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Sitting next to a dropout: Study success of students with peers that came to the lecture hall by a different route

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Abstract: Higher education brings together students from diverse educational backgrounds, including students, who after dropping out of a first course of study, transferred to an academically less demanding institution. While peers are important contributors to student success, the influence of those dropouts with a knowledge advantage on first-time students is largely unexplored. Using an administrative data set covering every individual in the Swiss higher education system, we study the impact of the presence of academically better prepared students on the study success of first-time students. Our identification strategy relies on conditional idiosyncratic variations in the proportion of returning dropouts in university of applied sciences cohorts. We find negative effects of university dropouts who re-enroll in the same subject on the success of first-time students. In contrast, dropouts who change subjects are positively associated to the success of their new peers. Using causal machine learning methods, we find that the effects (a) are non-linear and (b) vary for different proportions of dropouts in university of applied sciences cohorts.

Keywords: University dropouts; peer effects; better prepared students; causal machine learning

JEL classification: A23, C14, I23

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1 Introduction

Becoming inspired or motivated by peers is crucial for a good learning experience, and the influence of specific types of individuals on their peers in the context of education is the focus of a large and growing literature (for an early overview, see, e.g., Epple & Romano, 2011 or more recent articles, like Briole, 2021 or Humlum & Thorsager, 2021). As an increasing number of young adults are enrolling in higher education, a larger number will drop out for different reasons (Bertola, 2021), such as having financial problems, choosing the wrong major, failing to meet the educational demands of a higher education institution, or failing to score high enough in classes graded on the curve. Not all these dropouts leave the education system, however, but many of them try to obtain their educational qualifications with a new attempt at another, potentially academically less demanding, higher education institution.

When more students re-enroll at other higher education institutions, knowing the influences of dropouts on their peers is of growing interest to politics and society. However, peer effects are primarily studied for compulsory education, such as kindergarten (Bietenbeck, 2020), elementary school (Gottfried, 2013), lower-secondary school (Balestra, Eugster, & Liebert, 2020; Balestra, Sallin, & Wolter, 2021) or high school (Lavy, Silva, & Weinhardt, 2012), with much less known about peer effects in higher education. Furthermore, studies on peer effects in higher education usually look at very specific settings, such as small groups formed for specific purposes like room- and dorm-mates in college (Sacerdote, 2001), study groups (Poldin, Valeeva, & Yudkevich, 2016; Berthelon, Bettinger, Kruger, & Montecinos-Pearce, 2019), orientation week groups (Thiemann, 2021), small class sections (Feld & Zölitz, 2017), or are gender- (Stinebrickner & Stinebrickner, 2006) or field-specific (Brunello, De Paola, & Scoppa, 2010).

While all these studies are helpful for understanding specific situations in higher education, none covers the phenomena of the impact of changes in the composition of the student body created by an influx of students (dropouts) from academically more demanding universities re-enrolling in academically less demanding institutions on students enrolled for the first-time. Such peer-effects may differ from peer-effects found in study cohorts that have enrolled together and differ in relation to their innate ability or behavior but not in terms of prior study experience. With this study we contribute to several types of literature. First, to the literature on peer effects in higher education by investigating not only small or specific groups of students in one or a few institutions but investigating entire cohorts of the entire system of higher education. Second, to the dropout literature analyzing the influence of higher education dropouts by investigating the impact of varying proportions of those (on average) academically better prepared dropouts re-enrolling in academically less demanding universities. Third, to the methodological literature by applying recent methods from the causal machine learning literature (for early overviews see Athey, 2017; Athey & Imbens, 2019) to investigate, among others, the in linear regression models implicitly used assumption of a constant treatment effect for our continuous treatment variable.

Higher education systems worldwide are often stratified in institutions of academically high demands on academic student performance, and others with lower academic requirements or demands and a good match of student quality and institution quality is important (Arcidiacono, Aucejo, & Hotz, 2016). Therefore, academically better prepared students are selected through systemic or institution-based admission procedures into more demanding universities and vice versa. Even if this is intended to achieve the best possible match between a student's abilities and the requirements of a university, it still does not guarantee success in their studies for all students, and those dropping out of the more demanding institutions and programs, might try their luck in an institution with lower demands and requirements.

The Swiss higher education system offers students, comparable to many European countries, the choice of two distinct types of institutions: More theory oriented, academically more demanding universities and academically less demanding universities of applied sciences (UAS). University dropouts are, on average, better prepared academically compared to students first enrolled in a UAS: They have (on average) more and higher quality academic knowledge from upper secondary school, because they took more years of formal schooling, and they have already acquired some university knowledge before transferring to UAS. To account for different degrees of academic preparedness, we distinguish two types of university dropouts: those enrolling in UAS in the same field from which they dropped out of their university, and those enrolling in a different field. The average same-field university dropouts might be better prepared for UAS studies, as they already had been exposed to subject-specific content at a higher educational level.

To analyze the peer effect of academically better prepared university dropouts on fellow students in UAS, we use administrative data on about 100,000 students entering a UAS in the Swiss higher education system from 2009 through 2018. Study success (or lack thereof) for first-time enrolled UAS bachelor students is measured by graduation within four or five years (success) or dropping out of the UAS within one or two (failure). Our identification strategy relies on conditional idiosyncratic variations in the proportion of university dropouts in these UAS cohorts. We check alternative identification strategies that rely on variations within institutes and fields of study over cohorts, as well as variations within institutes and years, both resulting in robust estimates.

Investigating the impact of the total proportion of university dropouts on first enrolled UAS students study success, we find a null effect. Importantly, this (average) null effect masks two opposing effects, namely positive associated to the proportion of different field, and negative associated to the proportion of same field university dropouts. Effects are found both in the short and the long run, including graduation within five years after enrollment. Moreover, the effects are driven mainly by full-time students and are found only in larger cohorts (i.e., 50 or more students). The additional use of causal machine learning methods (Kennedy, Ma, McHugh, & Small, 2017; Semenova & Chernozhukov, 2021) reveals no problems with the functional form assumptions of linear additive baseline confounders. However, the effects turn out to be both non-linear and dependent not only on the treatment intensity, i.e., the amount of increase in the proportion of dropouts in a cohort, but also on the treatment level. The non-linear (U-shaped) relationship between the proportion of dropouts and the UAS peers' likelihood of dropping out or succeeding reveals a maximized study success when the proportion of university dropouts in a cohort is around 7 percent.

The rest of the paper is structured as follows. Section 2 discusses the related literature. Sections 3 and 4 present the institutional setting, the data used in the analysis, and descriptive statistics. Section 5 describes the empirical methodology, Section 6 presents the results of the empirical analysis, and Section 7 shows the results of various robustness checks. Section 8 concludes.

2 Related Literature

UAS students enrolled in the higher education system for the first time (hereafter, “first-time UAS students”) who are exposed to (on average) academically better prepared dropouts from universities might either suffer from negative effects or benefit from positive ones. Theoretically, such effects can act through diverse channels (Feld & Zölitz, 2017). One is the possibility of channels related to lecturers, rather than student peers (Brodaty & Gurgand, 2016). Fassinger (1995), studying class participation, finds negative effects of a faster teaching pace on students’ confidence and comprehension.[1] Similarly, a professor’s favoring a selective group of students showed negative effects on the other students. Duflo, Dupas, & Kremer (2011) find evidence that students benefit from changes in the teaching style of the lecturer who

[1] Fritschner (2000) finds that participation in college classes differs for first-year students and experienced students.

reacts to changes in the composition of the student body. Having some students who can answer more difficult or technical questions, might motivate the lecturer to increase both the teaching speed and content difficulty for all students in class. However, such an effect does not necessarily have to occur: Booij, Leuven, & Oosterbeek (2017) find no teaching adjustments to different group compositions in business and economics tutorials in the Netherlands. Besides the changes in lecturing styles due to the presence of particular students, these students can also have an impact on the grading style of lectures, i.e., grading on a curve (Calsamiglia & Loviglio, 2019), and thereby indirectly affect the study success of the peers.

Another plausible indirect peer effect, not resulting from a direct interaction between peers or changes in the behavior of lecturers because of the presence of a particular group of peers, is a discouragement effect. The presence of better prepared peers leads to worsening in the relative ranking within a class or cohort and might thereby discourage the first-time students. Rogers & Feller (2016) find such a discouragement effect from the presence of high-ability peers. When expectations are too high, low- and medium-ability peers might exert lower effort. However, the opposite effect is also possible, as shown especially by the peer effect literature on the presence of gifted peers.

In most cases the literature on the influence of the presence of high ability students on their peers finds positive effects.[2] Hanushek, Kain, Markman, & Rivkin (2003) find classmates benefiting from high achieving peers for elementary school students in Texas. Burke & Sass (2013) find no or small but positive peer effects for compulsory school students from Florida by following them over six years. They also find a treatment heterogeneity that depends on the peers' own ability. If the peer is of low ability the gifted peer has a negative impact and vice versa. In a long-term study, Chetty et al. (2011) find that high ability students in kindergarten

[2] The effect of repeaters in primary and secondary school classes appears related to our analyses (e.g., Gottfried, 2013; Hill, 2014; Bietenbeck, 2020). In contrast to university dropouts – who, by transferring down to an academically less demanding UAS, are among the high-ability students there – repeaters are usually of lower ability (Lavy, Paserman, & Schlosser, 2012).

and primary school have a positive impact on peers' future earnings and college attendance. Balestra, Sallin and Wolter (2021) find mostly positive and long-lasting peer effects when gifted classmates are present in lower secondary education but find also considerable heterogeneity in the effects by characteristics of the gifted students and the peers. Finally, as is so often the case, the study results are not uniform across all empirical studies. Although Lavy, Silva, & Weinhardt (2012) find evidence for negative effects of low achieving students on their peers, they find no evidence of positive impacts of high ability students on peer's educational outcomes in the context of English secondary schools.

More related to our study, in higher education Sacerdote (2001) and Carrell, Fullerton, & West (2009) both find positive peer effects of the presence of high ability students for room- and dorm-mates in college. For the Netherlands Feld & Zölitz (2017) find positive peer effects in randomly assigned groups of 10-15 students in university. For study groups Poldin, Valeeva, & Yudkevich (2016) and Berthelon, Bettinger, Kruger, & Montecinos-Pearce (2019) find positive peer effects in universities in Russia and Chile. Thiemann (2021) finds negative effects of high ability peers in orientation week groups at a Swiss university on short- and long-term study success. Although almost all studies focus on small groups, there is a notable exception by Humlum & Thorsager (2021) using the entire field-by-institute cohort for universities and UAS in Denmark. They find a decreasing dropout probability for students if confronted to higher ability peers in their cohort in both types of institutions.

In summary, the literature on peer effects does not present a consistent picture. The channels through which students influence their peers are not always obvious, the influences are often non-linear and heterogeneous, both in terms of the characteristics of the potentially influencing student and the influenced peers.

3 Institutional setting

In Switzerland the higher education system builds on two distinct types of universities, the conventional (academic) universities and the universities of applies sciences (UAS). In contrast to conventional universities, UAS are a younger type of higher education institution, founded before the turn of the millennium mainly with the purpose to give people with vocational education and training the possibility to access directly higher education. In addition, unlike theory-based academic universities, UAS focus more on application-oriented education, which is generally somewhat less academically demanding. As an example of the latter, studies in arts or social work were grouped in UAS and have no similar counterparts in traditional universities. Many programs, on the other hand, have both a more theoretical variant in conventional universities and a more applied form in UAS, such as business administration, technical sciences, or architecture. The two types of higher education institution differ therefore both in terms of access to study and type of education offered. Admission to a university requires an (academic) baccalaureate, which is obtained when graduating from (academic) baccalaureate schools. In contrast, the admission to UAS is also possible with other qualifications but requires at least a professional baccalaureate, which is obtained in parallel to a vocational qualification or in an extra year of general education after the vocational education.[3] Compared to holders of an (academic) baccalaureate, holders of a professional baccalaureate have received about one to two years(s) less general education.

In general, UAS lectures take place in classes according to a highly standardized and mandatory schedule, comparable to those in secondary schools. Once cohorts (in the same field of study) become too large, they are divided into several classes as they attend lectures. While

[3] This leads to the interesting situation that switcher from universities to UAS, who were underperforming academically compared to their original peers, potentially have two advantages over their new peers. Firstly, they were more likely to have had an academic education at upper secondary level before entering higher education and secondly, and more importantly, they had already acquired one and sometimes two years of university knowledge before transferring to UAS. This leads to the fact that compared to their original peers, they certainly cannot be described as particularly gifted, but compared to their new peers, they can due to their knowledge advantage.

the degrees issued by the UAS and those of universities, may differ in terms of academic requirements, both enjoy similar success on the labor market (Backes-Gellner & Geel, 2014).

Unlike in most countries, students with a Swiss university admission qualification are free to choose the university they want to attend and the subject[4] they want to study, regardless of their grade point average. The free choice is possible because access to the academic baccalaureate schools is very restrictive. Only about 20 percent of a cohort obtains an academic baccalaureate degree, while the vast majority attains a vocational education and training qualification – with or without the professional baccalaureate. At UAS, there are aptitude tests in various fields, namely in music, theatre and other arts, design, applied psychology, applied linguistics, sport, health and social work. In some subjects, the aptitude tests are highly selective, while in others, aptitude assessments non-existent or not very selective.

4 Data and descriptive statistics

Our administrative data comprises every student enrolled in the Swiss education system. For our analysis, we investigate all students entering a bachelor program at a Swiss UAS between 2009 and 2018.[5]

We define a "cohort" as all students starting their studies in the same year, in the same UAS, in the same field, and in the same type of group (full-time or part-time). We define "university dropouts" as students previously enrolled at a conventional (Swiss) university in one of the three years prior to re-enrolling at an UAS, and not having obtained a degree at the university. The treatment of interest is the proportion of university dropouts in a cohort. To

[4] Exceptions are medicine and sport sciences.

[5] We removed (a) students enrolled in distance learning and private colleges, because these types of education are very different from UAS, (b) teachers subjects that are usually taught at universities of teacher education, (c) individuals with double entries because we cannot uniquely assign them to a subject, (d) subjects taught at various locations within a specific UAS as we cannot identify which students are in the same cohort, (e) individuals enrolled at a university more than three years prior to entering the UAS are removed, as we can neither classify them as first enrolled at UAS, nor university dropouts, (f) cohorts with fewer than 5 students, (g) individuals aged younger than 18 or older than 35 at entry, and (h) students living outside of Switzerland prior to starting their studies.

distinguish two types of dropouts, we create variables showing the proportion of them in their original field of study and in different fields of study.[6]

Table 1:Descriptive statistics, selective variables.

	(1) First-time UAS	(2) University dropouts
Proportion univ. dropouts	0.059 (0.047)	0.083 (0.062)
Proportion univ. dropouts SF	0.028 (0.035)	0.042 (0.048)
Proportion univ. dropouts DF	0.031 (0.033)	0.041 (0.040)
Dropout after 1 year	0.071	0.023
Dropout after 2 years [1)]	0.115	0.050
Graduation within 4 years [2)]	0.698	0.800
Graduation within 5 years [3)]	0.761	0.842
Cohort size	105.457 (111.932)	101.339 (117.454)
Age	22.354 (2.748)	22.490 (1.757)
Gender	0.472	0.524
Non-Swiss	0.072	0.068
Full time	0.781	0.894
Restricted Access	0.352	0.403
# Master studies at UAS	17.542 (5.926)	17.796 (5.386)
# Master studies at UAS in studied field	2.098 (1.716)	2.042 (1.725)
Distance: hometown to UAS (in km)	58.462 (61.245)	63.388 (65.668)
Travel time: hometown to UAS (in min)	43.581 (37.913)	46.377 (40.809)
Regional baccalaureate proportion	20.011 (4.872)	21.049 (4.748)
Admission type: Academic baccalaureate	0.170	0.926
Admission type: Professional baccalaureate (any type)	0.634	0.028
N	102,100	7,684

Notes: Average values. Standard deviation for non-binary variables in parentheses. [1)] 91,003 / 6,788, [2)] 69,034 / 5,149 and [3)] 58,399 / 4,289 observations. univ. = university; SF = same field; DF = different field. For the (treatment) variables in column (2) the proportions are calculated excluding the individual itself. Shown admission types do not sum to 1 as other admission types are possible. For the full descriptive statistics see Table 7 in Appendix A.1.

To measure the success of UAS students, we construct variables indicating whether the student dropped out within the first (or second) year after enrolling in the UAS, as well as whether the student graduated within four or five years after enrolling in the subject, they had initially enrolled in. To analyze the effect of the proportion of the academically better prepared university dropouts on first-time UAS students (102,100 observations), we remove the university dropouts (7,684 observations) from the sample for the main analysis. Table 1 offers

[6] "Field" is defined in a broader sense by the 1-digit International Standard Classification of Education (ISCED), which identifies fields within university and UAS in the same framework. To investigate the robustness of this choice, in section 7 we redefine the classification by the 2-digit ISCED fields.

descriptive statistics on the treatments (first three rows), the outcomes (next four rows), and various characteristics. The full table, including all available covariates, appears in Table 7 in Appendix A.1.

Table 1 shows the average values for the treatments, which are slightly higher for the university dropouts (in column 2) than for the first-time UAS students (in column 1). Our main outcome measures show, that about 7 percent of first-time UAS students drop out of their studies within one year, and about 76 percent graduate within five years. Even though the university dropouts, by definition, did not succeed in their previous studies, their success rates at the UAS are all higher than those of the first-time UAS students. The descriptive evidence confirms our expectation that university dropouts are on average among the academically better prepared students in each cohort although they failed at the universities. The average cohort size is of about 100 students for both, first-time UAS students and university dropouts and the composition of the student body in terms of gender and non-Swiss students is also similar for both groups.

Furthermore, no substantial differences appear for (a) proportions of students in restricted access studies, (b) the number of master programs at the UAS, (c) age, (d) distance and travel time from the hometown to the UAS, and (e) the regional baccalaureate proportion. In contrast, university dropouts more frequently select themselves into full-time studies (about 90 vs. 78 percent) and predominantly earned their higher education entrance through the academic baccalaureate track of Swiss upper secondary school (92.6 percent), while the first-time UAS students accessed university came mostly via the vocational track (63.4 percent), as described in the previous section.

5 Empirical strategy

The goal of this paper is to investigate the impact of academically better prepared university dropouts on first-time UAS students study success. Our identification relies on a conditional idiosyncratic variation of the proportion of university dropouts in cohort, with the key identification assumption of a conditionally random selection into treatment. Our selection-on observables approach formalizes to the following linear baseline model[7]:

$$Y_{icfst} = \alpha + \beta A_{cfst} + \gamma X_{icfst} + \varepsilon_{icfst},$$

where Y_{icfst} is one of the four outcomes as binary indicators for study success for each individual i. The (continuous) treatments A_{cfst} are defined as proportion of university dropouts in cohort, i.e., are the same for all individuals in the same cohort c. X_{icfst} contain covariates - on the level of the individual i, the cohort c, the field of study f, the institution s, and/or the year t - necessary to fulfil the conditional independence assumption, implying that $\varepsilon_{icfst} = e_{icfst}$ is an idiosyncratic error term. All covariates contained in X_{icfst} are predetermined.

To assume conditional independence, we include several potential confounders, controlling for their potential dependence with the outcome, i.e., study success at the UAS, and the treatment, i.e., the proportion of university dropouts in the cohort. For the baseline model X_{icfst} thus contains several indicators and information as described below. It is likely that some fields are harder to study, as well as some institutes are more selective. Therefore, we expect differences in the proportions of university dropouts by institutions and fields of study, as well as different study success by fields and/or institutes. Full time studies lead to faster graduation compared to part time and are more attractive to former university students. Some majors are subject to restricted access, which might reduce the number of university dropouts in cohort,

[7] For the main analysis, the data is sampled to include only first-enrolled UAS students, i.e., the university dropouts are removed from the data set. In the complementary analysis in Section 6.2 only the university dropouts are sampled to investigate the effect of the proportion of university dropouts on the university dropouts in UAS cohorts themselves. For this, the baseline model is slightly modified as the treatment, i.e., the proportion of university dropouts in cohort does not take the individual itself into account; formally: $D_{(-i)cfst}$.

while having already restrictively selected students might lead to faster graduation and lower dropout probability.

We further control for the distance from the hometown prior to the enrolment in the UAS. For the decision to apply to an institution, Griffith & Rothstein (2009) and others have found the distance to the institution to be an obstacle. Thus, larger distances might be related to a sophisticated selection into cohort, as well as higher motivation to perform well in studies. Another motivating factor to perform well in studies and to select into specific universities and programs are the number of Masters courses offered at the respective UAS. In most programs at UASs, the bachelor's degree is considered the standard degree. Nevertheless, many study programs also offer the possibility of master's degrees, but to a very different extent. Therefore, it cannot be ruled out that more talented students select those programs and universities that offer more master's degrees. It is also important to control for the size of the cohort, since it is not only directly related to the treatment, which is defined as proportions in cohorts, but also potentially related to study success (e.g., Kara, Tonin, & Vlassopoulos, 2021).

Furthermore, we control for various regional factors, such as the regional baccalaureate rate, the total number of university dropouts in the same field of study at the university nearest to the UAS and the language region. While we are confident that the conditional independence assumption holds for this essential set of potential confounders, we challenge several of the explicit and implicit assumptions of this baseline model.

First, additional to those covariates just discussed, we also include binary indicators for the years, individuals' characteristics, like age or gender, and cohort specifics, like the proportion of females or non-Swiss in cohort. The full set of covariates can be found in Appendix A.1, Table 7.

Second, we consider the possibility that certain UAS students might choose institutions or programs because they expect few (or perhaps many) university dropouts in them. Two observations argue against a selective choice with respect to this information: In Appendix B we provide some evidence that in Switzerland geographical proximity of the institution to the hometown of a student is a major driver of selecting an UAS. About 85 percent of first-time students enroll at the UAS geographically closest to their hometown that offers their subject of choice (Table 9 in Appendix B). Then we show in a placebo outcome test, that the decision not to choose the closest UAS is unrelated to the proportion of university dropouts in cohort (Table 10 in Appendix B). Third, we conduct a placebo treatment test in Appendix D.4, in which we replace the actual treatment by proportions of university dropouts two years in the future that cannot reject the unconfoundedness hypothesis.

Fourth, there might be the case of some unobserved confounding in the investigated years in the institutes, i.e., $\varepsilon_{icfst} = \varphi_{st} + e_{icfst}$. To account for such a possibility, in which e.g., specific institutes' reputation or monetary resources increased (decreased) over time, and it therefore became more (less) attractive for university dropouts and study success for regular UAS students was affected, we use a model including year by institutes fixed effects. Fifth, there might be some unobserved confounding related to institutes and field of study, i.e., $\varepsilon_{icfst} = \varphi_{fs} + e_{icfst}$. Vardardottir (2015) illustrated in an application for Swiss secondary school the potential importance of cohort by track FE instead of cohort and track indicators. Thus, we include a model specification using institutes by field of study fixed effects.

Sixth, to check both the linear additivity assumption of the linear models and if flexibility in functional forms of the confounding variables is needed, we use a causal machine learning method suggested by Semenova and Chernozhukov (2021), which is described below. While we are confident that we cover all the potential confounding factors with our data, we cannot be sure that including them in their baseline form is sufficient.[8] For this reason, we include the

[8] Exemplary, distances between the hometown and the UAS might matter in a very different way for the UAS in the Italian speaking part of the country compared to an UAS in an urban German speaking city. Therefore, interactions of variables or more flexible functional forms would be needed.

causal machine learning method that is completely agnostic to the functional forms of the confounding influences.

Seventh, we challenge the assumption of a constant treatment effect and perform the estimation with a nonparametric kernel method introduced by Kennedy, Ma, McHugh, and Small (2017). The importance of investigating this lies in the challenge that evaluating continuous response variables is conceptually non-trivial. In contrast to binary indicators, in which an increase in the treatment intensity from 0 to 1 is investigated, the continuity offers some challenges. In practice it is not clear whether an increase in a treatment (proportion) from 0 to 5 percent and from 5 to 10 percent should have a similar effect or follow similar patterns. However, when using linear regression models, it is implicitly assumed, that the effect evolves in some specific ad-hoc determined functional form, e.g., linear or quadratic for an increasing treatment, and that the effect is the same irrespectively of the baseline value. The first implicit assumption might lead to overlooking of a real effect, e.g., if assuming a linear relationship when it is in fact u-shaped. The second assumption might lead to wrong conclusions if an effect is observed for a specific setup only, while extrapolation falsely suggests that this is independent of the level of the treatment.

Keeping this in mind, our baseline estimates are conducted with a linear regression model. Using a local, non-parametric methodology in a second approach helps us to pin down effects for the various baseline-effect combinations for which continuous treatments allow. Both additional approaches from the causal machine learning literature, the non-parametric methodology (Kennedy et al., 2017) and the best linear prediction method (Semenova and Chernozhukov, 2021) build on the same first step. A pseudo-outcome is constructed as follows:

$$\xi(Z,\pi,\mu)=\frac{Y-\mu(X,A)}{\pi(A|X)}\int\pi(A|x)dP(x)+\int\mu(x,A)dP(x),$$

where the nuisance functions $\mu(X, A)$, the mean outcome given covariates and the treatment, i.e., the regression function of the outcome on the covariates and treatment, and $\pi(A|X)$, the conditional treatment density given controls, i.e., the generalized propensity score, need to be estimated. Both nuisances are estimated using a random forest algorithm (Breiman, 2001), which offers substantial flexibility as a global and nonparametric method combined with excellent predictive power. The resulting orthogonal score $\xi(Z, \pi, \mu)$ is free from confounding influences and doubly robust in a sense that only (at least) one of the two nuisance function estimators need to be consistent, not both.

The second step differs as the effect curve $E(Y^a) = E(\xi(Z, \pi, \mu)|A = a)$, i.e., the average potential outcome for given treatment levels, is estimated by a non-parametric (kernel) regression (Kennedy et al., 2017) or a linear regression (Semenova & Chernozhukov, 2021) of the doubly robust pseudo-outcome on the treatment variable. While the first approach is very flexible in the form of the treatment effect, the latter approach, the best linear approximation, could be made more flexible by using different base functions of the treatment variable like polynomials or binary indicators partitioning on the support of the treatment variable. To obtain comparable results we stay with the linear approximation to abolish one assumption at a time, and though we obtain a coefficient that is comparable in its form and interpretability to the usual linear regression estimates.[9]

6 Results

The presentation of our results is divided into two parts. In Section 6.1 we present the results for the effect of the proportion of university dropouts on the study success of first-time UAS students. The main effects are estimated with different specifications and the evidence is completed by group specific subset effects afterwards. While the focus in the main part of the

[9] For more details and theoretical guarantees of the approaches, the interested reader is referred to Kennedy et al. (2017) and Semenova & Chernozhukov (2021).

article is on the outcome dropout within 1 year at the UAS, the Appendices provide additional information on the other outcomes. In Section 6.2 we then show the effect on the university dropouts themselves. Additional robustness checks are presented in Section 7.

6.1 Effects on first-time UAS students

Table 2: Effects of university dropouts on first-time UAS students' dropout after 1 year

	(1) Baseline linear model	(2) Full linear model	(3) Fixed effects model	(4) Fixed effects model	(5) Best Linear Prediction
Panel A: all univ. dropouts					
Proportion univ. dropouts in cohort	-0.033	0.001	-0.003	0.021	-0.059
	(0.024)	(0.028)	(0.030)	(0.046)	(0.054)
Panel B: univ. dropouts enrolled in the same field (SF) at UAS					
Proportion SF univ. dropouts in cohort	0.082**	0.086***	0.085**	0.093*	0.119***
	(0.032)	(0.033)	(0.035)	(0.056)	(0.035)
Panel C: univ. dropouts enrolled in a different field (DF) at UAS					
Proportion DF univ. dropouts in cohort	-0.168***	-0.163***	-0.164***	-0.132***	-0.166***
	(0.035)	(0.040)	(0.036)	(0.040)	(0.028)
Base covariates	X	X	X	X	X
All covariates		X	X	X	
Institute-by-Year FE			X		
Institute-by-Field FE				X	

Notes: Linear regression (columns (1)-(4)), Best Linear Prediction in column (5). 102,100 observations. Each panel with a different treatment. Each column in each panel of the table represents a separate regression. univ. = university. More detailed results can be found in Appendix C, Table 11 (Panel A), Table 12 (Panel B), and Table 13 (Panel C). Standard errors are clustered on the cohort (columns (1), (2) and (5)), the institute by year (column (3)), or the institute by field (column (4)) level. *Base covariates* include binary institution and field indicators, cohort size, indicators for full/part time studies, and restricted access fields, distance from the place of living to the UAS, cantonal baccalaureate rate, the number of same field masters' studies at the UAS and the number of nationwide university dropouts in the same field. Additionally, *all covariates* include year indicators, individuals age, indicators for gender and being non-Swiss, the total number of masters' studies at the UAS, traveling time from the place of living to the UAS, indicator for the type of admission indicator, the proportion of academic, professional, and specialized baccalaureates, as well as other Swiss and foreign admission types in cohort, proportion of females in cohort, proportion of non-Swiss in cohort. *, **, and *** signal statistical significance at the 10, 5, and 1 % level, respectively.

Table 2, panel A shows the effects of the total proportion of university dropouts on the study success of first-time UAS students. In column (1) the baseline model including the essential control variables shows a statistically not significant effect of -0.033. Including all control variables in column (2), the institute by year fixed effects in column (3), the institute by field fixed effects in column (4), as well as the best linear prediction in column (5) does neither change the magnitude of the coefficient by much, nor the statistical significance.

Separating the same field and different field university dropouts into two different groups (Panels B and C), however, shows statistically significant effects for both groups but with a different direction of the effect. Thus, not differentiating between dropouts in the same field and dropouts changing the field of study masks the two different effects that university dropouts have on the study success of first-time UAS students. Coefficients in Panel B vary minimally between 0.082 and 0.093 for the classical methods in columns (1)-(4) and are slightly higher in column (5) using the best linear prediction method. In Panel C, estimates vary between -0.132 and -0.168, and are all statistically significant. The results imply that the higher the proportion of university dropouts in the same field of study, the higher is the dropout risk of first-time UAS students and the opposite for the impact of the proportion of different field of study university dropouts on the probability to dropout for the first-time UAS students.

Table 3 reports the impact of university dropouts on medium- and long-run outcomes for first-time UAS students. While panel A is taken for comparison from Table 2, panels B, C, and D report estimations for different outcomes - dropout from UAS within two years, as well as graduation within four and five years. Estimations shown in column (4) consists of both treatment variables, proportions of same and different field dropouts.[10] Each panel in Table 3 shows again insignificant estimates around zero for the total proportion of university dropouts in a cohort. Effect sizes increase in magnitude for dropout from UAS within two years when separating same and different field university dropouts compared to dropouts within the first year. Panels C and D, looking at graduation success after four or five years instead of dropouts

[10] Goldsmith-Pinkham, Hull, and Kolesar (2021) show that linear regressions with multiple treatment variables lack causal interpretation, even if assumptions hold for each single treatment variable. Thus, estimations with multiple treatment variables (column 4) are only provided to show that the treatment effects are insensitive to inclusion of the respective other treatment variables, i.e., to hold the other treatment variables value constant.

risks also show somewhat bigger effect sizes. The positive effect of different field university dropouts, on the study success is of similar magnitude.

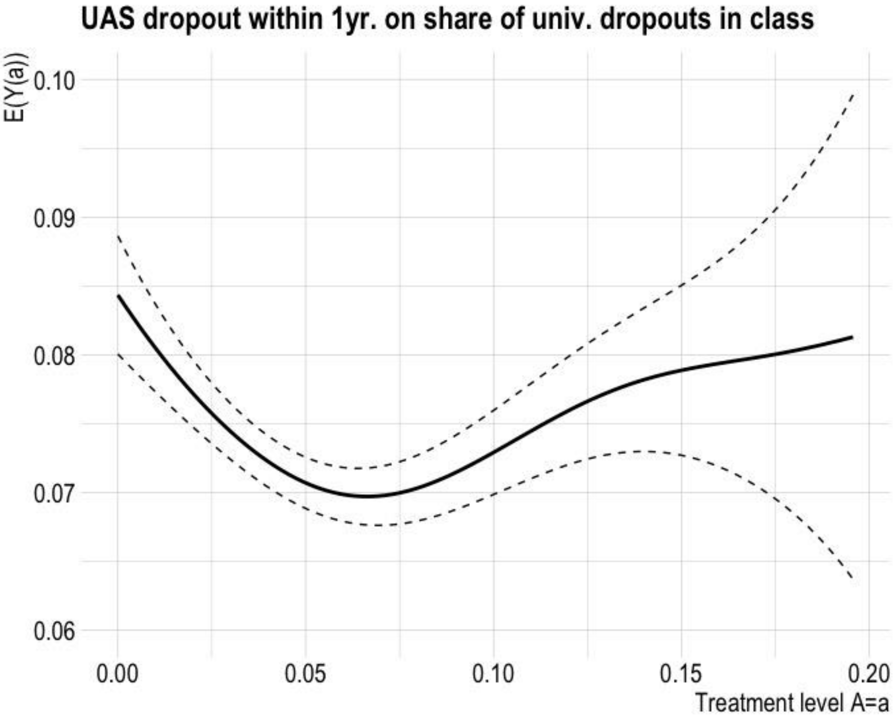
Table 3: Results for different outcomes

	(1)	(2)	(3)	(4)
*Panel A: Dropout from UAS within **1 year***				
Proportion univ.	-0.033			
dropouts in the cohort	(0.024)			
Proportion univ. SF		0.082**		0.075**
dropouts in the cohort		(0.032)		(0.032)
Proportion univ. DF			-0.168***	-0.164***
dropouts in the cohort			(0.035)	(0.035)
*Panel B: Dropout from UAS within **2 years***				
Proportion univ.	-0.038			
dropouts in the cohort	(0.033)			
Proportion univ. SF		0.157***		0.146***
dropouts in the cohort		(0.046)		(0.045)
Proportion univ. DF			-0.266***	-0.259***
dropouts in the cohort			(0.047)	(0.047)
*Panel C: UAS graduation within **4 years***				
Proportion univ.	-0.077			
dropouts in the cohort	(0.074)			
Proportion univ. SF		-0.378***		-0.364***
dropouts in the cohort		(0.092)		(0.091)
Proportion univ. DF			0.296**	0.274**
dropouts in the cohort			(0.118)	(0.117)
*Panel D: UAS graduation within **5 years***				
Proportion univ.	-0.006			
dropouts in the cohort	(0.068)			
Proportion univ. SF		-0.323***		-0.300***
dropouts in the cohort		(0.094)		(0.093)
Proportion univ. DF			0.363***	0.340***
dropouts in the cohort			(0.099)	(0.098)

Notes: Linear regression. Each panel with a different outcome and 102,100 (Panel A), 91,003 (Panel B), 69,034 (Panel C) and 58,399 (Panel D) observations. Each column in each panel of the table represents a separate regression. univ. = university; SF = same field; DF = different field. Baseline specification of Table 2, i.e., control variables include institution and field fixed effects, cohort size, indicators for full/part time studies, and restricted access fields, distance from the place of living to the UAS, cantonal baccalaureate rate, the number of Masters' studies at the UAS and the number of nationwide university dropouts in the same field. For Panel A tables in Appendix C document the sensitivity to including more control variables. Various other robustness checks can be found in Section 7. Standard errors are clustered on a cohort level. *, **, and *** signal statistical significance at the 10, 5, and 1 % level, respectively.

With the estimation results presented in Tables 2 and 3 we needed to impose an important assumption, which is linearity in the effect. Further, it is imposed that the in cohort existing level of the treatment, i.e., the proportion of university dropouts, is irrelevant for the size of the effect. In the following we resolve these assumptions and show estimates for the UAS students' probability to dropout within one year (almost) without functional form restrictions. Since estimating treatment effect for each level and increase in the treatment intensity would be very complex and cumbersome the doubly robust nonparametric estimation shows the expected outcome for each level of the treatment.[11]

Figure 1: Effects by treatment level - proportion of university dropouts in cohort



Notes: E(Y^a) on the y-axis depicts the expected value of first-time UAS students that dropped out by the end of the first year for each value of the treatment level, i.e., the proportion of university dropouts in cohort (x-axis).

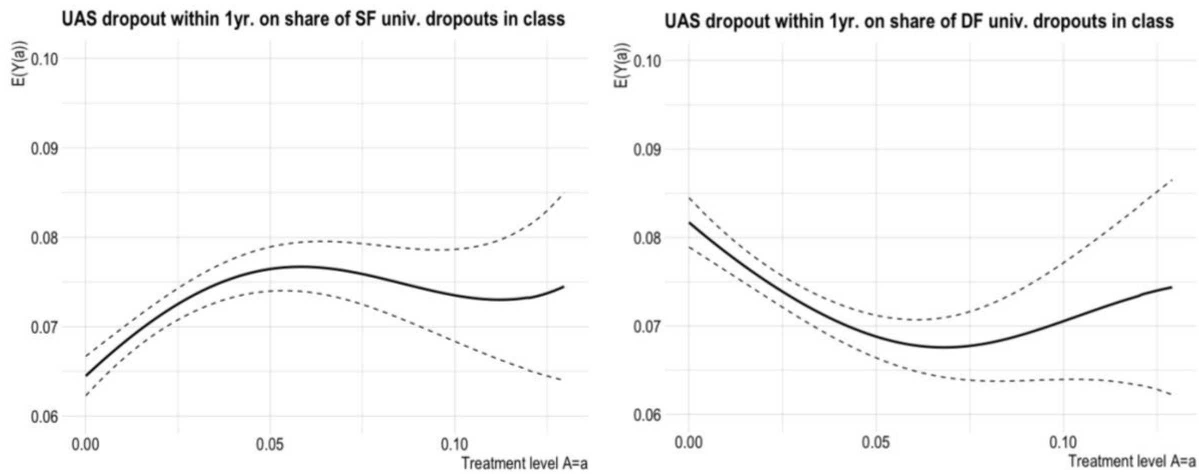
Figure 1 reveals an interesting pattern for the total proportion of university dropouts in a cohort on the dropout of first-time UAS students within the first year. The expected dropout probability decreases first for an increasing treatment level until the minimum UAS dropout probability is reached for a proportion of about 7 percent university dropouts in cohort, then the dropout proportion for higher treatment intensity rises again. For these higher treatment levels,

[11] To obtain classical treatment effects one might calculate the difference of the expected outcomes for two treatment levels and divide this by the treatment dose, i.e., $\tau_{a1,a2} = \frac{E(Y^{a1})-E(Y^{a2})}{|a1-a2|}$.

however, the confidence intervals, not least because of very few observations in this area of treatment, also increase substantially and make it difficult to interpret these results.

Thus, additional to the insignificant linear regression null result Figure 1 adds three conclusions. 1) The effect is locally different, as for cohorts with small proportions of university dropouts between 0 and 7 percent adding university dropouts increases the study success of first-time UAS students, whereas for cohorts with higher proportions of university dropouts, additional university dropouts increase the dropout rates of first-time UAS students. 2) The optimal proportion of university dropouts in UAS cohorts is therefore around 7 percent in a cohort. 3) We have enough observations to obtain precise estimates for treatment levels lower than about 15 percent after that confidence intervals widen substantially. While single linear regression coefficients suggest that the effect is present for the full support, we cannot credibly interpret effects for proportions of university dropouts in cohort of above 15 percent.

Figure 2: Effects by treatment level for same (left) and different field (right) dropouts



Notes: $E(Y^a)$ on the y-axis depicts the expected value of first-time UAS students that dropped out by the end of the first year for each value of the treatment level, i.e., the proportion of same field (left) and different field (right) university dropouts in cohort.

For the other treatment variables Figure 2 offers some insight. On the left side are the estimates for the proportion of same field dropouts. For these the UAS first-time student dropout probability increases with a rising proportion of university dropouts up to a proportion of 5 - 7 percent. Above this treatment level, the dropout rates of first-time UAS students do not increase any more with higher proportions of university dropouts. For different field university dropouts, the estimates show the reverse effect. The dropout probability of first-time UAS students decreases until proportions of university dropouts reaches a proportion of 7 percent, and after that potentially increases again, though the deteriorating estimation precision does not allow a firm conclusion. Appendix D.1 offers additional insights into the effect for the long-run outcome graduation from UAS within five years. Figures 3 and 4 in Appendix D.1 show a very similar pattern.

Table 4: Dropout within 1 year from UAS - by field of study category

	(1) STEM	(2) Humanities and arts	(3) Economics and administration	(4) Health and social work
Proportion univ. dropouts in cohort	0.022	0.064	-0.145	-0.036
	(0.040)	(0.052)	(0.092)	(0.032)
Proportion univ. same field dropouts in cohort	0.094**	0.111*	-0.025	0.098*
	(0.044)	(0.064)	(0.105)	(0.058)
Proportion univ. different field dropouts in cohort	-0.124**	0.032	-0.257*	-0.112***
	(0.058)	(0.071)	(0.133)	(0.039)
N	34,149	12,778	29,263	25,910

Notes: Linear regression. Outcome: Dropout from UAS within 1 year. Each cell represents a separate regression with the respective subsample of study fields in the field of study category. univ. = university. Table 8 in Appendix A.2 shows the detailed study programs contained in the field of study categories. Baseline specification as in Table 2. Standard errors are clustered on a cohort level. *, **, and *** signal statistical significance at the 10, 5, and 1 % level, respectively. P values from wald-tests for equality of the estimates for each treatment are for; Proportion university dropout in cohort: 0.14; Proportion university same field dropouts in cohort: 0.72; Proportion university same field dropouts in cohort: 0.16. Means of proportion university dropouts (same field) [different field] in cohort in the respective category are 0.065 (0.041) [0.025] for STEM; 0.061 (0.024) [0.037] for humanities and arts; 0.043 (0.025) [0.019] for economics and administration; and 0.066 (0.017) [0.049].

In the following we investigate effect heterogeneities, more specifically, whether the effects depend on the field of study at the UAS (Table 4). In STEM (in column (1)) and health and social work (in column (4)) fields of study the effects are similar to the average effects for all study programs. Insignificant effects are found for different field dropouts in the humanities and arts (in column (2)) cohorts, as well as for same field dropouts in economics and administration (in column (3)) fields of study. However, in total, the estimated coefficients are all non-significantly different from each other for the proportion of university dropouts (WALD test for equality of coefficients p-value: 0.14), proportion same field university dropouts (0.72) and different field university dropouts (0.16).

Table 5: Effects by subgroups

	(1)	(2)	(3)	(4)
	Dropout from UAS within 1 year		UAS graduation within 5 years	
Panel A:	Baseline			
Prop. univ. do		-0.033 (0.024)		-0.006 (0.068)
Prop. univ. do SF		0.082** (0.032)		-0.323*** (0.094)
Prop. univ. do DF		-0.168*** (0.035)		0.363*** (0.099)
Panel B:	Cohort size			
	<= 50 students	> 50 students	<= 50 students	> 50 students
Prop. univ. do	-0.005 (0.032)	-0.029 (0.039)	-0.016 (0.086)	-0.016 (0.122)
Prop. univ. do SF	0.042 (0.042)	0.176*** (0.050)	-0.085 (0.106)	-0.627*** (0.164)
Prop. univ. do DF	-0.059 (0.045)	-0.267*** (0.055)	0.066 (0.121)	0.670*** (0.161)
Panel C:	Gender			
	Female	Male	Female	Male
Prop. univ. do	-0.085*** (0.033)	0.014 (0.033)	0.061 (0.094)	-0.066 (0.078)
Prop. univ. do SF	0.093* (0.051)	0.083** (0.040)	-0.536*** (0.144)	-0.178* (0.099)
Prop. univ. do DF	-0.216*** (0.044)	-0.105** (0.050)	0.517*** (0.116)	0.129 (0.132)
Panel D:	Type of studies			
	Full-time	Part-time	Full-time	Part-time
Prop. univ. do	-0.004 (0.025)	-0.196** (0.089)	-0.055 (0.071)	-0.019 (0.206)
Prop. univ. do SF	0.125*** (0.032)	-0.184 (0.118)	-0.379*** (0.095)	-0.164 (0.293)
Prop. univ. do DF	-0.162*** (0.036)	-0.220* (0.125)	0.335*** (0.103)	0.242 (0.327)
Panel E:	Admission to studies			
	Restricted	Not restricted	Restricted	Not restricted
Prop. univ. do	-0.092*** (0.033)	0.004 (0.033)	0.019 (0.102)	-0.073 (0.082)
Prop. univ. do SF	0.021 (0.060)	0.061 (0.039)	-0.191 (0.198)	-0.184* (0.098)
Prop. univ. do DF	-0.171*** (0.044)	-0.102* (0.055)	0.160 (0.132)	0.137 (0.145)
Panel F:	Type of admission certificate			
	Academic bacc.	Prof. bacc.	Academic bacc.	Prof. bacc.
Prop. univ. do	0.007 (0.031)	-0.013 (0.031)	-0.034 (0.089)	-0.070 (0.074)
Prop. univ. do SF	0.097** (0.048)	0.081** (0.040)	-0.313** (0.125)	-0.242*** (0.093)
Prop. univ. do DF	-0.071** (0.036)	-0.148*** (0.046)	0.208* (0.112)	0.181 (0.119)

Notes: Each estimate results from a separate linear regression on the respective subsample, which are sampled according to the headlined groups. Standard errors are clustered on the cohort level. Control variables used are the same as in the baseline, for which in Panel A the results are taken for comparison from the main results Table 2, column (1). univ. = university; do = dropout; SF = same field; DF = different field; Prof. = professional. *, **, and *** signal statistical significance at the 10, 5, and 1 % level, respectively.

The results of the effect heterogeneity by different subgroups of UAS students is shown in Table 5. Linear subgroup effects for the dropout within one year and the graduation from UAS within five years are presented in columns (1) and (2), as well as (3) and (4). In Panel B results suggest that the effect of the proportion of same and different field university dropouts in cohort disappears for small cohorts with less than 50 students, while effects are larger in magnitude for large cohorts compared to the baseline results in Panel A.[12]

While the effects are larger in magnitude for females compared to males in panel C, they are present for both genders. For part time studies in panel D, we find rather inconclusive estimates. Students enrolled in full time studies clearly drive the results. Dividing the fields into restrictive and non-restrictive entrance requirements in panel E shows the same signs for the coefficients, not always statistically significant but no particular differences, and effects are also rather homogenous for students entering with academic or a professional baccalaureate in panel F.

6.2 Effects on the university dropouts

Table 6: Effect on university dropouts at UAS

	Drop out of UAS within…		Graduate in UAS within…	
	…1 year	…2 years	…4 years	…5 years
Proportion SF univ. dropouts	0.044	0.107	-0.095	-0.042
	(0.046)	(0.070)	(0.134)	(0.157)
Proportion DF univ. dropouts	-0.105***	-0.150**	0.264*	0.218
	(0.036)	(0.061)	(0.148)	(0.148)
Individual is SF dropout	-0.012***	-0.025***	0.053***	0.036***
	(0.004)	(0.007)	(0.013)	(0.013)
N	7691	6795	5156	4296

Notes: Each column represents a separate linear regression with the respective outcome in the respective subsample. Standard errors (in parentheses) are clustered on a cohort level. Same set of control variables as the baseline estimation in Table 2. univ. = university; SF = same field; DF = different field. *, **, and *** signal statistical significance at the 10, 5, and 1 % level, respectively.

Looking at the impact that university dropouts in UAS programs have on the study success of other university dropouts, in Table 6 one can see similar effects as for UAS first-time students if there are different field university dropouts present. Conversely, we do not find

[12] While the binarization threshold of 50 students is chosen ad-hoc to obtain two similar sized subsamples, results are in line with Table 14 in Appendix D.1, in which instead of sample splitting an interaction term of cohort size and the treatment variables are added to the estimation model. For an increasing cohort size effects on dropout from UAS within one year increases (decreases) the effect for an increasing proportion of same (different) field dropouts and vice versa for graduating from UAS within five years.

statistically significant peer effects of same field university dropouts on university dropouts, but the coefficient signs are the same as for the effects on UAS first-time students.

Even though in this subsection we only provide correlational evidence, the estimates for the binary variable for *the individual is a same field dropout* indicates that they have a higher probability not to drop out of UAS studies, as well as to graduate within four and five years, potentially due to accumulated prior field specific knowledge in their university studies. This is in line with our argumentation about same field dropouts throughout the article.

7 Robustness

Additional to the results already presented this chapter provides several indicators of robustness for the main results. Table 15 in Appendix D.3 shows the results of various tests. In panel B we remove cohorts with fewer than 10 students, since small cohorts might be combined with other cohorts and the effects could be subject to our cohort definitions. In panel C.1 and C.2 the binary indicators for the fields of studies are replaced by more detailed indicators with 18 or 66 categories. In panel D we construct the treatment variables in a narrower definition of same field. Table 7 in Appendix A.1 shows these variables descriptively, with lower (higher) mean proportions of same (different) field dropouts in cohorts. Results for all these robustness checks are in line with the presented baseline results. If we remove the study fields which are specific to the UAS, i.e., not offered at a university (Appendix D.3, Table 15, panel E) we still find the same peer effects for same field, but effects are statistically not significant for different field university dropouts. Conversely, this probably also means that the positive peer effects of dropouts from universities can be observed mainly in subjects that are only offered at UASs and were, by definition, there can only be university dropouts from other subjects.

Moreover, since effects might evolve due to some unobserved factors over time, in Appendix D.2 we provide baseline estimates for each single year, all three treatments and the outcomes dropout from UAS within one year in Figure 5 and graduation within five years in Figure 6. We cannot observe any specific pattern that the effects increase or decrease substantially over time. Further, results are statistically no different from each other.

8 Conclusion

There is a growing literature on peer effects in higher education, to which this paper contributes. To date, students whose influence has been measured on their peers have generally been defined as those who stood out in the student body distribution as being more able, more talented, or simply performing better in their studies. Most of the empirical literature finds positive effects of such fellow students on their peers, although it is usually not possible to determine through which channels this influence unfolds. Possible channels are role model functions, direct interactions that lead to a spill-over of knowledge, or changes in the behavior of the lecturers that increase the pace of teaching for the benefit of the other students as well, not only the talented ones. In part, however, negative peer effects can also be found, not least on those students who are at the other end of the achievement distribution, and the explanations are quite compatible with the positive effects on the stronger students, namely that weaker students can benefit less from spill-overs of knowledge - also because they probably have fewer interactions with the talented peers - they are left behind due to the increasing pace of instruction, or else due to discouragement effects.

The contribution of this paper is that we look at another group of peers who can potentially have a positive or even negative impact on their fellow students. These are students who, before starting their studies at a university of applied sciences, had already begun but not completed studies at a conventional university. University dropouts are on average more likely than the average UAS student to have earned an academic baccalaureate as a university entrance certificate (while the regular UAS student has come by way of a professional baccalaureate) and come with some study experience at a university that should give the dropouts an advantage over their new fellow students. Our data allow us to divide the university dropouts into two distinct groups; a division that, as the empirical results show, is of utmost importance. Namely, those who, re-enroll in the same field of study again, simply at an academically less demanding institution, and those who, along with changing the type of university, also change the field of study.

While the former has a negative effect on their peers, i.e., increase the probability of early dropout and, in a mirror image, decrease the probability of successful graduation, the latter have exactly the opposite peer effect, i.e., their presence has a positive effect on the academic performance of first-time UAS students. As in the cited literature, it is also not possible to determine the exact reasons for these different effects. However, the results are compatible with hypotheses that students who have a very specific subject knowledge advantage either have a discouraging influence on their fellow students and or influence the nature of teaching or grading because their presence allows professors, for example, to apply stricter grading standards or to address more complex content in class more often and more quickly. Dropouts, on the other hand, who do not have a specific knowledge advantage, are more likely to simply be generally more able fellow students, as in the conventional peer effect literature, whose influence tends to have a positive effect on the peers' academic performance via the mechanisms already mentioned.

Thus, while the individual first-time student at a UAS is exposed to either positive or negative influences of university dropouts, no effects can be detected at the system level so far and this for two reasons. First, there are a similar number of university dropouts who study a different subject at the UAS as there are dropouts who change subjects, and the two effects neutralize. Second, the number of university dropouts is currently still so small that the effects, although statistically highly significant, cannot yet have a large impact in economic terms.

However, this could change if one or the other group of academically better prepared university dropouts taking up studies at academically less demanding institutions grows strongly. Exactly how such a change would then play out is difficult to determine at present because, as analyses show, the effects are non-linear and quite complex, i.e., depend on various parameters such as the size of the cohort. Not least for this reason - although, as mentioned, individual students are exposed to significant peer effects due to the presence of university dropouts - it is difficult to make educational policy recommendations, except for the point that everything suggests that the situation would have to be reassessed in the event of a larger increase in the proportion of university dropouts among students at a UAS.

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Appendices

Appendix A: Additional descriptive statistics

Appendix A.1: Full table of descriptive statistics

Table 7: Descriptive statistics, full table

	First-time UAS	Univ. dropouts
Treatment		
Proportion univ. dropouts	0.059 (0.047)	0.083 (0.062)
Proportion univ. dropouts SF	0.028 (0.035)	0.042 (0.048)
Proportion univ. dropouts DF	0.031 (0.033)	0.041 (0.040)
Proportion univ. dropouts SF (narrow field definition)	0.022 (0.033)	0.034 (0.046)
Proportion univ. dropouts DF (narrow field def.)	0.036 (0.036)	0.048 (0.043)
Outcome		
Dropout after 1 year	0.071	0.023
Dropout after 2 years [1)]	0.115	0.050
Graduation within 4 years [2)]	0.698	0.800
Graduation within 5 years [3)]	0.761	0.842
Covariates		
Cohort size	105.457 (111.932)	101.339 (117.454)
Age	22.354 (2.748)	22.490 (1.757)
Gender	0.472	0.524
Non-Swiss	0.072	0.068
Full time	0.781	0.894
Restricted Access	0.352	0.403
# Master studies at UAS	17.542 (5.926)	17.796 (5.386)
# Master studies at UAS in studied field	2.098 (1.716)	2.042 (1.725)
Distance hometown to UAS (in km)	58.462 (61.245)	63.388 (65.668)
Traveltime hometown to UAS (in min)	43.581 (37.913)	46.377 (40.809)
Cantonal baccalaureate rate	20.011 (4.872)	21.049 (4.748)
# univ. dropout in field / year	35.803 (63.245)	28.673 (56.699)
Proportion matura in cohort	0.189 (0.150)	0.259 (0.164)
Proportion professional baccalaureate in the cohort	0.561 (0.270)	0.467 (0.270)
Proportion specialized baccalaureate in the cohort	0.072 (0.143)	0.074 (0.135)
Proportion other CH baccalaureate	0.063 (0.104)	0.057 (0.093)
Proportion non-Swiss baccalaureate	0.095 (0.144)	0.126 (0.175)
Proportion females in cohort	0.478 (0.287)	0.494 (0.296)
Proportion non-Swiss in cohort	0.137 (0.127)	0.160 (0.149)
Institute		
Bern UAS	0.103	0.093
Haute Ecole	0.295	0.406
UAS NWS	0.073	0.067
UAS Zentralschweiz	0.080	0.069
SUPSI	0.036	0.040

UAS Ostschweiz	0.109	0.074
UAS Zurich	0.303	0.251
Year		
2009	0.089	0.080
2010	0.091	0.087
2011	0.092	0.093
2012	0.099	0.103
2013	0.100	0.101
2014	0.101	0.095
2015	0.104	0.112
2016	0.106	0.107
2017	0.109	0.106
2018	0.109	0.117
Field		
Architecture, building and planing	0.075	0.097
Engineering and IT	0.201	0.205
Chemistry and Life Sciences	0.047	0.056
Agriculture and forestry	0.012	0.015
Economics and services	0.313	0.224
Design	0.050	0.049
Sports	0.003	0.001
Music, theatre, arts	0.046	0.066
Applied linguistics	0.009	0.016
Social work	0.103	0.065
Applied psychology	0.013	0.007
Health	0.128	0.200
Admission Type		
Academic baccalaureate	0.170	0.926
Professional baccalaureate during apprenticeship – technical	0.124	0.005
Professional baccalaureate during apprenticeship – commercial	0.164	0.008
Professional baccalaureate during apprenticeship – others	0.041	0.001
Professional baccalaureate after apprenticeship – technical	0.112	0.005
Professional baccalaureate after apprenticeship – commercial	0.103	0.003
Professional baccalaureate after apprenticeship – others	0.090	0.006
Specialized baccalaureate	0.083	0.002
Other Swiss baccalaureate	0.093	0.016
Foreign baccalaureate	0.021	0.028
N	102,100	7,684

Notes: Average values. Standard deviation for non-binary variables in parentheses. [1)] 91,003 (6,788), [2)] 69,034 (5,149) and [3)] 58,399 (4,289) observations.

Appendix A.2: Field of study categories

Table 8: Detailed study program in study categories

Panel A: STEM
Architecture; civil engineering; spatial planning; landscape architecture; geomatics; wood technology; electrical engineering; computer science; telecommunications; micromechanics; systems engineering; mechanical engineering; mechatronics; industrial engineering; media engineering; building technology; aviation; optometry; transport systems; energy and environmental technology; information technology; biotechnology; food technology; life technology; chemistry; oenology; environmental engineering; molecular life sciences; life sciences technologies; agronomics; forestry
Panel B: Humanities and arts
Information sciences; communication; visual communication; product and industrial design; interior design; conservation and restoration; film; fine arts; literary writing; music and movement; music; contemporary dance; theatre; applied languages
Panel C: Economics and administration
Business economics; international business management; business information systems; facility management; hospitality management; tourisms; business law; international management
Panel D: Health and social work
fine arts, art, and design education; social work; applied psychology; nursing; midwifery; physiotherapy; occupational therapy; nutrition and dietetics; osteopathy; sports; medical radiology; health

Notes: Detailed study program as assigned to the field of study categories.

Appendix B: Empirical Strategy – Additional identification evidence

To provide additional evidence of the validity of the identification strategy we argue that in Switzerland selection into higher education institutions is largely driven by regional proximity of the institution. As can be seen in Table 9, 85 percent of UAS students start their studies at the UAS closest to their hometown that offers their subject of interest (Panel A). If removing field-institution combinations that are unique (Panel B), i.e., there is only one choice within Switzerland, 82 percent of students choose the closest institution offering their subject. For first-time students (Panel C) the percentage is slightly higher compared to university dropouts (Panel D). For subjects in which there is restricted access, i.e., it is not only the students' decision, about 80 percent (Panel E), and for those with no access restrictions (Panel F) about 88 percent of students choose the closest UAS. Even unconditionally on the subject of choice more than 72 percent decide to enroll in the geographically closest UAS (Panel G).

Table 9: Percentage of individuals that starts at nearest UAS that offers the subject

	Percentage that starts at nearest UAS that offers the subject
Panel A:	
all individuals	85.00 %
Panel B:	
w/o enrolled in subject offered by one single institution	81.84 %
Panel C:	
First-time UAS students	85.14 %
Panel D:	
University dropouts	83.07 %
Panel E:	
Subject with restricted access	79.74 %
Panel F:	
Subject non restricted access	87.89 %
	Percentage that starts at nearest UAS indep. of subject
Panel G:	
All individuals	72.55 %

Notes: Nearest UAS is measured as closest UAS to the hometown of the individual, as measured by route distance in google maps. Panels A-F are measured for the UAS offering the students' subject of choice. Panel G uses distance from the hometown to the main campus of any Swiss UAS. Results are equivalent if closeness is measured by google maps travel time.

Even though it is a small proportion of students not choosing the closest UAS Table 10 provides evidence that the selection away from the geographically closest UAS is not associated to the proportion of university dropouts in the cohort, i.e., our treatment variables. Regressions in Table 10 analyze if the proportion of university dropouts in cohort predicts the selection into an UAS that is not the geographically closest – measured binary indicator for the *non-closest UAS*. Panels A, B, and C use the different treatment variables used in the main analysis of the article. We find no concerning pattern as none of the nine regression coefficients show statistical significance and all coefficients are small in magnitude for each of the different specifications.

Table 10: Selection of UAS students into non-closest UAS & proportion of UH dropouts

	(1)	(2)	(3)
Panel A:			
University dropout	-0.046	-0.045	-0.030
	(0.149)	(0.143)	(0.092)
Panel B:			
University dropout SF	-0.037	0.029	0.019
	(0.320)	(0.223)	(0.187)
Panel C:			
University dropout DF	-0.052	0.014	-0.045
	(0.299)	(0.151)	(0.212)
Control variables			
Field FE		X	X
Institution FE			X

Notes: OLS regressions in different specifications. Sample selection as in the main results with only first-time UAS students (N=102,400). Outcome is non-closest UAS chosen (=1 if there is a UAS that offers the chosen subject geographically closer to the students' hometown, =0 if closest UAS is chosen.

Appendix C: Detailed estimation results

Table 11: Average effect of proportion univ. dropouts on dropout within 1 year in UAS

	(1) Base linear model	(2) Full linear model	(3) Fixed effect model	(4) Fixed effect model	(5) Best Linear Prediction
Proportion univ. do	-0.033	0.001	-0.003	0.021	-0.059
	(0.024)	(0.028)	(0.030)	(0.046)	(0.054)
Cohort size§	-0.008***	-0.006***	-0.007***	-0.004	
	(0.001)	(0.001)	(0.001)	(0.003)	
Full time	-0.037***	-0.026***	-0.026***	-0.025***	
	(0.003)	(0.003)	(0.003)	(0.003)	
# Master studies at FH,	-0.001	-0.002*	-0.002*	-0.001	
in same field	(0.001)	(0.001)	(0.001)	(0.002)	
Restricted admission	-0.059***	-0.062***	-0.061***		
	(0.006)	(0.008)	(0.007)		
Age		0.008***	0.007***	0.008***	
		(0.000)	(0.000)	(0.001)	
Gender		0.011***	0.011***	0.011***	
		(0.002)	(0.002)	(0.003)	
Proportion academic		0.033	0.039	0.034	
bacc. (in cohort)		(0.026)	(0.027)	(0.042)	
Proportion voc. bacc		0.041	0.046*	0.048	
(in cohort)		(0.025)	(0.024)	(0.048)	
Constant	0.111***	-0.077**	-0.059**	-0.095	0.075***
	(0.008)	(0.032)	(0.029)	(0.066)	(0.002)
Further controlling for:					
Base covariates	X	X	X	X	X
All covariates		X	X	X	
Field of study	X	X	X		X
Year		X		X	
Type of admission		X	X	X	
Institutes	X	X			X
Inst by year fixed effect			X		
Inst by field fixed effect				X	
Observations	102,100	102,100	102,100	102,100	102,100

Notes: Linear regression (columns (1)-(4)), Best Linear Prediction in column (5). Standard errors are clustered on the cohort (columns (1), (2) and (5)), the institute by year (column (3)), or the institute by field (column (4)) level. §cohort measured in hundreds. *Base covariates* include binary institution and field indicators, cohort size, indicators for full/part time studies, and restricted access fields, distance from the place of living to the UAS, cantonal baccalaureate rate, the number of same field masters' studies at the UAS and the number of nationwide university dropouts in the same field. Additionally, *all covariates* include year indicators, individuals age, indicators for gender and being non-Swiss, the total number of masters' studies at the UAS, traveling time from the place of living to the UAS, indicator for the type of admission indicator, the proportion of academic, professional, and specialized baccalaureates, as well as other Swiss and foreign admission types in cohort, proportion of females in cohort, proportion of non-Swiss in cohort. To be explicit field of study, year, type of admission and institute binary indicators are marked in the table separately. *, **, and *** signal statistical significance at the 10, 5, and 1 % level, respectively.

Table 12: Average effect of proportion SF univ. dropouts on dropout within 1 year in UAS

	(1) Base linear model	(2) Full linear model	(3) Fixed effect model	(4) Fixed effect model	(5) Best Linear Prediction
Proportion univ. do SF	0.082**	0.086***	0.085**	0.093*	0.119***
	(0.032)	(0.033)	(0.035)	(0.056)	(0.035)
Cohort size§	-0.008***	-0.006***	-0.007***	-0.004	
	(0.001)	(0.001)	(0.001)	(0.003)	
Full time	-0.039***	-0.027***	-0.027***	-0.025***	
	(0.003)	(0.003)	(0.003)	(0.003)	
# Master studies at FH,	-0.001	-0.002*	-0.002*	-0.001	
in same field	(0.001)	(0.001)	(0.001)	(0.002)	
Restricted admission	-0.060***	-0.062***	-0.061***		
	(0.006)	(0.008)	(0.007)		
Age		0.008***	0.007***	0.008***	
		(0.000)	(0.000)	(0.001)	
Gender		0.011***	0.011***	0.011***	
		(0.002)	(0.002)	(0.003)	
Proportion academic		0.027	0.032	0.031	
bacc. (in cohort)		(0.026)	(0.026)	(0.040)	
Proportion voc. Bacc.		0.042*	0.047*	0.048	
(in cohort)		(0.025)	(0.024)	(0.048)	
Constant	0.109***	-0.078**	-0.062**	-0.093	0.068***
	(0.008)	(0.032)	(0.029)	(0.065)	(0.002)
Further controlling for:					
Base covariates	X	X	X	X	X
All covariates		X	X	X	
Field of study	X	X	X		X
Year		X		X	
Type of admission		X	X	X	
Institutes	X	X			X
Inst by year fixed effect			X		
Inst by field fixed effect				X	
Observations	102,100	102,100	102,100	102,100	102,100

Notes: Linear regression (columns (1)-(4)), Best Linear Prediction in column (5). Standard errors are clustered on the cohort (columns (1), (2) and (5)), the institute by year (column (3)), or the institute by field (column (4)) level. §cohort measured in hundreds. *Base covariates* include binary institution and field indicators, cohort size, indicators for full/part time studies, and restricted access fields, distance from the place of living to the UAS, cantonal baccalaureate rate, the number of same field masters' studies at the UAS and the number of nationwide university dropouts in the same field. Additionally, *all covariates* include year indicators, individuals age, indicators for gender and being non-Swiss, the total number of masters' studies at the UAS, traveling time from the place of living to the UAS, indicator for the type of admission indicator, the proportion of academic, professional, and specialized baccalaureates, as well as other Swiss and foreign admission types in cohort, proportion of females in cohort, proportion of non-Swiss in cohort. To be explicit field of study, year, type of admission and institute binary indicators are marked in the table separately. *, **, and *** signal statistical significance at the 10, 5, and 1 % level, respectively.

Table 13: Average effect of proportion DF univ. dropouts on dropout within 1 year in UAS

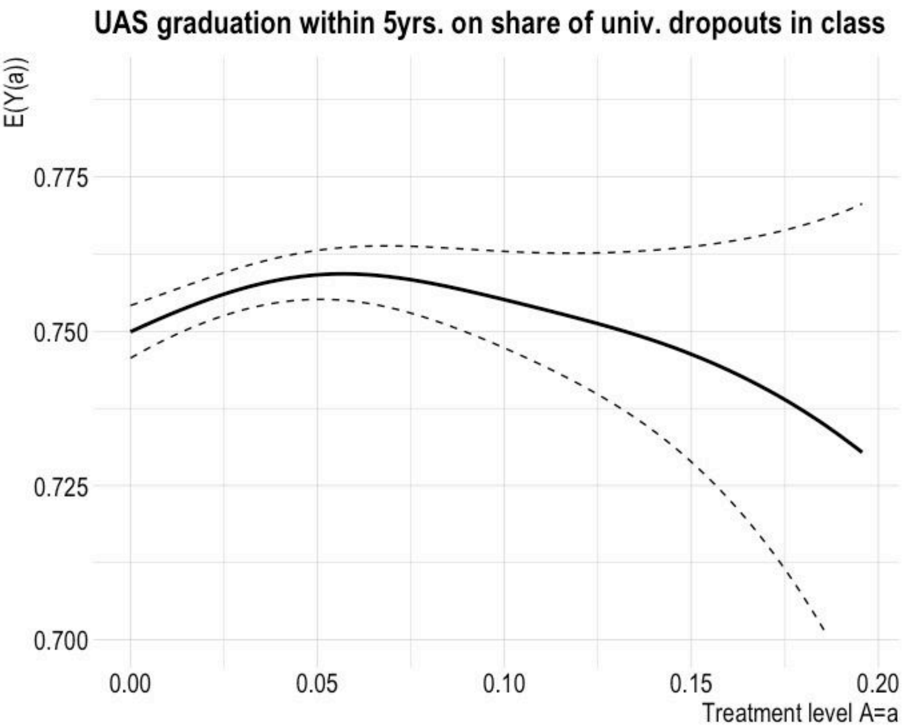
	(1) Base linear model	(2) Full linear model	(3) Fixed effect model	(4) Fixed effect model	(5) Best Linear Prediction
Proportion univ. do DF	-0.168***	-0.163***	-0.164***	-0.132***	-0.166***
	(0.035)	(0.040)	(0.036)	(0.040)	(0.028)
Cohort size§	-0.008***	-0.006***	-0.007***	-0.004	
	(0.001)	(0.001)	(0.001)	(0.003)	
Full time	-0.035***	-0.025***	-0.025***	-0.025***	
	(0.003)	(0.003)	(0.003)	(0.002)	
# Master studies at FH,	-0.001	-0.002	-0.001	-0.001	
in same field	(0.001)	(0.001)	(0.001)	(0.002)	
Restricted admission	-0.057***	-0.066***	-0.067***		
	(0.006)	(0.008)	(0.007)		
Age		0.008***	0.008***	0.008***	
		(0.000)	(0.000)	(0.001)	
Gender		0.011***	0.011***	0.011***	
		(0.002)	(0.002)	(0.003)	
Proportion academic		0.043	0.049*	0.038	
bacc. (in cohort)		(0.026)	(0.028)	(0.042)	
Proportion voc. bacc.		0.037	0.042*	0.043	
(in cohort)		(0.025)	(0.024)	(0.049)	
Constant	0.114***	-0.076**	-0.062**	-0.094	0.079***
	(0.008)	(0.017)	(0.029)	(0.066)	(0.001)
Further controlling for:					
Base covariates	X	X	X	X	X
All covariates		X	X	X	
Field of study	X	X	X		X
Year		X		X	
Type of admission		X	X	X	
Institutes	X	X			X
Inst by year fixed effect			X		
Inst by field fixed effect				X	
Observations	102,100	102,100	102,100	102,100	102,100

Notes: Linear regression (columns (1)-(4)), Best Linear Prediction in column (5). Standard errors are clustered on the cohort (columns (1), (2) and (5)), the institute by year (column (3)), or the institute by field (column (4)) level. §cohort measured in hundreds. *Base covariates* include binary institution and field indicators, cohort size, indicators for full/part time studies, and restricted access fields, distance from the place of living to the UAS, cantonal baccalaureate rate, the number of same field masters' studies at the UAS and the number of nationwide university dropouts in the same field. Additionally, *all covariates* include year indicators, individuals age, indicators for gender and being non-Swiss, the total number of masters' studies at the UAS, traveling time from the place of living to the UAS, indicator for the type of admission indicator, the proportion of academic, professional, and specialized baccalaureates, as well as other Swiss and foreign admission types in cohort, proportion of females in cohort, proportion of non-Swiss in cohort. To be explicit field of study, year, type of admission and institute binary indicators are marked in the table separately. *, **, and *** signal statistical significance at the 10, 5, and 1 % level, respectively.

Appendix D: Additional estimation results

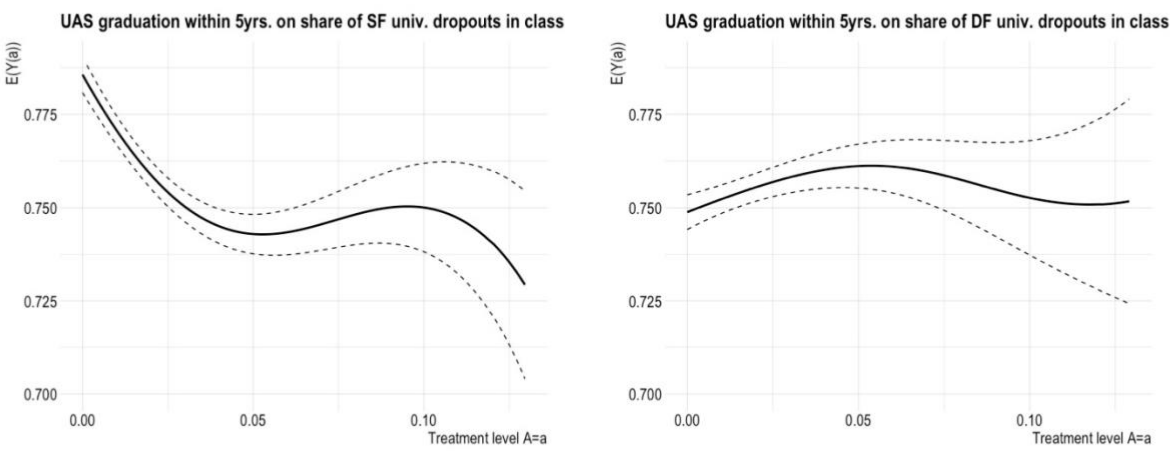
Appendix D.1: Other outcomes

Figure 3: Effects by treatment level, proportion of univ. dropouts; Graduation within 5 years



Notes: E(Y^a) on the y-axis depicts the expected value of first-time UAS students that graduated within five years for each value of the treatment level, i.e., the (total) proportion of university dropouts in cohort (x-axis).

Figure 4: Effects by treatment level, proportion of (SF/DF) univ. dropouts; Grad. within 5 years



Notes: E(Y^a) on the y-axis depicts the expected value of first-time UAS students that graduated within five years for each value of the treatment level, i.e., the proportion of (same field; left – different field; right) university dropouts in cohort (x-axis).

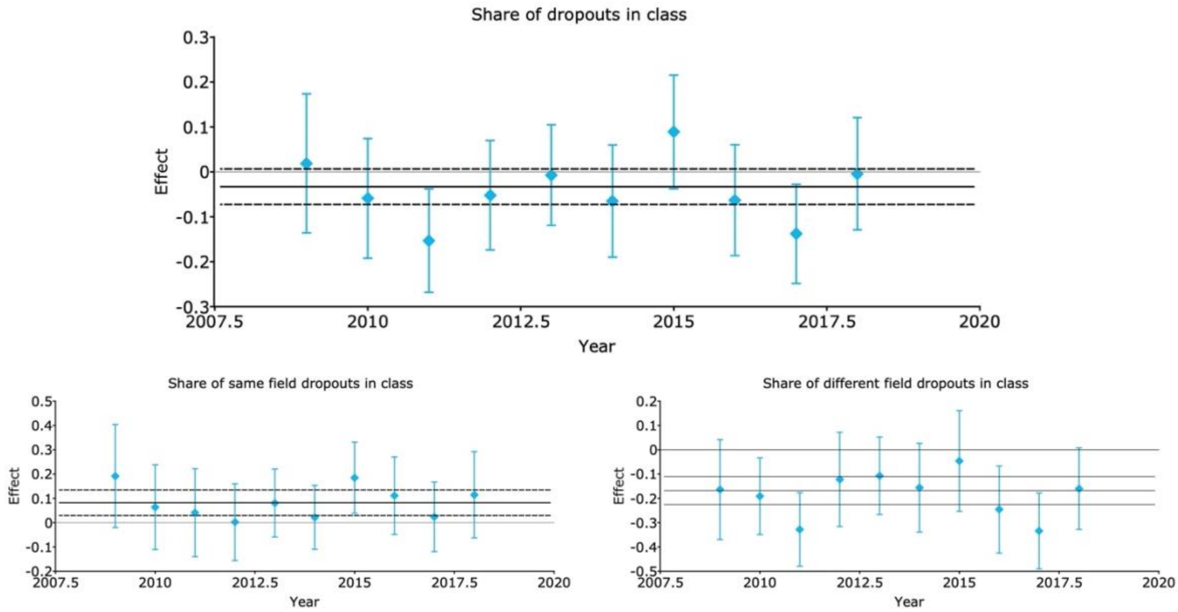
Table 14: Effects by size of the cohort

	Dropout from UAS within 1 year	Graduation from UAS within 5 years
Panel A: Proportion university dropouts		
Proportion univ.	0.003	-0.068
dropouts in cohort	(0.034)	(0.095)
Proportion x cohort size	-0.065	0.113
	(0.049)	(0.150)
Cohort size	-0.005*	0.015*
	(0.003)	(0.009)
Panel B: Proportion university same field dropouts		
Proportion univ. SF	-0.005	0.094
dropouts in cohort	(0.041)	(0.117)
Proportion x cohort size	0.122***	-0.611***
	(0.033)	(0.142)
Cohort size	-0.010***	0.034***
	(0.001)	(0.006)
Panel C: Proportion university different field dropouts		
Proportion univ. DF	-0.051	-0.119
dropouts in cohort	(0.040)	(0.106)
Proportion x cohort size	-0.182***	0.756***
	(0.041)	(0.111)
Cohort size	-0.002	-0.001
	(0.002)	(0.005)

Notes: Linear regressions. Standard errors (in parentheses) are clustered on the cohort. For ease of representation cohort size is divided by 100. Consequently, interpretation for the coefficient of cohort size is not an increase in 1, but 100 units. Specification is the baseline specification from Table 2 in the main text. Proportion x cohort size is the interaction term of the respective Proportion of university (SF/DF) dropouts in cohort times the cohort size (in hundreds). univ. = university; SF = same field; DF = different field. *, **, and *** signal statistical significance at the 10, 5, and 1 % level, respectively.

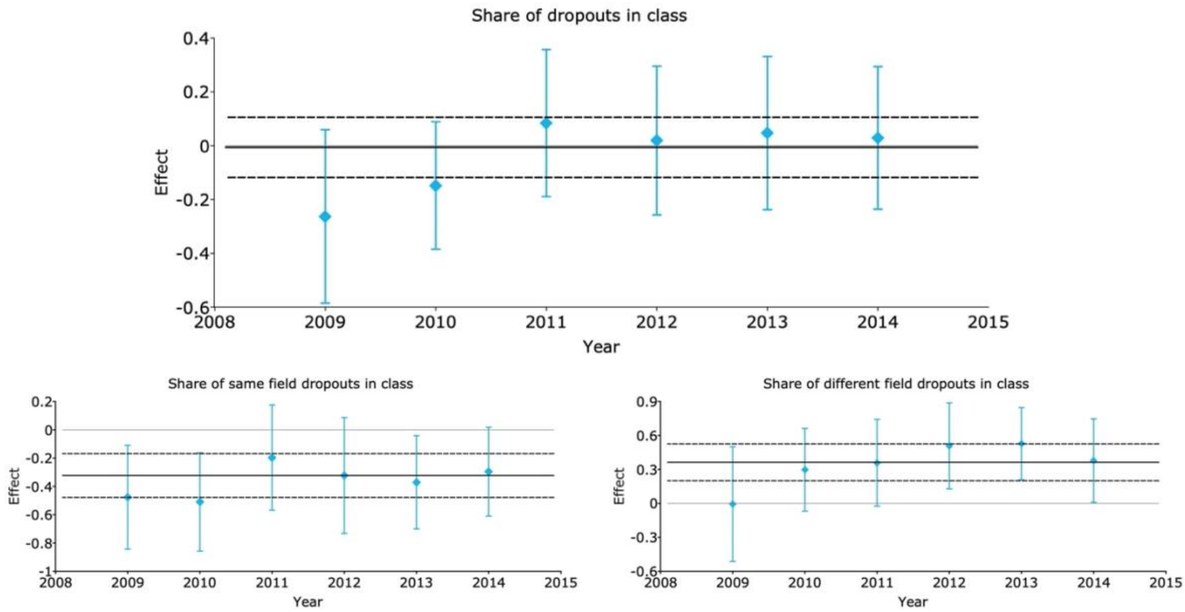
Appendix D.2: Additional subgroup results

Figure 5: Effects over time for outcome dropout within 1 year



Notes: Graph on the top is with proportion all dropouts, bottom left the same field and bottom right the different field dropouts. Blue circles represent the point estimate for each specific year from a separate regression, accompanied by the respective 90% confidence intervals. The black line is the average treatment effect for all years pooled, and the broken line is its 90% confidence interval.

Figure 6: Effects over time for outcome completion within 5 years



Notes: Graph on the top is with proportion all dropouts, bottom left the same field and bottom right the different field dropouts. Blue circles represent the point estimate for each specific year from a separate regression, accompanied by the respective 90% confidence intervals. The black line is the average treatment effect for all years pooled, and the broken line is its 90% confidence interval.

Appendix D.3: Robustness checks

Table 15: Robustness tests, results

	(1) Dropout from UAS within 1 year	(2) UAS graduation within 5 years
Panel A:	*Baseline*	
Proportion univ. do	-0.033 (0.024)	-0.006 (0.068)
Proportion univ. do SF	0.082** (0.032)	-0.323*** (0.094)
Proportion univ. do DF	-0.168*** (0.035)	0.363*** (0.099)
Panel B:	*Remove Cohorts with fewer than 10 students*	
Proportion univ. do	-0.032 (0.025)	-0.003 (0.069)
Proportion univ. do SF	0.089*** (0.033)	-0.328*** (0.095)
Proportion univ. do DF	-0.177*** (0.035)	0.376*** (0.100)
Panel C.1	*Controlling for fields of studies with 18 instead of 12 categories*	
Proportion univ. do	0.015 (0.026)	-0.045 (0.061)
Proportion univ. do SF	0.114*** (0.034)	-0.221*** (0.082)
Proportion univ. do DF	-0.106*** (0.036)	0.172* (0.091)
Panel C.2	*Controlling for fields of studies with 66 instead of 12 categories*	
Proportion univ. do	0.013 (0.027)	-0.044 (0.058)
Proportion univ. do SF	0.071* (0.036)	-0.255*** (0.082)
Proportion univ. do DF	-0.082** (0.034)	0.197** (0.090)
Panel D:	*Different definition of treatment variable*	
Proportion univ. do	-	-
Proportion univ. do SF§	0.091** (0.036)	-0.363*** (0.105)
Proportion univ. do DF§	-0.135*** (0.031)	0.273*** (0.088)
Panel E:	*Removing subjects, for which there is no university equivalent*	
Proportion univ. do	0.052* (0.031)	-0.092 (0.064)
Proportion univ. do SF	0.101*** (0.035)	-0.166** (0.077)
Proportion univ. do DF	-0.060 (0.045)	-0.023 (0.109)

Notes: Each estimate comes from a separate linear regression on the respective subsample. Standard errors (in parentheses) are clustered on the cohort level. Panel A, the baseline, taken from the main results Table 2, column (1). §Treatment variable is defined according to more detailed 2-digit ISCED subject classifications in Panel D (which only affects the same and different field classifications). univ. = university; do = dropout; SF = same field; DF = different field. *, **, and *** signal statistical significance at the 10, 5, and 1 % level, respectively.

Appendix D.4: Placebo treatment test

Table 16: Placebo treatment test results for different outcomes

	(1)	(2)	(3)
*Panel A: Dropout from UAS within **1 year***			
Proportion univ.	0.044		
dropouts in cohort	(0.027)		
Proportion univ. SF		0.033	
dropouts in cohort		(0.033)	
Proportion univ. DF			0.008
dropouts in cohort			(0.041)
*Panel B: Dropout from UAS within **2 years***			
Proportion univ.	-0.003		
dropouts in cohort	(0.035)		
Proportion univ. SF		-0.002	
dropouts in cohort		(0.043)	
Proportion univ. DF			-0.004
dropouts in cohort			(0.053)
*Panel C: UAS graduation within **4 years***			
Proportion univ.	0.024		
dropouts in cohort	(0.071)		
Proportion univ. SF		0.074	
dropouts in cohort		(0.086)	
Proportion univ. DF			-0.045
dropouts in cohort			(0.113)
*Panel D: UAS graduation within **5 years***			
Proportion univ.	0.031		
dropouts in cohort	(0.063)		
Proportion univ. SF		0.039	
dropouts in cohort		(0.079)	
Proportion univ. DF			0.021
dropouts in cohort			(0.095)

Notes: Linear regression. Proportion university dropouts in cohort are measures two years in the future, i.e., the 2010 cohort is placebo tested with the 2012 cohort proportion of university dropouts. Each panel with a different outcome and 88,664 (Panel A), 88,664 (Panel B), 67,340 (Panel C) and 56,935 (Panel D) observations. Each column in each panel of the table represents a separate regression. univ. = university; SF = same field; DF = different field. Same specification as main results of Table 3, i.e., control variables include institution and field fixed effects, cohort size, indicators for full/part time studies, and restricted access fields, distance from the place of living to the UAS, cantonal baccalaureate rate, the number of Masters' studies at the UAS and the number of nationwide university dropouts in the same field. Standard errors (in parentheses) are clustered on the cohort level. *, **, and *** signal statistical significance at the 10, 5, and 1 % level, respectively.

We add to the evidence that our unconfoundedness assumption holds by conducting a placebo treatment test. For the results in Table 16 we replaced the actual treatment by the proportion of university dropouts of the corresponding cohort two years in the future. We chose two years in the future to minimize the risk of overlap of the cohorts due to students taking semesters off or repeating classes. Besides the treatment, the estimations are unchanged to those observed as main results in Table 3. The population used for the estimation slightly changed, especially for Panel A and B, since we cannot observe future treatments for the two most recent years in which corresponding cohorts exist.

None of the coefficients in Table 16 is statistically significant and most are close to zero. Thus, we cannot reject the unconfoundedness hypothesis. While this does not imply that the conditional independence assumption in our case holds, it gives some evidence that it is plausible, while if we would have rejected the placebo null hypothesis there might be some unobserved confounding.