Increasing the effect of a remedial mathematics course by switching to an online format during the COVID-19 crisis: evidence from a German university

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Due to the COVID-19 crisis, many courses have been offered digitally. Using data from \( n = 1,173 \) business students participating in a preparatory mathematics course at a German university that covered the same content as in 2018, 2019 and 2020, we examine how students’ participation and the effect of the preparatory course changed. The data show that the participation rate has fallen slightly, but students’ participation is rather similar to preceding years. Interestingly, students have participated more intensively. There are clear signs of dishonesty in the self-test (use of a calculator) and significant changes in predictors of performance. In particular, the effect of students’ engagement in the course on their performance substantially increased. Further, we found a gender gap in performance affecting women. Finally, the data show that digital courses can be as effective as on-campus courses.

1. Introduction

When entering their studies, many students of economics have gaps in basic mathematical knowledge. In Germany, many universities offer preparatory courses that repeat school mathematics. In the course of the COVID-19 pandemic, these preparatory courses, like the entire teaching enterprise at many universities worldwide, were completely converted to digital teaching. One can assume that this will result in changes that affect both the participation and the impact on students’ skills of the courses. While in principle many advantages and disadvantages of digital offerings are known, there are few empirical results comparing digital courses with traditional on-site courses. In particular, such comparisons are often complicated by the fact that students have a choice between delivery modes.

At the University of Kassel, a preparatory course for economics students has been offered for years and has already been evaluated. This preparatory course is voluntary but has always been attended by a large number of students. In 2020, as a result of the pandemic, teaching was switched to a digital model.
without changing the content. We therefore understand the changes brought about by the COVID-19 crisis as a kind of quasi-experiment that arose because a cohort was unexpectedly forced to switch to an alternative model. Fortunately, we can draw on comparative data from both 2018 and 2019, which was collected using the same instruments as in 2020.

This study investigates possible differences between the on-campus and online implementations of the course and is therefore exploratory in its nature. Even if some assumptions about differences can be derived from the literature, the interaction of various factors has not been researched enough. The focus of the study is therefore on the description of the student cohort in comparison to the years before and changes in the predictors of mathematical performance. To measure this performance, the same test was used, which had to be worked on without help from people or technical devices (e.g. calculators). Since these conditions may not be replicated when studying at home, the validity of the test is examined as an important intermediate step.

2. Theoretical background

2.1. Preparatory courses—online and on campus presence

Preparatory mathematics courses are offered by most universities in Germany as optional courses that take place shortly before the beginning of the regular semester. These courses vary in length and content, depending on the study group the course is aimed at. Preparatory mathematics courses aimed at students starting their studies in economics and business administration (EBA) usually focus on repetition of secondary school mathematics, taking into account that basic mathematics skills are highly important for students’ performance in their economics classes (e.g. Ballard & Johnson, 2004; Cronin & Carroll, 2015; Espey, 1997).

The courses can usually be provided as online courses, on-campus courses or blended learning formats. Some universities usually offer online courses and on-campus courses at the same time and let students choose the format they prefer (e.g. Biehler et al., 2011). We know that one of the main reasons for students, in general, to attend a preparatory course—apart from wanting to improve their mathematics knowledge—is that they want to get to know their fellow students (Brown & Cronin, 2016). This is usually less expected and less pursued in online courses than in campus-based courses (Hochmuth et al., 2018). In a study by Fischer (2014, see also Biehler et al., 2011), 65% of the students chose on-campus courses instead of online/blended learning courses when given the choice. There are differences regarding different premises: students with a time-shortened degree (‘Fachhochschulreife’, based on a slightly simplified curriculum) instead of the full ‘Abitur’ (which is the regular secondary school degree that enables students to attend university), as well as students who chose mathematics on a basic level in secondary school tended to choose the attendance based format. Additionally, students enrolled in online courses had better ‘Abitur’ grades on average. The most common reasons for choosing the blended format were the possibility of free time management, of using the time better to work on individual deficits and of concentrating on the topics they did not know. The most common reasons for choosing the on-campus format were as follows: the possibility of talking to the lecturers personally, getting to know fellow students and getting to know how typical lectures worked. Based on these findings, it appears that students with stronger ties to mathematics are more likely to take online courses where they work more independently. Students with weaker ties to the mathematics subject are more likely to attend on-campus courses. In contrast, students with a more positive affective relationship with mathematics in the Reinhold et al. (2021) study expressed a greater desire to return to studying on campus after the pandemic.
2.2. Effects of preparatory course attendance on mathematics performance

The effect of mathematics preparatory courses on students’ mathematics performance is controversial. International studies on mathematics remediation often focus on remediation courses taking place during the semester, which are mandatory for students with low entry skills (Di Pietro, 2014; Bahr, 2008; Lagerlöf & Seltzer, 2009), which is a different situation from voluntary preparatory courses taking place before the start of the regular semester.

While there exist many studies that show students are better at the end of the course than at the beginning (e.g. Hochmuth et al., 2018; Greefrath & Hoever, 2016; Abel & Weber, 2014), only some studies focus on a comparison of students who attended a preparatory course and those who did not, with mixed results that seem to depend on the particular courses. Since students are not assigned randomly into groups of preparatory course participants and non-participants but choose whether they want to take part or not based on personal preferences unknown to the researchers, confounding variables need to be taken into account when studying the effect.

Greefrath & Hoever (2016) compared results in a test of secondary school mathematics at the beginning of students’ first year of university study and found that students in computer science and electrical engineering who attended a preparatory course achieved better results than non-participants. However, they only compared the outcomes without considering confounding variables such as school grades and motivational variables. Greefrath et al. (2017) confirmed these results at a different university, finding better results of preparatory course attendees in tests at the beginning of the first year (with small effect sizes), again without taking confounding variables into account.

Büchele (2020a) found positive short-term effects of attendance of preparatory mathematics courses for economics students on their mathematical competencies when controlling for socio-demographic and pedagogical-psychological variables.

There seem to be differences in online versus on-campus preparatory courses: Fischer (2014, see also Biehler et al., 2011) found that students enrolled in online preparatory courses achieved on average 4.8% more points in the mathematics test at the end of the course than students enrolled in the on-campus course when controlled for test results in the test at the beginning of the course.

2.3. Other predictors of study success

Apart from attendance at preparatory mathematics courses, different biographical, educational and pedagogic-psychological variables have been found to influence students’ study success in mathematics as well as in economics. Important biographical variables that predict study success are students’ prior grade point average (GPA) (Byrne & Flood 2008, Mallik & Lodewijks 2010), gender (Krohn & O’Connor, 2005; Mallik & Lodewijks, 2010; Mallik & Shankar, 2016; Mundia & Metussin, 2019) and graduation type (Laging & Voßkamp, 2017). Additionally, whether students have already taken the mathematics course and examination has an influence (Laging & Voßkamp, 2017). Affective variables such as mathematics self-efficacy (Byrne & Flood, 2008; Laging & Voßkamp, 2017; Mundia & Metussin, 2019) and interest in mathematics (Laging & Voßkamp 2017) also serve as predictors for students’ mathematics performance. Other motivational variables such as the perceived value of mathematics, mathematics self-concept and learning goal orientation cannot be completely overlooked as predictors (Laging & Voßkamp 2017). Moreover, surface learning strategies such as memorizing or repeating are known to negatively predict students’ performance (Laging & Voßkamp 2017, Liebendörfer et al. 2020). Furthermore, many of these factors can be considered as confounding variables, determining the mathematics performance as well as the participation in preparatory courses. Previous studies have
shown that controlling for these certain variables could lead to causally interpretable treatment effects (Büchele, 2020a; Büchele, 2020b).

2.4. Changes during the COVID-19 pandemic

In 2020, the teaching, learning and assessment situation was different because of the pandemic—all preparatory courses had to be implemented fully online. The COVID-19 crisis opened doors for digital learning environments, not only in mathematics (Mulenga & Marbán, 2020). University courses had to be implemented completely online spontaneously in the summer semester 2020 in Germany because of the pandemic. In the winter semester, a combination of digital and on-campus teaching was planned (with a focus on digital learning) but most of the planned on-campus courses had to switch to an online format after a few weeks due to the development of the pandemic.

In general, experimental studies find positive effects of digital learning approaches on students’ mathematics performance compared to traditional learning (see e.g. Lin et al., 2017a; Lin et al., 2017b; Zwart et al., 2017). However, the implementation of distance learning in the COVID-19 era came ad-hoc, and therefore, it is not clear which effects the different approaches had on students’ learning outcomes and motivation, particularly, since didactical concepts were still based on in-class learning.

The switch to digital learning brought organizational advantages, such as when students no longer needed to spend time on travelling to the university. However, this was offset by significant disadvantages, for example, because on-campus supports were no longer available (e.g. dining hall and library) and many students lost their jobs (Busse & Zeeb, 2020). Being unexpected, the pandemic demonstrated that many students were not ready for fully digital learning. Some lacked the technical equipment (Händel et al., 2020; Stammen & Ebert, 2020), and some also lacked prior experience with e-learning and necessary skills for digital learning (Aristovnik et al., 2020; Händel et al., 2020). In digital learning, students reported fewer peer contacts (Busse & Zeeb, 2020; Traus et al., 2020) and these all had to take place online. Overall, students received less support and feedback (Kindler et al., 2020). In addition, a vast majority of students lacked direct interaction with instructors (Traus et al., 2020). Particularly in mathematics, students cannot easily collaborate online because mathematical notation is necessary for communication, but the clean representation of mathematical formulas and expressions had not been found easy even for instructors in the sudden switch to digital teaching (Cassibba et al., 2020; Irfan et al., 2020).

When studying at home, many students also seemed to have problems focusing on their studies when both their studies and free time had to be in the same place (Kindler et al., 2020; Traus et al., 2020). Overall, many students experienced a higher workload and problems with work–life balance (Aristovnik et al., 2020; Kindler et al., 2020). This can also be explained by the fact that students now had to manage their learning processes more independently. In the survey by Traus et al. (2020), 48% of the students found this a disadvantage of their new learning situation. However, 63% of the students stated it as an advantage in that they can organize their work more flexibly. Thus, advantages and disadvantages may be closely related.

Looking at affective variables, however, the disadvantages seemed to clearly dominate. Significantly fewer students have experienced satisfaction in their studies; from over 75% pre-COVID to less than 33% now (Kindler et al., 2020), and many have experienced anxiety or other negative emotions through learning in isolation (Händel et al., 2020). This is particularly concerning as affective variables play a central role in self-regulated mathematics learning (e.g. Schukajlow et al., 2017).

Finally, it is important to keep in mind that the results were not uniform across the various groups (Händel et al., 2020), e.g. women, first-year students and students with financial problems were more affected in their emotional experience and personal circumstances (Aristovnik et al., 2020).
3. Research questions

The pandemic has led to a shift to online teaching, which brings multi-faceted changes. Against the background of some advantages and various disadvantages as well as different preferences and preparation of students for digital learning, we attempt with this study to describe the differences in students’ participation between traditional and digital teaching under pandemic conditions. We further seek to explore if there are changes in explaining students’ performance after completion of the course. In order to investigate effects on performance, it must also be ensured that an online performance test leads to results that compare to a classical test in the lecture hall. We thus pose the following research questions:

1. What changes in students’ participation, if any, resulted from the switch to digital pre-course instruction?
2. To what extent, if any, does the performance of first-semester students change?
3. Are patterns in the explanation of performance changing with respect to previous years?

4. Methods

4.1. Data and sample

The data were gathered in a preparatory mathematics course prior to an EBA study program at a mid-sized German university. The study is based on data of 1,173 students enrolled in EBA or related study programs (like economics education) in the years 2018, 2019 and 2020. Every year, approximately 450 students enroll in these degree programmes. This means that the sample covers most of the population. More precisely, we have responses from 410 students in 2018, 376 students in 2019 and 387 students in 2020. The differences in data gathering in 2020 (digital test and questionnaire instead of pen and paper) did not seem to affect the response rate.

Data were gathered via ex-post skill tests and questionnaires in the first mathematics lecture of each semester. However, due to the COVID-19 pandemic, the skill test and questionnaire in 2020 were provided online. This leads to some difficulties based on different test structures. To ensure the data gathering did not differ too much in the winter semester of 2020, the first mathematics lecture was taught live and the students had the same amount of time as usual to solve the skill test during the lecture. This led to a high response rate, which is comparable to the in-class skill tests of the previous years. The students were requested to solve the skill test without technological devices (calculators or CAS); however, there was no control for students using calculators or further help online, which is usually strictly forbidden and controlled for in the in-class setting. This leads to some differences in the cohorts’ results and upcoming analysis, which are discussed further in sections 5.1.2 and 5.3.

4.2. Variables

The skill test itself consisted of 26 tasks of secondary mathematics schooling standard (e.g. equations, functions and calculus) and had been used in previous studies (Laging & Voßkamp, 2017; Büchele, 2020a; Büchele, 2020b). Students could score a maximum of 26 points; one point for each task. Therefore, the average score on a task can also be interpreted as a success rate. The test covered computational skills as well as argumentation and changes of representation. We give some examples relating to calculator issues in Section 5.3. The accompanying questionnaire gathered various biographical, educational and psychological variables that may explain the mathematics performance of the
investigated students (Table 1). All data were gathered completely anonymously and all ethical standards of the university were adhered to.

Two variables, namely ‘mathematics performance’ (Y) and ‘preparatory course engagement’ (X2), are of special interest, while the other variables are mainly used as control variables for the upcoming analysis. While mathematics performance is somehow self-explanatory (points reached in the skill test), the preparatory course engagement needs some explanation. As mentioned above, students can voluntarily participate in the preparatory course and will then be formally counted as participants (variable X1). Since this binary information does not cover students’ engagement, students were additionally asked how many lectures and tutorials they attended and how many exercise sheets they completed (out of 10). This information was combined in a sum score and converted to a percentage. Therefore, the students’ course engagement is a combination of attendance and completion of exercises, if students participated in the preparatory course. The high internal consistency of this measure (Cronbach’s Alpha = 0.94) confirms our treatment on one scale.

Variables C3 and C4 record if a student already took the (credit-bearing) mathematics lecture or final exam in a previous semester and did not pass. Variable C5 controls for the student’s study programme. Most students were enrolled in Economic and Business Administration, the other students were mainly enrolled in Economics Education. Variable C6 indicates information on the students’ graduation type. This is necessary since students at this particular university can enroll with a regular secondary school degree (‘Allgemeine Hochschulreife’) or a time-shortened degree that has a lower educational value and is based on a slightly simplified and shortened curriculum (‘Fachhochschulreife’). Variable C7 gives information on the students’ secondary school GPA (the lower, the better). Additionally, students were asked how they rate their mathematics skills in general (on a scale from 1 to 5), which is considered as an indicator of their mathematics self-efficacy (P1). Pedagogic-psychological variables were assessed to control for common motivational and learning factors, such as mathematical interest (P2), learning goal orientation (P3), the perceived value of mathematics (P4), mathematics self-concept (P5) and memorizing strategies (P6). Variable P7 represents the level of extrinsic motivation. These variables were assessed.

| Code | Variable                                      | Coding          | Type   | Value Items | α*       | Mean (SD)  |
|------|-----------------------------------------------|-----------------|--------|-------------|----------|------------|
| Y    | Mathematics performance                       | Metric          | 0 to 26| 26          | 6.08 (4.41)|            |
| X_1  | Preparatory course participation               | Yes = 1 Binary  | 0 or 1 | 1           | 0.42     |            |
| X_2  | Preparatory course engagement (in percent)    | Sum score       | 0 to 100| 3           | .94      | 63.17 (25.80) |
| C_1  | Gender                                       | Female = 1 Binary | 0 or 1 | 1           | 0.47     |            |
| C_2  | Year of study                                | Metric          | 1 to 3 | 1           | 1.25 (0.58)|            |
| C_3  | Mathematics course already taken              | Yes = 1 Binary  | 0 or 1 | 1           | 0.13     |            |
| C_4  | Mathematics exam already taken                | Yes = 1 Binary  | 0 or 1 | 1           | 0.07     |            |
| C_5  | Course of study                              | No EBA = 1 Binary | 0 or 1 | 1           | 0.29     |            |
| C_6  | Graduation type                              | Short track = 0 Binary | 0 or 1 | 1           | 0.56     |            |
| C_7  | Prior GPA                                    | Lower = better  | Metric | 1 to 4 | 1         | 2.58 (0.59) |
| P_1  | Mathematics self-efficacy                     | Higher = better | Metric | 1 to 5 | 1         | 2.70 (0.89) |
| P_2  | Mathematics interest                          | Scale           | 1 to 6 | 4           | 0.94     | 3.46 (1.31) |
| P_3  | Learning goal orientation                     | Scale           | 1 to 6 | 5           | 0.85     | 3.45 (0.95) |
| P_4  | Perceived value of mathematics                | Scale           | 1 to 6 | 9           | 0.88     | 4.38 (0.84) |
| P_5  | Mathematics self-concept                      | Scale           | 1 to 6 | 3           | 0.89     | 3.35 (1.02) |
| P_6  | Memorizing strategy                           | Scale           | 1 to 6 | 5           | 0.65     | 3.78 (0.89) |
| P_7  | Extrinsic motivation                          | Metric          | 1 to 6 | 1           | 4.30     | 4.30 (1.37) |

*Cronbach’s alpha
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using scales that are widely proven and have been used in other studies (for more information on the used scales see Laging & Voßkamp, 2017). The internal consistency of memorizing strategy was acceptable, all other coefficients were very good.

4.3. Design
This study is built on a comparison of cohorts within a quasi-experimental design. In the years 2018 to 2020, first-year students could voluntarily participate in a so-called ‘preparatory course’, a developmental mathematics course that is most likely comparable to summer schools in the US. Each course was set before the beginning of the winter semesters and consisted of 10 sessions that were completed over 2–3 weeks and were accompanied by tutorials and exercise sheets. The topics were mostly based on secondary school mathematics. In the winter semesters of 2018 and 2019, the preparatory course was offered within an in-class structure. Due to the pandemic, the course was taught digitally in the winter semester of 2020. The lectures were prerecorded and provided via the video content management system ‘Panopto’, while the tutorials were held live via the video conference tool ‘Zoom’. Besides the aforementioned changes, the structure, content, exercises and lecturer kept the same for the winter semesters of 2018, 2019 and 2020.

This allows us to compare the different cohorts and to analyze the effects of the pandemic and the digital learning options on developmental mathematics courses and take a closer look at the differences of the ‘COVID-cohort’ of 2020.

4.4. Empirical approach
To analyse the students’ engagement (participation and attendance) and the effect of the preparatory course during the COVID crisis, we will compare the combined 2018 and 2019 cohorts to the 2020 Corona cohort once we have checked that there is no systematic difference in personal variables (see section 5.1). We will then compare students’ participation in section 5.2. Further, an unexplained difference in students’ performance between the two cohorts will be analysed (section 5.3) before comparing effects of the courses in section 5.4.

For the comparison of students’ engagement, simple \( t \)-test statistics were appropriate while the estimation of the preparatory course effects is more profound. Since students self-selected themselves into the preparatory course, a descriptive analysis could lead to biased estimations. Therefore, multiple regression analysis (with Stata version 15) was chosen as an identification strategy. Previous studies showed that the given control variables are sufficient to estimate unbiased effects (Büchele, 2020a; Büchele, 2020b). We want to point out that we will just report the upcoming results in section 5, while a deeper discussion of these results is shifted to section 6.

5. Results
5.1. Preliminary analysis
5.1.1. Descriptive statistics. Table 1 provides descriptive statistics (means) for the given variables. Firstly, on average, students scored about 6 out of 26 possible points in the skill test. Altogether 42% of the students decided to participate in the course. In the second stage, these 42% attended about two-thirds (63%) of the lectures and tutorials. Furthermore, 47% of the sample were females, 13% had already taken the mathematics course in a previous semester, while about half of them (7%) had taken the mathematics
Table 2. Variables compared by cohorts

| Code | Variable                        | Cohort of 2018 Mean [95% CI] | Cohort of 2019 Mean [95% CI] | Cohort of 2020 Mean [95% CI] |
|------|--------------------------------|------------------------------|------------------------------|------------------------------|
| C_1  | Gender                         | 0.47 [0.41; 0.51]            | 0.47 [0.41; 0.51]            | 0.47 [0.42; 0.52]            |
| C_2  | Year of study                  | 1.18 [1.13; 1.23]            | 1.23 [1.17; 1.28]            | 1.32 [1.25; 1.38]            |
| C_3  | Mathematics course already taken | 0.10 [0.06; 0.12]          | 0.12 [0.08; 0.15]            | 0.17 [0.12; 0.20]            |
| C_4  | Mathematics exam already taken | 0.03 [0.01; 0.05]            | 0.08 [0.05; 0.11]            | 0.08 [0.05; 0.11]            |
| C_5  | Course of study                | 0.27 [0.23; 0.32]            | 0.27 [0.23; 0.32]            | 0.32 [0.27; 0.37]            |
| C_6  | Graduation type                | 0.59 [0.54; 0.64]            | 0.56 [0.50; 0.60]            | 0.56 [0.51; 0.61]            |
| C_7  | Prior GPA                       | 2.51 [2.45; 2.57]            | 2.59 [2.53; 2.65]            | 2.61 [2.54; 2.66]            |
| P_1  | Mathematics self-efficacy      | 3.34 [3.25; 3.43]            | 3.29 [3.20; 3.38]            | 3.26 [3.16; 3.35]            |
| P_2  | Mathematics interest           | 3.43 [3.28; 3.56]            | 3.34 [3.20; 3.47]            | 3.57 [3.44; 3.70]            |
| P_3  | Learning goal orientation      | 3.40 [3.31; 3.50]            | 3.35 [3.24; 3.45]            | 3.54 [3.44; 3.63]            |
| P_4  | Perceived value of math        | 4.31 [4.22; 4.39]            | 4.36 [4.27; 4.44]            | 4.44 [4.35; 4.52]            |
| P_5  | Mathematics self-concept       | 3.35 [3.24; 3.45]            | 3.28 [3.17; 3.40]            | 3.38 [3.28; 3.48]            |
| P_6  | Memorizing strategy            | 3.69 [3.60; 3.78]            | 3.74 [3.65; 3.83]            | 3.79 [3.69; 3.88]            |
| P_7  | Extrinsic motivation           | 4.28 [4.13; 4.42]            | 4.35 [4.21; 4.49]            | 4.25 [4.12; 4.38]            |

examination but did not pass. The majority (71%) of the students was enrolled in EBA and 29% in other economic-related study programmes. About half (56%) of the students had a regular secondary school degree (variable C_6).

5.1.2. Comparison of cohorts. The study aims to analyze the students’ engagement in, and effects of, the given preparatory course during the Corona pandemic. Therefore, the upcoming analysis will focus on the comparison of the three cohorts (winter semesters of 2018, 2019 and 2020). However, the analysis is likely to be biased, if the cohort’s structure changed between 2018/2019 and 2020. To scrutinize this issue, Table 2 gives an overview of the control variables’ means and confidence intervals (CIs) (95%) separated by each cohort.

The 95% CIs overlap between the cohorts. Therefore, just slight differences and trends can be reported for the control variables. Consequently, the cohorts are comparable and the analysis is unlikely to be biased by different cohort structures.

However, due to the pandemic, the method of data gathering changed in 2020. As mentioned above, contrary to the pen-and-paper tests in the years 2018 and 2019, students took the skill test online in 2020 and supervision was not possible. This may lead to some bias as, for example, students might have used calculators or further help online for particular tasks. Table 3 shows the regression results for the determinants of mathematics performance. The dependent variable is the mathematics performance while the independent variables are the known control variables. Further on, to ensure possible differences are visible, cohort dummies are integrated into the regression analysis. For more convenient interpretations, we report unstandardized regression coefficients. Since we found proof of heteroscedasticity, we ran the regression with robust standard errors. However, we found no proof for non-linearity.

The regression revealed that the cohort of 2020 particularly showed higher performance. While the cohorts of 2018 and 2019 did not differ (2019 dummy), the 2020 cohort showed a significantly higher base level (about 1.5 points). Consequently, even controlled for various variables and the sample’s structures, the cohort of 2020 performed 1.5 points higher. However, it is unclear how this increase in performance could be explained. Either the data gathering (online test without supervision and calculator
bias) or the COVID circumstances are reasonable options. We further checked the control variables’ correlations that were found to be similar to other studies (e.g. Laging and Voßkamp, 2017). On average, students with higher preparatory course engagement, full high-school degree, higher mathematics self-efficacy and higher mathematics self-concept and students who already took the final mathematics examination performed better in the mathematics test, while students with lower (worse) high-school GPA, higher memorizing strategies and higher extrinsic motivation and female students performed worse. The preparatory course effect over all cohorts was positive, indicating that, on average, a 1% increase in students’ engagement leads to a 0.02 points (95% CI [0.013; 0.026]) higher test score. This means that students attending all lectures, tutorials and solving all exercise sheets (engagement score of 100%) outperformed non-participating students by approximately 2 points.

The regression analysis revealed no difference between the performance of the 2018 and 2019 cohorts (Table 3). As both cohorts also showed the same control variable values (Table 2), they were combined for further analysis.

### 5.2. Participation and attendance

Research question 1 addresses changes in students’ participation. To answer this question, we first compared how many students participated in the years 2018, 2019 and 2020. As mentioned above, students formally counted as participants if they attended at least one session of the preparatory course, although the majority of participating students showed higher attendance. Table 4 shows the number of students separated by participants, non-participants and cohorts.

#### Table 3. Determinants of mathematics performance

| Code | Variable                                           | Coefficient (robust SE) |
|------|----------------------------------------------------|-------------------------|
|      | Constant                                           | 5.06*** (1.27)          |
|      | Dummy 2019 (2018 reference)                        | 0.05 (0.24)             |
|      | Dummy 2020 (2018 reference)                        | 1.54*** (0.26)          |
| X_2  | Preparatory course engagement                      | 0.02*** (0.00)          |
| C_1  | Gender                                             | −0.75** (0.23)          |
| C_2  | Year of study                                      | 0.31 (0.28)             |
| C_3  | Mathematics course already taken                   | 0.58 (0.54)             |
| C_4  | Mathematics examination already taken              | 2.23*** (0.62)          |
| C_5  | Course of study                                    | 0.10 (0.24)             |
| C_6  | Graduation type                                    | 2.62*** (0.21)          |
| C_7  | Prior GPA                                          | −1.63*** (0.21)         |
| P_1  | Mathematics self-efficacy                          | 0.64*** (0.18)          |
| P_2  | Mathematics interest                               | 0.20 (0.12)             |
| P_3  | Learning goal orientation                          | −0.10 (0.14)            |
| P_4  | Perceived value of mathematics                     | 0.20 (0.14)             |
| P_5  | Mathematics self-concept                           | 0.64*** (0.17)          |
| P_6  | Memorizing strategy                                | −0.43*** (0.13)         |
| P_7  | Extrinsic motivation                               | −0.21* (0.09)           |
| N    |                                                    | 1.030                   |
| Adj. $R^2$ |                                           | 0.40                    |

***p < 0.001,  
**p < 0.01,  
*p < 0.05
Participation was similar in the years 2018 and 2019. In both years 45% of the students attended at least one course session. However, this number declined significantly (Chi-square = 6.54, df = 1 (pooled 18/19 cohort), \( p < 0.05 \)) in 2020. Only 37% of the students decided to participate in at least one session.

To describe which students were more likely to attend the preparatory course, we estimated a probit regression with the preparatory course participation as dependent and the variables \( C_1 \) to \( C_7 \) as independent variables. Table 5 shows the information on the determinants of students’ preparatory course participation and interaction effects of the 2020 cohort.

The results, however, stand in contrast to the descriptive findings of Table 4. Though the course participation in 2020 is still correlated negatively (see variable ‘dummy 20’), the effect loses statistical significance when controlling for the given variables. We assume that the non-significant cohort differences reported in Table 2 still adjust the 2020 participation effect. This means that not only the pandemic circumstances but also the cohort structure itself led to the decreasing participation in 2020. For instance, the variable ‘year of study’ (\( C_2 \)) negatively correlates with the participation decision. Students in the 2020 cohort, however, are enrolled in a higher semester, which mediates the 2020 participation effect.
Furthermore, male students and students with a higher (worse) prior GPA (C7) were less likely to participate at the preparatory course. Interaction variables control for further cohort effects. We only found that students enrolled in EBA were more likely to participate at the preparatory course in 2020 but cannot give an assumption why the study programme should affect the course choice in the pandemic year but not in previous years.

For the analysis of the students’ engagement, we took course participants into account only. This reduced the given sample size to 457 course-takers of whom full information is provided. The course engagement covers attended lectures, tutorials and solved exercises. While students’ engagement score in 2018/2019 was about 61%, the 2020 cohort showed a statistically significant higher mean of 69% (p < 0.01). Table 6 summarizes the t-statistics of the students’ engagement separated by the cohorts.

### Table 6. Preparatory course engagement

|                      | N  | Mean (t-value) | SE  | SD   | 95% CI         |
|----------------------|----|----------------|-----|------|----------------|
| Course engagement (in %) 2018/2019 | 319 | 60.81          | 1.59| 28.45| [57.68; 63.94] |
| Course engagement (in %) 2020       | 138 | 68.62          | 2.21| 26.00| [64.24; 73.00] |
| Difference            |    | 7.81 ** (2.76) | 2.82|      | [2.25; 13.36]  |

**p < 0.01

5.3. **Calculator issues**

Research question 2 asks about changes in students’ measured performance. Section 5.1.2 already pointed out some issues regarding the different methods of data gathering. Therefore, within this section, we will take a closer look at the individual tasks, investigating if and how using calculators could bias the upcoming analysis. There are mainly two concerns that have to be discussed. Firstly, one has to determine where the cohort differences (Table 3) come from, and if specific tasks have been solved significantly better in 2020. Secondly, one has to examine the resulting statistical bias for the preparatory course engagement. For instance, using calculators to solve tasks only leads to biased test results if one group, preparatory course participants or non-participants, shows disproportional usage. Table 7 provides information on students’ performance in the individual tasks compared by cohorts and group membership (preparatory course participants or non-participants).

Columns 2 and 3 show the mean of each task in the years 2018/19 and the year 2020, respectively. In column 4, the mean differences are pointed out; tasks 1, 2, 4, 5, 7, 8, 12, 16, 21, 24 and 26 have been solved significantly better, while task 20 has been solved worse in 2020 compared to the previous semester.

Note that tasks 1 (term simplification), 2 (fractions), 4 (exponents) and 5 (logarithm calculation) could be solved by simply entering the expression in a calculator, e.g. $32^{2/5}$ or $\log_3(1/9)$. Tasks 7 (fractions), 8 (power calculation), 12 (quadratic equation) and 24 (calculating the derivative of a polynomial) would require a computer algebra system because they include variables. Tasks 16 (interest rate calculation in a real-world situation), 21 (giving a reason for some property of a function) and 26 (giving a reason why the sum of two odd numbers is always odd) could not be solved directly even with a computer algebra system.

Other tasks could also be solved using a computer algebra system. They cover simplifying roots (task 10), solving cubic equations (task 15) and calculating derivatives of non-polynomials (tasks 23 and 25). The other tasks required changes of representation (e.g. real world situations, algebraic or graphical representation of functions) or included argumentation, e.g. giving arguments why graphs of certain functions will never intersect (task 20).
| Task | Mean 2018/19 | Mean 2020 | Diff. | Mean 2018/19 non-participants | Mean 2018/19 participants | Diff. | Mean 2020 non-participants | Mean 2020 participants | Diff. |
|------|--------------|-----------|-------|------------------------------|---------------------------|-------|---------------------------|----------------------|-------|
| 1    | 0.10         | 0.26      | 0.16* | 0.09                         | 0.11                       | 0.02  | 0.28                       | 0.23                 | −0.05 |
| 2    | 0.50         | 0.63      | 0.13* | 0.48                         | 0.53                       | 0.05  | 0.63                       | 0.64                 | 0.01  |
| 3    | 0.26         | 0.28      | 0.02  | 0.27                         | 0.24                       | −0.03 | 0.28                       | 0.30                 | 0.02  |
| 4    | 0.07         | 0.41      | 0.34* | 0.06                         | 0.09                       | 0.03  | 0.40                       | 0.44                 | 0.04  |
| 5    | 0.06         | 0.33      | 0.27* | 0.04                         | 0.09                       | 0.05* | 0.27                       | 0.46                 | 0.23* |
| 6    | 0.64         | 0.60      | −0.04 | 0.65                         | 0.64                       | −0.01 | 0.64                       | 0.56                 | −0.08 |
| 7    | 0.16         | 0.29      | 0.13* | 0.19                         | 0.13                       | −0.06 | 0.27                       | 0.33                 | 0.06  |
| 8    | 0.08         | 0.17      | 0.09* | 0.08                         | 0.08                       | 0.00  | 0.16                       | 0.19                 | 0.03  |
| 9    | 0.45         | 0.47      | 0.02  | 0.46                         | 0.44                       | −0.02 | 0.43                       | 0.55                 | 0.12  |
| 10   | 0.16         | 0.18      | 0.02  | 0.13                         | 0.20                       | 0.07  | 0.16                       | 0.23                 | 0.07  |
| 11   | 0.16         | 0.16      | 0.00  | 0.17                         | 0.17                       | 0.00  | 0.18                       | 0.14                 | −0.04 |
| 12   | 0.19         | 0.33      | 0.14* | 0.18                         | 0.21                       | −0.03 | 0.31                       | 0.38                 | 0.07  |
| 13   | 0.26         | 0.23      | −0.03 | 0.27                         | 0.26                       | −0.01 | 0.26                       | 0.21                 | −0.06 |
| 14   | 0.23         | 0.24      | 0.01  | 0.23                         | 0.23                       | 0.00  | 0.22                       | 0.29                 | 0.07  |
| 15   | 0.10         | 0.16      | 0.06  | 0.09                         | 0.12                       | 0.03  | 0.13                       | 0.24                 | 0.11  |
| 16   | 0.01         | 0.06      | 0.05* | 0.14                         | 0.11                       | −0.03 | 0.04                       | 0.06                 | 0.02  |
| 17   | 0.29         | 0.30      | 0.01  | 0.25                         | 0.33                       | 0.08* | 0.25                       | 0.39                 | 0.14* |
| 18   | 0.19         | 0.14      | −0.06 | 0.14                         | 0.27                       | 0.13* | 0.10                       | 0.21                 | 0.11* |
| 19   | 0.44         | 0.44      | 0.01  | 0.42                         | 0.48                       | 0.06  | 0.40                       | 0.53                 | 0.13* |
| 20   | 0.52         | 0.45      | −0.08* | 0.48                         | 0.59                       | 0.11* | 0.40                       | 0.56                 | 0.16* |
| 21   | 0.14         | 0.20      | 0.06* | 0.11                         | 0.19                       | 0.08* | 0.15                       | 0.28                 | 0.13* |
| 22   | 0.08         | 0.05      | −0.03 | 0.06                         | 0.09                       | 0.03  | 0.03                       | 0.09                 | 0.06  |
| 23   | 0.17         | 0.18      | 0.01  | 0.15                         | 0.21                       | 0.06  | 0.14                       | 0.25                 | 0.11  |
| 24   | 0.07         | 0.14      | 0.06* | 0.07                         | 0.08                       | 0.01  | 0.09                       | 0.22                 | 0.13* |
| 25   | 0.05         | 0.10      | 0.05* | 0.05                         | 0.05                       | 0.00  | 0.08                       | 0.15                 | 0.07  |
| 26   | 0.18         | 0.22      | 0.04  | 0.17                         | 0.19                       | 0.02  | 0.20                       | 0.26                 | 0.06  |

*p < 0.05

Our analysis of the effect of the preparatory course during the COVID crisis might be affected by a calculator bias if this bias was unevenly distributed between course participants and non-participants. We thus analysed differences in students’ performance separated by preparatory course participation for the cohorts of 2018/19 and 2020 in columns 5 to 10 of Table 6.

Preparatory course participants in 2018/19 showed similar performance as non-participants in most of the tasks. Only in tasks 5, 17, 18, 20 and 21 did participants perform better. More importantly, preparatory course participants and non-participants of the 2020 cohort showed comparable results since the students show better performance in tasks 5, 17, 18, 20 and 21 as well. Only tasks 19 and 24 were also solved significantly better by the preparatory course participants in 2020. All tasks from 17 onwards focused on functions. In sum, there were no major group differences in the relevant tasks between the 2018/2019 and 2020 cohorts.

5.4. **Comparison of preparatory course effects**

To answer research question 3 focusing on possible changes in patterns in the explanation of students’ performance, we ran a multiple regression analysis. The dependent variable was the skill test performance, while preparatory course engagement, as well as the given controls, were the independent
### Table 8. Preparatory course and cohort effects

| Code   | Variable                                      | Coefficient | Robust SE | 95% CI          |
|--------|-----------------------------------------------|-------------|-----------|-----------------|
|        | Constant                                      | 9.14**      | 1.46      | [6.27; 12.02]   |
|        | Dummy 20                                      | 2.22        | 1.85      | [−1.41; 5.85]   |
| X_2    | Prep. course engagement                       | 0.014***    | 0.004     | [0.006; 0.021]  |
| C_1    | Gender                                        | −0.31       | 0.25      | [−0.81; 0.18]   |
| C_2    | Year of study                                 | 0.31        | 0.29      | [−0.26; 0.88]   |
| C_3    | Mathematics course already taken              | 0.41        | 0.58      | [−0.73; 1.56]   |
| C_4    | Mathematics exam already taken                | 2.27**      | 0.61      | [1.07; 3.46]    |
| C_5    | Course of study                               | 0.33        | 0.27      | [−0.20; 0.86]   |
| C_6    | Graduation type                               | 2.52***     | 0.24      | [2.06; 2.99]    |
| C_7    | Prior GPA                                     | −1.69***    | 0.21      | [−2.09; −1.26]  |
| P_1    | Mathematics self-efficacy                     | 0.74***     | 0.20      | [0.34; 1.13]    |
| P_2    | Mathematics interest                          | 0.19        | 0.12      | [−0.04; 0.42]   |
| P_3    | Learning goal orientation                     | −0.10       | 0.14      | [−0.38; 0.18]   |
| P_4    | Perceived value of mathematics                | 0.22        | 0.14      | [−0.05; 0.49]   |
| P_5    | Mathematics self-concept                      | 0.58**      | 0.17      | [0.24; 0.92]    |
| P_6    | Memorizing strategy                           | −0.42***    | 0.13      | [−0.68; −0.17]  |
| P_7    | Extrinsic motivation                          | −0.20*      | 0.09      | [−0.37; −0.03]  |
|        | Dummy 20 × prep. course engagement            | 0.020***    | 0.007     | [0.01; 0.03]    |
|        | Dummy 20 × gender                             | −1.32***    | 0.49      | [−2.28; −0.35]  |
|        | Dummy 20 × year of study                      | 0.11        | 0.59      | [−1.05; 1.26]   |
|        | Dummy 20 × course already taken               | 0.34        | 1.01      | [−1.64; 2.32]   |
|        | Dummy 20 × course of study                    | −1.37*      | 0.53      | [−2.41; −0.32]  |
|        | Dummy 20 × graduation type                    | 0.48        | 0.47      | [−0.44; 1.39]   |
|        | Dummy 20 × prior GPA                          | 0.16        | 0.47      | [−0.76; 1.08]   |
|        | Dummy 20 × self-efficacy                      | −0.18       | 0.30      | [−0.77; .40]    |

| N      | 1,030                                         |
| Adj. $R^2$ | 0.43                                      |

*** $p < 0.001$
** $p < 0.01$
* $p < 0.05$

Variables. To address heteroscedasticity, the analysis was again performed with robust standard errors. Table 8 summarizes the results. As mentioned above, the Cohort of 2018/2019 was pooled and compared to the COVID cohort of 2020 via the interaction terms.

The effect of students’ engagement in the preparatory course was positive and significant ($p < 0.001$). Students showing higher engagement in attending lectures, tutorials and solving exercises showed a higher performance in the skill test. Altogether, preparatory course participants (all cohorts) performed up to 1.4 points higher if they attended all lectures and tutorials and worked on all exercises (engagement score of 100%). However, fully participating students of 2020 got an average advantage of up to 2 points in the skill test (Interaction effect ‘dummy 20 × course engagement’). The possible reasons for the higher preparatory course effect in 2020 will be discussed in the next section.

Furthermore, there was a gender gap in the 2020 sample (dummy 20 × gender). Female students performed significantly worse in 2020 compared to 2018/2019. Surprisingly, students enrolled in EBA performed as well worse in 2020 (dummy 20 × course of study). These results will also be discussed below. The further correlations were expectable so far: students with a higher secondary school degree ($C_6$) performed better, as well as students who already took the final mathematics examination in a previous semester ($C_4$) or students with a lower (better) prior GPA ($C_7$). The affective variables $P_1$
(self-efficacy), P₂ (interest) and P₅ (self-concept) correlated positively, while P₆ (memorizing) and P₇ (extrinsic motivation) correlated negatively with the test performance.

6. Discussion
We used identical test instruments on biographical and affective variables to examine the extent to which students in a preparatory course under pandemic conditions differed from students in the two cohorts previously. Further, we examined whether patterns differed in explaining achievement. As we found no substantial difference between the two samples of 2018 and 2019, we combined them for the analysis.

6.1. Answers to the research questions
Research question 1 addressed changes regarding students’ participation. We found that fewer students of the 2020 cohort decided to participate in the preparatory course (37% compared to 45%). Neither the cohort dummy nor most of its interaction terms, however, were significant in the regression explaining students’ participation. Only non-EBA students had a slightly higher participation in 2020. It thus seemed that the mechanisms for participation seemed comparable, but the cohort was composed differently. In particular, there were fewer first-year students who attend the preliminary course particularly frequently. Thus, online courses seem to be attended by similar students in terms of their biographical data if they are the only option. This result may seem surprising given that one of the main reasons for students to attend a preparatory course is that students want to get to know fellow students (Fischer, 2014; Hochmuth et al. 2018). In addition, other studies reported a lack of technical equipment (Händel et al., 2020; Stammen & Ebert, 2020) or prior experience with e-learning and necessary skills for digital learning (Aristovnik et al., 2020; Händel et al., 2020) that might have lowered students’ participation. Possibly, these barriers are reflected in the different sample composition, as students struggling with online teaching might not have opted for studying in this semester.

The participating students showed an increased engagement with regards to viewing lectures, attending tutorials and solving exercise sheets. This result is surprising given that some studies found students to have problems focusing on their studies at home during the pandemic (Kindler et al., 2020; Traus et al., 2020). Yet, students might have achieved a higher participation but experienced other burdens (e.g. emotional). According to the aforementioned idea that students may have not participated because of their wish to get to know their peers, students in the course might have shown higher engagement possibly because only those who principally wanted to learn mathematics took part in the course. An additional explanation could be given by the circumstances in the pandemic since there was not much else to do for the students regarding free-time activities.

Research question 2 addressed changes in students’ performance after the switch to online teaching. Superficially, our answer is that students improved in the test. A more in-depth analysis revealed clear indicators that the performance measured is not directly comparable. Students had been asked not to use calculators and similar aids in previous years. However, an increase in performance of the 2020 cohort on tasks that are particularly easy to solve with a calculator or computer algebra system is evident. This supports the assumption that at least some students used further help to solve the given tasks, particularly as the performance in these tasks raised significantly. This may or may not mean that they intentionally violated the rules. Some students may have been less attentive at home when the rules were explained, or they may have assumed an exception for themselves if they also solved comparable tasks in school with the calculator. It is well known that students in mathematics under pressure to perform are likely
to copy solutions when they have the opportunity (Liebendörfer & Göller, 2016; Rønning, 2017). Why they should do this without performance pressure is an open question. Connections to self-esteem seem possible here, for example. Didactically, however, it is an important issue because important feedback is lost and possibly more meaningful learning actions are replaced.

In any case, the result shows that even voluntary in-home tests cannot be directly compared with the (voluntary) performance in the lecture hall. However, there was no improvement in some tasks that can also be solved using a calculator. These tasks were more complex (e.g. the calculation of derivatives of non-polynomials). It is possible that some students would have used a calculator here if they had known how to solve the tasks using it. The significant differences of tasks 16, 20, 21 and 26 could be results of the digital preparatory course, the COVID cohort itself or some statistical variance that cannot be precisely specified.

The data further suggest that there is similar usage of calculators in both groups, participants and non-participants. Tasks that were solved better in 2020 were solved equally well by participants and non-participants. This means, even if students used calculators and therefore falsely improved their performance in 2020, this should not bias our analysis of students’ performance (RQ3).

Research question 3 addressed possible changing patterns in the explanation of students’ performance. Generally, students’ engagement in the preparatory course positively predicted their test scores. However, there was a clear difference in the effect of their engagement. Given full engagement (100% engagement score), students performed 1.4 points higher than non-participating students. The descriptive results showed that participating students in all cohorts had an advantage in tasks 17 to 21, which cover the topic of ‘functions’. In 2020, there were additional 2 points for full engagement as indicated by the interaction term. These results indicate that in digital learning, personal engagement might be more important than in traditional settings. Possibly, students could focus more strongly on their personal deficits, which is a major motive for students to choose online courses in mathematics (Fischer, 2014). Another explanation could be that in traditional settings, less engaged students may use their peers for support with mathematics. This is an open question to be investigated further. Although it is not statistically significant, we should note that the 2020 cohort dummy is about 2 points higher for the 2020 cohort. This might reflect the calculator effect.

Further, there was a gender gap in the 2020 sample. Women performed significantly worse than men in 2020, unlike 2018/2019. This could have been because male students are more likely to ‘break the rules’ and use a calculator more often. We used mean comparisons and also multiple regression to analyse in more detail whether men are better due to the calculator effect. This cannot be ruled out, but predominantly men generally seem to perform better in these cohorts across all tasks. Similar gender gaps had already been found in earlier years (Büchele 2020a), thus there might be general differences in students’ performance in these populations. With the pandemic in mind, however, it is also worth considering that women working from home, in particular, have greater domestic responsibilities. In particular, they may have had children to care for. Women were generally reported to be more affected in their emotional experiences and personal circumstances during the pandemic (Aristovnik et al., 2020).

We could also see that non-EBA students were less successful particularly in 2020. This group had increased its participation in 2020, possibly having connections to factors we did not control in our study.

The correlations of the control variables were expected. Students with a higher secondary school degree (C_6) performed better, as well as students who already took the final mathematics examination in a previous semester (C_4) or students with a lower (better) prior GPA (C_7). Self-efficacy, self-concept and interest but not value predicted performance, which fits the role of mathematics as a service subject. Further, extrinsic motivation and memorizing were negative predictors of performance. Given all the changes during the pandemic (see section 2.4), and the possibility of random effects by chance due
to multiple testing, it is rather surprising to see mostly similar patterns in students’ participation and performance.

6.2. Strengths and limitations
Among the strengths of the present work is that it is based on comparable cohorts, content and instruments. Nevertheless, it must be taken as a limitation that comparing cohorts hardly yields a causal relationship as we confront self-selection processes and unknown confounding variables are not controllable. Further, the simultaneous changes in both treatment structure and test structure (from physical to online) may have resulted in hidden effects similar to the calculator effect we found. For instance, we cannot make sure that students did not get help from family members or friends in the skill test of 2020.

In our statistical analysis, we have not adjusted p-values for multiple testing. This decision was made to avoid false-negative results as the study is exploratory, but it may give false-positive results. Therefore, we did not overinterpret single findings but tried focusing on consistent patterns across several variables whenever possible.

We should thus not overinterpret these results. In an exploratory sense, this study provides many indications as to which aspects should be investigated in more detail. In particular, this study did not yet record the specific stresses students had or how they organized their daily learning, which should be covered in future research.

6.3. Practical implications
The data confirmed that we need developmental mathematics courses in higher education, even in study programmes like economics. Students were not able to solve most of the tasks that are considered basic knowledge for their future lectures.

In addition, both future research and teaching should be designed bearing in mind that some students will use digital technologies even if it is not allowed to and there is no negative consequence of not solving a task (e.g. negative marking).

Our data have shown that online courses may have very positive effects even outperforming on-campus courses, which, of course, may have other benefits like helping students interact with each other. We should seek ways to help students engage in their courses and consider offering digital courses or blended courses to combine the advantages of both formats.

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