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Should We Trust Math Preparatory Courses? Am Empirical Analysis on the Impact of Students' Participation and Attendance on Short- and Medium-Term Effects

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Should We Trust Math Preparatory Courses? An Empirical Analysis on the Impact of Students' Participation and Attendance on Short- and Medium-Term Effects*

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Abstract

Remedial courses, particularly in math, have become indispensable in today's higher education landscape. However, large scale evaluation studies investigating the effectiveness of such courses find mixed results which is only one reason why remedial courses should not be trusted as a functional instrument in general. Besides the unclear impact on students' skills, research mostly does not control properly for the students' attendance in these courses. This study gives an insight into the differences in students' participation, attendance and the resulting consequences for short-, and medium term effects. Therefore, over three periods of time, data on several variables and standardized skill-test outcomes was raised, leading to a sample of N=1,236 students enrolled in subjects of economics to investigate short term effects, while a subsample of N=501 students could be matched to measure a medium term effect using a fixed-effects approach.

Keywords: Program Evaluation; Math Remediation; Higher Education; Math Skills; Freshmen Students

1 Introduction

The German higher education system suffers from unprepared freshman students, especially in math. Reasons for that can mainly be found in federal policies. Compared with industrialized countries, the graduation rate of higher education institutions is below average in Germany. For instance, in 2017, the rate of 25- to 34-year-olds with tertiary education was at 31.3% for Germany compared to 44.5% for the OECD average (OECD, 2018). For that reason, university access in Germany has been changed in two ways over the last decades. Firstly, access was improved for students without classical secondary school degrees. As a result, students can now enroll, among others, with technical degrees. In addition, to these access improvements, several universities in the federal state of Hesse (including the University of Kassel and universities of applied sciences) also allow students to enroll with a shorter secondary school degree that has a lower educational value and is based on a simplified and shortened curriculum ("Fachhochschulreife"); as students with this type of degree show lower academic skills, particularly in math and math-related subjects, those higher education institutions encounter a special type of unprepared students. Secondly, the rate of students receiving a (regular) secondary school degree, which still is the standardized entrance qualification for higher education, increased significantly from 33.9% in 2010 to 40.3% in 2017. As politically intended, the rate of freshman students in higher education increased as well. While 46% of a cohort decided to pursue tertiary education in 2010, this number had risen to 57% in 2017 (Destatis, 2018). The problem is that these increasing rates are not a result of improved secondary education but rather built on decreasing curriculum and test standards which result in, on average, worse preconditions for the upcoming tertiary (math) education. For instance, one can observe grade inflation in secondary school degrees, particularly during the last decade. While in 2007 only about 1% of the students graduated with the best possible grade, this number had nearly doubled to about 1.8% in 2016 (KMK, 2018).

Therefore, secondary math education falls, at least partly, into the area of responsibility of higher education institutions. The necessity of compensating insufficient math skills in combination with growing student numbers force universities into offering math remedial programs. While math remediation or remediation in general is a controversially discussed topic in the United States (of America) (Bahr, 2008), it is highly accepted in Germany. However, empirical evidence is rare. In contrast to the United States, where the impact of (math) remediation is sufficiently investigated finding mixed results (e.g. Bettinger and Long, 2009; Calcagno and Long, 2008), there is hardly any such evidence for math remediation in Germany. However, impact evaluations are highly necessary since the structure and organization of German math remediation shows major differences in comparison to its US equivalent. Besides two different course formats (intensive preparatory courses and semester-long bridging courses), remediation in Germany is mostly voluntary with no need to pass these courses successfully.

All in all, this study provides solutions and results for several research issues of preparatory courses. At first, participation and attendance, which are often used as synonyms in cases of remedial courses, will be investigated.

In additional steps, short-term effects of participation and attendance of a preparatory course will be pointed out. Finally, I will measure a causal midterm effect of the preparatory course, finding that, in contrast to initial thoughts, the remedial course does not show an effect at that stage anymore. To this end, data was raised at the Department of Economics at the University of Kassel. Over three periods of time (winter semesters of 2012, 2014 and 2016), students in degree programs of Economics and Business Administration (EBA) and Educational Economics (EE) were asked to participate in math skill tests and questionnaires. Altogether, information of N=1,236 students has been gathered to investigate short-term effects and the role of attendance, while a second sample and subset of the first sample including N=391 students could be matched to measure a midterm effect a few weeks later.

2 Background

2.1 Math Remediation in Germany

Math remediation in Germany differs from remedial programs in the US or other European countries in several ways. First of all, since math remediation is mostly non-compulsory, students can decide themselves whether they participate in such courses or not. Secondly, remedial courses are rarely centralized and therefore not organized on a superior institutional level. Usually, remedial math courses are, if required, offered separately by each department of a university and since there is just voluntary participation, there is no need for further organization or databases to control for students' attendance, acceptance or passing the remediation at all. Furthermore, lecturers usually have no information on who is participating in remedial courses since students often do not have to register for the course. Finally, there are structural differences between the various countries' remedial courses. Math remediation in Germany consists of three different course offers. An intensive preparatory course, set prior to the beginning of the (first) semester as well as a bridging course and math support centers, with the latter two options offered over the course of each semester.

Preparatory courses are the most popular remedial course the German higher education system relies on. These courses usually reach the largest number of freshman students and act as preparation for the whole course of study. Therefore, this kind of remediation is set prior to the beginning of the students' studies and is structured as an intensive course from two to five weeks. Topics are revisions of secondary school math (e.g. terms, equations, functions, and calculus) or preparations for the upcoming course of study (e.g. proof techniques) to ease the transition from secondary to tertiary mathematics. The topics and designs of these courses highly depend on the degree program and the students' average previous knowledge. For instance, math remediation in courses of economics and business administration usually focuses on topics of secondary math schooling and lasts about two weeks, while preparatory courses for subjects of engineering or maths last up to five weeks. Besides the length, preparatory courses in Germany also differ in their structure. While most of them offer tutorials and exercises to solidify the subject matter, the courses have different implementations. Some courses are completely online-based or provided in a blended-learning format, whereas other courses are classroom-based only. This, for example, is one subject German research in math remediation has focused on. Preparatory courses are enjoying great popularity in Germany, but the research findings focusing on them are at least questionable. Many German studies and reports just suggest how to implement math remediation and give descriptive information (Bausch et al., 2014, Hoppenbrock et al., 2016), but evidence for the impact of remediation, especially on math skills, is rare. The few German studies that have a look at students' math outcomes related to remediation are either not designed to measure causal effects (Greefrath and Neugebauer, 2017) or measure short-term effects under control of certain variables (Voßkamp and Laging, 2014, Laging and Voßkamp, 2017). Although the German project "WiGeMATH"[1] focuses on describing, analyzing and comparing different support programs as well as investigating effects of math remediation, there is no study investigating causal effects of math preparatory courses on math skills in Germany yet. This is a different situation on an international level. Several evaluation studies, particularly in the US or UK, estimate effects of remedial programs finding mixed results. Studies that find positive effects of remediation on math skills are, for instance, Boatman and Long (2018) or Scott-Clayton and Rodriguez (2015), while Martorell and McFarlin (2011) or Di Pietro (2014) just find minor effects or no effects at all. Reasons for the lack of evaluation studies in Germany are probably data issues. Self-selection and a shortage of test results and covariates due to voluntary participation

[1] effects and success conditions of mathematics learning support in the introductory study phase

complicate the measuring of causal impacts since common methods like regression discontinuity or difference-in-difference designs cannot be applied easily.

While a preparatory course aims at refreshing secondary math skills and preparing for the whole course of study, a bridging course is linked to the main lecture and intends to support students with mathematical basics just in time and when they are especially relevant to the lectures' topics. Therefore, a bridging course is usually structured inside the semester with weekly lectures and the topics can spread widely from basic secondary to tertiary mathematics. Because of the structural differences compared to preparatory courses, bridging courses should be evaluated separately. For instance, a small-scaled study investigating causal effects of a bridging course at a German university finds that participating in this kind of remedial course offer on a regular basis enhances students' math skills and the chance of passing the final math exam significantly (Author, 2018). The third remedial offer German universities provide on a regular basis is math support centers. Throughout the semester and at least once a week, tutors or lecturers function as coaches in an open learning environment. They help students solve their exercise sheets, give further references or answer further questions that might arise[2]. Evaluations of support centers are quite difficult because attending students are highly selected and information about confounding variables is rare. Therefore, studies concentrate more on a descriptive analysis that is not suitable for causal interpretations (see e.g. Bhaird, Morgan, and O'Shea, 2009 and Matthews et al., 2013).

[2]For more information about support centers, see for example Matthews et al., 2013

2.2 Evaluation of Preparatory Courses

Preparatory courses intend to help freshman students during the transition from secondary to tertiary mathematics or rather make the entry phase of their studies overall easier. Therefore, the improvement of math skills is not the only parameter worth investigating. One could also determine the effects of remediation on factors like math anxiety, self-efficacy or learning strategies. However, whether student participation in math preparatory courses leads to improved math skills still seems to be the most important determinant of successful studies. Especially medium- and long-term effects of math preparatory courses are not sufficiently investigated. For instance, Laging and Voßkamp (2017) just report positive short-term math outcomes, which is not surprising, given that students recently took part in an intensive math course. It is highly relevant whether students can still benefit from intensive preparatory course participation after a few weeks or in the final exam. Further questions are whether mathematical content from over eight years of secondary school education can easily be reprocessed in a few weeks and how those intensive courses influence the students' short- and long-term math outcomes compared to semester-long courses. In psychological theory, the so-called spacing effect suggests that course content spread over a longer time period leads to better learning and retention (Dempster, 1988), which should have a positive impact on students' skills and grades. Surprisingly, empirical studies do not match this theory. Daniel (2000) gives a good overview of the structure and research on time-shortened courses and states that different studies in different subjects find different long-term results (from positive to negative effects on intensive course participants). Regarding short-term outcomes, studies show a positive or at least an equal effect of intensive courses compared to semester-long courses. More recent studies also find either no differences in student performance between different course formats (Carrington, 2010) or positive effects of intensive courses in general (Austin and Gustafson, 2006; Kucsera and Zimmaro, 2010).

Although the majority of studies find, in general, positive effects for intensive courses, these findings cannot easily be transferred onto preparatory courses. First, since there is no need to pass the preparatory course, one can assume different learning habits as those examined in the empirical research where courses are graded. Students do not feel high pressure, despite having to pass a final exam at the end of the semester which is not present yet. Also, the preparatory course content is either taught in the first math lectures of the semester or has to be learned by the students in order to keep up with the lecture. Students suffering from insufficient math skills have to take part in the preparatory course, learn the critical content on their own or participate in further support programs during the semester. Therefore, it is not unusual for students to make use of more than one remedial offer. A comparison or experimental design in which students either participate in an intensive preparatory course or other course offers during the semester such as bridging courses does not seem reasonable in this case because the courses differ too much in their contents and structures. Consequently, the relevant question for an evaluation of remediation of this kind is whether students who did not participate in preparatory courses can compensate the missing treatment during the semester and, vice versa, whether treated students do still show better math skills halfway through the semester.

2.3 Further Procedure

Following the argumentation of this chapter, I will give an insight into different issues of the evaluation of math remediation. At first, I will give a descriptive overview of the students' participation and actual attendance at a math preparatory course which differs significantly. Secondly, this issue will be transferred to the estimation of the short-term effects of the remedial offer. Finally, I will measure a causal mid-term effect of the preparatory course by estimating the compensating effects of the student who did not take part.

3 Method

3.1 Design

Data from three different periods was raised at the Department of Economics at the University of Kassel to evaluate short- and medium term outcomes of a math preparatory course. In the years of 2012, 2014 and 2016, a total of 1,236 students took a math skill test (entry test) and answered a related questionnaire. A subsample of 501 students also took part in a second skill test (midterm test) and questionnaire in the middle of the semester. Data was raised completely anonymously. Figure 1 gives an overview of the study's quasi-experimental panel design.

[Figure 1 near here]

Both skill tests consist of 30 tasks of secondary math schooling (e.g. terms, equations, functions, and calculus). The tests are about equally difficult, being composed of different but comparable tasks (Laging and Voßkamp, 2017). Both points in time at which data was gathered were set after the treatment. This seems surprising at first since the treatment in a difference in difference or fixed-effects design is usually set between the points of data collections. In this case, the study's design does not lead to a classical difference-in-difference effect on the treated students but results in a compensative effect on the students that did not take part in the preparatory course.

3.2 Sample

In the first main math lecture, the students took part in the entry test and questionnaire. Since the main math lecture is a first-year course, most of the relevant students attended at least the first lecture, and therefore, took part in the entry test. Every year, about 450 freshman students enroll in the degree programs of EBA (300) and EE (150). The sample size of 1236 students allows the conclusion that the sample covers for most of the population. The midterm test was conducted nine to ten weeks later in the middle of the semester and took place in the main lecture as well. Due to different reasons, only a part of the first sample could be matched to the midterm test results. Firstly, attendance in the main lecture was not compulsory. Students could skip classes, and therefore, not take the midterm test although the tests were not announced. Secondly and more importantly, since only about 200 to 250 students take the final exam at the end of the semester, most of the missing students totally dropped out of the main lecture. This is possible because students in Germany usually can structure their studies themselves. This means, that students who do not feel well prepared or overextended could easily shift the math module into another semester. Additionally, for students enrolled in EE, the math course was an elective module in the years of 2012 and 2014. Not surprisingly, EE students dropped the class primary. Of course, this leaves a selected sample behind which will be discussed later. But since these leftover students are most likely to pass the math module, they seem especially relevant for a medium term effect. Due to these issues, the study handles two different samples. The first sample of 1,236 students is used to measure the short-term effect of the math preparatory course as they all took part in the entry test shortly after the preparatory course. The second sample of the remaining 501 students is used to measure a medium term effect.

Table 1 provides information on the students' math outcomes at the entry test T_0 and midterm test T_1.

[Table 1 near here]

One can see an overall lack of students' secondary math skills. On average, the first sample reached only about 6.5 points (out of a maximum of 30 points), while the more selected subsample just reached about 8.2 points on the same test. The difference between those two samples makes sense, considering that the students in the second sample also took part in the second test in the middle of the semester, while other students dropped out or did not attend the math lecture. This indicates, a priori, different student characteristics. For the second sample, one can see the skill improvement over the semester. In the midterm test, the same 501 students reached on average about 11.5 points, which is an increase of 3.3 points.

3.3 Participation vs. Attendance

Most of the studies evaluating remedial programs just consider formal participation of students in remedial courses which is often equaled to actual attendance. The authors either assume that students can be enrolled compulsorily in remediation (for instance, due to low ACT scores) or can choose on their own whether to participate in a remedial course or not. In most of the common large-scale papers (e.g. Bettinger and Long, 2009, Boatman and Long, 2018), the word "attendance" does not even appear. Only De Paola and Scoppa (2014) control for attendance, finding a positive correlation regarding the gained credits after the first two years of college. So far, the usual data provides information on whether a student (successfully) participated in a remedial program or not. However, this binary information does not tell anyone anything about the students' actual attendance in the lectures or tutorials unless attendance is mandatory and checked by lists. Evaluation results could easily be biased by students being formally counted as remediation participants but hardly attending any lectures and consequently not passing relevant courses. For reliable results, the students' actual attendance has to be recorded.

As attendance lists are not practical in larger courses, the students were asked in the ex-post questionnaire whether they participated in the preparatory course and if so, how many lectures and tutorials (out of eight in each case) they actually attended. Due to the anonymous design, social desirability should not be a major concern. All in all, students could participate in a maximum of 16 course dates. To give an overview, the students of both samples are clustered in four further groups, depending on their actual attendance those consist of students who attended one to four course dates (up to 25 % of the course), five to eight course dates (25% to 50%), nine to 12 course dates (50% to 75%) or 13 to 16 course dates (over 75%). Consequently, while students in the first group could not actually be counted as participants, students in the second group showed low participation, students in the third group displayed medium participation and students in the fourth group fully participated in the preparatory course.

[Table 2 near here]

Table 2 summarizes the students' answers. For the first sample, 613 out of the 1,236 students said that they did participate in the preparatory course, while 623 indicated that they did not take part. Six of the 623 non-participants actually attended at least one lecture or tutorial of the preparatory course but did not count themselves as participants. The situation is different when looking at the students indicating that they did participate in the preparatory course. From 613 students stating they participated, only 324 attended 13 course dates or more and indicated, so far, full attendance. 138 students attended nine to twelve lectures or tutorials. The remaining 157 students, a number that equals about a quarter of all self-declared participants, just showed low or nearly no attendance at all. The attendance rates are similar in the more selected second sample. Although the group of students, who indicated high attendance constitutes about two-thirds of all participants, a fifth of all students attended less than half of all course dates. This shows that participation and actual attendance in remedial courses cannot be considered the same as one another and have to be controlled for in further research. One cannot assume that just because a student declared participation or course enrollment is mandatory, he or she shows full attendance and takes the remedial offer seriously. This is a major problem for the evaluation of these courses in general, as they usually search for average effects. If attendance is not mandatory, one has to assume biased results because students are considered to receive the treatment, regardless of whether they showed low or high attendance.

3.4 Skill-test Results

Table 3 provides descriptive information on the average skill test results, organized according to the students' attendance and different samples.

[Table 3 near here]

For both samples, one can assume that increased attendance, on average, leads to higher test results in the entry test (Y_0). In comparison, students who participated in at least 25% of the preparatory course performed equally well or better than students who never made use of the remedial course offer. Only those attending less than 25% of the preparatory course performed worse than non-participants, which indicates an issue of self-selection. Since there is no other explanation for why students attending at least some lectures should perform worse than students never participating in the remedial offer, one has to assume biased descriptive results which will be controlled for in the further analysis.

Although the descriptive midterm test results (Y_1) for the second sample are similarly biased, they indicate a direction. Every group improved their math skills during the semester (ΔY), but the students who never attended the preparatory course showed the most progress. The difference-in-difference estimator gives a more accurate interpretation and illustrates that the non-participants are compensating the missing treatment over all groups. For example, the students in the second sample, showing above 75% attendance in the preparatory course, reached 1.90 points more in the entry test and 1.21 points more in the midterm test than students who never participated. Consequently, the difference in difference effect is -0.69 (1.21 - 1.90) and can easily be seen as a compensative effect. Although the course participants still reach about one point more in the midterm test, the non-participants could make up 0.69 points during the semester. Of course, these descriptive results do not control for self-selection and should not be considered causal evidence. One cannot assume that participants have the same characteristics or a similar learning behavior during the semester as non-participants. This affects the estimation and will be controlled for in the midterm analysis by taking further variables into account.

3.5 Variables

With the entry and midterm tests, students were asked to answer a questionnaire that collected crucial biographical, educational, study-specific and pedagogic-psychological variables. These 21 control variables are sorted into three different categories. The baseline variables (B_k) are time-independent (influencing the test performance at T_0 as well as T_1) and consist of educational and biographical variables which can considered as determinants of math skills and higher education performance in general (Laging and Voßkamp, 2017; Mallik and Shankar, 2016; Mallik and Lodewijks, 2010; Byrne and Flood, 2008; Krohn and O'Connor, 2005). The second category consists of the time-dependent semester variables S_k (only influencing the test performance at T_1) that control for the students' attendance and engagement during the semester. The final category (P_k) is composed of different pedagogical and psychological scales. Table 4 gives an overview.

[Table 4 near here]

A few variables need further explanations. B_3 is a dummy variable that checks whether a student already took the math course in a previous semester and did not take or pass the final exam. B_4 indicates information on the student's course of study. Most of the students are either enrolled in Economics and Business Administration (EBA) or Educational Economics (EE), with just a few students having Economics as their minor subject. As mentioned above, students can either enroll with a full or shortened secondary degree, a premise which is controlled for with B_5. The variables B_6 and B_7 provide information on the student's previous grades in school. This is measured on a scale from 1 to 4 for the overall GPA and 1 to 5 for the average math grade in secondary school. It is important to know that the German grading system differs from that of most other countries: the better the students' performance, the lower their grade (from 1 to 6), with a 4 being barely sufficient. The last baseline variable (B_8) controls for the student's self-efficacy; to that end, students were asked to judge their own math skills in general on a scale from one to five.

The semester variables provide information on the students' math engagement during the semester. For S_1 to S_5, students were asked how often they attended the respective course offer on a scale from 1 to 6 (1 = never; 6 = at all times). Besides the preparatory course, students can attend several traditional and remedial courses. Of course, there is the main math lecture (S_1), which is accompanied by tutorials (S_2). Furthermore, students can solve exercise sheets (S_3), make use of additional remedial offerings like a support center (S_4) or a semester-long bridging course (S_5). S_6 measures how many hours a student spent studying for math each week (attendance in the math lecture and tutorials not included) and S_7 controls for the number of courses a student took besides the math course.

The pedagogical and psychological variables control for common motivational and learning factors such as math interest (P_1), control strategies (P_3) or math anxiety (P_4). The scales have been employed in several studies and were developed especially for math[3]. The Cronbach's Alpha is calculated within the first sample and shows overall sufficient or good values. In the questionnaires, the students responded to the same items at both points in time. Consequently, one can identify the changes in those variables during the semester which is particularly relevant for the second sample. With the exception of math anxiety (P_4), t-statistic shows that all the other pedagogical variables' means decline significantly. Because of the fixed-effects design,

[3]For more information on the scales used, see Laging and Voßkamp (2017)

I will only take the differences of the pedagogical and psychological variables into account for measuring a causal midterm effect.

4 Empirical Strategy

4.1 Short-term Analysis

Since the study's design includes two different samples (one for short-term and one for medium-term effects), two different models were applied. For the short-term analysis, I run a multivariate OLS-regression model with the first sample (N = 1,236). The dependent variable is the entry test result, while the independent variables are a treatment dummy (preparation course participation) and all baseline as well as pedagogical and psychological variables. By doing this, one can identify determinants of the students' math performance in the entry test (Y_0), and thus draw conclusions on the influence the preparatory course has on the entry test results. Furthermore, the model should not only provide information on the short-term effect of the preparatory course but give an overview on the matter of the students' attendance. To this end, the effect is estimated for the five different subsamples (see Table 2). While the treatment group in each model is based on the students' actual attendance, the control group (non-participants) remains unchanged for each analysis. Since the relevant variables for the short-time measurement are sorted into two different categories, the categories are included in the model separately.

The first model (model 1.1) estimates the entry test results (Y_0) as the dependent variable by including the treatment dummy T, and the nine baseline variables (B_k) as independent variables. The same regression is estimated five times, namely once for each treatment group. Since the sample is summarized from three different periods (2012, 2014 and 2016), additional year dummies will check for possible year specific characteristics. In a second step (model 1.2), the pedagogical and psychological variables (P_k) are included.

Model 1.1:

$$Y_0 = \alpha\, T + \beta_1\, \mathrm{d}_{12} + \beta_2\, \mathrm{d}_{14} + \beta_3\, \mathrm{d}_{16} + \sum_{k=1}^{9} \gamma_k B_k + \varepsilon$$

Model 1.2:

$$Y_0 = \alpha\, T + \beta_1\, \mathrm{d}_{12} + \beta_2\, \mathrm{d}_{14} + \beta_3\, \mathrm{d}_{16} + \sum_{k=1}^{9} \gamma_k B_k + \sum_{k=1}^{6} \delta_k P_k + \varepsilon$$

4.2 Medium term Analysis

To estimate the medium-term effect, a fixed effect regression is applied. For causal inference, the model must hold the common trend assumption which supposes a parallel trend regarding the outcome variable in the treatment and control groups. This means, that between the two points of measurement students in the control group must show a similar development in their math skills as students in the treatment group. Since the students self-selected themselves into the treatment and control groups, this cannot be expected for the given samples. Furthermore, since only students with an attendance rate of over 75% can be considered as actual participants, the midterm effects will be examined for this group only.

All in all, two general issues apply. Firstly, one can easily imagine that students participating in an optional preparatory course show, compared to non-participants, higher engagement and different learning behavior during the semester. These are time-dependent variables, leading to an estimation bias toward the treatment variable. Secondly, besides the variables influencing the outcome between entry and midterm test, one should also check for the students' time-independent characteristics which are the baseline variables B_k. Although the fixed-effects design covers for most of the initial observable and unobservable bias, it cannot be generally assumed that the baseline variables do not influence the parallel trend. For instance, even though a student's secondary school GPA will not change between the two points in time anymore, one can assume that a higher GPA leads to a higher understanding and therefore biased estimations within the meaning of the common trend assumption.

4.2.1 Controlling for Selection Bias

To control for these two issues, a particular strategy has to be applied. The first problem can easily be solved by including the semester variables (S_k) into the regression analysis as control variables. As a result, the effect of the preparatory course will be adjusted by the students' engagement as far as participating in lectures, tutorials, further support programs and their weekly study hours are concerned. The differences in the set of pedagogical and psychological variables (ΔP_k) will be controlled for as well.

The second problem is that the baseline variables influence the test results in T_0 as well as in T_1. As mentioned above, this is an issue which is not automatically controlled for by the fixed effects design, particularly in the context of this study and its self-selected samples. To make sure that the initial differences in the treatment and control groups will not lead to biased estimations, I will use a propensity-score-matching process.

4.2.2 Propensity Score Estimation

In a first step, by means of a probit regression the propensity score $PS(X)_i$ is estimated for each student within all the baseline variables B_k and, subsequently, the propensity score is implemented in the regression model as a weighting. Hirano, Imbens, and Ridder (2003) show that having a fixed-effects regression and taking $PS(X)_i/(1 - PS(X)_i)$ as the regression weight for untreated and 1 for treated students generates an efficient difference in difference estimator[4]. This allows including the baseline variables and, therefore, controlling for structural differences by homogenizing the treatment and control groups. Table 5 gives an overview of the probit regression results.

[Table 5 near here]

The estimation shows that particularly the variables B_1 to B_4 and B_9 are determinants for the students' choice to (fully) participate in the preparatory course. First of all, female students seem more likely to participate. Furthermore, students in their second or third year of study, as well as students who already took the math course in a previous semester, are less likely to participate. This is not surprising since the preparatory course is an offer particularly for freshman students. However, students in a higher semester who do not feel well prepared for the math module are welcomed as well.

[4] for a further study following this particular strategy also see Mu and Walle (2011)

Surprisingly, the classical performance variables (B_5 to B_8) do not affect the treatment choice. The education gap shows a significant positive effect, which means that students who do not enter the higher education system right after their secondary school degree are more likely to take the preparatory course.

The region of common support was defined between 0.0137 and 0.8671 with a propensity score median of 0.5196. This led to an exclusion of three students. The sample's size for further medium term analysis is now 391 students, of whom 198 did not and 193 fully participated (attendance $>$ 75%) the preparatory course.

4.2.3 Models for Medium term Analysis

For a better comparison, the categories of variables will be implemented one by one.

Model 2.1 (FE):

$$\Delta Y = \alpha T + \varepsilon$$

Model 2.2 (FE):

$$\Delta Y = \alpha T + \sum_{k=1}^{6} \gamma_k \Delta P_k + \varepsilon$$

Model 2.3 (FE):

$$\Delta Y = \alpha T + \sum_{k=1}^{6} \gamma_k \Delta P_k + \sum_{k=1}^{7} \beta_k S_k + \varepsilon$$

Model 2.4 (FE-WLS):

$$\Delta Y = \alpha T + \sum_{k=1}^{6} \gamma_k \Delta P_k + \sum_{k=1}^{7} \beta_k S_k + \varepsilon$$

Model 2.1 estimates the uncontrolled effect of the preparatory course which is the same as in Table 3. In Model 2.2, the differences in pedagogical variables are included. Model 2.3 controls for the differences in semester variables as well. With model 2.4 the ps-weighting is included. In this study, the treatment takes place prior to the first and second measurement of the math performance (see Figure 1) which is unusual for a fixed-effects estimation. This leads to a negative treatment-coefficient and measures compensational effects of the group of students who did not take part in the preparatory course.

5 Results

5.1 Short term Effects

Table 6 shows the OLS-regression results of models 1.1 and 1.2. The models show a good fit, explaining 75% to about 79% of the variance. The first two columns present the results for the whole sample of N=1,236 students. Whether a student participated in the preparatory course is measured by the student's individual assessment of their participation as described in Table 2. The subsequent columns provide information on each subsample, depending on the students' actual attendance. The values indicate positive short-term effects of the preparatory course and one can summarize that attendance is beneficial. Not surprisingly, the group showing hardly any attendance (up to 25%) in the preparatory course does not benefit from the treatment at all. Students who participated in 25 to 50% of all lectures and tutorials show a significant and positive correlation, with an estimated additional point in the entry test compared to the non-participants. This value rises with an increase in the students' attendance. Students attending between 50 and 75% of all course dates score about 1.9 additional points, while for the group of students showing the highest attendance, the preparatory course pays off the most with a short-term effect of about 2.5 points.

[Table 6 near here]

The different effect sizes should be considered further. First, it is necessary to define students' participation in the treatment. The model including all students with the self-assessment of their participation (N=1,236) shows an average 2-point-effect, while students with an actual attendance rate of more than 75% can reach about 2.5 additional points. Consequently, not controlling for attendance leads to an underestimation of the preparatory course's effect. Secondly, one can see a significant increase when the models control for pedagogical and psychological variables as well. Controlling for these variables adjusts the treatment estimator in a positive manner, which can be attributed to different reasons. For instance, one could assume that the average math anxiety of students who choose to participate in the preparatory course is higher, a fact that also negatively correlates with their math performance.

Furthermore, it is worth looking at the coefficients of the baseline variables. The models indicate a gender effect which results in women's test scores being, on average, one point lower than those of male students (B_1). Students mostly benefit from a classical secondary school degree (B_5) and having already taken the main math course in a previous semester (B_3), both of which can be attributed to about three additional points in the entry test. Since a higher secondary school GPA indicates lower skills, the prior GPA (B_6) correlates negatively with the test results; the same applies to self-efficacy (B_8). No significant effect can be reported for the variables B_2 (years of study), B_4 (course of study) and, surprisingly, the average math grade in secondary school (B_7). Further analysis shows that the math grade effect disappears when taking the self-efficacy (B_8) into account. The simple question of how students judge their own math skills in general, determines math skills better than the secondary school math grade does. This matches up with the idea, that the German education system is regionally decentralized and students can access the higher education system with different degrees. Consequently, one cannot assume that the same math grade stands for similar math skills. Of course, this could be an effect limited to Germany or, even further, this specific university. While the education gap (B_9) has a large impact on the decision whether to participate in the preparatory course, it does not affect the entry test results at all. The pedagogical and psychological variables P_1, P_3, P_4 and P_6 show significant effects in most of the analysis. As one can expect, a higher interest in mathematics (P_1) and a higher self-concept of math (P_6) correlates positively with the entry test performance, while math anxiety ($P4$) shows a negative correlation. A higher value in the scale of control strategies (P_3) seems to result in poorer performance, which cannot be explained reasonably.

5.2 Medium term Effects

Since just the students with an attendance rate of over 75% can be considered as actual participants and also show the best short-term results from the treatment, the midterm effects will be examined for this group only. This cut leads to a sample of 391 students, of which 193 are located in the treatment group and 198 belong to the control group. A few missing values reduce the sample to 386 students in models 2.3 and 2.4. Table 7 shows the difference-in-difference effects which are interpretable as compensative effects of the group of non-participants. Model 2.1 estimates a non-significant ($p = 0.083$) descriptive effect of about 0.7 points which is the exactly identical effect as in Table 3. Including the differences in pedagogical variables the effect rises to 0.8 ($p = 0.052$). The largest increase can be seen by implementing the semester variables. Model 2.3 gives a compensational effect of about 1.4 points. Controlling for the baseline bias via the regression weight corrects the compensational effect by only 0.1 points to a final effect of about 1.5 points.

[Table 7 near here]

Altogether, in model 2.4 the calculated compensative effect is about 1.5 points. This means, adjusted for the students' self-selection and engagement during the semester, the students who did not participate in the preparatory course could make up 1.5 points compared to the group of students who attended regularly. Furthermore, considering the purely descriptive test results in Table 3, it stands out that the group of students attending more than 75% of the course scores, in contrast to the non-participants, one additional point (Y_1) in the midterm test. In connection with the true compensative effect, which is 0.8 points higher than the descriptive effect (model 2.4 vs. 2.1), this leads to a nearly full math skill compensation in the group of non-participants. In other words, the main reason that students who took part in the preparatory course were able to perform better in the midterm test than students who did not participate is that the former students also showed a higher engagement (attendance in lectures, tutorials, bridging course, etc.) during the semester. Since the non-participants show this skill compensation compared to the students exhibiting the highest short-term effect and attendance, one cannot expect any other outcomes for the three other groups of students that attended less. Consequently, it cannot be established that the preparatory course has a midterm effect.

Furthermore, model 2.2 and 2.3 also gives information about the influence of the pedagogical and semester variables on students' skill development. One can see, that the change in the pedagogical variables did not influence the increased knowledge significantly. However, only the variables S_3 and S_5 seemed to have a significant impact on the math skill gain over the semester. Students solving assignments and doing the exercise sheets on a regular basis show a higher increase in their math skills. Also, students who attend the bridging course regularly could enhance their math skills, compared to those students who did not participate in the bridging course. This result matches a study investigating the effects of such a course (Author, 2018). Attendance in the main lecture, tutorials or support center as well as the workload throughout the semester did not affect the skill development significantly. The coefficients of control variables in model 2.4 are not reported.

The weighting might adjust the treatment effect in a correct manner but does not lead to true coefficients for the control variables.

6 Discussion

The results show a positive short-term outcome for students who attended the preparatory course regularly. The effect rises nearly linearly with each group attending more lectures and tutorials (see Table 6). So far, there is nothing surprising in these observations. Many studies find a positive correlation between attendance and performance (see e.g. Dey, 2018, Chen and Lin, 2008, Marburger, 2006). More importantly, however, are the consequences educational research has to draw from these findings. There is a particular lack of information on students' attendance in large-scale math remedial studies. Large-scale data sets often just provide information on whether a student has to participate or pass remedial math courses, but not whether a student did actually attend them. Consequently, one has to deal with two stages of selection-bias. At the first stage, especially in voluntary remedial course models, one has to control for the students' self-selection with regards to the treatment. Most research designs control for this kind of bias. Famous approaches are, among others, difference-in-difference, instrumental variable and discontinuity regression designs. But further, these findings suggest that research should check for a second stage selection-bias of students who already belong to the treatment group. Given that only about half of all self-assessed "participants" actually attended the preparatory course sufficiently, one has to expect biased results when not controlling further for attendance, even if causal study designs were applied. In the case of this study, not controlling for further attendance led to an underestimation of the treatment effect by 25%.

Although only the treated students with the best short-term results were considered for the analysis, I could not find a significant preparatory course effect anymore. Even though the treated group still shows a better performance in the midterm test one can see that this is only because these students show a higher engagement in learning math during the semester as well. Descriptive comparisons of the semester variables between the treatment and control groups confirm this conclusion. With no reportable outcome in the middle of the semester, it is highly unlikely that there should be long-term effects. Consequently, there is no need to examine math performance at a later point in time.

It is unclear whether the results of this study should lead to the conclusion that preparatory courses should not be offered at all. While the study indeed finds a full compensation of the treatment, it also demonstrates that treated students exhibit a higher attendance in lectures and additional offers during the semester. It is not apparent, however, why treated students show more engagement during the semester. One reason could be that students who participated in the preparatory course have a more realistic self-efficacy and, therefore, try to compensate for their missing skills. Consequently, the question that arises is, what preparatory courses can do to help students during their transition from secondary to tertiary education because these courses are not only designed to enhance the students' math performance. Equally important goals are to ease the entry-phase by giving students a smooth start into the new education system, showing them their gaps in math knowledge and consequently, leading freshman students to a more realistic self-efficacy. Following this reasoning, better performance in the midterm test could be attributed to the preparatory course participation after all. Another question that cannot be answered in this paper but should be considered for further research is, whether preparatory course participants show a higher resilience and remain in the math lecture while other students drop out.

The results of this study are stable regarding internal validation. It is clear that the presented OLS coefficients for the short-term analysis are more precise than the descriptive results in Table 3 since the students show a linear increase in their treatment outcome depending on their course participation. Particularly the treatment effect of the first group of students with an attendance rate of under 25% is adjusted; there is no longer a negative effect as there was during the descriptive analysis. This seems reasonable considering that no participation should also lead to no effect. Therefore, the coefficients are trustworthy, and even if one cannot exclude all probable bias, the estimated effects are suitable. While the inference of the short-term effects required discussion, the medium-term effects are clear so far. The fixed-effects design covers for unobservable bias and the included time-dependent variables support the common trend assumption, while propensity scores are just used to balance the treatment and control groups over their baseline variables and adjust the treatment effect.

This study has some limitations that have to be addressed. First of all, since the skill tests and course topics are built on secondary school math, the study's results just consider the impact on these math skills. Furthermore, the study just includes a two-week preparatory course for study programs in Economics and Business Administration and Educational Economics. Even if typical remediation for these study programs is filled with topics of secondary school math, one should not easily transfer the results to remediation in studies of engineering or mathematics, especially because typical preparatory courses in these degree programs last up to five weeks. Secondly, although the results are clear for the used samples, the reduction from the first to the second sample is very high. Since participation in both tests was not compulsory and students drop out of or do not attend the math lecture in the middle of the semester anymore, the second sample is highly selected. Of those 324 students who took the entry test and attended more than 75% of the preparatory course's lectures and tutorials, only 193 could be matched in the midterm test. It is not possible to determine whether the missing 131 students in the treatment or the missing 425 students in the control group would achieve similar medium term results.

In fact, this issue of external validation needs further discussion. While the first sample in the entry test covers most of the population, this cannot be expected for the second sample. As aforementioned more than half of the students who took the entry test could not be reached in the midterm test. Reasons for that can mainly be found on a superiorly level. The system of higher education in Germany is, compared to the US, extremely liberal. Attendance is not compulsory, either in the remedial courses nor in the main lectures. Therefore, students self-select themselves into those classes. Furthermore, even if students show insufficient math skills, they are not forced to attend, take or pass math remediation. This is an issue concerning the complete higher education landscape in Germany and the consequence for research in this field is substantial. Firstly, research can hardly fall back on popular evaluation methods like regression discontinuity approaches, since there is no threshold beyond students must take or at least pass remediation. Secondly, there is no further information who takes remediation at all. Large scale university databases are non-existent. And thirdly, without mandatory attendance, students drop out of the relevant courses and cannot be traced back to generate sufficient panel data. This is a major problem, concerning German research in general and cannot be solved easily.

Besides these systemic reasons why students cannot be reached at the second point in time, it is worth having a look at the students' individual characteristics. Therefore, a logistic regression is performed. Table 8 reports the odds ratio and z-values for the baseline and pedagogical variables, measuring which of these are primarily responsible for student course drop out. The dependent variable is a dummy, whether a student could (1) or could not (0) be matched to the first sample.

[Table 8 near here]

The logistic regression was performed three times with three different samples (all students, treatment group and control group). Therefore, one can compare the different groups regarding their drop out characteristics. The results show, that a higher score in the entry tests leads to a higher chance to remain in the course. This indicates, that students with higher math skills are more likely to take the mid term test. This is the same for female students (B_1). Students enrolled in EBA (B_4) as well as students with a regular secondary school degree (B_5) and a higher (better) prior GPA (B_6)

did also show a higher resilience.

With regard to the selection effect in this study, a comparison between the treatment and control groups is necessary. The entry test score determines the drop out in the treatment group as well as in the control group. Especially problematic are those variables influencing the drop out in just one of the groups. This is particularly the case for variables B_1, B_3, B_4, B_7, P_2 and P_6.

In summary, there is a selection effect from the first to the second sample. The second sample consists, compared to the first sample, of higher skilled students. This is indicated by the entry test score and variables B_5 and B_6 Furthermore, female students are overrepresented. However, the drop out of students enrolled in EE is not surprising since math is an elective module for those students. Additionally, the students in the treatment and control group in the second sample show some differences compared to those in the first sample. This leads to limited midterm results. However, the estimation of the midterm effect is correct and unlikely biased for the examined students but is hardly representative regarding the students' population in general. Otherwise, it has to be pointed out that the students in the second sample represent a realistic picture of students in this course in the middle of the semester.

7 Conclusion

This study shows how math remediation and particularly math preparatory courses influence students' short- and medium-term math performance. With two skill tests at the beginning and in the middle of the semester, students' participation in a math preparatory course was evaluated. Whereas students benefit not only from formal participation but mostly from attending the preparatory course, I cannot find an effect after a few weeks anymore. The results show that the only reason students who participated in the preparatory course achieve better math outcomes in the midterm test than their non-participant counterparts is that those students are more engaged during the semester. Whether it is the preparatory course participation that leads to this increased engagement could not be determined in this study but should be considered in further research. Even if the study did not find the preparatory course to have a medium-term effect on the math skills of the given sample, one cannot generally rule out effects on other economic subjects with a high math affinity. However, a study by Lagerlöf and Seltzer (2009) did examine the effects of math remediation on economic subjects and did not find effects for most of the examined courses either.

Altogether, the question of what math preparatory courses can and should do to prepare freshman students for their upcoming studies can still not be answered. To combat the lack of attendance, one could consider compulsory math remediation with mandatory attendance for students who show insufficient math skills. However, checking for attendance in courses with hundred of students seems not practical at all and, as this study shows, might only generate a short-term impact. Even if students could be forced to attend lectures and tutorials of preparatory courses, due to motivational factors, one could not expect the same outcomes as for students who accept the course voluntarily. All in all, one should keep in mind that these courses cannot compensate for the insufficient math skills of freshman students, but do not appear superfluous in general.

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Tables and Figures

Table 1: Outcome Variables Compared by Different Samples

Code	Description	Type	Value	Items	Sample 1 Mean (SD)	Sample 2 Mean (SD)
Y_0	math skill at T_0	metric	0 to 30	30	6.51 (4.71)	8.19 (5.01)
Y_1	math skill at T_1	metric	0 to 30	30	–	11.48 (5.64)
ΔY	$Y_1 - Y_0$	metric			–	3.29 (3.87)
N					1236	501

Table 2: Comparison of Students' Participation and Actual Attendance

		student answers dummy (0/1)	actual student attendance up to 25% (rel. freq.)	25% to 50% (rel. freq.)	50% to 75% (rel. freq.)	over 75% (rel. freq.)	$\sum$ N
Sample 1 participation	Yes	613	54 (8,7%)	103 (16,6%)	138 (22,3%)	324 (52,5%)	619
	No	623					617
$\sum$ N		1236					1236
Sample 2 participation	Yes	303	14 (4,6%)	43 (14,2%)	53 (17,5%)	193 (63,7%)	303
	No	198					198
$\sum$ N		501					501

Table 3: Descriptive Entry and Midterm Test Results

	Attendance prep. course	Y_0 (SD)	Differences	Y_1 (SD)	ΔY	Differences in Differences	N
Sample 1	Never	5.70 (4.45)					617
	below 25%	4.85 (4.03)	-0.85				54
	25% to 50%	6.76 (4.33)	1.06				103
	50% to 75%	7.00 (4.72)	1.30				138
	above 75%	8.03 (5.00)	2.33				324
Sample 2	Never	7.27 (4.97)		11.19 (6.12)	3.92		198
	below 25%	6.42 (4.74)	-0.85	8.39 (5.62)	1.97	-1.95	14
	25% to 50%	7.49 (4.86)	0.22	8.88 (5.25)	1.39	-2.53	43
	50% to 75%	9.08 (5.37)	1.81	12.16 (5.52)	3.08	-0.84	53
	above 75%	9.17 (4.81)	1.90	12.40 (4.96)	3.23	-0.69	193

Table 4: Variables Compared by Different Samples

						Sample 1	Sample 2	
Code	Description	Type	Value	Items	CA*	$\text{Mean}_{[T_0]}$(SD)	$\text{Mean}_{[T_0]}$(SD)	$\text{Mean}_{[T_1]}$(SD)
B_1	Gender (female = 1)	binary	0 or 1	–	–	0.49	0.53	
B_2	Year of study	metric	1 to 3	–	–	1.19 (0.49)	1.16 (0.47)	
B_3	Math course already taken (Yes = 1)	binary	0 or 1	–	–	0.11	0.11	
B_4	Course of study (EBA = 1)	binary	0 or 1	–	–	0.68	0.76	
B_5	Graduation type (short-track = 0)	binary	0 or 1	–	–	0.56	0.67	
B_6	Prior GPA	metric	1 to 4	–	–	2.52 (0.55)	2.44 (0.53)	
B_7	Math grade in sec. school	metric	1 to 5	–	–	2.64 (0.92)	2.54 (0.88)	
B_8	Math self-efficacy	metric	1 to 5	–	–	3.29 (0.89)	3.11 (0.83)	
B_9	Education gap	metric	0 to 20	–	–	1.87 (2.20)	1.77 (1.58)	
S_1	Main math lecture attendance	metric	1 to 6	–	–	–	–	5.70 (0.64)
S_2	Math tutorial attendance	metric	1 to 6	–	–	–	–	4.94 (1.64)
S_3	Completion of exercise sheets	metric	1 to 6	–	–	–	–	5.00 (1.31)
S_4	Math support center attendance	metric	1 to 6	–	–	–	–	1.40 (1.06)
S_5	Bridging course attendance	metric	1 to 6	–	–	–	–	2.08 (1.86)
S_6	Study hours	metric	0 to 20	–	–	–	–	4.73 (3.05)
S_7	Number of other courses	metric	0 to 10	–	–	–	–	4.08 (1.23)
P_1	Math interest	scale	1 to 6	4	0.86	3.47 (1.31)	3.58 (1.27)	3.45 (1.24)
P_2	Learning goal orientation	scale	1 to 6	5	0.84	3.52 (0.93)	3.57 (0.88)	3.41 (0.90)
P_3	Control strategies	scale	1 to 6	5	0.84	4.04 (1.04)	4.09 (1.02)	3.75 (1.03)
P_4	Math anxiety	scale	1 to 6	3	0.80	3.99 (1.36)	3.89 (1.36)	3.91 (1.35)
P_5	Perceived value of math	scale	1 to 6	9	0.70	4.55 (0.76)	4.59 (0.73)	4.30 (0.75)
P_6	Math self-concept	scale	1 to 6	3	0.71	3.46 (0.99)	3.62 (0.92)	3.37 (0.96)
N						1236	504	

*Cronbach's Alpha

Table 5: Probit regression results

Variables	short description	Coefficients	z-value
B_1	Gender	0.517***	3.77
B_2	Year of study	-0.685**	-3.29
B_3	Course already taken	-0.951*	-2.51
B_4	Study program	0.477**	2.95
B_5	Graduation type	-0.001	-0.01
B_6	Prior GPA	-0.014	-0.09
B_7	Math grade	0.112	1.05
B_8	Self-efficacy	-0.09	-0.92
B_9	Education gap	0.875*	2.38
Dependent variable	Participation dummy (attendance $>$ 75%)		
N	394		
Pseudo R^2	0.143		

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

Table 6: Determinants of Math Performance in the Entry Test

Variables	Participation by student		Attendance below 25%		Attendance 25% to 50%		Attendance 50% to 75%		Attendance over 75%	
	Model 1.1	Model 1.2	Model 1.1	Model 1.2	Model 1.1	Model 1.2	Model 1.1	Model 1.2	Model 1.1	Model 1.2
Prep. course	1.72***	1.97***	-0.04	0.23	0.92*	1.10**	1.61***	1.87***	2.35***	2.50***
2012 dummy	13.97***	10.60***	12.50***	12.28***	12.80***	10.99***	13.09***	11.75***	13.25***	9.59***
2014 dummy	13.14***	9.83***	12.24***	12.07***	12.44***	10.65***	12.54***	11.26***	12.79***	9.16***
2016 dummy	13.58***	10.28***	12.14***	12.00***	12.53***	10.76***	12.79***	11.58***	12.95***	9.37***
B_1	-1.25***	-1.09***	-1.20***	-0.92**	-1.16***	-0.89**	-1.04***	-0.82**	-1.32***	-1.20***
B_2	-0.23	-0.29	0.26	-0.03	-0.18	-0.30	-0.16	-0.23	-0.10	-0.19
B_3	2.75***	2.89***	2.81***	2.91***	2.81***	2.92***	2.88***	3.01***	2.85***	3.01***
B_4	0.08	0.17	0.48	0.47	0.61*	0.46	0.36	0.51	0.23	0.37
B_5	3.36***	3.19***	2.73***	2.61***	2.92***	2.76***	2.92***	2.72***	3.18***	3.10***
B_6	-1.59***	-1.89***	-1.47***	-1.55***	-1.43***	-1.60***	-1.46***	-1.59***	-1.46***	-1.76***
B_7	-0.13	0.18	-0.18	-0.19	-0.08	-0.18	-0.17	-0.02	-0.09	0.23
B_8	-1.51***	-0.63**	-1.22***	-0.66**	-1.29***	-0.57*	-1.37***	-0.64**	-1.51***	-0.66**
B_9	0.02	0.00	-0.01	-0.03	-0.01	-0.03	0.01	-0.05	0.02	0.01
P_1		0.40**		0.32		0.27		0.27		0.47**
P_2		0.07		0.29		0.29		0.31		-0.01
P_3		-0.58***		-0.53**		-0.56**		-0.57**		-0.67***
P_4		-0.35**		-0.39**		-0.36**		-0.42**		-0.27*
P_5		-0.21		-0.52**		-0.42*		-0.47*		-0.18
P_6		0.97***		0.56*		0.81**		0.78**		1.06***
N	1236	1236	670	670	720	720	755	755	941	941
Adj. R^2	0.776	0.789	0.742	0.754	0.752	0.765	0.754	0.768	0.774	0.787

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

Table 7: Midterm Preparatory Course Effects

Variable	Model 2.1	Model 2.2	Model 2.3	Model 2.4
Constant	8.207*** (0.142)	8.257*** (2.142)	7.938*** (2.103)	8.146*** (2.277)
compensational effect	-0.698 (0.401)	-0.784 (0.402)	-1.432** (0.415)	-1.504** (0.439)
P_1		-0.193 (0.297)	-0.165 (0.291)	
P_2		0.586 (0.320)	0.444 (0.315)	
P_3		-0.535 (0.307)	-0.402 (0.299)	
P_4		-0.070 (0.205)	-0.157 (0.198)	
P_5		-0.321 (0.257)	-0.278 (0.251)	
P_6		0.681* (0.340)	0.380 (0.338)	
S_1			0.327 (0.327)	
S_2			0.151 (0.151)	
S_3			0.181*** (0.181)	
S_4			-0.112 (0.183)	
S_5			0.287** (0.110)	
S_6			-0.016 (0.071)	
S_7			-0.013 (0.163)	
N	391	391	386	386
Overall R^2	0.103	0.137	0.124	0.120
Within R^2	0.453	0.466	0.518	0.500

***p<0.001; **p<0.01; *p<0.05

Table 8: Students' drop out characteristics

Variable	all students	treatment group	control group
et points	1.12*** (6.70)	1.09* (2.57)	1.09*** (3.50)
B_1	1.43** (2.73)	2.64*** (3.51)	1.04 (0.21)
B_2	1.02 (0.10)	0.77 (-0.49)	1.38 (1.62)
B_3	0.61 (-1.80)	3.40 (0.82)	0.51* (-2.03)
B_4	1.72*** (3.77)	2.41** (2.93)	1.35 (1.45)
B_5	1.43** (2.53)	1.46 (1.28)	1.58* (2.20)
B_6	0.75* (-2.00)	0.71 (-1.08)	0.61* (-2.44)
B_7	1.11 (0.986)	1.65* (2.24)	1.17 (1.00)
B_8	0.81 (-1.82)	1.07 (0.24)	0.78 (-1.53)
B_9	1.03 (1.00)	1.05 (0.79)	0.99 (-0.33)
P_1	0.96 (-0.65)	1.24 (1.57)	0.87 (-1.29)
P_2	1.02 (0.29)	0.73 (-1.79)	1.32* (2.22)
P_3	0.85 (-1.89)	0.94 (-0.32)	0.80 (-1.70)
P_4	1.02 (0.24)	1.00 (-0.04)	0.95 (-0.55)
P_5	1.01 (0.12)	0.82 (-1.01)	0.89 (-0.85)
P_6	1.15 (1.14)	2.05** (2.60)	1.11 (0.54)
N	1236	324	617
Pseudo R^2	0.100	0.162	0.092

***p<0.001; **p<0.01; *p<0.05

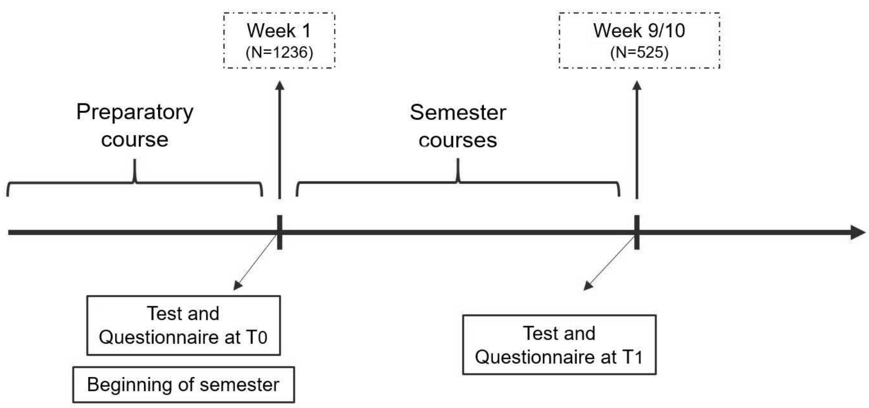

Figure 1: Overview of the study design