

# Pre-Analysis Plan (PAP): Information on Time Investments in Higher Education

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## 1. Motivation and Research Questions

University students continuously have to decide about the amount of time and effort that they want to invest in their studies. This requires answers to questions such as how much effort and what kind of challenges they will face in the future, what originally led them to take up their studies, and whether anything has changed about their original motivation. Often, however, the necessary information is uncertain, not salient enough, has been forgotten, or was never available in the first place.

The goal of the present research project is to investigate the effects of providing students with information about various dimensions of time investment on academic achievement. More specifically, in the first treatment arm of our intervention students are informed about the time that similar students typically spent on studying. This information is then used in the second and third treatment arm to inform students about the time they have already invested in their studies and the time that they will have to invest in each subsequent semester of studying, respectively.

Treatment two is our main treatment of interest and is motivated by recent research outside the context of education which shows that sunk (monetary) costs can positively influence decisions, as they remind individuals of the original evaluation of and motivation for a project and thus provide signals for decisions in the present (see, e.g., Baliga and Ely 2011 and Hong et al. 2019). At the same time, research by Cunha and Caldieraro (2009) shows that sunk time investments can also affect decision-making through an effort justification mechanism. The first treatment is included to independently test the effects of the social information about the time that similar students spent on studying. We conduct the third treatment to study the effects that the information about study time has if it is framed as a variable cost of the remaining future semesters and to compare it to the effects of framing study time as a sunk time investment.

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

1. What is the effect of framing the information on the time investments of studying as a sunk cost (= sunk time investment, STI condition)?
2. What is the effect of framing the information on the time investments of studying as variable costs for future semesters (= future time investment, FTI condition), and how does it compare to the STI condition?
3. What is the effect of framing the information on the time investments of studying as social information (SI) about the time similar students dedicate to studying and how does it compare to the effects of the STI and FTI condition?

## 2. Sample

We conduct our intervention at a German university of applied sciences with a sample of 4,719 students from three different cohorts who are studying towards one of 21 bachelor's degrees and who re-enrolled for the summer semester 2022. The students in the three cohorts have been studying for seven, five, and one semester and re-enrolled for their eighth, sixth, and second semester, respectively (a cohort of students who have been enrolled for three semesters was not included, as they are part of another intervention). Table 1 shows the number of students by study programs and cohorts:

*Table 1: Observations by cohorts and study programs*

<b>Study program/Cohort</b>	<b>8<sup>th</sup> sem.</b>	<b>6<sup>th</sup> sem.</b>	<b>2<sup>nd</sup> sem.</b>
Applied Chemistry	34	53	76
Applied Materials Science	34	37	43
Applied Mathematics and Physics	24	36	34
Civil Engineering	94	103	129
Business Administration	222	274	340
Electrical Engineering and Information Technology	83	143	174
Building Services Engineering	18	18	41
Energy Process Engineering	21	30	30
Computer Science	45	77	91
International Business	48	70	82
International Business and Technology	44	45	67
Management in Organic and Sustainability Business	18	25	20
Mechanical Engineering	85	114	170
Mechatronics/Precision Engineering	36	51	50
Media Engineering	44	43	56
Computer Science and Media	24	33	40
Medical Engineering	45	63	79
Social Work	188	223	270
Journalism of Technology	23	30	51
Process Engineering	23	28	22
Information Systems and Management	46	86	73
<b>Total</b>	<b>1,199</b>	<b>1,582</b>	<b>1,938</b>

We will not exclude students from the analysis sample who drop out at any point after the start of the intervention. One special feature of the second semester cohort is that almost all of the students, i.e., 1,927 of them, were part of an intervention during their first study semester. That intervention consisted of three groups. Two treatment groups were informed about the earnings of recent graduates in their study program and one of the two treatment groups was additionally made aware that these potential future earnings represent the opportunity cost of a longer duration.<sup>5</sup> As shown in Table 2, the two interventions are orthogonal to each other.

### 3. Design of the Intervention

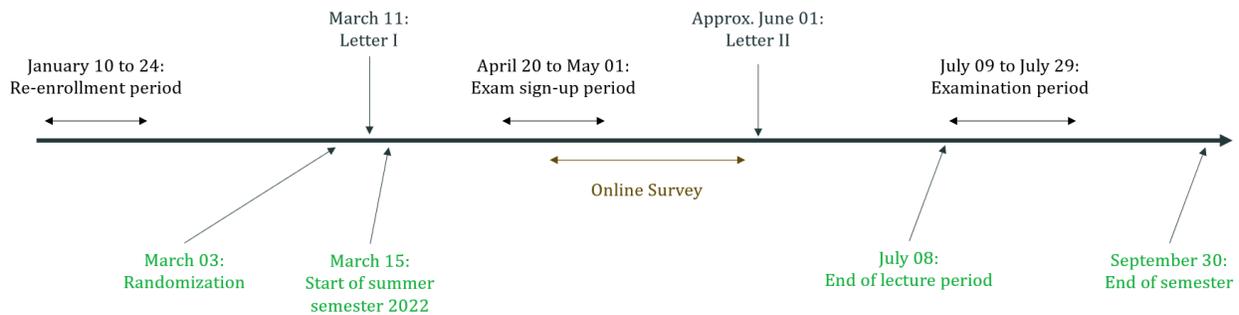


Figure 1: Intended timeline of the intervention

Figure 1 shows the intended timeline of our intervention, which starts shortly before the start of the summer semester 2022. Using administrative data on students' background characteristics, on March 03, we randomized 4,719 students into four different treatment groups (see Section 4 for information on the randomization procedure). On March 11, students of all treatment groups received a first unannounced (physical) letter by mail (we describe the contents of the letters for the different treatment conditions in detail below). Around June 01, i.e., about five weeks before the beginning of the examination 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 kind of information is also publicly available on web pages and other informational materials of the university.

**Social information (SI):** The letters include the same information that the control group receives. In addition, they contain information on the average number of hours that students enrolled in the same study program with similar characteristics (sex, age, university semester as well as grade, type, and place of the university entrance qualification) spent on studying per week during the semester. Specifically, the letters state that "Students similar

<sup>5</sup> That intervention is registered at <https://www.socialscisceregistry.org/trials/8375>.

to you dedicate an average of **XX.X hours per week** to their studies during the semester.” and a footnote provides further information on the sources for that information and how similar students are defined. We describe how we calculate/estimate the average hours spent on studying per week in more detail in Section 4.

**Sunk time investment (STI):** The letters include the same information that the social information group receives. In addition, directly after the social information, the letters state the following: “From your first semester until today, you have therefore invested an estimated **X,XXX hours** in your current study program (as of XX.XX.2022).” To calculate this number, we multiply the hours shown in the social information with the number of weeks that a student has been studying their current study program, assuming that the lecture and examination period of one semester jointly comprise a total of 18 weeks (this information is also provided to students in a footnote in the letter).

**Future time investment (FTI):** The letters include the same information that the social information group receives. In addition, directly after the social information, the letters state the following: “In each future semester of your current study program, you will therefore invest an estimated **XXX hours**.” To calculate this number, we multiply the hours shown in the social information with the number of weeks in a semester, assuming that the lecture and examination period of one semester jointly comprise a total of 18 weeks (this information is also provided to students in a footnote in the letter).

## 4. Data Preparation and Randomization Procedure

### 4.1 Prediction of the average number of hours spent on studying

To provide the individualized social information that is the basis for our treatments, we used data from surveys that we conducted at the university in the three prior semesters and in which we asked students: “Please think about the current semester: on average, how many hours per week do you dedicate to your studies?”<sup>6</sup>. We regressed answers to this question (N=1,359) on students’ sex, their age (at enrollment) and age squared, a dummy that indicates whether the first semester of their current study program was also their first semester at any university, the grade of their university entrance qualification (typically the high school GPA) and the grade squared, a dummy that indicates if their entrance qualification is the “Abitur”<sup>7</sup>, and whether they obtained their entrance qualification in Bavaria (i.e., the state in which the university is located). Based on this regression, we predicted the average number of hours that students spent on studying per week for all students in our intervention sample.<sup>8</sup>

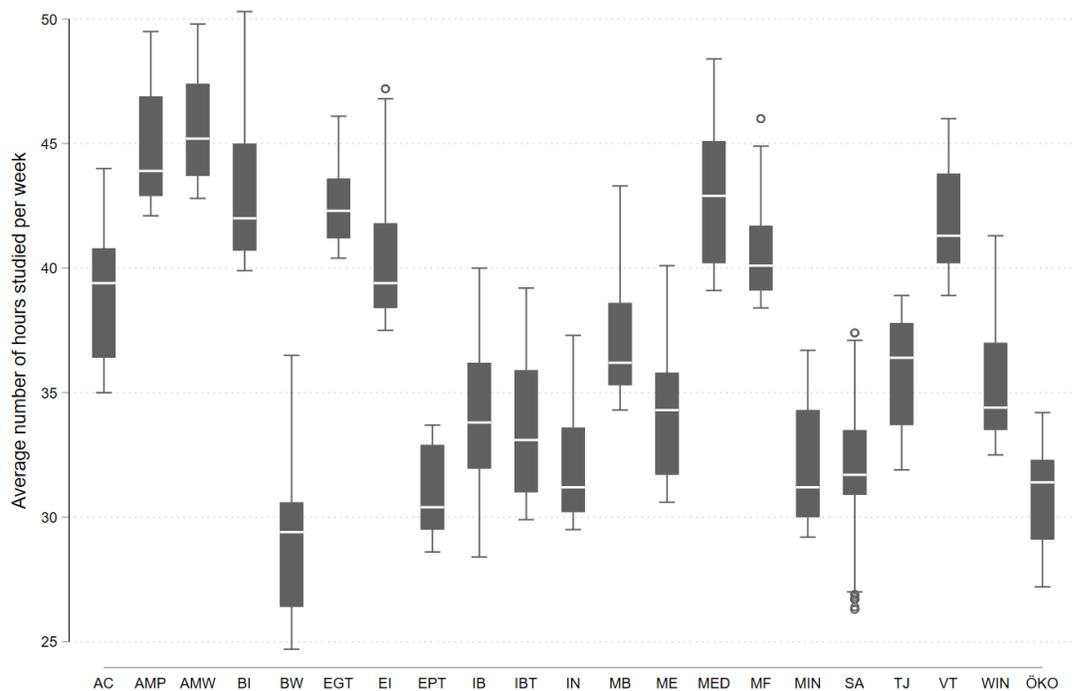
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<sup>6</sup> The question further reads “Please include all study activities, such as seminars or lectures you attend in person, streaming lectures, watching dubbed presentations, or video tutorials as well as your own study of lecture notes, textbooks, etc.”.

<sup>7</sup> The Abitur is 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”).

<sup>8</sup> The grade of the entrance qualification/high school GPA was missing for 40 observations in our sample. To keep the sample complete, we imputed those values based on a linear regression of the high school GPA on age at enrollment, a female dummy, time since high school graduation in years at enrollment, a high school degree

To prevent problems with outliers we made some changes to the data before and after prediction. To reduce the effects that outliers among the answers to the survey question have on the final predictions, we set all outliers to the adjacent values of the overall distribution (0 and 75), where the adjacent values are the highest value not greater than  $p75 + 3/2 \text{ iqr}$  ( $= \text{interquartile range } \text{iqr} = p75 - p25$ ) and the lowest value not less than  $p25 - 3/2 \text{ iqr}$ . As a results of this, 33 outliers at the top of the distribution were set to 75. After obtaining the predictions and depending on the number of observations within cohorts and study programs, we additionally winsorized the predicted values such that approximately 4 values (i.e., the number of experimental groups) at the bottom and the top of the distribution in each study program and cohort are set to the 1<sup>st</sup> to 20<sup>th</sup> and 99<sup>th</sup> to 80<sup>th</sup> percentile of the corresponding distribution. These adjusted predictions were then rounded to the first decimal place. Figure 2 shows box plots of the resulting predictions for the average number of hours spent on studying per week for the 21 study programs.



*Figure 2: Predictions of average number of hours studied per week by study programs (after outlier corrections)*

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Abitur dummy, a high school degree not from Bavaria dummy, a first semester at any university dummy, the date at which a student re-enrolled for the summer semester 2022 as well as study program dummies, and the interaction of all aforementioned variables with cohort dummies.

## 4.2 Stratification and randomization

The main goal of our randomization procedure was to achieve balance with respect to the whole distribution of the predicted average number of hours studied per week. To this end, the random assignment of students to the four experimental groups was conducted within blocks that we constructed in the following way: First, within cohorts and study programs, we further split our sample at the median of the average number of hours studied per week distribution to construct subgroups of above- and not-above-median students. Within these subgroups, we further stratified our sample by performing threshold blocking using the *R quickblock* package (Higgins et al., 2016). As the distance measure for the creation of blocks, we only considered the average number of hours studied per week. To allow for the formation of multiple homogeneous blocks in as many study programs as possible, minimal block sizes range between 16 (larger study programs) and 8 (smaller programs). The minimal block size of 8 was chosen to have at least two units per experimental condition in each block, in order to be able to calculate standard errors for the treatment effects (cf. Athey and Imbens 2017). Initial blocks with less than 16 observations were not considered for the threshold blocking. In total, we get 371 Blocks across the three cohorts and 21 study programs (101, 121, and 149 in the 8<sup>th</sup>, 6<sup>th</sup>, and 2<sup>nd</sup> semester cohort, respectively). Figures 2 and 3 illustrate the formation of blocks for the study programs Business Administration and Media Engineering. The subsequent within-block randomization using equal assignment probabilities was performed with *Stata's randtreat* command (Carril, 2017).

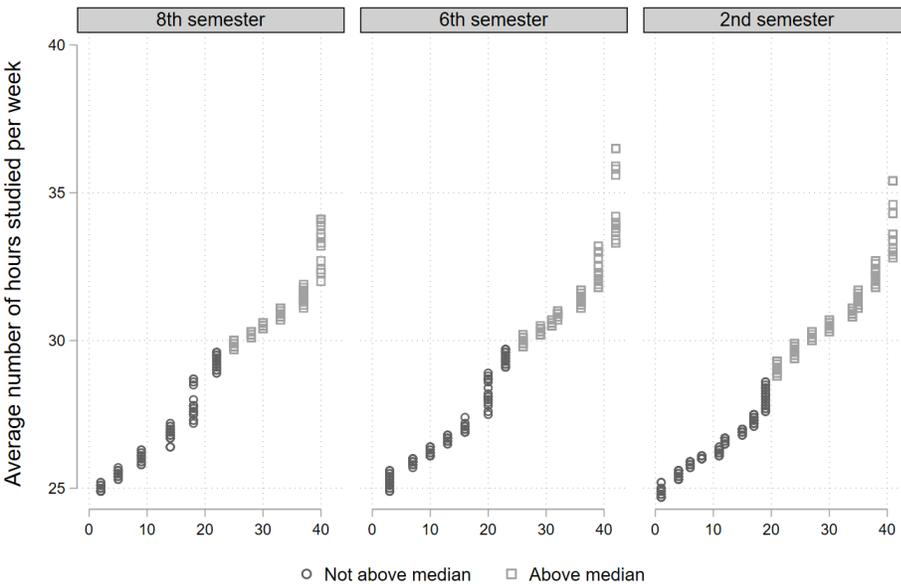


Figure 3: Example for threshold blocking in Business Administration, minimal allowed block size = 16, x-axis depicts block IDs.

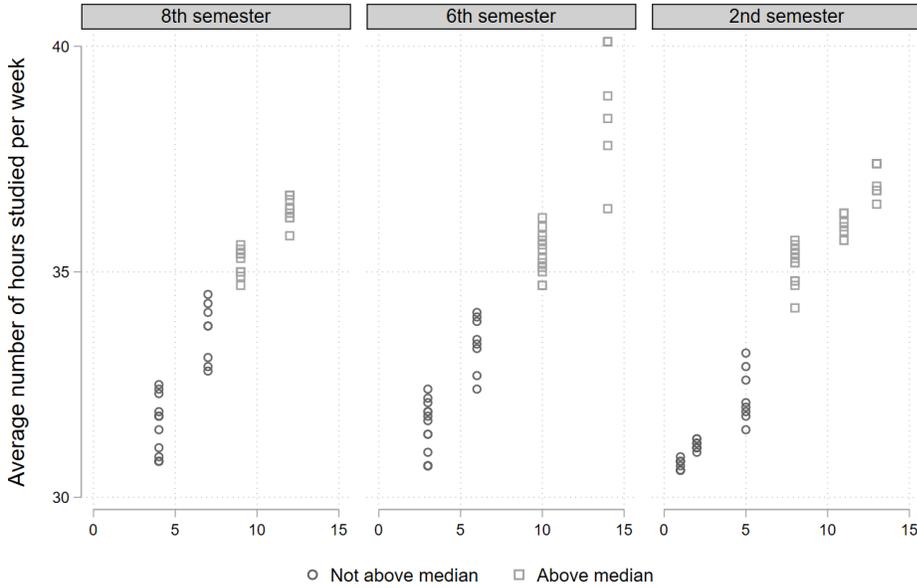


Figure 4: Example for threshold blocking in Media Engineering, minimal allowed block size = 8, x-axis depicts block IDs.

Table 2 shows the number of observations per experimental group as well as balancing characteristics for the variable used to construct the block (and the two variables that were afterwards calculated based on the average number of hours per week), the variables used for the prediction of the average number of hours, two additional variables (time since high school graduation in years (at enrollment) and the date at which students re-enrolled for the summer semester 2022), and, for the 2<sup>nd</sup> semester cohort, the treatment status in the intervention that was conducted in the 1<sup>st</sup> semester. The F-tests used for the construction of the p-values are based on regressions that control for block dummies and use robust standard errors. Tables 4 to 8 in the Appendix additionally show summary statistics and balancing properties in the subgroups of above- and not-above median students as well as in each of the three cohorts. Figure 5 shows kernel density plots of the average number of hours studied per week by cohorts and experimental groups and provides evidence that the variable is well balanced across the entire distribution.

Table 2: Summary statistics and balancing properties

	<b>T0</b>	<b>SI</b>	<b>STI</b>	<b>FTI</b>	<b>p-value F-test<sup>a)</sup></b>
<i>Blocking variable(s)</i>					
Avg. # of hours per week	35.542	35.446	35.544	35.529	0.789
Total # of hours invested	2465.926	2463.172	2477.652	2475.603	0.399
Total # of hours fut. sem.	639.769	638.046	639.789	639.513	0.753
<i>Variables used for average number of hours prediction</i>					
High school GPA	2.458	2.477	2.477	2.464	0.754
Age (at enrollment)	21.447	21.458	21.530	21.369	0.638
Female	0.396	0.390	0.392	0.397	0.930
HS degree "Abitur"	0.540	0.535	0.535	0.522	0.843

HS deg. outside Bavaria	0.142	0.137	0.142	0.141	0.996
First uni. sem. (at enr.)	0.720	0.737	0.727	0.723	0.800
<i>Additional variables</i>					
Years s. HS grad. (at enr.)	1.794	1.809	1.743	1.715	0.662
Re-enr. date for sum. 22	22664.191	22664.148	22664.201	22664.215	0.995
N	1,173	1,186	1,172	1,188	
<i>Treatment status in the first semester opportunity cost intervention<sup>b)</sup></i>					
Control	0.339	0.308	0.366	0.323	0.264
Earnings information	0.326	0.366	0.320	0.331	0.437
Opportunity cost	0.329	0.320	0.312	0.337	0.853
Not included	0.006	0.006	0.002	0.008	0.513
N	484	487	481	486	

Notes: a) The F-tests used for the construction of the p-values are based on regressions that control for block dummies and use robust standard errors. b) Only includes students from 2<sup>nd</sup> semester cohort, with whom another intervention was conducted in the first semester of their studies.

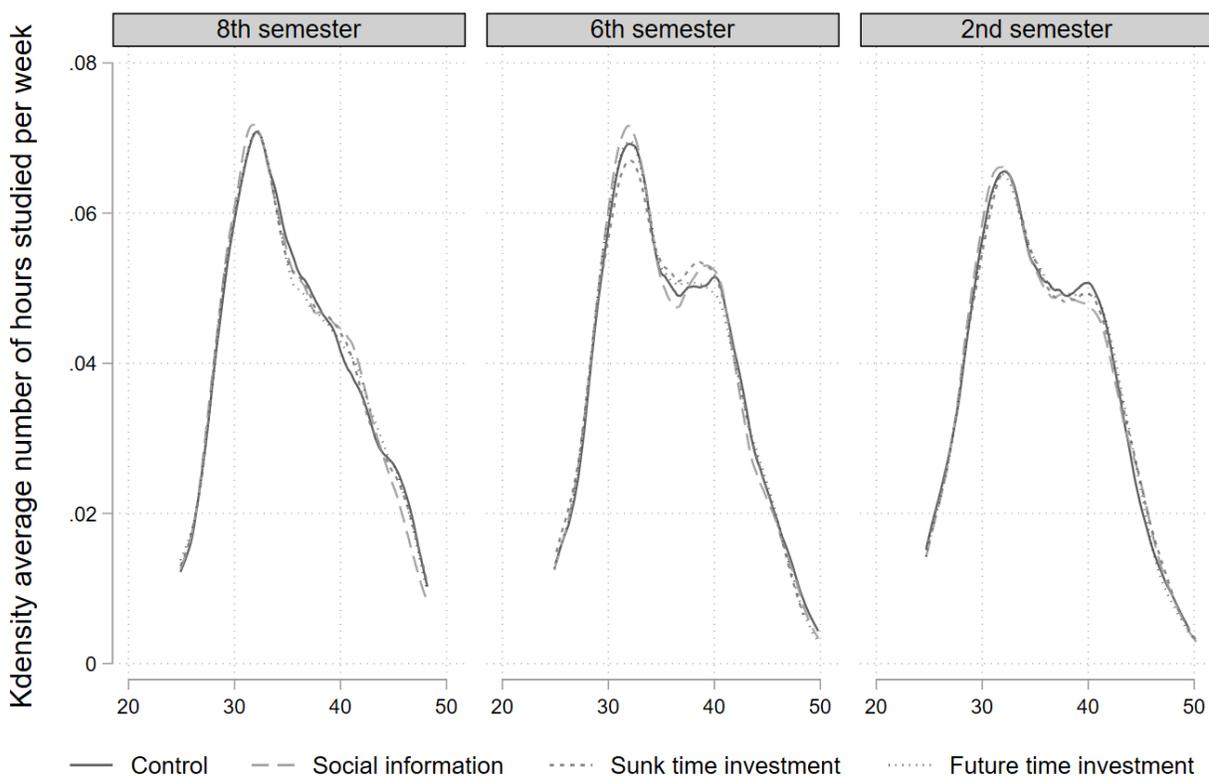


Figure 5: Kernel density of the average number of hours studied per week by cohorts and experimental groups

## 5. Statistical Power

Assuming  $\alpha = 0.05$ , in Table 3, we show minimum detectable effect sizes  $d$  for comparisons between two of the experimental groups for powers of 60% and 80% and for an assumed  $R^2$  of 0.00, 0.20, and 0.40 across a range of samples that correspond to the analyses described in Section 8. The two latter  $R^2$  are based on our experience with data from previous cohorts that shows that the variables used for blocking explain up to 40% of the variance in our main outcomes. In our second specification (see Section 8), we will also control for students' pre-treatment performance, which will probably result in an even higher  $R^2$ .

*Table 3: Minimum detectable effect sizes for treatment effect estimates between two experimental groups*

<b>Sample</b>	<b>Power</b>	<b>N<sup>a</sup></b>	(1) <b><math>d, R^2 = 0.00</math></b>	(2) <b><math>d, R^2 = 0.20</math></b>	(3) <b><math>d, R^2 = 0.40</math></b>
<i>All cohorts</i>	0.6	2,360	0.091	0.082	0.071
	0.8	2,360	0.115	0.104	0.090
<i>- abv. median</i>	0.6	1,150	0.131	0.117	0.101
	0.8	1,150	0.165	0.148	0.128
<i>- not abv. med.</i>	0.6	1,208	0.127	0.114	0.099
	0.8	1,208	0.161	0.144	0.125
<i>8<sup>th</sup> sem. cohort</i>	0.6	600	0.181	0.162	0.140
	0.8	600	0.229	0.205	0.177
<i>6<sup>th</sup> sem. cohort</i>	0.6	790	0.158	0.141	0.122
	0.8	790	0.200	0.179	0.156
<i>2<sup>nd</sup> sem. cohort</i>	0.6	970	0.142	0.128	0.110
	0.8	970	0.180	0.161	0.140

Notes: a) Total size of the respective subgroup divided by two and rounded to the next even number. Effect sizes  $d$  in Column (1) are calculated with the Stata power twomeans command. Effect sizes in Columns (2) and (3) are calculated with the Optimal Design software (Spybrooks et al., 2011).

## 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. Some of the information from those sources was used in the randomization procedure and we plan to use some of it as covariates.

The university will also provide us with information on the number of exams/credits that students sign up for<sup>9</sup> and with information on students' academic achievements, e.g., number of attempted and passed course credits, GPA, dropout, and graduation. We will use information from these sources for our outcome variables and to measure students' baseline, i.e., pre-treatment, performance, which we will include as control variables in our second specification.

*Online-Self-Assessments (OSAs):* During the enrollment process, students of nine 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 of the second semester cohort that takes about five minutes to complete. The module includes questions on subjects such as time preferences, procrastination tendencies, sunk 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 sunk cost consideration, the time students spent on studying, students' beliefs about the time other students spent on studying, students' expected and intended study duration, earnings expectations, as well as questions on non-cognitive outcomes such as stress, study satisfaction, and satisfaction with life in general.

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<sup>9</sup> 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.

## 7. Variables

*Primary outcomes:* Our primary outcomes of interest are the number of passed course credits, students' GPA, and whether students drop out of their study program (all measured at the end of the summer semester 2022). Since we have no clear hypothesis which of those variables should most be affected by our intervention, we will additionally create an index based on the standardized inverse-covariance weighted average of those outcomes (Anderson, 2008; Schwab et al., 2020). For the eighth semester cohort we will also consider whether students graduated successfully in the summer semester 2022.<sup>10</sup>

*Explanatory outcomes:* Course credits signed-up for and attempted. Time spent on studying, students' beliefs about the time that other students spent on studying, and the confidence in those beliefs, as well as the intended and expected study duration.

*Secondary outcomes:* To study whether our interventions negatively affect students' well-being, we will also study effects on non-cognitive outcomes such as stress, study satisfaction, and satisfaction with life in general. We will also create a well-being index 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). This includes the variables used for the prediction of the average time spent on studying and the two additional covariates shown in Table 2 as well as measures of students' baseline performance (as of March 14, 2022, the final day of the winter semester 2021/22), i.e., their accumulated course credits, their current GPA (missing values imputed)<sup>11</sup>, a dummy if the GPA is missing, and whether they re-enrolled for the summer semester 2022.<sup>12</sup> 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).

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<sup>10</sup> The scheduled study duration of all study programs included in our sample is seven semesters, meaning that the students included in the 8<sup>th</sup> semester cohort are already one semester behind schedule. In the 6<sup>th</sup> semester cohort, on the other hand, students are not supposed to graduate in the summer semester 2022.

<sup>11</sup> The GPA can be missing for students who have not attempted or passed any (graded) exams/credits. To avoid losing these observations when including measures of baseline performance, within each cohort, we will impute the baseline GPA based on a linear regression on all other covariates and a set of study program dummies.

<sup>12</sup> Our sample already excludes all students who did not re-enroll for the summer semester 2022 until March 01, which is when we received the data used for the randomization on March 03. However, for administrative reasons additional pre-treatment dropouts and graduations can occur until March 14, the end of the winter semester 2021/22, which results in these observations ultimately not being re-enrolled and not studying in the summer semester 2022.

## 8. Analyses

### 8.1 Main Analyses

We will perform our main analyses using OLS regressions with the following baseline specification:

$$y_i^k = \alpha_0 + \alpha_1 SI_i + \alpha_2 STI_i + \alpha_3 FTI_i + \mathbf{s}_i + \varepsilon_i,$$

where  $y_i^k$  is the primary outcomes of interest,  $SI_i$ ,  $STI_i$ , and  $FTI_i$  are dummies for being randomized in the respective treatment groups, and  $\mathbf{s}_i$  are FE that control for the random assignment within blocks. In a second specification, we will add a vector  $\mathbf{x}_i$  that includes the covariates and measures of baseline performance specified in Section 7.

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

1.  $H_0: \alpha_1 = 0$  vs.  $H_1: \alpha_1 \neq 0$ .
2.  $H_0: \alpha_2 = 0$  vs.  $H_1: \alpha_2 \neq 0$ .
3.  $H_0: \alpha_3 = 0$  vs.  $H_1: \alpha_3 \neq 0$ .
4.  $H_0: \alpha_1 = 0, \alpha_2 = 0, \alpha_3 = 0$  vs.  $H_1: \alpha_j \neq 0$  for at least one  $j = 1, 2, 3$ .
5.  $H_0: \alpha_2 - \alpha_1 = 0$  vs.  $H_1: \alpha_2 - \alpha_1 \neq 0$ .
6.  $H_0: \alpha_3 - \alpha_1 = 0$  vs.  $H_1: \alpha_3 - \alpha_1 \neq 0$ .
7.  $H_0: \alpha_3 - \alpha_2 = 0$  vs.  $H_1: \alpha_3 - \alpha_2 \neq 0$ .

Some outcomes are not observed for all students. For instance, the GPA is only observed for students who pass at least one graded exam/module, and all outcomes from the post-treatment online surveys that we consider in the explanatory and secondary analyses are only observed for students who answer the respective question. In these cases, we will study whether observing these outcomes is affected by treatment and, if applicable, adjust for potential differences using inverse probability weighting.

### 8.2 Explanatory and Secondary Analyses

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

1. We will study whether effects of the intervention are heterogeneous with respect to whether students placed above the median of the average number of hours spent on studying distribution or not (see Section 4.2 on stratification).
2. Additionally, we will study heterogeneity with respect to the average number of hours spent on studying using the continuous measure itself, standardizing it both within and across cohorts and study programs.
3. We will study whether effects of the intervention are heterogenous across cohorts.

4. To further investigate potential changes in students' behavior and beliefs, we will study treatment effects on our explanatory outcomes.
5. We plan to use data from the OSAs and online survey to study whether the treatment effects depend on survey measures of how prone students are to the sunk cost bias.
6. To study whether our interventions negatively affect students' well-being, we will also study effects on our secondary outcomes.
7. For the second cohort, we will explore whether the treatment effects depend on the treatment status in the first semester intervention that informed treated students about future earnings (see Section 2).

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## Appendix

Table 4: Summary statistics and balancing properties – students who are on or below the median time spent on studying

	<b>T0</b>	<b>SI</b>	<b>STI</b>	<b>FTI</b>	<b>p-value F-test<sup>a)</sup></b>
<i>Blocking variable(s)</i>					
Avg. # of hours per week	33.644	33.600	33.647	33.614	0.690
Total # of hours invested	2337.378	2357.778	2358.811	2335.338	0.677
Total # of hours fut. sem.	605.615	604.815	605.658	605.056	0.687
<i>Variables used for average number of hours prediction</i>					
HS GPA	2.564	2.547	2.566	2.555	0.843
Age (at enrollment)	20.659	20.587	20.574	20.710	0.620
Female	0.153	0.142	0.155	0.140	0.375
HS degree “Abitur”	0.557	0.508	0.531	0.517	0.415
HS deg. outside Bavaria	0.013	0.023	0.012	0.025	0.140
First uni. sem. (at enr.)	0.698	0.745	0.736	0.683	0.034
<i>Additional variables</i>					
Years s. HS grad. (at enr.)	1.399	1.290	1.244	1.421	0.222
Re-enr. date for sum. 22	22664.685	22664.224	22664.551	22664.251	0.600
N	600	612	599	606	

Notes: a) The F-tests used for the construction of the p-values are based on regressions that control for block dummies and use robust standard errors.

Table 5: Summary statistics and balancing properties – students who are above the median time spent on studying

	<b>T0</b>	<b>SI</b>	<b>STI</b>	<b>FTI</b>	<b>p-value F-test<sup>a)</sup></b>
<i>Blocking variable(s)</i>					
Avg. # of hours per week	37.529	37.416	37.526	37.523	0.727
Total # of hours invested	2600.531	2575.544	2601.885	2621.651	0.374
Total # of hours fut. sem.	675.532	673.477	675.469	675.390	0.701
<i>Variables used for average number of hours prediction</i>					
HS GPA	2.347	2.402	2.385	2.369	0.530
Age (at enrollment)	22.273	22.387	22.530	22.056	0.117
Female	0.651	0.655	0.639	0.665	0.580
HS degree “Abitur”	0.522	0.564	0.539	0.527	0.391
HS deg. outside Bavaria	0.277	0.258	0.277	0.263	0.801
First uni. sem. (at enr.)	0.742	0.728	0.717	0.765	0.255
<i>Additional variables</i>					
Years s. HS grad. (at enr.)	2.208	2.362	2.264	2.021	0.119
Re-enr. date for sum. 22	22663.674	22664.068	22663.836	22664.177	0.429
N	573	574	573	582	

Notes: a) The F-tests used for the construction of the p-values are based on regressions that control for block dummies and use robust standard errors.

Table 6: Summary statistics and balancing properties – 8<sup>th</sup> semester cohort

	<b>T0</b>	<b>SI</b>	<b>STI</b>	<b>FTI</b>	<b>p-value F-test<sup>a)</sup></b>
<i>Blocking variable(s)</i>					
Avg. # of hours per week	35.522	35.321	35.478	35.474	0.481
Total # of hours invested	4475.796	4450.510	4470.168	4469.758	0.483
Total # of hours fut. sem.	639.415	635.790	638.604	638.520	0.465
<i>Variables used for average number of hours prediction</i>					
HS GPA	2.402	2.418	2.442	2.401	0.604
Age (at enrollment)	21.373	21.437	21.384	21.166	0.637
Female	0.439	0.403	0.439	0.440	0.603
HS degree “Abitur”	0.568	0.527	0.568	0.536	0.691
HS deg. outside Bavaria	0.119	0.127	0.135	0.129	0.860
First uni. sem. (at enr.)	0.728	0.733	0.693	0.735	0.635
<i>Additional variables</i>					
Years s. HS grad. (at enr.)	1.726	1.831	1.694	1.663	0.816
Re-enr. date for sum. 22	22663.330	22663.917	22664.020	22663.977	0.295
N	294	300	303	302	

Notes: a) The F-tests used for the construction of the p-values are based on regressions that control for block dummies and use robust standard errors.

Table 7: Summary statistics and balancing properties – 6<sup>th</sup> semester cohort

	<b>T0</b>	<b>SI</b>	<b>STI</b>	<b>FTI</b>	<b>p-value F-test<sup>a)</sup></b>
<i>Blocking variable(s)</i>					
Avg. # of hours per week	35.661	35.512	35.546	35.564	0.737
Total # of hours invested	3209.491	3196.083	3199.152	3200.760	0.737
Total # of hours fut. sem.	641.932	639.233	639.845	640.158	0.715
<i>Variables used for average number of hours prediction</i>					
HS GPA	2.457	2.459	2.473	2.482	0.909
Age (at enrollment)	21.687	21.587	21.470	21.417	0.530
Female	0.390	0.386	0.381	0.398	0.974
HS degree “Abitur”	0.539	0.549	0.523	0.505	0.570
HS deg. outside Bavaria	0.162	0.135	0.144	0.140	0.652
First uni. sem. (at enr.)	0.663	0.719	0.753	0.720	0.051
<i>Additional variables</i>					
Years s. HS grad. (at enr.)	2.009	2.019	1.780	1.764	0.181
Re-enr. date for sum. 22	22663.797	22663.271	22663.595	22663.720	0.666
N	395	399	388	400	

Notes: a) The F-tests used for the construction of the p-values are based on regressions that control for block dummies and use robust standard errors.

Table 8: Summary statistics and balancing properties – 2<sup>nd</sup> semester cohort

	<b>T0</b>	<b>SI</b>	<b>STI</b>	<b>FTI</b>	<b>p-value F-test<sup>a)</sup></b>
<i>Blocking variable(s)</i>					
Avg. # of hours per week	35.457	35.470	35.583	35.535	0.707
Total # of hours invested	638.219	638.464	640.491	639.599	0.705
Total # of hours fut. sem.	638.219	638.464	640.491	639.599	0.705
<i>Variables used for avg. # of hours prediction</i>					
HS GPA	2.493	2.528	2.504	2.488	0.672
Age (at enrollment)	21.297	21.366	21.671	21.456	0.392
Female	0.376	0.386	0.370	0.370	0.764
HS degree “Abitur”	0.523	0.530	0.524	0.527	0.988
HS deg. outside Bavaria	0.140	0.144	0.143	0.150	0.943
First uni. sem. (at enr.)	0.760	0.754	0.728	0.718	0.354
<i>Additional variables</i>					
Years s. HS grad. (at enr.)	1.659	1.624	1.743	1.707	0.932
Re-enr. date for sum. 22	22665.035	22665.010	22664.805	22664.770	0.948
<i>Treatment status in the first semester opportunity cost intervention</i>					
Control	0.339	0.308	0.366	0.323	0.264
Earnings information	0.326	0.366	0.320	0.331	0.437
Opportunity cost	0.329	0.320	0.312	0.337	0.853
Not included	0.006	0.006	0.002	0.008	0.513
N	484	487	481	486	

Notes: a) The F-tests used for the construction of the p-values are based on regressions that control for block dummies and use robust standard errors.