ERASMUS UNIVERSITY ROTTERDAM

Erasmus School of Economics

Bachelor Thesis Economics and Business Economics

Effectiveness of a mandatory mathematics summer course before the start of university

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Abstract

Students face many challenges associated with the transition from high school to higher education. To ease this transition, universities offer various activities before the start of a programme. This paper adds to the literature on the relationship between pre-academic activities and academic performance. More specifically, I investigate the effect of a study choice activity on academic performance. I draw on a discontinuity at a large university, wherein prospective first-year students with a low math grade in high school are forced to do a mathematical summer course before the start of their studies to estimate the causal effect of the mathematical summer course on academic performance. I show that the policy has no average effect on the grades or the amount of credits students obtain during their first year of higher education.

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1 Introduction

In the Netherlands, around 110 thousand students annually enrol in higher education for the first time (CBS, 2023). A third of these students drop out of their chosen programme in their first year, mainly because they feel they have made the wrong study choice (Ulriksen, Madsen, & Holmegaard, 2010). Students face several challenges associated with the transition from high school to higher education, for example, building new relationships, gaining confidence in their academic capabilities and increasing the effort they need to put into their studies compared to high school (Barefoot, 2008; Gale & Parker, 2014; Harvey, Drew, & Smith, 2006; Tinto, 2012; Yorke, et al., 1997). This necessitates that universities help students transition from high school to higher education as smoothly as possible to improve academic performance. Hence, universities offer various activities before the start of a programme.

The Erasmus School of Economics (ESE) requires certain students to take a summer mathematics course on an online platform before starting their studies. In this way, students can get used to studying by getting acquainted with its aspects already during the summer. Because of this, students will be better prepared and are off to a flying start, aiming to contribute to an easier transition. Since the bachelor programmes at the ESE are highly mathematical, a sufficient level of mathematics is needed. This stems from previous research showing that students who took the Science and Technology track in secondary school are more successful in economics due to the greater focus on mathematics in high school (Arnold & Straten, 2012). Therefore, the ESE offers this math course to students they think need it most based on their high school mathematics grades. Because a strict cutoff is used in determining whether the summer course is necessary, I can draw on a discontinuity to estimate the causal effect of the mathematical summer course on academic performance. For Dutch students with Mathematics A in high school, the summer course is mandatory with an average math grade below 7.5 and for students with Mathematics B with an average lower than 6.5. The ESE has two goals with this math course. First, they want to make students more aware of their study choice, and second, they want to prepare students as well as possible (Studiekeuzeactiviteit, 2023). This research addresses the second goal; do students academically perform better after following the math course before their studies?

Besides the importance of a smooth transition for students, this is also in the interest of universities as governments have focused much on performance-based funding (Jongbloed & Koelman, 1996). As explained by former research, universities in the Netherlands receive funding based on the number of graduates, not the number of students enrolled (De Koning, Loyens, Rikers, Smeets, & Van der Molen, 2013). Hence, a smooth transition that improves academic performance is in the interest of both students and universities.

Hence, I examine the summer course's effect on students' academic performance in this paper. Focus is on both short-term outcomes, such as course results, and medium-term outcomes, such as the number of credits obtained in the first year of the bachelor. I use a dataset that consists of students who enrolled in the bachelor programmes Economics and Business Economics or Economics of Taxation at Erasmus University Rotterdam in the years 2020 and 2021.

Firstly, using this data, I estimate the effect of the summer course on the grade one obtained for the course 'Introduction to Mathematics'. This is of great interest as this course has a direct relation with the summer course since the content of the summer course prepares students for the content of this first-year course. Also, this course is scheduled in the first block of the year and, thus the first time students face mathematics at university. Therefore, I can check whether students perform better mathematically when following the math course in the summer via this grade since there has yet to be any influence from other courses. I find that the policy has little to no average effect on the grades for this course.

Secondly, the effect of the summer course is estimated on the grade for the course 'Microeconomics'. This effect shows the indirect effect of having followed the summer course. Indirect as the mathematical skills of a student are not directly being tested but are needed to answer the questions in this course. Hence, this effect is more interesting since this is the ESE's real purpose with the summer course. As the ESE is not concerned with whether students can do mathematics but whether they can do economics. This is the first core economics course of the programme, and therefore the first time student will need to use their mathematical skills for economic purposes. Again, the impact on the grade is found to be small to negligible.

Lastly, I estimate the effect of the summer course on the amount of ECTS students obtain in the first year of the bachelor programmes.[1] This shows the effect on the entire study progress of students in the first year of having followed the summer course by assessing the effect on the total amount of ECTS obtained. The results show that the policy has little to no average effect on academic performance, measured in the amount of obtained ECTS in the first year.

In light of the many concerns regarding student well-being (Adema, 2023), universities need to make the transition as smooth as possible for their students. This makes this research socially relevant, as it assesses a policy that is thought to make the transition easier for prospective students. The effects of this transaction and the effects that will have on the further course of students' studies have a long-

[1] ECTS stands for European Transfer Credit System and is a typical measurement standard in Europe for student performance. One ECTS should be equivalent to 28 hours of studying.

term impact on society as specific components may appeal more to some students rather than others, and this can lead to more inequality in terms of gender and socio-economic status to name a few.

The organisation of this paper is as follows. Section 2 provides a literature review. Section 3 describes the setting and the data used in this paper. Section 4 describes the methodology. Section 5 presents the results, and Section 6 the robustness checks. Section 8 concludes.

2 Literature Review

A general academic ability, such as basic mathematical, reading and writing skills, is needed to perform academically (Campbell, 1990). In many theories on academic success, ability has been an essential determinant for this success (Bean, 2005; Tinto, 1975) and is also frequently used for selection in academic admission procedures (Harackiewicz, Barron, Tauer, & Elliot, 2002). Often this ability is measured through high school grades or certain test scores. Because of this, we expect that the high school grades that determine whether the math course in this research is mandatory are good determinants for one's academic success. This idea is in line with research which suggests that academic performance in preparatory education is an important determinant of study progress (Ballard & Johnson, 2004). Predictions like high school grades are significant indicators for the study progress in the first year of one's studies (Soppe, 2022). They should therefore play a role in admission procedures for higher education (Zwick, 2017). Because the summer course ought to improve students' math skills, and as these are supposed to be an important determinant for academic success, the summer course is expected to positively affect academic performance.

Soppe (2022) also examined different types of matching procedures on their effectiveness as experienced by students and in relation to final enrolment and first-year study success. Intensive matching, such as matching days and online courses, are the most effective as students tend to take the advice they are given more seriously. Due to the intensity of the summer course in this research, it will likely be effective based on Soppe's findings. A quasi-experimental research has already shown that the non-corrected effect of completing the same online math course used in this research is more significant than the effects of prior mathematical education on academic success in the form of a test grade. A substantial treatment effect remains when correcting for potential selection effects (Tempelaar, Rienties, Giesbers, & Van der Loeff, 2012). However, in that research, the math course was voluntary for prospective students, and therefore, there is likely a selection bias. The fact that the course is compulsory for students within this research allows for overcoming selection bias, and a counterfactual can be found using a Regression Discontinuity Design. As a result, I aim to provide an updated view of the effectiveness of the summer course.

Interventions before the start of university, such as 'summer schools', contribute to the study success during the programme's first phase (Hatt, Baxter, & Tate, 2009; Porter & Swing, 2006). Students perform faster and better thanks to a flying start and binding at an early stage. This aligns with the idea that the transition from high school to higher education should be as smooth as possible. Porter and Swing (2006) show that helping students with this transition contribute to the student's intention to continue to study, for example, by paying attention to factors such as study skills, campus policy and engagement, and connection with fellow students. Leest, Van Langen and Smeets (2022) find evidence that following a mathematical summer school positively affects the result of a math test at the beginning of a programme. The two summer programmes in this research were aimed at brushing up the substantive knowledge that prospective students need to get off to a good start with higher education. By allowing students to gain this knowledge before their studies, the connection improves in terms of basic knowledge; students have more confidence, more realistic expectations and or better results. Again, based on this former research, we expect a positive effect on academic performance.

3 Setting and Data

3.1 Setting – High School

In the Netherlands, children follow one of three types of secondary education (high school) after primary school, which type depends on a student's academic level. The first type is VMBO, which lasts four years; the second is HAVO, which lasts five years; and VWO, which lasts six years. Only with a VWO diploma are students allowed to enter university. In the first couple of years, students follow a broad curriculum and starting in the fourth year, students specialise by enrolling in a certain track. Also, four different types of math can be chosen; Mathematics A, B, C and D. Mathematics A mainly focuses on skills related to statistics and prepares students for a study in the direction of 'Behaviour and Society' where statistics play an important role. Mathematics C can be seen as a light version of type A. According to many students, Mathematics B is considered to be more difficult. This is likely because it is more abstract than type A. The focus lies on mathematics-related themes in technology, like algebra, differentials and functions. Mathematics D is an extra deepening course that can only be taken together with Mathematics B and cannot be followed independently. High school grades follow the Dutch grading system, which consists of a 1-10 scale, with 1 being the lowest grade and 10 the highest. A grade is sufficient from a 5.5.

3.2 Setting – University

This paper, looks at students from the Dutch bachelor programmes Economics and Business Economics and Economics of Taxation at Erasmus University Rotterdam. The nominal duration of both programmes is three years. Similar to the curriculum in high school, the first two years consist of a broad range of subjects and in the third year students can specialise in a different direction within the field of economics. This paper focuses on the first year, which is identical for both the programmes and consists of 10 regular courses and the course Academic Skills which add up to 60 ECTS credits. The same grading system, a 1-10 scale, applies as in high schools and a grade is sufficient from a 5.5. Students will have to pass all courses in order to pass the first year. However, compensation is allowed for three failed courses with grades between 4.5 and 5.5 within certain clusters. Three resits are also allowed at the end of the academic year. Each year consists of five blocks of eight weeks containing two courses, except the fourth, which contains three.

The course Introduction to Mathematics is taught in the first block of the year and yields four credits upon completion. The grade consists of assignments that count for 5%, a mid-term that determines 20% and a final test that makes up for 75% of the grade. The learning objectives of the course consist of gaining an understanding of the role that mathematics plays in economics, dealing with mathematics in such a way that the student will be able to recognise the subjects of mathematics later in his or her studies, and if necessary to study the subjects independently, and to develop sufficient mathematical skills to be able to study economics.

Microeconomics is taught in the year's second block and yields eight credits upon completion. The grade consists of an essay that counts for 20% of the final grade, a mid-term that determines 10%, and a final test that counts for 70%. The learning objectives of the course consist of reproducing and interpreting concepts in key areas in microeconomics: choice and decision making, information and uncertainty, household and business behaviour, organisations and markets, allocation and wealth and behavioural economics, reproducing and interpreting concepts in key areas of mesoeconomics: market structures and functioning, business strategy, business objectives and functioning, and the ability to use standard mathematical methods commonly used in microeconomics.

3.3 Setting – Study Choice Check

Because there are many dropouts in the first year of higher education, in 2014, the law 'Quality and Diversity' was introduced in the Netherlands, which aims to increase the match between students and programme. According to this law, students must apply before May 1 for programmes that start in September. Universities are obligated to offer these prospective students a so-called 'study choice check', which consists of offering study choice activities. Universities can require students to participate in the activities. There are many ways in which they offer this 'study choice check' and universities are free in their choice of one. For example, some universities offer questionnaires, and other summer courses, and some even organise entire 'matching' days. Based on the results of these activities, students receive a non-binding advice from the university regarding the match with their chosen study programme. This Dutch law is why the ESE offers the compulsory math course from this research and provides the basis for the aforementioned first goal the ESE has with this course. However, this research will focus on ESE's second goal: Preparing students for their studies.

For the study choice check, upcoming ESE students must fill in a mandatory questionnaire before starting their studies. Depending on the results of this questionnaire, some students are obligated to follow an online math course in the ALEKS learning platform since the cohort 2014-2015. This course is designed to prepare prospective students for the mathematics level needed during the programme. Based on the questionnaire, students can receive a positive, warning or negative study choice advice. When a prospective student receives a warning or negative advice, he or she must complete the summer course before the registration can be completed. The ESE suspects that the math skills are insufficient for those students to complete the programme successfully. This follows from an extensive literature that shows the importance of mathematical skills for study success in economics (Arnold & Straten, 2012; Ballard & Johnson, 2004; Swope & Schmitt, 2006). The math course is an online course that adapts to the student's knowledge, starting with an entry test that assesses the level of mathematics a student has. Based on the results of this first test, the remainder of the course is organised. In this way, each student has a unique course meeting their individual needs. Students need to complete their entire trajectory before August 12 to be admitted to the programme. Students do not receive a grade and can only succeed if they complete the entire course before the deadline. Login codes are given on the first of June, giving students 72 days to complete the online course. The course is entirely in English and the average time a student needs to complete the course is 30 hours. The system is sensitive to fraud because only the login codes are required to access the course environment. This can lead to students not going through the course themselves, which could negatively bias the results.

In the questionnaire, prospective students must fill in their math type and the final grade for the second-to-last year of high school (5 VWO) and the same for the last year of high school (6 VWO). Since the last year of high school does not have to be over yet, this grade can be provisional. To determine whether the summer course should be taken, the average over the two grades is considered. For students who have done Mathematics A, the course is mandatory with an average lower than 7.5 and for students who have done Mathematics B when the average is lower than 6.5. Students who have done Mathematics C in high school are not admissible for the programmes at the ESE. When a prospective student does not have a Dutch VWO diploma and is not math deficient but is admissible, the summer course is also compulsory. In Appendix B more detailed scheme of the procedure of the study choice check can be seen in Figure B.1. However, because of the setup of the analysis, I do not take these students into account and only use data on students with a Dutch VWO diploma who have done either Mathematics A or B.

3.4 Data

For this research, I use data on 1163 students that have enrolled in either the Dutch bachelor Programme Economics and Business Economics or the bachelor Programme Fiscal Economics at the ESE from two cohorts; 2020 and 2021. This data has been provided directly by the ESE organisation and have been anonymised before use.

The data include high school information from the students, such as what type of mathematics (A or B) was taken and the average grade for this type of mathematics for both 5 and 6 VWO. The average between these two grades determines whether a student must take the summer course. For students who followed Mathematics A in high school, this average grade is denoted by *MathAA* and for students who followed Mathematics B by *MathBA*. The dummy variable *Mathtype* takes on the value one for students with Mathematics A and zero for students with Mathematics B.

Academic performance is measured through several variables. The variable *Introduction to math* denotes the grade for the course Introduction to Mathematics and the variable *Microeconomics* is the grade for the course Microeconomics before any resits are taken. So, for both, this is the grade in the first round. Also, variables about the amount of ECTS students obtain are included after possible resits and compensation (denoted *CreditsDEF*).

A set of confounding variables are included related to academic performance. The dummy variable *Gender* is defined, which takes on the value one for female and zero for male students. Although general ability is supposed to be similar for females and males (Carvalho, 2016), female students achieve higher grades and obtain more ECTS (Conger & Long, 2010). Therefore this variable is included. The student's age when starting the programme (denoted *Age*) is included as older students are supposed to achieve higher grades (Etcheverry, Clifton, & Roberts, 2008; Sheard, 2001). Finally, a dummy variable is generated for the programme choice: *Programme* takes on the value one for students enrolling in the Economics and Business Economics programme and zero for students enrolling in the Economics of Taxation programme. Because effects between cohorts can be different, year fixed-effects are also included for both years. The dummy variable *Year* takes on the value one for the 2021 cohort and zero for the 2020 cohort.

3.4.1 Summary Statistics

Tables 1 and 2 summarise the data. It compares students with a high school math grade on the left of the threshold to students with a grade on the right of the threshold separately for students that followed Mathematics A and Mathematics B in high school. Table 1 compares students that followed Mathematics A in high school with a grade below 7.5 to those with a grade above 7.5 and Table 2 compares students with a Mathematics B grade below 6.5 to those whose grade was above 6.5. The second and third panel restricts the sample to the two courses of interest, where the unit of observation is the number of students that participated in the first round of exams. Column (3) shows the difference in means left and right of the cutoff. Section 4 presents the main balancing tests showing the differences at the cutoff. Both tables include the full sample. The main estimates are based on smaller samples of students. These are the optimal bandwidths for the dependent variables of interest relative to an MSE criterion for the entire sample of students (Calonico, Cattaneo, Farrell, & Titiunik, 2017). Tables A.1 to A.6 in Appendix A present summary statistics for the six samples used separately.

Table 1 shows that forced students score 1.43 standard deviations worse for Introduction to Mathematics and 0.88 standard deviations worse for Microeconomics, despite following the online math course during the summer. These students also obtain fewer ECTS. The same applies to students with Mathematics B (Table 2). Note that after restricting the sample in Tables A.1 to A.6 in Appendix A, less or no statistical differences are found. Column (3) in Tables 1 and 2 implies that students left and right of the cutoff have some differences in terms of gender and age. Note, however, that these gender differences are statistically insignificant according to the main balancing tests presented in Section 4 and that the main estimates in Section 5 are robust to controls for age.

Table 1 *Summary statistics Mathematics A*

	Math Grade type A		
Variable	**[0, 7.5)**	**[7.5, 10]**	**Diff.**
Student level (all students)			
Gender	0.15	0.28	0.13***
	(0.36)	(0.45)	(0.04)
Programme	0.16	0.18	0.02
	(0.36)	(0.39)	(0.3)
Age	18.56	18.40	-0.16*
	(1.25)	(0.98)	(0.10)
Year	0.44	0.47	0.03
	(0.50)	(0.50)	(0.05)
CreditsDEF	29.55	41.48	11.87***
	(26.10)	(24.10)	(2.25)
Observations	358	183	541
Course level (first takers)			
Introduction to math	4.25	5.70	1.43***
	(1.75)	(1.69)	(0.17)
Observations	316	161	477
Course level (first takers)			
Microeconomics	5.42	6.30	0.88***
	(1.51)	(1.63)	(0.17)
Observations	235	147	382

*This table shows the mean values for each of the variables. Standard deviations are in parentheses in the first two columns and standard errors are in parentheses in the last column. Asterisks denote statistical significance for differences in means. Significance levels: *<10%; **<5%; ***<1%.*

Table 2 *Summary statistics Mathematics B*

	Math Grade type B		
Variable	**[0, 6.5)**	**[6.5, 10]**	**Diff.**
Student level (all students)			
Gender	0.15	0.37	0.21***
	(0.36)	(0.48)	(0.04)
Programme	0.09	0.10	0.00
	(0.29)	(0.29)	(0.02)
Age	18.47	18.64	0.17*
	(1.04)	(1.25)	(0.10)
Year	0.53	0.53	0.02
	(0.50)	(0.50)	(0.04)
CreditsDEF	42.24	52.61	10.25***
	(24.30)	(17.15)	(1.85)
Observations	244	300	544
Course level (first takers)			
Introduction to math	5.98	7.31	1.32***
	(1.36)	(1.23)	(0.12)
Observations	232	286	518
Course level (first takers)			
Microeconomics	5.69	6.87	1.18***
	(1.48)	(1.37)	(0.13)
Observations	211	267	478

*This table shows the mean values for each of the variables. Standard deviations are in parentheses in the first two columns and standard errors are in parentheses in the last column. Asterisks denote statistical significance for differences in means. Significance levels: *<10%; **<5%; ***<1%.*

3.4.2 Preview Results

Figures 1 to 3 examine the effects on the three dependent variables separately for students with Mathematics A and B. The figures plot these variables against the average high school math grade, where the difference at the cutoff measures the impact of the summer math course. Figure 1 suggests that for both types of students, the summer math course positively affects the grade for the course Introduction to Mathematics, with a larger positive effect for the sample of students with Mathematics B. Figure 2 suggests a positive effect on the grade for Microeconomics for students with Mathematics A and a small negative effect for Mathematics B. Lastly, Figure 3 suggests that the course positively impacts the amount of ECTS a student obtains in the first year of the bachelor with a larger positive effect for the sample of students with Mathematics B.

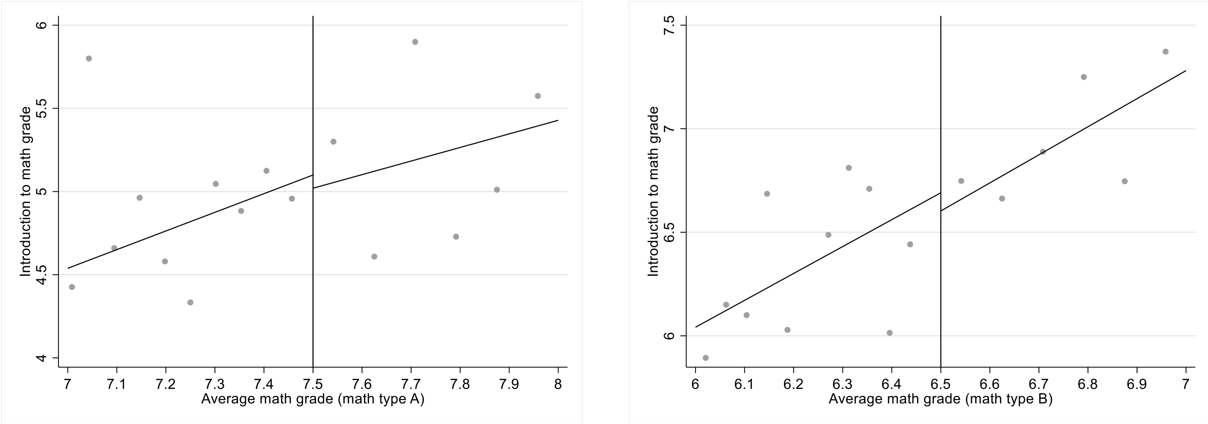

Figure 1 *Introduction to Mathematics grade*

Notes:

1. *Locally linear is estimated upon a bandwidth of 0.5, which depends in the left and right figure due to the different cutoffs.*
2. *Mathematics A on the left and Mathematics B on the right.*

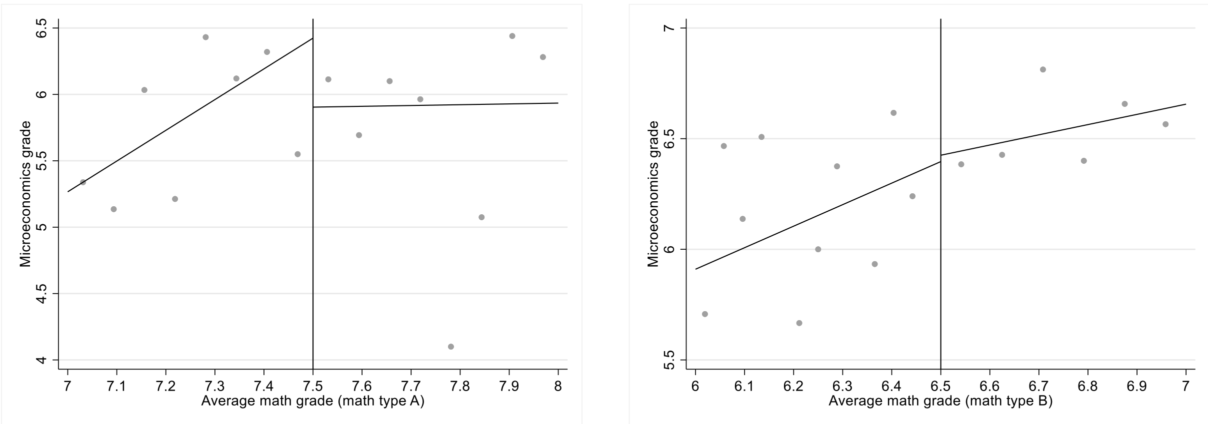

Figure 2 *Microeconomics grade*

Notes:

1. *Locally linear is estimated upon a bandwidth of 0.5, which depends in the left and right figure due to the different cutoffs.*
2. *Mathematics A on the left and Mathematics B on the right.*

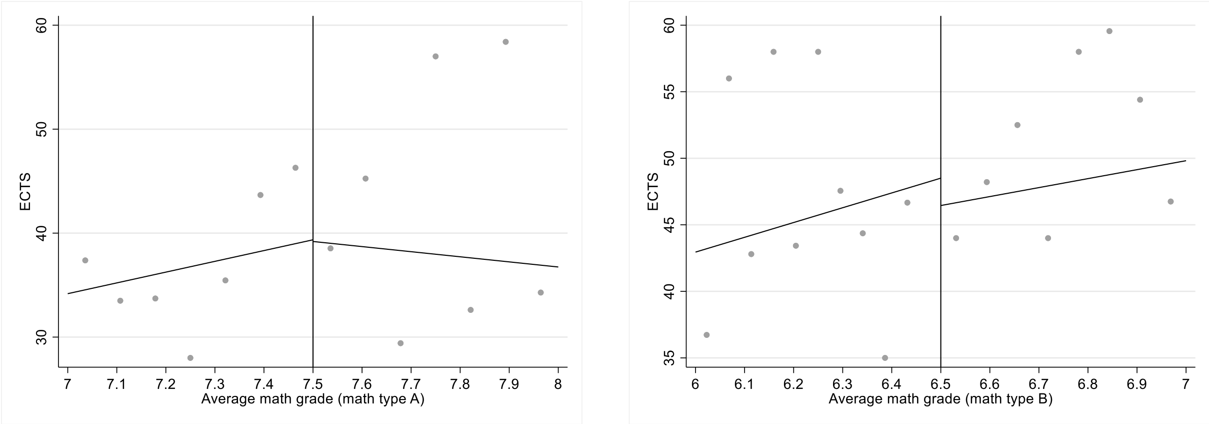

Figure 3 *ECTS*

Notes:

1. *Locally linear is estimated upon a bandwidth of 0.5, which depends in the left and right figure due to the different cutoffs.*
2. *Mathematics A on the left and Mathematics B on the right.*

4 Methodology

Treatment 'Mathematics Course' is a deterministic function of the running variable 'Math Grade' because the high school math grade determines whether a student should take the math course. For students who followed Mathematics A in high school, this means:

$$Mathematics\ Course = \begin{cases} 1\ if\ MathA < 7{,}5 \\ 0\ if\ MathA \geq 7{,}5 \end{cases}$$

More generally, this implies:

$$T_i = \begin{cases} 1\ if\ X_i < c \\ 0\ if\ X_i \geq c \end{cases}$$

A lower threshold applies to students who followed Mathematics B in high school. For them, this means:

$$Mathematics\ Course = \begin{cases} 1\ if\ MathB < 6{,}5 \\ 0\ if\ MathB \geq 6{,}5 \end{cases}$$

More generally, this implies:

$$T_i = \begin{cases} 1\ if\ X_i < b \\ 0\ if\ X_i \geq b \end{cases}$$

For Dutch students that followed Mathematics A in high school, the math course is mandatory with an average grade lower than 7.5 and for students with Mathematics B with an average lower than 6.5. Individuals with an average of 7,49 are expected to have similar abilities to those with an average of

7,51. Because of this, the jump in the outcome variable at the threshold can be interpreted as the causal effect. Hence, there is a natural comparison group ('counterfactual') and any differences in academic performance can be attributed to the effect of following the math course during the summer. The same reasoning applies to students who followed Mathematics B in high school but then around the threshold of 6,5. Because of this, I can draw on a discontinuity to estimate the causal effect of the mathematical summer course on academic performance.

Conditional expectations are assumed to be continuous around both cutoffs. This continuity assumption can fail if students can control the average math grade in high school (Cattaneo, Idrobo, & Titiunik, 2019b; Lee, 2008). However, students do not know where the cutoff is and therefore, cannot aim for a grade just above it. Also, the assignment for the summer course is based on the student's average high school math grade; therefore students lose control over the precise grade as it is accumulated. Both these circumstances favour the continuity of conditional expectations at the cutoffs.

I will analyse the effects of following the summer course differentiated by the type of mathematics followed in high school on academic performance using a regression discontinuity design around the different thresholds for students who followed Mathematics A and B in high school. Also, the analysis will be performed based on pooled data from the two types of students, which means that the sample contains both Mathematics A and Mathematics B students. For this, the grades are standardised around the cutoff 7.5 for students with Mathematics A and around 6.5 for students with Mathematics B. The effects using the pooled will be analysed as the pooled data shows the average effect for the full sample of students enrolled. The unpooled data can show possible differences in the effectiveness between students with Mathematics A and B. For both, the following regression equation is used:

$$Y_i = \beta_0 + \beta_1 * Math\ grade + \rho * f(T_i) + \beta_j * X_j + \varepsilon_i \tag{1}$$

Where Y_i first measures the academic performance of a student i expressed by the grade for 'Introduction Mathematics'. The ρ denotes the Average Treatment Effect on the Treated (ATT) and therefore is the effect that we are interested in as this is the effect of following the math course on one's grade. However, there are three students to the right of the cutoff who, despite not being required to take the course, did take the summer course. This means that an Intention-To-Treat (ITT) analysis has actually been done. Nevertheless, because it only applies to three students within the sample, it can still be referred to as the Treatment Effect on the Treated. $f(T_i)$ is a smooth function of the forcing variable that can vary to the left and right of the cutoff. The observations are weighted by a triangular kernel, which assigns less weight to the observations further from the cutoff. β_1 measures the effect of the mathematics grade and the last part of the equation contains the control variables X_j, the year fixed effects, gender, age and the programme of a student.

Secondly, Y_i measures the academic performance of a student i expressed by the grade for the course Microeconomics. The same equation is used as above. Lastly, Y_i measures the academic performance of a student i expressed by the amount of ECTS credits obtained by a student. Again, the same equation is used as above.

The estimates for the first research question are based on the sample of students within a bandwidth of 0.503 of 7.5 for students with Mathematics A and for students with Mathematics B within a bandwidth of 0.708 of 6.5. For the second research question, bandwidths of 0.432 of 7.5 and 0.711 of 6.5 are used. Lastly, bandwidths of 0.640 of 7.5 and 0.753 of 6.5 are used for the estimates for the third research question. All of these are the optimal bandwidths for the dependent variables of interest relative to an MSE criterion for the entire sample of students (Calonico, Cattaneo, Farrell, & Titiunik, 2017). For the pooled data, the estimates are based on the sample of students within a bandwidth of 0.883 of the cutoff for the first research question, a bandwidth of 0.643 for the second research question and a bandwidth of 0.881 of the cutoff for the last research question. Again, these are all the optimal bandwidths for the dependent variables of interest relative to an MSE criterion for the entire sample of students.

4.1 Continuity Assumption

4.1.1 Density Test

To examine the validity of the continuity assumption, I use a test developed to test for a discontinuity in the probability for the average high school math grade at 7.5 for Mathematics A and 6.5 for Mathematics B (Cattaneo, Jansson, & Ma, 2018). If students could manipulate their average high school math grade a jump just above 6.5 and 7.5 is expected. Figure 4 summarises the test results for students who did Mathematics A and Figure 5 for students who did Mathematics B. Figure 4 shows no evidence of bunching for students who did Mathematics A. The bias-corrected discontinuity test statistic is -0.88 with a p-value of 0.45. Therefore, there is no statistical evidence of systematic manipulation of the running variable. Also, for those students that did Mathematics B, no evidence of bunching is shown as can be seen in Figure 5. The bias-corrected discontinuity test statistic is 0.75 with a p-value of 0.45. Meaning that there again is no evidence of systematic manipulation of the running variable.

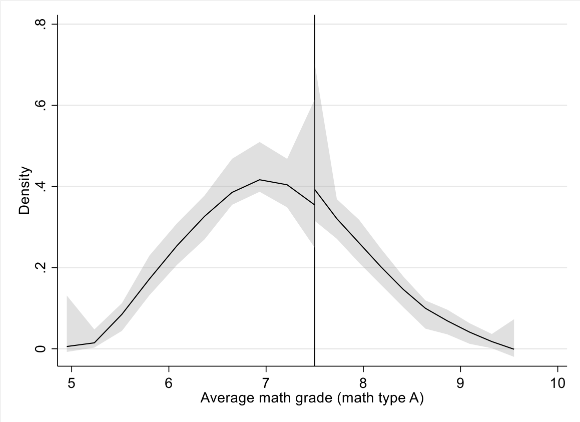

Figure 4 *Discontinuity in density test – Mathematics A*

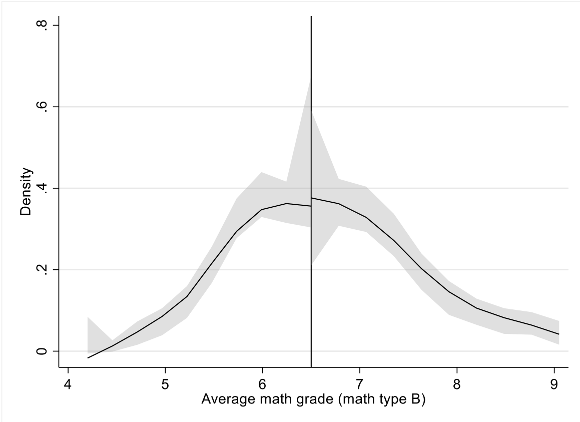

Figure 5 *Discontinuity in density test – Mathematics B*

4.1.2 Balancing Tests

Next, Equation 1 has been used to check whether students on the right and left of the cutoffs are similar, where instead of the two grades for the courses or the amount of ECTS, the dependent variables are personal characteristics. Table 3 presents estimates of Equation 1 for students with Mathematics A in the top three panels and for students with Mathematics B in the lower three panels, separated per optimal bandwidth. Students with Mathematics A are similar in terms of gender and the chosen programme to the left and right of the cutoff. However, their age differs as older students are underrepresented to the right of the cutoff. This can be problematic if older students obtain higher grades through manipulation, creating a discontinuity in the conditional expectations at the cutoff. In Section 5, I will show that the results are robust to controls for age. Students with Mathematics B are similar in terms of age and programme to the left and right of the cutoff but differ in gender. However, a density manipulation test by gender implies that the probability density around the cutoff is continuous for both males and females. Results are presented in Figures A.1 and A.2 in Appendix A.

Table 3 *Balancing tests around the cutoffs*

	Gender (1)	Age (2)	Programme (3)
Math A grade below 7.5	-0.05	1.41***	0.05
	(0.24)	(0.35)	(0.12)
Observations	223	223	223
Math A grade below 7.5	-0.01	1.38***	0.08
	(0.26)	(0.36)	(0.12)
Observations	173	173	173
Math A grade below 7.5	-0.14	1.24***	0.01
	(0.20)	(0.32)	(0.12)
Observations	261	261	261
Math B grade below 6.5	0.18*	0.46	0.12
	(0.11)	(0.42)	(0.12)
Observations	306	306	306
Math B grade below 6.5	0.18*	0.46	0.12
	(0.11)	(0.42)	(0.12)
Observations	306	306	306
Math B grade below 6.5	0.15	0.50	0.13
	(0.10)	(0.41)	(0.12)
Observations	323	323	323

*The outcome variable is at the top of each column. From the top to the bottom panel, the bandwidth is 0.503, 0.432, 0.640, 0.708, 0.711 and 0.753. The kernel is triangular. Standard errors in parentheses. Significance levels: *<10%; **<5%; ***<1%.*

4.1.3 Mass Points

Finally, there can be concerns about having enough mass points for a continuity-based RDD. However, there are 97 unique values for the average math grade for the 173 students in the smallest estimation sample of 7.068-7.932 for students with Mathematics A, amounting to approximately one grade value for every two students. For the smallest estimation sample of 5.792-7.208 for students with Mathematics B, there are even 115 unique values for the 306 students, amounting to approximately one grade value for every three students. These are usually sufficient for a continuity-based RDD (Cattaneo, Idrobo, & Titiunik, 2019a).

5 Results

5.1 Results – Pooled Data

Table 4 reports estimates for academic performance based on pooled data from the two types of students. Meaning that the sample contains both Mathematics A and Mathematics B students. The top panel reports estimates for student grades for the course Introduction to Mathematics, the middle panel for the course Microeconomics and the bottom panel reports the estimates for the number of ECTS students obtained in the bachelor programme's first year. Column (1) shows the estimate when not controlled for potential year fixed-effects and personal characteristics but does include a dummy variable indicating the type of mathematics in high school. Columns (2) and (3) show that the estimates do not change when controlling for year fixed-effects and personal characteristics. The points estimates are statistically not different from zero, implying that the summer math course had little to no effect on academic performance.

Note that all standard errors reported in this paper are probably slightly too small as they are not adjusted for clustering at the individual level.

Table 4 Academic performance – pooled data

	(1)	(2)	(3)
Math grade below cutoff	0.05	-0.07	-0.06
	(0.30)	(0.35)	(0.35)
Year FE	No	Yes	Yes
Personal characteristics	No	No	Yes
Observations	604	604	604
Math grade below cutoff	-0.16	0.15	0.19
	(0.33)	(0.41)	(0.40)
Year FE	No	Yes	Yes
Personal characteristics	No	No	Yes
Observations	414	414	414
Math grade below cutoff	-1.29	-3.67	-0.50
	(4.68)	(5.76)	(5.57)
Year FE	No	Yes	Yes
Personal characteristics	No	No	Yes
Observations	653	653	653

Notes:

1. *The outcome variable is the grade for the course Introduction to Mathematics in the top panel, the grade for Microeconomics in the middle panel and the number of ECTS in the bottom panel.*
2. *The test statistics that are displayed is the bias-corrected discontinuity test statistic with robust variance estimator.*
3. *Controls for personal characteristics are age, gender and programme.*
4. *The bandwidth is 0.883 in the top panel, 0.643 in the middle panel and 0.881 in the bottom panel (MSE optimal bandwidths for the baseline RD specifications with a control for the type of mathematics in high school). The kernel is triangular.*
5. *Standard errors in parentheses.*
6. *Significance levels: *<10%; **<5%; ***<1%.*

5.2 Results – Unpooled Data

Tables 5 to 7 separately evaluate the policy effect for the two student types. Table 5 reports estimates for students' grades for the course Introduction to Mathematics based on data from the sample of students with Mathematics A in the top panel and those from the sample of students with Mathematics B in high school in the bottom panel. Column (1) shows the estimate when not controlled for potential year fixed-effects and personal characteristics. Columns (2) and (3) show that the estimates stay the same when controlling for year fixed-effects and personal characteristics for students with Mathematics A. In column (3), the estimate does differ for students with Mathematics B when controlling for personal characteristics. However, the estimate remains statistically insignificant. For the sample of students with Mathematics A, the point estimates are negative, yet not statistically different from zero. This implies that the summer math course had little to no effect on the academic performance expressed in the grade for the course Introduction to Mathematics. The same goes for the sample of students with Mathematics B.

Table 5 *Introduction to Mathematics*

	(1)	(2)	(3)
Math grade A below 7.5	-0.01	-0.07	-0.07
	(0.52)	(0.63)	(0.64)
Year FE	No	Yes	Yes
Personal characteristics	No	No	Yes
Observations	196	196	196
Math grade B below 6.5	0.06	0.04	-0.06
	(0.44)	(0.53)	(0.52)
Year FE	No	Yes	Yes
Personal characteristics	No	No	Yes
Observations	291	291	291

Notes:

1. *The test statistics that are displayed is the bias-corrected discontinuity test statistic with robust variance estimator.*
2. *Controls for personal characteristics are age, gender and programme.*
3. *The bandwidth is 0.503 in the top panel and 0.708 in the bottom panel (MSE optimal bandwidths for the baseline RD specifications with no controls). The kernel is triangular.*
4. *Standard errors in parentheses.*
5. *Significance levels: *<10%; **<5%; ***<1%.*

The estimates from the sample of students with Mathematics A for students grades for the course Microeconomics are reported in the top panel of Table 6 and for those with Mathematics B in the bottom panel. Again, column (1) reports the estimates when not controlling for year fixed-effect and personal characteristics and columns (2) and (3) show that the estimates do not change when controlling for those two. All point estimates do not statistically differ from zero, implying that the impact from the summer math course is again small to negligible for students' grades. Although not statistically significant, the estimates are positive for the sample of students with Mathematics A and negative for those with Mathematics B.

Table 6 *Microeconomics*

	(1)	**(2)**	**(3)**
Math grade A below 7.5	0.08	1.08	1.17
	(0.64)	(0.80)	(0.81)
Year FE	No	Yes	Yes
Personal characteristics	No	No	Yes
Observations	130	130	130
Math grade B below 6.5	-0.02	-0.09	-0.15
	(0.38)	(0.44)	(0.42)
Year FE	No	Yes	Yes
Personal characteristics	No	No	Yes
Observations	265	265	265

Notes:

1. *The test statistics that are displayed is the bias-corrected discontinuity test statistic with robust variance estimator.*
2. *Controls for personal characteristics are age, gender and programme.*
3. *The bandwidth is 0.432 in the top panel and 0.711 in the bottom panel (MSE optimal bandwidths for the baseline RD specifications with no controls). The kernel is triangular.*
4. *Standard errors in parentheses.*
5. *Significance levels: *<10%; **<5%; ***<1%.*

Lastly, Table 7 reports the estimates for the number of ECTS students obtained in the bachelor programme's first year. Where the top panel reports those estimates from the sample of students with Mathematics A and the bottom panel from the sample of students with Mathematics B. Again, the estimates do not differ when controlling for year fixed-effects and personal characteristics (columns (2) and (3)) and the estimates are insignificant and do therefore again imply that the impact is small to negligible, despite these being negative for students with Mathematics A and negative for students with Mathematics B.

Table 7 *ECTS*

	(1)	(2)	(3)
Math grade A below 7.5	-5.29	-14.02	-9.87
	(7.05)	(8.83)	(9.02)
Year FE	No	Yes	Yes
Personal characteristics	No	No	Yes
Observations	261	261	261
Math grade A below 6.5	0.91	1.14	3.38
	(6.82)	(8.41)	(7.75)
Year FE	No	Yes	Yes
Personal characteristics	No	No	Yes
Observations	323	323	323

Notes:

1. *The test statistics that are displayed is the bias-corrected discontinuity test statistic with robust variance estimator.*
2. *Controls for personal characteristics are age, gender and programme.*
3. *The bandwidth is 0.640 in the top panel and 0.753 in the bottom panel (MSE optimal bandwidths for the baseline RD specifications with no controls). The kernel is triangular.*
4. *Standard errors in parentheses.*
5. *Significance levels: *<10%; **<5%; ***<1%.*

6 Robustness

In Section 5 above, I already showed that the results are robust to controlling for year fixed-effects and personal characteristics. This is positive, especially with the possible gender and age imbalance found in Sections 3 and 4.

In addition, some placebo tests were performed to test for discontinuities at fake cutoffs. For the sample of students with Mathematics A, a fake cutoff of 6.5 was used and one of 7.5 was used for those with Mathematics B. Results are reported in Table A.7 and Table A.8 in Appendix A. Both Tables report the absence of significant discontinuities at the fake cutoffs for a 10% significance level, except for two.

However, positively for the robustness of the results of this paper, these two do not show a significant discontinuity for a 5% and 1% significance level.

Lastly, the estimates in Table A.9 in Appendix A show the probability of participating in the tests in the first round for both courses. Both estimates are not statistically different from zero. This implies that the summer math course had little to no effect on the probability of participating in the first round of exams. This is positive, as it would be problematic if students who have undergone the treatment are more inclined to take the test in the first round, as this could influence the results.

7 Conclusion

I draw on a discontinuity at a large Dutch university, wherein prospective students with a low high school math grade were forced to do a mathematical summer course before the start of university to estimate the causal effect of study choice activities on academic performance. Academic performance has been measured through the grades students obtain for two courses and the total amount of ECTS in the first year. The estimates imply that the students that took the summer course cannot expect higher grades or a higher amount of ECTS obtained in the first year. Some, however not statistically significant, evidence is found that the summer course has a negative impact on academic performance. Note that the effects are estimated around the cutoffs and that there may be effects further away from both cutoffs.

After carrying out the analysis, the main consideration is that the effects estimates are lower than expected since we do not observe any estimates that are statistically different from zero, implying that the policy had little to no effect on students' academic performance. These results can have problematic implications for policy when extrapolated by third parties and used to prove that such study choice activities do not impact academic performance. This necessitates further research into the precise content and procedure of the summer course. For example, in the current setup, students can have someone else do the course for them instead of doing it themselves, as the system is not proof for fraud, as explained in Section 3.3. This could explain why most of the point estimates were negative, implying a negative effect of the summer course, as it did not improve students' math skills in this way and therefore did not contribute to their academic performance. There may also be issues concerning the course content that prevents students from brushing up on the knowledge they need to get off to a good start. The research has some limitations as it only consists of students from the Netherlands due to the setup of the course. This can be problematic, as activities aimed at easing the transition to higher education may even be more important for students from abroad. As a result, I recommend further research into these activities in which international students are also involved.

To conclude, I want to stress the relevance of this paper for policymakers in higher education. There are many problems students face at university and this paper suggests that a policy aimed at reducing these problems does not seem to have an effect on academic performance. Hence, it would be highly relevant for policymakers to reevaluate the effectiveness of such policies.

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Appendix A

Table A.1 *Summary statistics Mathematics A – Introduction to Mathematics*

	Math Grade type A		
Variable	**[6.997, 7.5)**	**[7.5, 8.003]**	**Diff.**
Student level (all students)			
Gender	0.18	0.28	0.10*
	(0.39)	(0.45)	(0.06)
Programme	0.15	0.19	0.04
	(0.35)	(0.40)	(0.05)
Age	18.44	18.51	0.06
	(1.15)	(1.04)	(0.15)
CreditsDEF	36.21	38.15	1.95
	(25.05)	(24.64)	(3.33)
Observations	117	106	223
Course level (first takers)			
Introduction to math	4.76	5.19	0.43*
	(1.57)	(1.52)	(0.22)
Observations	106	90	196
Course level (first takers)			
Microeconomics	5.70	5.91	0.22
	(1.42)	(1.37)	(0.21)
Observations	91	81	172

*This table shows the mean values for each of the variables. Standard deviations are in parentheses in the first two columns and standard errors are in parentheses in the last column. Asterisks denote statistical significance for differences in means. Significance levels: *<10%; **<5%; ***<1%.*

Table A.2 *Summary statistics Mathematics B – Introduction to Mathematics*

	Math Grade type B		
Variable	**[5.792, 6.5)**	**[6.5, 7.208]**	**Diff.**
Student level (all students)			
Gender	0.17	0.28	0.12**
	(0.38)	(0.45)	(0.05)
Programme	0.09	0.13	0.03
	(0.29)	(0.33)	(0.04)
Age	18.49	18.75	0.03*
	(1.04)	(1.42)	(0.14)
CreditsDEF	46.03	49.59	3.57
	(22.64)	(20.14)	(2.46)
Observations	148	158	306
Course level (first takers)			
Introduction to math	6.31	6.99	0.68***
	(1.27)	(1.25)	(0.15)
Observations	143	148	291
Course level (first takers)			
Microeconomics	6.04	6.59	0.56***
	(1.35)	(1.29)	(0.16)
Observations	130	135	265

*This table shows the mean values for each of the variables. Standard deviations are in parentheses in the first two columns and standard errors are in parentheses in the last column. Asterisks denote statistical significance for differences in means. Significance levels: *<10%; **<5%; ***<1%.*

Table A.3 *Summary statistics Mathematics A – Microeconomics*

	Math Grade type A		
Variable	**[7.068, 7.5)**	**[7.5, 7.932]**	**Diff.**
Student level (all students)			
Gender	0.18	0.29	0.11*
	(0.39)	(0.46)	(0.06)
Programme	0.14	0.20	0.06
	(0.35)	(0.40)	(0.06)
Age	18.44	18.47	0.03
	(1.07)	(0.96)	(0.15)
CreditsDEF	35.82	39.11	3.29
	(25.36)	(24.33)	(3.78)
Observations	88	85	173
Course level (first takers)			
Introduction to math	4.82	5.11	0.29
	(1.61)	(1.51)	(0.25)
Observations	80	74	154
Course level (first takers)			
Microeconomics	5.84	5.83	-0.02
	(1.41)	(1.32)	(0.24)
Observations	65	65	130

*This table shows the mean values for each of the variables. Standard deviations are in parentheses in the first two columns and standard errors are in parentheses in the last column. Asterisks denote statistical significance for differences in means. Significance levels: *<10%; **<5%; ***<1%.*

Table A.4 *Summary statistics Mathematics B – Microeconomics*

	Math Grade type B		
Variable	**[5.789, 6.5)**	**[6.5, 7.211]**	**Diff.**
Student level (all students)			
Gender	0.17	0.28	0.12**
	(0.38)	(0.45)	(0.05)
Programme	0.09	0.13	0.03
	(0.29)	(0.33)	(0.04)
Age	18.49	18.75	0.03*
	(1.04)	(1.42)	(0.14)
CreditsDEF	46.03	49.59	3.57
	(22.64)	(20.14)	(2.46)
Observations	148	158	306
Course level (first takers)			
Introduction to math	6.31	6.99	0.68***
	(1.27)	(1.25)	(0.15)
Observations	143	148	291
Course level (first takers)			
Microeconomics	6.04	6.59	0.56***
	(1.35)	(1.29)	(0.16)
Observations	130	135	265

*This table shows the mean values for each of the variables. Standard deviations are in parentheses in the first two columns and standard errors are in parentheses in the last column. Asterisks denote statistical significance for differences in means. Significance levels: *<10%; **<5%; ***<1%.*

Table A.5 *Summary statistics Mathematics A - ECTS*

	Math Grade type A		
Variable	**[6.86, 7.5)**	**[7.5, 8.14]**	**Diff.**
Student level (all students)			
Gender	0.20	0.27	0.07
	(0.40)	(0.44)	(0.05)
Programme	0.15	0.20	0.05
	(0.36)	(0.40)	(0.05)
Age	18.46	18.47	0.02
	(1.14)	(1.03)	(0.13)
CreditsDEF	35.33	39.80	4.47
	(25.57)	(24.45)	(3.10)
Observations	138	123	261
Course level (first takers)			
Introduction to math	4.76	5.39	0.62***
	(1.53)	(1.53)	(0.20)
Observations	124	106	230
Course level (first takers)			
Microeconomics	5.72	6.05	0.33
	(1.42)	(1.53)	(0.21)
Observations	105	95	200

*This table shows the mean values for each of the variables. Standard deviations are in parentheses in the first two columns and standard errors are in parentheses in the last column. Asterisks denote statistical significance for differences in means. Significance levels: *<10%; **<5%; ***<1%.*

Table A.6 *Descriptive statistics Mathematics B - ECTS*

	Math Grade type B		
Variable	**[5.747, 6.5)**	**[6.5, 7.253]**	**Diff.**
Student level (all students)			
Gender	0.17	0.30	0.13***
	(0.37)	(0.46)	(0.05)
Programme	0.10	0.12	0.02
	(0.29)	(0.33)	(0.03)
Age	18.48	18.74	0.26*
	(1.03)	(1.41)	(0.14)
CreditsDEF	46.24	49.93	3.69
	(22.47)	(19.81)	(2.36)
Observations	157	166	323
Course level (first takers)			
Introduction to math	6.27	7.03	0.76***
	(1.32)	(1.24)	(0.15)
Observations	152	156	308
Course level (first takers)			
Microeconomics	5.99	6.63	0.64***
	(1.38)	(1.29)	(0.16)
Observations	139	143	282

*This table shows the mean values for each of the variables. Standard deviations are in parentheses in the first two columns and standard errors are in parentheses in the last column. Asterisks denote statistical significance for differences in means. Significance levels: *<10%; **<5%; ***<1%.*

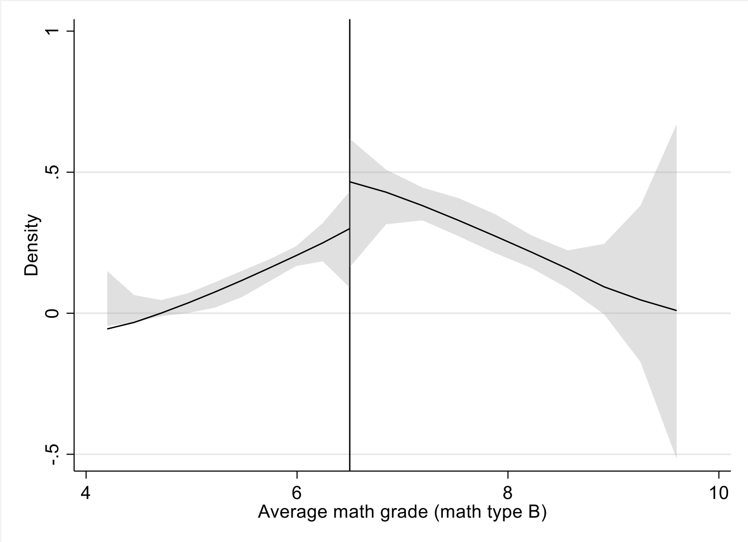

Figure A.1 *Discontinuity in density test for females– Mathematics B*

Notes:

6. *Figure uses a second-order polynomial for density estimation and a third-order for the bias-correction estimate. The kernel is triangular and confidence intervals use jackknifed standard errors.*
7. *The bias-corrected discontinuity test statistic is 0.26 with a p-value of 0.79, meaning the null hypothesis of no discontinuity around the cutoff cannot be rejected.*

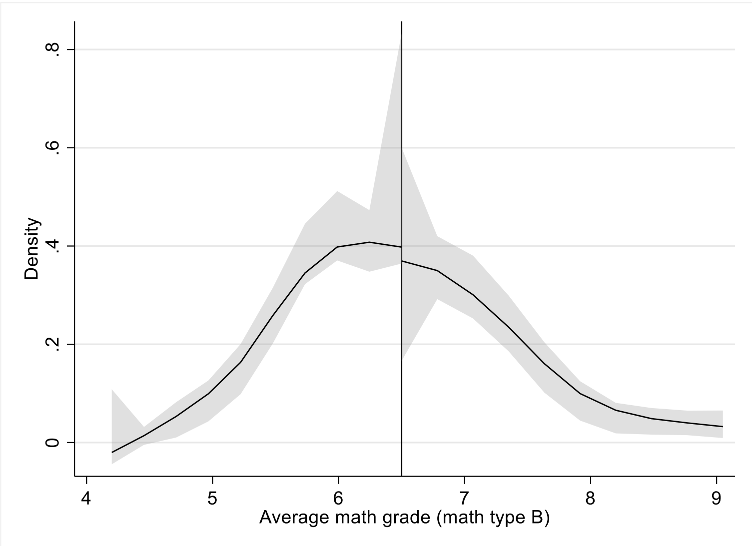

Figure A.2 *Discontinuity in density test for males– Mathematics B*

Notes:

1. *Figure uses a second-order polynomial for density estimation and a third-order for the bias-correction estimate. The kernel is triangular and confidence intervals use jackknifed standard errors.*
2. *The bias-corrected discontinuity test statistic is 0.15 with a p-value of 0.88, meaning the null hypothesis of no discontinuity around the cutoff cannot be rejected.*

Table A.7 *Placebo test - Mathematics A*

	(1)	(2)	(3)
Math grade below 6.5	0.88	1.35	24.10*
	(0.84)	(0.94)	(12.98)
Observations	153	84	123

Notes:

1. *The test statistics that are displayed is the bias-corrected discontinuity test statistic with robust variance estimator. Dependent variable is the grade for Introduction to Mathematics in column (1), the grade for Microeconomics in column (2) and in (3) it is the amount of ECTS obtained.*
2. *The bandwidths are MSE optimal. For column (1) this implies a bandwidth of 0.418, for column (2) one of 0.348 and for the last a bandwidth of 0.319.*
3. *Controls for personal characteristics are age, gender and programme.*
4. *The kernel is triangular.*
5. *Standard errors in parentheses.*
6. *Significance levels: *<10%; **<5%; ***<1%.*

Table A.8 *Placebo test- Mathematics B*

	(1)	(2)	(3)
Math grade below 7.5	1.06*	-0.43	-3.77
	(0.60)	(0.54)	(4.67)
Observations	104	107	168

Notes:

1. *The test statistics that are displayed is the bias-corrected discontinuity test statistic with robust variance estimator. Dependent variable is the grade for Introduction to Mathematics in column (1), the grade for Microeconomics in column (2) and in (3) it is the amount of ECTS obtained.*
2. *The bandwidths are MSE optimal. For column (1) this implies a bandwidth of 0.444, for column (2) one of 0.461 and for the last a bandwidth of 0.639.*
3. *Controls for year fixed-effects and personal characteristics (age, gender and programme) are included.*
4. *The kernel is triangular.*
5. *Standard errors in parentheses.*
6. *Significance levels: *<10%; **<5%; ***<1%.*

Table A.9 *Participation in the first round of exams*

	(1)	(2)
Math grade below cutoff	-0.08	-0.02
	(0.06)	(0.10)
Observations	653	615

Notes:

1. *The test statistics that are displayed is the bias-corrected discontinuity test statistic with robust variance estimator. Dependent variable is a dummy variable indicating whether the test for the course Introduction to Mathematics is taken or not in column (1) and a dummy variable indicating whether the test for the course Microeconomics is taken or not in column (2).*
2. *The bandwidths are MSE optimal. For column (1) this implies a bandwidth of 0.882 and for column (2) one of 0.792.*
3. *Controls for math type, year fixed-effects and personal characteristics (age, gender and programme) are included.*
4. *The kernel is triangular.*
5. *Standard errors in parentheses.*
6. *Significance levels: *<10%; **<5%; ***<1%.*

Appendix B

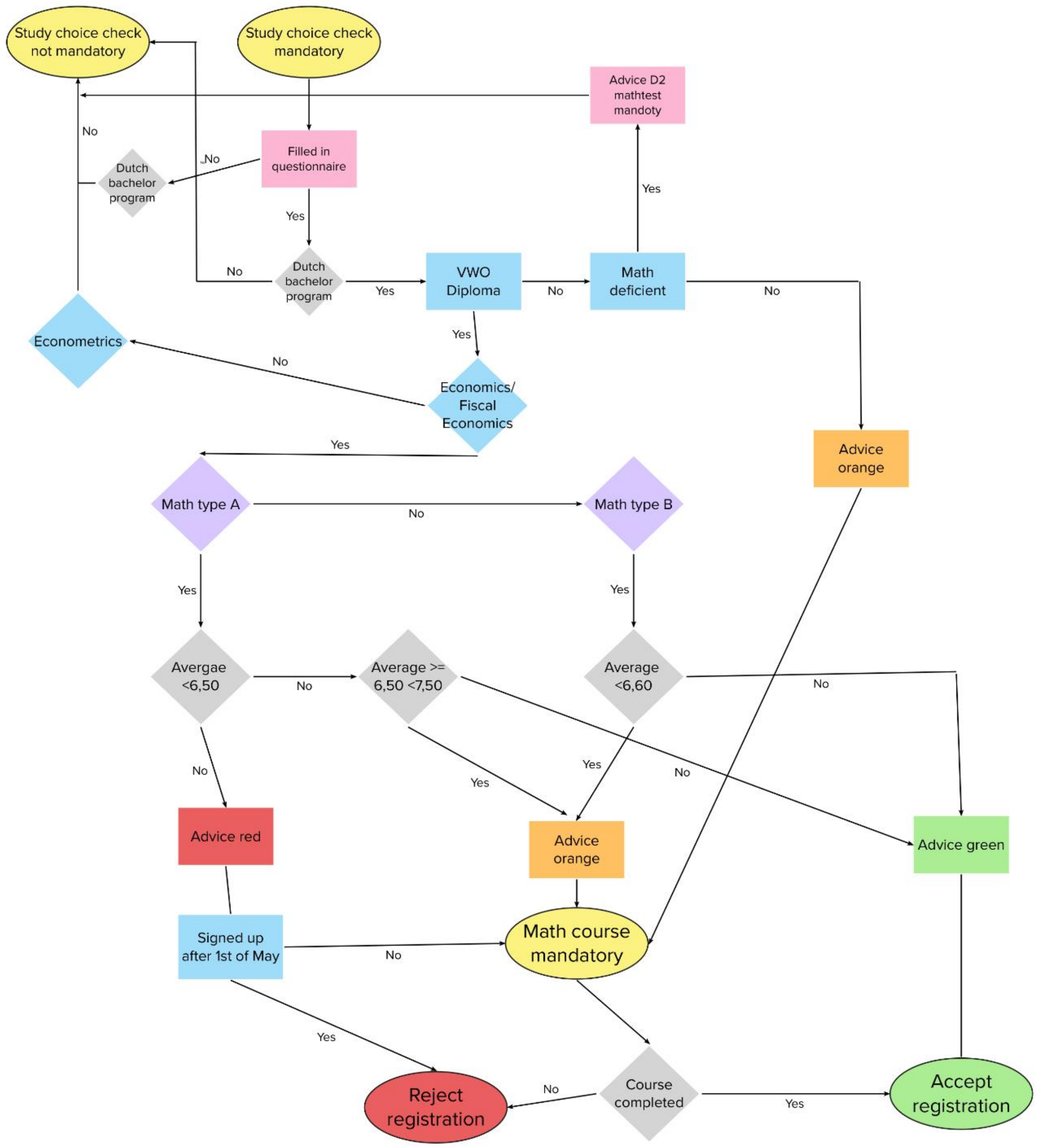

Figure B.1 *Procedure Study Choice Check*