Opportunity cost neglect in higher education

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Abstract: Neglecting opportunity costs is a common cognitive bias that can impede effective decision-making. While laboratory experiments have demonstrated that making opportunity costs salient can influence decisions, evidence from real-world settings remains limited. In a preregistered field experiment (n = 2,222), we examine the impact of informing students about the opportunity cost of delayed graduation – specifically, the foregone salary for each semester graduation is postponed. Our findings reveal that highlighting the opportunity cost of delayed graduation does not improve academic performance. On the contrary, our treatment leads to an increase in the dropout rate of 28 %. Heterogeneity analyses show that the treatment increases first-semester dropout rates especially among students with a high probability of dropping out. However, by the third semester, dropout rates converge across groups, suggesting that the intervention may prompt earlier dropout decisions. This earlier dropout could be beneficial, as it allows students to pursue alternative career paths sooner.

Keywords: Opportunity Cost, Randomized Field Experiment, Higher Education

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1 Introduction

Making informed decisions requires not only access to accurate information but also the ability to integrate it effectively into the decision-making process. This includes accounting for all relevant costs, including opportunity costs (OC) – the benefits of the next best alternative. However, the behavioral bias of opportunity cost neglect often leads individuals to overlook these costs, resulting in suboptimal decisions (Maguire et al., 2023). While several laboratory experiments have shown that making opportunity costs salient can influence decision-making (Frederick et al., 2009; Plantinga et al., 2018), evidence from real-world settings remains limited. To our knowledge, only Kristal and Whillans (2020) and Hefti et al. (2021) have investigated the effects of salient opportunity costs in field experiments, with mixed results.

This paper presents evidence on whether highlighting opportunity costs influences high-stakes, real-world decisions in higher education. Specifically, we present evidence from a pre-registered randomized field experiment conducted with an incoming cohort of bachelors students at a German university of applied sciences. The study examines the effect of making the opportunity costs of delayed graduation salient on academic performance during the first semester.

Targeting students at the start of their academic journey is particularly relevant, as staying on track during the early semesters is critical for timely graduation. Moreover, students at this stage are less likely to recognize the financial costs associated with delayed graduation, given that the consequences lie in the distant future. The experiment consists of two treatment groups, both of which receive two postal letters during the semester with the treatment information. The first treatment arm (*T1*) receives information about the gross annual first-year salaries (full-time) of recent graduates from the same study program. The second treatment arm (*T2*) receives the same information as *T1* but additionally also receives the information that extending studying beyond the regular study time incurs costs equivalent to half a year's salary per semester. By incorporating the two treatment arms, we can distinguish whether an effect is due to the earnings information or due to salience of opportunity costs. To measure academic performance our main outcomes are the number of credit points (CP) signed up for, attempted, and passed. In addition our data also contains secondary outcomes such as the GPA and the dropout rate.

We find that explicitly stating the opportunity cost of delaying graduation does not lead to the intended positive effect on exam sign-up, attempts, or passing. Regardless of expecting a positive effect on study performance, based on the 95% confidence interval,we can rule out positive effects that are larger than 0.05 SD and therefore economically irrelevant.

While we do not find a positive effect on our main outcomes, we observe an increase in the dropout rate at the end of the first semester among students in *T2* by 2.8 percentage

points (p = 0.085). Notably, this effect is only present in the opportunity cost group (*T2*) and not in the group that received only earnings information, where no significant effect is observed.

To further investigate the effect on dropout, we predict the probability of dropping out in the first semester using data from a different cohort. Based on these predictions, we divide the sample at the median into a dropout-prone group (high predicted dropout probability) and a persistence-prone group (low predicted dropout probability). Among students in the dropout-prone group, we find that *T2* increases the dropout rate at the end of the first semester by 5.9 pp (p = 0.025), while there is no significant effect in the persistence-prone group. Delving deeper, we observe that the entire effect is driven by women in the dropout-prone group, where the dropout rate increases by 11.5 pp (p = 0.005).

Beyond the immediate effects, we analyze medium-term outcomes by tracking performance data through the second and third semesters. While the increase in first-semester dropout was not the intended effect of the treatment, it may still represent a positive outcome. Students on the margin of dropping out could benefit from exiting earlier, as it allows them to pursue alternative career paths sooner. Supporting this interpretation, our findings show that by the end of the third semester, dropout rates in the dropout-prone group converge between *T2* and the control group.

In the control group, students tend to drop out later, suggesting that the first-semester increase in dropout observed in *T2* may ultimately be beneficial by enabling students in this group to explore alternative paths earlier in their academic journey.

Regarding potential mechanisms, we argue that the information on opportunity costs in *T2* shows how costly delayed graduation can be. Especially students who know they have a high likelihood of graduating late who likely believed this does not come at any cost may now reconsider their career options. Another plausible explanation is that the treatment not only highlights the opportunity cost of delayed graduation but also implicitly underscores the broader opportunity cost of studying itself. This heightened awareness of the true costs of studying may prompt students already contemplating dropping out to act on this decision earlier in their academic journey.

Higher education provides a valuable setting for examining the effects of making opportunity costs salient on real-world decision-making. At the start of their studies, students are often unaware of the opportunity cost of delayed graduation specifically, the foregone salary they could earn by graduating on time. To complete their degree within the standard study duration of seven semesters, students must earn an average of 30 CP per semester.[1] Falling behind in the first semester creates a significant challenge, as catching up would require

[1]Under the European Credit Transfer System, students are expected to earn 30 CP per semester to reach the 210 CP required for graduation, corresponding to a nominal study duration of 7 semesters. However, the average time to graduation at the institution where the experiment takes place is 8.6 semesters.

exceeding the average workload in subsequent semesters, which is often difficult, or accepting a delayed graduation. Highlighting opportunity costs early in the program may improve study performance in the first semester, reducing the likelihood of students falling behind and increasing the chances of graduating on time.

Despite economic theory suggesting that individuals factor in opportunity costs when making optimal decisions, recent data highlights a trend of delayed graduations in various countries. Across OECD countries less than 40% graduate on time (OECD, 2022).[2] Students in OECD countries do not only take much longer to graduate, 23% of students leave university without obtaining a degree after all (OECD, 2022).

Although delayed graduation has consequences for society in general as well as for the individual[3], it could be a rational decision at the individual level. However, there is good reason to believe that considering opportunity costs is not part of the decision making process. Despite being easily available, students are often unaware of the returns to higher education (Wiswall and Zafar, 2015*b*). Additionally, they may not be aware of the opportunity costs of delayed graduation, such as the forgone salary earnings during the extra semesters studied. The decision to graduate on time is not made right before graduation, but rather an accumulation of decisions on how much effort to invest in each semester. Therefore, it is likely that students do not consider the opportunity cost of an additional semester, especially in the beginning of their university studies.

Related literature. Our research contributes to the literature in two key ways. First, it advances the understanding of opportunity cost neglect by investigating whether explicitly highlighting the opportunity costs of delayed graduation impacts academic performance. This study is among the first field experiments to examine whether information about opportunity costs can influence real-world, high-stakes decisions. Previous research has primarily focused on hypothetical scenarios, as first demonstrated by Frederick et al. (2009), who showed that making the opportunity cost of a hypothetical purchase salient reduced willingness to buy. This approach has been replicated across domains such as charity and public policy with similar results (Plantinga et al., 2018; Zhang et al., 2017; Moche et al., 2020; Persson and Tinghög, 2020). Additionally, studies suggest that opportunity costs are relevant in intertemporal choices, where emphasizing future payoffs highlights the implicit costs of immediate consumption (Spiller, 2019; Zhao et al., 2015; Read et al., 2017). A meta-analysis

[2] In Germany, only 32% of Bachelor and Masters students graduate on time (Destatis, 2021). Even in the US, where the explicit costs of studying are among the largest in the world, less than half of all students studying towards a four-year degree, graduate within that time period (NCES, 2022)

[3] In Germany, every student costs society an average of $19,608. In the US, this number is almost doubled at $35,347 (see OECD data from 2022, `https://www.compareyourcountry.org/snaps/education-at-a-glance-2022/en/4358/2019/OAVG`, retrieved on Feb. 20th, 2025). Delayed graduation results in delayed access to the skilled workforce, which is particularly problematic during times of skilled worker shortages. It also delays tax contributions and contributions to the social security system

by Maguire et al. (2023) finds a significant effect of $d = 0.22$ (Cohen's d) for opportunity cost salience, though these studies are predominantly hypothetical. This underscores the need for research examining whether these findings extend to real-world decisions.

To date, only two field experiments have explored the impact of salient opportunity costs on behavior, with mixed results. Kristal and Whillans (2020) tested whether highlighting the opportunity cost of driving alone would increase carpooling among registered users of a carpooling service but found no effect. Conversely, Hefti et al. (2021) examined the impact of emphasizing the energy savings from purchasing an efficient air conditioner, framed in relatable terms (e.g., boxes of milk). They found that the treatment reduced demand for the more efficient model, as it corrected consumers' overestimated savings. These mixed results highlight the complexity of applying opportunity cost salience in real-world contexts and the need for further investigation. Our study contributes to this line of research by testing the salience of opportunity costs in the domain of higher education, providing evidence on how it can influence high-stakes decisions such as academic performance and dropout behavior.

Second, we contribute to the literature on the impact of labor market information on college students. To our knowledge, this is the first study to examine whether providing students with information about labor market returns affects their academic performance. Previous research has largely focused on how labor market returns influence college enrollment and major selection. Early work by Willis and Rosen (1979) posited that college enrollment decisions are based on expected returns. However, studies on earnings expectations among college students reveal significant biases. For example, Wiswall and Zafar (2015*b*) and Conlon (2021) find that students consistently underestimate population earnings. Providing accurate earnings information has been shown to affect students beliefs about returns to education (Berkes et al., 2022; Wiswall and Zafar, 2015*b*) and influence their choice of major (Wiswall and Zafar, 2015*a*; Conlon, 2021). In the German context, Peter and Zambre (2017) show that providing high school students with information about the earnings premium for college graduates increases college intentions, particularly among those from non-academic backgrounds. Similarly, Stinebrickner and Stinebrickner (2014) demonstrate that earnings expectations influence college dropout decisions.

Our findings add to this body of work by showing that providing earnings information alone does not impact academic performance. Furthermore, we provide new evidence that framing earnings information as an opportunity cost can influence decision-making in a high-stakes, real-world setting.

The remainder of this paper is organized as follows: first, we describe the institutional background of our study followed by the empirical approach, the results section, and the conclusion.

2 Institutional background, Data, and Research Design

The study was conducted at a large public university of applied sciences in Germany. Unlike research-oriented universities, universities of applied sciences in Germany emphasize practical training.[4] In the fall of 2021, approximately 37% of students in Germany were enrolled at a university of applied sciences.[5]

Our study focuses on an incoming cohort of 2,222 students pursuing bachelors degrees across 21 study programs, most of which are STEM-related. The five largest programsBusiness Administration, Social Work, Mechanical Engineering, Electrical Engineering and Information Technology, and Civil Engineeringcomprise just over half of the sample (see Table A.1 for an overview of the study programs and corresponding student numbers).[6]

In contrast to higher education systems in countries like the United States, where students often declare their major after enrollment, students in Germany select their field of study before starting university. This feature of the German system allows us to analyze the treatments impact across different fields of study, which is particularly relevant because anticipated starting salariesand therefore the opportunity cost of an additional semestervary significantly by program.

All study programs are organized based on the European Credit Transfer System (ECTS), and the standard study duration is seven semesters. In order to graduate on time, students need to earn an average of 30 credit points (CP) per semester, totaling 210 CP throughout their program. Previous study groups have shown an average program length of 8.5 semesters across all programs (with a standard deviation of 1.3), indicating that students typically require on average 1.5 additional semesters to complete their studies.

2.1 Data

For the implementation and the analysis of the experiment we use four different data sources.

Earnings data: To calculate the expected earnings after graduation, we use aggregated data from surveys of recent graduates from graduation cohorts between 2009/10 and 2018/19 (N =1,660), which include information on gross hourly starting salaries. Based on this information, we calculated gross annual salary for full-time employment (38.2 hours

[4] For example, students are required to complete a mandatory internship, typically during the fourth or fifth semester of their studies.

[5] Federal Statistical Office of Germany, `https://www.destatis.de/DE/Themen/Gesellschaft-Umwelt/Bildung-Forschung-Kultur/Hochschulen/Tabellen/studierende-insgesamt-bundeslaender.html`

[6] The sample includes nearly all bachelors programs offered at the university, with the exception of Design and Architecture.

per week, incl. end-of-year bonus of 0.25 monthly salaries) in base year 2020. The average salary from our calculation is 48,745, which is comparable to the average (Bachelor and Master) starting salary in Bavaria according to the job portal *Stepstone*, which is 46,854 (Heming et al., 2020).

OSA data: Students complete an Online Self-Assessment (OSA) prior to commencing their studies, which includes a short section specifically designed for our study, asking questions such as salary expectations, time preferences, procrastination tendencies and opportunity cost considerations. The OSA is mandatory for nine study programs, while students from the remaining programs may participate voluntarily, resulting in data from 1,121 students.

Administrative data: We use administrative data consisting of students' pre-randomization background information. Additionally, we obtain data from the university's examination office after the intervention semester (first semester). This data includes the number of credits attempted and passed, the grade point average (GPA), and dropout statistics. Furthermore, we utilize records from the examination office, consisting of students' performance and progress at the end of the third semester, to assess prospective midterm results.

Survey data: Midway during the semester we administered a web-based post-treatment survey in which we ask students about their expected earnings after graduation, current financial situation, number of study hours, and non-cognitive outcomes (Tables C.2, C.3, C.4, C.5 list all the OSA and survey questions).

2.2 Research Design

Students were randomly assigned to one of three groups: 739 students were assigned to the control group, while 740 and 743 students were assigned to the two treatment groups, respectively. The control group received a letter containing information about university-provided counseling and support services (see Figures C.1 to C.4).

The first treatment group, referred to as the Earnings Information (EI) group, received the same information as the control group, along with additional details about the average gross annual starting salary of recent graduates from the same or similar study programs (see Figure C.2 for the design of the EI group letter).

The second treatment group, the Opportunity Cost (OC) group, received all the information provided to the EI group, with an additional explicit statement highlighting the opportunity cost of an extra semester. Specifically, the OC treatment letter included the sentence: "How will this affect your plans for further study? Each additional semester of study may result in the loss of approximately half of this salary." (see Figure C.3 for the design of the OC group letter).

To provide context for the letters, all groups were informed that a survey of students from a previous cohort had revealed a desire for more information on career prospects and that the university was testing different ways of delivering this information.

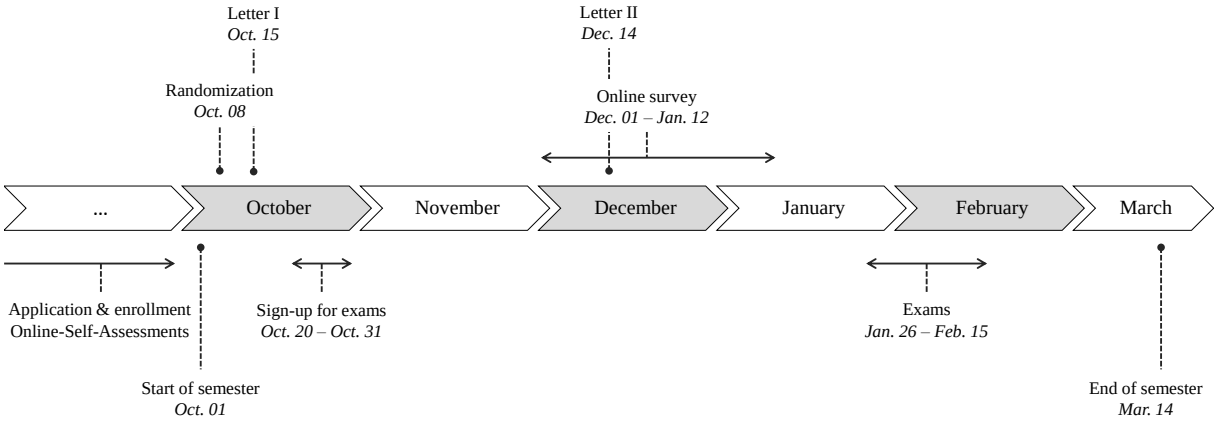
All groups received two postal letters during the semester. The first letter was sent in the third week of the semester, just before the start of the exam sign-up period. The second letter, containing the same information as the first, was sent just before the Christmas break, approximately four weeks before the examination period began.

Additionally, students were invited to participate in an online survey shortly before the second letter was sent. A detailed timeline of the experiment is provided in Figure 1.

This research design allows us to test two key questions. First, does informing students about the opportunity cost of delayed graduation in the beginning of their university studies improve their academic performance in the first semester? Second, does simply providing information about potential future labor market outcomes affect first-semester academic performance? By comparing the two treatment arms, we can determine whether any observed effects in the OC group are specifically due to the salience of opportunity costs or merely the result of providing earnings information.

We hypothesize that making the opportunity cost of delayed graduation salient will motivate students to avoid falling behind in their studies and to aim for on-time graduation.

Figure 1: Timeline of intervention



Notes: Timeline of the experiment

The experiment was conducted during the 2021/22 winter semester, in the midst of the COVID-19 pandemic. By this time, most lectures and exams had returned to face-to-face formats, although certain study regulations had not yet been fully normalized. However, our survey indicates that this did not affect students' perceptions of the ideal study duration, as they still believed it to be seven semesters. Therefore, we do not anticipate any significant impact of the pandemic on our results.

Randomization Randomization was carried out performing threshold blocking within study programs using the R quickblock package (Higgins et al., 2016). We used the Mahalanobis distance with respect to students' high school GPA, their gender, and a proxy for procrastination.[7] Minimal block sizes range from 6 in smaller programs to 21 in larger programs for a total of 120 blocks. The subsequent within block-randomization was performed with Stata's randtreat command Carril (2017) using equal assignment probabilities. Further details are provided in the pre-analysis plan in Appendix D.

3 Empirical Approach

Descriptive characteristics and balancing properties. For the later analyses, it is important that the randomization was successful in achieving balance between the control and treatment groups. In Table 1, we assess this by reporting descriptive statistics for the three experimental groups and p-values from F-tests for the joint significance of the treatment dummies. These are based on regressions of the respective covariates on treatment group indicators, controlling for randomization strata fixed effects (FE). The exercise shows that our randomization results in a well-balanced sample.[8]

Main analysis. To estimate the average treatment effects of our intervention, we primarily rely on the following specification:

$$Y_i^k = \alpha_0 + \alpha_1 \textit{T1: salary info}_i + \alpha_2 \textit{T2: salary \& OC info}_i + \boldsymbol{x_i}\alpha_3 + \boldsymbol{s_i} + \varepsilon_i, \tag{1}$$

where Y_i^k is the outcome of interest, *T1: salary info*$_i$ and *T2: salary & OC info*$_i$ are dummies for being randomized in the respective treatment groups, and $\boldsymbol{s_i}$ are FE controlling for the random assignment within strata. In a second specification, we include the vector $\boldsymbol{x_i}$ containing the covariates listed in Table 1. Based on this equation, we test whether $\alpha_1 = 0$, $\alpha_2 = 0$, and whether $\alpha_2 - \alpha_1 = 0$. Note that the effects we estimate should be interpreted as intention to treat effects, since we do not know whether students open and read the letters.

In designing the intervention, we hypothesized that making students aware of the OC of delayed graduation would accelerate their study progress. In our pre-analysis plan (see Appendix D), we therefore specified the number of signed-up, attempted, and passed course

[7] To construct the proxy, we used Statas swindex command by Schwab et al. (2021) to calculate the standardized inverse-covariance weighted average (Anderson, 2008) of the date of application for the study program and the date of enrollment. The date of enrollment was first standardized within study programs, due to differences in the timelines of the enrollment periods between study programs.

[8] The low p-values from the F-tests for joint significance of the treatment dummies for the high school GPA ($p = 0.219$) and the procrastination index ($p = 0.098$) are partly due to the fact that these covariates – and gender – were used to construct the randomization strata, resulting in very high R^2 (0.70 and 0.63, respectively).

Table 1: Descriptive statistics and balancing properties

	(1) T0: Control	(2) T1: Salary info	(3) T2:Salary & OC info	(4) p-value F-test
Covariates used for blocking				
High school GPA	2.538	2.527	2.508	0.219
Procrastination index	0.008	-0.034	0.026	0.098
Women	0.367	0.362	0.363	0.677
Other covariates				
Age	21.683	21.617	21.607	0.918
Time since HS degree	1.805	1.743	1.808	0.873
First university semester	0.732	0.739	0.708	0.337
HS degree "Abitur"	0.521	0.522	0.514	0.916
N	739	740	743	

Notes: Columns (1) to (3) report the means of the covariates, separately for the three experimental groups. The p-values from the F-tests of joint significance reported in Column (4) are based on regressions that control for strata FE and use robust standard errors. In Germany, 1.0 is the best and 4.0 is the worst possible grade in the high school GPA (= grade of the university entrance qualification). The procrastination index is the inverse-covariance weighted average of the date of application to the study program and the date of enrollment. The latter was first standardized within study programs to account for differences in the enrollment periods. First university semester indicates whether this is the first semester at any university. High school degree "Abitur" refers to the German general track high school degree. It is one of the two main secondary school degrees in the tracked school system in Germany that qualifies students to study at a university of applied sciences; the other being the vocational track degree (Fachhochschulreife).

credits in the first semester as our primary outcome variables Y_i^k. However, we also use the estimation equations described here to study effects on our secondary academic achievement outcomes (students' GPA and dropout behavior).

Statistical power of the main analysis. After receiving information on the number of students that enrolled in our intervention cohort, we performed ex-ante power calculations for our main analysis (see Table A.2). Depending on the assumed R^2 (0.00 to 0.40), our study has 60% (80%) power to detect effect sizes between 0.090 and 0.115 (0.114 and 0.146) standard deviations (SD).Thus, our study is well powered to detect effect sizes which would be considered medium for an intervention in an educational context (Kraft, 2020, 2023), and effect sizes that have previously been reported for studies on opportunity cost neglect.[9]

Secondary analyses. Besides studying effects on the main administrative academic achievement outcomes signed-up, attempted, and passed course credits, we also study effects on the GPA and on dropout behavior. Additionally, we pre-registered to study effects on survey outcomes, such as students' salary expectations and non-cognitive outcomes, and to study heterogeneity along our blocking dimensions as well as along information about students' preferences collected in the OSAs (see Appendix D). When estimating effects on sur-

[9] Cohen's d in the meta-analysis on opportunity cost neglect by Maguire et al. (2023) is 0.22.

vey outcomes and in heterogeneity analyses using information from the OSAs, we adjust the estimation equation to include study program FE instead of strata FE.[10] In terms of selection into the survey and OSAs, Tables A.3 and A.4 show that there is no difference in participation by treatment status (≈ 54% and ≈ 18%, respectively).

4 Pre-registered analysis of first-semester effects

In this section, we present the results of the pre-specified first-semester analysis. To do so, we first present and discuss the treatment effects on our primary and secondary academic achievement outcomes. Subsequently, we explore potential mechanisms underlying our main effects, including heterogeneous effects along students' prior salary expectations, their time preferences, and effects on non-cognitive outcomes.

4.1 Signed-up, passed, and attempted course credits

With students' pre- and post-treatment salary expectations in mind, we now turn to analyzing the effects of our intervention on the signed-up, attempted, and passed first-semester course credits. For each of these outcomes, we present treatment effects based on Equation 1 in Figure 2 and Table A.5 in the appendix.

Regression results from then analysis of the main outcomes, signed up CP, attempted CP, and passed CP in Figure 2 and Table A.5 show no effect of the treatments. Columns (1) and (2) show that *T1* and *T2* reduce the number of course credits signed up for slightly by 0.217 to 0.363 ($p = 0.661$ to 0.452) and 0.385 to 0.440 ($p = 0.389$ to 0.444), respectively. However, all estimates are imprecisely measured.

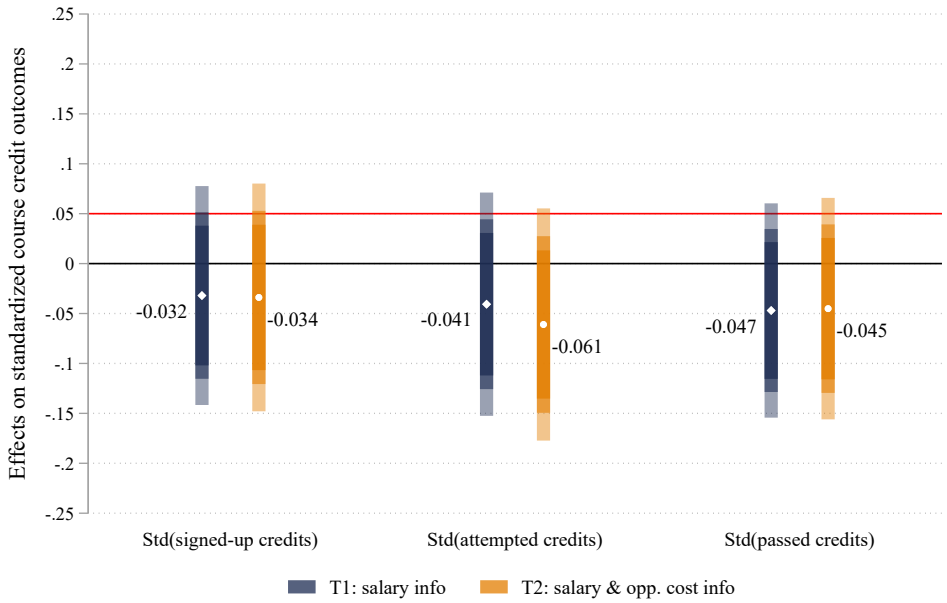
The same is true for attempted and passed CP. For *T1*, the estimates in columns (3) and (4) of Table A.5 are again slightly negative with the point estimates again imprecisely estimated.

Considering students' passed course credits, the effects of *T1* and *T2* are similar again. As reported in columns (5) and (6) of Table A.5, for both treatments there is no effect on the number of passed course credits.

Taken together, these results indicate that the treatment does not have a statistically or economically significant positive impact on any of the main outcomes. Figure 2 includes a horizontal red line at an effect size of 0.05 SD, which serves as the threshold for a small effect in education studies as anything below 0.05 SD is considered small (Kraft, 2020). Based on the 95% confidence intervals for all point estimates, we can rule out any effects larger than

[10] We do this in light of the reduced number of observations in the survey and OSA samples. Because of the fine-grained nature of the strata we constructed, we would otherwise effectively lose the observations of those strata in which there is not enough remaining variation in treatment assignment.

Figure 2: Effects on signed, attempted, and passed credits



Notes: The graph results from OLS regressions based on Equation 1. *Controls:* High school GPA, procrastination index, age, time since graduation, and dummies for women, high school degree Abitur, and first semester at any university. 99%, 95%, and 90% confidence intervals based on robust standard errors are shown.

0.05 SD and therefore conclude that there is no economically meaningful impact.

If anything, both treatments, but particularly *T2*, slightly reduce the number of CP signed-up, attempted, and passed in the first-semester. That is, the direction of the effect is in the exact opposite of the effects that we hoped to induce with our intervention. In principle, this response could be driven by students trying to increase their likelihood of graduating by slowing down their progress. However, Table A.6 shows that the proportion of students signing up, attempting, and passing zero credits is increased by the treatments suggesting that treatments may actually lead students to abandon their studies altogether. Below we assess this further by considering the effects on our secondary achievement outcomes.

4.2 GPA, dropout, and overall academic achievement

In Columns (1) and (2) of Table 2, we first consider whether the treatment has an effect on students' **GPA**. We find that neither treatment has a discernible effect on students GPA as the GPA for both groups increases only slightly by 0.018 to 0.021 grade points ($p = 0.639$ to 0.576) (*T1*) and 0.015 to 0.026 grade points ($p = 0.700$ to 0.479) (*T2*), respectively.[11]

[11] Since the German grading scale goes from 1.0 to 4.0 with 1.0 being the best possible grade, an increase in the GPA translates to a decrease in performance

Table 2: Treatment effects on GPA, dropout, and academic achievement index

	GPA		Dropout		Achiev. index	
	(1)	(2)	(3)	(4)	(5)	(6)
T1: salary info	0.018	0.021	-0.002	0.002	-0.001	-0.014
	(0.038)	(0.037)	(0.016)	(0.015)	(0.051)	(0.051)
T2: salary & OC info	0.015	0.026	0.028*	0.028*	-0.097*	-0.095*
	(0.038)	(0.037)	(0.016)	(0.016)	(0.053)	(0.052)
T2-T1	-0.003	0.005	0.030*	0.026	-0.096*	-0.082
	(0.039)	(0.037)	(0.016)	(0.016)	(0.053)	(0.053)
Strata FE	yes	yes	yes	yes	yes	yes
Controls	no	yes	no	yes	no	yes
N	1,599	1,599	2,222	2,222	2,222	2,222
Control mean	2.45	2.45	0.10	0.10	0.00	0.00
(SD)	(0.71)	(0.71)	(0.30)	(0.30)	(1.00)	(1.00)

Notes: GPA N/A indicates whether the GPA is observed for a student. *GPA* is students grade point average at the end of the semester and is only observed for students who passed at least one graded course (1.0 is the best and 4.0 the worst possible GPA). *Dropout* indicates whether a students dropped out of their study program by the end of the semester. *Achievement index* is the inverse-covariance weighted average of the number of passed course credits, the GPA, and the dropout indicator. *Controls:* High school GPA, procrastination index, age, time since graduation, and dummies for women, high school degree Abitur, and first semester at any university. Robust standard errors in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Related to the aforementioned notion that our treatment may lead students to abandon their studies altogether, we consider effects on **dropout** at the end of the first semester in Columns (3) and (4). For *T1*, we find no effect on students' decision to drop out. This tentatively suggests that providing students with information about their future salary prospects may have the effect of slowing students' progress. For *T2*, on the other hand, we find an increase in the dropout rate of 2.8 pp ($P = 0.080$ to 0.085; Column (3) and (4)). Relative to the control group dropout rate of 10%, this is an increase of 28%. The effect of *T2* is also 2.6 to 3.0 pp larger than the effect of *T1* ($p = 0.109$ to 0.064), suggesting that the increase in dropout is in fact driven by focusing students' attention on opportunity costs, and not by the salary information itself.

To account for the fact that these are only our secondary outcomes, and to reduce concerns about multiple hypothesis testing, we also estimate effects on the inverse-covariance weighted average of the number of passed course credits, the GPA, and the dropout indicator (Anderson, 2008), i.e., an **index of students' academic achievement** in the first semester (Columns (5) and (6)). The results of this exercise are consistent with our findings on dropout: while *T1* has no effect on students' academic achievement, *T2* leads to a reduction of 0.095 and 0.097 SD ($p = 0.069$ and 0.068); the difference between the effects of the two treatments corresponds to 0.082 to 0.096 SD ($p = 0.120$ to 0.072).

4.3 Post-treatment salary expectations

Does the salary information that we provide in our treatments lead to a shift in students' expectations? To examine this, in the post-treatment online survey, we again asked students to estimate the current average gross annual salary for full-time employment in the first year after graduation. Table A.7 shows that *T2* increases students' average salary expectation in the first year after graduation by 6,100 to 6,800. In addition, the confidence in these estimates is also significantly increased by approximately 6 pp compared to the control group. While the expectation for the own salary in the first year after graduation is not affected by *T2*, the confidence in the estimates is also increased by approximately 6 pp for the own salary estimate. *T1*, on the other hand, has no effect on students' salary expectations or the confidence in the expectation.

4.4 Post-treatment survey outcomes

In addition, we pre-registered to analyze the treatment effect on non-cognitive outcomes measured in the post-treatment online survey. Table A.8 shows a significant negative treatment effect from *T2* on the freedom to design ones studies and on personal development. While life satisfaction, stress, and study satisfaction are not significantly affected, an index for all variables together is significantly negative affected by *T2*. Notably, the negative effects are less pronounced for *T1*. For *T1*, freedom to organize their studies and study satisfaction is negatively affected. The index has a negative point estimate as well but is imprecisely measured.

One caveat of this analysis is that the response rate in the online survey is only around 18%. While Table A.4 shows that there is no differential participation by treatment status and that the effect of *T2* on the achievement index is also negative in the survey sample (although less pronounced and not significant), it also indicates that the survey sample is very positively selected. That is, the academic achievement in the control group is 0.35 SD better compared to the full sample and the achievement is much more homogeneous (SD of 0.33 instead of 1). In particular, almost no students who end up dropping out, participated in the survey. It is therefore not clear whether the treatment effects on the non-cognitive outcomes extrapolate to the full sample.

5 Exogenous stratification by predicted dropout probability

It is possible that the effect on dropout is even larger for a subgroup of students due to countervailing positive and negative effects for different groups of students. Therefore, we want to gain some insight into whether this is likely to be the case and who is actually driving the

negative first-semester treatment effects in the full sample. One question we want to answer is whether the increase in dropout is due to students who would have dropped out anyway in later semesters or to students who decided to drop out only because of the treatment. In the following exploratory analysis, we therefore examine the heterogeneity of treatment effects along the (counterfactual) probability of dropping out in the first semester. This will provide evidence as to whether it's the students with a high or low probability of dropping out that drive the negative treatment effects.

For the analysis, we use exogenous stratification. First, in a different cohort of students from the same study programs and semester, we regress students dropout probability after the first semester on study program FE and our set of control variables. Next, we predict the dropout probability in the control and treatment groups. Finally, we split the sample at the median of the predicted dropout probability to obtain two exogenous strata: low and high probability dropouts. We then interact our treatment indicators with a dummy for the high-probability stratum to examine heterogeneity by students predicted (counterfactual) dropout. Based on this model, Table 3 shows the results for the high and low dropout probability strata on the achievement index and dropout.

Table 3: Treatment effects on academic achievement index and dropout by predicted dropout strata

Semester	Ach ind		Dropout	
	(1)	(2)	(3)	(4)
T1: salary info	0.030	0.020	-0.010	-0.007
	(0.084)	(0.082)	(0.026)	(0.025)
T2: salary & OC info	-0.200**	-0.204**	0.059**	0.059**
	(0.088)	(0.086)	(0.027)	(0.026)
T1*low probability stratum	-0.073	-0.060	0.020	0.016
	(0.103)	(0.102)	(0.031)	(0.031)
T2*low probability stratum	0.213**	0.222**	-0.063*	-0.065**
	(0.105)	(0.103)	(0.032)	(0.032)
T1+T1*low prob. stratum	-0.043	-0.040	0.010	0.009
	(0.059)	(0.060)	(0.018)	(0.018)
T2+T2*low prob. stratum	0.012	0.018	-0.004	-0.005
	(0.057)	(0.058)	(0.017)	(0.017)
Strata FE	yes	yes	yes	yes
Controls	no	yes	no	yes
N	2,222	2,222	2,222	2,222
Control mean high probability stratum	-0.18	-0.18	0.15	0.15
Control mean low probability stratum	0.19	0.19	0.06	0.06

Notes: Achievement index is the inverse-covariance weighted average of the number of passed course credits, the GPA, and the dropout indicator. *Dropout* indicates whether a students dropped out of their study program by the end of the semester. *Controls:* High school GPA, procrastination index, age, time since graduation, and dummies for women, high school degree Abitur, and first semester at any university. Robust standard errors in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 3 shows that the negative effects of T2 that we observe in the first semester are entirely driven by students in the high dropout probability stratum. For them, the treatment decreases academic achievement by 0.204 SD (p = 0.017, columns (1) and (2)). There is no

effect for students in the low dropout probability stratum. Columns (3) and (4) of Table 3 show that the decrease in academic achievement is in part due to an increase in dropout among students in the high dropout probability group as the dropout rate increases by 5.9 pp (p = 0.025). Again, there is no effect on dropout for students in the low dropout probability stratum. Interestingly, *T1* has no significant effect for the high probability stratum (0.02 SD for academic achievement, p = 0.53; and -0.01 pp for dropout, p = 0.78).

The results show two things: first, the effect on dropout and the achievement index is driven by students who have a high probability to dropout after the first semester. Second, the effect only persists if the information includes opportunity costs as only informing students on expected future earnings does not have any effect. The additional information that a longer study duration incurs opportunity costs leads students who have a higher dropout probability to actually make the decision to drop out.

In the next section, we aim to qualify these results by exploring how the effects of our intervention evolve in the medium term. In particular, we are interested in finding out whether these short-term negative effects are likely to have persistent negative effects on students educational trajectories. To this end, we investigate treatment effects in the second and third semester and show that the achievement gap between treated and controls converges. In doing so, we provide evidence that the negative treatment effects in the first semester are driven by students who would likely have dropped out by the third semester.

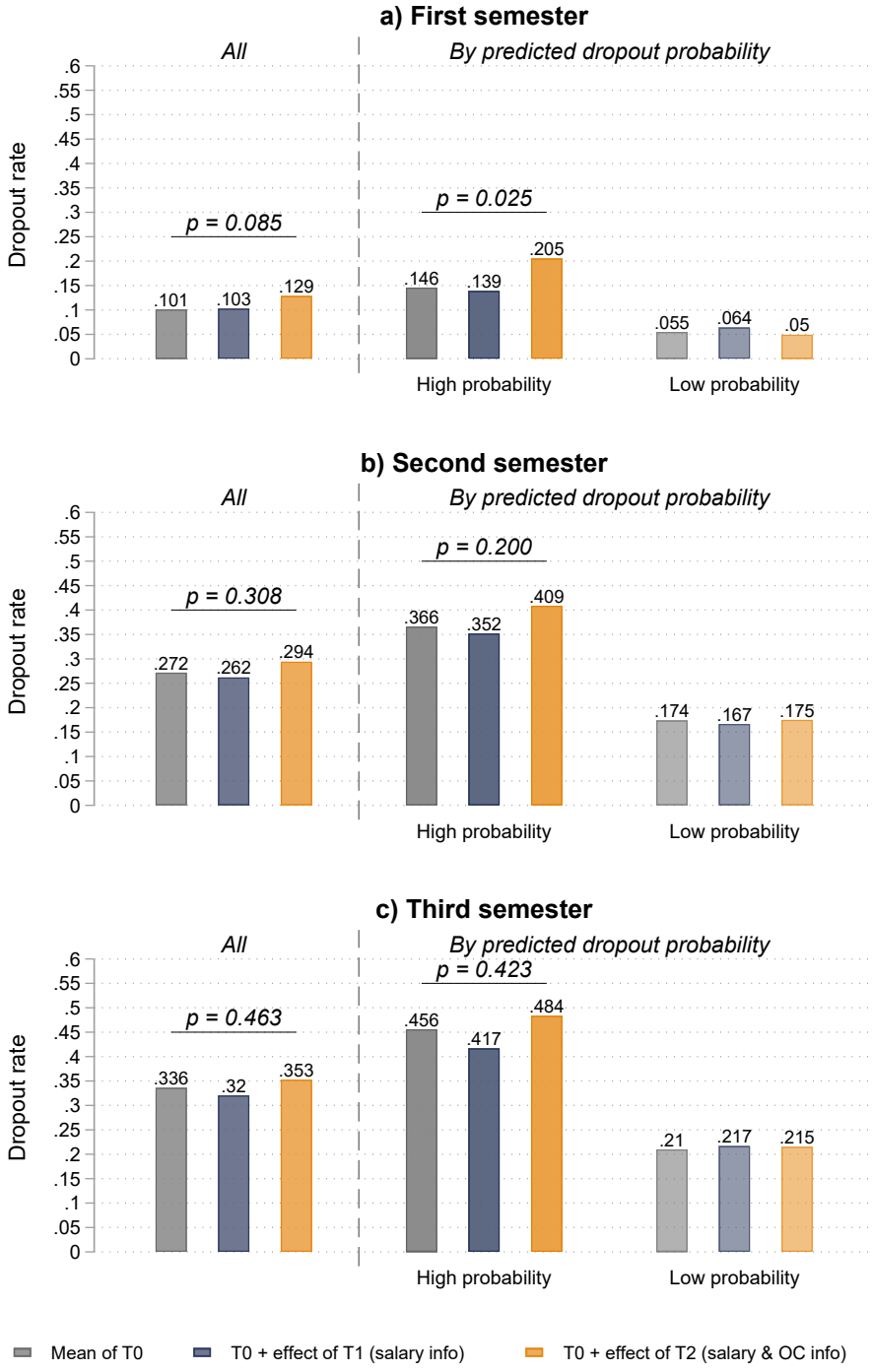
5.1 Medium term effects in second and third semester

Given the substantial returns to tertiary education and the increase in dropout we find in the first semester, one might be concerned that students are worse off as a result of our intervention. To provide more evidence on this and on the downstream effects of our intervention, we continue the exploratory analyses and explore effects in the second and third semester[12]. Basically, there are two possible scenarios: First, the gap between treatment and controls may remain the same or even widen, suggesting that the negative effects of focusing students attention on the monetary aspects of studying persist and that our intervention may even have negative long-term effects on degree attainment. Second, the gap may start to converge, which would suggest that the treatment causes students to bring forward their decision to drop out.

In Figure 3 and Table A.9, we present estimates of the effects on dropout in the second and third semester as well es the effects for the high and low dropout probability strata in each semester (results are also displayed in Table A.10). The left hand side of Figure 3 shows the overall effect in the second and third semester on dropout. The estimated coefficients show that in the second and third semester, the negative effect of *T2* on dropout falls to 2.2

[12]Results for the full sample are displayed in table A.11 and A.12

Figure 3: Treatment effects on dropout until third semester by predicted dropout strata



Notes: The left-hand sides of the graph shows the overall dropout rate. The right-hand sides shows the dropout rate for students in the high dropout probability and the low dropout probability strata, respectively. Dropout indicates whether a students dropped out of their study program by the end of the respective semester. Regressions include the following controls: High school GPA, procrastination index, age, time since graduation, and dummies for women, high school degree Abitur, and first semester at any university

pp (p = 0.308) and 1.7 pp (p = 0.463), respectively, and is no longer statistically significant at any conventional level. The same is true for the overall effect on the achievement index in

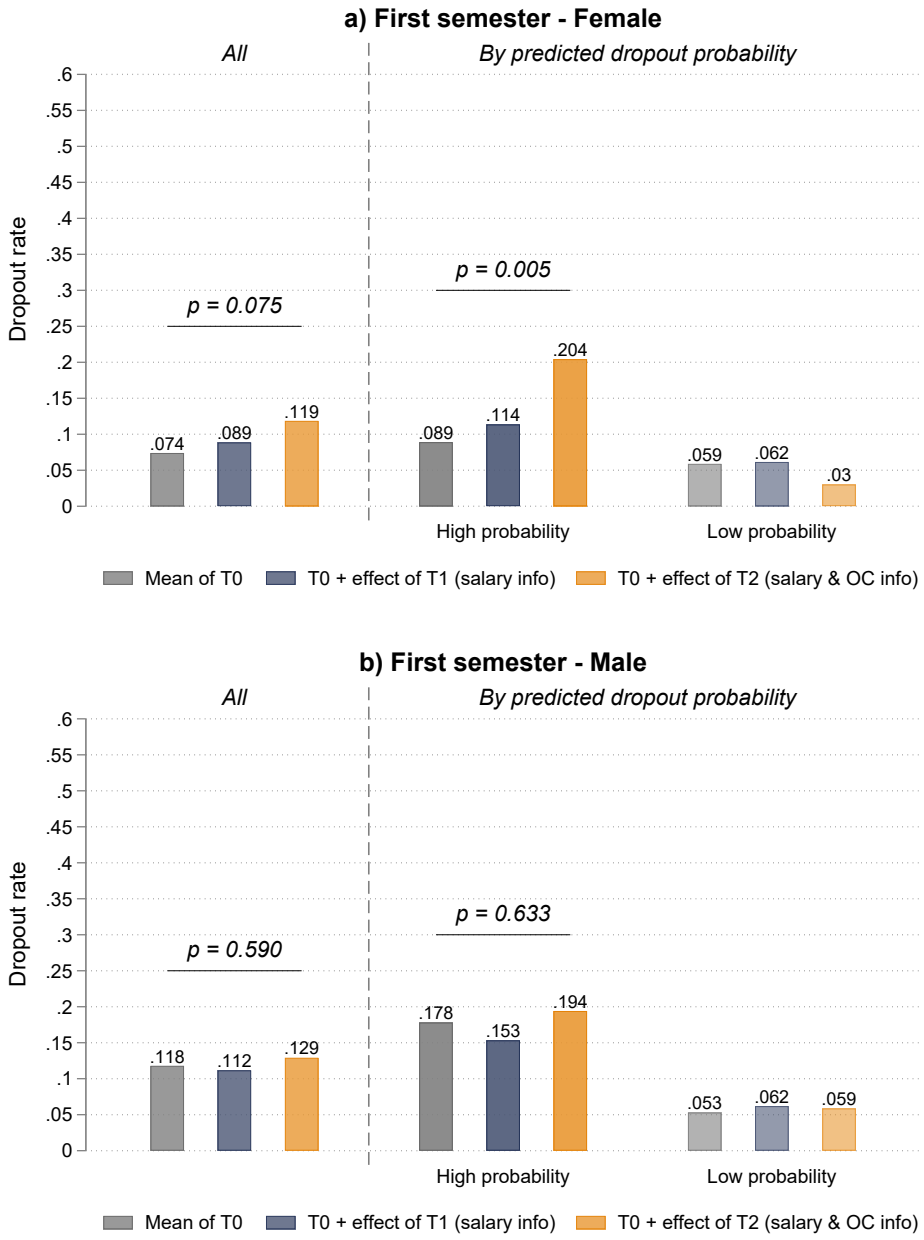
Table A.10, which is reduced to 0.057 SD ($p = 0.213$) and 0.041 SD ($p = 0.352$) in the second and third semester, respectively. The same holds for the group with a high probability to drop out. The estimated coefficient on dropout decreases to 4.3 pp ($p = 0.200$) in the second semester and 2.8 pp ($p = 0.423$) in the third semester, both coefficients are not statistically significant at any conventional level. The gap for the achievement index also converges for students in the high dropout probability stratum as the estimated coefficient decreases to 0.103 SD ($p = 0.143$) in the second semester and 0.071 SD ($p = 0.285$) in the third semester. This suggests that dropout and the academic performance of treated and controls converges over time and that the negative effects we found for the first semester do not persist over the following semesters. Results indicate that students who have a high probability to dropout in the first semester do so at higher rate in the treatment group. While the treatment group does not drop out at a higher rate after three semesters, they do so earlier which may be interpreted as a positive result as these students can look for alternative career paths sooner.

5.2 Gender effects

To further investigate the effect on dropout for dropout prone students, we analyze whether the treatment effect varies with respect to our threshold blocking dimensions – procrastination, high school GPA, and gender. While no heterogeneous treatment effect on dropout is observed with respect to procrastination or high school GPA (see Table A.13), we observe a significant interaction effect for female students who are prone to drop out. Figure 4 further illustrates the dropout effects: the top panel shows results for females, while the bottom panel displays those for males. The figure demonstrates that the treatment effect on dropout is almost entirely driven by dropout-prone female students (corresponding regression results are in Table A.14). In the full sample, the dropout rate for females in *T2* increases by 4.5 percentage points ($p = 0.075$). Among dropout-prone females, this increase is even larger at 11.5 percentage points ($p = 0.005$), relative to the control group. No effect, however, is observed in the persistence-prone group. Turning to the lower panel for men, there is no significant effect on dropout rates in either the full sample or the dropout-prone subgroup in *T2*. Since the effect on dropout in the first semester is driven by females who are prone to drop out, it is not surprising that the increase in the dropout rate does not persist into the following two semesters. As shown in Figure A.1, there is no significant effect for dropout-prone females in the second and third semesters, suggesting that the initial increase comes from students who would have dropped out anyway.[13]

[13] There is also no effect for males as shown in Figure A.2

Figure 4: Treatment effects on dropout until third semester by predicted dropout strata for female and male students



Notes: Graph on the top shows the dropout rate for females, and the graph on the bottom for males. The left-hand sides of each graph show the overall dropout rate. The right-hand sides show the dropout rate for students in the high dropout probability and the low dropout probability strata, respectively. Dropout indicates whether a student dropped out of their study program by the end of the respective semester. Regressions include the following controls: High school GPA, procrastination index, age, time since graduation, and dummies for women, high school degree Abitur, and first semester at any university.

5.3 Potential mechanisms behind the negative effects on dropout

We designed our intervention with two goals in mind. First, and more fundamentally, we sought to investigate whether far-reaching educational decisions are also subject to opportunity cost neglect, something that has been shown primarily for hypothetical decisions in

the lab. Second, we hypothesized that informing students about the returns to their degree and making the opportunity cost of delayed graduation salient would increase their effort and accelerate their progress. The differential effects of providing only salary information in *T1* versus additionally highlighting the opportunity cost of delayed graduation in *T2* suggest that students are indeed not fully considering opportunity cost in their decision making. Unexpectedly, however, the result is lower academic achievement due to higher dropout. We show that this is even more evident for students with a high probability to dropout – i.e. students who have a high uncertainty about dropping out. Furthermore, we show that this effect is primarily driven by female students who are prone to dropping out. An increase in the dropout rate is particularly surprising given that we find evidence that students tend to underestimate their potential future salary prior to the treatment (Figure A.3).[14] One would expect that informing students the potential starting salary is larger than expected increases motivation leading to better academic performance.

One possible explanation for the effect on dropout is that the treatment makes the cost of delayed graduation more salient. Students who expect to graduate later than the nominal time may suddenly realize that every additional semester incurs significant costs costs they may not have previously considered when deciding whether to continue their studies. This increased cost salience could be especially influential for dropout-prone students, who already face high uncertainty about continuing their studies and are on the margin of dropping out.

Another possible mechanism for the observed increase in dropout in the first semester is that the treatment (re)directs students' attention to the monetary aspects of studying in general. In particular, it is possible that the information about future salaries leads students to think about what they could earn in the labor market today, i.e. their current opportunity cost. Especially for students who are already considering dropping out, thinking about the opportunity cost of studying in general may give them the additional information they need to make the decision to drop out. This may also explain why students who would have dropped out in the second or third semester do not wait, but rather drop out in the first semester because they are now aware of the true cost of studying (or the cost of waiting to decide to drop out). This reasoning is consistent with recent literature on the effects of the introduction of tuition fees in Germany (Henao et al., 2023) who find similar results after an increase in the explicit cost of studying. Thinking about opportunity costs in general, students with the intention of dropping out realize that each semester they postpone the decision whether or not to drop out comes at a cost.

This effect may be stronger for female students for three reasons.

First, the discrepancy between their prior salary expectations and the information pro-

[14] This is true for male and female students.

vided in the treatment letters appears to influence female students behavior. For students who greatly underestimate their potential salary, the cost of delayed graduation is higher than expected – and vice versa. In Table 4, we present heterogeneous effects by interacting the treatment variables with the deviation between the expected salary and the information shown in the treatment letters. The salary deviation is centered around the mean, so the first two rows display the effect for students with an average deviation. Female students with a mean deviation have a 7.7 percentage point (p = 0.106) to 8.6 percentage point (p = 0.067) higher dropout rate in the OC group. This effect becomes even stronger when the sample is restricted to female students with a high dropout probability (columns (3) and (4)). Notably, there is no effect for the salary information group. Moreover, for every one standard deviation increase in the deviation (with the mean being roughly 10,000, an increase implies the deviation moves closer to the amount shown in the treatment letters), the dropout rate decreases by about 7 percentage points (p = 0.07 to 0.09). In other words, the effect on dropout is significantly larger for students whose salary expectations deviate more from the treatment information. One possible explanation is that an unexpectedly higher starting salary signals increased study costs, which may be particularly true for students expecting to study longer than the nominal duration.

Second, female students are likely to pay more attention to the information letter sent by the university. A reference point that this is indeed the case is that the participation in the voluntary post-treatment survey is 10 pp higher for women compared to men. Thus, women may read the information presented in the treatment letters at a higher rate and take the information written in the letters more serious.

Third, there are differences in personality traits between men and women as women in general are more risk averse (Borghans et al., 2009; Falk and Hermle, 2018). Results from the OSAs confirm this as women in our sample are also more risk averse(see Table A.15. Being risk averse could result for women in the control group to wait longer with the decision to drop out as this may be the riskier choice depending of whether outside career options are known and available. Indeed, results from the control group show that female students have a 6 pp lower dropout rate in the first semester ($p = 0.029$). However, there is no significant difference in the dropout rate between male and female students in the control group at the end of the second semester as the dropout rate for female students in the control group is 4 pp higher in the second semester (although this difference is imprecisely measured – $p = 0.21$). This confirms that women, in the absence of the OC treatment, wait longer until they make the decision to drop out. Giving women information about the opportunity costs of delayed graduation may then lead those students with a high uncertainty about dropping out to decide to drop out sooner despite being more patient and risk averse.

Table 4: Treatment effects for women on dropout by pre-treatment salary expectations

	All female students Own salary dev.		Dropout prone female students Own salary dev.	
	(1)	(2)	(3)	(4)
T1: salary info	-0.017	-0.017	-0.011	-0.033
	(0.038)	(0.040)	(0.063)	(0.066)
T2: salary & OC info	0.086*	0.077	0.125*	0.115
	(0.047)	(0.047)	(0.072)	(0.073)
Own salary deviation (in 10,000€centered)	-0.010	-0.010	-0.009	-0.011
	(0.014)	(0.013)	(0.017)	(0.015)
T1*own salary deviation	0.002	0.006	-0.001	0.018
	(0.024)	(0.024)	(0.043)	(0.045)
T2*own salary deviation	-0.068*	-0.072*	-0.070	-0.078
	(0.041)	(0.040)	(0.050)	(0.050)
Study program FE	yes	yes	yes	yes
Controls	no	yes	no	yes
N	265	265	151	151

Notes: Own salary deviation is the difference between students' pre-treatment expectations about their own first year gross salary and the information provided by our treatments (in 10,000€). All answers below 10,000 were disregarded. *Controls:* High school GPA, procrastination index, age, time since graduation, and dummies for women, high school degree Abitur, and first semester at any university. Robust standard errors in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

6 Conclusion

Opportunity costs appear in every decision individuals have to make. In the lab setting, making the opportunity costs of a hypothetical decision salient significantly affects the decision on hand (Frederick et al., 2009; Plantinga et al., 2018). It is, however, not clear whether salient opportunity costs also affect (high-stakes) real world decisions. In the context of higher education, we show that making the opportunity cost of delayed graduation salient does not have the expected positive effects on academic performance. Based on the 95% confidence interval, we rule out a positive effect that is greater than 0.05 SD and therefore economically relevant. On the contrary, we observe that the treatment increases dropout in the first semester by 2.8 pp. We further show that this effect is driven by students with a higher probability to dropout in the first semester and among those students primarily females. Medium-term analyses, however, reveal that the increase in dropout may actually be a beneficial outcome as the effect is driven by students who would have dropped out by the end of the third semester anyways. Earlier dropout means students could potentially enter the labor market directly after dropping out instead of one or two semesters later. Because we only observe this effect when opportunity costs of delayed graduation are made salient, merely providing information on expected future labor market returns does not influence study performance. Our results reveal the need for further research on opportunity cost neglect in high stake real world decisions.

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Appendices (For online publication)

A Additional tables and figures

Table A.1: Characteristics of the study programs

Study program	(1) STEM	(2) Numerus clausus	(3) Salary info	(4) Own OSA	(5) OSA Resp. rate	(6) *N*
Applied Chemistry	yes	no	48,028	yes	71.11%	90
Applied Materials Science	yes	no	49,963	yes	43.14%	51
Applied Mathematics and Physics	yes	no	48,028	yes	73.81%	42
Building Services Engineering	yes	no	51,608	no	7.27%	55
Business Administration	no	yes	46,925	yes	91.25%	377
Civil Engineering	yes	yes	49,061	yes	28.93%	159
Computer Science	yes	yes	54,260	yes	26.04%	96
Computer Science and Media	yes	yes	48,267	no	27.27%	44
Electrical Engineering and Information Technology	yes	no	55,450	yes	83.42%	193
Energy Process Engineering	yes	no	49,192	yes	64.71%	34
Information Systems and Management	yes	yes	52,153	no	35.00%	80
International Business	no	yes	42,852	yes	48.91%	92
International Business and Technology	yes	yes	52,934	no	25.35%	71
Journalism of Technology	no	no	40,526	yes	70.27%	74
Management in Organic and Sustainability Business	no	yes	46,925	no	26.09%	23
Mechanical Engineering	yes	no	59,027	yes	82.32%	198
Mechatronics/Precision Engineering	yes	no	59,541	yes	36.23%	69
Media Engineering	yes	yes	45,742	no	37.70%	61
Medical Engineering	yes	no	59,388	yes	78.65%	89
Process Engineering	yes	no	47,195	yes	51.85%	27
Social Work	no	yes	39,906	no	3.70%	297

Table A.2: Ex-ante power analysis

$1-\beta$	N	δ ($R^2 = 0.00$)	δ ($R^2 = 0.20$)	δ ($R^2 = 0.40$)
0.6	1,480	0.115	0.105	0.090
0.8	1,480	0.146	0.130	0.114

Notes: The table reports minimum detectable effect sizes from ex-ante power analysis assuming $\alpha = 0.05$ for the comparison between two experimental groups using using the *Optimal Design* software (Spybrook et al., 2011). The assumed R^2 of 0.20 and 0.40 are based on analyses with previous cohorts that indicated that the variables used for blocking would explain up to 40% of the variance in passed first semester credits.

Table A.3: Treatment effects on OSA participation and treatment effect in OSA sample

	OSA participation		TE on ach. index in OSA sample	
	(1)	(2)	(3)	(4)
T1: salary info	-0.023	-0.026	-0.022	-0.020
	(0.020)	(0.020)	(0.069)	(0.068)
T2: salary & OC info	-0.004	-0.002	-0.089	-0.105
	(0.020)	(0.020)	(0.070)	(0.069)
T2-T1	0.019	0.025	-0.067	-0.085
	(0.019)	(0.019)	(0.073)	(0.072)
Strata FE	yes	yes	–	–
Study prog. FE	–	–	yes	yes
Controls	no	yes	no	yes
N	2,222	2,222	1,186	1,186
Control Mean	0.54	0.54	0.01	0.01
(SD)	(0.50)	(0.50)	(0.94)	(0.94)

Notes: OSA participation indicates whether a student has spent more than zero seconds on the OSA. *Academic achievement index* is the inverse-covariance weighted average of the number of passed course credits, the GPA, and the dropout indicator. *Controls:* High school GPA, procrastination index (not in Columns 1 and 2), age, time since graduation, and dummies for women, high school degree Abitur, and first semester at any university. Robust standard errors in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A.4: Treatment effects on survey participation and treatment effect in survey sample

	Survey participation		TE on ach. index in svy. sample	
	(1)	(2)	(3)	(4)
T1: salary info	-0.015	-0.017	-0.035	-0.039
	(0.019)	(0.019)	(0.052)	(0.050)
T2: salary & OC info	0.012	0.011	-0.054	-0.062
	(0.020)	(0.020)	(0.054)	(0.055)
T2-T1	0.027	0.028	-0.019	-0.023
	(0.019)	(0.019)	(0.062)	(0.059)
Strata FE	yes	yes	–	–
Study program FE	–	–	yes	yes
Controls	no	yes	no	yes
N	2,222	2,222	389	389
Control Mean	0.18	0.18	0.35	0.35
(SD)	(0.38)	(0.38)	(0.33)	(0.33)

Notes: Survey participation indicates whether a student has spent more than zero seconds on the online survey. *Academic achievement index* is the inverse-covariance weighted average of the number of passed course credits, the GPA, and the dropout indicator. *Controls:* High school GPA, procrastination index (not in Columns 1 and 2), age, time since graduation, and dummies for women, high school degree Abitur, and first semester at any university. Robust standard errors in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A.5: Treatment effects on signed-up, attempted, and passed course credits

	Signed up credits		Attempted credits		Passed credits	
	(1)	(2)	(3)	(4)	(5)	(6)
T1: salary info	-0.217	-0.363	0.358	-0.533	-0.446	-0.623
	(0.494)	(0.483)	(0.579)	(0.568)	(0.569)	(0.552)
T2: salary & OC info	-0.440	-0.385	-0.809	-0.799	-0.505	-0.598
	(0.511)	(0.502)	(0.601)	(0.591)	(0.587)	(0.570)
T2-T1	-0.223	-0.022	-0.451	-0.266	-0.059	0.025
	(0.512)	(0.501)	(0.605)	(0.595)	(0.580)	(0.566)
Control mean	24.24	24.24	19.37	19.37	15.67	15.67
(SD)	(11.13)	(11.13)	(12.89)	(12.89)	(13.27)	(13.27)
Strata FE	yes	yes	yes	yes	yes	yes
Controls	no	yes	no	yes	no	yes
N	2,222	2,222	2,222	2,222	2,222	2,222

Notes: Controls: High school GPA, procrastination index, age, time since graduation, and dummies for women, high school degree Abitur, and first semester at any university. Robust standard errors in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A.6: Treatment effects on signed-up, attempted, and passed course credits – share with zero CP

	Signed-up = 0		Attempted = 0		Pass = 0	
	(1)	(2)	(3)	(4)	(5)	(6)
T1: salary info	0.001	0.006	0.008	0.014	0.019	0.024
	(0.014)	(0.014)	(0.019)	(0.019)	(0.019)	(0.019)
T2: salary & OC info	0.020	0.017	0.033*	0.032*	0.031	0.033*
	(0.015)	(0.014)	(0.019)	(0.019)	(0.020)	(0.019)
T2-T1	0.019	0.011	0.025	0.019	0.012	0.009
	(0.015)	(0.014)	(0.020)	(0.019)	(0.020)	(0.020)
Strata FE	yes	yes	yes	yes	yes	yes
Controls	no	yes	no	yes	no	yes
N	2,222	2,222	2,222	2,222	2,222	2,222
Control mean	0.09	0.09	0.19	0.19	0.25	0.25
(SD)	(0.29)	(0.29)	(0.39)	(0.39)	(0.43)	(0.43)

Notes: Number = 0 indicates whether a student signed-up, attempted, or passed zero CP. *Controls:* High school GPA, procrastination index (not in Columns 1 and 2), age, time since graduation, and dummies for women, high school degree Abitur, and first semester at any university. Robust standard errors in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A.7: Treatment effects on post-treatment salary expectations and confidence

	Avg. salary		Avg. salary confidence		Own salary		Own. salary confidence	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
T1: salary info	491.321	542.838	0.840	0.948	-7,495.950	-6,809.758	-0.693	-0.537
	(2,841.466)	(2,871.979)	(3.317)	(3.406)	(5,804.068)	(5,892.267)	(3.497)	(3.541)
T2: salary & OC info	6,787.776***	6,189.182**	6.252**	5.948*	1,225.154	-310.385	6.116*	5.675*
	(2,594.722)	(2,659.028)	(3.135)	(3.192)	(5,359.810)	(6,567.376)	(3.116)	(3.192)
T2-T1	6296.455*	5646.344	5.413*	4.999	8721.104**	6499.373*	6.809**	6.211*
	(2516.601)	(2526.421)	(3.177)	(3.268)	(2753.695)	(2894.009)	(3.213)	(3.287)
Control mean	36215.39	36215.39	60.96	60.96	42920.01	42920.01	56.40	56.40
(SD)	(20074.50)	(20074.50)	(20.90)	(20.90)	(46138.23)	(46138.23)	(21.60)	(21.60)
Study prog. FE	yes	yes	yes	yes	yes	yes	yes	yes
Controls	no	yes	no	yes	no	yes	no	yes
N	303	303	299	299	286	286	278	278

Notes: Avg. salary and *own salary* are the answers to the questions "What do you believe is the current average gross annual salary for full-time employment in the first year after graduating with a Bachelors degree in your current degree program?" and "Now imagine that you received your Bachelors degree in the program you are currently studying. What do you believe is the gross annual salary that you would earn during the first and the tenth year after graduating if you worked full time?". Confidence in *average salary* and *own salary* are the answers to the question "How certain are you about this estimate?" that is asked after students report their estimates of the average and their own future salary in the post-treatment survey (answers from "0% = Not sure at all" to 100% = "Completely sure and "no answer"). *Controls:* High school GPA, procrastination index, age, time since graduation, and dummies for women, high school degree Abitur, and first semester at any university. Robust standard errors in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A.8: Treatment effects on non-cognitive outcomes

	Life sat.		Perf. pressure		Freedom		Pers. dev.		Stress		Study sat.		Index	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
T1: salary info	-0.058	-0.053	0.027	0.007	-0.288**	-0.280**	-0.112	-0.116	0.202	0.163	-0.284**	-0.272*	-0.176	-0.160
	(0.130)	(0.128)	(0.133)	(0.132)	(0.129)	(0.131)	(0.132)	(0.133)	(0.132)	(0.129)	(0.137)	(0.138)	(0.131)	(0.130)
T2: salary & OC info	-0.090	-0.109	0.081	0.098	-0.378***	-0.350***	-0.267**	-0.234*	0.067	0.096	-0.204	-0.177	-0.289**	-0.286**
	(0.121)	(0.125)	(0.126)	(0.128)	(0.124)	(0.125)	(0.126)	(0.125)	(0.125)	(0.122)	(0.127)	(0.128)	(0.121)	(0.123)
T2-T1	-0.032	-0.057	0.053	0.091	-0.090	-0.070	-0.155	-0.118	-0.135	-0.067	0.080	0.095	-0.113	-0.126
	(0.137)	(0.135)	(0.136)	(0.136)	(0.134)	(0.135)	(0.141)	(0.147)	(0.130)	(0.128)	(0.148)	(0.151)	(0.140)	(0.141)
Study prog. FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Controls	no	yes	no	yes	no	yes	no	yes	no	yes	no	yes	no	yes
N	370	370	361	361	357	357	359	359	362	362	349	349	379	379
Control Mean	0.04	0.04	-0.02	-0.02	0.21	0.21	0.11	0.11	-0.05	-0.05	0.16	0.16	0.00	0.00
(SD)	(0.98)	(0.98)	(0.98)	(0.98)	(0.96)	(0.96)	(0.91)	(0.91)	(1.00)	(1.00)	(0.86)	(0.86)	(1.00)	(1.00)

Notes: The table shows answers to the survey questions "How satisfied are you with your life, all things considered?" (0 = completely unsatisfied, 10 = completely satisfied; -1 "No answer"). "If you think of the current semester: To what degree do you agree with the following statements about your studies? With my studies I associate...*performance pressure, freedom to organize studying according to my plans, personal development, stress*" (1=Completely disagree, 7=Completely agree; -1 "No answer"), "And how satisfied are you with your studies, all things considered?" (0 = completely unsatisfied, 10 = completely satisfied; -1 "No answer"). . Robust standard errors in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A.9: Treatment effects until third semester on dropout by predicted dropout strata

Semester	First		Second		Third	
	(1)	(2)	(3)	(4)	(5)	(6)
T1: salary info	-0.005	0.002	-0.028	-0.018	-0.062*	-0.051
	(0.025)	(0.024)	(0.033)	(0.033)	(0.035)	(0.035)
T2: salary & OC info	0.059**	0.057**	0.034	0.035	-0.002	0.001
	(0.026)	(0.026)	(0.034)	(0.034)	(0.035)	(0.034)
T1*high achievement stratum	0.006	-0.004	0.028	0.011	0.084*	0.067
	(0.031)	(0.031)	(0.044)	(0.043)	(0.046)	(0.046)
T2*high achievement stratum	-0.061*	-0.059*	-0.024	-0.026	0.034	0.032
	(0.033)	(0.032)	(0.045)	(0.044)	(0.047)	(0.046)
T1+T1*high achiev. stratum	0.001	-0.002	0.001	-0.007	0.023	0.015
	(0.019)	(0.020)	(0.028)	(0.028)	(0.030)	(0.030)
T2+T2*high achiev. stratum	-0.002	-0.003	0.011	0.009	0.032	0.033
	(0.019)	(0.019)	(0.028)	(0.028)	(0.030)	(0.030)
Strata FE	yes	yes	yes	yes	yes	yes
Controls	no	yes	no	yes	no	yes
N	2,222	2,222	2,222	2,222	2,222	2,222
Control mean low ach. stratum	0.13	0.13	0.36	0.36	0.46	0.46
Control mean high ach. stratum	0.07	0.07	0.18	0.18	0.21	0.21

Notes: Dropout indicates whether a students dropped out of their study program by the end of the semester. *Controls:* High school GPA, procrastination index, age, time since graduation, and dummies for women, high school degree Abitur, and first semester at any university. Robust standard errors in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A.10: Treatment effects until third semester on academic achievement index by predicted dropout strata

Semester	First		Second		Third	
	(1)	(2)	(3)	(4)	(5)	(6)
T1: salary info	0.018	-0.007	0.050	0.020	0.110*	0.081
	(0.079)	(0.078)	(0.068)	(0.066)	(0.065)	(0.064)
T2: salary & OC info	-0.194**	-0.190**	-0.078	-0.088	-0.014	-0.029
	(0.085)	(0.083)	(0.070)	(0.069)	(0.066)	(0.065)
T1*high achievement stratum	-0.040	-0.003	-0.089	-0.036	-0.180**	-0.128
	(0.102)	(0.102)	(0.093)	(0.091)	(0.091)	(0.089)
T2*high achievement stratum	0.195*	0.192*	0.049	0.064	-0.040	-0.024
	(0.107)	(0.105)	(0.095)	(0.092)	(0.091)	(0.089)
T1+T1*high achiev. stratum	-0.022	-0.010	-0.039	-0.015	-0.070	-0.047
	(0.065)	(0.065)	(0.063)	(0.062)	(0.063)	(0.061)
T2+T2*high achiev. stratum	0.001	0.002	-0.029	-0.025	-0.054	-0.053
	(0.064)	(0.063)	(0.063)	(0.061)	(0.063)	(0.061)
Strata FE	yes	yes	yes	yes	yes	yes
Controls	no	yes	no	yes	no	yes
N	2,222	2,222	2,222	2,222	2,222	2,222
Control mean low ach. stratum	-0.15	-0.15	-0.35	-0.35	-0.40	-0.40
Control mean high ach. stratum	0.15	0.15	0.37	0.37	0.42	0.42

Notes: Achievement index is the inverse-covariance weighted average of the number of passed course credits, the GPA, and the dropout indicator. *Controls:* High school GPA, procrastination index, age, time since graduation, and dummies for women, high school degree Abitur, and first semester at any university. Robust standard errors in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A.11: Treatment effects in second semester full sample

	Number of CP passed		GPA		Dropout		Achiev. index	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
T1: salary info	0.487	0.070	0.025	0.029	-0.014	-0.010	0.012	-0.002
	(1.067)	(1.023)	(0.033)	(0.031)	(0.022)	(0.021)	(0.046)	(0.045)
T2: salary & OC info	-0.407	-0.627	0.011	0.022	0.022	0.022	-0.052	-0.057
	(1.096)	(1.055)	(0.034)	(0.032)	(0.022)	(0.022)	(0.047)	(0.046)
T2-T1	-0.894	-0.698	-0.014	-0.008	0.037*	0.032	-0.064	-0.055
	(1.102)	(1.066)	(0.034)	(0.032)	(0.022)	(0.022)	(0.048)	(0.047)
N	2,222	2,222	1,683	1,683	2,222	2,222	2,222	2,222
Control mean	31.12	31.12	2.51	2.51	0.27	0.27	0.00	0.00
(SD)	(24.45)	(24.45)	(0.65)	(0.65)	(0.45)	(0.45)	(1.00)	(1.00)
Strata FE	yes	yes	yes	yes	yes	yes	yes	yes
Controls	no	yes	no	yes	no	yes	no	yes

Notes: Number of credits is the number of passed credits at the end of the second semester. *Number* = 0 indicates whether a student passed zero course credits by the end of the second semester. *Number* ≥ 60 indicates whether a student passed more than 60 course credits by the end of the second semester. *GPA N/A* indicates whether the GPA is observed for a student at the end of the second semester. *GPA* is students grade point average at the end of the second semester and is only observed for students who passed at least one graded course (1.0 is the best and 4.0 the worst possible GPA). *Dropout* indicates whether a students dropped out of their study program by the end of the second semester. *Achievement index* is the inverse-covariance weighted average of the number of passed course credits, the GPA, and the dropout indicator. *Controls:* High school GPA, procrastination index, age, time since graduation, and dummies for women, high school degree Abitur, and first semester at any university. Robust standard errors in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A.12: Treatment effects in third semester full sample

	Number of CP passed		GPA		Dropout		Achiev. index	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
T1: salary info	0.702	0.072	0.015	0.021	-0.021	-0.016	0.028	0.013
	(1.606)	(1.540)	(0.032)	(0.030)	(0.023)	(0.023)	(0.045)	(0.044)
T2: salary & OC info	-1.066	-1.389	-0.000	0.012	0.015	0.017	-0.031	-0.041
	(1.643)	(1.585)	(0.033)	(0.031)	(0.023)	(0.023)	(0.046)	(0.044)
T2-T1	-1.768	-1.461	-0.015	-0.009	0.036	0.032	-0.059	-0.054
	(1.664)	(1.611)	(0.032)	(0.031)	(0.023)	(0.023)	(0.046)	(0.045)
N	2,222	2,222	1,707	1,707	2,222	2,222	2,222	2,222
Control mean	46.45	46.45	2.53	2.53	0.34	0.34	0.00	0.00
(SD)	(36.75)	(36.75)	(0.64)	(0.64)	(0.47)	(0.47)	(1.00)	(1.00)
Strata FE	yes	yes	yes	yes	yes	yes	yes	yes
Controls	no	yes	no	yes	no	yes	no	yes

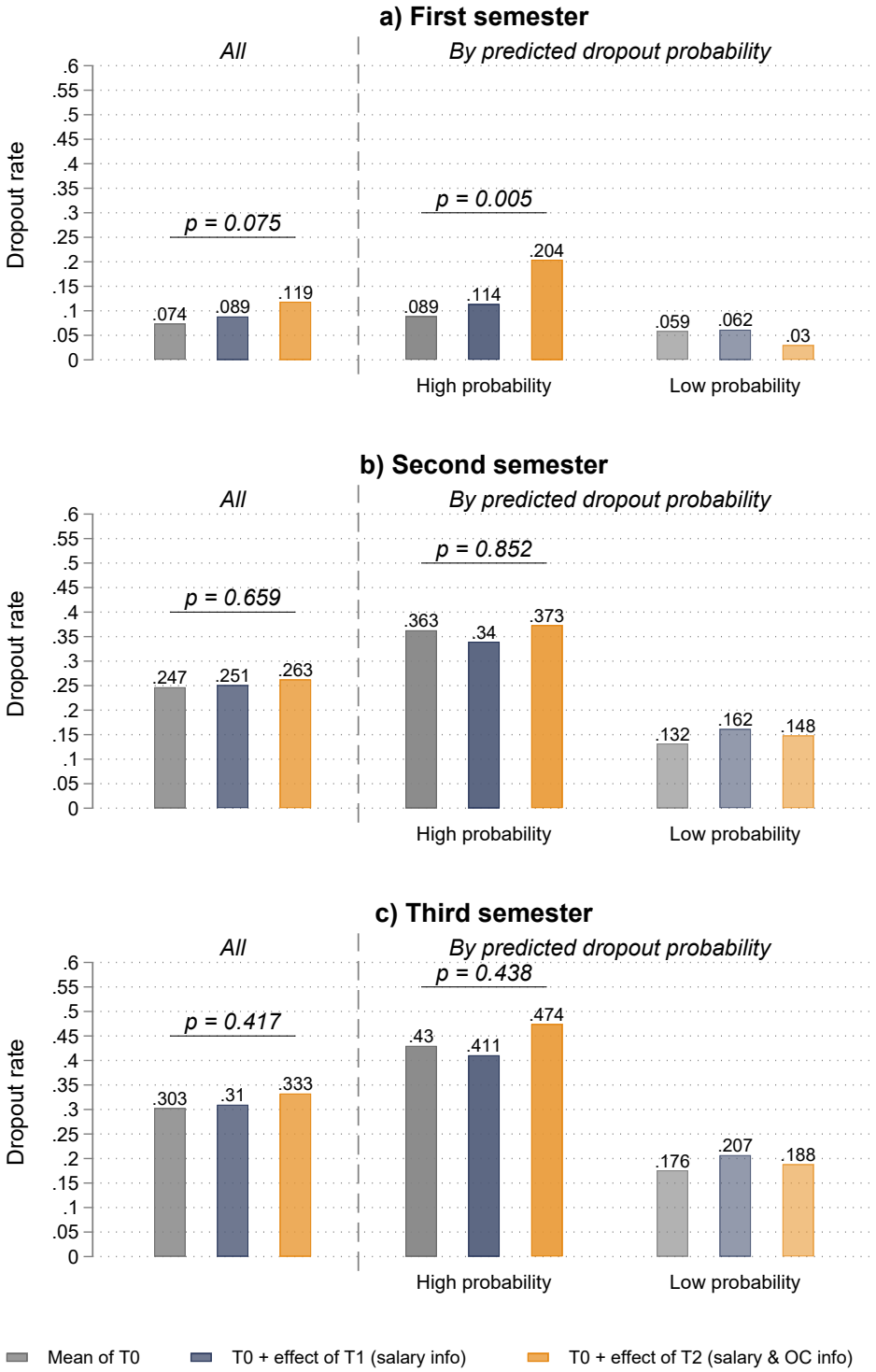
Notes: Number of credits is the number of passed credits at the end of the third semester. *Number* = 0 indicates whether a student passed zero course credits by the end of the third semester. *Number* ≥ 60 indicates whether a student passed more than 60 course credits by the end of the third semester. *GPA N/A* indicates whether the GPA is observed for a student at the end of the third semester. *GPA* is students grade point average at the end of the third semester and is only observed for students who passed at least one graded course (1.0 is the best and 4.0 the worst possible GPA). *Dropout* indicates whether a students dropped out of their study program by the end of the third semester. *Achievement index* is the inverse-covariance weighted average of the number of passed course credits, the GPA, and the dropout indicator. *Controls:* High school GPA, procrastination index, age, time since graduation, and dummies for women, high school degree Abitur, and first semester at any university. Robust standard errors in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A.13: Treatment effects by other blocking dimensions for dropout prone students

	Procrastination)		std(HS GPA)		Gender	
	(1)	(2)	(3)	(4)	(5)	(6)
T1: salary info	0.012	0.014	-0.006	-0.003	-0.024	-0.025
	(0.029)	(0.029)	(0.028)	(0.027)	(0.036)	(0.035)
T2: salary & OC info	0.081***	0.084***	0.054*	0.051*	0.020	0.017
	(0.031)	(0.030)	(0.029)	(0.028)	(0.035)	(0.034)
Procrastination index	0.121***	0.132***				
	(0.028)	(0.028)				
T1*procras. index	-0.019	-0.028				
	(0.034)	(0.034)				
T2*procras. index	-0.036	-0.044				
	(0.035)	(0.034)				
STD(high school GPA)			-0.004	-0.019		
			(0.023)	(0.024)		
T1*Std(HS GPA)			-0.003	0.000		
			(0.028)	(0.028)		
T2*Std(HS GPA)			0.010	0.016		
			(0.028)	(0.027)		
Female					-0.063	-0.082
					(0.062)	(0.063)
T1*female					0.046	0.059
					(0.053)	(0.052)
T2*female					0.104*	0.109**
					(0.055)	(0.054)
Strata FE	yes	yes	yes	yes	yes	yes
Controls	no	yes	no	yes	no	yes
N	1,111	1,111	1,111	1,111	1,111	1,111

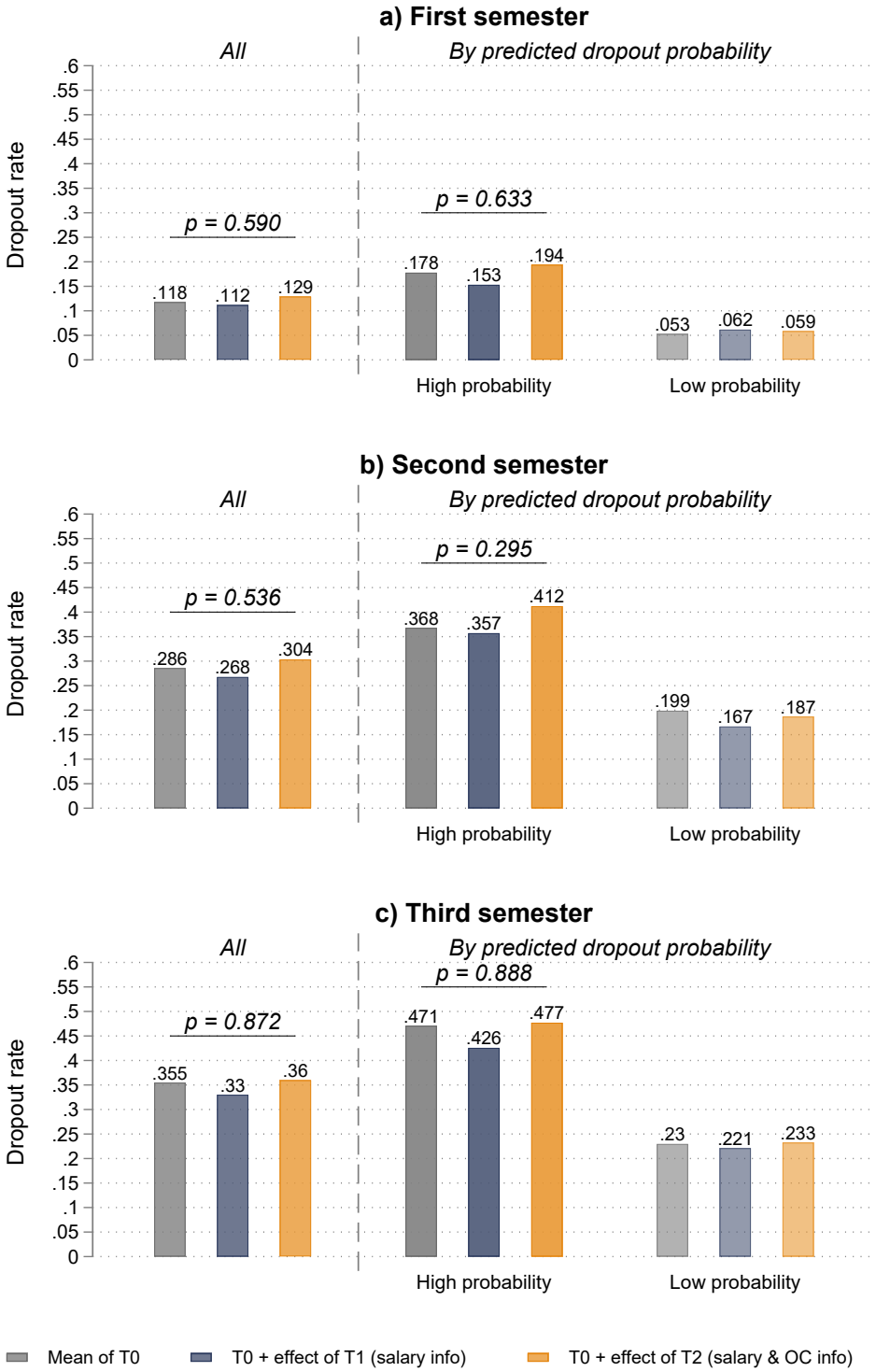
Notes: Controls: High school GPA (not in Columns 1 and 2), procrastination index, age, time since graduation, and dummies for women (not in Columns 3 and 4), high school degree Abitur, and first semester at any university. Robust standard errors in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Figure A.1: Treatment effects on dropout until third semester by predicted dropout strata – female students



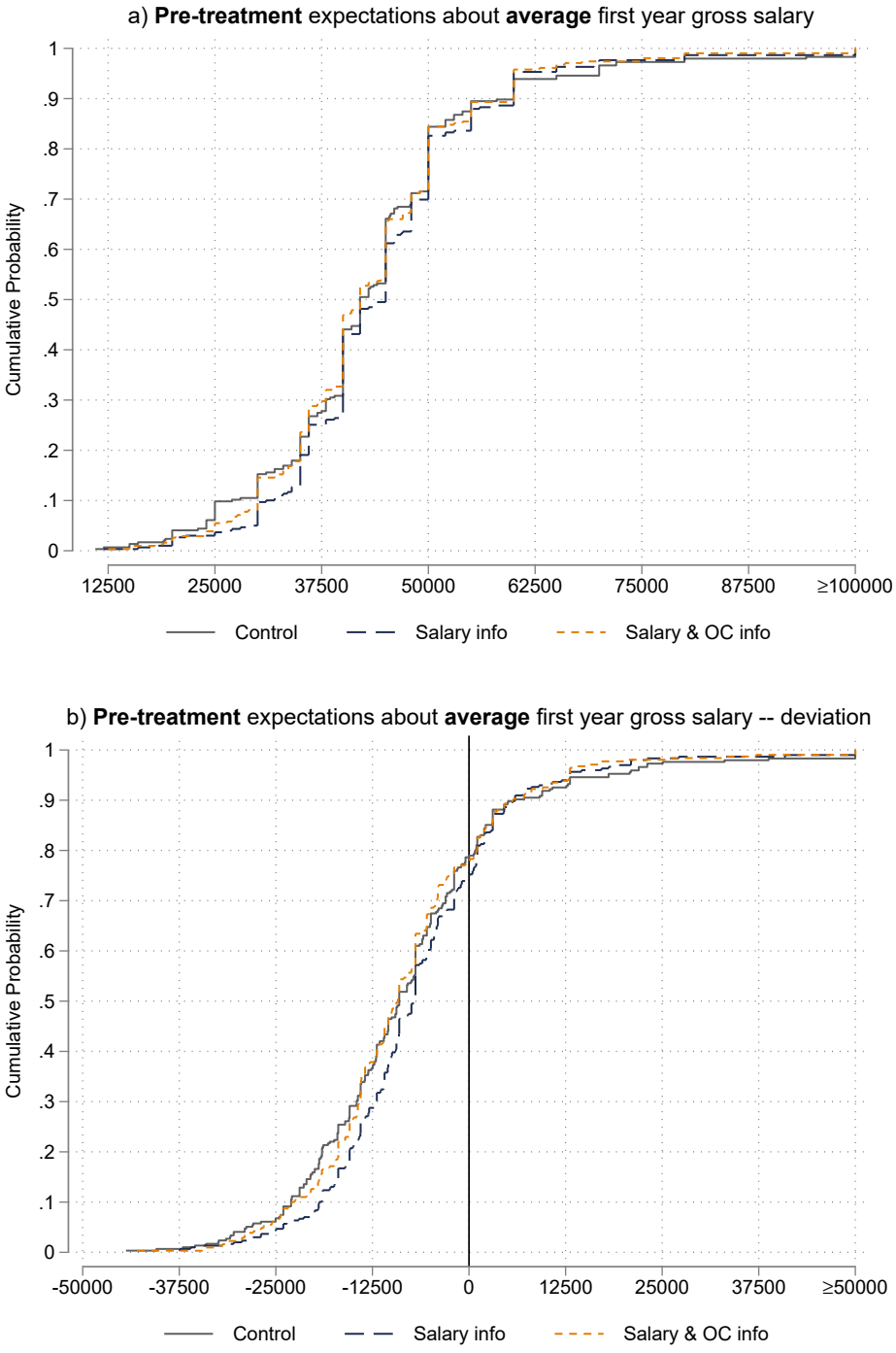
Notes: The left-hand sides of the graph shows the overall dropout rate. The right-hand sides shows the dropout rate for students in the high dropout probability and the low dropout probability strata, respectively. Dropout indicates whether a students dropped out of their study program by the end of the respective semester. Regressions include the following controls: High school GPA, procrastination index, age, time since graduation, and dummies for women, high school degree Abitur, and first semester at any university

Figure A.2: Treatment effects on dropout until third semester by predicted dropout strata – male students



Notes: The left-hand sides of the graph shows the overall dropout rate. The right-hand sides shows the dropout rate for students in the high dropout probability and the low dropout probability strata, respectively. Dropout indicates whether a students dropped out of their study program by the end of the respective semester. Regressions include the following controls: High school GPA, procrastination index, age, time since graduation, and dummies for women, high school degree Abitur, and first semester at any university

Figure A.3: Pre-treatment expectation about average first year salary



Notes: Panels a) and b) are based on the OSA question "What do you believe is the current **average gross annual salary** for full-time employment in the **first year after graduating with a bachelor's degree** in the degree program for which you are answering these OSA questions?" (students could choose to provide "no answer"). Panels a) and b) show the cumulative distributions of the respective variables, only answers > 10,000 were included, winsorized at 100,000€ and 50,000€, respectively. $N = 903$

Table A.14: Treatment effects on dropout until third semester on academic achievement index by predicted dropout strata – female students

Semester	First		Second		Third	
	(1)	(2)	(3)	(4)	(5)	(6)
T1: salary info	0.015	0.025	-0.033	-0.023	-0.028	-0.019
	(0.039)	(0.038)	(0.057)	(0.056)	(0.059)	(0.058)
T2: salary & OC info	0.119***	0.115***	0.007	0.010	0.040	0.044
	(0.043)	(0.042)	(0.057)	(0.056)	(0.059)	(0.058)
T1*high achievement stratum	-0.017	-0.022	0.058	0.053	0.055	0.050
	(0.048)	(0.048)	(0.072)	(0.071)	(0.076)	(0.075)
T2*high achievement stratum	-0.150***	-0.144***	0.001	0.006	-0.037	-0.032
	(0.051)	(0.049)	(0.071)	(0.071)	(0.076)	(0.075)
T1+T1*high achiev. stratum	-0.002	0.003	0.025	0.030	0.027	0.031
	(0.029)	(0.030)	(0.044)	(0.043)	(0.048)	(0.048)
T2+T2*high achiev. stratum	-0.031	-0.029	0.008	0.016	0.002	0.012
	(0.026)	(0.027)	(0.043)	(0.043)	(0.047)	(0.047)
Strata FE	yes	yes	yes	yes	yes	yes
Controls	no	yes	no	yes	no	yes
N	809	809	809	809	809	809
Control mean low ach. stratum	0.09	0.09	0.36	0.36	0.43	0.43
Control mean high ach. stratum	0.06	0.06	0.13	0.13	0.18	0.18

Notes: Controls: High school GPA, procrastination index, age, time since graduation, and dummies for women, high school degree Abitur, and first semester at any university. Robust standard errors in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A.15: Gender effect on risk taking

	Risk taking	
	(1)	(2)
Female	-0.426***	-0.332**
	(0.133)	(0.133)
Study program FE	yes	yes
Controls	no	yes
N	1147	1147
Control mean	6.68	6.68
(SD)	(1.94)	(1.94)

Notes: Risk taking is the answer to the OSA question "In general, how willing are you to take risks?" (answers from "0 = completely unwilling to do so" to 10 = "very willing to do so and "no answer"). *Controls:* High school GPA, procrastination index, age, time since graduation, and dummies for women, high school degree Abitur, and first semester at any university. Robust standard errors in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

B Additional analyses

Other potential mechanisms: In addition to the potential mechanisms reported in the main part of the paper, we also pre-registered to analyze whether students time preferences, the financial situation, the extent to which they consider opportunity costs moderate the treatment effects, and whether study programs moderate the effects. Because we only find effects in the main sample on dropout and the effect is driven by dropout prone students, we report the following results on dropout in the dropout prone group.

Heterogeneity by students' time preferences. It is conceivable that students who strongly discount the future are less affected by information about future salaries. Similarly, they are less likely to care about the opportunity cost of delayed graduation because it is still several years away. To examine heterogeneity along this dimension, we interact the treatment indicators with the procrastination index used for stratification and with the patience and procrastination questions from the Global Preference Survey (GPS, Falk et al. (2018)), which we included in the OSAs. The estimates are reported in Table B.1. We find no significant interaction between any of our time preference measures and our treatments. If anything, students who are more likely to procrastinate according to our administrative measure and students who are more patient according to the GPS measure may respond more positively to *T1*. We also find no significant effect in the subsample of female students who are prone to drop out as Table B.2.

Heterogeneity by whether students financial situation. Next, we explore whether students current financial situation is a moderating factor. Students with little money available each month may react stronger to the treatment information because the may profit more from timely graduation and an increase in money available from labor market income. We find no significant difference in money available per month between the treatment groups and the control group. However, as Table B.3 displays no interaction effect from the amount of money available on dropout and the achievement index (as mentioned before, there is only one person among students with high dropout probability, who dropped out in the first semester, who answered the survey question on money available which is why we also include the achievement index in this table). The same holds for female students who are prone to drop out as Table B.4 shows.

Heterogeneity by students' tendency to neglect opportunity costs. The response to our treatments may depend on whether students generally neglect opportunity cost in their decision making. In the case of *T1*, students' who usually consider opportunity cost may be aware that their potential future salary is at the same time also the opportunity cost of a longer study duration. The response to the salary information may therefore be stronger for these students. Directly highlighting the opportunity cost in *T2* may lead to less pronounced differences between students who usually

consider opportunity cost and those who usually neglect them. However, even if the opportunity cost are made salient, the latter group may still fail to incorporate the opportunity cost in their decision making, because knowledge of the opportunity cost may not be sufficient to apply them in practice. To examine whether the tendency to neglect opportunity cost moderates our effects, we included questions in the OSAs about whether students consider opportunity cost when planning to spend time on activities or when making a purchase (see notes in Table B.5 for more details). In Table B.5, we examine whether the treatment effects depend on students' tendency to neglect opportunity cost in the activity (Columns (1) and (2)) and purchase (Columns (3) and (4)) domains. That is, we use the inverse of the original scale so that the main effects of our treatments can be interpreted as effects for individuals who most strongly consider opportunity cost in their decision making. For *T2*, we find no significant effect from either domain. In *T1*, we find a small positive interaction between opportunity cost neglect and *T1* of 0.026 to 0.028 pp (p = 0.083 to 0.061) and a negative effect for those who fully consider opportunity cost of 0.142 to 0.146 pp (p = 0.086 to 0.059) in the activity domain but no significant effect in the purchase domain. Furthermore, Table B.6 shows that there is also no interaction effect for the subsample of female students who are prone to drop out.

Heterogeneity by study programs. Treatment effects may be stronger in some study programs compared to others. Because the expected starting salary depends on the study program, the information in the treatment letters differ between study programs. To evaluate whether study programs affect the response to the treatments, we group them together in two groups – study programs in STEM fields and non STEM fields. In addition, we also group them in high salary study programs and low salary programs. Table B.7 shows that neither STEM study programs nor high salary programs have a moderating effect on dropout in the dropout prone group. The same holds once again for the subsample of female students who are prone to drop out as Table B.8 shows.

Table B.1: Treatment effects on dropout by time preferences for dropout prone students

	GPS: Patience		GPS: Procras.	
	(1)	(2)	(3)	(4)
T1: salary info	0.005	-0.001	-0.001	-0.007
	(0.034)	(0.035)	(0.035)	(0.035)
T2: salary & OC info	0.043	0.038	0.041	0.038
	(0.036)	(0.036)	(0.036)	(0.036)
std(GPS: patience)	0.003	0.003		
	(0.011)	(0.011)		
T1*std(GPS: patience)	-0.028	-0.025		
	(0.018)	(0.018)		
T2*std(GPS: patience)	-0.003	-0.005		
	(0.018)	(0.018)		
std(GPS: procrastination)			-0.004	-0.004
			(0.010)	(0.010)
T1*std(GPS: procras.)			-0.001	-0.001
			(0.015)	(0.015)
T2*std(GPS: procras.)			0.004	0.005
			(0.014)	(0.014)
Study program FE	yes	yes	yes	yes
Controls	no	yes	no	yes
N	624	624	614	614

Notes: std(GPS: patience are the standardized answers to the question "How willing are you to give up something that is beneficial for you today in order to benefit more from that in the future?" (answers from "0 = completely unwilling to do so" to "10 = very willing to do so" and "no answer"). *std(GPS: procrastination* are the standardized answers to the statement "I tend to postpone tasks even if I know it would be better to do them right away." (answers from "0 = does not describe me at all" to "10 = describes me perfectly" and "no answer"). *Controls:* High school GPA, age, time since graduation, and dummies for women, high school degree Abitur, and first semester at any university. Robust standard errors in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table B.2: Treatment effects on dropout by time preferences for dropout prone students

	GPS: Patience		GPS: Procras.	
	(1)	(2)	(3)	(4)
T1: salary info	0.038	0.014	0.054	0.029
	(0.054)	(0.056)	(0.055)	(0.059)
T2: salary & OC info	0.137**	0.112*	0.115*	0.097
	(0.066)	(0.068)	(0.062)	(0.065)
std(GPS: patience)	-0.005	-0.006		
	(0.025)	(0.024)		
T1*std(GPS: patience)	-0.014	-0.012		
	(0.032)	(0.033)		
T2*std(GPS: patience)	0.041	0.045		
	(0.037)	(0.035)		
std(GPS: procrastination)			-0.006	-0.005
			(0.014)	(0.014)
T1*std(GPS: procras.)			0.002	0.000
			(0.023)	(0.024)
T2*std(GPS: procras.)			0.024	0.026
			(0.023)	(0.023)
Study program FE	yes	yes	yes	yes
Controls	no	yes	no	yes
N	218	218	214	214

Notes: std(GPS: patience are the standardized answers to the question "How willing are you to give up something that is beneficial for you today in order to benefit more from that in the future?" (answers from "0 = completely unwilling to do so" to "10 = very willing to do so" and "no answer"). *std(GPS: procrastination* are the standardized answers to the statement "I tend to postpone tasks even if I know it would be better to do them right away." (answers from "0 = does not describe me at all" to "10 = describes me perfectly" and "no answer"). *Controls:* High school GPA, age, time since graduation, and dummies for women, high school degree Abitur, and first semester at any university. Robust standard errors in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table B.3: Treatment effects on dropout and achievement index by money available per month for dropout prone students

	Money per month		Dropout		Ach ind	
	(1)	(2)	(3)	(4)	(5)	(6)
T1: salary info	-104.444	-96.641	-0.005	0.003	0.075	0.039
	(120.954)	(109.035)	(0.012)	(0.013)	(0.062)	(0.057)
T2: salary & OC info	-25.273	-71.428	0.015	0.021	-0.060	-0.116
	(115.588)	(102.063)	(0.020)	(0.026)	(0.071)	(0.092)
Money per month			-0.000	0.001	0.003	-0.004
			(0.001)	(0.002)	(0.004)	(0.006)
T1*Money			0.000	-0.001	-0.002	0.004
			(0.001)	(0.002)	(0.007)	(0.009)
T2*Money			0.001	0.000	-0.005	0.003
			(0.002)	(0.002)	(0.007)	(0.008)
Study program FE	yes	yes	yes	yes	yes	yes
Controls	no	yes	no	yes	no	yes
N	116	116	116	116	116	116
Control mean	661.72	661.72				
(SD)	(497.73)	(497.73)				

Notes: Money per month is the answer to the online survey question "How much money do you have at your disposal on average each month during the current semester?" (open answer and "no answer"). *Controls:* High school GPA, procrastination index, age, time since graduation, and dummies for women, high school degree Abitur, and first semester at any university. Robust standard errors in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table B.4: Treatment effects on dropout and achievement index by money available per month for dropout prone students – female students

	Money per month		Dropout		Ach ind	
	(1)	(2)	(3)	(4)	(5)	(6)
T1: salary info	-241.223	-154.002	0.000	0.000	0.026	0.042
	(217.008)	(170.233)	(0.000)	(0.000)	(0.054)	(0.058)
T2: salary & OC info	-97.224	-31.235	0.000	0.000	-0.058	-0.053
	(242.166)	(178.538)	(0.000)	(0.000)	(0.067)	(0.070)
Money per month			0.000	0.000	0.006*	0.003
			(0.000)	(0.000)	(0.003)	(0.005)
T1*Money			0.000	0.000	0.002	0.002
			(0.000)	(0.000)	(0.007)	(0.008)
T2*Money			0.000	0.000	-0.002	0.001
			(0.000)	(0.000)	(0.005)	(0.007)
Study program FE	yes	yes	yes	yes	yes	yes
Controls	no	yes	no	yes	no	yes
N	59	59	59	59	59	59
Control mean	782.41	782.41				
(SD)	(601.72)	(601.72)				

Notes: Money per month is the answer to the online survey question "How much money do you have at your disposal on average each month during the current semester?" (open answer and "no answer"). *Controls:* High school GPA, procrastination index, age, time since graduation, and dummies for women, high school degree Abitur, and first semester at any university. Robust standard errors in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table B.5: Treatment effects on dropout by opportunity cost neglect for dropout prone students

	OCN: activities		OCN: purchases	
	(1)	(2)	(3)	(4)
T1: salary info	-0.146	-0.142	0.021	0.025
	(0.092)	(0.091)	(0.105)	(0.105)
T2: salary & OC info	0.010	0.012	0.128	0.129
	(0.103)	(0.102)	(0.114)	(0.113)
OCN: activities	-0.009	-0.007		
	(0.012)	(0.011)		
T1*OCN: activities	0.028*	0.026*		
	(0.016)	(0.016)		
T2*OCN: activities	0.005	0.004		
	(0.017)	(0.017)		
OCN: purchases			0.001	0.005
			(0.013)	(0.012)
T1*OCN: purchases			-0.002	-0.004
			(0.017)	(0.017)
T2*OCN: purchases			-0.014	-0.016
			(0.018)	(0.018)
Study program FE	yes	yes	yes	yes
Controls	no	yes	no	yes
N	617	617	617	617

Notes: OCN: activities is the inverse of the mean of the answers to the following two statements: "Before spending time on a particular activity, I consider other specific activities that I would not be able to spend time on." and "When Im faced with the decision to spend time on a particular activity, I try to imagine other activities I might spend my time on." (answers from "0 = does not describe me at all" to "10 = describes me perfectly" and "no answer"). *OCN: purchases* is the inverse of the mean of the answers to the following two statements: "When Im faced with an opportunity to make a purchase, I try to imagine things in other categories I might spend that money on." and "Before I make a particular purchase, I consider other specic items that I would not be able to buy." (answers from "0 = does not describe me at all" to "10 = describes me perfectly" and "no answer"). *Controls:* High school GPA, procrastination index, age, time since graduation, and dummies for women, high school degree Abitur, and first semester at any university. Robust standard errors in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table B.6: Treatment effects on dropout by opportunity cost neglect for dropout prone students – female students

	OCN: activities		OCN: purchases	
	(1)	(2)	(3)	(4)
T1: salary info	-0.167	-0.138	0.014	0.057
	(0.149)	(0.145)	(0.195)	(0.196)
T2: salary & OC info	0.129	0.158	0.140	0.191
	(0.175)	(0.179)	(0.222)	(0.213)
OCN: activities	-0.004	0.006		
	(0.021)	(0.020)		
T1*OCN: activities	0.041	0.031		
	(0.027)	(0.027)		
T2*OCN: activities	-0.005	-0.014		
	(0.031)	(0.031)		
OCN: purchases			0.001	0.013
			(0.026)	(0.026)
T1*OCN: purchases			0.007	-0.003
			(0.033)	(0.033)
T2*OCN: purchases			-0.006	-0.021
			(0.038)	(0.036)
Study program FE	yes	yes	yes	yes
Controls	no	yes	no	yes
N	218	218	217	217

Notes: OCN: activities is the inverse of the mean of the answers to the following two statements: "Before spending time on a particular activity, I consider other specific activities that I would not be able to spend time on." and "When Im faced with the decision to spend time on a particular activity, I try to imagine other activities I might spend my time on." (answers from "0 = does not describe me at all" to "10 = describes me perfectly" and "no answer"). *OCN: purchases* is the inverse of the mean of the answers to the following two statements: "When Im faced with an opportunity to make a purchase, I try to imagine things in other categories I might spend that money on." and "Before I make a particular purchase, I consider other specic items that I would not be able to buy." (answers from "0 = does not describe me at all" to "10 = describes me perfectly" and "no answer"). *Controls:* High school GPA, procrastination index, age, time since graduation, and dummies for women, high school degree Abitur, and first semester at any university. Robust standard errors in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table B.7: Treatment effects on dropout by study program characteristics for dropout prone students

	Stem		High salary	
	(1)	(2)	(3)	(4)
T1: salary info	-0.042	-0.027	-0.015	-0.008
	(0.041)	(0.040)	(0.033)	(0.033)
T2: salary & OC info	0.084*	0.095**	0.067*	0.065*
	(0.045)	(0.043)	(0.036)	(0.034)
T1*STEM	0.052	0.036		
	(0.053)	(0.052)		
T2*STEM	-0.040	-0.057		
	(0.057)	(0.055)		
T1*high salary			0.017	0.009
			(0.053)	(0.052)
T2*high salary			-0.021	-0.017
			(0.055)	(0.053)
Strata FE	yes	yes	yes	yes
Controls	no	yes	no	yes
N	1111	1111	1111	1111

Notes: High salary study program indicates programs for which our treatment informs students about an average annual gross starting salary above 49,000€ (see Table A.1). *Controls:* High school GPA, procrastination index, age, time since graduation, and dummies for women, high school degree Abitur, and first semester at any university. Robust standard errors in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table B.8: Treatment effects on dropout by study program characteristics for dropout prone students – female students

	Stem		High salary	
	(1)	(2)	(3)	(4)
T1: salary info	-0.011	0.010	0.014	0.029
	(0.051)	(0.050)	(0.045)	(0.044)
T2: salary & OC info	0.148**	0.151***	0.129***	0.118**
	(0.060)	(0.057)	(0.049)	(0.048)
T1*STEM	0.065	0.051		
	(0.080)	(0.082)		
T2*STEM	-0.077	-0.092		
	(0.086)	(0.084)		
T1*high salary			0.021	0.015
			(0.097)	(0.102)
T2*high salary			-0.065	-0.045
			(0.101)	(0.099)
Strata FE	yes	yes	yes	yes
Controls	no	yes	no	yes
N	401	401	401	401

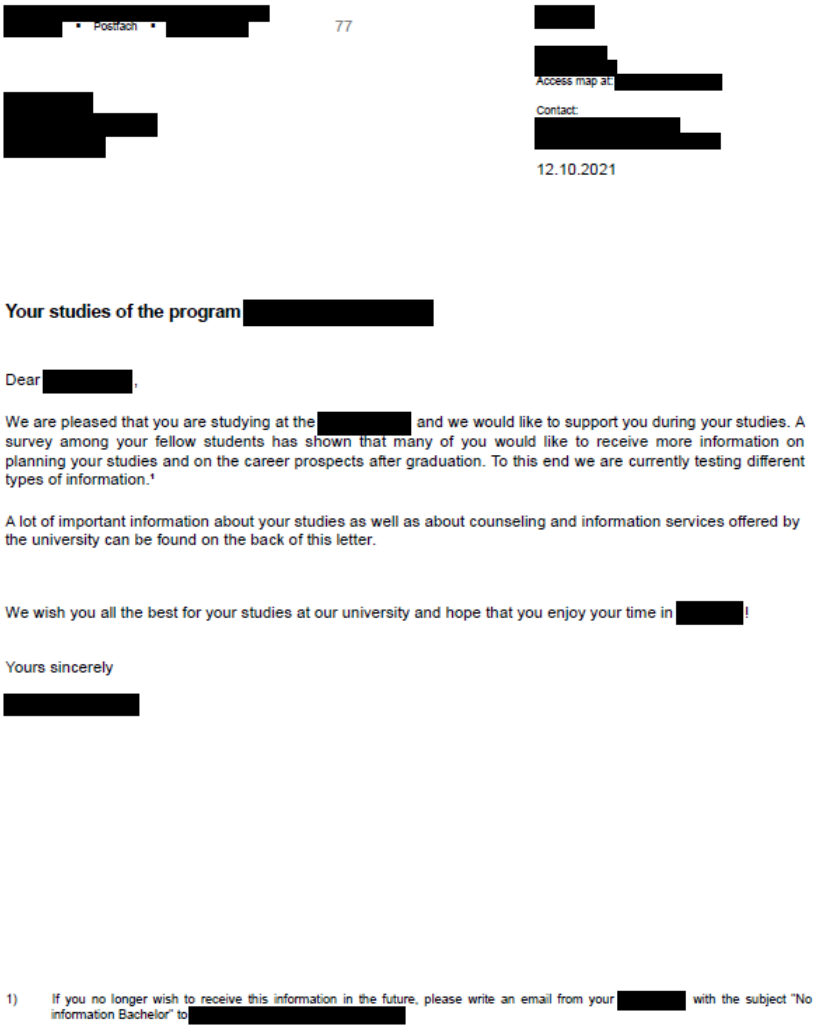
Notes: High salary study program indicates programs for which our treatment informs students about an average annual gross starting salary above 49,000€ (see Table A.1). *Controls:* High school GPA, procrastination index, age, time since graduation, and dummies for women, high school degree Abitur, and first semester at any university. Robust standard errors in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table B.9: Variable descriptions

Variable	Description
Treatment Variables	
Treatment	Random assignment to the treatment groups.
Stratification and control Variables	
Study program	Indicators for study programs.
Age	Age in years at randomization.
Female	Indicator for being female.
High school GPA	Final high school grade point average (1=best, 4=worst). Missing values imputed.
Time since HS graduation	Years since high school graduation
Procrastination index	Index of date of application and date of enrollment (standardized inverse-covariance weighted average)
HS degree abitur	Indicator for a general track degree (Abitur); reference category includes vocational track degree (Fachhochschulreife) and students who hold other degrees.
Outcome Variables	
Sign-up CP	Number of CP signed up for after the sign-up period.
Attempted CP	Number of CP attempted.
Passed CP	Number of CP passed.
GPA	Grade point average in the second semester (1=best, 4=worst); failed exams are not included in calculation.
Dropout	Indicator for having dropped out of the study program after treatment.
Earnings expectation	Earnings expectation in post-treatment survey
Confidence	Confidence in earnings expectation

C Experimental materials and survey questions

Figure C.1: Letters students in the control group received



[redacted] • Postfach • [redacted] 77

[redacted]

[redacted]

[redacted]
Access map at: [redacted]
Contact:
[redacted]

12.10.2021

Your studies of the program [redacted]

Dear [redacted],

We are pleased that you are studying at the [redacted] and we would like to support you during your studies. A survey among your fellow students has shown that many of you would like to receive more information on planning your studies and on the career prospects after graduation. To this end we are currently testing different types of information.[1]

A lot of important information about your studies as well as about counseling and information services offered by the university can be found on the back of this letter.

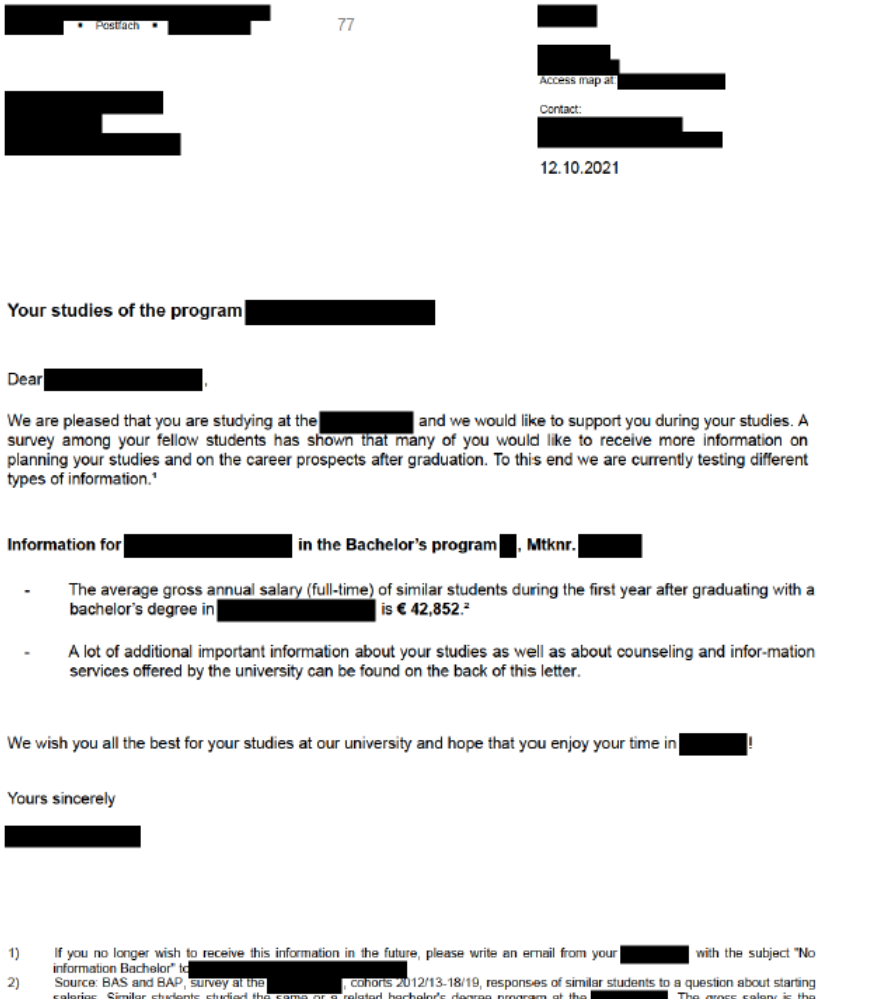
We wish you all the best for your studies at our university and hope that you enjoy your time in [redacted]!

Yours sincerely

[redacted]

1) If you no longer wish to receive this information in the future, please write an email from your [redacted] with the subject "No information Bachelor" to [redacted]

Figure C.2: Letters students in the EI group received



[redacted] • Postfach • [redacted] 77

[redacted]

[redacted]
[redacted]
Access map at: [redacted]
Contact:
[redacted]

12.10.2021

Your studies of the program [redacted]

Dear [redacted],

We are pleased that you are studying at the [redacted] and we would like to support you during your studies. A survey among your fellow students has shown that many of you would like to receive more information on planning your studies and on the career prospects after graduation. To this end we are currently testing different types of information.[1]

Information for [redacted] **in the Bachelor's program** [redacted]**, Mtknr.** [redacted]

- The average gross annual salary (full-time) of similar students during the first year after graduating with a bachelor's degree in [redacted] is **€ 42,852**.[2]
- A lot of additional important information about your studies as well as about counseling and infor-mation services offered by the university can be found on the back of this letter.

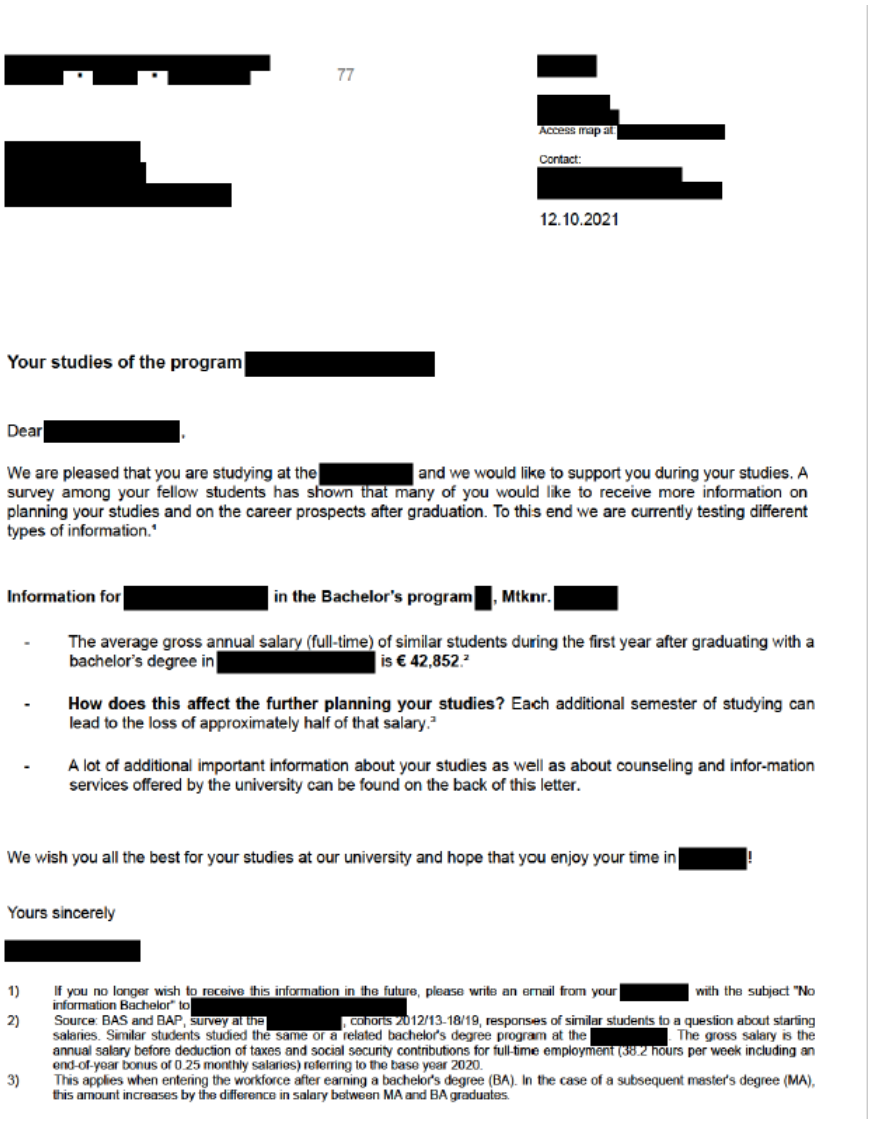
We wish you all the best for your studies at our university and hope that you enjoy your time in [redacted]!

Yours sincerely

[redacted]

1) If you no longer wish to receive this information in the future, please write an email from your [redacted] with the subject "No information Bachelor" to [redacted]
2) Source: BAS and BAP, survey at the [redacted], cohorts 2012/13-18/19, responses of similar students to a question about starting salaries. Similar students studied the same or a related bachelor's degree program at the [redacted]. The gross salary is the annual salary before deduction of taxes and social security contributions for full-time employment (38.2 hours per week including an end-of-year bonus of 0.25 monthly salaries) referring to the base year 2020.

Figure C.3: Letters students in the OC group received



[redacted] 77

[redacted]

[redacted]

[redacted]

Access map at [redacted]

Contact:

[redacted]

12.10.2021

Your studies of the program [redacted]

Dear [redacted],

We are pleased that you are studying at the [redacted] and we would like to support you during your studies. A survey among your fellow students has shown that many of you would like to receive more information on planning your studies and on the career prospects after graduation. To this end we are currently testing different types of information.[1]

Information for [redacted] in the Bachelor's program [redacted], Mtknr. [redacted]

- The average gross annual salary (full-time) of similar students during the first year after graduating with a bachelor's degree in [redacted] is **€ 42,852**.[2]
- **How does this affect the further planning your studies?** Each additional semester of studying can lead to the loss of approximately half of that salary.[3]
- A lot of additional important information about your studies as well as about counseling and infor-mation services offered by the university can be found on the back of this letter.

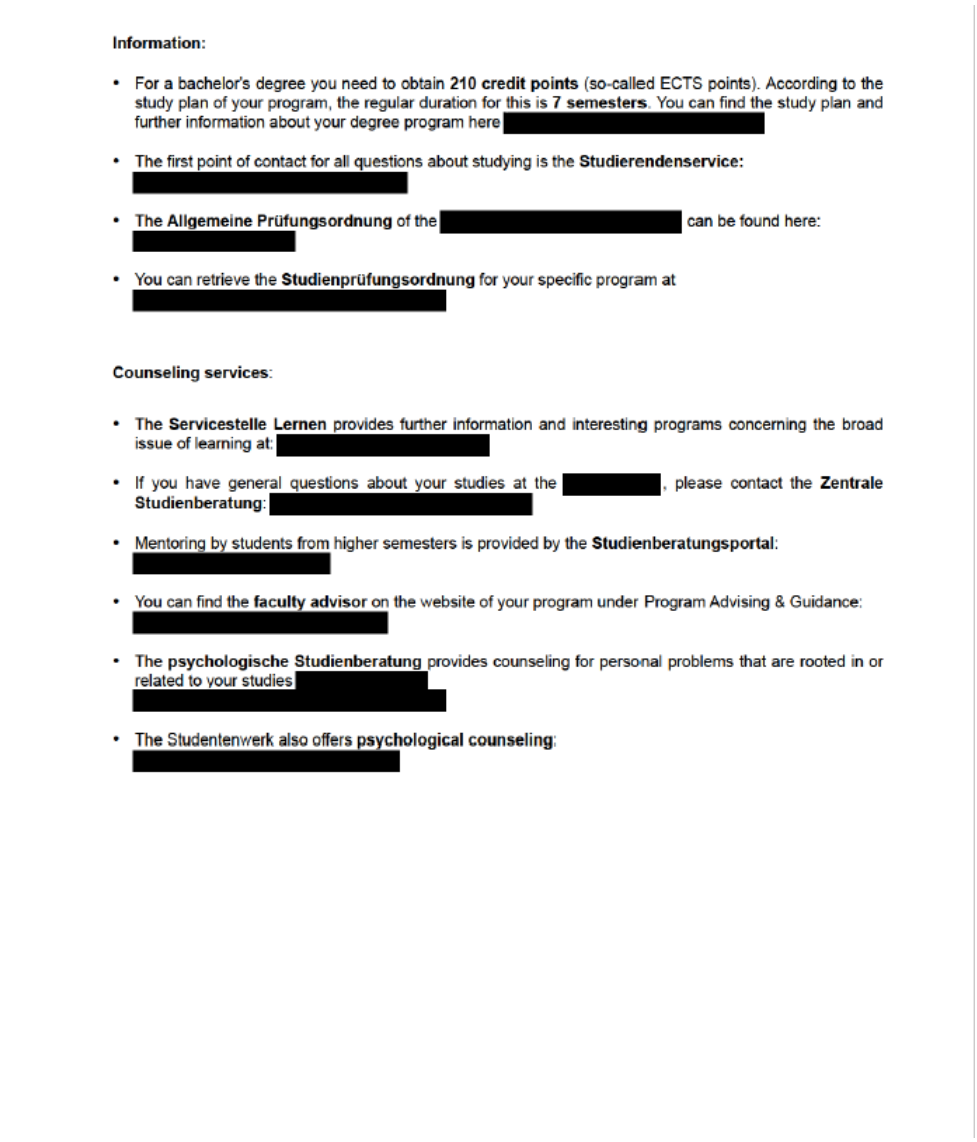
We wish you all the best for your studies at our university and hope that you enjoy your time in [redacted]!

Yours sincerely

[redacted]

1) If you no longer wish to receive this information in the future, please write an email from your [redacted] with the subject "No information Bachelor" to [redacted]
2) Source: BAS and BAP, survey at the [redacted], cohorts 2012/13-18/19, responses of similar students to a question about starting salaries. Similar students studied the same or a related bachelor's degree program at the [redacted]. The gross salary is the annual salary before deduction of taxes and social security contributions for full-time employment (38.2 hours per week including an end-of-year bonus of 0.25 monthly salaries) referring to the base year 2020.
3) This applies when entering the workforce after earning a bachelor's degree (BA). In the case of a subsequent master's degree (MA), this amount increases by the difference in salary between MA and BA graduates.

Figure C.4: Treatment letter: second page - all groups



Information:

- For a bachelor's degree you need to obtain **210 credit points** (so-called ECTS points). According to the study plan of your program, the regular duration for this is **7 semesters**. You can find the study plan and further information about your degree program here [redacted]
- The first point of contact for all questions about studying is the **Studierendenservice:** [redacted]
- The **Allgemeine Prüfungsordnung** of the [redacted] can be found here: [redacted]
- You can retrieve the **Studienprüfungsordnung** for your specific program at [redacted]

Counseling services:

- The **Servicestelle Lernen** provides further information and interesting programs concerning the broad issue of learning at: [redacted]
- If you have general questions about your studies at the [redacted], please contact the **Zentrale Studienberatung:** [redacted]
- Mentoring by students from higher semesters is provided by the **Studienberatungsportal:** [redacted]
- You can find the **faculty advisor** on the website of your program under Program Advising & Guidance: [redacted]
- The **psychologische Studienberatung** provides counseling for personal problems that are rooted in or related to your studies [redacted]
- The Studentenwerk also offers **psychological counseling:** [redacted]

Table C.1: OSA survey

No.	Question	Answer format
	Next are some questions that allow the University to learn something about how future students assess themselves on average and what they expect from the study program. This will help us to optimize the courses offered and the teaching methods for our future students. There are no right or wrong answers to these questions. We analyze the answers only on aggregate. There will be no inferences to individual people.	
1	What do you believe is the current average gross annual salary for full-time employment in the first year after graduating with a bachelor's degree in the degree program for which you are answering these OSA questions? Please provide the gross annual salary (NOT: monthly salary!), i.e., the salary before taxes.	[__ Euro; -1 "No answer"]
	How certain are you about this estimate?	[0%, 10%, 20%, 30%, , 100%]
2	Now imagine that you received your Bachelors degree in the program you are currently studying. What do you believe is the gross annual salary that you would earn during the first and the tenth year after graduating if you worked full time? Please provide the gross annual salary (NOT: monthly salary!), i.e., the salary before taxes. Gross annual salary during the first year after graduating:	[__ Euro; -1 "No answer"]
	How certain are you about this estimate?	[0%, 10%, 20%, 30%, , 100%]
	Gross annual salary during the tenth year after graduating:	[__ Euro; -1 "No answer"]
	How certain are you about this estimate?	[0%, 10%, 20%, 30%, , 100%]
3	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?	[Yes, No; -1 "No answer"]
	If you cycled 40 minutes to the same concert: would you stay until the end?	[Yes, No; -1 "No answer"]
	And if you cycled 5 minutes to the same concert: would you stay until the end?	[Yes, No; -1 "No answer"]
4	Following next are four statements about yourself. How well do they describe you? • *When Im faced with an opportunity to make a purchase, I try to imagine things in other categories I might spend that money on.* • *Before spending time on a particular activity, I consider other specific activities that I would not be able to spend time on.* • *Before I make a particular purchase, I consider other specic items that I would not be able to buy.* • *When Im faced with the decision to spend time on a particular activity, I try to imagine other activities I might spend my time on.*	[Scale from 0-10 (0 = does not describe me at all; 10 = describes me perfectly); -1 "No answer"]
5	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?	[Yes, No; -1 "No answer"]
	Now suppose you bought exactly the same bottle (brand, quantity and quality) of juice for 2. Would you finish drinking it?	[Yes, No; -1 "No answer"]
	And if you bought exactly the same bottle of juice for 1? Would you finish drinking it?	[Yes, No; -1 "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?	[Yes, No; -1 "No answer"]
6	We now ask for your willingness to act in a certain way. • In general, how willing are you to take risks? • How willing are you to give up something that is beneficial for you today in order to benefit more from that in the future? • How willing are you to punish someone who treats you unfairly, even if there may be costs for you (e.g., in the form of money, time, or reputation)? • How willing are you to punish someone who treats others unfairly, even if there may be costs for you (e.g., in the form of money, time, or reputation)? • How willing are you to give to good causes without expecting anything in return?	[0-10; 0 = Completely unwilling to do so, 10 = Very willing to do so; -1 = No answer]
7	Finally, How well do the following statements describe you a person? • When someone does me a favor, I am willing to return it. • If I am treated very unjustly, I will take revenge at the first occasion, even if there is a cost to do so (e.g., in the form of money, time, or reputation). • When I meet new people, I assume they have only the best intentions. • I tend to postpone tasks even if I know it would be better to do them right away.	[0-10; 0 = Completely unwilling to do so, 10 = Very willing to do so; -1 = No answer]

Table C.2: Post-treatment survey: general questions

No.	Question	Answer format
1	First, we would like to ask you to indicate your age:	[(0-99)__]; -1 "No answer"]
2	Are you	[Male, Female, Divers, No answer]
3	Before we get to the actual topic of the survey, we would like to ask you about your satisfaction with your life in general:	
	How satisfied are you with your life, all things considered?	[Scale from 0-10 (0=Completely unsatisfied, 10=Completely satisfied); -1 "No answer"]

Table C.3: Post-treatment survey: study questions

No.	Question	Answer format
1	What motivates you to learn during your studies? To what extent do you agree with the following statements? *I study,* • *because I am intrinsically motivated, e.g., out of interest and enthusiasm for the con-tent of my studies, out of curiosity, or because I like that the content of my studies is challenging.* • *in order to have greater opportunities later in life, e.g., higher chances of employment or financial security.* • *because I want to be among the best, e.g., I want to perform better than others in the exams and in my studies.*	[Scale from 1-7 (1=Completely disagree, 7=Completely agree); -1 "No answer"]
2	Please think about the current Semester: On average, how many hours per week do you dedicate to your studies? 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.	[__ (0 - 168) hours per week; -1 "No answer"]
3	If you think of the current semester: To what degree do you agree with the following statements about your studies? With my studies I associate... • *performance pressure* • *freedom to organize studying according to my plans* • *personal development* • *stress*	[Scale from 1-7 (1=Completely disagree, 7=Completely agree); -1 "No answer"]
4	Regardless of how your studies are going right now, how many semesters will it ideally take you to complete the Bachelors degree in your current study program? If you plan to drop out of your current study program, please answer with does not apply (-2)	[__(1-20) semesters; -1 "No answer"; -2 "Does not apply"]
5	And realistically, how many semesters do you think it will take you to complete the Bach-elors degree in your current study program? If you plan to drop out of your current study program, please answer with does not apply (-2)	[__(1-20) semesters; -1 "No answer"; -2 "Does not apply"]
6	Next, we would like to know more about your interaction with other students in your study program. With how many students from your current study program are you in contact so closely that you regularly exchange or discuss course materials or plan on studying for exams together?	[__(0-99); -1 "No answer"]
7	How many of these contacts have you met during an introductory week or during orien-tation days at the beginning of your studies?	[__(0-99); -1 "No answer"; -2 "Does not ap-ply"]
8	In the following we would like to ask you some questions about how you finance your studies. What sources do you use to finance your living in the current semester?	[Financial support from parents, partner, or relatives ;Student financial aid according to BAföG; Bank loan for student finance, e.g., a student loan from the KfW banking group; Own income from employment; Vocational training pay, e.g. from a dual course of study; Own resources that were acquired or saved up before studying; Scholarship, except of BAföG; State benefits, e.g. child allowance, housing allowance, orphans al-lowance or orphans pension, but not stu-dent financial aid (BAföG); Other sources of finance (what other sources of finance is this exactly); No answer]
9	How much money do you have at your disposal on average each month during the cur-rent semester? Please think about all of the previously mentioned financial sources. Im-portant: Please also take into account sums that other people pay directly to third parties for you, e.g., transfers of rent to your landlord.	*(0-9999)__ euros per month; -1 = "No an-swer"*
10	Do you intend to pursue a Masters degree after completing your Bachelors degree?	[No; Yes, as directly as possible after com-pletion of the Bachelors degree; Yes, but not before I have acquired some professional experiences; Yes, but I am not sure yet at what time; No answer]
11	And how satisfied are you with your studies, all things considered?	[Scale from 0-10 (0=Completely unsatisfied, 10=Completely satisfied); -1 "No answer"]

Table C.4: Post-treatment survey: labor market questions

No.	Question	Answer format
	Now follow some questions about the labor market prospects after a Bachelor's degree.	
1	What do you believe is the current average gross annual salary for full-time employment in the first year after graduating with a Bachelor's degree in your current degree program?	
	Please provide the gross annual salary (NOT: monthly salary!), i.e., the salary before taxes.	[__ Euro; -1 "No answer"]
	How certain are you about this estimate?	[0%, 10%, 20%, 30%, , 100%]
2	Now imagine that you received your Bachelors degree in the program you are currently studying: What do you think, how likely is it that you will find a job within the first 6 months after graduating?	[0%, 10%, 20%, 30%, , 100%]
3	Now imagine that you received your Bachelors degree in the program you are currently studying. What do you believe is the gross annual salary that you would earn during the first and the tenth year after graduating if you worked full time?	
	Please provide the gross annual salary (NOT: monthly salary!), i.e., the salary before taxes. Gross annual salary during the first year after graduating:	[__ Euro; -1 "No answer"]
	How certain are you about this estimate?	[0%, 10%, 20%, 30%, , 100%]
	Gross annual salary during the tenth year after graduating:	[__ Euro; -1 "No answer"]
	How certain are you about this estimate?	[0%, 10%, 20%, 30%, , 100%]

Table C.5: Post-treatment survey: personality questions

No.	Question	Answer format
	Finally, we would like to ask you some general questions about yourself.	
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?	[Yes, No; -1 "No answer"]
	If you cycled 40 minutes to the same concert: would you stay until the end?	[Yes, No; -1 "No answer"]
	And if you cycled 5 minutes to the same concert: would you stay until the end?	[Yes, No; -1 "No answer"]
2	Following next are four statements about yourself. How well do they describe you?	[Scale from 0-10 (0 = does not describe me at all; 10 = describes me perfectly); -1 "No answer"]
	• *When Im faced with an opportunity to make a purchase, I try to imagine things in other categories I might spend that money on.* • *Before spending time on a particular activity, I consider other specific activities that I would not be able to spend time on.* • *Before I make a particular purchase, I consider other specic items that I would not be able to buy.* • *When Im faced with the decision to spend time on a particular activity, I try to imagine other activities I might spend my time on.*	
3	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?	[Yes, No; -1 "No answer"]
	Now suppose you bought exactly the same bottle (brand, quantity and quality) of juice for 2. Would you finish drinking it?	[Yes, No; -1 "No answer"]
	And if you bought exactly the same bottle of juice for 1? Would you finish drinking it?	[Yes, No; -1 "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?	[Yes, No; -1 "No answer"]
4	We now ask for your willingness to act in a certain way.	[Scale from 0-10 (0 = does not describe me at all; 10 = describes me perfectly); -1 "No answer"]
	• *In general, how willing are you to take risks?* • *How willing are you to give up something that is beneficial for you today in order to benefit more from that in the future?* • *How willing are you to punish someone who treats you unfairly, even if there may be costs for you (e.g., in the form of money, time or reputation)?* • *How willing are you to punish someone who treats others unfairly, even if there may be costs for you (e.g., in the form of money, time or reputation)?* • *How willing are you to give to good causes without expecting anything in return?*	
5	How well do the following statements describe you a person?	[Scale from 0-10 (0 = does not describe me at all; 10 = describes me perfectly); -1 "No answer"]
	• *I tend to postpone tasks even if I know it would be better to do them right away.* • *When someone does me a favor, I am willing to return it.* • *If I am treated very unjustly, I will take revenge at the first occasion, even if there is a cost to do so (e.g., in the form of money, time, or reputation).* • *When I meet new people, I assume they have only the best intentions.*	
6	You now have the opportunity to let us know what kind of additional information and support you need from the university or faculty for successful studies.	[Open]

D Pre-analysis plan

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

Lars Behlen[1], Raphael Brade[2], Oliver Himmler[3], and Robert Jäckle[4]

October 19, 2021

1. Motivation and Research Questions

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

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

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[4] Nuremberg Institute of Technology, Germany. Email: robert.jaeckle@th-nuernberg.de.

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

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

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

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

2. Sample

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

Table 1: Observations by study program

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

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

3. Design of the Intervention

Figure 1: Intended timeline of the intervention

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

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

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

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

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

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

4. Randomization Procedure

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

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

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

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

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

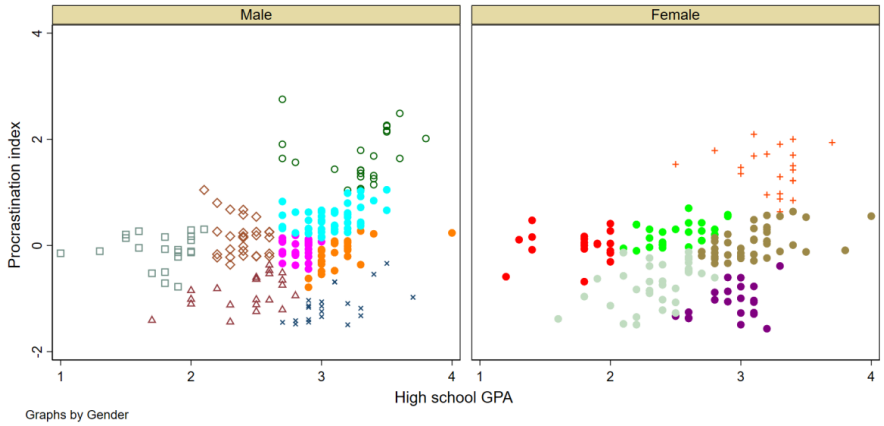

Figure 2: Threshold blocking in Business Administration (minimal allowed block size = 21)

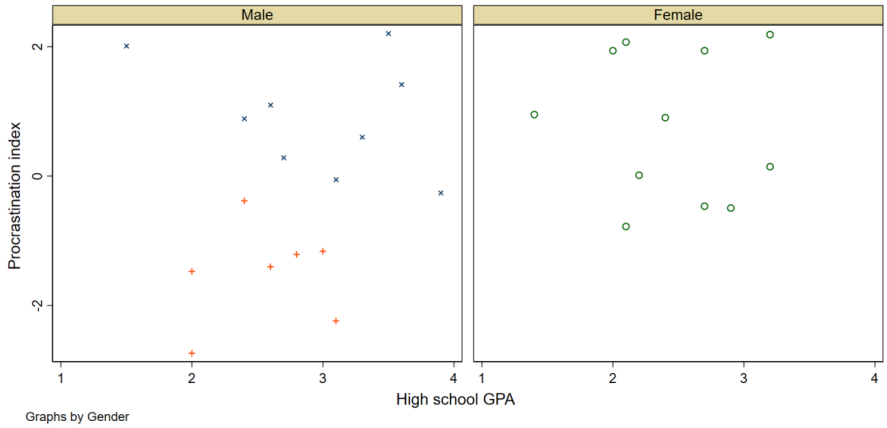

Figure 3: Threshold blocking in Process Engineering (minimal allowed block size = 6)

Table 2: Summary statistics and balancing properties

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

5. Statistical Power

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

Table 3: Minimum detectable effect sizes

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

6. Data Sources

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

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

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

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

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

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

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

7. Variables

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

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

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

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

8. Analyses

8.1 Main Analyses

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

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

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

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

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

8.2 Explanatory and Secondary Analyses

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

1. Using the respective survey outcomes, we will study treatment effects on students' expectations about future earnings as well as the accuracy of and the confidence in those beliefs.
2. We plan to use data from the OSAs to study whether the treatment effects depend on students' pre-treatment earnings expectations and their opportunity cost consideration.
3. To study the net effects of our intervention, i.e., whether students buy gains on the course credit dimension with declines in performance on other outcome dimensions, we will re-run the main analyses with our secondary outcomes (GPA, dropout, and non-cognitive outcomes).
4. Since the GPA is only observed for students who pass at least one graded module and because all outcomes from the online survey are only observed for students who answer the respective question, we will study whether observing these outcomes is affected by treatment and, if applicable, control for potential differences using inverse probability weighting.

8.3 Exploratory Analyses

For exploratory analyses we are mainly interested in the following:

1. We will explore whether treatment effects are heterogeneous with respect to the dimensions used in the threshold blocking procedure. I.e., we will study if treatment effects are heterogeneous with respect to students' procrastination tendencies, their high school GPA (= a proxy for ability), their gender, and across study programs. Since many study programs have only a small number of observations (see Table 1), we will group study programs into broader fields of study.
2. We plan to explore heterogeneity with respect to time preferences and procrastination tendencies which we measure based on questions in the OSAs.
3. We plan to explore heterogeneity with respect to students' current financial situation, which we measure in the online survey. Since the online survey is conducted post-treatment, we will first study whether treatment affects item nonresponse and the answering behavior.

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