara (2021), who experimentally assigned Italian middle school students an online tutor during the pandemic and report positive effects on performance and well-being. The magnitude of their results is comparable to the magnitude we find in the subjects covered by the program. There is only little research on higher education interventions during the pandemic, despite worse student outcomes in higher education (Bird et al., 2020; Altindag et al., 2021; Kofoed et al., 2021; Rodriguez-Planas, 2020, 2022). In an earlier paper, we show that

[6] In line with the hypothesis that disorganization drives lower effectiveness, Patterson (2018) experimentally studies commitment devices, alerts, and distraction blocking tools in a MOOC and finds positive effects for treated students.

[7] Lavecchia et al. (2016) provide a recent review of behavioral interventions in (higher) education.

mentoring focused on student self-organization improves student motivation, but only raises student achievement among already well-performing students (Hardt et al., 2020). We thus contribute by studying the effectiveness of remote tutoring in (online) higher education during the pandemic. While the pandemic is a special situation for many students (Jaeger et al., 2021), we are convinced that the sizable and plausible effects of our intervention carry lessons for improving higher education after universities have fully returned to regular, in-person teaching.

2 Experimental Setting and Design

2.1 Experimental Setting

Our setting is typical of public universities during the pandemic. The undergraduate program *Economics and Business Studies* at the intervention university requires students to collect 180 credits to graduate, which is expected after three years. The study plan assigns courses worth 30 credits to each semester which corresponds to six courses each worth five credits. Administrative data show that large shares of students do not complete 30 credits per semester, delaying their graduation. The salient study plan and target of achieving 30 credits per term, the fact that most students typically register for exams worth these credits, and data from prior terms that suggest that students do not seem to study as much as intended suggests that many students have problems in self-organizing and/or studying efficiently.

Due to the Covid pandemic, in the summer term 2021 all courses of the School of Business, Economics, and Society were conducted in online format. To this end, the university acquired licenses of *Zoom* (already before the summer term 2020), an online video conference tool used widely in academic settings during this pandemic to digitize classes and seminars and to provide remote education. While the exact implementation of online teaching differs by subject and instructor, this should make the setting similar to the setting of other academic institutions around the globe during this pandemic. The exams were taken in person at the city's trade fair sites.

We leveraged the shift to online teaching induced by the pandemic to assess the effectiveness of remote tutoring programs. One may worry that this pandemic situation was very different from other online education settings (Jaeger et al., 2021). While this is certainly true, our intervention took place over one year after the beginning of the pandemic. Thus, instructors already had some experience teaching virtually via Zoom since this was the third term in which the university did so (Orlov et al., 2021; Altindag et al., 2021). Also, formal lockdowns ended in early May 2021, shortly

after the onset of the intervention. Thus, the situation was more normal and much improved relative to the early phases of the pandemic.

We overall believe that our results carry implications for the time in which universities return to in-person teaching. First, we do not observe strong impacts on some survey questions that should capture pandemic effects. Most importantly, treated students' self-assessed mental health is no different than control students', irrespective of which measure we analyze. Second, the magnitude of our effects is comparable to tutoring interventions in other settings in primary and secondary education that took place in person (Nickow et al., 2020).

2.2 The Tutoring Program

In the first week of the semester, students were informed via e-mail about the launch of a new small-group tutoring program in micro- and macroeconomics designed specifically for students in the second semester of the study program. Students were informed that the program had a capacity constraint and that places would be allocated randomly. They were invited to express their interest in the program through a webpage. The page asked for the students' consent to use their personal and administrative information for research purposes in anonymized form and for their consent to pass along their name and e-mail address to tutors. We sent reminder e-mails to students who did not visit the registration webpage within two days. After closing the registration, we randomly assigned all students who had expressed their interest in the program to either a treatment or control group. The number of students assigned to treatment was determined by the program's capacity. Students assigned to the treatment group were invited via e-mail to participate in the tutoring program and received further program-related information. Students in the treatment group were then randomly assigned to tutoring groups of either two or three students. Students assigned to the control group were informed via e-mail that they could not participate in the program.

The tutoring program focused on advancing students' knowledge of microeconomics and macroeconomics, two compulsory courses in the second term of their study program, and on inducing peer-to-peer interaction. Students in the treatment group were instructed to meet with their tutoring group every two weeks. During those meetings, the tutoring groups were supposed to work on problem sets and exams from previous teaching terms. Importantly, all problem sets and study materials provided to the students in the treatment group were also available to students in the control group via the department's e-learning platform. In every other week (i.e., when the tutoring groups did not meet to work on problem sets), tutors met with the groups to discuss any issues that the tutoring group had while solving the problem

sets and exams from previous terms. During the session, the tutor then explained the problems, asked for the issues that students had while solving the problem set, and potentially also offered general advice on how to study effectively or on anything else that was related to the students' second term, depending on students' demand. Each tutoring session lasted for 90 minutes. During the teaching term, each tutoring group was supposed to meet with their tutor for five tutoring sessions.

The idea of the program was to (i) induce students to take up tutoring services, (ii) induce peer-to-peer interaction between students in an online environment where this sort of interaction is largely missing and (iii) provide a commitment device to ensure that students study regularly during the term in an (online) environment where external structure (e.g., resulting from a fixed time schedule) is missing. Students who fully complied with the program had up to an additional 90 minutes per week where they actively worked through problems in micro- and macroeconomics while interacting with peers.

As outlined before, students who had expressed their interest in the program but were not offered a slot in the randomization serve as our control group. Students in the control group did not receive small-group tutoring, but they had the opportunity to attend the regular general practice sessions for students in both microeconomics and macroeconomics. The regular general practice sessions were open to all students (including those in the treatment group) and took place on a weekly basis, were much less personalized, and did not directly induce peer-to-peer interaction. In terms of content, these sessions and the materials available to control group students were identical to what tutors and student groups discussed in our intervention. In microeconomics, there were also additional (online) practice tests (not counting towards students' grade) that all students could take. In summary, relative to what the control group received in terms of study resources, our program aimed at personalizing teaching without changing the contents or study materials students had access to.

2.3 Recruitment of Tutors

In total, we hired 15 tutors. Work contracts were specified such that each tutor could handle a maximum of four groups of two to three students. We included an about equal number of 2-person and 3-person groups. With 60 groups in total, the tutoring program's maximum capacity therefore was about 150 students. All tutors were students who successfully completed the courses that the program focuses on and during the summer term of 2021 were enrolled in the fourth or sixth semester of the

study program. The program could thus be scaled up easily and at low cost. Including one additional student for a three-month period would cost about €60.[8]

Shortly before the start of the tutoring program, all tutors took part in a kick-off meeting. In this meeting, the research team explained the purpose and the general structure of the program and laid out the planned sequence and contents of the tutoring sessions to be held with each student group. The tutors could also ask questions. The tutors were informed about the fact that the program's capacity was limited and that a random subset of all students in the second term who showed interest would be allowed to participate.

2.4 Sampling and Random Assignment to Treatment and Control Group

About 790 students enrolled for the study program Business Studies for the fall semester of 2020. We excluded from the experiment students who dropped out after the first semester, who were not formally in their second semester, for example because of having been enrolled at another university before and having already completed courses from the first or second semester of the study program without having taken these exams at the university, and students who completed less than a full course (5 credits) in the first term.[9] This leaves us with 714 students entering the second term. These students were invited to participate in the tutoring program in the first week of the term. 226 students responded to this invitation and registered their interest in the program (see Table A.1 for summary statistics relative to the student population).

We randomly assigned students to the treatment group with a probability of around 2/3 to fill all slots, and the other interested students to the control group. The randomization was done in office by a computer. We used a stratified randomization scheme with gender and number of credits completed in the first semester (three bins) as strata variables.[10] In the end, from the 226 students interested in the program, 145 were sampled into the treatment group and 81 into the control group. Students in the treatment group could drop out at any time with no penalty. If dropouts led to tutoring groups with only one student left, we reassigned the remaining student to another tutoring group of the same tutor.

[8] Tutors were employed for three months, with work contracts on four hours per week and monthly net pay of about €160. Employer wage costs were about €200 per month and tutor.

[9] In Germany, some students enroll at a university because as students they have access to social security benefits, e.g. to subsidized health insurance.

[10] We dropped students from the sample who were credited for courses in the second semester and earned the credits in an earlier term (either at the same university, or elsewhere). Such credits often show up with some delay in the administrative data.

3 Data and Empirical Strategy

3.1 Data

Survey Data

After the final tutoring sessions and before the beginning of the exam period, we invited all 226 students in the experimental sample to an online survey. It was conducted on an existing platform at the department that is regularly used to survey students. Students who completed the survey, which lasted around ten minutes, received a payoff of €8.00. The survey elicited the students' assessment of their study effort and behavior as well as their self-perceived (mental) health.

We study the impacts of the tutoring program on study behavior because the program was designed to induce students to continuously study throughout the term in small tutoring groups. The questions relating to study behavior include questions on students' motivation, continuous study behavior, contact to other students, timely exam preparation and sufficient effort to reach term goals. We study the impacts of the tutoring on mental health since the small-group nature of the program, as well as it being among the first formal group interactions in these students' university life, may alleviate feelings of isolation pervasive in online teaching during the pandemic (e.g., Browning et al., 2021; Logel et al., 2021). The mental health questions comprise questions on students' happiness, feelings of stress, anxiety, depression, feelings of being disconnected, sense of belonging, and overall mental health. The full set of questions is shown in Appendix B.1.

Our pre-registered primary outcomes from these surveys are (i) a study behavior index and (ii) a mental health index. Both indices standardize each reply to a question in the respective area to have mean zero and standard deviation one in the control group and then build the unweighted sum of the standardized variables (Kling et al., 2007). We coded both indices such that higher values indicate more positive outcomes. The survey was online in the week before the beginning of the examination period to avoid spillovers from exams to the survey. We use all submitted survey responses. Out of the 226 students in the experimental sample, 142 students (62.8% of the sample) participated and participation was balanced across treatment and control group (see Table B.3 in the Online Appendix).

Administrative Data

We collected registry data from the university in early October 2021 to measure all outcomes related to academic achievement. Our pre-registered primary academic outcome is the total number of credits students earned in the courses microeconomics

and macroeconomics, the subjects covered by the program. Passing a subject gives students 5 credits each. We also focus on students' average grade in both subjects, running from 0 (fail grade) to 4 (best grade).[11] We note that GPA is, in principle, affected by the student's decisions on whether to take either exam. However, analyzing the impact of the program on GPA can reveal whether effects on credits earned came at the expense of grades. It can also reveal whether there is an effect on student achievement in parts of the distribution where extensive margin effects on passing exams are unlikely to arise. Finally, we also obtained data on the exact number of points scored in the two exams and use this information to provide a more continuous measure of student outcomes in microeconomics and macroeconomics. Following Angrist et al. (2009), we did not exclude students who withdrew from the sample. These students were coded as having zero earned credits and no GPA. We assign a value of zero points in an exam if the student did not participate in it.

The exams took place in person between end of July and September 2021 (i.e., after the end of the teaching period). In addition to information on individual exam participation and success, the registry data also contain background information on individual students (enrollment status, gender, age, type of A-level degree, and A-level GPA (coded from 1 as the worst to 4 as the best grade)).

3.2 Balancing Checks and Take-Up

Balancing Checks

Table 1 reports differences in means and standardized differences in students' characteristics. The characteristics comprise gender, age (in years), high-school GPA, a dummy for the most common type of high school certificate ("Gymnasium"), a dummy for students who obtained their high school certificate abroad, credits earned in the first term, a dummy for being in their first year at university, and a dummy for part-time students.[12] As can be seen from Table 1, the treatment and control groups were well balanced across all characteristics.

To assess the quality of our survey data, we repeat the balancing checks using our survey respondents. We also study selection into survey participation by mean-comparison tests between survey participants and non-participants. Table B.3 in the Online Appendix shows that the likelihood of survey completion is unrelated to treatment assignment. Within the sample of participants, treatment and control group

[11] In Germany, a reversed scale is used, with 1 being the best and 4 the worst passing grade. We recoded the GPA to align with the U.S. system.

[12] Students can be in the first year of the study program, but in a more advanced year at university if they were enrolled in a different program before. About 6% of students are enrolled as part-time students because their studies are integrated into a vocational training program.

Table 1: Summary Statistics by Treatment Status

	Control	Treatment	Difference	Std. diff.
Female	0.51	0.50	-0.00	-0.00
	(0.50)	(0.50)	(0.07)	
Age	21.82	21.39	-0.44	-0.11
	(2.76)	(2.66)	(0.37)	
High-school GPA	2.39	2.43	0.04	0.05
	(0.62)	(0.59)	(0.08)	
Top-tier high-school type	0.65	0.70	0.04	0.06
	(0.48)	(0.46)	(0.06)	
Foreign univ. entrance exam	0.09	0.11	0.02	0.06
	(0.28)	(0.31)	(0.04)	
Earned credits in first term	23.17	23.82	0.66	0.06
	(7.85)	(8.26)	(1.13)	
First enrollment	0.69	0.68	-0.01	-0.01
	(0.46)	(0.47)	(0.06)	
Part-time student	0.06	0.06	-0.01	-0.02
	(0.24)	(0.23)	(0.03)	
Obs.	81	145	226	226

Note: This table shows means of administrative student data (standard deviations in parentheses) by treatment status, together with differences between means and corresponding standard errors (in parentheses) and standardized differences. In the line where we report high-school GPA we need to drop 11 observations where we do not have information on students' high-school GPA.

are balanced across all characteristics. Students who participated in the survey differ slightly from students who did not participate in that participants are more likely to be enrolled at university for the first time.

Take-Up

Out of the 226 students in the experimental sample, 145 students were assigned to treatment and thus could participate in the small-group tutoring sessions. Table A.2 in the Online Appendix shows the actual program take-up (i.e., how many students actually participated in the sessions). 91 percent of treatment group students met with their tutors or groups at least once. Female and male students are similarly likely to take up the offer of receiving tutoring services conditional on placement in the program. Because of the very strong take-up, we refrain from reporting IV regressions where we use treatment assignment as an instrument for actual program take-up. IV results are similar to OLS regressions following the specification discussed in the following subsection and available from the authors on request.

3.3 Estimation

To evaluate the effects of the small-group remote tutoring program, we estimate the equation

$$y_i = \alpha + \beta Treatment_i + \gamma X_i + \epsilon_i, \tag{1}$$

where y_i is the outcome of student i, $Treatment_i$ is an indicator for (random) treatment assignment, and X_i is the vector of strata variables. The vector thus contains a female indicator and indicators for the tercile of credits completed in the winter term 2020 the student belongs to. The tercile indicators flexibly control for baseline academic perfomance. We report robust standard errors that allow for clustering at the tutoring group level for students in the treatment group. We additionally account for issues arising from multiple hypothesis testing and report p-values that adjust for the family-wise error rate (FWER) using the procedure of Steinmayr (2020), an extension of List et al. (2019) allowing for control variables and clustered standard errors.

We considered it likely that the effects of tutoring would differ by student characteristics. First, online education shows more negative effects for weaker students (e.g., Figlio et al., 2013; Bettinger et al., 2017). We thus expected heterogeneous effects by credits earned in the first term.[13] Second, male students show worse outcomes in online relative to in-person teaching, relative to female students (e.g., Figlio et al., 2013; Xu and Jaggars, 2014). However, take-up rates in other (mentoring) programs have typically been higher for female students (e.g., Angrist et al., 2009).[14] Thus, it was ex-ante unclear in which direction a potential heterogeneity by gender would go.

We study treatment effect heterogeneity by including an interaction between the variable capturing the dimension of heterogeneity and the treatment indicator, joint with the variable capturing the dimension itself. In addition, we study treatment effect heterogeneity by splitting the sample along the dimension. For the effects by prior performance, we also split the sample into terciles of prior performance and estimate baseline regressions in these subsamples.

[13] We also show results from an endogenous stratification approach in Online Appendix C.5 following Abadie et al. (2018) and Ferwerda (2014). We find similar results.

[14] In our context, male students seem to benefit more from similar (mentoring) interventions, if anything (Hardt et al., 2020), while take-up rates in such programs seem to be higher for female students (e.g., Angrist et al., 2009).

4 Results

4.1 Effects on Study Behavior and Mental Health

We first study the effects of the tutoring program on self-reported study behavior and (mental) health outcomes. As dependent variables, we use indices that aggregate answers to questions concerning both topics in our survey (Kling et al., 2007) and that are coded such that higher values indicate more positive outcomes. Table 2 shows the result from this analysis. Column (1) shows that treated students report substantially improved study behavior. The treatment effect is sizeable and amounts to around a quarter of a standard deviation in the control group. A more detailed analysis reveals that the program significantly increased the students' motivation, led to more continuous studying, and increased contact to other students (see Table B.4 in the Appendix). Instead, Column (2) shows that the mental health index is entirely unaffected by the treatment. This is also true for each underlying element of the mental health index (see Table B.5 in the Appendix).[15]

Thus, our results suggest that the tutoring program worked as intended, in the sense that it improved students' study behavior and increased their contact to other students. In contrast, the mental health of students was not affected by the treatment.[16]

4.2 Impacts on Primary Outcomes

In Figure 1, we plot our main academic outcomes by treatment status. In Panel (a) of the figure, we plot the credits earned in micro- and macroeconomics by treatment. Students can either obtain 0, 5, or 10 credits, depending on whether they pass neither of the two courses, one of them, or both. The figure shows that the treatment lowered the likelihood of not passing any course by around 12pp (or 24% of the control group mean). Correspondingly, the treatment increased the likelihood of reaching 5 credits by 2.2pp (9%) and the likelihood of passing both courses by 9.8pp (40%).[17] Did the increase in credits earned come at the expense of students' grades? Panel (b) plots the GPA across both courses for those students that obtained a grade. The panel shows that the increase in credits earned documented in Panel (a) came along with a

[15] Note that this does not arise due to students' unwillingness to report mental health issues: around 60% of students respond to the depression question stating they often or very often felt depressed during the term, in line with evidence of low mental health among students during the pandemic (e.g., Lai et al., 2020; Browning et al., 2021).

[16] All corresponding tables are in Online Appendix B. The statements are shown in Online Appendix B.1. Note that we treat the ordinal scales as if they were cardinal scales. Using ordered probit or ordered logit models renders qualitatively identical findings.

[17] Figure C.1 in the Online Appendix also shows means for students who were not interested in participating in the program.

Table 2: Impacts of Tutoring on Study Behavior and Health

	Study index	Health index
Avg. effect	0.26**	-0.00
	(0.12)	(0.12)
	[0.06]	[0.97]
Obs.	142	142

Note: This table shows impacts of peer tutoring on indices of survey responses adapting Equation 1 and following Kling et al. (2007). We thus standardize responses to each underlying question to a z-score and sum all responses. The "study index" comprises answers to questions on students' motivation, continuous study behavior, contact to other students, timely exam preparation and sufficient effort to reach term goals. The "health index" comprises answers to questions on students' happiness, feelings of stress, anxiety, depression, feeling disconnected, sense of belonging, overall mental health, and physical health. For the full set of survey questions, please see Online Appendix B.1. The corresponding tables can be found in Online Appendix B.2. Standard errors in parentheses allow for clustering at the tutoring group level for treated students. The associated p-values are denoted by stars: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. In brackets, we show p-values adjusting for the family-wise error rate following Steinmayr (2020).

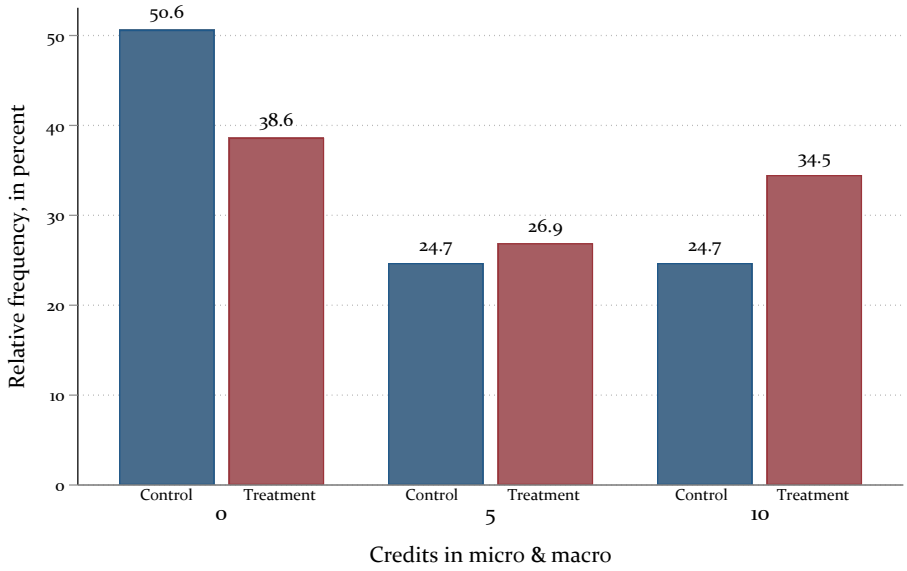
clear improvement of students' GPA in these courses. This shows that the treatment improved students' academic outcomes in the treated courses throughout.

We quantify these impacts in Table 3. The table shows average differences between the treatment and control groups for academic outcomes in the subjects covered by the program. Column (1) shows the impacts on credits earned in microeconomics and macroeconomics. Each of the two subjects is worth 5 credits, meaning that students could earn between zero and 10 credits across both subjects. Column (1) shows that on average, students in the control group earn only 3.7 credits, pointing to substantial difficulties of many students to cope with the contents of the subjects covered by the program. Students who received a treatment offer earned around one credit more than students who did not, an increase of around 29% relative to the control group mean. Column (2) shows that treated students at the same time outperform control group students in terms of GPA by around one grade level.[18] Thus, students were not only more likely to pass the subjects covered by the tutoring program, they also received better grades.

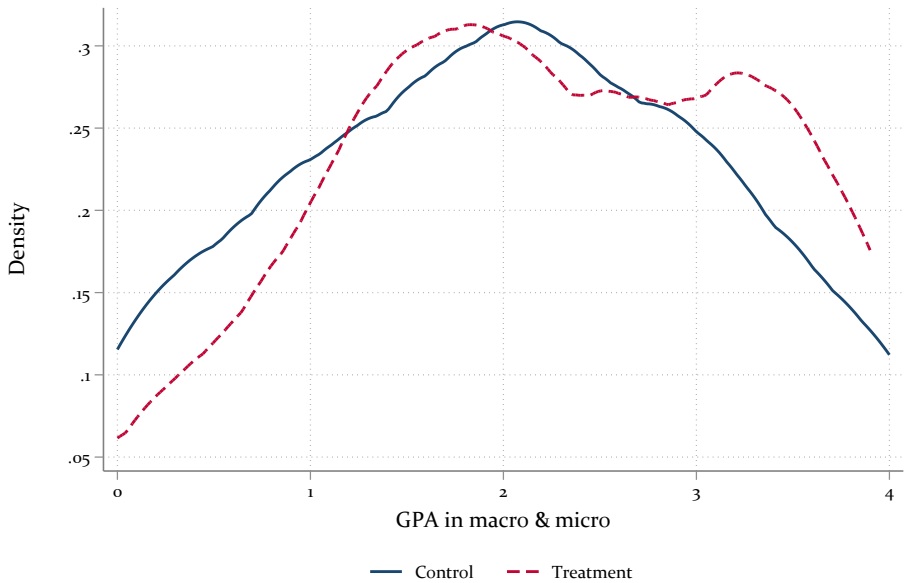
[18]The grading system in Germany allows to deviate from natural numbers in steps of 0.3.

Figure 1: Distribution of Academic Outcomes by Treatment Status

(a) Histogram of Credits Earned in Micro and Macro by Treatment Status



(b) Kernel Density Plots of Student GPA in Micro and Macro by Treatment Status



Note: The figure in panel (a) shows the relative frequency of obtaining either 0, 5, or 10 credits in microeconomics and macroeconomics by treatment status. The figure in panel (b) presents unadjusted Kernel density plots by treatment status using as an outcome the GPA in microeconomics and macroeconomics (running from 0=fail grade to 4=best).

Table 3: Average Impacts of Remote Tutoring on Student Outcomes

Dependent Variable:	Credits earned	GPA	Ex. score (Std.)
	(1)	(2)	(3)
Treatment	1.06**	0.35**	0.27**
	(0.45)	(0.16)	(0.10)
	[0.04]	[0.03]	[0.02]
Mean control	3.70	1.99	-0.18
Obs.	226	152	226

Note: This table shows impacts of remote tutoring on administrative student outcomes using Equation 1. In column (1), we show impacts on credits earned in micro- and macroeconomics, the two subjects covered by the tutoring program. Each completed course amounts to 5 earned credits. Column (2) shows impacts on students' GPA across the two subjects. The number of observations differs from Column (1) since we have several students who do not earn any credits in these subjects. Column (3) shows impacts on points earned in the exams, setting to zero all observations where students did not participate in the exams. This variable is then standardized to have mean zero and standard deviation one for all students. Standard errors in parentheses allow for clustering at the tutoring group level for treated students. The associated p-values are denoted by stars: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. In brackets, we show p-values adjusting for the family-wise error rate following Steinmayr (2020).

To compare the magnitudes of these effects to results in the literature on tutoring interventions before higher education, Column (3) uses z-scores of points earned in both exams as a continuous measure of student achievement.[19] The estimate shows that treated students earn around 0.3 standard deviations more points than students in the control group, a large effect for education standards. This result is similar in magnitude to the effectiveness of tutoring interventions before higher education (Carlana and La Ferrara, 2021; Nickow et al., 2020).

Overall, Table 3 suggests that the effects of the small-group tutoring program on study behavior translate into strong effects on performance. In more detailed regressions shown in Appendix C.2, we find that this result is primarily driven by the effect the program had on student achievement in microeconomics. The relative magnitudes of the results on microeconomics and macroeconomics are well aligned with qualitative information obtained from the tutors that in the sessions with their tutoring groups, they spent around 2/3 of the time on average discussing topics and problems in microeconomics, and only about 1/3 of the time on macroeconomics.[20]

4.3 Heterogeneity of Effects

As outlined, we expected treatment effects to differ by prior student performance. This can be measured through the students' performance in the first term. Figure 2

[19] We standardize the variable to have mean zero and standard deviation one. Before doing so, we code students who did not participate in an exam as having earned zero points.

[20] We analyze the effectiveness of tutoring per subject and minute in Appendix C.3.

shows the key result from this analysis using credits earned in subjects covered by the program as the dependent variable. We find that the treatment effect is largest for students in the second tercile of the prior student performance distribution. The point estimate for weak students is insignificant, but sizable, suggesting that the treatment more than doubled credits earned on average. For good students, there are no effects on credits earned. In Appendix C.4, we repeat this analysis using student GPA as the dependent variable. The results suggest positive impacts of comparable magnitude on the GPA of all types of students.[21]

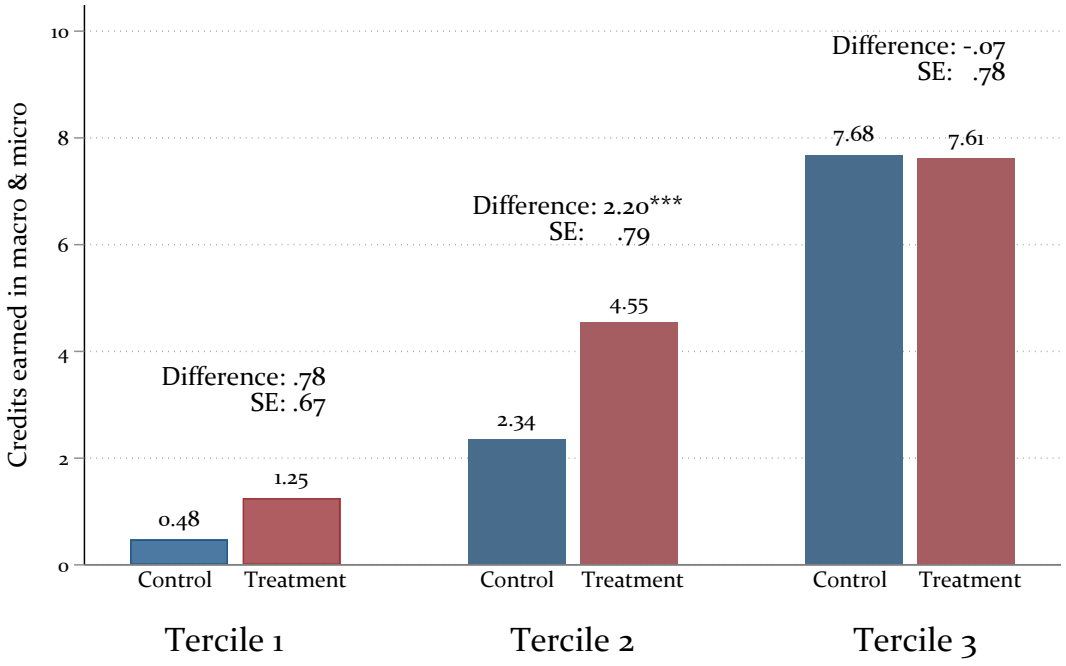
We also investigated the heterogeneity of effects by student gender. In Appendix Table C.5, we show the results from this analysis. Female and male students benefit similarly from the tutoring in terms of credits earned, but females benefit a bit more in terms of GPA, although the difference is insignificant. We also studied whether the effects of tutoring are larger for students tutored by female than by male tutors as well as gender interactions (e.g., Dee, 2005, 2007; Hoffmann and Oreopoulos, 2009). We study this in Table C.6 in the Appendix. We find some differences for men, who seem to be more effectively tutored by male than by female tutors.

Nickow et al. (2020) report that typically, tutors more distant in age and hierarchy are more effective than peer tutors. In additional heterogeneity analyses, we therefore also study whether the effects of tutoring are larger when students are tutored by more senior (from the 6th term) or by less senior (from the 4th term) tutors. We find no such effect (Online Appendix Table C.7). Finally, we also investigate whether the effects of tutoring are larger in two-person or three-person tutoring groups (Table C.8 in the Online Appendix). We find that, if anything, larger groups are more effective.

Overall, the heterogeneity analysis thus returns some interesting patterns. The tutoring program reduced outcome inequality in credits earned, while benefiting good students nevertheless by raising their average grade across the subjects covered by the treatment. Female and male students benefit similarly from the program. Finally, the tutoring, if anything, works even better in slightly larger groups of three tutored students than in smaller groups of two.

[21] In Online Appendix C.5, we follow Abadie et al. (2018) and Ferwerda (2014) and estimate effects using endogenous stratification approaches. In line with the analysis above, students in the lower and middle part of the distribution of predicted outcomes in the summer term seem to benefit most from the program in terms of credits earned. In terms of GPA, the impacts are highest for well-performing students.

Figure 2: Effects on Credits Earned by Prior Performance



Note: This figure shows how students' credits earned in the summer term 2021 relate to students' prior performance as measured by students' credits earned in the winter term.

4.4 Spillovers to Other Subjects

We now investigate whether students' performance in subjects not covered by the tutoring program was affected by the treatment as well. Ex-ante, it is unclear whether we should expect spillover effects. And if there are spillover effects, it is ex-ante unclear in which direction these effects should go. On the one hand, students could benefit from spillovers for example through using their math skills trained in micro- and macroeconomics for other subjects as well. On the other hand, the tutoring may shift students' attention towards the subjects covered and away from the remaining subjects.

Table 4 therefore splits the compulsory courses in the second term into treated and non-treated subjects. The first two columns show the impacts of the tutoring program on treated compulsory courses and thus repeat the results in Table 3. Column (3) shows the impact on credits earned in non-treated compulsory courses. The effect is slightly negative, but insignificant. Relative to the mean of the control group, it is small, at 4%. Column (4) shows that the impact on students' GPA in non-treated compulsory courses is similarly small and insignificant. Thus, the tutoring intervention

Table 4: Average Impacts of Remote Tutoring on Student Outcomes

	Treated ST courses		Non-treated ST courses	
Dependent Variable:	Credits earned	GPA	Credits earned	GPA
	(1)	(2)	(3)	(4)
Treatment	1.06**	0.35**	-0.42	0.07
	(0.45)	(0.16)	(0.77)	(0.11)
	[0.08]	[0.07]	[0.58]	[0.73]
Mean control	3.70	1.99	11.05	2.14
Obs.	226	152	226	192

Note: This table shows impacts of remote tutoring on administrative student outcomes in treated and non-treated subjects using Equation 1. In column (1), we show impacts on credits earned in micro- and macroeconomics, the two subjects we treated. Each completed course amounts to 5 earned credits. Column (2) shows impacts on students' GPA across the two subjects. The number of observations differs from Column (1) since we have several students who do not earn any credits in these subjects. Column (3) shows impacts on credits earned in all compulsory second term courses that we did not treat in the tutoring intervention, leaving out micro- and macroeconomics. The non-treated courses are Financial Mathematics, Data Management, Econometrics, and Marketing. Column (4) shows impacts on students' GPA in these non-treated courses. Standard errors in parentheses allow for clustering at the tutoring group level for treated students. The associated p-values are denoted by stars: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. In brackets, we show p-values adjusting for the family-wise error rate following Steinmayr (2020).

does not seem to have had any spillover effects to non-treated compulsory courses. This suggests that the tutorials improved student outcomes through subject-specific teaching instead of teaching broader (study) skills.

5 Conclusion

This paper presents field-experimental evidence on the potential role of remote small-group tutoring programs in (online) higher education. In our program, first year students were tutored by more advanced student tutors in groups of two or three. For our experiment, we leveraged the online teaching environment at a German public university induced by the Covid pandemic.

We find that the tutoring program improved the students' study behavior, but left the students' self-reported mental health unaffected. The improvements in study behavior translate to economically and statistically significant impacts on earned credits and students' GPA in the subjects covered by the program. The magnitude of these effects are similar to the effectiveness of tutoring interventions before higher education (Nickow et al., 2020). We finally show that tutoring reduces outcome inequality among students and that slightly larger groups work similarly well than smaller groups.

Our results show the effectiveness of remote tutoring to improve student outcomes and study behavior in higher education. While transferring field experimental results obtained during a pandemic to other settings is certainly a challenge, the sum of our findings leads us to believe that our results carry implications for the time in which universities return to their (new) normal way of teaching. Online-only higher education has been on the rise already before the pandemic and demand for online tutoring services in higher education is expected to further increase in post-pandemic times.

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APPENDIX: FOR ONLINE PUBLICATION ONLY UNLESS REQUESTED OTHERWISE

A Who Participated in the Program?

Table A.1: Summary Statistics by Interest in Program

	Response to invitation to register for tutoring			
	Non-Registered	Registered	Difference	Std.diff.
	(1)	(2)	(3)	(4)
Female	0.45	0.50	0.06	0.08
	(0.50)	(0.50)	(0.04)	
Age	21.27	21.54	0.27	0.07
	(2.54)	(2.70)	(0.21)	
High-school GPA	2.38	2.41	0.04	0.04
	(0.59)	(0.60)	(0.05)	
Top-tier high-school type	0.78	0.68	-0.10***	-0.15
	(0.42)	(0.47)	(0.03)	
Foreign univ. entrance exam	0.05	0.10	0.05**	0.13
	(0.22)	(0.30)	(0.02)	
Earned credits in first term	21.24	23.59	2.34***	0.19
	(9.58)	(8.10)	(0.74)	
First enrollment	0.76	0.69	-0.07**	-0.12
	(0.43)	(0.47)	(0.04)	
Part-time student	0.10	0.06	-0.04*	-0.11
	(0.30)	(0.23)	(0.02)	
Obs.	488	226	714	714

Note: This table shows means of administrative student data by registration status, together with differences between means and corresponding standard errors (in parentheses) and standardized differences. Registered students form our treatment and control groups.

Table A.2: Actual Take-Up

Dependent Variable:	Take up		
	Overall	Female	Male
Treatment	0.91***	0.92***	0.90***
	(0.02)	(0.03)	(0.03)
Obs.	226	114	112

Note: This table shows results of regressions of program take-up on treatment assignment controlling for student gender (where possible) and credits earned in the winter term. Column (1) uses as dependent variable a dummy whether students met at least once with their group or their tutor. Columns (2) and (3) use the same dependent variable as Column (1) but split the sample into female and male students, respectively. Standard errors allow for clustering at the tutoring group level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B Additional Survey Information and Evidence

B.1 Survey Questions and Sorting into Survey Participation

In table B.1, we show the exact questions that we asked students in the survey. The survey was conducted in German, which is the official language of the program. All responses are measured on a five-point Likert scale where higher values indicate higher agreement with the question. We recoded all questions such that higher agreement means better outcomes (e.g., lower levels of anxiety). Table B.3 shows that participation is balanced across treatment and control group, although survey participants slightly differ from non-participants on their observed characteristics.

Table B.1: Survey Questions

Panel A: Study behavior

Label	Question
Motivation	I was able to motivate myself well during the virtual summer semester.
Continuous studying	I was able to cope well with the challenge of continuously studying for courses during the virtual summer semester.
Exchange with others	In the virtual summer semester, I was able to have an exchange about study matters with other students.
Timely exam prep.	In the virtual summer semester, I started my exam preparation on time.
Sufficient effort	Measured against my goals for this semester, my effort to study during the lecture period was sufficient.

Panel B: Health

Label	Question
Happiness	I was often in good spirits during this lecture period.
Stress	I was often stressed during this lecture period.
Anxiety	I was often nervous or anxious during this lecture period.
Depression	I was often depressed or listless during this lecture period.
Disconnectedness	I often felt lonely during this lecture period.
Sense of belonging	I felt like I belonged at FAU during the lecture period.
Mental health	During this lecture period, my overall psychological well-being was [ ].

Table B.3: Sorting into Survey Participation

	Survey participation				Within survey			
	Non-participants	Participants	Difference	Std.diff.	Control	Treatment	Difference	Std.diff.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment group	0.64	0.64	-0.00	-0.00				
	(0.48)	(0.48)	(0.07)					
Female	0.44	0.54	0.10	0.14	0.63	0.49	-0.13	-0.19
	(0.50)	(0.50)	(0.07)		(0.49)	(0.50)	(0.09)	
Age	21.79	21.40	-0.39	-0.10	21.60	21.28	-0.32	-0.09
	(2.93)	(2.55)	(0.37)		(2.78)	(2.43)	(0.45)	
High-school GPA	2.36	2.45	0.09	0.11	2.49	2.42	-0.06	-0.07
	(0.56)	(0.62)	(0.08)		(0.66)	(0.59)	(0.11)	
Top-tier high-school type	0.73	0.65	-0.07	-0.11	0.61	0.68	0.07	0.11
	(0.45)	(0.48)	(0.06)		(0.49)	(0.47)	(0.08)	
Foreign univ. entrance exam	0.10	0.11	0.01	0.02	0.10	0.11	0.01	0.03
	(0.30)	(0.31)	(0.04)		(0.30)	(0.31)	(0.05)	
Earned credits in first term	23.65	23.55	-0.11	-0.01	23.53	23.56	0.03	0.00
	(9.13)	(7.46)	(1.12)		(7.22)	(7.64)	(1.31)	
First enrollment	0.58	0.75	0.16**	0.25	0.80	0.71	-0.09	-0.15
	(0.50)	(0.44)	(0.06)		(0.40)	(0.45)	(0.08)	
Part-time student	0.05	0.06	0.02	0.05	0.08	0.05	-0.02	-0.07
	(0.21)	(0.24)	(0.03)		(0.27)	(0.23)	(0.04)	
Obs.	84	142	226	226	51	91	142	142

Note: This table shows selection into survey participation. The first four columns show means administrative student data of participants and non-participants along with differences between both groups. The next four columns show means and differences in administrative student data by initial treatment assignment among survey participants. We estimated whether the differences between groups are statistically significant using t-tests in Columns (3) and (7) and using standardized differences in Columns (4) and (8). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B.2 Regression Results

Table B.4: Treatment Effects on Assessment of Own Motivation and Study Effort

Dep. V.:	Motivation	Cont. studying	Contact other stud.	Timely exam prep.	Suff. effort
	(1)	(2)	(3)	(4)	(5)
Treatment	0.26*	0.44**	0.49**	0.07	-0.01
	(0.15)	(0.17)	(0.19)	(0.17)	(0.17)
	[0.21]	[0.04]	[0.04]	[0.89]	[0.97]
M. c.	2.33	2.51	1.92	2.65	2.94
Obs.	142	142	142	142	142

Note: This table shows impacts of remote peer tutoring on survey outcomes, adapting equation 1. The odd-numbered columns use OLS, estimating intent-to-treat effects. The even-numbered columns use (random) treatment assignment variable as an instrument for initial program take-up, estimating treatment-on-the-treated effects. All dependent variables are measured on a five-point Likert scale where higher outcomes indicated more agreement with the question. The questions underlying the dependent variables are on students' motivation during the summer term (Column 1); whether they studied continuously throughout the term (Column 2); whether they had frequent contact to other students (Column 3); whether they prepared for their exams timely (Column 4); and whether they provided sufficient effort to reach their semester goals (Column 5). Standard errors in parentheses allow for clustering at the tutoring group level for treated students. The associated p-values are denoted by stars: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. In brackets, we show p-values adjusting for the family-wise error rate following Steinmayr (2020).

Table B.5: Treatment Effects on (Mental) Health Outcomes

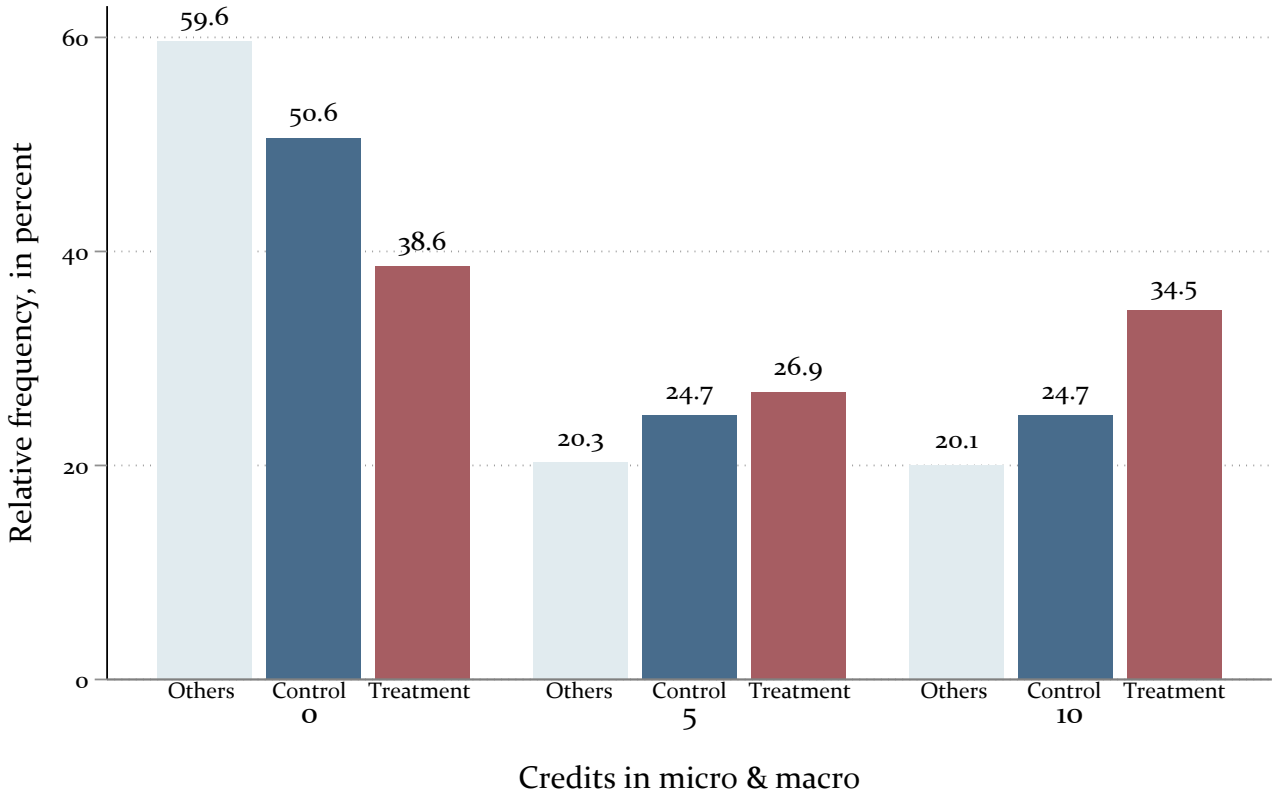
Dependent Variable:	Happiness	Stress	Anxiety	Depression	Disconnected	Sense of Belonging	Mental Health
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treat.	-0.00	-0.12	-0.10	-0.08	-0.05	0.02	0.23
	(0.19)	(0.20)	(0.19)	(0.20)	(0.24)	(0.19)	(0.16)
	[0.98]	[0.98]	[0.99]	[0.98]	[0.99]	[0.99]	[0.59]
M.c.	2.80	2.49	2.59	2.43	2.59	2.12	2.78
Obs.	142	142	142	142	142	142	142

Note: Note: This table shows impacts of remote peer tutoring on mental health survey outcomes, adapting equation 1. We recoded all replies such that higher values are more desirable. The odd-numbered columns use OLS, estimating intent-to-treat effects. The even-numbered columns use (random) treatment assignment variable as an instrument for initial program take-up, estimating treatment-on-the-treated effects. All dependent variables are measured on a five-point Likert scale where higher outcomes indicated more agreement with the question. The questions underlying the dependent variables are on students' happiness during the summer term (Column 1); their perception of stress (Column 2); their levels of anxiety and nervousness (Column 3); their symptoms of depression (Column 4); their feelings of disconnectedness (Column 5); their sense of belonging (Column 6); and their total mental health (Column 7). Standard errors in parentheses allow for clustering at the tutoring group level for treated students. The associated p-values are denoted by stars: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. In brackets, we show p-values adjusting for the family-wise error rate following Steinmayr (2020).

C Additional Results for Administrative Student Outcomes

C.1 Distribution of Outcomes by Treatment Status

Figure C.1: Average Credits Earned in Micro and Macro by Treatment Status Including Non-Participants



Note: This figure shows the relative frequency of obtaining certain earned credits in microeconomics and macroeconomics by treatment status including non-participants represented by "Others".

C.2 Impacts by Subject

Table C.1: Impacts by Subject

Course:	Microeconomics			Macroeconomics		
Dep. Var.:	Credits	Grade	Points (Std.)	Credits	Grade	Points (Std.)
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.67***	0.50***	0.29***	0.39	0.23	0.14
	(0.25)	(0.19)	(0.10)	(0.31)	(0.21)	(0.13)
	[0.02]	[0.02]	[0.01]	[0.47]	[0.41]	[0.29]
Mean control	2.04	2.11	-0.19	1.67	1.93	-0.09
Obs.	226	130	226	226	106	226

Note: This table shows impacts of remote tutoring on administrative student outcomes by course. Columns (1) to (3) use student outcomes in microeconomics as dependent variable. Columns (4) to (6) use student outcomes in macroeconomics as dependent variable. Columns (1) and (4) use credits earned in the respective subject as dependent variable. Each completed course amounts to 5 earned credits. Columns (2) and (5) use students' grade in the subject as dependent variable. Columns (3) and (6) use points earned in the exam as dependent variable, normalized to have mean zero and standard deviation one. In these columns, we code students who did not participate in the exam as having scored zero points. We control for student gender and prior achievement (our strata variable) in all columns. Standard errors in parentheses allow for clustering at the tutoring group level for treated students. The associated p-values are denoted by stars: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. In brackets, we show p-values adjusting for the family-wise error rate following Steinmayr (2020).

C.3 Effects per Minute of Tutoring

In this subsection, we analyze the effects per minute of tutoring. For that purpose, we run IV regressions using as outcomes credits earned and GPA in the subjects covered by the program, separately for both subjects. Our main explanatory variable is the total number of minutes of tutoring a student received in the respective subject over the full term. We instrument this measure of the intensity of tutoring by the indicator for random treatment assignment. The measures of the intensity of tutoring are constructed as follows. First, we use the total number of minutes a student participated in tutoring sessions with or without the tutor obtained from protocols of the respective zoom sessions. Second, after the end of the program, we surveyed the tutors on the relative share (in percent) of time they spent on discussing topics and problems related to either microeconomics or macroeconomics per tutoring group. We then derive tutoring group-specific intensity measures from multiplying the group-specific total number of minutes of tutoring received with the group-specific percentage time shares. For control group students, tutoring intensity is coded as 0. We report robust standard errors that allow for clustering at the tutoring group level.

Our survey among tutors documents that the average tutoring group spent about 2/3 of the time on microeconomics, and about 1/3 on macroeconomics. This corresponds closely with the findings from Table C.1, showing that about 2/3 of the overall impact of the intervention on credits earned in the subjects covered by the program (plus 1.06 credits, see Table 3) comes from microeconomics (plus 0.67 credits).

In Table C.2, we show impacts of tutoring per minute. Adjusting the point estimate in column (1) to reflect a linear probability model instead of credits earned to facilitate interpretability, we find that 90 minutes of interaction with peers in a tutoring group (i.e., one full session in our program) increase the likelihood of passing the microeconomics exam by $0.0004 \times 90 = 0.036$, or about 3.6 percentage points. Column (3) shows that the effects are very similar for macroeconomics, although the coefficient is estimated with more noise. Columns (2) and (4) show corresponding impacts on students' grades in microeconomics and macroeconomics. Again, there are no significant differences between tutoring impacts per minute on micro- and macroeconomics. We conclude that there is no evidence that our intervention was differentially effective between subjects once we control for differences in the intensity of tutoring.

Note that given the average performance of control group students in microeconomics, one would need fewer than 3 sessions of 90 minutes each in the subject to shift these students to more likely pass the course than not. Because of the lower average performance of students in macro, one would need over 7 sessions to shift these

Table C.2: Average Impacts of Minutes of Tutoring on Student Outcomes

	Micro		Macro	
Dependent Variable:	Pass	Grade	Pass	Grade
	(1)	(2)	(3)	(4)
Treatment	0.0004***	0.0011***	0.0004	0.0009
	(0.0001)	(0.0004)	(0.0003)	(0.0008)
Mean control	0.41	2.11	0.33	1.93
Mean duration treat.	360.42	360.42	202.45	202.45
Obs.	226	130	226	106

Note: This table shows impacts of IV estimates of the overall intensity of remote tutoring (measured in overall minutes of tutoring over the term) instrumented by the random treatment assignment on administrative student outcomes in treated and non-treated subjects. In column (1), we show impacts on the probability to pass the exam in microeconomics, and in Column (2) on students' grade in microeconomics. The number of observations differs from Column (1) since not all students earn credits in this subject. Column (3) shows impacts on the probability to pass the exam in macroeconomics, and Column (4) on students' grade in macroeconomics, again with a differing number of observations due to non-participation in the exam. Standard errors in parentheses allow for clustering at the tutoring group level for treated students. As a benchmark, we also show the mean intensity of tutoring in the treatment group per subject. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

student to rather than not pass the course. These analyses suggest that tutoring is a very effective way to improve student outcomes.

C.4 Impacts by Credits Earned in Winter Term

Table C.3: Heterogeneity by credits earned in winter term

Panel A: Credits earned in Micro & Macro				
	Interaction	First tercile	Second tercile	Third tercile
	(1)	(2)	(3)	(4)
Treatment	1.11	0.78	2.20***	-0.07
	(0.85)	(0.67)	(0.79)	(0.78)
Treatment · credits (WT)	-0.00			
	(0.04)			
Mean control	3.70	0.48	2.34	7.68
Obs.	226	57	91	78
Panel B: GPA in Micro & Macro				
	Interaction	First tercile	Second tercile	Third tercile
Treatment	-0.20	0.44	0.42	0.27
	(0.48)	(0.76)	(0.28)	(0.20)
Treatment · credits (WT)	0.02			
	(0.02)			
Mean control	1.99	0.77	1.59	2.42
Obs.	152	16	63	73

Note: This table shows impacts of remote tutoring on administrative student outcomes by prior student performance as measured by credits earned in the winter term. In Panel (A), we show impacts on credits earned in micro- and macroeconomics, the two subjects we treated. Each completed course amounts to 5 earned credits. Panel (B) shows impacts on students' GPA across the two subjects. The number of observations differs from Panel (A) since we have several students who do not earn any credits in these subjects. In both panels, we show the interaction effect in Column (1). In the remaining columns, we split the sample by students' tercile of total earned credits in the winter term, our strata variables. We control for student gender in all columns. Standard errors in parentheses allow for clustering at the tutoring group level for treated students. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

C.5 Endogenous Stratification

Table C.4: Endogenous Stratification

Panel A: Credits earned			
Predicted Outcome Group:	Low	Middle	High
	(1)	(2)	(3)
Repeated split sample			
Coefficient	0.62	2.29	-0.02
Std. Err.	0.58	0.84	0.76
Leave-one-out			
Coefficient	0.46	2.18	0.08
Std. Err.	0.73	1.00	0.84
Panel B: GPA			
	(1)	(2)	(3)
Repeated split sample			
Coefficient	0.11	0.16	0.54
Std. Err.	0.36	0.24	0.23
Leave-one-out			
Coefficient	0.12	0.08	0.48
Std. Err.	0.52	0.41	0.30

Note: This table shows impacts of peer tutoring on administrative student outcomes by students' predicted outcome group ("Group"), following the procedures outlined in Abadie et al. (2018) and using the Stata package `estrat` by Ferwerda (2014). We use students' gender, students' earned credits in the winter term, and students' high-school GPA as predictors. All regressions control for student gender and earned credits in the winter term. We use 100 RSS repetitions and 500 bootstrap repetitions, with 136 treated and 79 control observations since we do not have students' high school GPA for 11 observations. In Panel A, the "low" group has 72 observations, the "middle" group 71 observations, and the "high" group 72 observations. The "low" group has 61 observations, the "middle" group 62 observations, and the "high" group 62 observations in Panel B.

C.6 Effects by Student Gender

Table C.5: Tutoring Effectiveness by Student Gender

Panel A: Credits earned in Micro & Macro			
	Interaction	Female	Male
	(1)	(2)	(3)
Treatment	1.04	1.08**	1.02
	(0.68)	(0.54)	(0.69)
Treatment · female	0.04		
	(0.83)		
Mean control	3.70	3.41	4.00
Obs.	226	114	112
Panel B: GPA in Micro & Macro			
	Interaction	Female	Male
Treatment	0.27	0.43**	0.25
	(0.26)	(0.20)	(0.26)
Treatment · female	0.17		
	(0.33)		
Mean control	1.99	1.86	2.14
Obs.	152	78	74

Note: This table shows the impact of tutoring on student outcomes by gender. Panel A uses the number of credits earned in microeconomics and macroeconomics in the summer term 2021 as the dependent variable. Panel B uses students' GPA in microeconomics and macroeconomics in the summer term 2021 as the dependent variable. All columns control for the number of credits earned in the winter term and the first column also controls for student gender. Standard errors allow for clustering at the tutoring group level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

C.7 Tutoring Differences by Tutor Gender

In this subsection, we provide descriptive evidence on differences in tutoring by tutor gender. Table C.6 shows impacts of having a female tutor on credits for which students registered in the summer term, credits earned, and GPA. If anything, male tutors seem to be a bit more efficient. This is more pronounced for male tutees, whose performance under tutoring also differs substantially more across their tutor's gender. For female students, tutor gender does not seem to matter much. Our findings therefore show partial support for results in the literature that matching characteristics of students and instructors improves student learning (Dee, 2005, 2007; Hoffmann and Oreopoulos, 2009). The results are noisy, however.

Table C.6: Tutoring Effectiveness by Tutor Gender

Dependent Variable:	Credits earned in Micro & Macro			
	Female tutor	Male tutor	Female tutor	Male tutor
	(1)	(2)	(3)	(4)
Treatment	0.79	1.34***	0.57	1.64**
	(0.57)	(0.51)	(0.82)	(0.74)
Treatment · female			0.45	-0.56
			(1.00)	(0.95)
Mean control	3.70	3.70	3.70	3.70
Obs.	151	156	151	156

Note: This table shows the impact of tutor gender on outcomes. All columns use the number of credits earned in microeconomics and macroeconomics in the summer term 2021 as the dependent variable. Columns (1) and (3) use students tutored by female and Columns (2) and (4) use students tutored by male tutors as the treatment group. All columns use non-tutored students as control group. All columns control for the number of credits earned in the winter term and for student gender. Standard errors allow for clustering at the tutoring group level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

C.8 Effects by Tutor Seniority

Table C.7: Tutoring Effectiveness by Tutor Seniority

Dependent Variable:	Credits earned in Micro & Macro	
	6^{th} term tutor	4^{th} term tutor
	(1)	(2)
Treatment	1.14*	1.04**
	(0.59)	(0.51)
Mean control	3.70	3.70
Obs.	148	159

Note: This table shows the impact of tutoring on student outcomes by tutor seniority. Column (1) uses as treament group students tutored by tutors in their 6th term, while Column (2) uses students tutored by tutors in their 4th term. Both columns use untreated students as control group. All columns use the number of credits earned in microeconomics and macroeconomics in the summer term 2021 as the dependent variable. All columns control for the number of credits earned in the winter term and for student gender. Standard errors allow for clustering at the tutoring group level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

C.9 Effects by Group Size

Table C.8: Descriptive Results on Tutoring Effectiveness by Group Size

Dependent Variable:	Credits earned in Micro & Macro	
	Large group	Small group
	(1)	(2)
Treatment	1.81***	1.03
	(0.55)	(0.62)
Mean control	3.70	3.70
Obs.	147	136

Note: Note: This table shows the impact of tutoring on student outcomes by tutoring group size. Column (1) uses as treament group students tutored in groups of three, while Column (2) uses students tutored in groups of two. Both columns use untreated students as control group. All columns use the number of credits earned in microeconomics and macroeconomics in the summer term 2021 as the dependent variable. All columns control for the number of credits earned in the winter term and for student gender. Standard errors allow for clustering at the tutoring group level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$