Relative Feedback During COVID-19

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February 27, 2025

Preliminary, please do not cite or quote.

Abstract

We conducted a field experiment during the COVID-19 pandemic that provides new bachelor students with ongoing relative performance feedback (RPF) on their accumulated credit points. The RCT results in lower credit accumulation and higher dropout rates. To explore this further, we compare the intervention groups with pre-pandemic cohorts, showing: 1) During the pandemic, likely due to relaxed study regulations and the lack of opportunities for peer comparison, students earned fewer credits and exhibited lower dropout rates. 2) Driven by students with below-average first-semester credits, RPF brought dropout rates close to pre-pandemic levels. We discuss potential mechanisms behind our findings and carefully argue that the increase in dropouts may be beneficial, as it could have mitigated delayed dropouts, allowing students to explore alternative career paths sooner.

Keywords: Relative Feedback, COVID-19, Higher Education, Randomized Field Experiment

JEL Classification: D83, D91, I21, I23, C93

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We would like to thank Zouhier Kassaballi for his valuable suggestions and his assistance in drafting this text. We are also grateful to Lars Behlen for his support regarding the literature review, and Amelie Müller for her editorial work. Anna Bauer, Pauline Wagner, Clara Rattmann, and Maximilian Herrmann provided excellent research assistance. We gratefully acknowledge financial support from the German Federal Ministry of Education and Research under grant 16PX21003A, 16PX21003B and administrative support from the Nuremberg Institute of Technology. This RCT is registered under AEA RCT No. 7442.

1 Introduction

At the beginning of their studies, university students have only incomplete information about how well their abilities match their chosen degree program. Upon arriving at university, they learn how well they fit the program both from their own performance (see e.g., Altonji, 1993; Manski, 1989; and Manski and Wise, 1983) and by comparing themselves with others (see e.g., Azmat & Iriberri, 2010; and Ertac, 2005). This feedback influences their decision on how much effort to invest and, for those on the margin, whether to continue or drop out of their studies. Research, for example by Stinebrickner and Stinebrickner (2012, 2014), shows that more than 40% of early dropouts in the first two years are due to learning about one's academic abilities. However, both mechanisms – learning from personal performance and social comparison – were impaired during the COVID-19 pandemic.

In this paper, we present the results of a relative performance feedback (RPF) intervention conducted with new bachelor's students during COVID-19. We compare their academic trajectories from the first to the fourth semester with those of non-experimental, pre-pandemic cohorts between 2014 and 2018. COVID-19 led to strict contact restrictions and transitioned university teaching worldwide to online formats. This created a unique situation where social comparison through personal interaction was nearly eliminated. In addition, changes in exam regulations, such as the suspension of failed exams, made it more difficult for students to learn from their own academic performance. This setup allows for the following contributions: First, using register data from over 2,300 students, we provide evidence for how academic performance and dropout behavior changed due to the pandemic. Second, the pandemic offers a unique opportunity to measure the effects of relative performance feedback in a setting where the experimental control group lacks alternative sources of performance feedback.

Our natural field experiment (Harrison and List, 2004) was conducted at one of the largest universities of applied sciences in Germany. The study involved 2,370 bachelor students who began 21 different degree programs in October 2020, during the second wave of the pandemic in Germany and most of Europe. The first three semesters of this cohort were characterized by online teaching and contact restrictions, and their first four study semesters have been also affected by relaxed exam regulations (see Section 2.2 for details). All students who re-enrolled for the second semester were randomly assigned to a control group and two treatment groups: i) Relative performance feedback (RPF), and ii) RPF with normative framing (RPFN). RPF was first provided in the second semester through two letters – one at the beginning and one at the end of the semester – informing students about how their credit points compared to others in the same study program. The normative framing group was provided with the same information as the RPF group, but those below (above) the average in terms of credit performance additionally received encouraging (approving) normative messages. The encouraging messages aimed to motivate students to improve their study progress, while the goal of the approving norms was to prevent them from resting on their achievements. Students in the control group only received information about their own accumulated credits (absolute performance feedback, APF). The procedure was repeated in subsequent semesters with updated information. We follow the students' academic trajectories up to the fourth semester.

Our results show that both treatment arms lowered students' credit accumulation and increased dropout rates, while grades were not affected. By the end of the fourth semester, students receiving RPFN accumulated 3.6 credits fewer than the control group, a significant difference, while those with RPF saw an insignificant reduction of 1.7 credits. This decline was largest among students with below-average pre-treatment credits, with their credit accumulation decreasing by a statistically significant 3.3 (RPF) to 4.1 credits (RPFN). For above-average students, the two treatments had no significant effect on credit accumulation. The negative effect on earned credits is primarily driven by a significant rise in dropout rates. Overall, our intervention increased dropout rates by 6 percentage-points (PP) in the RPF group and by 4 PP for those receiving RPF with normative frames. Among below-average students, the dropout rates rose by 10 PP in the RPF group and 6 PP for RPFN, both differences being statistically significant, while above-average students were again unaffected.

The higher attrition in the treatment groups is not necessarily a negative outcome. If the pandemic led to unusually low dropout rates, the control group's counterfactual dropout rate – had there been no pandemic – would likely have been higher. In this case, the increase in attrition caused by the feedback treatments may have helped prevent delayed dropouts that would otherwise have been postponed to later semesters. This can be seen as a beneficial outcome as it means that students may choose alternative, better suited career paths earlier. We investigate this by comparing COVID-19 students with pre-pandemic cohorts from the same university between 2014 and 2018. Our findings are twofold: First, during COVID-19, students earned fewer credits and had lower dropout rates compared to pre-pandemic cohorts. Specifically, by the end of the fourth semester, the control group had earned an average of 3.9 fewer credits and had a dropout rate that was 9 PP lower than that of the pre-pandemic cohorts (both differences being statistically significant). Second, the interventions, driven by below-average students, brought dropout rates close to pre-COVID levels (RPF: 28%; RPFN: 30%; control group: 24%; pre-pandemic cohorts: 33%). Looking at the reasons the university reported for attrition, we find that in the control group 'switching to other programs' (6%), 'abandoning studies' (14%), and 'failed degrees' (0%) were lower than before the pandemic (10%, 16%, and 7%) , with the latter being a result of the fact that, during this time, due to changes in study regulations, students could no longer fail. Our intervention appears to have encouraged students to switch programs (8-9%) or abandon their studies (16-17%), aligning these dropout reasons with pre-pandemic levels.

At this point, it is important to note that we plan to update this paper with data on academic trajectories beyond the fourth semester. This will enable us to investigate whether dropout rates in the control group also returned to pre-pandemic levels after the COVID-19 restrictions were abandoned, and whether study attrition in the treatment groups stabilized at pre-pandemic levels. If the long-term results showed that dropout rates in all groups converge, it would suggest that the increase in dropouts due to relative performance feedback was, in fact, beneficial and may have helped prevent delayed dropouts.

Regarding mechanisms, we hypothesize that that the first result – fewer credits and lower dropouts during the pandemic – is driven by several factors. One possible explanation are changes in the study regulations. Specifically, the extension of the nominal study duration and the suspension of forced dropouts may have reduced the incentive to progress quickly. In addition, the contact restrictions may have increased the uncertainty about the opportunities to switch study programs and potential outside options on the labor market, which likely deterred students from dropping out. Another factor is the lack of peer interaction, which may have prevented students from comparing their performance to others, leading to less awareness of their (under-) performance and potentially delaying the decision to drop out. Similarly, since lower credit accumulation was probably accompanied by taking fewer course and receiving fewer grades, this may have also slowed down the learning process regarding students' own academic abilities. Finally, as below-average students remained enrolled for longer, their weaker performance may have led to lower credit accumulation.

We attribute the second result – the increase in dropouts due to our intervention – mainly to social learning through RPF (see Festinger, 1954; Azmat & Iriberri, 2010; Dobrescu et al., 2021; Ertac, 2005). During the pandemic, our RPF (and RPFN) intervention may have acted as a substitute for the diminished social interaction. For those in the treatment groups who realized they were underperforming relative to their peers, this likely reduced motivation and effort, potentially increasing dropout rates. Similarly, feedback indicating a low rank may have negatively impacted students' self-confidence and perceptions of their abilities, which can also foster higher dropouts (Denning, Murphy and Weinhardt, 2023; Elsner and Isphording, 2017; Murphy and Weinhardt, 2020). The fact that social learning had no (or even negative) effects on the study progress of above-average students does not necessarily contradict social comparison theory as an underlying mechanism. During the COVID phase, the nominal study duration was extended, and job market prospects were uncertain. Both may have made faster academic progress less attractive. In the RPFN group approving norms may have further reinforced this, leading students to use the relaxed regulations as an opportunity to regress to the average or 75th percentile.

Contributions to the literature. First, we add to the literature on relative performance feedback in higher education. In this context, prior research has typically focused on providing students with feedback on their grade point average (GPA), often yielding no significant improvements or even negative effects on performance (Cabrera and Cid, 2017, Azmat et al., 2019). Other studies have examined performance feedback on intermediate measures, such as mid-term exams or exercises on online platforms. These interventions have shown positive effects on performance within the specific course (Tran and Zeckhauser, 2012, Kajitani et al., 2020) and in some cases, led to positive spillover effects beyond the targeted course (Dobrescu et al., 2021). Similar to our study, Brade et al. (2022, 2023) provide relative feedback on course credits and show that it accelerates graduation and improves grades. Building on the contributions of previous literature, our study uniquely provides RPF to an entire cohort of students at a large university, encompassing 21 different degree programs. In addition, the provision of encouraging and approving norms, along with the opportunity to test their effects against RPF without norms, represents a novel approach.

Second, our study contributes to the question of how relative performance feedback works during the pandemic – without the possibility of personal peer contact. To the best of our knowledge, there is only one study that addresses a related topic. Bertoni's and Parkam's (2024) research is part of the rank literature in schools. They compare newly founded classes during the pandemic, in which pupils were unaware of their rank within the class, with pre-existing classes, where pupils could assess their rank through social learning in the years before the pandemic. They find that the absence of social interactions reduces the impact of ordinal ranks on test scores. Our study complements Bertoni and Parkam (2024): while they demonstrate that social learning about one's rank – and consequently about one's abilities – did not or only partially occur during the pandemic, our study examines how actively providing relative (rank) feedback can potentially address the issue of missing interactions in contexts such as the pandemic or other anonymous settings, including very large degree programs or online courses.

Third, our study generally contributes to the literature about the impact of the COVID-19 pandemic on students in higher education. Similar to our findings in the control group during the first four semesters, evidence from the United States suggests that a considerable number of students delayed graduation due to the pandemic (Aucejo et al., 2020). Evidence pointing in the same direction stems from an experimental study on the impact of online teaching on student performance during the pandemic. It reveals a negative effect on student performance, with students in online classes performing significantly worse than their peers who attended in-person classes (Kofoed et al., 2024). Finally, using observational data from Italy, DePaola and Scoppa (2023) found a decline in student performance, with students earning 1.4 fewer credit points, during the first semester of the pandemic. While these studies predominantly focus on the early stages of the COVID-19 crisis, the long-term effects of the pandemic on student success in higher education remain largely unclear. Our contribution to this literature is twofold: First, we compare academic performance during and before the pandemic, finding that students earned fewer credits while maintaining the same GPA and experiencing lower dropout rates. Second, we examine a medium-term timespan of four semesters, with all of it occurring during COVID-related restrictions and changes in study regulations were in place.

The remainder of this paper is organized as follows: Section 2 provides the institutional background, describes the COVID-related restrictions in place during the intervention and outlines the design of our intervention. Section 3 describes the data and estimation methodology used in the analysis. Section 4 presents the results of the field experiment, while Section 5 compares the intervention cohort with earlier non-pandemic cohorts. Section 6 provides a theoretical discussion of our findings, and Section 7 concludes.

2 Institutional Background, Corona Restrictions and Intervention Design

2.1 Institutional Background

Our feedback intervention took place at a German university of applied sciences (UAS). It began in the second semester and included 2,370 students who re-enrolled in 21 Bachelor programs (see Table A 1 for details) for the upcoming summer semester until March 22, 2021 (the time when the randomization took place). By this time, 219 students who had initially started their programs in the winter term had already dropped out. This setting represents a substantial portion of the German higher education system: In 2020, approximately 38% of the German student population attended UAS (Statistisches Bundesamt, 2020), with most of the programs included in our study being offered not only at USAs but across all types of universities. Some of these programs, such as Business, Mechanical Engineering, and Computer Science, are among the most popular nationwide (Statistisches Bundesamt, 2020).

The bachelor's programs in our study adhere to the European Credit Transfer System (ECTS). There standard degree structure is designed for completion within seven semesters, i.e., to graduate on time, students must accumulate 210 credits, averaging 30 credits per semester. In practice, however, students typically require around 8.5 semesters to complete their degrees, with a standard deviation (SD) of approximately one semester. Throughout their studies, students have access to real-time information regarding their absolute academic progress – credits earned and GPA – via the university's web portal. Notably, the university does not provide students with any information about their relative performance, making our intervention, which focuses on relative feedback, a novel aspect of their academic experience.

2.2 Corona-related Restrictions and Changes in Study Regulations

Our intervention cohort began their studies in the midst of the COVID-19 pandemic, with most classes held online from Winter Semester 2020/21 until Summer Semester 2021. During Winter Semester 2021/22, the "3G" rule (recovered, vaccinated, tested) applied, and, although in-person classes were planned, COVID-19 waves in fall led to a quick return to online teaching. In Summer Semester 2022, in-person classes resumed under the "2G" rule (vaccinated or recovered), though many classes still remained online. By Winter Semester 2022/23, normality had largely returned. In sum, personal contact among the students in our cohort was hardly possible at the start of their studies and remained severely limited until the fourth semester.

During this period, several study and examination regulations were also suspended. Most notably, failed exams were erased, meaning that failing an exam (even multiple times) would not result in forced dropouts. In addition, the standard study duration ("Regelstudienzeit") for all Bachelor's programs was extended by four semesters, allowing students more time to complete their studies and receiving government financial support for a longer time period. All regular study policies were reinstated in Summer Semester 2023.

2.3 Design of the Intervention

The 2,370 students in our intervention were assigned to three experimental groups (T0: control (absolute performance feedback, APF), T1: relative performance feedback (RPF), and T2: RPF + normative messages) using a stratification and re-randomization approach.[1] Stratification was based on two key factors: their specific study program and whether they performed above or below average in the first semester. This stratification resulted in 42 strata. Within the strata, we used a re-randomization process based on Banerjee et al. (2017) to achieve the best balance across the following variables: first-semester credit points (CP), a dummy indicating whether first-semester GPA data were missing, gender, age at university entry, high school GPA, date of enrollment, and a dummy variable indicating participated in a pre-treatment survey. This approach ensures comparability across the treatment and control groups and allows for a causal assessment of the effects of the intervention.

Table 1 provides summary statistics of the re-randomization and further pre-treatment variables to test whether our randomization procedure successfully balanced observed characteristics across both treatment groups and the control group. Column 4 provides p-values for a joint orthogonality test. We find no significant differences for any of the students' observable characteristics. Specifically, the students in the three experimental groups had almost identical educational outcomes in high school and by the end of their first semester (baseline), in terms of number of credits earned and their university grade point average (GPA).[2]

[1] In the two groups T1 and T2, we additionally randomized the students into an opt-in group (T1-a and T2-a) and an opt-out group (T1-b and T2-b), so that they could decide for or against continued feedback letters from the second treatment semester onwards. However, only very few students in both groups actively opted in or out of the intervention. In this paper, we therefore pool T1-a (T2-a) and T1-b (T2-b).

[2] Of the 2,370 students that were made available to us by the university for randomisation, the administration later named three as subsequent dropouts in the first semester. These remain in our analyses of the experiment.

Table 1: Balancing Table

	Control Group	RPF	RPF + Normative Frame	Joint orthogonality test p-values	N
	(1)	(2)	(3)	(4)	(5)
High School (HS) GPA	2.599	2.586	2.581	0.835	2,370
	(0.58)	(0.59)	(0.61)		
HS Degree „Abitur"	0.528	0.514	0.508	0.723	2,370
	(0.49)	(0.50)	(0.50)		
Share of Female Students [a)]	0.347	0.353	0.382	0.215	2,370
	(0.47)	(0.47)	(0.48)		
Age (in years) [a)]	21.711	21.842	21.722	0.749	2,370
	(3.66)	(3.98)	(3.52)		
Enrollement date	29.Aug	29.Aug	29.Aug	0.842	2,370
	(22.13)	(21.46)	(21.8)		
Time since Grad. (in years)	1.947	2.088	1.973	0.627	2,370
	(2.80)	(3.25)	(1.97)		
Pre-Treatment Survey Part. [a)]	0.482	0.447	0.490	0.157	2,370
	(0.50)	(0.497)	(0.50)		
Baseline Credits (Sem. 1)[a)]	17.663	17.572	17.739	0.973	2,370
	(11.2)	(11.5)	(11.7)		
Baseline Univ. GPA (Sem. 1)	2.384	2.370	2.380	0.915	1,974
	(0.72)	(0.70)	(0.72)		
Univ. GPA not avail. (NA) [a)]	0.199	0.194	0.198	0.962	2,370
	(0.39)	(0.39)	(0.39)		
Baseline Dropout (Sem. 1)	0.000	0.001	0.002	0.240	2,370
Number of students	597	886	887	-	-

Note: a) Variables used in the re-randomization. The table shows the group means of pre-treatment variables for the control group, and the two treatment groups and their standard deviations in parentheses. HS degree "Abitur", Share of Female Students, Pre-Treatment Survey Participation, University GPA NA, and Baseline Dropout are binary variables. 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"). In Germany, 1.0 is the best and 4.0 is the worst possible grade. The last row reports the number of students in each group, and the last column indicates the available observations for each variable. The p-values in Column (4) are from F-tests based on regressions that control for strata FE and use robust standard errors. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Figure 1 outlines the timeline of our intervention during the first three semesters. In March 2021, we initiated the intervention by sending an unannounced physical letter to students. This letter provided personalized information regarding their relative academic performance. The specific details of the information included in these letters are described below. Approximately one month before the exam period, students received a second letter with updated performance information. While this letter largely mirrored the content of the first, it additionally emphasized the upcoming exam period. From the fourth semester onwards, we continued the intervention in the same way.

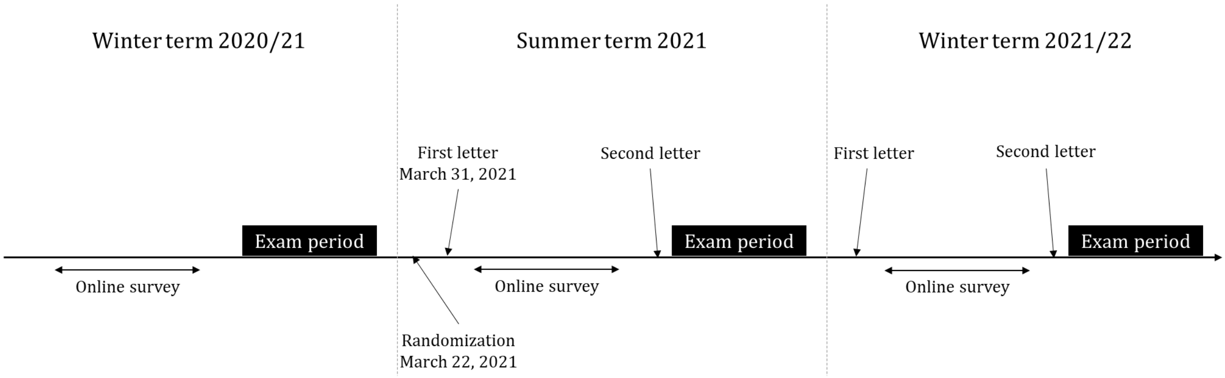

Figure 1. Timeline of the intervention during the first three semesters.

Note: In the fourth semester the intervention was continued in the same way. The data from the online surveys were not used in this version of the paper but will be analysed for future versions.

Depending on the experimental group, the letters included the following treatments:

Control Group – Absolute Performance Feedback (APF). Students in the control group received letters containing absolute performance feedback, which reported their personal performance in terms of credits earned and their grade point average (GPA). This information was already accessible to students via the university's web portal.

Treatment Group 1 – Relative Performance Feedback (RPF). In addition to their own performance data, students in this group received relative performance feedback. Their feedback included a bar chart comparing their performance (in terms of credits earned) to that of their peers in the same study program (see Figure 2). The bar chart displayed the performance of students at the 25th percentile (bottom 25%), the 75th percentile (top 25%), and the average (mean) performance. This comparative data was not available to students through the university portal or any other source. Although the letter also provided their GPA, no comparison was made between the student's GPA and that of their peers.

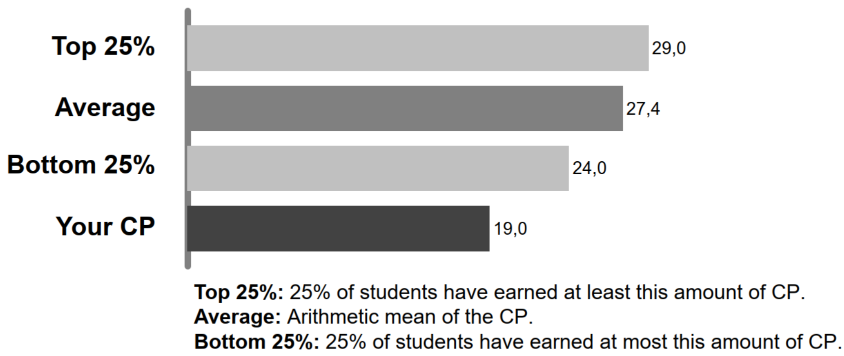

Figure 2. Example for the bar chart used as Relative Performance Feedback.

Treatment Group 2 – RPF + Normative Messaging. In this group, students received the same relative performance feedback as in Treatment Group 1, but with an additional message based on their position in the performance distribution. A message of encouragement was sent to students whose performance was below average to motivate improvement. Conversely, students who performed above average received an approving message that acknowledged their achievements and was meant to motivate them to maintain their performance rather than rest on their laurels and fall back to the average or 75th percentile (see Figure 3).[3]

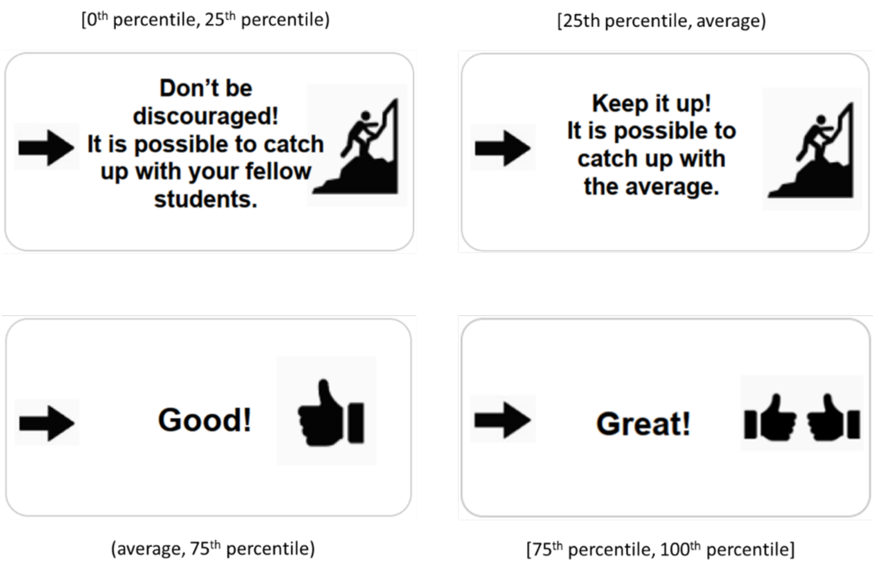

Figure 3. ***Encouraging and approving normative messages.***

[3] If a student's performance matched the average exactly, they were given an encouraging message, as past research (Brade et al., 2022) suggests that providing approving messages for average performance may have counterproductive effects.

3 Data and Estimation

To analyze the experimental cohort, we utilize administrative data provided by the university's examination office, which includes detailed records of students' academic performance and progress, such as the number of credits earned, their university GPA, and their dropout status. In addition to performance data, the university provided us with data on students' background characteristics. Some of this information was used in the (re-) randomization process, and some is additionally included as covariates in our analysis (for an overview see Table 1).

Comparison with previous cohorts. To assess the impact of the unique study conditions faced by this cohort due to the COVID-19 regulations we also use archived administrative data from 13,116 students who began studying at the same university between 2014 and 2018. Table A 2 in the Appendix shows that there are only few differences between the Corona and pre-COVID cohorts. Specifically, the same average high school grade point average (GPA) suggests that there were no systematic differences in terms of the students' abilities.

As discussed in Section 2.2, the pandemic significantly disrupted study regulations, with key changes including restrictions on in-person contact during lectures, seminars and university events, and relaxing regulations and deadlines. By comparing the 2020/21 experimental cohort with previous groups unaffected by these measures, we can explore how these altered conditions may have influenced academic outcomes.

Main Specification. Our main analyses focus on the treatment effects on credits earned and dropping out of the study program. We provide intention-to-treat effects from OLS estimations that compare the outcomes of the control and the treatment groups. We perform those analyses with the following specification:

$$y_i = \alpha_0 + \mathbf{T_i}\boldsymbol{\alpha_1} + \mathbf{x_i}\boldsymbol{\beta} + \boldsymbol{s_i} + \varepsilon_i, \tag{1}$$

where y_i is the outcome of interest, $\mathbf{T_i}$ is a set of treatment dummies and their respective coefficients $\boldsymbol{\alpha_1}$, and $\boldsymbol{s_i}$ are strata fixed effects. In an additional specification, we add a vector $\boldsymbol{x_i}$ that includes some of the covariates depicted in Table 1.

To keep our sample complete and not lose statistical power we set the first semester GPA to a constant value when missing and add a dummy that is equal to one if it is missing. When comparing the results of our experimental cohort with the pre-Corona cohorts, some of the covariates in (1) are not available. Thus, we change the initially pre-registered control-vectors and include study program fixed effects instead of strata fixed effects, the dummy on initial survey participation is not included, and for the first semester specifications in Figure A 2 and Figure A 3, the first semester performance is also not included.

Heterogeneity Analyses. To explore heterogenous treatment effects, we will estimate this specification not only in the full sample but also among the subsamples of students who earned either more or fewer credits than the arithmetic mean in the first semester. To estimate whether the treatment effects differ between the above and below average students we will include interactions of the treatment dummies with a dummy A_i, indicating whether a student placed above average with their first semester performance.

4 Main Results

4.1 Academic Performance

Figure 4 and Table A 3 in the Appendix show the main effects of our treatments on total credits earned by the end of the second, third, and fourth semester. They show that incorporating performance feedback coupled with normative frames negatively affects students' academic progress, while offering RPF alone does not significantly impact outcomes.

More specifically, after the second semester, there was no significant difference in the number of accumulated credits between the control and the RPF group (37.81 vs. 37.26 credits), while the RPF + Normative Framing group accumulated significantly fewer credits at around 36.57 CP. By the end of the fourth semester, RPF with normative frames led to a significant reduction in accumulated credits, lowering the total CP by 3.6 compared to the control group (p-value: 0.005). In contrast, students who received just RPF experienced a smaller and statistically insignificant reduction of about 1.7 credits (p-value: 0.19).

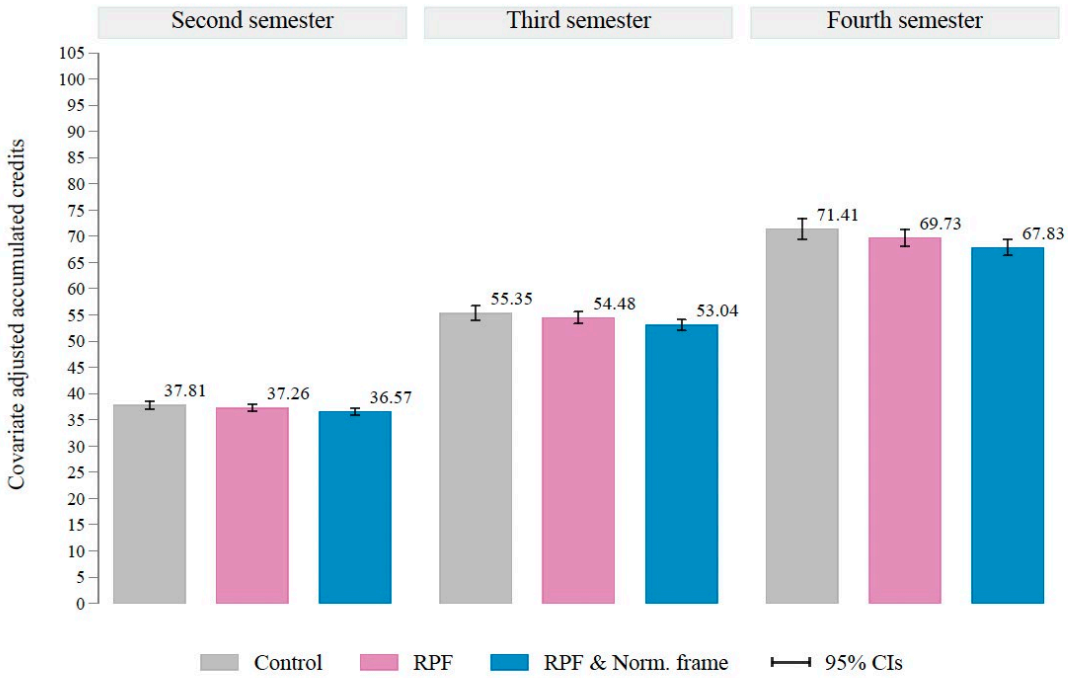

Figure 4. Accumulated credits by feedback type – full sample.

Note: N = 2,370. The results are based on OLS estimations, with the outcome variable being total credits earned. Covariates: strata fixed effects, female dummy, age at enrolment, HS GPA, time since HS degree, HS degree "Abitur", a dummy indicating participation in the pre-treatment survey, CP obtained in the first semester, first semester GPA, a dummy for missing first semester GPA. The reported control means are measured at the average of all covariates, reflecting the adjusted mean of the control group within the regression model.

Secondary Outcomes – Grades. Our feedback refers to obtained credit points and therefore to study progress. A slowdown in this progress could mean that students are placing more emphasis on the quality (grades) of individual course outcomes. On the other hand, it could also imply that students are reducing their overall effort, leading to a decrease in both the quantity and quality of their performance. In Figure A 1 in the Appendix, we therefore analyze the effects of our intervention on the grade point average (GPA) after the second, third, and fourth semester. Overall, we find no treatment effects on GPA.

Heterogeneity by First Semester Performance. To further explore who drives the observed effects on credits, we conduct heterogeneity analyses based on whether students performed below or above average in terms of the number of the credit points they have earned pre-treatment in the first semester (see Figure 5 and Figure 6, and Table A 4 and Table A 5 in the Appendix). The distinction between being placed above-average or below-average also determined whether they received an approving (above-average) or encouraging (below-average) norm in the second treatment arm (see Section 2.3).

Among below-average students (Figure 5, Table A 4), both the RPF and the RPF with normative framing resulted in significant reductions in accumulated credits by the end of the fourth semester. Specifically, students in the RPF group experienced a decrease of 3.3 credits (p-value: 0.09), and those in the RPF with normative framing group – although the norms were encouraging – had a reduction of 4.1 credits (p-value: 0.03). This suggests that relative performance feedback, even when paired with encouraging norms, has a negative impact primarily on students who are already academically underperforming. As we will show in Section 4.2 this effect is largely driven by an increase in dropouts.

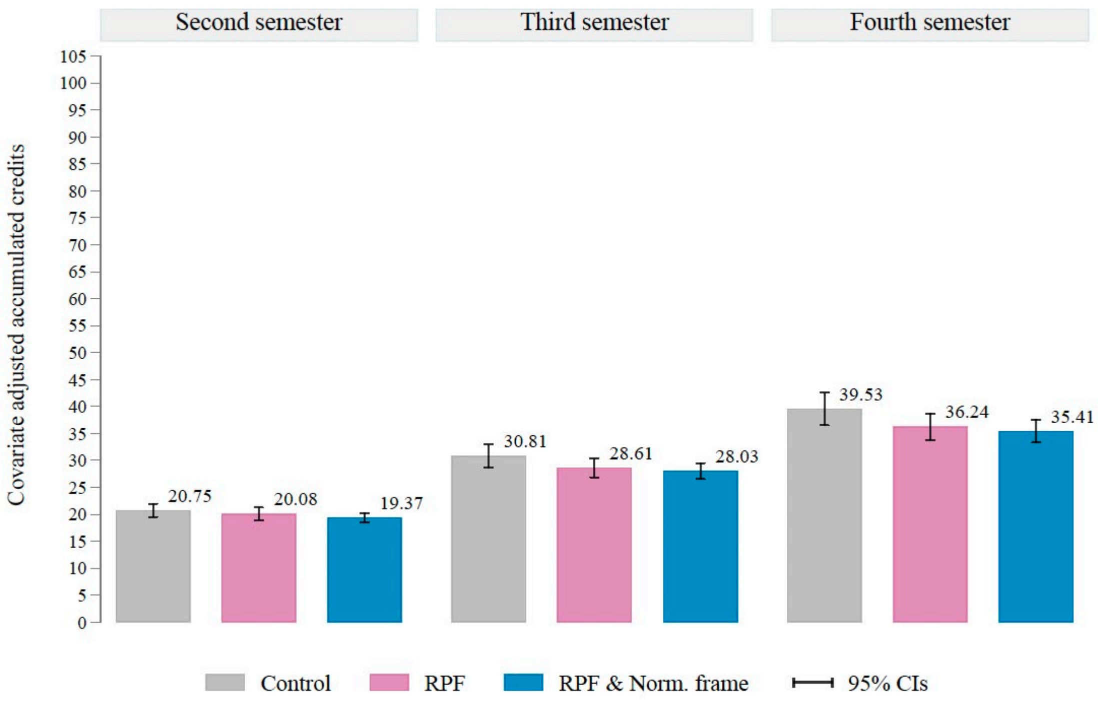

Figure 5. Accumulated credits by feedback type – below average students.

Note: N = 1,091. The results are based on OLS estimations, with the outcome variable being total credits earned. Covariates: strata fixed effects, female dummy, age at enrolment, HS GPA, time since HS degree, HS degree "Abitur", a dummy indicating participation in the pre-treatment survey, CP obtained in the first semester, first semester GPA, a dummy for missing first semester GPA. The reported control means are measured at the average of all covariates, reflecting the adjusted mean of the control group within the regression model.

In contrast, for above-average students (Figure 6, Table A 5), the RPF treatment had no significant effect on credit accumulation. Interestingly, while the RPF with approving norms reduced credits earned by above-average students by 2.5 (not significant at any conventional level, p-value: 0.12), the effect of RPF without norms is zero. One explanation for this may be the extension of the nominal study duration prescribed by the university ("Regelstudienzeit") and the poor job market prospects during the COVID-19 pandemic, which may have made a faster study progress less desirable. The approving norms "good" and "great" – contrary to their original intent – may have inadvertently reinforced this feeling, leading to a "boomerang effect", with students using the COVID period, with its relaxed study regulations and high uncertainty regarding the job market after a quick graduation, to regress to the average or 75th percentile in terms of study progress.

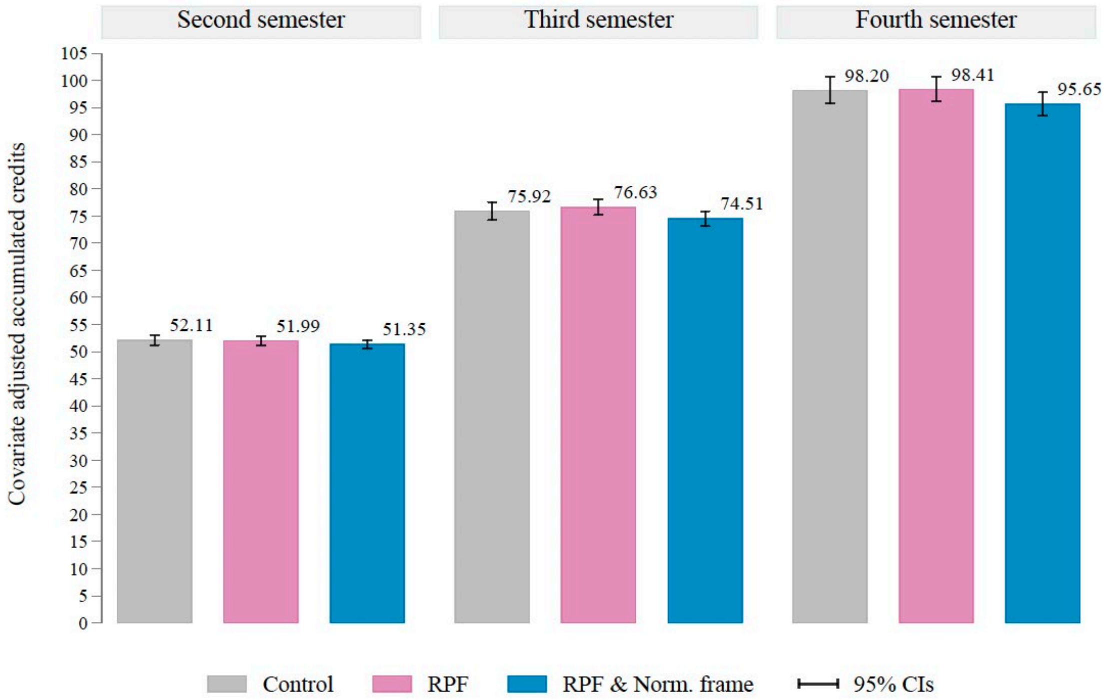

Figure 6. Accumulated credits by feedback type – above average students.

Note: N = 1,279. The results are based on OLS estimations, with the outcome variable being total credits earned. Covariates: strata fixed effects, female dummy, age at enrolment, HS GPA, time since HS degree, HS degree "Abitur", a dummy indicating participation in the pre-treatment survey, CP obtained in the first semester, first semester GPA, a dummy for missing first semester GPA. The reported control means are measured at the average of all covariates, reflecting the adjusted mean of the control group within the regression model.

4.2 Effects on Dropout

The reduced credit accumulation found so far may be due to either treated students passing fewer exams or more treated students dropping out of their programs compared to the control group, thus "mechanically" accumulating fewer credits. We therefore investigate the effects of the treatments on dropout rates by the end of the second, third, and fourth semesters (see Figure 7 and Table A 6).

While there were no significant differences in dropout rates between the experimental groups by the end of the second semester, substantial differences emerge afterwards. By the end of the fourth semester dropouts are significantly higher in both treatment groups, with the RPF group showing a 6-percentage-point (p-value: 0.001) increase and the RPF with normative framing showing a 4-percentage-point (p-value: 0.03) increase compared to the control group.

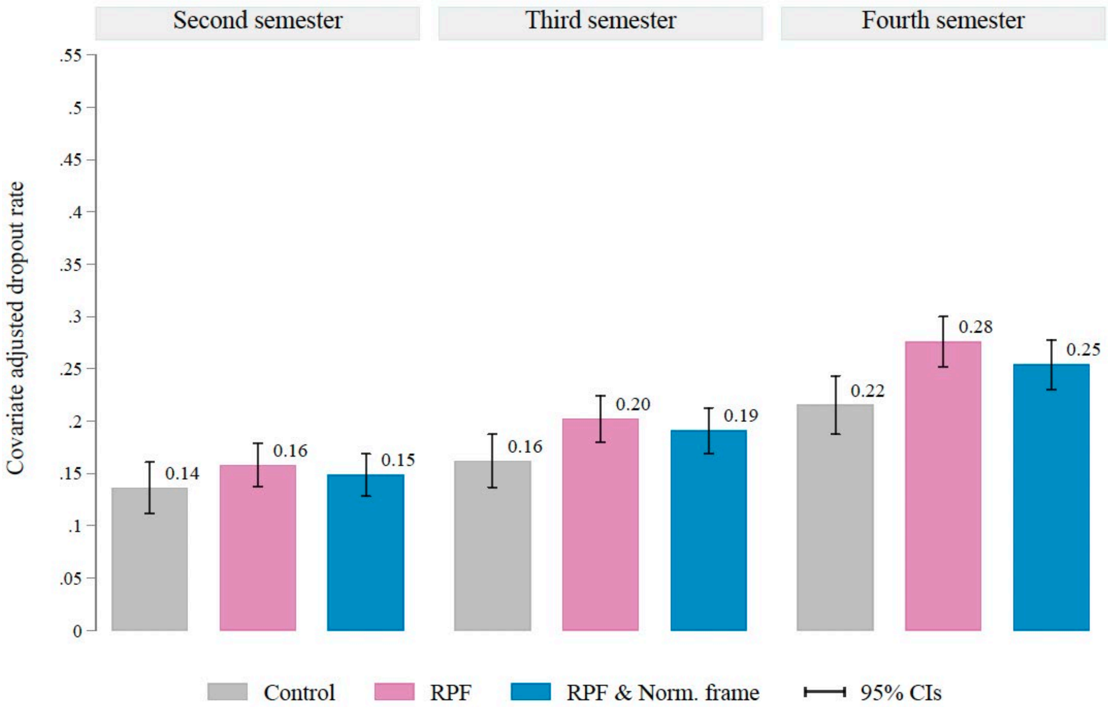

Figure 7. Dropout by feedback type – full sample.

Note: N = 2,370. The results are based on OLS estimations, with the outcome variable being dropout. Covariates: strata fixed effects, female dummy, age at enrolment, HS GPA, time since HS degree, HS degree "Abitur", a dummy indicating participation in the pre-treatment survey, CP obtained in the first semester, first semester GPA, a dummy for missing first semester GPA. The reported control means are measured at the average of all covariates, reflecting the adjusted mean of the control group within the regression model.

Heterogeneity by First Semester Performance. To explore heterogeneous effects, we again analyse the data by splitting the population into subgroups based on pre-treatment credit-performance (see Figure 8 and Figure 9, or Table A 7 and Table A 8 in the Appendix). As expected, the negative effects on dropout are primarily driven by below-average students, while there are no effects in the above-average subgroup. Among students who were below average, the RPF treatment led to a 10-percentage-point (PP) increase in the dropout rate by the end of the fourth semester (p-value: 0.03), and the RPF with normative framing resulted in a 6 PP increase (p-value: 0.10), suggesting that the inclusion of encouraging norms may have mitigated some of the impact of the RPF on dropout. Moreover, given these strong effects on dropout, one might have expected even larger negative effects on credit accumulation. The fact that this is not the case suggests that below-average (counterfactual) students in the control group who continue to study accumulate only very few credits.

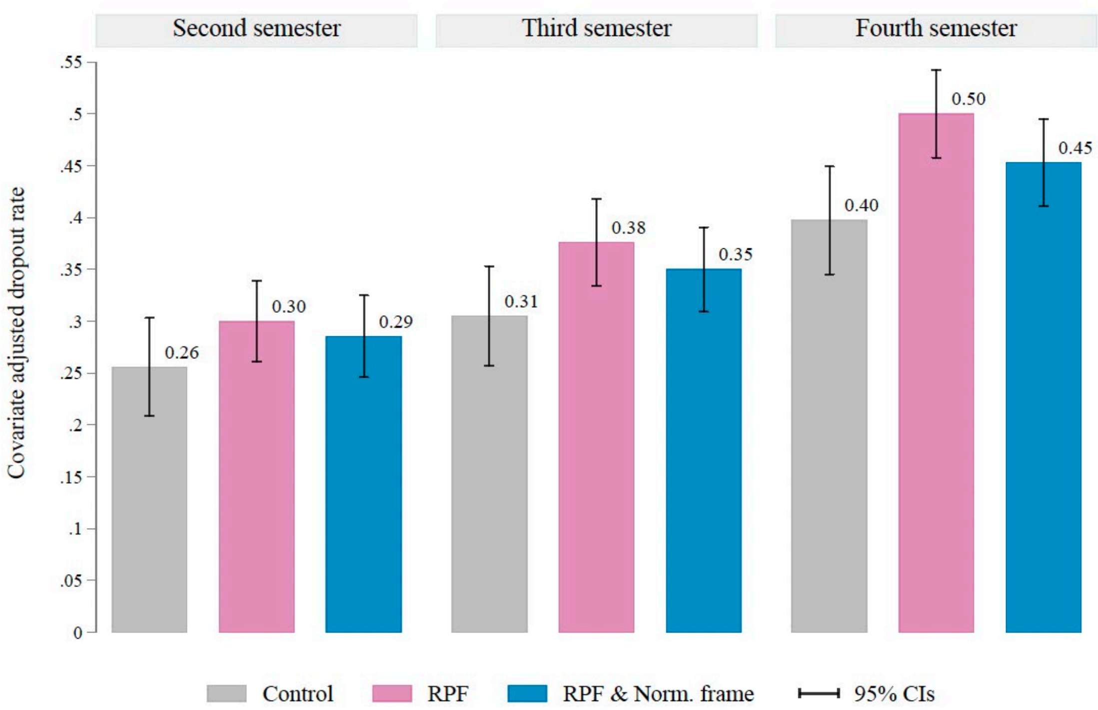

Figure 8. Dropout by feedback type – below average students.

Note: N = 1,091. The results are based on OLS estimations, with the outcome variable being dropout among below average students. Covariates: strata fixed effects, female dummy, age at enrolment, HS GPA, time since HS degree, HS degree “Abitur”, a dummy indicating participation in the pre-treatment survey, CP obtained in the first semester, first semester GPA, a dummy for missing first semester GPA. The reported control means are measured at the average of all covariates, reflecting the adjusted mean of the control group within the regression model.

The finding that students in the treatment groups had higher dropout rates than the control group is not necessarily negative. If the changes in study conditions during the pandemic (see Section 2.2) led to unusually low dropout rates, then the increase in dropout rates caused by the feedback treatment may have actually helped prevent delayed dropouts that would otherwise have been postponed to later semesters due to the pandemic. This could be a beneficial result, as it would allow students to choose alternative, potentially better suited career paths earlier. We will explore this argument further in the next section.

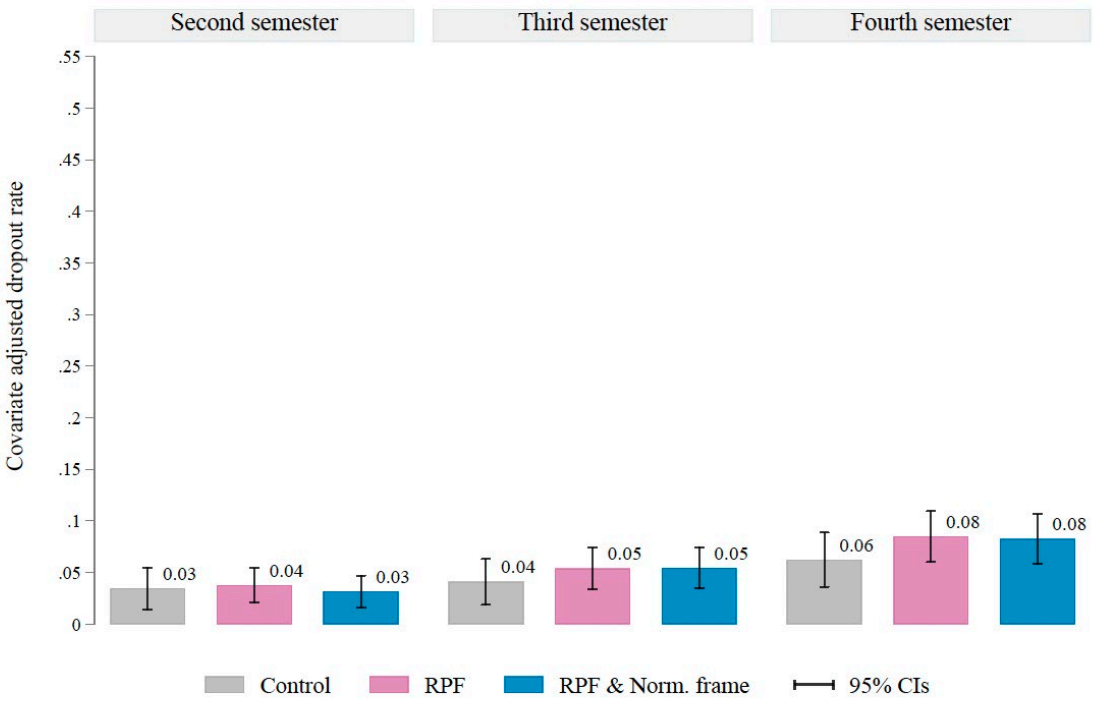

Figure 9. Dropout by feedback type – above average students.

Note: N = 1,279. The results are based on OLS estimations, with the outcome variable being dropout among above average students. Covariates: strata fixed effects, female dummy, age at enrolment, HS GPA, time since HS degree, HS degree "Abitur", a dummy indicating participation in the pre-treatment survey, CP obtained in the first semester, first semester GPA, a dummy for missing first semester GPA. The reported control means are measured at the average of all covariates, reflecting the adjusted mean of the control group within the regression model.

5 Comparison with Previous Cohorts

Our cohort began their studies in 2020 in the midst of the pandemic. During the crisis, students experienced unique and unprecedented academic conditions, in particular restrictions on face-to-face interaction and changes in study regulations (see Section 2.2 for details), which are likely to have influenced the results of our intervention.

To explore how the COVID crisis may have influence our results, in Figure A 2 and Figure A 3 in the Appendix, we first pool the three groups of the 2020 cohort and compare their progress between semesters 1 and 4 with the pre-COVID cohorts who started at the same university between 2014 and 2018. In Section 5.1 we then restrict the sample to students who re-enrolled for the second semester – the sample restriction of our intervention – and compare their study progress from the second semester onwards separately for the treatment and control groups with the earlier cohorts.

The results of the first comparison are the following: i) During the pandemic students accumulated significantly fewer credits, falling behind the 'pre-pandemics' by approximately 6.5 credits by the end of the fourth semester (significant at the 1% level; see Figure A 2). ii) The accumulation of fewer credits during the pandemic cannot be attributed to higher dropout rates. On the contrary, despite obtaining fewer credits, dropouts during the COVID crisis are significantly lower than those of previous cohorts, with a significant difference of 3 percentage points by the end of fourth semester (see Figure A 3). As we will show in Section 5.1, this difference would be even larger without our intervention.

Comparison of Experimental Groups with Previous Cohorts. Next, we separately compare the three experimental groups within the 2020 cohort – control, RPF, and RPF with normative framing – with the pre-Corona cohorts, focusing only on students who re-enrolled for the second semester (when the feedback intervention began). Figure A 2 and Figure A 3 show no systematic differences in the first-semester dropout rates and credits between the 2020 and the pre-pandemic cohorts, suggesting that selection effects are unlikely to influence the results.

Figure 10 illustrates that the pro-COVID cohorts accumulated approximately 72.3 credits by the end of the fourth semester. In contrast, the three intervention groups earned significantly fewer credits. Specifically, the control group earned on average 3.9 fewer credits (p-value: 0.013), the RPF group has 5.4 fewer credits, and the RPF with normative framing group lagged 7.3 credits behind, with the latter two differences being significant at the 1% level.

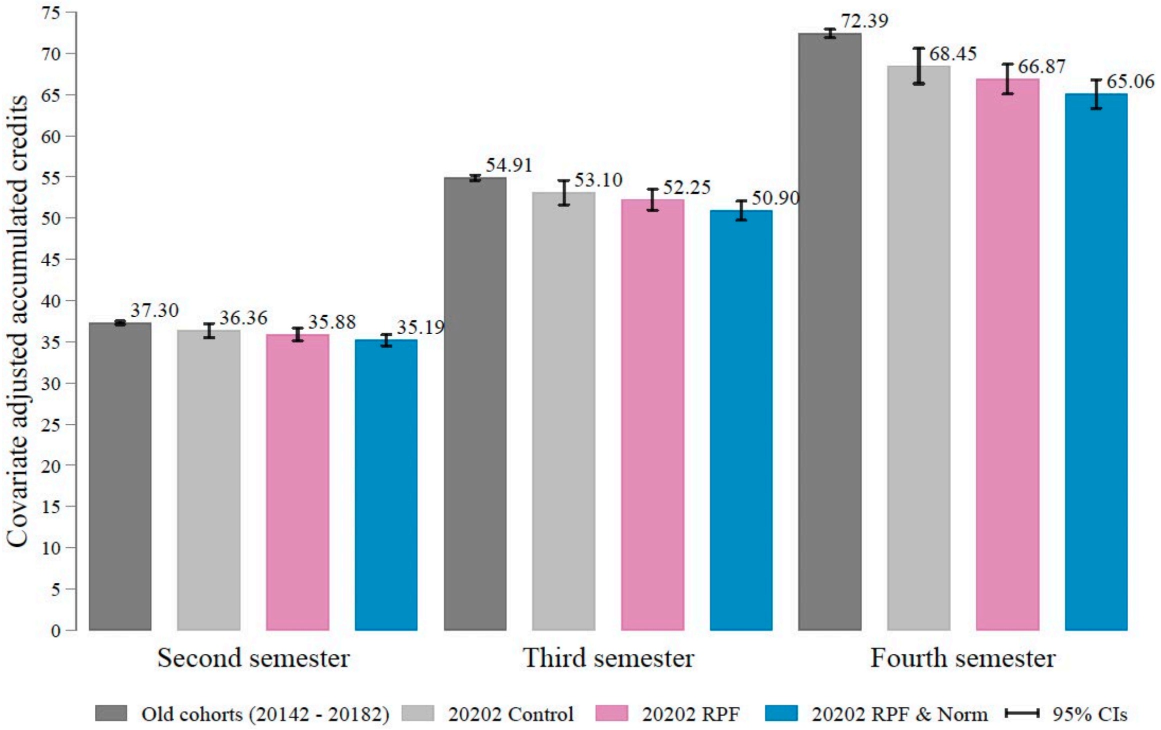

Figure 10. Accumulated credits by cohort and feedback type, pre-COVID and during COVID

Note: Pre-COVID: $N^{142\text{-}182}$ = 12,057; during COVID: N^{202} = 2,370. The results are based on OLS estimations, with the outcome variable being total credits earned. Covariates: strata fixed effects, female dummy, age at enrolment, HS GPA, time since HS degree, HS degree “Abitur”, a dummy indicating participation in the pre-treatment survey, CP obtained in the first semester, first semester GPA, a dummy for missing first semester GPA. The reported control means are measured at the average of all covariates, reflecting the adjusted mean of the control group within the regression model. ‘Cohorts 20142-182‘ refers to the average of the cohorts starting in the winter semester between the years 2014 and 2018. Only students who re-enrolled for the second semester are included.

Figure 11 depicts the dropout rates of the earlier cohorts and the three experimental groups. Comparing the control group with the previous cohorts reveals a considerable decline in dropout rates during the pandemic, despite the reduction in credits (see Figure 10). By the end of the fourth semester dropouts of the 2020 control group were a significant 9 percentage points lower than those of the ‘pre-pandemic’ cohorts, a substantial 27% reduction. In contrast, the two treatment groups exhibit dropout rates ranging from 28% to 30%, which are higher than those of the control group and more in line with the rates observed before the pandemic. These results indicate two things: i) As noted before, students studying under pandemic-related restrictions exhibit unusually low dropout rates. ii) The provision of relative performance feedback increased the low dropout rates, which may potentially have prevented delayed dropouts caused by the conditions during the pandemic – arguable a positive outcome, if the pandemic led students to postpone pursuing opportunities elsewhere.[4] In the next paragraph, we explore the reasons behind these dropouts, and we discuss the theoretical mechanisms that may have contributed to the increased dropouts caused by our interventions in Section 6.

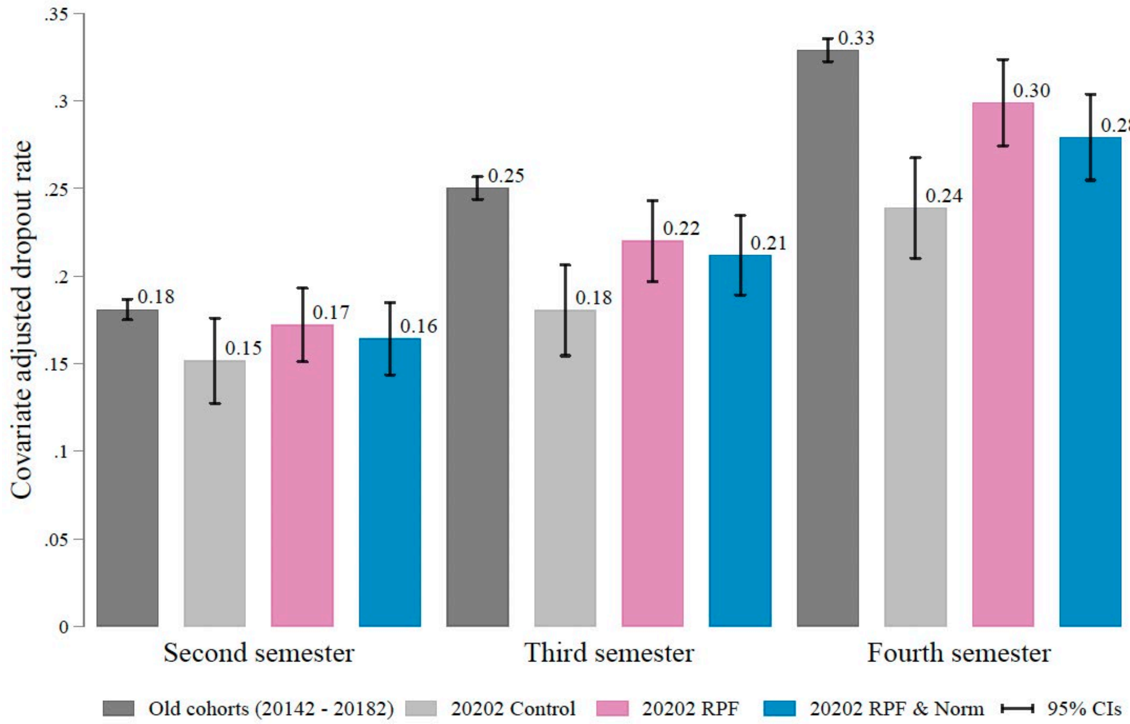

Figure 11. Dropout by cohort and feedback type, pre-COVID and during COVID.

Note: Pre-COVID: $N^{142\text{-}182}$ = 12,057; during COVID: N^{202} = 2,370. The results are based on OLS estimations, with the outcome variable being total credits earned. Covariates: strata fixed effects, female dummy, age at enrolment, HS GPA, time since HS degree, HS degree "Abitur", a dummy indicating participation in the pre-treatment survey, CP obtained in the first semester, first semester GPA, a dummy for missing first semester GPA. The reported control means are measured at the average of all covariates, reflecting the adjusted mean of the control group within the regression model. 'Cohorts 20142-182' refers to the average of the cohorts starting in the winter semester between the years 2014 and 2018. Only students who re-enrolled for the second semester are included.

Reasons why students drop out. Figure 12 provides further insights into the reasons for dropout, as recorded by the university. A key distinction of the 2020 cohort compared to earlier cohorts is the significant reduction in dropouts due to academic failure, which typically accounted for around 20% of dropouts in prior cohorts. Changes in study and examination regulations during the pandemic eliminated this reason, potentially explaining about two-thirds of the reduced dropout rate in the 2020 control group. Another notable difference is the rate of

[4] As discussed in detail in the conclusion, this argument also requires examining the developments in the control and treatment groups throughout the remainder of the study period, which we will address in an updated version of this paper.

students reporting program or university switching as a reason for dropping out. In previous cohorts, almost 10% of dropouts switched programs, compared to only 6% in the 2020 control group. The rate of students who probably fully abandoned their studies without re-enrolment (give up or no-re-enrolment) slightly decreased. Interestingly, the two treatment groups seem to encourage students both to switch universities or/and programs, and to abandon their studies without re-enrolment, bringing switching (abandoning) roughly back to (slightly above) pre-pandemic levels.

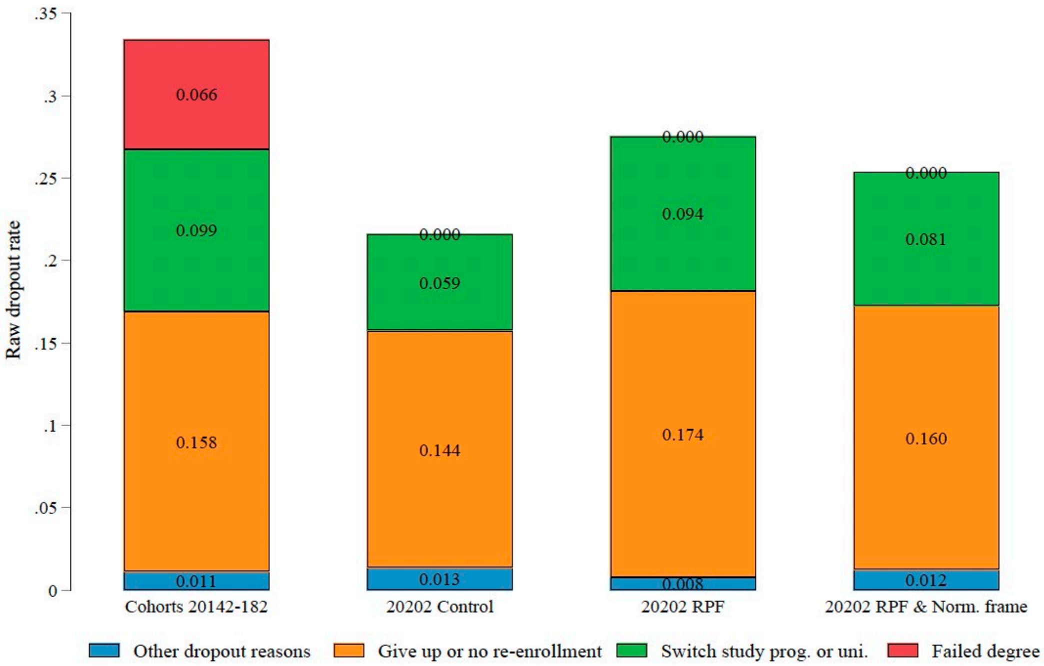

Figure 12. Reasons for dropouts by cohort and feedback type, fourth semester.

Note: ‘Cohorts 20142-182‘ refers to the average of the cohorts starting in the winter semester between the years 2014 and 2018, before the pandemic. Study rules that lead to dropouts due to too many failed exams have been relaxed in 2020 due to the COVID-19 pandemic, leading to no dropouts due to such rules.

6 Discussion

Two main results emerge from the above: First, during the pandemic, students earned fewer credits while simultaneously having lower dropout rates compared to pre-pandemic cohorts. Second, driven by below-average students, the interventions brought dropout rates in the treatment groups closer to pre-COVID levels. In the following we discuss possible mechanisms behind these results.

6.1 Lower Credit Accumulation and Lower Dropouts During the Pandemic.

First, we summarize potential reasons for the slower study progress and lower dropout rates during the pandemic:

1) Changes in study regulations. The extension of the nominal study duration ("Regelstudienzeit"), which allowed students to study for up to four additional semesters without facing forced dropout or losing financial aid (see Section 2.2 for details), may have reduced the incentive to progress quickly. This idea is also supported by the results of Bratti et al. (2024). They show, outside the context of the pandemic, that a change of study regulations in the opposite direction – a reduction of permitted exam retakes – improves students' exam pass rates and credit accumulation.

Moreover, the suspension of forced dropouts due to too many failed exams during COVID19 enabled students to stay enrolled longer. This is illustrated in Figure 12, which shows the absence of any forced dropouts during the pandemic.

2) Uncertainty. The pandemic induced uncertainty regarding a) the feasibility of switching to other degree programs, e.g., because students may have limited access to academic advisors or program coordinators, b) the outside options on the labor market after abandoning their studies, and c) overall job market prospects after graduation. The latter may have slowed down study progress, while the first two factors likely contributed to reduced dropout rates. Supporting this, Figure 12 shows that dropout rates due to 'abandoning studies' or 'switching to other programs' were lower during the pandemic compared to earlier cohorts.

3) Learning about one's academic abilities. Students can learn from their grades whether their abilities are sufficient and appropriate for their study program, and may adjust their academic choices accordingly (see, e.g., the seminal work of Altonji, 1993; Manski, 1989; Manski and Wise, 1983). Importantly, Stinebrickner and Stinebrickner (2012, 2014) show that the rate of early dropouts between the first and second years would be reduced by more than 40% if students did not learn about their academic performance and abilities. Given our finding that students earned fewer credits per semester during the pandemic, this learning process might have progressed more slowly, thereby contributing to lower dropout rates.

4) Lack of social interaction and social learning. One's academic abilities are not only assessd via grades but also through social comparisons (see Azmat & Iriberri, 2010, Ertac, 2005, Festinger, 1957). However, the lack of in-person interaction during face-to-face classes and university events likely impaired this mechanism, potentially resulting in reduced effort, less earned credits and slower academic progress during the COVID crisis. Supporting this, Bertoni and Parkam (2024) demonstrate that COVID-related contact rerstrictions during the first year of middle school reduced the impact of ordinal rank (a form of social comparison similar to RPF) on test scores.

Similarly, social learning likely also played a role in reducing dropouts compared to pre-pandemic cohorts. Without social interactions, students – especially those performing below average – may not have realized that they achieved fewer credits than their peers, making them persist longer in their programs. Moreover, the pandemic likely also led to the missed opportunity (e.g., in classroom discussions) to learn that others in similar situations plan to or have already dropped out, or – since the pandemic led to fewer dropouts – there was simply a lack of such references.

5) Delayed dropout. Finally, the decline in dropouts during the pandemic, particularly among below-average students, probably means that weaker students – who typically progress more slowly – remain enrolled longer than usual. This could "mechanically" have led to a corresponding decrease in average credit accumulation.

6.2 Increased Dropouts Through Relative Feedback

Figure 11 in Section 5.1 illustrates that the feedback intervention brought dropout rates in the 2020 cohort closer to pre-pandemic levels. This may be attributed to the following factors.

As noted in Point 4 in Section 6.1, the lack of peer comparison in the control group may have led to more students staying enrolled despite of slow study progress in terms of credit points. In contrast, students in the treatment groups with relative feedback could adjust their beliefs about their study progress and academic abilities (see Azmat & Iriberri, 2010; Dobrescu et al., 2021; and Ertac, 2005). Especially those below average may have realized that they were underperforming compared to their peers, which likely reduced motivation and ultimately increased dropout rates, especially through switches to other programs or universities. Similarly, our relative feedback may have signalled a low rank relative to other students, affecting students' self-confidence and perceptions of their abilities (Bertoni and Parkam, 2024, Denning, Murphy and Weinhardt, 2023; Elsner and Isphording, 2017; Murphy and Weinhardt, 2020), which may also have contributed to higher dropout rates.

7 Conclusion

The COVID-19 pandemic has had various impacts on university students. Changes in exam regulations, altered expectations regarding outside options, slower development of students' awareness of their abilities, and the lack of opportunities for social comparison through peer interactions may all have contributed to changes in study behavior. Our findings show that, compared to pre-pandemic cohorts, students earned fewer credits and exhibited lower dropout rates, while grades remained unchanged. However, providing students with relative feedback on their accumulated credits during COVID-19 helped bring dropout rates back to near pre-pandemic levels by the fourth semester. This rise in dropouts was also accompanied by a decline in credit accumulation, while grades remained unaffected.

The fact that our interventions brought dropout rates close to pre-pandemic levels could suggest that one of the main factors behind the reduced dropout rates during this period may have been the lack of opportunities for social comparison, with other pandemic-induced changes having a smaller impact. The relative feedback allowed students to compare their academic progress with that of their peers, and likely prompted below-average students to recognize their underperformance, thereby reducing motivation and ultimately leading to an increase in dropout rates.

To further validate our findings, it is crucial to track students beyond the fourth semester. This will allow us to examine whether (i) dropout rates in the control group returned to pre-pandemic levels after the COVID-related restrictions were fully lifted, and (ii) dropout rates in the treatment groups stabilized at pre-pandemic levels instead of continuing to rise. These analyses will be presented in an updated version of this paper.

If the long-term results showed that dropout rates in all groups converged, it would suggest that the increase in dropouts due to relative performance feedback could, in fact, have been beneficial, as it may have helped prevent delayed dropouts and allowed students to explore alternative career paths earlier. Additionally, it would suggest that relative performance feedback could also be valuable in other educational settings with limited personal contact or anonymous study conditions, such as large degree programs, online courses, evening classes, or part-time programs.

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Appendix

Table A 1: Observations by study program

Study program	Freq.
Applied Chemistry	97
Applied Mathematics and Physics	48
Civil Engineering	213
Business Administration	382
Electrical Engineering and Information Technology	171
Building Services Engineering	32
Energy Process Engineering	26
Computer Science	99
International Business	89
International Business and Technology	62
Management in Organic Business	27
Mechanical Engineering	225
Mechatronics/Precision Engineering	78
Media Engineering	62
Computer Science and Media	59
Medical Engineering	136
Social Work	327
Journalism of Technology	60
Process Engineering	24
Materials Engineering	39
Information Systems and Management	114
Total	2,370

Table A 2: Comparison of Pre-Study Characteristics: COVID vs. 2014-2018 Cohorts

	2014-2018 cohorts	COVID-cohort	T-test p-Values
	(1)	(2)	(4)
High School (HS) GPA	2.62	2.60	0.16
	(0.61)	(0.60)	
HS Degree „Abitur"	0.42	0.51	0.00***
	(0.49)	(0.50)	
Share of Female Students	0.37	0.36	0.35
	(0.47)	(0.47)	
Age (in years)	22.05	21.84	0.01*
	(3.66)	(3.98)	
Time since Grad. (in years)	1.82	2.06	0.00***
	(2.80)	(3.25)	
Number of students	13,116	2,589	-

Note: The table shows the group means of pre-study variables for cohorts starting between 2014 and 2018 and the COVID intervention cohort 2020 and their standard deviations in parentheses. HS degree "Abitur", Share of Female Students, Baseline Dropout, and Share with zero CP are binary variables. 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"). In Germany, 1.0 is the best and 4.0 is the worst possible grade. The p-values in Column (3) are from t-tests of equality of means. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A 3: Effects on accumulated credits – by feedback type, full sample

	Second semester		Third semester		Fourth semester	
	(1)	(2)	(3)	(4)	(5)	(6)
RPF	-0.541	-0.551	-0.890	-0.871	-1.675	-1.686
	(0.700)	(0.524)	(1.115)	(0.903)	(1.556)	(1.303)
RPF+Norm. Frame	-1.154*	-1.236**	-2.167**	-2.311***	-3.337**	-3.572***
	(0.680)	(0.491)	(1.103)	(0.876)	(1.530)	(1.269)
Observations	2370	2370	2370	2370	2370	2370
R^2	0.664	0.818	0.633	0.769	0.591	0.721
Strata	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes
Control mean	37.675	37.675	55.188	55.188	71.142	71.142
Control SD	(22.234)	(22.234)	(33.501)	(33.501)	(44.417)	(44.417)

Note: The results were computed by OLS estimations, with the main outcome variable being total credits earned. Covariates: strata fixed effects, female dummy, age at enrolment, HS GPA, time since HS degree, HS degree "Abitur", a dummy indicating participation in the pre-treatment survey, CP obtained in the first semester, first semester GPA, a dummy for missing first semester GPA. The reported control means are the plain controls mean without covariate adjustment.

Table A 4: Effects on accumulated credits – by feedback type, below-average students

	Second semester		Third semester		Fourth semester	
	(1)	(2)	(3)	(4)	(5)	(6)
RPF	-0.913	-0.666	-2.618	-2.200	-3.758	-3.294*
	(1.213)	(0.853)	(1.857)	(1.413)	(2.504)	(1.988)
RPF+Norm. Frame	-2.117*	-1.378*	-3.894**	-2.780**	-5.463**	-4.109**
	(1.170)	(0.765)	(1.834)	(1.338)	(2.460)	(1.893)
Observations	1091	1091	1091	1091	1091	1091
R^2	0.405	0.723	0.387	0.678	0.345	0.624
Strata	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes
Control mean	21.047	21.047	31.278	31.278	40.087	40.087
Control SD	(19.646)	(19.646)	(29.962)	(29.962)	(39.365)	(39.365)

Note: The results were computed by OLS estimations, with the main outcome variable being total credits earned. Covariates: strata fixed effects, female dummy, age at enrolment, HS GPA, time since HS degree, HS degree "Abitur", a dummy indicating participation in the pre-treatment survey, CP obtained in the first semester, first semester GPA, a dummy for missing first semester GPA. The reported control means are the plain controls mean without covariate adjustment.

Table A 5: Effects on accumulated credits – by feedback type, above-average students

	Second semester		Third semester		Fourth semester	
	(1)	(2)	(3)	(4)	(5)	(6)
RPF	-0.217	-0.119	0.603	0.714	0.126	0.211
	(0.780)	(0.611)	(1.322)	(1.125)	(1.932)	(1.680)
RPF+Norm. Frame	-0.332	-0.757	-0.683	-1.410	-1.510	-2.542
	(0.769)	(0.599)	(1.312)	(1.106)	(1.903)	(1.650)
Observations	1279	1279	1279	1279	1279	1279
R^2	0.188	0.512	0.179	0.411	0.135	0.347
Strata	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes
Control mean	52.069	52.069	75.884	75.884	98.025	98.025
Control SD	(11.905)	(11.905)	(19.850)	(19.850)	(27.978)	(27.978)

Note: The results were computed by OLS estimations, with the main outcome variable being total credits earned. Covariates: strata fixed effects, female dummy, age at enrolment, HS GPA, time since HS degree, HS degree "Abitur", a dummy indicating participation in the pre-treatment survey, CP obtained in the first semester, first semester GPA, a dummy for missing first semester GPA. The reported control means are the plain controls mean without covariate adjustment.

Table A 6: Effects on dropout – by feedback type, full sample

	Second semester		Third semester		Fourth semester	
	(1)	(2)	(3)	(4)	(5)	(6)
RPF	0.021	0.022	0.040**	0.040**	0.061***	0.061***
	(0.017)	(0.016)	(0.018)	(0.017)	(0.019)	(0.019)
RPF+Norm. Frame	0.014	0.012	0.032*	0.029*	0.041**	0.039**
	(0.017)	(0.016)	(0.018)	(0.017)	(0.019)	(0.019)
Observations	2370	2370	2370	2370	2370	2370
R^2	0.210	0.276	0.245	0.304	0.279	0.339
Strata	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes
Control mean	0.137	0.137	0.162	0.162	0.216	0.216
Control SD	(0.345)	(0.345)	(0.369)	(0.369)	(0.412)	(0.412)

Note: The results were computed by OLS estimations, with the main outcome variable being the dropout rate. Covariates: strata fixed effects, female dummy, age at enrolment, HS GPA, time since HS degree, HS degree "Abitur", a dummy indicating participation in the pre-treatment survey, CP obtained in the first semester, first semester GPA, a dummy for missing first semester GPA. The reported control means are the plain controls mean without covariate adjustment.

Table A 7: Effects on dropout – by feedback type, below-average students

	Second semester		Third semester		Fourth semester	
	(1)	(2)	(3)	(4)	(5)	(6)
RPF	0.041	0.044	0.071**	0.071**	0.105***	0.103***
	(0.033)	(0.031)	(0.034)	(0.033)	(0.036)	(0.034)
RPF+Norm. Frame	0.034	0.029	0.054	0.045	0.068*	0.056
	(0.033)	(0.031)	(0.034)	(0.032)	(0.036)	(0.034)
Observations	1091	1091	1091	1091	1091	1091
R^2	0.117	0.228	0.140	0.246	0.138	0.261
Strata	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes
Control mean	0.256	0.256	0.303	0.303	0.394	0.394
Control SD	(0.437)	(0.437)	(0.460)	(0.460)	(0.489)	(0.489)

Note: N = 1,091. The results are based on OLS estimations, with the outcome variable being dropout of below average students. Covariates: strata fixed effects, female dummy, age at enrolment, HS GPA, time since HS degree, HS degree "Abitur", a dummy indicating participation in the pre-treatment survey, CP obtained in the first semester, first semester GPA, a dummy for missing first semester GPA. The reported control means are the plain controls mean without covariate adjustment.

Table A 8: Effects on dropout – by feedback type, above-average students

	Second semester		Third semester		Fourth semester	
	(1)	(2)	(3)	(4)	(5)	(6)
RPF	0.003	0.003	0.013	0.013	0.023	0.022
	(0.013)	(0.014)	(0.015)	(0.015)	(0.019)	(0.018)
RPF+Norm. Frame	-0.003	-0.003	0.013	0.014	0.017	0.020
	(0.013)	(0.013)	(0.015)	(0.015)	(0.018)	(0.018)
Observations	1279	1279	1279	1279	1279	1279
R^2	0.021	0.032	0.031	0.041	0.039	0.058
Strata	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes
Control mean	0.034	0.034	0.041	0.041	0.063	0.063
Control SD	(0.182)	(0.182)	(0.198)	(0.198)	(0.242)	(0.242)

Note: N = 1,279. The results are based on OLS estimations, with the outcome variable being dropout of above average students. Covariates: strata fixed effects, female dummy, age at enrolment, HS GPA, time since HS degree, HS degree "Abitur", a dummy indicating participation in the pre-treatment survey, CP obtained in the first semester, first semester GPA, a dummy for missing first semester GPA. The reported control means are the plain controls mean without covariate adjustment.

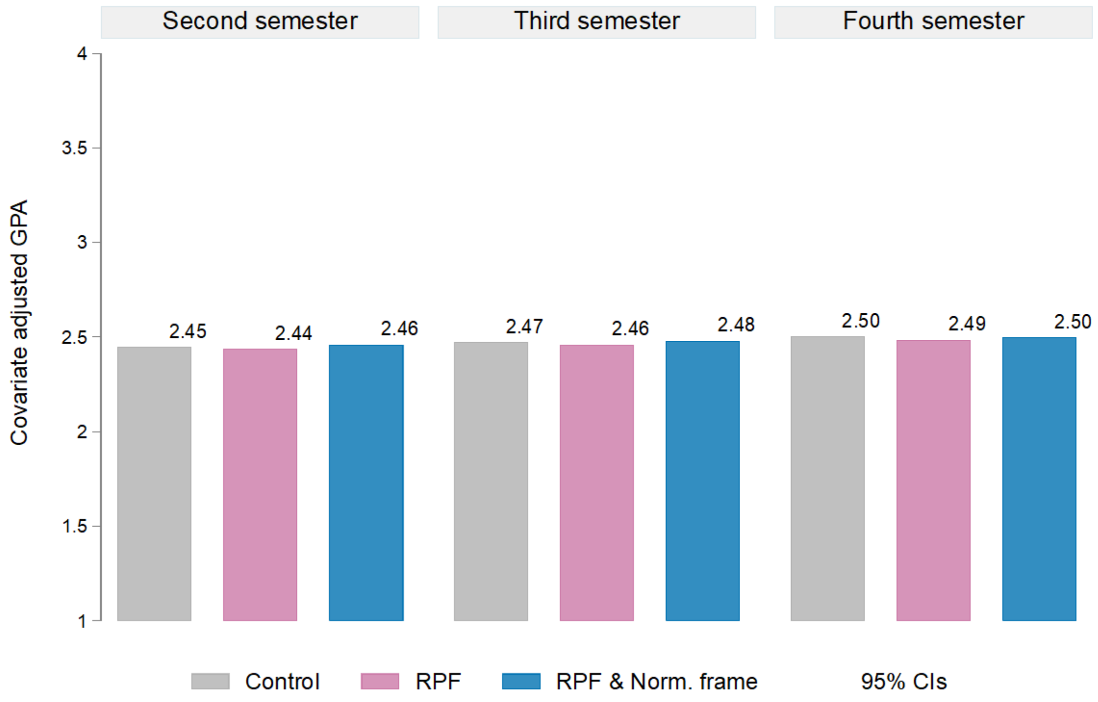

Figure A 1: GPA by feedback type.

Note: N = 1,974. The results are based on OLS estimations, with the outcome variable being GPA. Covariates: strata fixed effects, female dummy, age at enrolment, HS GPA, time since HS degree, HS degree "Abitur", a dummy indicating participation in the pre-treatment survey, CP obtained in the first semester, first semester GPA, a dummy for missing first semester GPA. The reported control means are measured at the average of all covariates, reflecting the adjusted mean of the control group within the regression model.

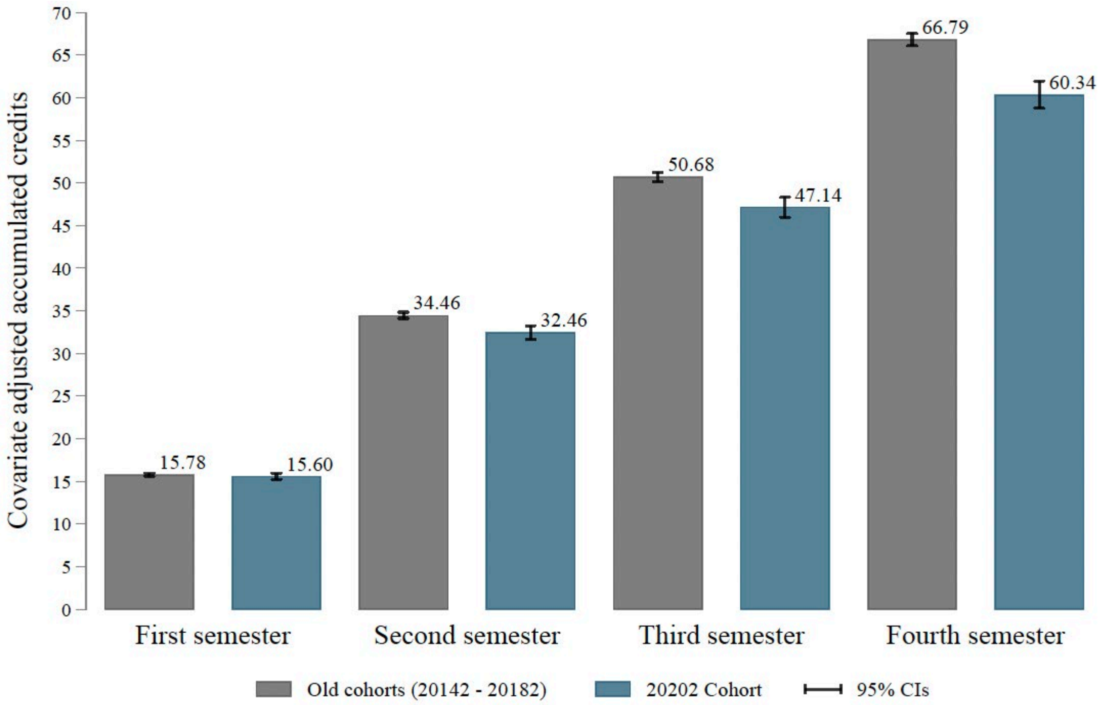

Figure A 2 Accumulated credits by cohort, pre-COVID and during COVID.

Note: Pre-Covid: $N^{142\text{-}182}$ = 13,116; during Covid: N^{202} = 2,589. The results are based on OLS estimations, with the outcome variable being the total number of earned credits. Covariates: study program fixed effects, female dummy, age at enrolment, HS GPA, time since HS degree, HS degree "Abitur". The reported control means are measured at the average of all covariates, reflecting the adjusted mean of the control group within the regression model. "Cohorts 20142-182" refers to the average of the cohorts starting in the winter semester between the years 2014 and 2018.

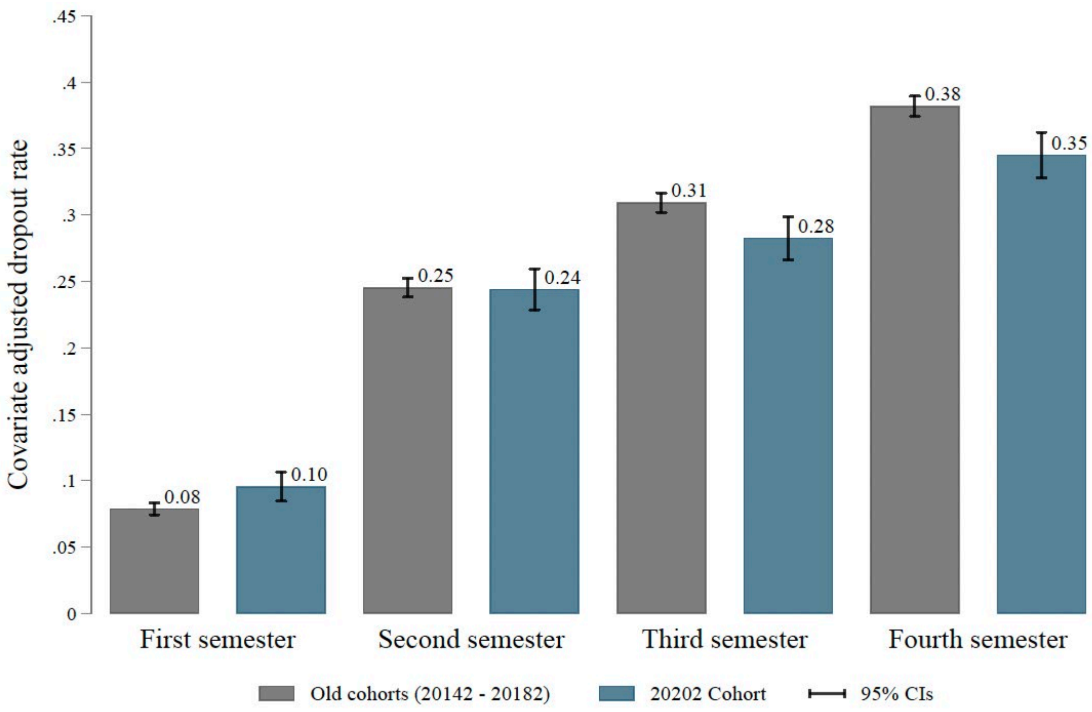

Figure A 3. Dropout by cohort, pre-COVID and during COVID.

Note: Pre-Covid: $N^{142\text{-}182}$ = 13,116; during Covid: N^{202} = 2,589. The results are based on OLS estimations, with the outcome variable being dropouts. Covariates: study program fixed effects, female dummy, age at enrolment, HS GPA, time since HS degree, HS degree "Abitur". The reported control means are measured at the average of all covariates, reflecting the adjusted mean of the control group within the regression model. 'Cohorts 20142-182' refers to the average of the cohorts starting in the winter semester between the years 2014 and 2018.