Pre-Analysis Plan (PAP): Opportunity Cost Neglect in Higher Education

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1. Motivation and Research Questions

University students in many countries often take much longer than the prescribed time to graduate with a degree. For example, in Germany and in other OECD countries only about 40% of students manage to graduate within the regular study duration (Statistisches Bundesamt 2018; OECD 2019). From an individual perspective, long study durations imply directs costs, e.g., in the form of tuition fees, but also opportunity costs such as the foregone earnings due to later employment. Contrary to standard economic theory, recent literature suggests that individuals often only account for opportunity costs in their decision making when these costs are made salient (Frederick et al., 2009; Plantinga et al., 2018). It is therefore conceivable that opportunity costs are also neglected when it comes to study related decisions. Given that the opportunity costs of a longer study duration lie in the future, it seems particularly likely that those costs are not taken into account by students when deciding on their optimal effort level at the beginning of their studies.

Against this background, the intervention presented in this PAP tests whether explicitly pointing out opportunity costs of a prolonged study duration increases academic performance in the first semester. To this end, treated students are provided with information about the gross annual starting salary from recent graduates of the same or a similar study program and they are informed that each additional semester until graduation can imply the loss of half of that potential salary. Since research shows that students often have biased and inaccurate expectations about future earnings and that correcting those beliefs may lead to behavioral changes (Wiswall & Zafar, 2015; Conlon, 2021), we also include a treatment group that only receives information on the potential earnings without explicitly pointing out the potential loss of income that can accompany a longer study duration. This

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allows to test to what extent the effects of the first treatment are driven by the earnings information.

With the intervention and the analysis presented below, we plan to answer the following main research questions:

1. Does information on the opportunity cost of a prolonged study duration lead to increased academic achievement in the first semester on performance dimensions that are directly related to the duration of studies, i.e., course credits signed-up for, course credits attempted, and, most importantly, course credits passed?

2. Is explicitly stating that a long study duration can imply a loss of income more effective than just providing students with information on the gross annual starting salary of recent graduates?

2. Sample

We conduct our intervention at a German university of applied sciences with 2,222 incoming first semester students who enroll in one of 21 bachelor's programs in the winter semester 2021/22. Table 1 shows the number of students per study program:

Table 1: Observations by study program

Study program	**Freq.**
Applied Chemistry	90
Applied Mathematics and Physics	42
Civil Engineering	159
Business Administration	377
Electrical Engineering and Information Technology	193
Building Services Engineering	55
Energy Process Engineering	34
Computer Science	96
International Business	92
International Business and Technology	71
Management in Organic and Sustainability Business	23
Mechanical Engineering	198
Mechatronics/Precision Engineering	69
Media Engineering	61
Computer Science and Media	44
Medical Engineering	89
Social Work	297
Journalism of Technology	74
Process Engineering	27
Applied Materials Science	51
Information Systems and Management	80
Total	2,222

We will not exclude students from the analysis sample who drop out at any point after the treatment.

3. Design of the Intervention

Figure 1: Intended timeline of the intervention

Figure 1 shows the intended timeline of our intervention, which starts at the beginning of the winter semester 2021/22. Using administrative data on students' background characteristics, on October 08, we randomized 2,222 students into three different treatment groups (see Section 4 for information on the randomization procedure). On October 15, we sent a first unannounced (physical) letter by mail to students of all treatment groups (we describe the contents of the letters for the different treatment conditions in detail below). Around December 20, i.e., about four weeks before the beginning of the exam period, students will receive a second letter. The informational content of the second letter will be the same. The goal is to make the information salient at a time when students start preparing for their exams. In addition, it is planned to invite students to a post-treatment online survey between the first and second letter.

Depending on the experimental group, the letters include the following information:

Control group (**T0**): Letters for students in the control group contain information about counseling and information services offered by the university. This information is also publicly available on the web page of the university.

Earnings information (**EI**): The letters include the same information that the control group receives. In addition, they contain information on the average gross starting salary per year of recent graduates who studied the same or a similar program as the individual that receives the letter. Specifically the letter states that "the average gross annual salary (full-time) of similar students during the first year after graduating with a bachelor's degree in *study program* is **€ XX,XXX**".[5]

[5] The salary is based on aggregated data from surveys among graduates from previous cohorts that provide information on average gross hourly starting salaries. Based on this data we calculated gross annual salaries for full-time employment (38.2 hours per week including an end-of-year bonus of 0.25 monthly salaries) referring to the base year 2020.

Opportunity cost (**OC**): The letters include the same information that the earnings information (EI) group receives. In addition, directly after the earnings information, the letter states the following: "**How does this affect the further planning of your studies?** Each additional semester of studying can lead to the loss of approximately half of that salary."

4. Randomization Procedure

Students were assigned to one of the three experimental groups within blocks that we constructed by performing threshold blocking within study programs using the *R quickblock* package (Higgins et al., 2016). As a distance measure for the creation of blocks, we used the Mahalanobis distance with respect to students' high school GPA[6], their gender, and a proxy for procrastination of which we know that it is highly predictive of passed course credits.[7] To allow for the formation of multiple homogeneous blocks in all study programs, minimal block sizes range between 21 (larger study programs) and 6 (smaller programs). In total, we construct 120 Blocks across the 21 study programs. Figures 2 and 3 illustrate the formation of blocks for the study programs Business Administration and Process Engineering. The subsequent within-block randomization using equal assignment probabilities was performed with *Stata*'s *randtreat* command (Carril, 2017).

Table 2 shows the number of observations per experimental group as well as balancing characteristics for the variables used to construct the blocks and for four additional variables (age, time since high school graduation in years, a dummy for whether it is the first semester at a university at all, and a high school degree "Abitur" dummy[8]). The F-tests used for the construction of the p-values are based on regressions that control for block dummies and robust standard errors.

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[6] The high school GPA was missing for 12 observations. To keep the sample complete, we imputed those values based on a linear regression of the high school GPA on age, a female dummy, time since high school graduation in years, a high school degree Abitur dummy, the procrastination index, a first semester at any university dummy as well as study program dummies, and the interaction of the study program dummies with the other variables.

[7] To construct the proxy, we used *Stata*'s *swindex* command by Schwab et al. (2020) to calculate the standardized inverse-covariance weighted average (Anderson, 2008) of the date of application for the study program and the date of enrollment. The date of enrollment was first standardized within study programs, due to differences in the timelines of the enrollment periods between study programs.

[8] High school degree Abitur refers to the German general track degree. It is one of the two main secondary school degrees in the tracked school system in Germany that qualifies students to study at a University of Applied Sciences; the second being the vocational track degree (Fachhochschulreife).

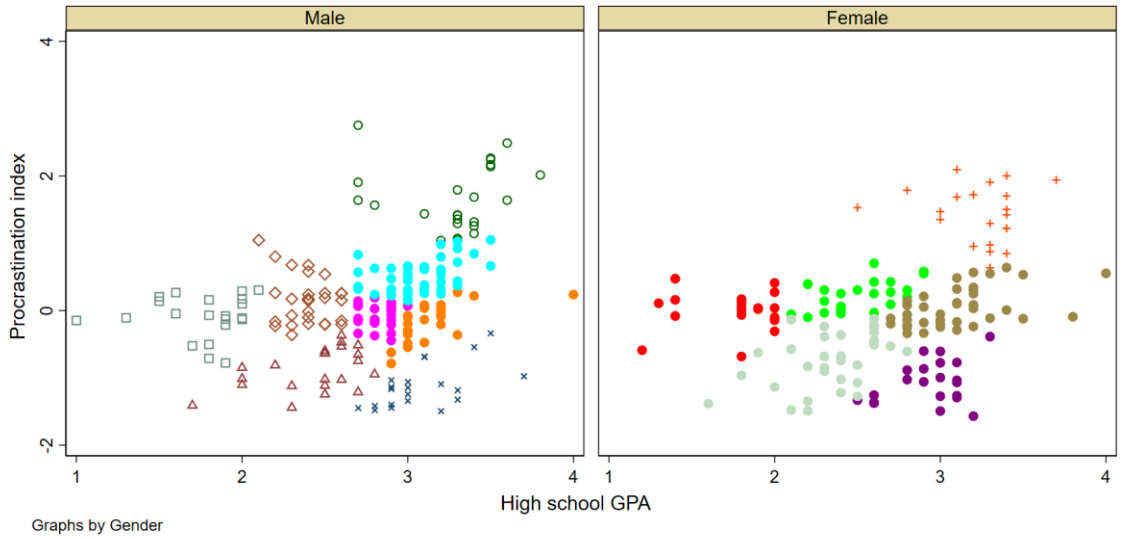

Figure 2: Threshold blocking in Business Administration (minimal allowed block size = 21)

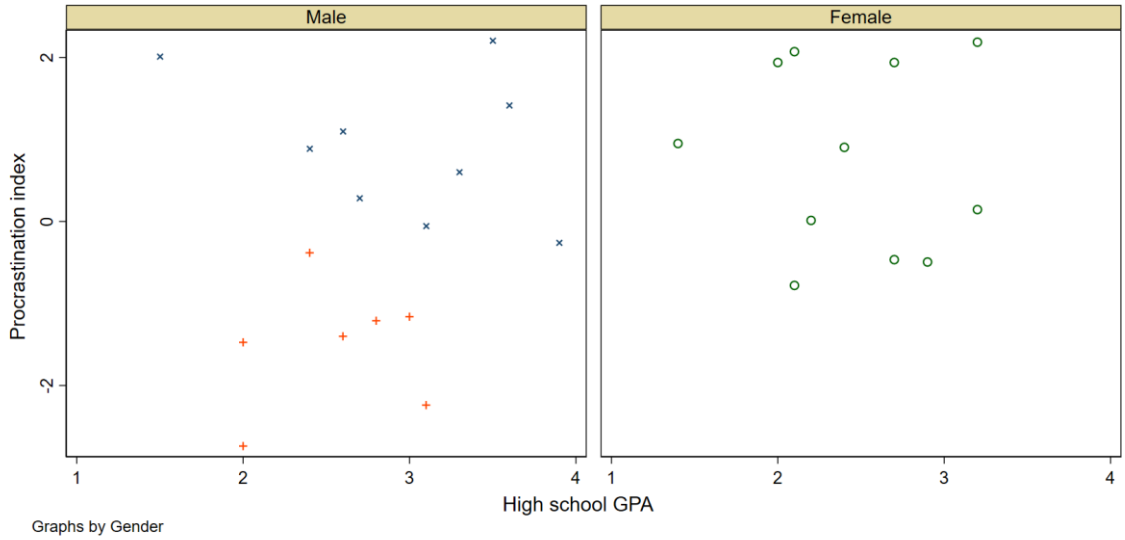

Figure 3: Threshold blocking in Process Engineering (minimal allowed block size = 6)

Table 2: Summary statistics and balancing properties

	T0	**EI**	**OC**	**p-value F-test**
HS GPA	2.538	2.527	2.508	0.219
Procrastination index	0.008	-0.034	0.026	0.098
Female	0.367	0.362	0.363	0.677
Age	21.683	21.617	21.607	0.918
Time s. grad. (years)	1.805	1.743	1.808	0.873
First university semester	0.732	0.739	0.708	0.337
HS degree Abitur	0.521	0.522	0.514	0.916
N	739	740	743	

5. Statistical Power

Assuming alpha = 0.05, we calculated effect sizes for comparisons between the experimental groups using the Stata *power twomeans* command for an R^2 of 0.00 (Column 3) and, using the *Optimal Design* software (Spybrooks et al., 2011), for assumed R^2 of 0.20 and 0.40 (Columns 4 and 5). The two latter R^2 are based on analyses with previous cohorts that show that the variables used for blocking (study program dummies, the procrastination index, high school GPA, and the female dummy) explain up to 40% of the variance in passed first semester credits.

Table 3: Minimum detectable effect sizes

Power	N	Delta (R^2 = 0.00)	Delta (R^2 = 0.20)	Delta (R^2 = 0.40)
0.6	1480	0.115	0.105	0.090
0.8	1480	0.146	0.130	0.114

6. Data Sources

For the analyses of the effects of the intervention, we plan to use data from the following sources:

Administrative data: The university provides us with administrative data on students' background characteristics and information from the application process. Some of the information from those sources was used in the randomization procedure and we plan to use some of it as covariates and for potential heterogeneity analyses.

The university will also provide us with information on the number of exams/credits that students sign up for[9] and with information on students' academic achievements, e.g., number of attempted and passed course credits, GPA, and dropout. We will use information from these sources for our outcome variables.

Online-Self-Assessments (OSAs): During the enrollment process, students of 9 study programs are obliged to complete a subject specific online self-assessment. Students from the other programs can also take those subject specific self-assessments or a voluntary general self-assessment. We were allowed to include a short module in the OSAs that takes about 5 minutes to complete. The module includes questions on subjects such as time preferences, procrastination tendencies, opportunity cost consideration, and earnings expectations. We plan to match the data from the OSAs with the administrative data.

Online surveys: We will invite students to participate in a voluntary online survey. Among others, it will include questions on expected earnings, the, students' current financial

[9] To take exams students have to sign up for them in advance during the sign-up period (see Figure 1). However, depending on the study program, students can later deregister from taking the exams that they signed up for; either during a specific deregistration period or by simply not showing up to the exam.

situation, the expected and intended study duration, as well as questions on non-cognitive outcomes such as intrinsic and extrinsic motivation, stress, and life and study satisfaction.

7. Variables

Primary outcome(s): The primary outcomes of the intervention are the number of course credits signed-up for, attempted, and passed in the first semester.

Explanatory outcome(s): Students' beliefs about expected earnings and the confidence in those beliefs from the post-treatment online survey.

Secondary outcomes: To study the net effects of our interventions, i.e., whether students trade off performance gains on the credit dimension with losses on other dimensions, we will also study effects on students' GPA, their dropout behavior, and on non-cognitive outcomes measured with the online surveys. When studying multiple non-cognitive outcome measures, we will also construct indices based on the standardized inverse-covariance weighted average of those outcomes (Anderson, 2008; Schwab et al., 2020).

Covariates: In some of our regression specifications we will not only include block fixed effects (FE) but also additional covariates (see Section 8). Currently, this includes all covariates shown in Table 2. For the selection and inclusion of any additional covariates in the specifications of our main analyses beyond those just mentioned, e.g., to increase the precision of the estimates, we will rely on the double post-lasso approach proposed by Belloni et al. (2014).

8. Analyses

8.1 Main Analyses

In our main analyses we will focus on the effects on the number of course credits signed-up for, attempted, and passed in the first semester. We will perform those analyses using OLS regressions with the following baseline specification:

$$y_i^k = \alpha_0 + \alpha_1 EI_i + \alpha_2 OC_i + \boldsymbol{s_i} + \varepsilon_i,$$

where y_i^k is the outcome of interest, EI_i and OC_i are dummies for being randomized in the respective treatment groups, and $\boldsymbol{s_i}$ are FE that control for the random assignment within blocks. In an additional specification, we will include a vector $\boldsymbol{x_i}$ that includes the covariates specified in Section 7.

Based on those specifications, we will test the following hypotheses:

1. $H_0: \alpha_1 = 0; H_1: \alpha_1 \neq 0.$
2. $H_0: \alpha_2 = 0; H_1: \alpha_2 \neq 0.$
3. $H_0: \alpha_2 - \alpha_1 = 0; H_1: \alpha_2 - \alpha_1 \neq 0.$

8.2 Explanatory and Secondary Analyses

We are planning to run the following explanatory and secondary analyses:

1. Using the respective survey outcomes, we will study treatment effects on students' expectations about future earnings as well as the accuracy of and the confidence in those beliefs.

2. We plan to use data from the OSAs to study whether the treatment effects depend on students' pre-treatment earnings expectations and their opportunity cost consideration.

3. To study the net effects of our intervention, i.e., whether students buy gains on the course credit dimension with declines in performance on other outcome dimensions, we will re-run the main analyses with our secondary outcomes (GPA, dropout, and non-cognitive outcomes).

4. Since the GPA is only observed for students who pass at least one graded module and because all outcomes from the online survey are only observed for students who answer the respective question, we will study whether observing these outcomes is affected by treatment and, if applicable, control for potential differences using inverse probability weighting.

8.3 Exploratory Analyses

For exploratory analyses we are mainly interested in the following:

1. We will explore whether treatment effects are heterogeneous with respect to the dimensions used in the threshold blocking procedure. I.e., we will study if treatment effects are heterogeneous with respect to students' procrastination tendencies, their high school GPA (= a proxy for ability), their gender, and across study programs. Since many study programs have only a small number of observations (see Table 1), we will group study programs into broader fields of study.

2. We plan to explore heterogeneity with respect to time preferences and procrastination tendencies which we measure based on questions in the OSAs.

3. We plan to explore heterogeneity with respect to students' current financial situation, which we measure in the online survey. Since the online survey is conducted post-treatment, we will first study whether treatment affects item nonresponse and the answering behavior.

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