Making Sunk Study Time Salient – A Field Experiment in Higher Education

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Abstract: *This paper presents a field experiment that provides university students with information about their study time investments to activate the sunk-cost (SC) effect. Three treatments are tested: one provides information about the study time of similar peers, the second frames peer study time as sunk costs, and the third as future costs. Across all treatments, we find no statistically significant effects on any pre-registered outcomes: GPA, credits, exam sign-up, dropouts, graduation, study and life satisfaction, stress, and related indices. The small standard errors suggest that the lack of significance is due to small, policy-irrelevant treatment effects rather than low statistical power. Heterogeneity analyses show no differences between students in early, mid, or late semesters, nor between subgroups whose peer study time is above or below the median. Unlike previous studies, we find no evidence that the SC treatment specifically affects students prone to the SC bias.*

Keywords: *Information Treatment, Sunk-Cost Effect, Higher Education, RCT*
JEL: *I23, C93, D91*

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I. Introduction

Rational, fully informed individuals should ignore costs that have already been incurred and cannot be recovered when making choices. Yet, both theoretical and experimental findings show that this normative approach is often ignored in practice. On the contrary, many individuals tend to increase their engagement in a project as the amount of time or money already spent rises – a behavior well known as the sunk-cost effect (c.f. Arkes and Blumer, 1985; Thaler, 1980).

In this paper, we present the results of a field experiment that investigates the effects of providing university students with information about different dimensions of time investment on academic performance. The main treatment aims to activate the sunk-cost (SC) effect by making the time students have already spent studying salient. Our goal is to use the SC effect to benefit students by increasing their effort, thereby counteracting other common biases that contribute to poor academic performance,[1] [2] such as lack of self-control, limited attention, or an inaccurate self-assessment.[3] To isolate the sunk-cost effect, three treatments are implemented: one provides students with information about the average weekly study time spent by similar peers, the second frames this peer study time as sunk costs, and the third frames the information as a variable investment for future semesters.

According to the literature, the sunk-cost effect can influence studying through several mechanisms: 1) Students may derive additional utility (`transaction' or `acquisition utility') if they continue or intensify their previous study efforts (cf. Arkes and Blumer, 1985; Thaler, 1980). 2) Sunk study time may act as a heuristic, signaling the initial intention and motivation of studying (c.f. Baliga and Ely, 2011; Hong et al., 2019), which may help students decide how much to invest in future semesters. 3) Students may increase their study effort because they are averse to potential losses (in past study time) or due to the desire for consistent decisions (Ashraf et al., 2010; Eyster, 2002; Thaler, 1980). 4) Lastly, Cunha and Caldieraro (2009) suggest that non-monetary sunk costs can trigger an effort-justification mechanism, prompting individuals to account for past time investments, when making decisions.[4] [5]

The natural field experiment (Harrison and List, 2004) was conducted at one of Germany's largest universities of applied sciences, involving all 4,719 bachelor students enrolled in the 2nd, 6th, and 8th semesters across 21 different degree programs during the summer semester of 2022.[6] [7] The

[1] Improving decisions by using a bias to counteract other biases is, for example, described in Dhami (2016) and Loewenstein et al. (2013).
[2] Poor academic performance is a global issue, with many students failing to graduate or experiencing delays in completing their degrees. In OECD countries, for example, less than 40% of students complete their bachelor's degree within the planned timeframe, and approximately 23% have left tertiary education without obtaining a degree (OECD, 2022).
[3] Overview articles that describe common biases in education are, for example, Damgaard and Nielsen (2018), Koch et al. (2015), Lavecchia et al. (2016), and Leaver (2016).
[4] Most previous studies focus on monetary sunk costs. Cunha and Caldieraro (2009), as well as Navarro and Fantino (2009) show that the sunk-cost effect can also be observed with time resources.
[5] Coleman (2010) and Ketel et al. (2016) show that sunk costs can influence educational decisions. The fact that younger individuals in particular are affected by sunk costs (Strough et al., 2008; Strough et al., 2011) further supports the potential for such effects in the educational context.
[6] German universities operate on a two-semester system per year. Most degree programs start in fall, so students are typically in their 2nd, 4th, 6th, 8th, etc., semesters during the summer term. Students in the 4th semester were part of another intervention and therefore excluded from our sample.
[7] The scheduled duration for all study programs included in our sample is seven semesters, meaning that the students in the 8th semester cohort are already one semester behind schedule.

information treatments were sent by the university via postal letters four days before the semester began. To remind students of the information during the exam preparation period, students received a second letter five weeks before the final exam period, containing the same information as the initial letters.

The control group received a letter with general counseling and university services information, which was also included in the three treatment letters. The social information (SI) group was provided with personalized information about the average weekly study time of similar peers, with only a few students seeing the same predicted peer study time.[8] The second treatment framed this information as a sunk time investment (ST). In addition to the SI-treatment, it informs students about the time they have invested in their studies from the first semester to the present.[9] By combining the results of the first and second treatments, we aim to identify the pure sunk-cost effect, excluding factors such as social norms or peer effects implicitly included in the sunk-cost treatment. In the third treatment arm we supplemented the SI treatment with information about one's remaining variable time costs per future semester – the future time investments (FT).[10] This treatment serves as a control condition, making future study costs salient, as students themselves could infer information about future study costs from the SI and ST treatments.

We find null results for all variables specified as primary outcomes in the pre-analysis plan across all treatments. None of our interventions significantly affected passed course credits, GPA, dropouts, or graduation (the latter is analyzed only in the eighth-semester cohort). The effect sizes for credits, graduation and GPA are also negligible from a policy perspective. For example, the coefficients for GPA (ranging from 0.002 to 0.008 grade points) are minimal compared to an average GPA of 2.42 (with a standard deviation (s.d.) of 0.58). Given the very small standard errors (0.009), not even the bounds of the 95% confidence encompass economically meaningful treatment effects.[11] [12] Similarly, the pre-registered secondary outcomes – stress, study satisfaction, and life satisfaction (all assessed through a survey during the semester)[13] – showed no policy-relevant and statistically significant results.

Since it was unclear ex-ante which outcomes would be most affected, we created a performance index based on the standardized inverse-covariance weighted average of the main outcomes (Anderson, 2008; Schwab et al., 2020). The distribution of the index across all treatment groups is virtually identical to the distribution in the control group. The point estimates of regressing the index

[8] We predicted individual study time using an OLS regression with variables such as gender, age at enrollment, and time since high school graduation, based on a survey of 1,359 students. The survey was conducted in the three semesters prior to the intervention, asking students about their average weekly study time, including lectures, seminars, self-study, etc.

[9] To calculate this number, we multiply the hours shown in the SI-treatment by the number of weeks that a student has been enrolled in their current study program, assuming that the lecture and examination period of one semester together total 18 weeks.

[10] This number is calculated by multiplying the hours shown in the SI-treatment by the 18 weeks that the lecture and examination period of one semester last.

[11] According to a study by Kraft (2020), which summarizes almost 750 randomized control trials in education, an effect size of 0.1 standard deviations (or below) is considered "small". Our GPA effect ranges from 0.3% to 1.3% of a standard deviation, and even at the upper bound of the 99% confidence interval, the effect size would still be only 2.5% to 3.1% of a standard deviation. When considered in absolute (or relative) terms, the effects are also small: for example, with an effect size of 0.008 students would see their GPA worsen from 2.42 to 2.43 grade points, reflecting a modest decrease of 0.33%.

[12] Only for dropouts with insignificant parameters between -0.5 and -1.2 percentage points, the bounds of the confidence intervals (SE: 0.1) compared to the control mean of 9.7% (SD: 0.3) may be economically relevant. However, even in this case, the standardized effect sizes (Cohen's d) are very small, ranging between -0.0167 and -0.04.

[13] The survey was voluntary, with a response rate of 10%.

on the treatments range between 0.5 and 3.7 percent of a standard deviation (not statistically significant) and are therefore not relevant from a policy perspective.[14] In the pre-analysis plan we showed that we could detect effect sizes between 7 to 10 percent of a standard deviation at the 5 percent significance level. Importantly, with standard errors of the index estimates between of 0.026 and 0.027, we would have been able to detect the expected minimum effect sizes. Therefore, the lack of significant results is due to the small point estimates, not low study power.

We also tested for heterogeneity along several pre-registered dimensions but did not find any results. First, for all treatments, it is possible that the effects vary depending on the presented peer study time. Therefore, we split the sample at the median of the personalized study time predictions to check for different effects for students above or below this threshold. However, treatment effects across all treatments on all main outcomes and the index remained economically small and statistically insignificant. Second, since the amount of sunk time investments varies with the number of semesters, and since it is possible that higher costs lead to stronger sunk-cost effects, we analyze whether the effects differ based on whether students were in the early (2nd semester cohort), middle (6th semester cohort), or final stage (8th semester cohort) of their studies.[15] Again, across all treatments no statistically or educationally relevant effects were found. Third, we interacted the two dimensions but once again did not find any systematic differences within the cohorts, low vs. high study time groups.

We begin investigating the mechanism behind our null results by examining whether the treatment effects dissipate too early to influence the main outcomes that realize only at the end of the semester. At the university where our study is conducted, students are required to sign up for their exams just four weeks into the semester.[16] We use this variable to explore whether our treatments have affected students' intentions to increase their performance early on. However, we find no significant treatment effect on the number of exams students sign up for.[17]

Second, we use survey data collected midway through the semester, with a response rate of 10%, to examine whether there is an effect on study time. The patterns of results are inconsistent across treatments. While the SI and the FT treatments increase study time by approximately 4 hours per week, the sunk-cost treatment reduces study time by 3.1 hours. These effects are policy-relevant in size, but none of them are statistically significant. We also measured students' expectations about how much time they think others in the same degree program are studying. The results are not statistically significant either, the SI and the FT increase expectations by about 3 hours, and the ST is close to zero (0.6 hours).

Lastly, for the 2nd semester cohort, we were permitted to include questions aimed at identifying students' sunk-cost proneness in an online self-assessment (OSA) survey, which was conducted by

[14] We also found no significant results using an index that summarizes the secondary outcomes stress, study satisfaction, and overall life satisfaction.
[15] Naturally, it is also possible that effects of the social information and variable cost treatments exhibit heterogeneity.
[16] Sign-up is required to attend an exam, but there are no consequences for not showing up.
[17] We also examined cohort heterogeneity for these results but only found an effect on sign-ups within the SI-treatment group in the 8th semester cohort. However, there was no significant treatment effect on attempted or passed exams in this group, indicating that the effect dissipated by the end of the semester.

the university before students' first semester enrollment. Since the OSAs are mandatory for some degree programs, the response rate was 50%. In contrast to Ketel et al. (2016), we do not find differential treatment effects among students prone to the sunk-cost effect.

As we will discuss below, the null results align with findings in the literature on information treatments. Therefore, since none of the different treatments showed any effects on academic outcomes, two explanations are possible. First, similar to Oreopoulos and Petronijevic (2019), and Oreopoulos et al. (2022) the impact of our interventions on study time may simply not be large enough to translate into a change of academic outcomes. Second, since the study time estimates are inconclusive across treatment arms and not statistically significant, it is also likely that the interventions were not 'strong' enough or that students did not perceive, understand, or remember the information we provided to them.

Contribution to the literature. In a simple human capital model (Becker [1964] 1993; Mincer 1974), rational individuals should remain unaffected by any of the above treatments. However, due to information frictions, limited attention, missing salience, or imperfect memory, students may lack the necessary information to make optimal decisions in their studies.[18] One way to address this is through information interventions (see e.g., Frey and Meier, 2004; Dizon-Ross, 2018; Jensen, 2010; Kling et al., 2012).

In educational settings, students have been provided with various types of information, including financial aid (e.g., Bettinger et al., 2012; Dinkelman and Martinez, 2014; Hoxby and Turner, 2015), returns to schooling and potential earnings (e.g., McGuigan et al., 2014; Oreopoulos and Dunn, 2013; Berkes et al., 2022; Wiswall and Zafar, 2015a, 2015b), and other topics like plagiarism (Dee and Jacob, 2012), or information about the educational experiences of adults and famous scientists (Dinkelman and Martinez, 2014; Lin-Siegler et al., 2016).[19] Our study contributes to this literature by informing students about the study time of similar peers,[20] the sunk time costs they have already invested, and the variable costs of the remaining semesters. The null results align with the mixed findings in the existing literature. While some studies, such as those on parental support, show positive effects, others, such as research on information about returns to schooling in developed countries or financial aid, report little or no effects on educational outcomes (see Damgaard and Nielsen, 2018).

Secondly, we contribute to the literature on the sunk-cost bias, which often reports large behavioral effects (see the meta-analysis by Roth et al., 2015). For example, Arkes and Blumer (1985) demonstrate the sunk-cost effect in the context of theater subscriptions, Ho et al. (2018) find that car usage is positively affected by the sunk registration fee, and Staw and Hoang (1995)

[18] Classical discussions on salience and perception effects can be found in Tversky and Kahneman (1981) and Kahneman and Tversky (1984). Broadbent (1958), Bordalo et al. (2013), Chetty et al. (2009), DellaVigna (2009), and others model attention as a scarce resource and/or assume that individuals place greater weight on salient attributes. Limited attention and salience are, for example, studied in the context of delivery fees on eBay (Hossain and Morgan, 2006); taxes that are not explicitly stated (Chetty et al., 2009); investors who fail to adequately incorporate new information (Huberman and Regev, 2001). Forgetting or imperfect memory are discussed, for example, in Ericson (2017), DellaVigna and Malmedier (2006), or Baliga and Ely (2011) as a cause of irrational behavior such as procrastination or the sunk cost bias.
[19] Details can be found in the overviews of Damgaard and Nielsen (2018), Koch et al. (2015), Lavecchia et al. (2016), and Leaver (2016).
[20] An interesting note regarding study time investment is the paper by Babcock and Marks (2011). They document a significant decrease in academic time investment by full-time students in the U.S. from 40 hours per week on coursework in 1961 to 27 hours by 2003.

document the impact of sunk draft orders on professional basketball players' playing time. Two recent studies are Beknazar-Yuzbashev et al. (2024) and Ronayne et al. (2021). Beknazar-Yuzbashev et al. (2024) found a small but significant effect (0.09 SD or 1.1 minutes) in an online experiment with varying ticket prices, but no impact of ad duration on video abandonment in a YouTube field study with over 11,000 videos. This may be due to the extensive margin: longer ads led to more users leaving before the video began. In the study by Negrini et al. (2022), the authors found an opposite sunk-cost effect in hypothetical investment decisions.

Since we measure academic sunk cost in terms of study time, the papers by Cunha and Caldieraro (2009) and Navarro and Fantino (2009) are particularly relevant, as they demonstrate the existence of a sunk-cost effect in time resources. In contrast to the existing literature, our study does not show a sunk-cost effect. However, since our complementary treatments also do not change behavior, it seems reasonable that the absence of the effect could be due to the missing perception of the information provided, rather than the lack of a sunk-cost effect.

Finally, the only studies we are aware of on sunk-cost effects in (higher) education are by Coleman (2010) and Ketel et al. (2016). The former examines a hypothetical situation where students choose between different course fees and finds that those with higher fees are more likely to invest more time in the course. In a field experiment, Ketel et al. (2016) randomly assign discounts on university course fees. They find no effect on overall course attendance or performance, but show a negative relationship between the size of the discount and course attendance for a group of students identified as sunk-cost prone. Our research examines the importance of sunk costs in time not just for one course, but for 21 entire degree programs, making it potentially applicable to universities worldwide. In addition, based on hypothetical survey questions on being sunk-cost prone by Ashraf et al. (2010), Ketel et al. (2016), and Strough et al. (2014), we test whether a sunk-time effect occurs for this subset of students, but find no evidence to support it.

The remainder of the paper is structured as follows: Section II outlines our information interventions, provides details of the RCT and the datasets used, and describes the definition of our key variables of interest. Section III presents the empirical strategy. Sections IV and V report the main results of the information intervention and explore potential mechanism. Section VI concludes.

II. Institutional Background, Research Design, and Data

A. Institution and Research Design

The field experiment was implemented at a university of applied sciences (UAS) in Germany during the summer semester of 2022. It involves the entire bachelor's population of 4,719 students enrolled in the 2nd, 6th, and 8th semesters across 21 different degree programs.[21] This set up reflects

[21] German universities follow a two-semester system each year. Most degree programs begin in the fall, meaning students are typically in their 2nd, 4th, 6th, 8th, etc., semesters during the summer term. In the paper, we sometimes refer to the 2nd, 6th, and 8th semester cohorts as 2021, 2019, and 2018 cohorts.

a substantial share of the German higher education system. In 2022, 40% of the German student population were enrolled in UAS institutions (Statistisches Bundesamt, 2023).

The typical duration of all study programs in our sample is seven semesters, i.e. students in the 8th semester cohort are already one semester behind schedule, and students in the 2nd and 6th semester are in the first and second stages of their degree programs. Access to the full student population of the respective cohorts eliminates any selection bias.

Timeline. Figure 1 shows the timeline of the intervention and the semester schedule. The randomization was conducted shortly before the summer semester 2022 started. Relying on administrative university records of all re-enrolled students, we used the background characteristics of the students to randomize 4,719 students into three treatment arms and one control group. Four days before the semester started, all students received a first unannounced postal letter sent to their home addresses. 10 weeks later and 5 weeks ahead of the final exam period, students received a 2nd identical letter to increase the salience of the treatments in the critical exam preparation period. A post-treatment online survey was administered between the 1st and 2nd letter. The university conducted the online self-assessment (OSA) before students' enrollment in their first semester. For the 2021 cohort, the university's administration allowed us to include additional questions in the OSA.

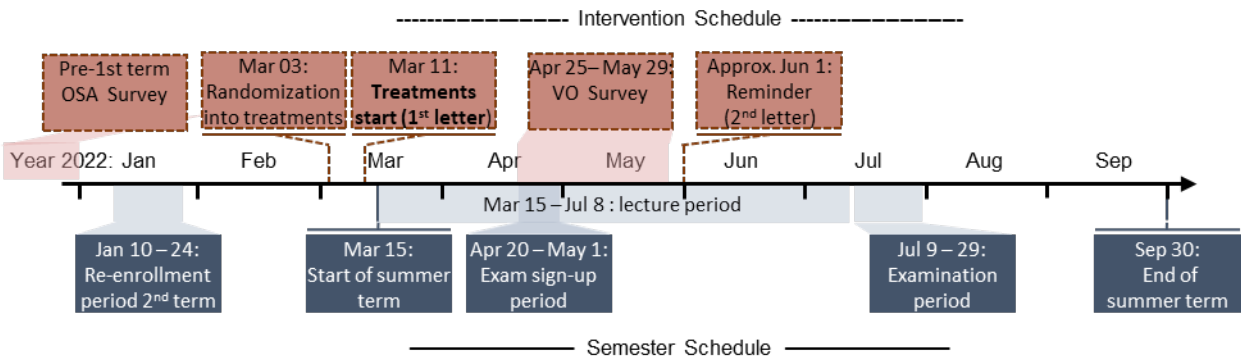

FIGURE 1. TIMELINE OF THE INTERVENTION AND UNIVERSITY SEMESTER

Notes: The figure shows the timeline of the intervention and the university semester for summer term of 2022.

Design of the Intervention. The letter sent to the *control group (CO)* contains information about counseling and information services offered by the university (the original German wording of the letters are depicted in Figure A 1, Panel (a) in the Appendix). This kind of information is also publicly available on web pages and in other informational materials of the university, and we also include it in the letters of the other three treatment arms.

The *social information treatment (SI,* Figure A 1, Panel (b)) provides information regarding the time students with similar characteristics (sex, age, university semester as well as grade, type, and place of the university entrance qualification) spent studying per week during the semester. Consequently, it offers insights a fully rational student with incomplete information about the time input, necessary to successfully complete a study program, may utilize to revise their investment choices. The following statement is made in the letter *"Students similar to you dedicate an average of* ***[estimate] hours per week*** *to their studies during the semester.[2]"*. The footnote delineates the sources of that information and the criteria for defining similar students.

Motivated by the literature on sunk cost discussed above, the *sunk time investment treatment (ST)* incorporates a sunk-cost framing by adding the sentence *"From your first semester until today, you have therefore invested an estimated* ***[estimate] hours*** *in your current study program (as of [date]) [3]"* (see Figure A 1, Panel (c)). The footnote outlines how we arrived at this number. It was calculated by multiplying the hours shown in the SI treatment by the number of weeks that a student has been studying their current study program, assuming that the lecture and examination period of one semester collectively comprise a total of 18 weeks.

In the *future time investment treatment (FT,* Figure A 1, Panel (d)), study time is framed as the variable costs of the remaining future time investment necessary to complete the study program. In addition to the statement provided in the SI treatment, the letter contains the following statement: *"In each future semester of your current study program, you will therefore invest an estimated* ***[estimate] hours****."*.

Predicted Study Time. In all treatments, we rely on individualized social information about the study time of the students. To predict the study time we used the following approach: In the three semesters prior to the intervention, we conducted surveys asking students: *"Please think about the current semester: on average, how many hours per week do you dedicate to your studies?"*.[22]

Based on a sample of 1,359 students who responded to the surveys, we estimated linear prediction of study time by a running an OLS regression of reported study time on socio-demographic variables like gender, age at enrollment, time since high school degree, and the re-enrollment date.[23] This information was then reported in the SI and in all other treatment groups.

For the ST group, we calculate the sunk time by multiplying the predicted weekly study time by the number of weeks the students have studied between their first semester and the present, assuming 18 weeks of active study per semester.

In the FT group we simply multiply the predicted study time per week by 18 (the number of active study weeks per semester).[24]

Randomization. We used stratified randomization to allocate the students into the treatment arms and the control group. 371 strata were formed using information about cohort, study program, and the predicted study time. Since study achievements (GPA, credits) for the semester prior to the treatment were not available at the time of randomization, we could not use them for the randomization process, but we included them as control variables in the estimations. Within each

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[22] 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.".

[23] In the pre-analysis plan, we provide detailed information on all variables included in the model, as well as information, on how we handled with extreme predictions. The pre-analysis plan also includes detailed descriptive statistics on the study time predictions used in the intervention.

[24] All students were informed on the methodology that we used to derive the study time predictions, In a footnote of the information letters, we explained how the study time information for the respective treatment group was computed.

strata, students were then assigned with equal probability to either one of the three treatment groups or the control group. Further details are described in the pre-analysis plan.

B. Data

Administrative Data. We have access to the university records for the entire population of bachelor's students. The record includes socio-economic background information collected during the application process, such as high school GPA, gender, age at enrollment, and information about the state of residence prior enrollment. Additionally, the records contain information on students' academic achievements, including the number of attempted and passed course credits, GPA, dropout status, and graduation data.

Survey data. We further match the administrative records to survey data collected prior to and after the intervention. Independently of our RCT, the university conducts online self-assessments (OSA) during the enrollment period before the first semester. For students of nine study programs participation in the OSA survey is mandatory, while participation is optional for students in other study programs. We were permitted to add a 5-Minute survey module to the OSAs prior to the first semester of the 2021 cohort. The module included questions about time preferences, procrastination tendencies, sunk cost considerations, and earnings expectations.

Two months after the treatment started, we invited students to a voluntary online (VO) survey. In the survey we collected information on sunk-cost considerations, study time considerations, and earnings expectations. We also asked questions on non-cognitive outcomes such as stress, study satisfaction, and satisfaction with life in general.

C. Variable Definitions

Academic achievement, planned and attempted exams. Our main interest lies in the effect of the treatments on students' academic achievements, measured by dropout rates, successful graduation, passed course credits points, and the grade point average (GPA). We use credit points instead of the number of courses passed, as credit points account for differences in course length and are measured in ECTS units, which make this performance measure comparable across universities in Europe.[25] To summarize all performance measures into one index, we compute their standardized inverse-covariance weighted average (Anderson 2008; Schwab et al. 2020).

During the treatment semester, we have also access to the exam registration data. This data set includes information on the planned study performance of students measured by their exam sign-up four weeks into the semester. Sign-up is not binding and therefore proxies the indented study performance in the post-treatment semester. Furthermore, we also observe whether students actually showed-up in the exam and use this variable to measure `attempted' credits.

Survey measures on study effort, stress, and well-being. To better understand the mechanisms behind potential effects on study performance, we use measures from the post-treatment survey to

[25] The abbreviation ECTS refers to the European Credit Transfer and Accumulation System. We also constructed a second 'net' credit point measure for which we deducted transferred credits from other study programs from the overall amount of credit points.

estimate effects on study time, beliefs about others' study time, confidence in those beliefs, as well as the intended and expected study duration. To assess potential side-effects, we rely on Likert-scale measures on self-reported stress, study satisfaction, satisfaction with life in general and a summary index of these measures (Anderson, 2008).

Background characteristics from the university enrollment register. We have access to all information that students are required to submit during the application process. This includes gender, high school GPA, age at initial enrollment, the type and date of the high school degree (A-level), as well as the state in which the high school degree was obtained. Additionally, we can observe whether students are enrolled for the first time and the specific re-enrollment date for each semester.

III. Descriptives and Empirical Strategy

A. Descriptives and Balancing Properties

Table 1 presents the pre-treatment study performance, predicted study time, and the baseline characteristics for each experimental group, based on the full population of students in the 2nd, 6th, and 8th semester cohorts of 2022. Unlike the other variables, academic achievements from the pre-treatment semesters were only available after randomization and, therefore, could not be used to optimize the randomization process.

TABLE 1—BASELINE CHARACTERISTICS & BALANCING

	Control Group	Social Information (SI) Treatment	Sunk Time (ST) Treatment	Future Time (FT) Treatment	Joint Orthogonality Test (p-value)
Main Outcomes (baseline values, $t-1$)					
1[Dropout]	0.003	0.007	0.003	0.005	0.45
1[Graduation]	0.011	0.008	0.009	0.01	0.83
Credits Points (ECTS)	91.6	89.3	89.1	91.3	0.76
Net Credits Points (ECTS)	90.1	87.7	87.8	89.6	0.79
GPA (1 = very good – 4 = sufficient)	2.41	2.40	2.46	2.43	0.11
1[Missing GPA]	0.091	0.096	0.082	0.087	0.66
Further Variables					
Predicted Study Time (hours per week)	35.5	35.4	35.5	35.5	0.97
Female	0.40	0.39	0.39	0.40	0.98
High School GPA (1 = very good, 6 = insufficient)	2.46	2.48	2.48	2.46	0.81
1[A-Level]	0.54	0.54	0.54	0.52	0.84
Age at First Enrollment (years)	21.4	21.5	21.5	21.4	0.70
Time Betw. School Degree and Enrollment (years)	1.8	1.8	1.7	1.7	0.76
1[First Study Program]	0.72	0.74	0.73	0.72	0.80
1[Schooling Outside of Bavaria]	0.14	0.14	0.14	0.14	0.98
Observations	1,173	1,186	1,172	1,188	

Notes: The table shows the group means of main outcomes at baseline, along with additional baseline variables collected after randomization but before the intervention began, for the control group and three treatment groups. The last column reports the p-value of an F-test testing whether the treatment arms predict the respective baseline outcome or any of the additional variables. Variables in brackets with a leading digit 1 (1[…]) are binary. The last row reports the number of students in each group. Small differences in group sizes result from the randomization being conducted within strata blocks, with some blocks having sizes that were not multiples of four (the number of randomization groups).
Data set: Main Sample. Full population of students from the 2018, 2019, and 2021 cohorts, N = 4,719.

Students in our cohort typically dedicate an average of 35.5 hours per week to their studies, which includes attending lectures, seminars, and self-study. Their average school leaving grade is 2.46

(1 = very good – 4 = sufficient).[26] The average age of students in our group is 21.7 years, closely aligning with the overall average for all first-year students at research-focused universities and universities of applied sciences in Germany in 2022, reported as 21.2 by Statistisches Bundesamt (2023).

The last column of the table reports the p-values from an F-test to investigate whether the treatment and control groups differ on the pre-treatment variables. Based on the test, we cannot reject the hypothesis of joint orthogonality for any of the pre-treatment variables. However, there are some differences in (net) credit points between the control and the SI and ST treatment groups, with a gap of approximately (2.4) 2.5 credits. The control group has a mean of (90.1) 91.6 (net) credits and a standard deviation of (71.9) 72.6, so these differences represent (3.3%) 3.4% of a standard deviation, or roughly half a course more completed in the control group. Consistent with the pre-analysis plan, we control for all pre-treatment performance measures. This improves the efficiency of our estimates and helps correct for potential differences in students' pre-treatment achievements.

B. Estimation

We define Y_{ist} as post-treatment outcome of student i in randomization strata s at the end of semester t. The treatment indicators $SI_{is,t-1}$, STI_{ist-1}, and $FTI_{is,t-1}$ are equal to one if the student is in the respective treatment group, and zero otherwise. We include all students who were initially randomized in the analyses, even if they withdrew from their studies after the intervention began, and estimate intention-to-treat (ITT) effects using the following linear OLS regression:

$$(1) \qquad Y_{ist} = \alpha_0 + \alpha_1 SI_{is,t-1} + \alpha_2 STI_{is,t-1} + \alpha_3 FTI_{is,t-1} + \boldsymbol{\beta}'\boldsymbol{X}_{is,t=0} + \boldsymbol{\gamma}'\boldsymbol{Y}_{is,t-1} + \boldsymbol{\delta}_{s,t-1} + \varepsilon_{ist}.$$

The vector $\boldsymbol{X}_{is,t=0}$ includes individual background characteristics from the university enrollment records. Additionally, we control for the full set of pre-treatment study performance measures ($\boldsymbol{Y}_{is,t-1}$) in all specifications to enhance the precision of our estimates and to account for potentially remaining pre-treatment differences.[27] The inclusion of strata fixed effects $\boldsymbol{\delta}_{s,t-1}$ further improves precision. We report robust standard errors that allow for heteroscedastic error terms ε_{ist}. When presenting the results, we test for pairwise difference across treatment effects α_1, α_2, α_3, and for the joint significance of all treatments using an F-test.

Our main outcomes are from university register data, ensuring no attrition. For secondary outcomes from the online survey, we estimate propensity scores and use inverse-probability weighting to adjust for any selection based on observables.

[26] The grade of the entrance qualification/high school GPA is missing for 40 observations. 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 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.

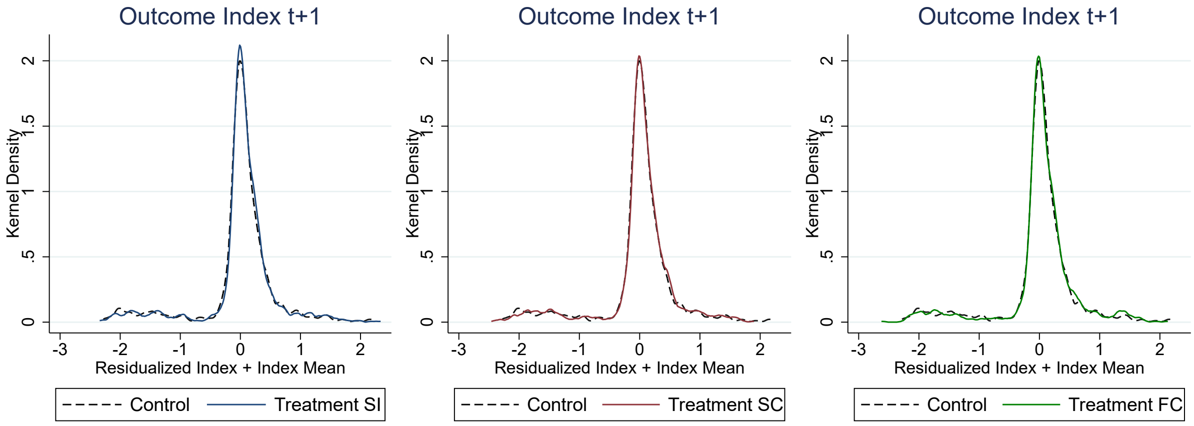
[27] The vector of baseline performance measures (pre-treatment; t-1) includes binary indicators for dropouts and degree completion, the number of obtained ECTS credits (raw score, and net of transferred credits), and the university GPA. GPA is only observed for students who pass at least one graded exam/module. If the baseline value is missing, we impute the GPA and include a missing indicator variable.

IV. Treatment Effects

A. Index of Main Study Performance Outcomes

Figure 2 compares the distribution of the performance index, based on the main outcomes (dropout rates, successful graduation, passed course credits points, and GPA) across the three treatment groups and the control group. We construct the density by first partialing out baseline outcomes, control variables, and strata fixed effects, following the specification in Column (4) of Table 2. We then estimate the kernel densities and add the mean to the residualized index to preserve the scale.

The distributions of all treatment arms are virtually identical to the control group density. The regression results in Table 2 support the impression gained from Figure 2. In none of the specifications, any treatment effects are significantly different from zero. Effects sizes are economically small, with point estimates ranging from 0.5 to 3.7 percent of a standard deviation. At the bottom of all regression tables, we report p-values for a test on joint significance of all treatments (H_0: SI = ST = FT = 0), and tests for pairwise differences among the treatment arms (H_0: SI = ST, H_0: SI = FT, H_0: ST = FT). None of these tests reported in Table 2 is close to any conventional significance levels.



(A) (B) (C)

FIGURE 2. MAIN EFFECT ON STUDY PERFORMANCE INDEX

Notes: Figure 2 shows the distribution of the post-treatment study performance, which cannot be explained by pre-treatment group differences, at the end of the semester for the three treatment groups compared to the control group. Residuals are estimated from a regression of the post-treatment on the full vector of baseline outcomes $\boldsymbol{Y}_{is,t-1}$ as described in Section III.B, and baseline controls $\boldsymbol{X}_{is,t=0}$, i.e., enrollment age, school GPA (German scale, and a missing dummy), time between school degree and university enrollment, and binary variables for being female, having an A-level degree, started the first study attempt, graduated from a non-Bavarian school. Panel A shows the social information treatment and the control group, Panel B and C compare the control group to the sunk time investment and future time investment group. The probability density functions are computed with an Epanechnikov kernel with bandwidth h derived from the Silverman rule (Silverman (1986), pp. 47-48) with $h = 0.9An^{-1/5}$, where n is the number of observations and $A = \min(\mathit{standard\ deviation}, \mathit{interquartile\ range}/1.349)$.
Data set: Main Sample. Full population of students from the 2018, 2019, and 2021 cohorts (see Table 1 for descriptives).

In the pre-analysis plan, we conducted a power analysis demonstrating that we would be able to detect effects sizes as small as 7 to 10 percent of a standard deviation at the 5 percent significance level. With standard errors of the treatment effect estimates of around 2.6/2.7 percent, it is evident that our study would have had sufficient power to detect effect sizes as small as the ones outlined in the pre-analysis plan. Therefore, the lack of significant treatment effects is not due to low power of our study, but rather stems from the very small point estimates.

TABLE 2—TREATMENT EFFECTS ON STUDY PERFORMANCE

	Dep. Var.: Study Performance Index				
	(1)	(2)	(3)	(4)	(5)
SI Treatment	0.020	0.022	0.028	0.027	0.025
	(0.027)	(0.027)	(0.027)	(0.026)	(0.026)
ST Treatment	0.005	0.005	0.011	0.012	0.011
	(0.027)	(0.027)	(0.027)	(0.026)	(0.026)
FT Treatment	0.033	0.035	0.036	0.037	0.034
	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)
Outcomes in t-1	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	Yes	Yes
Cohort FE	No	No	Yes	Yes	No
Study Program FE	No	No	No	Yes	No
Strata FE	No	No	No	No	Yes
R-squared	0.57	0.57	0.58	0.59	0.63
Observations	4,719	4,719	4,719	4,719	4,719
Outcome Descriptives (control group)					
Mean	0	0	0	0	0
Median	0.27	0.27	0.27	0.27	0.27
SD	1	1	1	1	1
Min	-3.15	-3.15	-3.15	-3.15	-3.15
Max	1.19	1.19	1.19	1.19	1.19
(Joint) Significant Tests (p-values)					
H_0: SI = ST = FT = 0	0.588	0.542	0.511	0.510	0.577
H_0: SI = ST	0.553	0.524	0.518	0.555	0.594
H_0: SI = FT	0.639	0.636	0.745	0.717	0.714
H_0: ST = FT	0.286	0.266	0.328	0.336	0.368

Notes: The table shows intention-to-treat (ITT) effects of the overall study performance of students in all three treatment arms. The outcome is a standardized study performance index following Anderson (2008) with weights estimated in the control group sample. Controls for performance differences at baseline (outcomes in t-1) include the full vector of baseline outcomes as described in Section III.B. Baseline controls include: enrollment age, school GPA (German scale, and a missing dummy), time between school degree and university enrollment, and indicators for being female, having an A-level degree, started the first study attempt, graduated from a non-Bavarian school. Ordinary least squares estimates. Robust standard errors in parentheses.

Data set: Main Sample. Full population of students from the 2018, 2019, and 2021 cohorts, N = 4,719 (see Table 1 for descriptives).
*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

B. Main Study Performance Outcomes

In Table 3, we report the treatment effects for each study performance outcome (dropout, successful graduation, passed course credits, and GPA) separately, all of which were used to compute the performance index. Consistent with the index results, treatment effects on all individual outcomes are statistically indistinguishable from zero.

Since all performance measures in Table 3 have economically interpretable scales, we do not standardize them. However, we report descriptive statistics for each outcome to facilitate interpretation, based on the control group sample. For instance, the insignificant point estimates of the treatment effects in Column (5) of Table 3 range from 0.002 to 0.008 grade points. Given an average GPA of 2.42 (with a s.d. of 0.58), these estimates are essentially zero, leading to the conclusion that none of the treatments has a policy-relevant effect on GPA. Additionally, the standard errors of the GPA treatment effects are very small (= 0.009), so even at its bounds, the 95% confidence intervals do not include economically meaningful treatment effects.

TABLE 3—TREATMENT EFFECTS ON MAIN PERFORMANCE OUTCOMES

Dep. Var.:	1[Dropout]	1[Graduation]	Credits	Net Credits	GPA
	(1)	(2)	(3)	(4)	(5)
SI Treatment	-0.009	-0.005	0.280	0.445	0.002
	(0.010)	(0.010)	(0.436)	(0.415)	(0.009)
ST Treatment	-0.005	-0.002	0.249	0.265	0.008
	(0.010)	(0.010)	(0.440)	(0.417)	(0.009)
FT Treatment	-0.012	0.002	-0.102	-0.031	0.001
	(0.010)	(0.010)	(0.435)	(0.413)	(0.009)
Outcomes in t-1	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Strata FE	Yes	Yes	Yes	Yes	Yes
R-squared	0.35	0.50	0.98	0.98	0.88
Observations	4,719	4,719	4,719	4,719	4,373
Outcome Descriptives (control group)					
Mean	0.097	0.11	108.7	106.6	2.42
Median	0	0	117	115	2.44
SD	0.30	0.32	74.0	73.1	0.58
Min	0	0	0	0	1.03
Max	1	1	222.5	216	4
(Joint) Significant Tests (p-values)					
H_0: SI = ST = FT = 0	0.674	0.898	0.777	0.621	0.802
H_0: SI = ST	0.699	0.704	0.944	0.669	0.470
H_0: SI = FT	0.738	0.464	0.380	0.254	0.908
H_0: ST = FT	0.471	0.727	0.425	0.482	0.415

Notes: The table shows intention-to-treat (ITT) effects of the three treatment arms on main performance outcomes. Column 1 and 2: Dummy variables equal to 1 if the student dropped out or graduated at the end of the semester. Column 3 and 4: raw ECTS credit score and net ECTS score corrected for transferred credits. Colum 5: University grade point average (GPA, German university scale from 1 (very good) to 4 (satisfactory)) with lower values indicate better outcomes. Controls for performance differences at baseline (Outcomes in t-1) subsume the full vector of baseline outcomes as described in Section III.B. Baseline controls include: enrollment age, school GPA (German school scale from 1 (very good) to 6 (unsatisfactory), and a missing dummy), time between school degree and university enrollment, and indicators for being female, having an A-level degree, started the first study attempt, graduated from a non-Bavarian school. Ordinary least squares estimates. Robust standard errors in parentheses.
Data set: Main Sample. Full population of students from the 2018, 2019, and 2021 cohorts).
*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

C. Treatment Effect Heterogeneities

Study time heterogeneity. In our treatment groups, students receive personalized information based on the predicted study time of similar peers. Due to the individual prediction, students usually see different study times, even when belonging to the same treatment group. Since it is unclear ex-ante how individuals will respond to their treatments,[28] we split the sample at the median of the study time distribution to examine whether treatment effects vary based on predicted study time. In the control group, those with below-median predicted study time are more likely to drop out (11% vs. 8% for those above median), while their study performance otherwise is quite similar (see the lower part of Table 4 for the control group descriptives).

As shown in Table 4, treatment effects remain economically small and statistically insignificant for all outcomes, both for students with low and high study time predictions. Therefore, predicted study time is not a relevant dimension for treatment effect heterogeneity.

[28] For example, in the social information group, a student with a relatively high predicted peer study time might perceive the treatment as an incentive to increase their study time, while a student with low peer study time might use the treatment to justify a low study effort.

TABLE 4— TREATMENT EFFECT HETEROGENEITY BY PREDICTED STUDY TIME

Dep. Var.:	1[Dropout]		1[Graduation]		Net Credits		GPA		Index	
Pred. Study Time:	low	high	low	high	low	high	low	high	low	high
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
SI Treatment	-0.004	-0.011	0.006	-0.018	0.377	0.472	0.013	-0.008	0.008	0.035
	(0.015)	(0.013)	(0.014)	(0.014)	(0.604)	(0.575)	(0.013)	(0.013)	(0.039)	(0.035)
ST Treatment	-0.020	0.012	-0.013	0.010	0.029	0.462	0.001	0.016	0.051	-0.036
	(0.015)	(0.014)	(0.013)	(0.014)	(0.595)	(0.587)	(0.013)	(0.014)	(0.038)	(0.036)
FT Treatment	-0.022	-0.001	0.011	-0.008	-0.120	0.022	0.009	-0.005	0.054	0.010
	(0.015)	(0.014)	(0.014)	(0.014)	(0.593)	(0.576)	(0.014)	(0.013)	(0.039)	(0.035)
Outcomes in t-1	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Strata FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.36	0.35	0.49	0.52	0.98	0.98	0.87	0.89	0.61	0.64
Observations	2,417	2,302	2,417	2,302	2,417	2,302	2,232	2,141	2,417	2,302
Outcome Descriptives (control group)										
Mean	0.11	0.080	0.11	0.12	106.8	106.5	2.44	2.40	-0.054	0.057
Median	0	0	0	0	119	114	2.46	2.41	0.25	0.27
SD	0.32	0.27	0.31	0.32	73.3	72.9	0.54	0.61	1.05	0.95
Min	0	0	0	0	0	0	1.19	1.03	-3.15	-3.15
Max	1	1	1	1	216	213	4	4	1.10	1.19
(Joint) Significant Tests (p-values)										
H_0: SI = ST = FT = 0	0.342	0.430	0.316	0.210	0.860	0.749	0.714	0.371	0.341	0.280
H_0: SI = ST	0.265	0.097	0.152	0.041	0.564	0.987	0.363	0.098	0.235	0.053
H_0: SI = FT	0.246	0.451	0.727	0.468	0.406	0.439	0.760	0.811	0.227	0.475
H_0: ST = FT	0.923	0.364	0.080	0.183	0.802	0.460	0.565	0.155	0.947	0.217

Notes: The table shows intention-to-treat (ITT) effects for students with below and above median predicted study time. Column 1 and 2: Dummy variables equal to 1 if the student dropped out or graduated at the end of the semester. Column 3 and 4: raw ECTS credit score and net ECTS score corrected for transferred credits. Colum 5: University grade point average (GPA, German university scale from 1 (very good) to 4 (satisfactory)) with lower values indicate better outcomes. Controls for performance differences at baseline (Outcomes in t-1) subsume the full vector of baseline outcomes as described in Section III.B. Baseline controls include: enrollment age, school GPA (German scale, and a missing dummy), time between school degree and university enrollment, and indicators for being female, having an A-level degree, started the first study attempt, graduated from a non-Bavarian school. Ordinary least squares estimates. Robust standard errors in parentheses.
Data set: Main Sample. Full population of students from the 2018, 2019, and 2021 cohorts, N = 4,719 (GPA: N = 4,373). *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Cohort specific treatment effects. Since sunk time investments increase with the number of semesters studied, and higher sunk costs may lead to stronger effects, we analyze whether treatment effects differ depending on whether students are in the early (2nd semester cohort), middle (6th semester cohort), or final (8th semester cohort) stage of their studies.[29]

Appendix B includes cohort-specific treatment estimates for the performance index and its underlying outcome measures. Tables 8, 9, and 10 provide the estimates for the treatment effects on the performance index for the 2018, 2019, and 2021 cohort, respectively. In all cohorts, treatment effects are neither large in size, nor statistically significant. The results for the separate performance outcomes align with this conclusion, indicating that the treatments do not affect any particular cohort (see Tables 11, 12, and 13 in Appendix B).

Finally, Tables 17, 18, and 19 in Appendix B report study time heterogeneity (as analyzed in Table 4) for each cohort separately. Again, no cohort shows systematic differences in the treatment effects for subgroups whose predicted study time is above or below the median.

[29] Of course, it is also possible that effects of the social information and variable cost treatments exhibit heterogeneity.

D. Secondary Outcomes

In Appendix C, Table 20 presents the results of treatment regressions on self-reported survey measures of stress, study and life satisfaction, as well as a well-being index based on these variables. We find no significant treatment effects on these outcomes. The treatments neither led to any negative effects, such as increased pressure to study more, nor did they have positive effects on life or study satisfaction.

V. Analysis of Mechanisms

The results reported in Section IV demonstrate that the treatments were not effective in altering outcomes such as exam passing and grades, which are determined during the exam phase at the end of the semester. In this section, we investigate potential reasons for the absence of treatment effects. First, we examine whether treatment effects fade out too early to influence study outcomes at the end of the semester. Second, we analyze average study effort during the semester, and, finally, we investigate whether students who are more prone to the sunk-cost effect are more likely to respond to the sunk-time treatment.

A. Effect on Measures of Study Ambitions

To test the hypothesis that treatment effects on students' behavior are temporary and dissipate too early to impact study performance, we use data on exam registrations in the treatment semester from the university's examination office. The letters containing our information treatments were sent out at the beginning of the semester. About six weeks into the semester, on May 20, 2022, the exam registration period started. Signing up for an exam reflects students' initial intent to take a course and participate in the exam, even though they could still choose not to attend the final exam without any consequences.

Table 5 reports treatment effects on signed-up and attempted exams, measured in credit points students would earn if they passed them. Using these outcomes, we can investigate whether students initially set ambitious exam goals that faded when the time came to participate. To get the full picture, Table 5 also includes passed exams in the treatment semester.

As the descriptive statistics in the lower half of Table 5 show, students in the control group, on average, sign up for exams worth 25.6 credits, participate in exams worth 20.4 credits, and ultimately accumulate 17.1 credits by passing exams. Once again, we find no significant treatment effects on these outcomes. The effect sizes and standard errors are roughly the same as those reported in Table 3.

Cohort heterogeneity. Interestingly, we observe a sizeable treatment effect in the 2018 cohort, i.e. specifically for those students who were already in their 8th semester (the regular study time is 7 semesters), for the social information treatment. Table 17 in Appendix B reports a statistically significant effect of 1.866 (s.e. = 0.809) of the social information treatment on the exam credits for which students signed up. The treatment effect decreases substantially to 1.035 credits for attempted exams and is close to zero for passed exams. This pattern may support the hypothesis that, in later semesters, the social information treatment could influence the study intentions of students in later semesters, but these intentions faded and did not result in an increase in study performance at the end of the semester. The absence of a similar sign-up effect in other cohorts may be due to a ceiling effect, as control group students in the 2019 and 2021 cohort already sign up to exams worth 29 credits (compared to 16.8 in the 2018 cohort8), which is close to the 30 credits per semester recommended by the university.

TABLE 5—TREATMENT EFFECTS ON STUDY AMBITIONS

Dep. Var.:	Signed up Credits	Attempted Credits	Passed Credits
	(1)	(2)	(3)
SI Treatment	0.718	0.715	0.283
	(0.486)	(0.449)	(0.436)
ST Treatment	-0.068	0.200	0.250
	(0.472)	(0.442)	(0.440)
FT Treatment	0.479	0.147	-0.102
	(0.475)	(0.450)	(0.435)
Outcomes in t-1	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Strata FE	Yes	Yes	Yes
R-squared	0.38	0.40	0.39
Observations	4,719	4,719	4,719
Outcome Descriptives (control group)			
Mean	25.6	20.4	17.1
Median	27	21	17
SD	14.2	13.3	13.0
Min	0	0	0
Max	79	67	61
(Joint) Significant Tests (p-values)			
H_0: SI = ST = FT = 0	0.291	0.415	0.772
H_0: SI = ST	0.101	0.249	0.941
H_0: SI = FT	0.621	0.212	0.376
H_0: ST = FT	0.243	0.905	0.422

Notes: The table shows intention-to-treat (ITT) effects on study ambitions as measured by the number exams a student signed up for (Column 1), the number of exams a student attended (Column 2), and the number of passed exams (Column 3). All outcomes are measured in ECTS credits. Controls for performance differences at baseline (Outcomes in t-1) subsume the full vector of baseline outcomes as described in Section IV.B. Baseline controls include: enrollment age, school GPA (German scale, and a missing dummy), time between school degree and university enrollment, and indicators for being female, having an A-level degree, started the first study attempt, graduated from a non-Bavarian school. Ordinary least squares estimates. Robust standard errors in parentheses. *Data set*: Full sample of students from the 2018, 2019, and 2021 cohort.
*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

B. Effects on Study Effort

To assess whether the treatments affected students' own study time and their beliefs about the study time of their peers (in the same program), we conducted an online survey two months after the information letters were sent out. Participation in the survey was voluntary, with a response rate of 10.24 %. We use inverse probability weighting to correct for a potential bias due to selective survey participation. The small size of the survey sample limits the power to detect treatment effects.

Table 6 reports the results. We find relatively large, but imprecisely estimated effects on `own study time'. In both the social information and the future investment group, students report to study around 4.5 hours more per week (Column 1, Table 6). The point estimate for the sunk cost treatment is negative and statistically not significant, with a reduction of the study time of 3.1 hours per week. Compared to the control group's average study time of 33.9 hours per week (with a s.d. of 16.2), these effects are meaningful in size, but too imprecisely estimated to draw definitive conclusions. The effects on the beliefs about the study time of other students are smaller and statistically insignificant. We also do not find treatment effects on the beliefs about the ideal or realistic study duration.

TABLE 6—TREATMENT EFFECTS ON STUDY TIME INVESTMENT AND STUDY TIME EXPECTATIONS

Dep. Var.:	Own study time (hours/week)	Others' study time (hours/week)	Confidence in others' time estimate	Ideal study duration (semesters)	Realistic study duration (semesters)
	(1)	(2)	(3)	(4)	(5)
SI Treatment	4.410	3.048	0.074	-0.072	0.158
	(3.030)	(2.518)	(0.584)	(0.214)	(0.195)
ST Treatment	-3.087	0.657	0.029	-0.167	-0.226
	(4.584)	(2.836)	(0.512)	(0.188)	(0.222)
FT Treatment	4.620	2.955	-0.234	-0.251	-0.035
	(4.497)	(2.632)	(0.490)	(0.206)	(0.196)
Outcomes in t-1	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Strata FE	Yes	Yes	Yes	Yes	Yes
R-squared	0.62	0.72	0.63	0.66	0.78
Observations	483	483	483	483	483
Outcome Descriptives (control group)					
Mean	33.9	33.4	4.71	7.45	8.06
Median	35	30	5	7	8
SD	16.2	14.2	2.39	0.98	1.21
Min	3	4	0	2	3
Max	100	100	10	10	13
(Joint) Significant Tests (p-values)					
H_0: SI = ST = FT = 0	0.319	0.520	0.913	0.562	0.210
H_0: SI = ST	0.109	0.334	0.928	0.594	0.036
H_0: SI = FT	0.959	0.965	0.549	0.292	0.257
H_0: ST = FT	0.233	0.347	0.554	0.614	0.328

Notes: The table shows intention-to-treat (ITT) effects on self-reported measures of students' own study time, their beliefs on the study of peers, and estimates on the ideal and realistic study duration. Study time is measure in hours per week. Study duration is reported in study semester. Controls for performance differences at baseline (Outcomes in t-1) subsume the full vector of baseline outcomes as described in Section IV.B. Baseline controls include: enrollment age, school GPA (German scale, and a missing dummy), time between school degree and university enrollment, and indicators for being female, having an A-level degree, started the first study attempt, graduated from a non-Bavarian school. Weighted least squares estimates. Robust standard errors in parentheses.
Data set: Online survey sample of students from the 2018, 2019, and 2021 cohort.
*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

C. Interaction with Being `Prone to the Sunk-Cost Bias'

For students in the 2021 cohort we assessed how likely they would consider sunk costs as relevant in hypothetical choices in the pre-treatment online self-assessment survey (see Appendix D for survey questions). Based on that, we constructed a standardized sunk-cost index (Anderson, 2008), and interacted the index with the treatment indicators. Participation in the OSA survey was mandatory in some study programs and as a result about 50 percent of the 1,938 of the 2nd semester students participated. We use inverse probability weighting to correct the estimates in Table 7 for selective participation in the OSAs.

Overall, we find no evidence that the effects differ significantly between the two groups (none of the interaction term parameters are significantly different from zero). Specifically, in contrast to Ketel et al. (2016), we do not find different treatment effects for students prone to the sunk-cost bias. If anything, we observe marginally significant negative treatment effects in the social information treatment group on credits for those students with a sunk cost bias close to the sample average of the control group. The average treatment effects for the 2021 cohort are reported in Table 13 in Appendix B. For the entire 2021 cohort, the social information treatment does not affect credits.

TABLE 7—TREATMENT EFFECTS AND SUNK-COST BIAS

Dep. Var.:	1[Dropout]	Credits	Net Credits	GPA
Sample: 2021 cohort	(1)	(2)	(3)	(4)
SI Treatment	0.005	-1.706*	-1.802*	0.019
	(0.034)	(0.978)	(0.968)	(0.038)
ST Treatment	-0.023	0.129	0.133	0.065
	(0.035)	(1.010)	(0.995)	(0.041)
FT Treatment	-0.031	0.661	0.656	0.045
	(0.036)	(1.007)	(1.003)	(0.046)
Sunk Cost Index (SC)	0.030	-0.227	-0.270	-0.038
	(0.025)	(0.687)	(0.686)	(0.026)
SI x SC-Index	-0.030	-0.219	-0.156	0.034
	(0.033)	(1.024)	(1.014)	(0.035)
ST x SC-Index	-0.014	-0.696	-0.741	0.041
	(0.033)	(1.052)	(1.045)	(0.038)
FT x SC-Index	0.001	0.362	0.460	0.049
	(0.035)	(1.014)	(1.021)	(0.045)
Outcomes in t-1	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Strata FE	Yes	Yes	Yes	Yes
R-squared	0.49	0.87	0.87	0.79
Observations	1,018	1,018	1,018	844
Outcome Descriptives (control group)				
Mean	0.21	31.9	30.9	2.60
Median	0	35	35	2.65
SD	0.41	23.4	22.7	0.61
Min	0	0	0	1.24
Max	1	80	67	4
(Joint) Significant Tests (p-values)				
H_0: SI = ST = FT = 0	0.664	0.078	0.056	0.394
H_0: SI = ST	0.415	0.065	0.048	0.185
H_0: SI = FT	0.256	0.014	0.011	0.486
H_0: ST = FT	0.803	0.599	0.604	0.603

Notes: The table shows the heterogeneity of intention-to-treat (ITT) effects with respect to. The outcomes are similar to the ones reported in Table 2 and Table 3. The effects on graduation cannot be estimated, as none of the students in the 2021 cohort had graduated yet. The sunk cost index is a standardized index following Anderson (2008) with weights estimated in the control group sample. OSA survey questions on sunk cost considerations are displayed in Appendix D. Controls for performance differences at baseline (Outcomes in t-1) subsume the full vector of baseline outcomes as described in Section III.B. Baseline controls include: enrollment age, school GPA (German scale, and a missing dummy), time between school degree and university enrollment, and indicators for being female, having an A-level degree, started the first study attempt, graduated from a non-Bavarian school. Weighted least squares estimates. Robust standard errors in parentheses.
Data set: Pre-treatment OSA survey sample of students from the 2021 cohort.
*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

VI. Conclusion

This paper describes a field experiment conducted with over 4,000 bachelor's students at various stages of their studies, designed to examine the effects of providing them with information about their study time investments to activate the sunk-cost effect. To isolate the SC-effect, three different treatments were tested: one provided students with information about the average study time of similar peers, the second framed peer study time as sunk costs, and the third framed it as future (variable) costs. Across all treatments, we find both economical and statistical null effects on any of the pre-registered outcomes, including GPA, credits earned, exam sign-up rates, dropouts, graduation rates, and measures of study and life satisfaction, and stress.

We also test for heterogeneous treatment effects: First, we explore whether the effects vary depending on the presented peer study time. Second, given that the amount of sunk time investments differs across study stages, we examine whether we observe different effects in the 2nd, 6th, and 8th semester cohort. Our analyses reveal no treatment effects in these subgroups, and interactions between the two dimensions of heterogeneity show no significant effects, too.

Regarding mechanisms, we find that 1) the exam sign-up rate at the beginning of the semester does not increase, 2) the average study time measured in a survey increases for the social information and future investment treatments, but decreases for the sunk-cost treatment. However, none of these results are statistically significant, and the analyses are based on a smaller sample of 10% of the initial population. 3) The sunk-cost effect does also not manifest in a group of students prone to the sunk-cost bias.

Given the design of our study and the null results across all groups, it seems likely that our treatments did not sufficiently increase the salience of the information provided. As a result, they neither activated the sunk-cost effect, nor did they induce effects on the main outcomes (credits, dropout rates, and GPA), but there is weak evidence that they may have influenced self-reported study time in a survey. Whether the study time already invested can impact future academic effort and performance through the sunk-cost effect therefore remains a question for future research. A mere written reference to the sunk study time investments in a letter, however, is not sufficient for this purpose.

Appendix

A. Intervention Letters– Experimental Items

Figure A.1 shows the relevant sections of the letters sent to students in the respective treatment arms.

Ihr Studium des Fachs *studiengang*

Guten Tag *Vorname Nachname* (aus Adressfeld übernehmen),

herzlich willkommen im Sommersemester 2022. Gerne möchten wir Sie bei Ihrem Studium unterstützen. Eine Umfrage unter Ihren Mitstudierenden hat ergeben, dass sich viele mehr Informationen zur Studienplanung wünschen. Daher testen wir aktuell verschiedene Informationsangebote.[1]

Auf der Rückseite dieses Schreibens finden Sie viele wichtige Informationen zu Ihrem Studium sowie zu Beratungs- und Informationsangeboten der Hochschule.

Wir wünschen Ihnen weiterhin viel Freude und Erfolg beim Studieren an unserer Hochschule!

Viele Grüße,

Ihr KoSIMA Team

(a) Control Group

wünschen. Daher testen wir aktuell verschiedene Informationsangebote.[1]

Informationen für Vorname Nachname im Bachelorstudiengang stg, Matnr. matrikelnr

- Ihnen ähnliche Studierende beschäftigen sich während des Semesters im Durchschnitt **XX,X(=avg_time) Stunden pro Woche** mit ihrem Studium.[2]
- Auf der Rückseite dieses Schreibens finden Sie viele weitere wichtige Informationen zu Ihrem Studium sowie zu Beratungs- und Informationsangeboten der Hochschule.

Wir wünschen Ihnen weiterhin viel Freude und Erfolg beim Studieren an unserer Hochschule!

(b) Social Information Treatment (SI)

wünschen. Daher testen wir aktuell verschiedene Informationsangebote.[1]

Informationen für Vorname Nachname im Bachelorstudiengang stg, Matnr. matrikelnr

- Ihnen ähnliche Studierende beschäftigen sich während des Semesters im Durchschnitt **XX,X(=avg_time) Stunden pro Woche** mit ihrem Studium.[2]
- Sie haben daher seit dem ersten Semester bis heute schätzungsweise **XXX,X(=total_time) Stunden** in Ihren aktuellen Studiengang investiert (Stand: XX.XX.20XX).[3]
- Auf der Rückseite dieses Schreibens finden Sie viele weitere wichtige Informationen zu Ihrem Studium sowie zu Beratungs- und Informationsangeboten der Hochschule.

Wir wünschen Ihnen weiterhin viel Freude und Erfolg beim Studieren an unserer Hochschule!

(c) Sunk Time Investment Treatment (ST)

wünschen. Daher testen wir aktuell verschiedene Informationsangebote.[1]

Informationen für Vorname Nachname im Bachelorstudiengang stg, Matnr. matrikelnr

- Ihnen ähnliche Studierende beschäftigen sich während des Semesters im Durchschnitt **XX,X(=avg_time) Stunden pro Woche** mit ihrem Studium.[2]
- Sie werden daher in jedem zukünftigen Semester Ihres aktuellen Studiengangs schätzungsweise **XXX,X(=future_time) Stunden** investieren.[3]
- Auf der Rückseite dieses Schreibens finden Sie viele weitere wichtige Informationen zu Ihrem Studium sowie zu Beratungs- und Informationsangeboten der Hochschule.

Wir wünschen Ihnen weiterhin viel Freude und Erfolg beim Studieren an unserer Hochschule!

(d) Future Time Treatment (FT)

FIGURE A 1. SCREEN SHOTS OF LETTERS IN ALL TREATMENT ARMS

B. Cohort-Specific Effects

Main Index Results

TABLE 8—TREATMENT EFFECTS ON STUDY PERFORMANCE (2018 COHORT)

	Dep. Var.: Study Performance Index				
Sample: 2018 cohort	(1)	(2)	(3)	(4)	(5)
SI Treatment	0.018	0.019	0.019	0.019	0.017
	(0.021)	(0.020)	(0.020)	(0.020)	(0.019)
ST Treatment	0.002	0.003	0.003	0.002	0.001
	(0.021)	(0.022)	(0.022)	(0.021)	(0.021)
FT Treatment	-0.010	-0.009	-0.009	-0.010	-0.011
	(0.020)	(0.019)	(0.019)	(0.019)	(0.019)
Outcomes in t-1	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	Yes	Yes
Cohort FE	No	No	Yes	Yes	No
Study Program FE	No	No	No	Yes	No
Strata FE	No	No	No	No	Yes
R-squared	0.70	0.70	0.70	0.71	0.73
Observations	1,199	1,199	1,199	1,199	1,199
Outcome Descriptives (control group)					
Mean	0.55	0.55	0.55	0.55	0.55
Median	0.57	0.57	0.57	0.57	0.57
SD	0.42	0.42	0.42	0.42	0.42
Min	-2.66	-2.66	-2.66	-2.66	-2.66
Max	1.19	1.19	1.19	1.19	1.19
(Joint) Significant Tests (p-values)					
H_0: SI = ST = FT = 0	0.670	0.652	0.652	0.643	0.669
H_0: SI = ST	0.492	0.483	0.483	0.478	0.477
H_0: SI = FT	0.218	0.209	0.209	0.204	0.220
H_0: ST = FT	0.596	0.590	0.590	0.583	0.612

Notes: The table shows intention-to-treat (ITT) effects of the overall study performance of students in all three treatment arms for students in the 2018 cohort. The outcome is a standardized study performance index following Anderson (2008) with weights estimated in the control group sample. Controls for performance differences at baseline (Outcomes in t-1) subsume the full vector of baseline outcomes as described in Section III.B. Baseline controls include: enrollment age, school GPA (German scale, and a missing dummy), time between school degree and university enrollment, and indicators for being female, having an A-level degree, started the first study attempt, graduated from a non-Bavarian school. Ordinary least squares estimates. Robust standard errors in parentheses.
Data set: Full population of students from the 2018 cohort, N = 1,199.
*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

TABLE 9—TREATMENT EFFECTS ON STUDY PERFORMANCE (2019 COHORT)

	Dep. Var.: Study Performance Index				
Sample: 2019 cohort	(1)	(2)	(3)	(4)	(5)
SI Treatment	-0.011	-0.007	-0.007	-0.008	-0.011
	(0.025)	(0.026)	(0.026)	(0.026)	(0.026)
ST Treatment	-0.038	-0.031	-0.031	-0.030	-0.033
	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)
FT Treatment	0.001	0.007	0.007	0.006	0.002
	(0.024)	(0.024)	(0.024)	(0.024)	(0.025)
Outcomes in t-1	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	Yes	Yes
Cohort FE	No	No	Yes	Yes	No
Study Program FE	No	No	No	Yes	No
Strata FE	No	No	No	No	Yes
R-squared	0.67	0.68	0.68	0.68	0.71
Observations	1,582	1,582	1,582	1,582	1,582
Outcome Descriptives (control group)					
Mean	0.31	0.31	0.31	0.31	0.31
Median	0.40	0.40	0.40	0.40	0.40
SD	0.59	0.59	0.59	0.59	0.59
Min	-3.15	-3.15	-3.15	-3.15	-3.15
Max	1.15	1.15	1.15	1.15	1.15
(Joint) Significant Tests (p-values)					
H_0: SI = ST = FT = 0	0.478	0.574	0.574	0.598	0.547
H_0: SI = ST	0.337	0.396	0.396	0.438	0.427
H_0: SI = FT	0.659	0.610	0.610	0.587	0.583
H_0: ST = FT	0.160	0.176	0.176	0.188	0.183

Notes: The table shows intention-to-treat (ITT) effects of the overall study performance of students in all three treatment arms for students in the 2019 cohort. The outcome is a standardized study performance index following Anderson (2008) with weights estimated in the control group sample. Controls for performance differences at baseline (Outcomes in t-1) subsume the full vector of baseline outcomes as described in Section III.B. Baseline controls include: enrollment age, school GPA (German scale, and a missing dummy), time between school degree and university enrollment, and indicators for being female, having an A-level degree, started the first study attempt, graduated from a non-Bavarian school. Ordinary least squares estimates. Robust standard errors in parentheses.
Data set: Full population of students from the 2019 cohort, N = 1,582.
*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

TABLE 10—TREATMENT EFFECTS ON STUDY PERFORMANCE (2021 COHORT)

	Dep. Var.: Study Performance Index				
Sample: 2021 cohort	(1)	(2)	(3)	(4)	(5)
SI Treatment	0.044	0.043	0.043	0.039	0.038
	(0.059)	(0.058)	(0.058)	(0.058)	(0.057)
ST Treatment	0.038	0.034	0.034	0.034	0.034
	(0.058)	(0.059)	(0.059)	(0.057)	(0.057)
FT Treatment	0.079	0.076	0.076	0.073	0.071
	(0.058)	(0.058)	(0.058)	(0.057)	(0.057)
Outcomes in t-1	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	Yes	Yes
Cohort FE	No	No	Yes	Yes	No
Study Program FE	No	No	No	Yes	No
Strata FE	No	No	No	No	Yes
R-squared	0.41	0.41	0.41	0.45	0.49
Observations	1,938	1,938	1,938	1,938	1,938
Outcome Descriptives (control group)					
Mean	-0.58	-0.58	-0.58	-0.58	-0.58
Median	-0.11	-0.11	-0.11	-0.11	-0.11
SD	1.20	1.20	1.20	1.20	1.20
Min	-3.15	-3.15	-3.15	-3.15	-3.15
Max	0.84	0.84	0.84	0.84	0.84
(Joint) Significant Tests (p-values)					
H_0: SI = ST = FT = 0	0.606	0.628	0.628	0.644	0.673
H_0: SI = ST	0.918	0.867	0.867	0.919	0.944
H_0: SI = FT	0.538	0.566	0.566	0.542	0.556
H_0: ST = FT	0.471	0.457	0.457	0.472	0.507

Notes: The table shows intention-to-treat (ITT) effects of the overall study performance of students in all three treatment arms for students in the 2021 cohort. The outcome is a standardized study performance index following Anderson (2008) with weights estimated in the control group sample. Controls for performance differences at baseline (Outcomes in t-1) subsume the full vector of baseline outcomes as described in Section III.B. Baseline controls include: enrollment age, school GPA (German scale, and a missing dummy), time between school degree and university enrollment, and indicators for being female, having an A-level degree, started the first study attempt, graduated from a non-Bavarian school. Ordinary least squares estimates. Robust standard errors in parentheses.
Data set: Full population of students from the 2019 cohort, N = 1,938.
*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Subcomponents of Performance Index

TABLE 11—TREATMENT EFFECTS ON MAIN PERFORMANCE OUTCOMES (2018 COHORT)

Dep. Var.:	Dropout	1[Graduation]	Credits	Net Credits	GPA
Sample: 2018 cohort	(1)	(2)	(3)	(4)	(5)
SI Treatment	-0.006	0.004	0.334	0.617	-0.002
	(0.008)	(0.034)	(0.764)	(0.721)	(0.005)
ST Treatment	-0.001	0.004	-0.211	-0.121	0.004
	(0.009)	(0.034)	(0.782)	(0.721)	(0.005)
FT Treatment	0.002	0.018	-1.234	-1.108	0.006
	(0.008)	(0.034)	(0.774)	(0.711)	(0.004)
Outcomes in t-1	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Strata FE	Yes	Yes	Yes	Yes	Yes
R-squared	0.22	0.39	0.94	0.95	0.99
Observations	1,199	1,199	1,199	1,199	1,198
Outcome Descriptives (control group)					
Mean	0.010	0.45	191.8	188.3	2.32
Median	0	0	198.5	196	2.32
SD	0.10	0.50	27.9	28.6	0.49
Min	0	0	53	44	1.25
Max	1	1	222.5	216	3.92
(Joint) Significant Tests (p-values)					
H_0: SI = ST = FT = 0	0.846	0.952	0.209	0.125	0.296
H_0: SI = ST	0.614	1.000	0.487	0.325	0.262
H_0: SI = FT	0.402	0.666	0.043	0.019	0.079
H_0: ST = FT	0.734	0.666	0.198	0.182	0.668

Notes: The table shows intention-to-treat (ITT) effects of the three treatment arms on main performance outcomes in the 2018 cohort. See the notes of Table 3 for a detailed description of the outcomes. Controls for performance differences at baseline (Outcomes in t-1) subsume the full vector of baseline outcomes as described in Section III.B. Baseline controls include: enrollment age, school GPA (German scale, and a missing dummy), time between school degree and university enrollment, and indicators for being female, having an A-level degree, started the first study attempt, graduated from a non-Bavarian school. Ordinary least squares estimates. Robust standard errors in parentheses.
Data set: Full population of students from the 2018 cohort.
*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

TABLE 12— TREATMENT EFFECTS ON MAIN PERFORMANCE OUTCOMES (2019 COHORT)

Dep. Var.:	1[Dropout]	1[Graduation]	Credits	Net Credits	GPA
Sample: 2019 cohort	(1)	(2)	(3)	(4)	(5)
SI Treatment	0.004	0.002	0.255	0.482	0.010*
	(0.010)	(0.005)	(0.769)	(0.695)	(0.005)
ST Treatment	0.013	0.001	0.493	0.434	0.011*
	(0.011)	(0.005)	(0.783)	(0.706)	(0.006)
FT Treatment	0.001	-0.003	-0.178	-0.029	0.003
	(0.010)	(0.004)	(0.735)	(0.674)	(0.005)
Outcomes in t-1	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Strata FE	Yes	Yes	Yes	Yes	Yes
R-squared	0.32	0.17	0.96	0.96	0.98
Observations	1,582	1,582	1,582	1,582	1,552
Outcome Descriptives (control group)					
Mean	0.023	0.0050	138.4	136.1	2.40
Median	0	0	154	151	2.40
SD	0.15	0.071	46.6	46.2	0.56
Min	0	0	0	0	1.15
Max	1	1	210	210	3.84
(Joint) Significant Tests (p-values)					
H_0: SI = ST = FT = 0	0.670	0.707	0.827	0.818	0.125
H_0: SI = ST	0.459	0.734	0.763	0.946	0.873
H_0: SI = FT	0.755	0.285	0.563	0.458	0.174
H_0: ST = FT	0.302	0.432	0.375	0.507	0.161

Notes: The table shows intention-to-treat (ITT) effects of the three treatment arms on main performance outcomes in the 2019 cohort. See the notes of Table 3 for a detailed description of the outcomes. Controls for performance differences at baseline (Outcomes in t-1) subsume the full vector of baseline outcomes as described in Section III.B. Baseline controls include: enrollment age, school GPA (German scale, and a missing dummy), time between school degree and university enrollment, and indicators for being female, having an A-level degree, started the first study attempt, graduated from a non-Bavarian school. Ordinary least squares estimates. Robust standard errors in parentheses.
Data set: Full sample of students from the 2019 cohort.
*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

TABLE 13—TREATMENT EFFECTS ON MAIN PERFORMANCE OUTCOMES (2021 COHORT)

Dep. Var.:	1[Dropout]	1[Graduation]	Credits	Net Credits	GPA
Sample: 2021 cohort	(1)	(2)	(3)	(4)	(5)
SI Treatment	-0.016	—	-0.142	-0.084	0.011
	(0.022)		(0.600)	(0.593)	(0.023)
ST Treatment	-0.015	—	-0.204	-0.113	0.020
	(0.022)		(0.615)	(0.607)	(0.023)
FT Treatment	-0.025	—	0.251	0.246	-0.002
	(0.022)		(0.625)	(0.614)	(0.024)
Outcomes in t-1	Yes	—	Yes	Yes	Yes
Controls	Yes	—	Yes	Yes	Yes
Strata FE	Yes	—	Yes	Yes	Yes
R-squared	0.34	—	0.84	0.84	0.77
Observations	1,938	—	1,938	1,938	1,623
Outcome Descriptives (control group)					
Mean	0.21	—	34.1	33.0	2.52
Median	0	—	40	36.5	2.53
SD	0.41	—	23.1	22.6	0.63
Min	0	—	0	0	1.03
Max	1	—	85	78	4
(Joint) Significant Tests (p-values)					
H_0: SI = ST = FT = 0	0.716	—	0.896	0.939	0.757
H_0: SI = ST	0.989	—	0.920	0.962	0.681
H_0: SI = FT	0.649	—	0.528	0.591	0.576
H_0: ST = FT	0.639	—	0.477	0.568	0.343

Notes: The table shows intention-to-treat (ITT) effects of the three treatment arms on main performance outcomes in the 2021 cohort. See the notes of Table 3 for a detailed description of the outcomes. The effects on graduation cannot be estimated, as none of the students in the 2021 cohort had graduated yet. Controls for performance differences at baseline (Outcomes in t-1) subsume the full vector of baseline outcomes as described in Section III.B. Baseline controls include: enrollment age, school GPA (German scale, and a missing dummy), time between school degree and university enrollment, and indicators for being female, having an A-level degree, started the first study attempt, graduated from a non-Bavarian school. Ordinary least squares estimates. Robust standard errors in parentheses.
Data set: Full sample of students from the 2021 cohort.
*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Median split by predicted study time

TABLE 14—TREATMENT EFFECT HETEROGENEITY BY PREDICTED STUDY TIME (2018 COHORT)

Dep. Var.:	1[Dropout]		1[Graduation]		Net Credits		GPA		Index	
Pred. Study Time:	low	high	low	high	low	high	low	high	low	high
Sample: 2018 cohort	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
SI Treatment	-0.008	-0.002	0.026	-0.031	1.254	0.132	-0.004	-0.000	0.025	0.005
	(0.013)	(0.007)	(0.049)	(0.047)	(1.047)	(0.987)	(0.006)	(0.007)	(0.032)	(0.018)
ST Treatment	-0.009	0.005	-0.027	0.032	-0.605	0.463	0.005	0.002	0.015	-0.011
	(0.014)	(0.008)	(0.049)	(0.047)	(1.023)	(0.997)	(0.006)	(0.007)	(0.034)	(0.020)
FT Treatment	-0.009	0.015	0.038	-0.011	-0.130	-1.933**	0.004	0.007	0.018	-0.043*
	(0.013)	(0.010)	(0.049)	(0.048)	(1.044)	(0.954)	(0.006)	(0.006)	(0.030)	(0.023)
Outcomes in t-1	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Strata FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.23	0.25	0.38	0.42	0.95	0.95	0.99	0.99	0.67	0.81
Observations	608	591	608	591	608	591	608	590	608	591
Outcome Descriptives (control group)										
Mean	0.020	0	0.44	0.46	188.3	188.3	2.34	2.29	0.51	0.58
Median	0	0	0	0	196	197	2.38	2.27	0.56	0.61
SD	0.14	0	0.50	0.50	29.4	27.8	0.42	0.56	0.47	0.34
Min	0	0	0	0	53	44	1.42	1.25	-2.66	-0.71
Max	1	0	1	1	216	213	3.60	3.92	1.10	1.19
(Joint) Significant Tests (p-values)										
H_0: SI = ST = FT = 0	0.875	0.441	0.526	0.578	0.340	0.072	0.524	0.627	0.868	0.284
H_0: SI = ST	0.985	0.524	0.262	0.168	0.079	0.754	0.227	0.754	0.783	0.546
H_0: SI = FT	0.964	0.181	0.797	0.663	0.189	0.043	0.207	0.242	0.832	0.102
H_0: ST = FT	0.979	0.438	0.168	0.367	0.651	0.020	0.886	0.473	0.930	0.283

Notes: The table shows intention-to-treat (ITT) effects for students with below and above median predicted study time in the 2018 cohort. The Outcomes are similar to the ones reported in Table 2 and Table 3. Controls for performance differences at baseline (Outcomes in t-1) subsume the full vector of baseline outcomes as described in Section III.B. Baseline controls include: enrollment age, school GPA (German scale, and a missing dummy), time between school degree and university enrollment, and indicators for being female, having an A-level degree, started the first study attempt, graduated from a non-Bavarian school. Ordinary least squares estimates. Robust standard errors in parentheses.
Data set: Full sample of students from the 2018 cohort.
*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

TABLE 15—TREATMENT EFFECT HETEROGENEITY BY PREDICTED STUDY TIME (2019 COHORT)

Dep. Var.:	1[Dropout]		1[Graduation]		Net Credits		GPA		Index	
Pred. Study Time:	low	high	low	high	low	high	low	high	low	high
Sample: 2019 cohort	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
SI Treatment	-0.003	0.015	0.014**	-0.011	0.819	0.173	0.012	0.008	0.010	-0.039
	(0.015)	(0.014)	(0.007)	(0.008)	(0.980)	(1.000)	(0.008)	(0.008)	(0.038)	(0.035)
ST Treatment	0.003	0.024	0.004	-0.003	0.944	-0.324	0.010	0.011	-0.006	-0.063
	(0.015)	(0.016)	(0.005)	(0.010)	(0.998)	(1.011)	(0.008)	(0.008)	(0.039)	(0.039)
FT Treatment	0.001	0.003	-0.001	-0.005	0.394	-0.492	0.007	-0.002	0.002	-0.003
	(0.015)	(0.012)	(0.003)	(0.009)	(0.950)	(0.959)	(0.007)	(0.008)	(0.037)	(0.031)
Outcomes in t-1	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Strata FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.36	0.28	0.22	0.18	0.96	0.97	0.98	0.99	0.69	0.73
Observations	827	755	827	755	827	755	810	742	827	755
Outcome Descriptives (control group)										
Mean	0.029	0.016	0	0.011	137.0	135.2	2.40	2.39	0.29	0.33
Median	0	0	0	0	152.5	147.5	2.39	2.40	0.43	0.37
SD	0.17	0.12	0	0.10	45.4	47.0	0.54	0.58	0.63	0.55
Min	0	0	0	0	0	0	1.19	1.15	-3.15	-3.15
Max	1	1	0	1	191	210	3.65	3.84	1.08	1.15
(Joint) Significant Tests (p-values)										
H_0: SI = ST = FT = 0	0.982	0.385	0.170	0.345	0.770	0.903	0.421	0.342	0.979	0.275
H_0: SI = ST	0.693	0.590	0.258	0.310	0.902	0.634	0.808	0.718	0.666	0.581
H_0: SI = FT	0.763	0.376	0.043	0.250	0.664	0.495	0.550	0.237	0.831	0.276
H_0: ST = FT	0.936	0.185	0.280	0.790	0.579	0.867	0.778	0.120	0.834	0.115

Notes: The table shows intention-to-treat (ITT) effects for students with below and above median predicted study time in the 2019 cohort. The Outcomes are similar to the ones reported in Table 2 and Table 3. Controls for performance differences at baseline (Outcomes in t-1) subsume the full vector of baseline outcomes as described in Section III.B. Baseline controls include: enrollment age, school GPA (German scale, and a missing dummy), time between school degree and university enrollment, and indicators for being female, having an A-level degree, started the first study attempt, graduated from a non-Bavarian school. Ordinary least squares estimates. Robust standard errors in parentheses.
Data set: Full sample of students from the 2019 cohort.
*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

TABLE 16—TREATMENT EFFECT HETEROGENEITY BY PREDICTED STUDY TIME (2021 COHORT)

Dep. Var.:	1[Dropout]		1[Graduation]		Net Credits		GPA		Index	
Pred. Study Time:	low	high	low	high	low	high	low	high	low	high
Sample: 2021 cohort	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
SI Treatment	0.001	-0.029	—	—	-0.422	0.325	0.020	0.002	-0.008	0.076
	(0.033)	(0.029)			(0.876)	(0.815)	(0.033)	(0.032)	(0.086)	(0.077)
ST Treatment	-0.038	0.011	—	—	-0.696	0.589	-0.011	0.045	0.103	-0.044
	(0.032)	(0.031)			(0.877)	(0.846)	(0.033)	(0.033)	(0.083)	(0.079)
FT Treatment	-0.045	-0.006	—	—	-0.238	0.825	0.006	-0.008	0.117	0.026
	(0.033)	(0.030)			(0.897)	(0.848)	(0.035)	(0.032)	(0.087)	(0.076)
Outcomes in t-1	Yes	Yes	—	—	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	—	—	Yes	Yes	Yes	Yes	Yes	Yes
Strata FE	Yes	Yes	—	—	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.34	0.34	—	—	0.83	0.85	0.75	0.80	0.47	0.51
Observations	982	956	—	—	982	956	814	809	982	956
Outcome Descriptives (control group)										
Mean	0.24	0.18	—	—	32.2	33.8	2.56	2.47	-0.68	-0.48
Median	0	0	—	—	36	36.5	2.56	2.50	-0.13	-0.11
SD	0.43	0.39	—	—	22.3	22.8	0.58	0.67	1.23	1.16
Min	0	0	—	—	0	0	1.24	1.03	-3.15	-3.15
Max	1	1	—	—	63	78	4	4	0.73	0.84
(Joint) Significant Tests (p-values)										
H_0: SI = ST = FT = 0	0.324	0.562	—	—	0.880	0.787	0.806	0.405	0.284	0.469
H_0: SI = ST	0.203	0.174	—	—	0.756	0.751	0.332	0.199	0.161	0.121
H_0: SI = FT	0.154	0.419	—	—	0.837	0.556	0.676	0.768	0.131	0.508
H_0: ST = FT	0.821	0.573	—	—	0.614	0.787	0.600	0.119	0.860	0.365

Notes: The table shows intention-to-treat (ITT) effects for students with below and above median predicted study time in the 2021 cohort. The Outcomes are similar to the ones reported in Table 2 and Table 3. Controls for performance differences at baseline (Outcomes in t-1) subsume the full vector of baseline outcomes as described in Section III.B. Baseline controls include: enrollment age, school GPA (German scale, and a missing dummy), time between school degree and university enrollment, and indicators for being female, having an A-level degree, started the first study attempt, graduated from a non-Bavarian school. Ordinary least squares estimates. Robust standard errors in parentheses.

Data set: Full sample of students from the 2021 cohort.

*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Study Ambitions

TABLE 17—TREATMENT EFFECTS ON STUDY AMBITIONS (2018 COHORT)

Dep. Var.:	Signed up Credits	Attempted Credits	Passed Credits
Sample: 2018 cohort	(1)	(2)	(3)
SI Treatment	1.866**	1.035	0.334
	(0.819)	(0.776)	(0.764)
ST Treatment	0.746	-0.157	-0.211
	(0.802)	(0.784)	(0.782)
FT Treatment	-0.012	-0.939	-1.234
	(0.796)	(0.790)	(0.774)
Outcomes in t-1	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Strata FE	Yes	Yes	Yes
R-squared	0.46	0.30	0.22
Observations	1199	1199	1199
Outcome Descriptives (control group)			
Mean	16.8	13.6	12.7
Median	15	14	14
SD	11.5	10.6	10.2
Min	0	0	0
Max	63	57	57
(Joint) Significant Tests (p-values)			
H_0: SI = ST = FT = 0	0.084	0.099	0.209
H_0: SI = ST	0.182	0.132	0.487
H_0: SI = FT	0.026	0.013	0.043
H_0: ST = FT	0.354	0.334	0.198

Notes: The table shows intention-to-treat (ITT) effects on study ambitions as measured by the number exams a student signed up for (Column 1), the number of exams a student attended (Column 2), and the number of passed exams (Column 3) in the 2018 cohort. All outcomes are measured in ECTS credits. Controls for performance differences at baseline (Outcomes in t-1) subsume the full vector of baseline outcomes as described in Section IV.B. Baseline controls include: enrollment age, school GPA (German scale, and a missing dummy), time between school degree and university enrollment, and indicators for being female, having an A-level degree, started the first study attempt, graduated from a non-Bavarian school. Ordinary least squares estimates. Robust standard errors in parentheses.
Data set: Full sample of students from the 2018 cohort.
*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

TABLE 18—TREATMENT EFFECTS ON STUDY AMBITIONS (2019 COHORT)

Dep. Var.:	Signed up Credits	Attempted Credits	Passed Credits
Sample: 2019 cohort	(1)	(2)	(3)
SI Treatment	0.556	0.971	0.262
	(0.860)	(0.810)	(0.768)
ST Treatment	-0.115	0.828	0.497
	(0.851)	(0.790)	(0.783)
FT Treatment	0.908	0.555	-0.180
	(0.830)	(0.779)	(0.735)
Outcomes in t-1	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Strata FE	Yes	Yes	Yes
R-squared	0.21	0.27	0.36
Observations	1582	1582	1582
Outcome Descriptives (control group)			
Mean	28.6	22.2	20.0
Median	29	24	21
SD	12.9	12.5	12.4
Min	0	0	0
Max	79	67	61
(Joint) Significant Tests (p-values)			
H_0: SI = ST = FT = 0	0.574	0.630	0.822
H_0: SI = ST	0.434	0.862	0.767
H_0: SI = FT	0.677	0.608	0.554
H_0: ST = FT	0.221	0.728	0.371

Notes: The table shows intention-to-treat (ITT) effects on study ambitions as measured by the number exams a student signed up for (Column 1), the number of exams a student attended (Column 2), and the number of passed exams (Column 3) in the 2019 cohort. Controls for performance differences at baseline (Outcomes in t-1) subsume the full vector of baseline outcomes as described in Section IV.B. Baseline controls include: enrollment age, school GPA (German scale, and a missing dummy), time between school degree and university enrollment, and indicators for being female, having an A-level degree, started the first study attempt, graduated from a non-Bavarian school. Ordinary least squares estimates. Robust standard errors in parentheses.
Data set: Full sample of students from the 2019 cohort.
*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

TABLE 19—TREATMENT EFFECTS ON STUDY AMBITIONS (2021 COHORT)

Dep. Var.:	Signed up Credits	Attempted Credits	Passed Credits
Sample: 2021 cohort	(1)	(2)	(3)
SI Treatment	-0.291	-0.159	-0.142
	(0.762)	(0.673)	(0.600)
ST Treatment	-0.791	-0.517	-0.204
	(0.724)	(0.665)	(0.615)
FT Treatment	0.206	0.150	0.251
	(0.765)	(0.691)	(0.625)
Outcomes in t-1	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Strata FE	Yes	Yes	Yes
R-squared	0.38	0.50	0.57
Observations	1938	1938	1938
Outcome Descriptives (control group)			
Mean	28.6	22.9	17.4
Median	30	25	20
SD	14.4	14.1	14.2
Min	0	0	0
Max	61	57	57
(Joint) Significant Tests (p-values)			
H_0: SI = ST = FT = 0	0.532	0.779	0.896
H_0: SI = ST	0.489	0.586	0.920
H_0: SI = FT	0.517	0.654	0.528
H_0: ST = FT	0.168	0.326	0.477

Notes: The table shows intention-to-treat (ITT) effects on study ambitions as measured by the number exams a student signed up for (Column 1), the number of exams a student attended (Column 2), and the number of passed exams (Column 3) in the 2021 cohort. Controls for performance differences at baseline (Outcomes in t-1) subsume the full vector of baseline outcomes as described in Section IV.B. Baseline controls include: enrollment age, school GPA (German scale, and a missing dummy), time between school degree and university enrollment, and indicators for being female, having an A-level degree, started the first study attempt, graduated from a non-Bavarian school. Ordinary least squares estimates. Robust standard errors in parentheses.
Data set: Full sample of students from the 2021 cohort.
*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

C. Survey Results on Subjective Well Being

TABLE 20—TREATMENT EFFECTS ON SUBJECTIVE WELL BEING

Dep. Var.:	Study Stress	Life Satisfaction	Study Satisfaction	Well-Being Index
	(1)	(2)	(3)	(4)
SI Treatment	0.247	0.017	0.029	-0.070
	(0.280)	(0.366)	(0.363)	(0.193)
ST Treatment	-0.064	0.380	0.165	0.148
	(0.259)	(0.361)	(0.397)	(0.186)
FT Treatment	-0.315	0.316	0.291	0.242
	(0.276)	(0.338)	(0.358)	(0.176)
Outcomes in t-1	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Strata FE	Yes	Yes	Yes	Yes
R-squared	0.59	0.57	0.58	0.58
Observations	574	574	574	574
Outcome Descriptives (control group)				
Mean	4.93	6.80	6.32	0.018
Median	5	7	7	0.19
SD	1.46	1.78	1.98	0.99
Min	1	2	0	-2.44
Max	7	10	10	2.43
(Joint) Significant Tests (p-values)				
H_0: SI = ST = FT = 0	0.264	0.543	0.860	0.233
H_0: SI = ST	0.247	0.319	0.726	0.239
H_0: SI = FT	0.047	0.348	0.496	0.061
H_0: ST = FT	0.300	0.860	0.725	0.580

Notes: The table shows intention-to-treat (ITT) effects on study stress, life satisfaction, study satisfaction, and a summary index of the three outcomes. Study stress is measured on a 7-point Likert scale with 1 equals "clearly do not agree" to 7 "fully agree". Life satisfaction and study satisfaction are both measured on a 10-point scale with 1 equals "completely unsatisfied" to 10 "completely satisfied". The well-being index summarizes the aforementioned outcomes following Anderson (2008) with weights estimated in the control group sample. Controls for performance differences at baseline (Outcomes in t-1) include the full vector of baseline outcomes as described in Section IV.B. Baseline controls include: enrollment age, school GPA (German scale, and a missing dummy), time between school degree and university enrollment, and indicators for being female, having an A-level degree, started the first study attempt, graduated from a non-Bavarian school. Ordinary least squares estimates. Robust standard errors in parentheses.
Data set: Survey sample of students from the 2018, 2019, and 2021 cohort.
*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

D. OSA-Questions on Sunk-Cost Effect

Question 1

Now suppose there is a free concert that lasts 90 minutes. To get to the concert, you ride your bike for 20 minutes. When the concert starts, you realize that you don't like the music. Would you stay until the end?

Answer: Yes, No, no answer

If you cycled 40 minutes to the same concert: would you stay until the end?

Answer: Yes, No, no answer

And if you cycled 5 minutes to the same concert: would you stay until the end?

Answer: Yes, No, no answer

Question 2

Now suppose you bought a bottle of juice for € 2. When you start to drink it, you realize you do not really like the taste. Would you finish drinking it?

Answer: yes, no, no answer

Now suppose you bought exactly the same bottle (brand, quantity and quality) of juice for € 2. Would you finish drinking it?

Answer: yes, no, no answer

And if you bought exactly the same bottle of juice for € 1? Would you finish drinking it?

Answer: yes, no, no answer

Now suppose you got exactly the same bottle of juice for free at the checkout as part of a marketing promotion. Would you finish drinking it?

Answer: yes, no, no answer

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