Economics of Education Review 93 (2023) 102372

Contents lists available at ScienceDirect

Economics of Education Review

journal homepage: www.elsevier.com/locate/econedurev

Sitting next to a dropout: Academic success of students with more educated peers

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ARTICLE INFO

JEL classification:
A23
C14
I23

Keywords:
University dropouts
Peer effects
Better prepared students
Causal machine learning

ABSTRACT

We investigate the impact of the presence of university dropouts on the academic success of first-time students in universities of applied sciences. Our identification strategy relies on quasi-random variation in the proportion of dropouts. The estimated average zero effect of dropouts on first-time students' success masks treatment heterogeneity and non-linearities. First, we find negative effects on the academic success of their new peers from dropouts who had re-enrolled in the same subject and, conversely, positive effects of dropouts changing subjects. Second, we use causal machine learning methods to find that the effects vary nonlinearly with different treatment intensities and prevailing treatment levels.

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; more recently, see, e.g., Bostwick & Weinberg, 2022, and Xu, Zhang & Zhou, 2022). As an increasing number of young adults are enrolling in higher education, a larger number will eventually drop out for different reasons (Bertola, 2022), such as having financial problems, choosing the wrong major, and failing to meet the educational demands of a higher education institution. While not all these dropouts leave the education system, many try to obtain an academic degree at another higher education institution, often with lower requirements than the initial institution. This leads to a situation where, on average, the dropouts are academically better qualified and prepared than their new peers, students enrolled in that institution for the first time (hereafter, "first-time students").

As increasing numbers of students are dropping out and re-enrolling at higher education institutions, knowing the influence of dropouts on their peers is of growing interest to policymakers and society. The peer effect literature has dealt with two different situations separately, which come together in a new way in this paper. So far, the focus has been either on the influence of more able students on their peers who have gone through the same educational path together, or on the influence of less able students on their peers who have met their new peers because of grade repetition. These two strands of the literature do not cover the impact of changes in the student body composition that result from an influx of higher education dropouts from institutions with high academic demands re-enrolling at another institution on first-time students at institutions with lower academic demands. Such dropouts, although failing at the demanding institutions, are likely to have more academic knowledge and experience (both from upper secondary school and their previous university studies) than their new peers who are first-time students at the institutions with lower academic requirements: they are (on average) academically above-average-prepared. Resulting peer effects may differ from those of students with high ability on their peers in cohorts that have enrolled together and that differ only in relation to their innate ability or behavior, but not in terms of prior studying experience.

This study provides new evidence on the impact of academically above-average-prepared (university) dropouts on first-time students. We

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https://doi.org/10.1016/j.econedurev.2023.102372
Received 4 July 2022; Received in revised form 6 February 2023; Accepted 7 February 2023
Available online 15 February 2023

estimate this impact by exploiting quasi-randomly varying proportions of university dropouts who re-enroll at another institution. To do so, we take advantage of the Swiss higher education system, which, as in many European countries, offers students the choice of two distinct types of institutions: the more academically demanding and theory-oriented universities (hereafter, "universities") and the more practically oriented universities of applied sciences (UAS).

Compared to first-time UAS students, university dropouts in Switzerland are, on average, academically better prepared than first-time UAS students both due to higher levels of academic knowledge acquired in upper secondary education and through their prior – although unfinished – university studies. This situation is comparable to that in other countries with a wide range of universities that differ in their admission selectivity, in which students drop out of more selective institutions and restart their studies at academically less demanding ones.

To account for different degrees of academic preparedness, we distinguish between two types of university dropouts: those enrolling in a UAS in the same field from which they dropped out and those enrolling in a different field. Given that the same-field university dropouts had already been exposed to relevant subject-specific content at the university level, they are, on average, even better prepared for their second entry into a higher education institution than those re-enrolling in a different field.

Thus far, peer effects have primarily been studied for compulsory education, such as kindergarten (Chetty et al., 2011), elementary school (Gottfried, 2013), lower-secondary school (Balestra, Eugster & Liebert, 2020, 2021) and high school (Lavy, Silva & Weinhardt, 2012). The impact of grade repeaters on their peers – investigated solely in compulsory schooling classes – consistently finds negative short-run effects (e.g., Bietenbeck, 2020; Gottfried, 2013; Hill, 2014; Lavy, Paserman & Schlosser, 2012; Xu et al., 2022) of the grade repeaters on their new peers. In contrast to the university dropouts in our study – who, by transferring down, become the high-ability students relative to their new peers – repeaters are usually of lower ability than their (non-repeating) new peers (Lavy et al., 2012).

Contrary to the negative effects of grade repeaters on their peers, most studies investigating the impact of high-ability students on their peers find positive effects on the latter. Hanushek, Kain, Markman and Rivkin (2003)) find classmates benefiting from high-achieving peers for elementary school students in Texas. Burke and Sass (2013) find no or small but positive peer effects for compulsory school students in Florida and a treatment heterogeneity depending on their peers' abilities. Balestra et al. (2021) find (a) mostly positive and long-lasting peer effects of gifted classmates in lower secondary education but (b) also considerable heterogeneity in the effects by characteristics of the gifted students and their peers. In higher education, both Sacerdote (2001) and Carrell, Fullerton and West (2009) find positive peer effects of the presence of high-ability students in US colleges. Positive high-ability peer effects are found in universities in the Netherlands (Feld & Zölitz, 2017), Russia (Poldin, Valeeva & Yudkevich, 2016), Chile (Berthelon, Bettinger, Kruger & Montecinos-Pearce, 2019), and Denmark (Humlum & Thorsager, 2021). Others, investigating effect heterogeneity, find positive effects only for females (Stinebrickner & Stinebrickner, 2006) or the hard sciences (Brunello, De Paola & Scoppa, 2010).

While all these studies are helpful for understanding specific situations in higher education, they are not directly comparable to our setting for the following two reasons. First, the high-ability students we study (university dropouts) came to their new institution with different educational backgrounds and have spent more years at educational institutions than first-time students. Second, studies on high-ability peer effects in higher education usually focus on very specific settings, such as small groups formed for specific purposes, e.g., room- and dormmates in college (Sacerdote, 2001), study groups (Berthelon et al., 2019; Poldin et al., 2016), orientation week groups (Thiemann, 2022), or small class sections (Feld & Zölitz, 2017). Effects at the cohort level are largely missing, except for Humlum and Thorsager (2021), who use Danish data on UASs to investigate high-ability peer effects.

To analyze the peer effect of academically above-average-prepared dropouts on their fellow first-time students, we use administrative data on the entire universe of about 100,000 bachelor students entering a Swiss UAS from 2009 through 2018. Academic success (or the lack thereof) for first-time 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 also examine alternative identification strategies, which rely on variations over cohorts within (a) institutes and fields of study and (b) institutes and years, both strategies resulting in robust estimates. Moreover, to estimate non-linear effects, we use causal machine learning methods.

In this study, we show an effect in higher education that can be easily overlooked due to its non-linearity and treatment heterogeneity. When we solely investigate the impact of the total proportion of university dropouts on first-time students' academic success, we find a statistically and economically zero effect—however, this (average) zero effect masks treatment heterogeneity and non-linear effects. First, the total zero effect results from two opposing effects. A positive effect associated with the proportion of different-field university dropouts, and a negative effect associated with the proportion of same-field university dropouts. The effects are observable both in the short and long run, including graduation within five years after enrollment. Second, with the additional use of causal machine learning methods, we find that the effects are non-linear and depend not only on the treatment intensity, i.e., the amount of increase in the proportion of dropouts in a cohort, but also on the prevailing level of the treatment. The non-linear relationship between the proportion of dropouts and the UAS peers' likelihood of either dropping out or succeeding reveals a maximized academic success when the proportion of university dropouts is around 5 to 7 percent of a cohort and ideally composed of different-field dropouts.

The rest of the paper is structured as follows. Section 2 presents the background, the data used in the analysis, and descriptive statistics. In Section 3, potential mechanisms are discussed. Section 4 describes the empirical methodology, and Section 5 gives the results of the empirical analysis and various robustness checks. Section 6 discusses the results, suggests policy implications, and concludes.

2. Setting and data

2.1. Background

In Switzerland, the university sector, which is mainly under public control and funding, consists of two distinct types of universities: the traditional (academic/research) universities and the universities of applied sciences (UAS). In contrast to universities, UASs are a newer type of higher education institution, founded only in the late 1990s, mainly to give people with vocational education and training the possibility to obtain a university education. Unlike in traditional universities, the bachelor's degree is considered the standard for most UAS programs. Nevertheless, several programs also offer the possibility of master's degrees. In addition, UASs focus more on application-oriented education, which is generally somewhat less academically demanding than at (theory-based) universities.

The two types of higher education institutions differ both in the type of education offered[2] and in terms of access to study. Admission to a

[2] In addition to a more theory-based and applied focus, some fields such as arts or social work are grouped in UASs and have no similar counterparts in traditional universities. However, many programs have both a more theoretical variant in traditional universities and a more applied form in UASs, such as business administration, STEM fields, or architecture.

Table 1
Descriptive statistics on first-time UAS students, selective variables.

Treatments	
Proportion univ. dropouts	0.059 (0.047)
Proportion univ. dropouts SF	0.028 (0.035)
Proportion univ. dropouts DF	0.031 (0.033)
Outcomes	
Dropout after 1 year	0.071
Dropout after 2 years [1)]	0.115
Graduation within 4 years [2)]	0.698
Graduation within 5 years [3)]	0.761
Covariates	
Cohort size	105.457 (111.932)
Age	22.354 (2.748)
Gender	0.472
Non-Swiss	0.072
Full time	0.781
Restricted Access	0.352
# Master studies at UAS	17.542 (5.926)
# Master studies at UAS in studied field	2.098 (1.716)
Distance: hometown to UAS (in km)	58.462 (61.245)
Travel time: hometown to UAS (in min)	43.581 (37.913)
Regional baccalaureate proportion	20.011 (4.872)
Admission type: Academic baccalaureate	0.170
Admission type: Professional baccalaureate (any type)	0.634
N	102,100

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

university requires an (academic) baccalaureate, which students receive when graduating from (academic) baccalaureate schools. However, access to baccalaureate schools is very restrictive: Only about 20 percent of a Swiss cohort obtains an academic baccalaureate degree, while the vast majority obtain vocational education and training qualifications. Admission to a UAS is also possible with other qualifications, such as a professional baccalaureate, which a student can obtain while in vocational education and training or during an extra year of general education following the vocational diploma.

UAS lectures generally follow a highly standardized 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.

2.2. The above-average-prepared university dropouts

The institutional setting leads to a situation where switchers, who were potentially underperforming academically compared to their original university peers, have better academic prerequisites than their new UAS peers. First, given the different admission requirements previously discussed, university dropouts were more likely to be a positive selection from the overall ability distribution. Second, they have had a more in-depth academic education at the upper secondary level before starting higher education. Third, they had already acquired one or more years of university knowledge before transferring to a UAS. Thus, their earlier education gives them an advantage over their newly arriving peers.

While we are unable to quantify differences in ability or preparedness at the time of entry into UAS studies in a way resembling, e.g., Arcidiacono, Aucejo and Hotz (2016) preparedness index, we can show from standardized PISA tests that university dropouts had significantly higher competencies in reading and mathematics at the end of lower-secondary education (see discussion and results in Appendix B.1) than first-time UAS students. Given that university dropouts have also received more general education than first-time UAS students, these competency differences are likely to increase in the years up to the UAS entry. This might also explain why university dropouts were more successful in their UAS studies than first-time UAS students – with significantly lower rates of dropout from the UAS and significantly higher rates of graduating from UAS (see Table A.4 in Appendix B.2).

To accommodate different levels of preparedness, we assess same- and different field university dropouts separately. Dropouts from the same field of study are presumed to have acquired some discipline-specific knowledge in their previous studies that gives them an advantage over their freshmen peers.[3] Indeed, for same-field university dropouts, in Table A.4, we observe higher academic success than for different-field university dropouts, for dropout and graduation rates. This suggests that there is an advantage generated through prior discipline-specific learning.

2.3. Data and descriptive statistics

Our administrative data from the LABB program (longitudinal analyses in education)[4] of the Swiss Federal Statistical Office comprises every student enrolled in the Swiss education system. For our analysis, we investigate all students entering a bachelor program at a Swiss UAS from 2009 through 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 who were previously enrolled at a (Swiss) university in one of the three years before enrolling at a UAS and who left before obtaining a degree. The treatment of interest is the proportion of university dropouts, i.e., the number of university dropouts divided by the total number of students in a cohort. To 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]

To measure the success of UAS students, we construct variables indicating (a) whether individual students dropped out within the first (or second) year after enrolling in the UAS and (b) whether individual students graduated within four or five years after enrolling in the subject in which they had initially enrolled. To analyze the effect of the

[3] Same-field combinations can be in subject that are offered under the same name at university and UAS, such as mechanical engineering. A dropout from e. g., ETH Zurich (university) to a UAS may already have prior knowledge from the modules Chemistry, Physics, Thermodynamics, Computer Science or Fluid Dynamics, which are also offered at the UAS – although not with exactly the same content. For another example, a transfer from the subject Business and Economics from a University to the subject Business Administration at a UAS, knowledge from prior modules Financial Accounting, Statistics, Mathematics, Micro- and Macroeconomics, among others, can be applied in similar UAS modules.

[4] For more information, see www.labb.bfs.admin.ch.

[5] We removed (a) students enrolled in distance learning and private colleges, whose types of education differ greatly from that of UASs; (b) subjects usually taught at universities of teacher education; (c) individuals with double entries, because we cannot uniquely assign them to a subject; and (d) subjects taught at various locations within a specific UAS, as we cannot identify which students are in the same cohort. We also removed (e) individuals enrolled at a university for more than three years before entering the UAS, as we cannot classify them either as first enrolled at UAS or as university dropouts; (f) cohorts with fewer than five students; (g) individuals aged younger than 18 or older than 35 at entry; and (h) students living outside Switzerland before starting their studies.

[6] The variables are constructed as the number of university dropouts who enrolled at the UAS in the same (in a different) field divided by the total number of students in a cohort. “Field” is defined in a broader sense by the 1-digit International Standard Classification of Education (ISCED), which identifies fields within universities and UAS in the same classification system. To investigate the robustness of this choice, in Section 5.3 we more narrowly define the classification by the 2-digit ISCED fields.

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	−0.036 (0.024)	0.001 (0.028)	−0.003 (0.030)	0.021 (0.046)	−0.042 (0.054)
Panel B: univ. dropouts enrolled in the same field (SF) at UAS					
Proportion SF univ. dropouts in cohort	0.079** (0.032)	0.086*** (0.033)	0.085** (0.035)	0.093* (0.056)	0.114*** (0.037)
Panel C: univ. dropouts enrolled in a different field (DF) at UAS					
Proportion DF univ. dropouts in cohort	−0.171*** (0.035)	−0.163*** (0.040)	−0.164*** (0.036)	−0.132*** (0.040)	−0.194*** (0.027)
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 shows a different treatment. Each column in each panel represents a separate regression. univ. = university. More detailed results appear in Appendix D, Table A.7 (panel A), Table A.8 (panel B), and Table A.9 (panel C). Standard errors are clustered on the cohort [columns (1), (2), and (5)], the UAS by year [column (3)], or the UAS by field [column (4)] level. *Base covariates* include binary institution, year, 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, number of same-field masters' studies at the UAS and number of nationwide university dropouts in the same field. Additionally, *all covariates* include individuals' age; indicators for gender and being non-Swiss; the total number of masters' studies at the UAS; travel time from the place of living to the UAS; indicator for the type of admission; the proportion of academic, professional, and specialized baccalaureates and other Swiss and foreign admission types in a cohort; the proportion of females in a cohort; and proportion of non-Swiss in a cohort. *,**, and *** signal statistical significance at the 10%, 5%, and 1% level, respectively.

proportion of university dropouts on first-time UAS students, we remove the university dropouts from the sample for the main analysis.[7] Table 1 offers 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 A.1 in Appendix A.1.

Table 1 shows the average values for the treatments, with about six percent dropouts in a cohort and about three percent each for same- and different-field dropouts. Our primary outcome measures show that about seven percent of first-time UAS students drop out of their studies within one year, and about 76 percent graduate within five years. The average cohort size is about 100 students, the student body gender composition is about half female and male, and non-Swiss students make up about seven percent of the sample. The majority of UAS students (63.4 percent) earned their higher education entrance diploma through the vocational education track.

3. Potential mechanisms

Although our data have certain advantages, such as comprehensive mapping of all students or no data loss due to non-response in surveys, they are limited in terms of the possibilities to investigate mechanisms for the effects found. We can, therefore, only hypothesize based on the existing literature on peer effects, which may or may not be consistent with the effects found. These hypotheses assume that the peer effects for students in the same field of study differ from those where university dropouts have changed their field of study. In the first case, the dropouts can transfer subject-specific knowledge to the new study and in the second case, only a general ability advantage over the new peers can play a role. Dropouts who do not have a field-specific knowledge advantage are likely to simply be generally more able fellow students, as posited in the conventional peer effect literature, whose influence tends to have a positive effect on their peers' academic performance (e.g., Berthelon et al., 2019; Feld & Zölitz, 2017; Humlum & Thorsager, 2021). The potential mechanisms are manifold and can hardly be investigated in detail. Better peers can act as positive role models, there can be direct positive spillover effects when the better students help the weaker students, or indirect effects when their involvement in the class makes the lecturers more effective.

If, on the other hand, a specific advantage in the knowledge of course content is added to a general difference in ability, the better-prepared students (in our case the same-field dropouts) may have a knowledge advantage that has negative effects on the academic performance of their fellow students. Again, without being able to prove the individual mechanism, because such a knowledge advantage can have a discouraging effect on the less well-prepared students (Rogers & Feller, 2016), or an influence on the nature of teaching (Brodaty & Gurgand, 2016; Duflo, Dupas & Kremer, 2011) or grading (Calsamiglia & Loviglio, 2019) that has a negative effect on less well-prepared students. Better prepared students allow professors, for example, to apply stricter grading standards or to discuss more complex content in class more often and more quickly and faster teaching pace and professors' favoring a selective group of students is found to carry negative effects for the average students (Fassinger, 1995).

Alternatively, effects might work through the rank of students within a cohort (for a review of this literature, see, Delaney & Devereux, 2022). Students that are higher ranked realize better educational outcomes (Bertoni & Nisticò, 2023; Denning, Murphy & Weinhardt, 2021; Elsner & Isphording, 2017; Fenoll, 2021; Murphy & Weinhardt, 2020) and vice versa.[8] Following this literature, having larger proportions of academically better-prepared students with field-specific knowledge occupying high-rank positions within the cohort could lead to negative spillovers for the average student.

While all these mechanisms are in line with negative effects on first-time students the indirect mechanisms that affect the lecturer rather than the student are more likely in larger, anonymous cohorts, while direct peer effects might be more likely to be observed in smaller classes.

[7] For the full sample estimation, including university dropouts, results appear in Appendix E.5. Table A.15 shows that the results are not sensitive to this choice.

[8] This effect could be induced by, e.g., higher effort provision (Gill et al., 2019), higher conscientiousness, perceived ability, and academic motivation (Pagani et al., 2021) or behavioral changes (Cicala et al., 2018).

Table 3
Results for different outcomes.

	(1)	(2)	(3)	(4)
*Panel A: Dropout from UAS within **1 year***				
Proportion univ. dropouts in the cohort	−0.036 (0.024)			
Proportion univ. SF dropouts in the cohort		0.079** (0.032)		0.072** (0.032)
Proportion univ. DF dropouts in the cohort			−0.171*** (0.035)	−0.167*** (0.035)
*Panel B: Dropout from UAS within **2 years***				
Proportion univ. dropouts in the cohort	−0.041 (0.033)			
Proportion univ. SF dropouts in the cohort		0.153*** (0.045)		0.142*** (0.045)
Proportion univ. DF dropouts in the cohort			−0.266*** (0.047)	−0.259*** (0.047)
*Panel C: UAS graduation within **4 years***				
Proportion univ. dropouts in the cohort	−0.077 (0.075)			
Proportion univ. SF dropouts in the cohort		−0.383*** (0.092)		−0.369*** (0.091)
Proportion univ. DF dropouts in the cohort			0.300** (0.118)	0.278** (0.118)
*Panel D: UAS graduation within **5 years***				
Proportion univ. dropouts in the cohort	−0.003 (0.068)			
Proportion univ. SF dropouts in the cohort		−0.321*** (0.094)		−0.299*** (0.093)
Proportion univ. DF dropouts in the cohort			0.365*** (0.098)	0.342*** (0.098)

Notes: Linear regression. Each panel shows 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 (column 1), i.e., control variables, include institution, year, and field fixed effects; cohort size; indicators for full-/part-time studies, and restricted-access fields; distance from place of living to the UAS; cantonal baccalaureate rate; the number of masters' studies at the UAS; and number of nationwide university dropouts in the same field. For panel A, tables in Appendix D document the sensitivity to including more control variables. Standard errors are clustered at the cohort level. *, **, and *** signal statistical significance at the 10%, 5%, and 1% level, respectively.

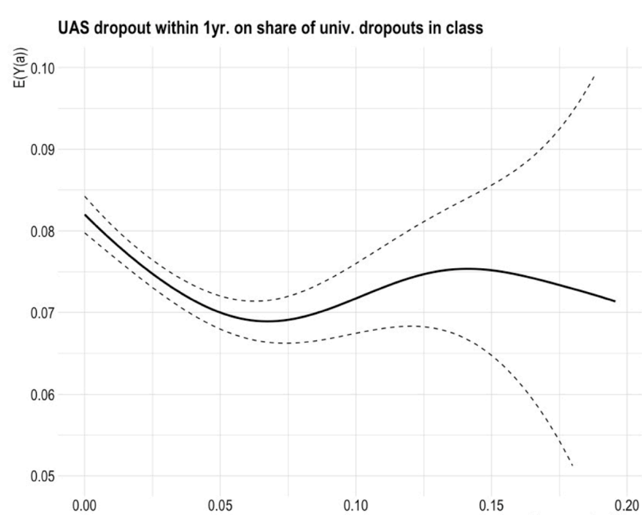

Fig. 1. Effects by treatment level - proportion of university dropouts in cohort.

4. Empirical strategy

This analysis investigates the impact of academically above-average-prepared university dropouts on the academic success of first-time UAS students. Our identification relies on a conditional idiosyncratic variation of the proportion of university dropouts in a cohort, with the key identification assumption of a conditionally random selection into treatment. Our approach can be formalized by the following linear baseline model:

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

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

As dropouts are (mostly) free to choose and select themselves into any UAS, we cannot regard our treatment, the proportion of university dropouts in cohorts, as completely random. We argue that, beyond the possibility of some UASs or some fields being more or less attractive to dropouts, there are no systematic selection effects confounding our estimates. Thus we can exploit this conditional idiosyncratic variation in the proportion of dropouts over cohorts. Nevertheless, we provide several (robustness) checks for the credibility of our estimates.

In the baseline model X_{icfst} contains certain indicators and information. Some fields are more difficult, just as some UASs are more selective.

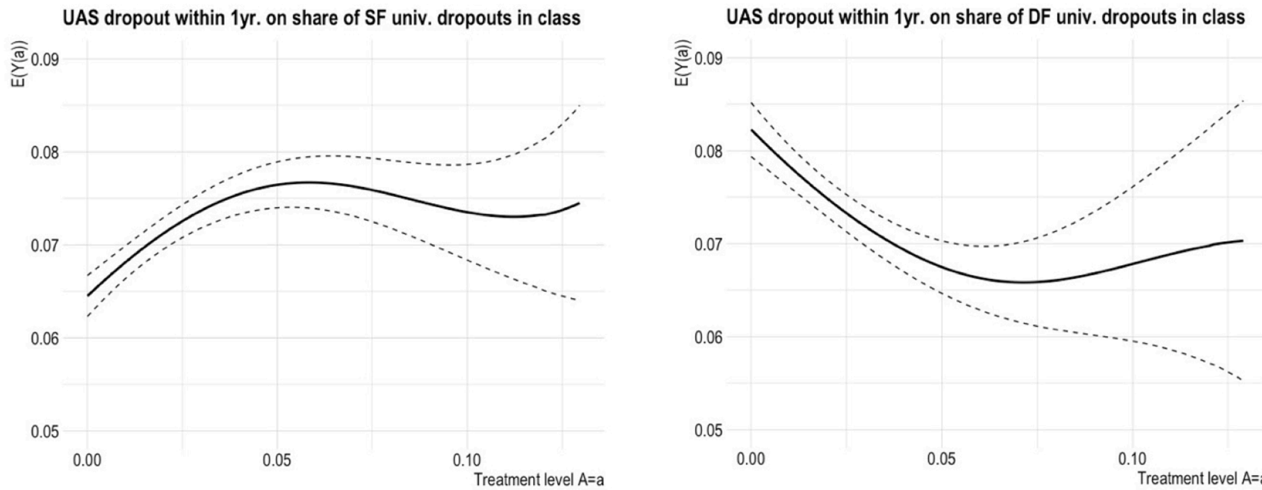

Fig. 2. Effects by treatment level for same (left) and different field (right) dropouts.

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	0.002 (0.041)	0.064 (0.052)	−0.145 (0.092)	−0.021 (0.034)
Proportion univ. same field dropouts in cohort	0.106** (0.045)	0.093 (0.065)	−0.025 (0.105)	0.102* (0.061)
Proportion univ. different field dropouts in cohort	−0.195*** (0.059)	0.032 (0.071)	−0.257* (0.133)	−0.091** (0.040)
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 in the field of study category. univ. = university. Table A.2 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 at the 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 the proportion of university dropouts in cohort: 0.23; the proportion of same-field university dropouts in cohort: 0.71; the proportion of different-field university dropouts in cohort: 0.06. Means of proportions of university dropouts (same field) [different field] in a 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] for health and social work.

Therefore, we expect differences in the proportions of university dropouts by institutions and fields of study, as well as different academic success by fields, institutes, or both. Thus, we include institution and field fixed effects in every specification. To account for potential differences over time we include year fixed effects. Full-time studies lead to faster graduation than do part-time studies and are more attractive to former university students. Some majors are subject to restricted access, which might reduce the number of former dropouts in a cohort, while restrictively selected students might graduate faster with a lower dropout probability. Moreover, we control for the cohort size, which is directly related to the treatment, defined as proportions in cohorts, and

Table 5
Effects by subgroups for dropout from UAS within 1 year.

Panel A:	(1) Baseline	(2)	WALD test for equality of (1) and (2)
Prop. univ. dropout	−0.036 (0.024)		
Prop. univ. dropout SF	0.079** (0.032)		
Prop. univ. dropout DF	−0.171*** (0.035)		
Panel B:	Cohort size <= 50 students	> 50 students	
Prop. univ. dropout	−0.004 (0.033)	−0.035 (0.039)	0.54
Prop. univ. dropout SF	0.044 (0.043)	0.171*** (0.049)	0.05
Prop. univ. dropout DF	−0.060 (0.046)	−0.271*** (0.055)	0.00
Panel C:	Gender Female	Male	
Prop. univ. dropout	−0.086*** (0.033)	0.008 (0.032)	0.04
Prop. univ. dropout SF	0.090* (0.051)	0.079** (0.039)	0.86
Prop. univ. dropout DF	−0.214*** (0.045)	−0.114** (0.049)	0.13
Panel D:	Type of studies Full-time	Part-time	
Prop. univ. dropout	−0.007 (0.025)	−0.197** (0.086)	0.03
Prop. univ. dropout SF	0.120*** (0.032)	−0.159 (0.115)	0.02
Prop. univ. dropout DF	−0.164*** (0.036)	−0.249** (0.124)	0.51
Panel E:	Admission to studies Restricted	Not restricted	
Prop. univ. dropout	−0.093*** (0.033)	0.004 (0.033)	0.04
Prop. univ. dropout SF	0.016 (0.058)	0.063 (0.039)	0.50
Prop. univ. dropout DF	−0.168*** (0.043)	−0.106* (0.055)	0.37
Panel F:	Type of admission certificate Academic bacc.	Prof. bacc.	
Prop. univ. dropout	0.006 (0.031)	−0.016 (0.031)	0.62
Prop. univ. dropout SF	0.099** (0.048)	0.080** (0.039)	0.76
Prop. univ. dropout DF	−0.074** (0.036)	−0.152*** (0.046)	0.18

Notes: Outcome is dropout from UAS within 1 year. Results for graduation within 5 years can be found in Table A.10. Each estimate results from a separate linear regression on the respective subsample; each is sampled according to the headlined groups. Standard errors are clustered at the cohort level. Control variables used are the same as in the baseline. univ. = university; SF = same field; DF = different field; Prof. = professional. *, **, and *** signal statistical significance at the 10%, 5%, and 1% level, respectively. The last column reports a p-value from a WALD test for equality of columns (1) and (2).

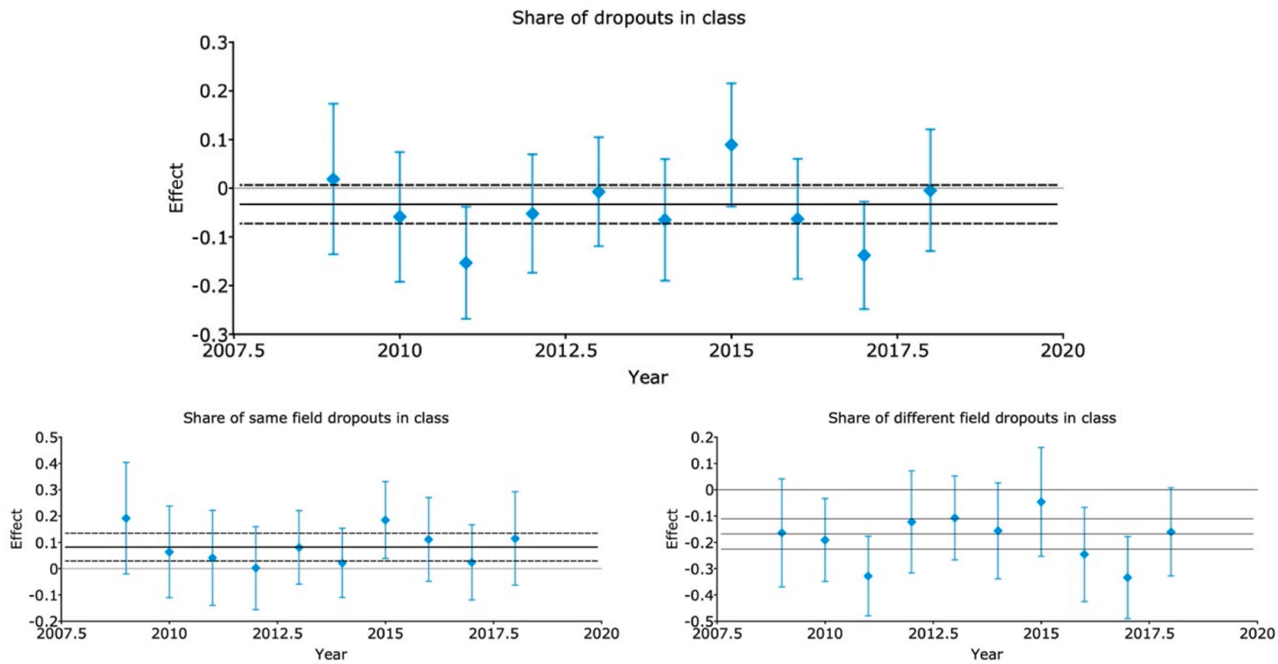

Fig. A.1. Effects by treatment level, proportion of univ. dropouts; Graduation within 5 years.
Notes: E(Y[a]) on the y-axis depicts the expected value of first-time UAS students that graduated within five years for each value of the treatment level, i.e., the (total) proportion of university dropouts in cohort (x-axis).

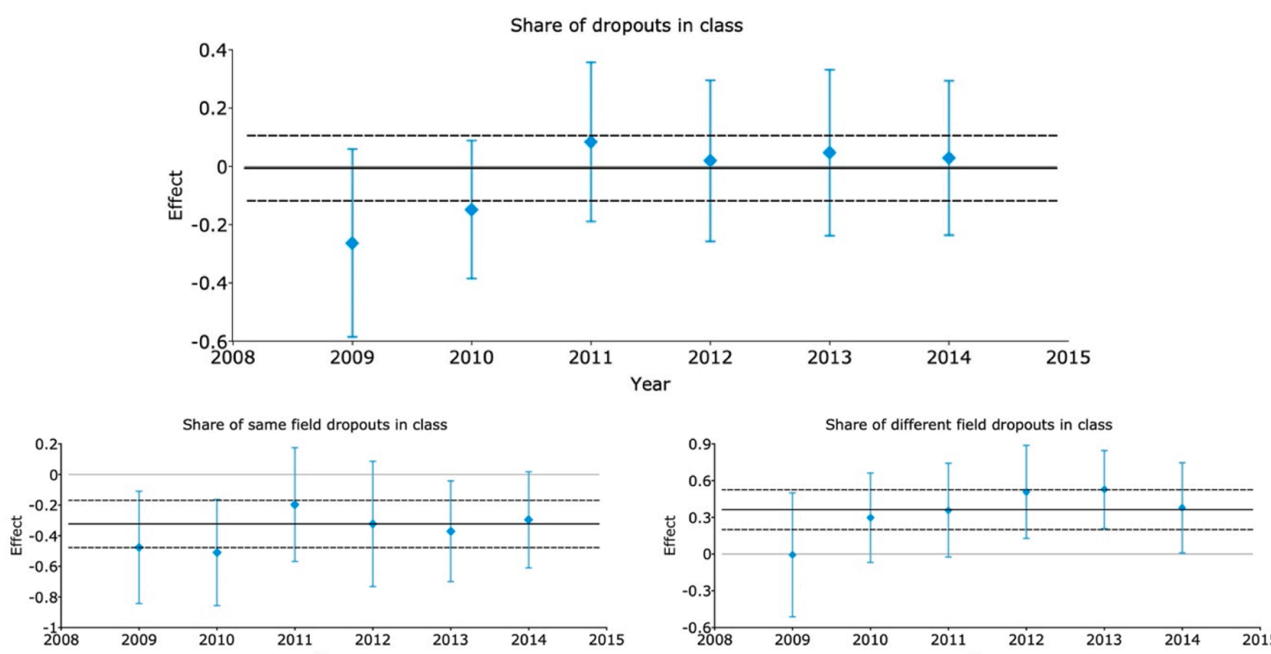

Fig. A.2. Effects by treatment level, proportion of (SF/DF) univ. dropouts; Grad. within 5 years.
Notes: E(Y[a]) on the y-axis depicts the expected value of first-time UAS students that graduated within five years for each value of the treatment level, i.e., the proportion of (same field; left – different field; right) university dropouts in cohort (x-axis).

Table A.1
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 definition)	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
	0.124	0.005

Table A.1 (*continued*)

	First-time UAS	Univ. dropouts
Professional baccalaureate during apprenticeship – technical		
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	7684

Notes: Average values. Standard deviation for non-binary variables in parentheses.
1) 91,003 (6788).
2) 69,034 (5149) and 3) 58,399 (4289) observations.

Table A.2
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.

potentially related to academic success (e.g., Kara, Tonin & Vlassopoulos, 2021; Lazear, 2001). Furthermore, we control for the distance from the student's hometown before enrolling in the UAS,[9] the number of masters courses offered at each UAS,[10] and various regional factors, (e.g., 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 variation in the proportion of dropouts in a cohort is conditionally idiosyncratic, we challenge several of the explicit and implicit assumptions of this baseline model. First, in addition to the covariates just discussed, we include individual

[9] For the decision to apply to a higher education institution, Griffith and Rothstein (2009) and others have found distance from the institution to be an obstacle. Thus larger distances might be related to a well-considered selection into a cohort, as well as higher motivation to perform well in studies.

[10] We cannot rule out the possibility that more talented students select programs and universities that offer more master's degrees.

Table A.3
Differential results in standardized PISA test scores in grade 9.

Panel A: PISA test, sample 2012 (SEATS)				
	Reading		Math	
	(1)	(2)	(3)	(4)
University dropout	0.464***	0.409***	0.456***	0.404***
	(0.097)	(0.101)	(0.100)	(0.103)
Field Fixed Effects	X		X	
Institution Fixed Effects	X		X	
Field by Institution FE		X		X
N	2139	2139	2139	2139

Panel B: PISA test, sample 2000 (TREE)		
	Reading	Math
	(1)	(2)
University dropout	0.556***	0.415**
	(0.154)	(0.202)
N	757	441

Notes: Data source: SEATS and TREE data. Outcome variables (test scores) are standardized. The reference group are UAS first-time students. Regression results for the differences in standardized PISA test scores in math and reading competencies of students who dropped out of university and enrolled in UAS, and first-time UAS students. Each column represents a separate linear regression. We cannot control for fixed effects for the TREE data in Panel B as no information is available about the field of study and the institution. Robust standard errors are in parentheses. *,**, and *** signal statistical significance at the 10, 5, and 1% level, respectively.

Table A.4
Predictive differences; first-time students and dropouts.

	(1) All	(2) All	(3) All	(4) Only dropouts
Panel A: Drop out of UAS within 1 year				
Individual is dropout	−0.046***			
	(0.002)			
Individual is SF dropout		−0.052***	−0.054***	−0.009**
		(0.003)	(0.003)	(0.004)
Individual is DF dropout		−0.040***	−0.038***	
		(0.003)	(0.003)	
F-Test of equality (p-value)		0.003	0.000	
N	109,784	109,784	109,784	7684
Panel B: Graduation from UAS within 5 years				
Individual is dropout	0.070***			
	(0.006)			
Individual is SF dropout		0.085***	0.089***	0.027**
		(0.009)	(0.009)	(0.013)
Individual is DF dropout		0.062***	0.054***	
		(0.009)	(0.008)	
F-Test of equality		0.082	0.005	
N	62,688	62,688	62,688	4289
Field Fixed Effects		X		
Institution Fixed Effects		X		
Field by Institution FE	X		X	X

Notes: Each column represents a separate linear regression with the respective specification. Standard errors (in parentheses) are clustered on a cohort level. SF = same field; DF = different field. F-Test of equality tests if the coefficient of *Individual is DF dropout* and *Individual is SF dropout* are statistically equal. *, **, and *** signal statistical significance at the 10, 5, and 1% level, respectively.

Table A.5
Percentage of individuals that starts at the 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 individual's hometown, 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 the distance from the hometown to the main campus of any Swiss UAS. Results are equivalent if closeness is measured by google maps travel time.

Table A.6
Selection of UAS students into non-closest UAS and 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.

characteristics (e.g., age and gender), and cohort specifics, (e.g., the proportion of females and non-Swiss in a cohort). The full set of covariates included appears in Appendix A.1, Table A.1.

Second, some unobserved confounding might occur in the investigated years in the UAS, i.e., $\varepsilon_{icfst} = \varphi_{st} + e_{icfst}$. To account for a possibility in which specific UASs' reputation or monetary resources increased (decreased) over time, thereby making them more (less) attractive to university dropouts and affecting academic success for first-time UAS students, we use a model including year-by-institution fixed effects. Third, there might be some unobserved confounding related to UASs and field of study, i.e., $\varepsilon_{icfst} = \varphi_{fs} + e_{icfst}$. In an application for Swiss secondary schools, Vardardottir (2015) illustrated the potential importance of cohort-by-track fixed effects instead of cohort and track indicators. We, therefore, include a model specification using institutions by field of study fixed effects.

Fourth, we consider the possibility that certain UAS students might choose either the UAS or a specific program because they expect few (or perhaps many) university dropouts in them. However, two observations argue against this form of selectivity: In Appendix C we provide evidence for Switzerland that the geographical proximity of the UAS to the student's hometown is a major selection driver. About 85 percent of first-time students enroll at the UAS which is geographically closest to their hometown and offers their subject of choice (Table A.5 in Appendix C). 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 a cohort (Table A.6 in Appendix C).

Fifth, we conduct a placebo treatment test in Appendix E.4, in which we replace the actual treatment with the proportions of university dropouts two years in the future. In this test we cannot reject the unconfoundedness hypothesis, supporting our identification strategy.

Moreover, we use advances in methodology to investigate method-specific assumptions. To check both the linear additivity assumption of the linear models and the possible necessity of flexibility in functional forms of the confounding variables, we use a causal machine learning method suggested by Semenova and Chernozhukov (2021). As we cannot be certain that controlling for variables in their baseline form is sufficient, we use a causal machine learning method that is completely independent of functional form dependencies that would point us to misspecifications in our baseline approach.[11] Apart from the linear additivity assumption, 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 potential non-linearity of effects lies in the complexity that, for evaluating continuous response variables, the treatment intensity and the prevailing level of the treatment can be diverse. In contrast to binary indicators, in which an increase in the treatment intensity from 0 to 1 is investigated, whether an increase in treatment (proportion) from 0 to 5 percent and from 5 to 10 percent should have a similar effect or follow similar patterns is unclear. However, linear regression models implicitly assume, 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 irrespective of the baseline value. The first implicit assumption might lead one to overlook a real effect, e.g., assuming a linear relationship when it is u-shaped. The second assumption might lead to incorrect conclusions if an effect is observed only for a specific setup, while extrapolation falsely suggests that the effect is independent of the level of the treatment.

Keeping its problems in mind, we conduct baseline estimates with linear regression. 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 & 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) must be estimated. We estimate both nuisances using a random forest algorithm (Breiman, 2001), which offers substantial flexibility as a global and nonparametric method and excellent predictive power. The resulting orthogonal score $\xi(Z,\pi,\mu)$ is free from confounding influences and doubly robust in the sense that only (at least) one of the two nuisance function estimators needs to be consistent, not both.

The second step differs, because the effect curve $E(Y^a) = E(\xi(Z,\pi,\mu)|A=a)$, i.e., the average potential outcome for given treatment levels, needs estimating either 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 second approach, the best linear approximation, can be made more flexible if we use different base functions of the treatment variable, such as polynomials or binary indicators partitioning on the support of the treatment variable. For comparability of results, we stay with the linear approximation to investigate one assumption at a time and obtain a coefficient that is comparable in its form and interpretability to the usual linear regression estimates.

5. Results

5.1. Main results

Table 2, panel A, shows the effects of the total proportion of university dropouts on the academic 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. Other columns in Table 2 include all control variables in column (2), the UAS by year fixed effects in column (3), the UAS by field fixed effects in column (4), and the best linear prediction in column (5). In none of the regressions the magnitude of the coefficient or the statistical significance differ considerably.

However, separating the same-field and different-field university dropouts into two different groups (panels B and C) shows statistically significant effects for both groups but a different direction of the effect. Higher proportions of same-field university dropouts increase the dropout risk of first-time UAS students. In contrast, a higher proportion of different-field dropouts reduces the probability of first-time UAS students dropping out. Coefficients for same-field university dropouts in panel B vary minimally between 0.082 and 0.093 with the classic methods in columns (1)-(4) and are slightly higher in column (5) with the best linear prediction method. In panel C, estimates for the proportion of different-field university dropouts vary between −0.132 and −0.194 and are all statistically significant. Not differentiating between same-field and different-field dropouts masks the two different effects that university dropouts have on the academic success of first-time UAS students.

Table 3 reports the impact of university dropouts on medium- and long-run outcomes for first-time UAS students. While we take panel A from Table 2 (column 1) for comparison, panels B, C, and D report estimations for different outcome variables: Dropout from UAS within two years, as well as graduation within four and five years. Estimations shown in column (4) consist of both treatment variables, the proportions of same- and different-field dropouts.[12] Each panel in Table 3 again shows insignificant estimates around zero for the total proportion of university dropouts in a cohort. When we separate same- and different-field university dropouts, effect sizes increase in magnitude for dropping out of UAS within two years compared to dropping out within the first year. Graduation success after four or five years (panels C and D) also show somewhat bigger effect sizes. The positive effect of different-field university dropouts, on their peers' academic success, is of similar magnitude.

For the estimation results presented in Tables 2 and 3, we impose an important assumption – linearity in the effect. Furthermore, we assume that the level of treatment present in the cohort, i.e., the proportion of university dropouts, is irrelevant to the size of the effect. To investigate the average effects in more detail, we resolve these assumptions and show non-linear estimates for the UAS students' probability of dropping

[11] For example, distances between the hometown and the UAS might matter in a very different way for a UAS in the Italian-speaking part of the country than for a UAS in an urban German-speaking city. In this case, interactions of variables or more flexible functional forms would be needed.

[12] Goldsmith-Pinkham, Hull, and Kolesar (2022) show that linear regressions with multiple treatment variables lack causal interpretation, even if assumptions hold for each treatment variable. Thus, we provide estimations with multiple treatment variable (column 4) only to show that the treatment effects are not sensitive to the inclusion of the other treatment variables, i.e., to hold the values of the other treatment variable constant.

Table A.7
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	−0.036	0.001	−0.003	0.021	−0.042
	(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	−0.036***	−0.026***	−0.026***	−0.025***	
	(0.003)	(0.003)	(0.003)	(0.003)	
# Master studies at FH, in same field	−0.002	−0.002*	−0.002*	−0.001	
	(0.001)	(0.001)	(0.001)	(0.002)	
Restricted admission	−0.058***	−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 bacc. (in cohort)		0.033	0.039	0.034	
		(0.026)	(0.027)	(0.042)	
Proportion voc. bacc (in cohort)		0.041	0.046*	0.048	
		(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)	(0.001)
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, year, 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 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.

out within one year (almost) without functional form restrictions. As estimating the treatment effect for each level and increase in the treatment intensity would be very complex and cumbersome, our doubly robust nonparametric estimation shows the expected outcome for each level of the treatment.[13]

Fig. 1 reveals a striking pattern for the total proportion of university dropouts in a cohort on first-time UAS students dropping out 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 seven percent university dropouts in a cohort. Then the dropout proportion for higher treatment intensity rises again. However, for these higher treatment levels, the confidence intervals also increase substantially, not least because of very few observations in this area of treatment, making interpreting results for higher treatment levels difficult.

Thus, in addition to the insignificant linear regression null result, Fig. 1 adds three insights. First, the effect is locally different, because for cohorts with small proportions of university dropouts (up to seven percent), adding university dropouts reduces the dropout probability of first-time UAS students, whereas for cohorts with higher proportions of university dropouts, additional university dropouts increase the dropout probability of first-time UAS students. Second, the optimal proportion of university dropouts in UAS cohorts is therefore around seven percent in a cohort. Third, we have enough observations to obtain precise estimates for treatment levels lower than about 15 percent, after which confidence intervals widen substantially. While single linear regression coefficients suggest that the effect is present for all treatment levels, we cannot credibly interpret effects for proportions of university dropouts in a cohort of above 15 percent.

Notes: $E(Y^a)$ on the y-axis depicts the expected value of first-time UAS students who 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).

Notes: $E(Y^a)$ on the y-axis depicts the expected value of first-time UAS students who 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 a cohort.

Moreover, non-linearities also exist and are consistent with the previous findings for the same- and different-field treatment variables. Fig. 2, on the left side, gives the estimates for the proportion of same-field dropouts, with the UAS first-time student dropout probability increasing with a rising proportion of university dropouts up to a proportion of five to seven percent. Above this treatment level, the dropout rates of first-time UAS students no longer increase 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 the proportion of university dropouts reaches seven percent, and after that potentially increases again, even though the deteriorating estimation precision does not allow a clear interpretation.

In all three cases, we detect a plateau effect. Once a certain

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

Table A.8
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	0.079**	0.086***	0.085**	0.093*	0.114***
	(0.032)	(0.033)	(0.035)	(0.056)	(0.037)
Cohort size§	−0.008***	−0.006***	−0.007***	−0.004	
	(0.001)	(0.001)	(0.001)	(0.003)	
Full time	−0.038***	−0.027***	−0.027***	−0.025***	
	(0.003)	(0.003)	(0.003)	(0.003)	
# Master studies at FH, in same field	−0.002	−0.002*	−0.002*	−0.001	
	(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 bacc. (in cohort)		0.027	0.032	0.031	
		(0.026)	(0.026)	(0.040)	
Proportion voc. Bacc. (in cohort)		0.042*	0.047*	0.048	
		(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, year, 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 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.

proportion of dropouts in a cohort is reached, an additional increase in the proportion has no further effect. Conversely, a small proportion of dropouts in a cohort is already enough to worsen/improve the outcomes for all others. However, it should be noted again that the interpretation for higher treatment levels is difficult, as there are quite few observations for these cases. Appendix E.1 offers additional insights into the effect for the long-run outcome of graduation from UAS within five years. Figs. A.1 and A.2 in Appendix E.1 show a similar pattern.

5.2. Heterogeneity

Following the findings in the high-ability peer effects literature, we investigate effect heterogeneities, for example, whether the effects are gender- (Stinebrickner & Stinebrickner, 2006) or subject- (Brunello et al., 2010) specific. In Table 4, we investigate whether the effects depend on the field of study at the UAS. For STEM in column (1) and health and social work in column (4), the effects are similar to the average effects for all programs. We find insignificant effects for different-field dropouts in the humanities and arts [in column (2)] cohorts and for same-field dropouts in economics and administration [in column (3)] fields of study. In total, the estimated coefficients are non-significantly different from one another for all dropouts and same-field dropouts.[14]

Table 5 shows the results of the effect heterogeneity by different subgroups of UAS students. The analysis is restricted to linear subgroup effects for dropping out within one year; results for graduating from a UAS within five years are similar and can be found in Appendix Table A.10. In panel B, the results suggest that the effect of the proportion of same- and different-field university dropouts in a cohort disappears for small cohorts (fewer than 50 students), while effects are

[14] Estimates for the proportion of university dropouts (WALD test for equality of coefficients p-value: 0.23), and proportion of same-field university dropouts (0.71) are non-significantly different. Proportion of different-field university dropouts (0.06) is slightly statistically different. The statistically insignificant point estimates have in common a low mean proportion of dropouts in each category, for different-field dropouts in humanities and arts the proportion is 0.019, for the same-field dropouts in economics and administration the proportion is 0.017. In the non-linear estimates we have already seen that the effects depend on the treatment level. Moreover, in Section 5.3 we investigate the effects for those subjects that have a counterpart in both UASs and universities, and those subjects that do not.

Table A.9
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	−0.171***	−0.163***	−0.164***	−0.132***	−0.194***
	(0.035)	(0.040)	(0.036)	(0.040)	(0.027)
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, in same field	−0.002	−0.002	−0.001	−0.001	
	(0.001)	(0.001)	(0.001)	(0.002)	
Restricted admission	−0.055***	−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 bacc. (in cohort)		0.043	0.049*	0.038	
		(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, year, 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 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 A.10
Effects by subgroups for graduation from UAS within 5 years.

Panel A:	(1) Baseline	(2)	WALD test for equality of (1) and (2)
Prop. univ. do	−0.003 (0.068)		
Prop. univ. do SF	−0.312*** (0.094)		
Prop. univ. do DF	0.365*** (0.098)		
Panel B:	Cohort size <= 50 students	> 50 students	
Prop. univ. do	−0.013 (0.089)	−0.007 (0.123)	0.97
Prop. univ. do SF	−0.044 (0.108)	−0.629*** (0.164)	0.00
Prop. univ. do DF	0.068 (0.123)	0.685*** (0.162)	0.00
Panel C:	Gender Female	Male	
Prop. univ. do	0.060 (0.093)	−0.063 (0.078)	0.31
Prop. univ. do SF	−0.536*** (0.144)	−0.177* (0.099)	0.04
Prop. univ. do DF	0.513*** (0.116)	0.132 (0.131)	0.03
Panel D:	Type of studies Full-time	Part-time	
Prop. univ. do	−0.053 (0.072)	0.013 (0.201)	0.75
Prop. univ. do SF	−0.377*** (0.095)	−0.223 (0.286)	0.61
Prop. univ. do DF	0.344*** (0.103)	0.287 (0.325)	0.87
Panel E:	Admission to studies Restricted	Not restricted	
Prop. univ. do	0.019 (0.100)	−0.069 (0.083)	0.50
Prop. univ. do SF	−0.201 (0.193)	−0.181* (0.099)	0.93
Prop. univ. do DF	0.166 (0.130)	0.139 (0.145)	0.89
Panel F:	Type of admission certificate Academic bacc.	Prof. bacc.	
Prop. univ. do	−0.031 (0.088)	−0.067 (0.075)	0.76
Prop. univ. do SF	−0.307** (0.125)	−0.239** (0.094)	0.66
Prop. univ. do DF	0.206* (0.122)	0.183 (0.119)	0.89

Notes: Each estimate results from a separate linear regression on the respective subsample; each is sampled according to the headlined groups. Standard errors are clustered at the cohort level. Control variables used are the same as in the baseline. 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 last column reports a p-value from a WALD test for equality of columns (1) and (2).

larger for large cohorts than in the baseline results in panel A.[15]

While the effects are larger in magnitude for females than males in panel C, they are present for both genders. For part-time studies in panel D, we find inconclusive estimates. Students enrolled in full-time studies, who form the majority, clearly drive the results. Dividing the fields into restrictive and non-restrictive entrance requirements in panel E shows the same signs for the coefficients. Effects are also homogenous for students entering with an academic or a professional baccalaureate (in panel F).

Until now, we analyzed the effects for different subgroups of UAS first-time students. Since university dropouts differ not only in their former fields of study but also in their (own) characteristics, we provide additional analyses according to two of the characteristics. Peer effects might be different depending on the gender of the dropouts. Also, the average time the dropouts have been at the university before they dropped out should imply a larger knowledge advantage for the dropouts in the cohort. Our results in Table A.12 show no differential effect for different mean proportions of female university dropouts. The results for the average years of study show a positive effect of more years of study on dropout from UAS within the first year, which is consistent with our hypothesis that a greater knowledge advantage decreases the academic success of first-time UAS students.

5.3. Robustness checks

In addition to the results presented thus far, this chapter provides several tests of the robustness of the main results. Table A.13 in Appendix E.3 shows the results of these tests. In panel B, we remove cohorts with fewer than 10 students, as small cohorts might be combined with other cohorts and the effects could be subject to our cohort definitions. In panels C.1 and C.2, we replace the binary indicators for the fields of study with more detailed indicators (18 and 66 categories). In panel D, we construct the treatment variables according to a narrower definition of same-field, i.e., by the 2-digit ISCED fields. Table A.1 in Appendix A.1 shows these variables descriptively, with lower (higher) mean proportions of same- (different-) field dropouts in the cohorts.

The results for all these robustness tests are in line with our baseline results. Even when we remove the fields of study specific to the UASs (Appendix E.3, Table A.13, panel E), we still find the same peer effects for same-field university dropouts. However, the effects are statistically not significant for different-field university dropouts. This likely also means that the positive peer effects of returning university dropouts can be observed mainly in subjects that are offered only at UASs and where, by definition, there can only be university dropouts from different fields.

Moreover, as effects might evolve over time due to some unobserved

[15] While the binarization threshold of 50 students is chosen ad hoc to obtain two similar-sized subsamples, results are in line with Table A.11 in Appendix E.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, the effects on dropping out of a 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.

Table A.11
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. dropouts in cohort	0.003	−0.149
	(0.034)	(0.126)
Proportion x cohort size	−0.072	0.010
	(0.050)	(0.231)
Cohort size	−0.005*	0.017
	(0.003)	(0.017)
Panel B: Proportion university same field dropouts		
Proportion univ. SF dropouts in cohort	−0.017	0.045
	(0.041)	(0.114)
Proportion x cohort size	0.136***	−0.559***
	(0.033)	(0.161)
Cohort size	−0.010***	0.025***
	(0.001)	(0.009)
Panel C: Proportion university different field dropouts		
Proportion univ. DF dropouts in cohort	−0.042	−0.260*
	(0.039)	(0.150)
Proportion x cohort size	−0.200***	0.590***
	(0.040)	(0.227)
Cohort size	−0.001	−0.002
	(0.002)	(0.011)

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.

Table A.12
Effects by university dropouts characteristics.

	Baseline	Years at university	Proportion female dropouts
Panel A: Proportion university dropouts on dropouts from UAS within 1 year			
Proportion univ. dropouts in the cohort	−0.036	−0.240***	0.005
	(0.024)	(0.071)	(0.039)
Proportion univ. dropout x Mean years at university		0.153***	
		(0.045)	
Proportion univ. dropouts x Mean proportion female dropouts			−0.079
			(0.066)
Mean years at university		−0.008***	
		(0.002)	
Mean proportion female dropouts			−0.003
			(0.005)
Panel B: Proportion SF university dropouts on dropouts from UAS within 1 year			
Proportion univ. dropouts in the cohort	0.079**	0.088	0.097**
	(0.032)	(0.101)	(0.046)
Proportion univ. dropout x Mean years at university		0.003	
		(0.058)	
Proportion univ. dropouts x Mean proportion female dropouts			−0.046
			(0.096)
Mean years at university		−0.001	
		(0.002)	
Mean proportion female dropouts			0.000
			(0.004)
Panel C: Proportion DF university dropouts on dropouts from UAS within 1 year			
Proportion univ. dropouts in the cohort	−0.171***	−0.319***	−0.155**
	(0.035)	(0.096)	(0.061)
Proportion univ. dropout x Mean years at university		0.129*	
		(0.067)	
Proportion univ. dropouts x Mean proportion female dropouts			−0.007
			(0.088)
Mean years at university		−0.004**	
		(0.002)	
Mean proportion female dropouts			−0.003
			(0.004)

Notes: Linear regressions. Standard errors (in parentheses) are clustered on the cohort. Specification is the baseline specification from Table 2 in the main text. Proportion x Mean years at university is the interaction term of the proportion of university dropouts in cohort times the average years that the university dropouts spent at the university (averaged by cohort). univ. = university; SF = same field; DF = different field. *, **, and *** signal statistical significance at the 10, 5, and 1% level, respectively.

factors, in Appendix E.2 we provide baseline estimates for each year separately, all three treatments for dropping out of the UAS within one year (in Fig. A.3) and graduating within five years (in Fig. A.4). We observe no specific pattern indicating that the effects increase or decrease substantially over time, and the results are statistically not different from one another.

6. Discussion and conclusion

This study contributes to a growing literature on peer effects in higher education. 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 better performing in their studies. Most of the empirical literature finds positive effects of such students on their peers. However, in part, negative peer effects can also be found.

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 UAS, had already begun but not completed studies at a traditional university. University dropouts have more general education at the upper-secondary level than the average UAS student and start with some prior study experience at a traditional university. Our data allow us to divide the university dropouts into two distinct groups, a division that the empirical results show to be very important – those who re-enroll in the same field of study, and those who change not only the type of university but also their field of study.

While the same-field group has a negative effect on their peers, i.e., they increase the probability of peers' early dropout and thus decrease the probability of successful graduation, the different-field group has a positive effect on the academic performance of first-time UAS students. Moreover, effects turn out to be of non-linear nature indicating an especially positive impact of those field-changers for having few rather than many or none of those peers in a cohort. The same-field groups' impact is also non-linear but having none as peer in a cohort is optimal.

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 for the following two reasons. First, there were – at least in the past – as many same-field university dropouts who studied at a UAS as there were different-field dropouts, and the two effects neutralize. Second, the number of university dropouts currently remains so small that the effects, although statistically highly significant, do not yet have a large impact in economic terms. However, this balance could change if one or the other group of academically-better-prepared university dropouts taking up studies at other institutions grows strongly.

CRediT authorship contribution statement

Daniel Goller: Conceptualization, Methodology, Software, Formal analysis, Data curation, Writing – original draft, Writing – review & editing, Project administration. **Andrea Diem:** Data curation, Writing – original draft, Writing – review & editing. **Stefan C. Wolter:** Conceptualization, Writing – original draft, Writing – review & editing.

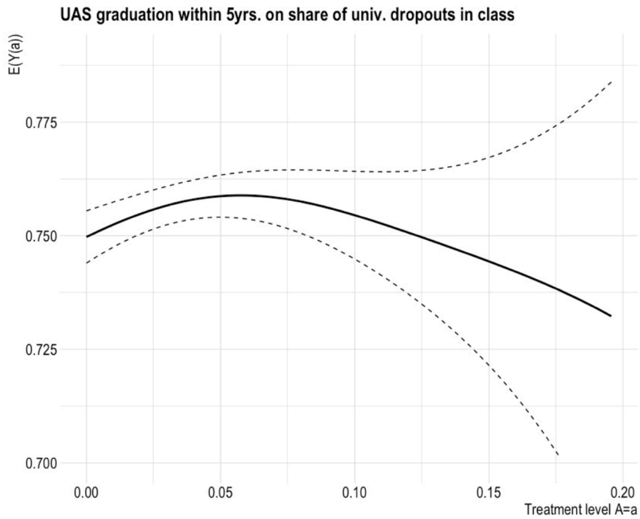

Fig. 3. Effects over time for outcome dropout within 1 year.
Notes: Graph on the top is with proportion all dropouts, bottom left the same field and bottom right the different field dropouts. Blue circles represent the point estimate for each specific year from a separate regression, accompanied by the 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. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Data availability

The authors do not have permission to share data.

Appendix A. Additional descriptive statistics

Appendix A.1. Full table of descriptive statistics

Appendix A.2. Field of study categories

Table A.13
Robustness tests, results.

Panel A:	(1) Dropout from UAS within 1 year *Baseline*	(2) UAS graduation within 5 years
Proportion univ. do	−0.036 (0.024)	−0.003 (0.068)
Proportion univ. do SF	0.079** (0.032)	−0.321*** (0.094)
Proportion univ. do DF	−0.171*** (0.035)	0.365*** (0.098)
Panel B:	*Remove Cohorts with fewer than 10 students*	
Proportion univ. do	−0.036 (0.025)	−0.000 (0.069)
Proportion univ. do SF	0.086*** (0.032)	−0.327*** (0.095)
Proportion univ. do DF	−0.179*** (0.035)	0.378*** (0.100)
Panel C.1	*Controlling for fields of studies with 18 instead of 12 categories*	
Proportion univ. do	0.012 (0.026)	−0.042 (0.061)
Proportion univ. do SF	0.112*** (0.033)	−0.217*** (0.082)
Proportion univ. do DF	−0.109*** (0.036)	0.173* (0.091)
Panel C.2	*Controlling for fields of studies with 66 instead of 12 categories*	
Proportion univ. do	0.009 (0.026)	−0.040 (0.058)
Proportion univ. do SF	0.063* (0.036)	−0.248*** (0.082)
Proportion univ. do DF	−0.084** (0.034)	0.199** (0.090)
Panel D:	*Different definition of treatment variable*	
Proportion univ. do	–	–
Proportion univ. do SF[§]	0.088** (0.035)	−0.358*** (0.105)
Proportion univ. do DF[§]	−0.137*** (0.032)	0.272*** (0.088)
Panel E:	*Removing subjects, for which there is no university equivalent*	
Proportion univ. do	0.041 (0.031)	−0.090 (0.064)
Proportion univ. do SF	0.093*** (0.035)	−0.167** (0.077)
Proportion univ. do DF	−0.072 (0.044)	−0.029 (0.110)

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.

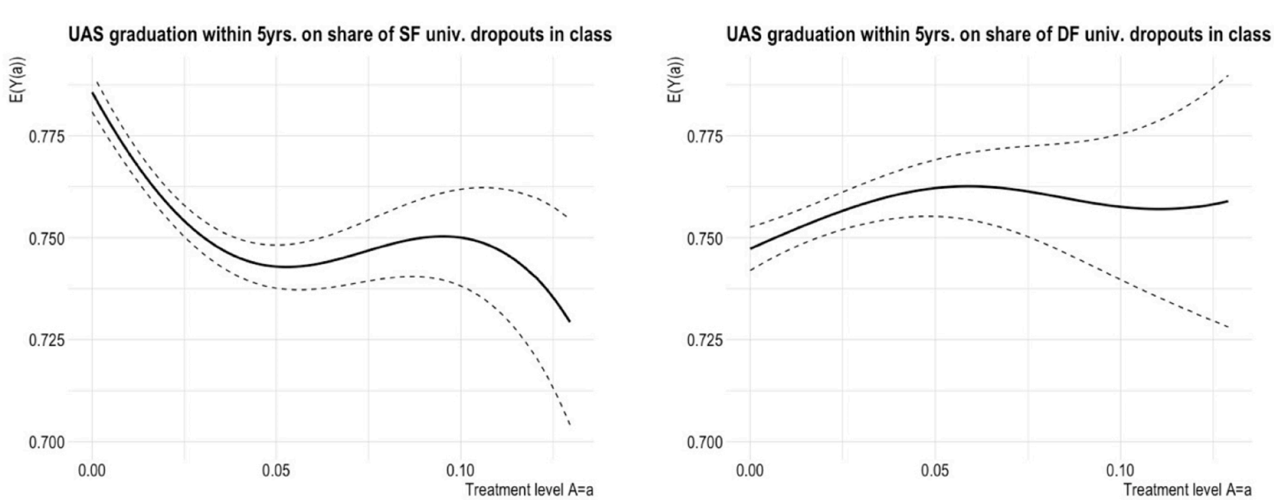

Fig. 4. Effects over time for outcome completion within 5 years.

Table A.14
Placebo treatment test results for different outcomes.

	(1)	(2)	(3)
*Panel A: Dropout from UAS within **1 year***			
Proportion univ. dropouts in cohort	0.045* (0.027)		
Proportion univ. SF dropouts in cohort		0.033 (0.033)	
Proportion univ. DF dropouts in cohort			0.013 (0.041)
*Panel B: Dropout from UAS within **2 years***			
Proportion univ. dropouts in cohort	−0.002 (0.034)		
Proportion univ. SF dropouts in cohort		−0.006 (0.043)	
Proportion univ. DF dropouts in cohort			0.004 (0.052)
*Panel C: UAS graduation within **4 years***			
Proportion univ. dropouts in cohort	0.022 (0.071)		
Proportion univ. SF dropouts in cohort		0.079 (0.086)	
Proportion univ. DF dropouts in cohort			−0.056 (0.113)
*Panel D: UAS graduation within **5 years***			
Proportion univ. dropouts in cohort	0.028 (0.063)		
Proportion univ. SF dropouts in cohort		0.045 (0.079)	
Proportion univ. DF dropouts in cohort			0.004 (0.094)

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, year, 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.

Appendix B. Academically better prepared university dropouts

Appendix B.1. Competence differences of first-time students and university dropouts

The SEATS (Swiss Educational Attainment and Transition Study) and the TREE (Transitions from Education to Employment) data allow us to examine differences in competencies between first-time UAS students and university dropouts in secondary school, 9th grade. The SEATS data links the national PISA 2012 sample in Switzerland with register data on the student's educational career. The register data originate from the LABB program of the Federal Statistical Office and contain yearly information on student enrollment and qualifications in all types of the Swiss education system. The TREE data is a panel study of 9th graders who participated in the national PISA 2000 survey, with nine waves until 2014.

Comparisons of the standardized PISA test scores in Table A.3 show that students who later dropped out of a university and subsequently entered a UAS had around 0.4 standard deviations higher reading and mathematics competencies at the end of lower secondary school than the first-time UAS students. The differences correspond to about 2/3 years of formal education and is thus economically relevant.

Table A.15
Main results for the full sample, first-time UAS and university dropouts.

	(1)	(2)	(3)	(4)
*Panel A: Dropout from UAS within **1 year***				
Proportion univ. dropouts in the cohort	−0.038* (0.022)			
Proportion univ. SF dropouts in the cohort		0.061** (0.028)		0.053** (0.027)
Proportion univ. DF dropouts in the cohort			−0.154*** (0.031)	−0.151*** (0.031)
*Panel B: Dropout from UAS within **2 years***				
Proportion univ. dropouts in the cohort	−0.042 (0.029)			
Proportion univ. SF dropouts in the cohort		0.124*** (0.040)		0.113*** (0.039)
Proportion univ. DF dropouts in the cohort			−0.237*** (0.042)	−0.230*** (0.042)
*Panel C: UAS graduation within **4 years***				
Proportion univ. dropouts in the cohort	−0.056 (0.068)			
Proportion univ. SF dropouts in the cohort		−0.304*** (0.084)		−0.290*** (0.083)
Proportion univ. DF dropouts in the cohort			0.256** (0.110)	0.236** (0.110)
*Panel D: UAS graduation within **5 years***				
Proportion univ. dropouts in the cohort	0.001 (0.063)			
Proportion univ. SF dropouts in the cohort		−0.275*** (0.086)		−0.252*** (0.085)
Proportion univ. DF dropouts in the cohort			0.322*** (0.090)	0.299*** (0.090)

Notes: Linear regression. Each panel with a different outcome and 109,784 (Panel A), 97,791 (Panel B), 74,183 (Panel C) and 62,688 (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 (column 1), 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 plus if the observation is a university dropout. Standard errors are clustered on a cohort level.*, **, and *** signal statistical significance at the 10, 5, and 1% level, respectively.

Appendix B.2. Differences of first-time students, same and different field dropouts

Appendix C. Empirical Strategy – Additional identification evidence

To provide additional evidence of the validity of the identification strategy, we argue that the regional proximity of the institution largely drives selection into higher education institutions in Switzerland. As can be seen in Table A.5, 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 unique field-institution combinations (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 with 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 with an unconditional choice of field of study, more than 72 percent decide to enroll in the geographically closest UAS (Panel G).

Even though it is a small proportion of students not choosing the closest UAS, Table A.6 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 A.6 analyze if the proportion of university dropouts in the cohort predicts the selection into a UAS that is not the geographically closest – measured as 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 A.5, Table A.6)

Appendix D. Detailed estimation results

Appendix E. Additional estimation results

Appendix E.1. Results for graduation from UAS within 5 years

Appendix E.2. Additional subgroup results

Appendix E.3. Robustness checks

Appendix E.4. Placebo treatment test

We add to the evidence that our unconfoundedness assumption holds by conducting a placebo treatment test. For the results in Table A.14, 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.

Only one of the coefficients in Table A.14 is statistically significant (a coefficient that is insignificant and zero throughout the main analysis) 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.

Appendix E.5. Results for all UAS students

While in the main body of the article the effect on the first-time UAS students in investigated, the university dropouts are removed from the sample. Table A.15 offers some insights into the results for all UAS students, the first-time UAS students and the university dropouts combined. Results are in line with the results for the main results table (Table 3) and interpretation is unchanged.(Table A.15)

References

Arcidiacono, P., Aucejo, E. M., & Hotz, J. (2016). University differences in the graduation of minorities in STEM fields: Evidence from California. *American Economic Review, 106*(3), 525–562.

Balestra, S., Eugster, B., & Liebert, H. (2020). Peers with special needs: Effects and policies. *The Review of Economics and Statistics*, 1–42.

Balestra, S., Sallin, A., & Wolter, S. C. (2021). High ability influencers? The heterogeneous effects of gifted classmates. *Journal of Human Resources*, 0920–11170R1.

Berthelon, M., Bettinger, E., Kruger, D. I., & Montecinos-Pearce, A. (2019). The structure of peers: The impact of peer networks on academic achievement. *Research in Higher Education, 60*, 931–959.

Bertola, G. (2022). University dropout problems and solutions. *Journal of Economics*, 1–28.

Bertoni, M., & Nisticò, R. (2023). Ordinal rank and the structure of ability peer effects. *Journal of Public Economics, 217*, Article 104797.

Bietenbeck, J. (2020). The long-term impacts of low-achieving childhood peers: Evidence from project STAR. *Journal of the European Economic Association, 18*(1), 392–426.

Bostwick, V. K., & Weinberg, B. A. (2022). Nevertheless she persisted? Gender peer effects in doctoral STEM programs. *Journal of Labor Economics, 40*(2), 397–436.

Breiman, L. (2001). Random forests. *Machine Learning, 45*, 5–32.

Brodaty, T., & Gurgand, M. (2016). Good peers or good teachers? Evidence from a French University. *Economics of Education Review, 54*, 62–78.

Brunello, G., De Paola, M., & Scoppa, V. (2010). Peer effects in higher education: Does the field of study matter? *Economic Inquiry, 48*(3), 621–634.

Burke, M. A., & Sass, T. R. (2013). Classroom peer effects and student achievement. *Journal of Labor Economics, 31*(1), 51–82.

Calsamiglia, C., & Loviglio, A. (2019). Grading on a curve: When having good peers is not good. *Economics of Education Review, 73*, Article 101916.

Carrell, S. E., Fullerton, R. L., & West, J. E. (2009). Does your cohort matter? Measuring peer effects in college achievement. *Journal of Labor Economics, 27*(3), 439–464.

Chetty, R., Friedman, J. N., Hilger, N., Saez, E., Schanzenbach, D. W., & Yagan, D. (2011). How does your kindergarten classroom affect your earnings? Evidence from project STAR. *The Quarterly Journal of Economics, 126*(4), 1593–1660.

Cicala, S., Fryer, R. G., & Spenkuch, J. L. (2018). Self-selection and comparative advantage in social interactions. *Journal of the European Economic Association, 16*(4), 983–1020.

Delaney, J., & Devereux, P. J. (2022). Rank effects in education: What do we know so far? In K. Zimmermann (Ed.), *Handbook of labor, human resources and population economics*. Cham: Springer.

Denning, J. T., Murphy, R., & Weinhardt, F. (2021). Class rank and long-run outcomes. *Review of Economics and Statistics*, 1–45.

Duflo, E., Dupas, P., & Kremer, M. (2011). Peer effects, teacher incentives, and the impact of tracking: Evidence from a randomized evaluation in Kenya. *American Economic Review, 101*(5), 1739–1774.

Elsner, B., & Isphording, I. E. (2017). A big fish in a small pond: Ability rank and human capital investment. *Journal of Labor Economics, 35*(3), 787–828.

Epple, D., & Romano, R. E. (2011). Peer effects in education: A survey of the theory and evidence. *Handbook of Social Economics, 1*, 1053–1163.

Fassinger, P. A. (1995). Understanding classroom interaction: Students' and professors' contributions to students' silence. *The Journal of Higher Education, 66*(1), 82–96.

Feld, J., & Zölitz, U. (2017). Understanding peer effects: On the nature, estimation, and channels of peer effects. *Journal of Labor Economics, 35*(2), 387–428.

Fenoll, A. A. (2021). The best in class. *Economics of Education Review, 84*, Article 102168.

Gill, D., Zdenka, K., Lee, J., & Prowse, V. (2019). First-place loving and last-place loathing: How rank in the distribution of performance affects effort provision. *Management Science, 65*(2), 494–507.

Goldsmith-Pinkham, P., Hull, P., & Kolesar, M. (2022). Contamination bias in linear regressions. arXiv:2106.05024v3.

Gottfried, M. A. (2013). The spillover effects of grade-retained classmates: Evidence from urban elementary schools. *American Journal of Education, 119*(3), 405–444.

Griffith, A. L., & Rothstein, D. S. (2009). Can't get there from here: The decision to apply to a selective college. *Economics of Education Review, 28*(5), 620–628.

Hanushek, E. A., Kain, J. F., Markman, J. M., & Rivkin, S. G. (2003). Does peer ability affect student achievement? *Journal of Applied Econometrics, 18*, 527–544.

Hill, A. J. (2014). The costs of failure: Negative externalities in high school course repetition. *Economics of Education Review, 43*, 91–105.

Humlum, M. K., & Thorsager, M. (2021). The importance of peer quality for completion of higher education. *Economics of Education Review*, Article 102120.

Kara, E., Tonin, M., & Vlassopoulos, M. (2021). Class size effects in higher education: Differences across STEM and non-STEM fields. *Economics of Education Review, 82*, Article 102104.

Kennedy, E. H., Ma, Z., McHugh, M. D., & Small, D. S. (2017). Non-parametric methods for doubly robust estimation of continuous treatment effects. *Journal of the Royal Statistical Society: Series B, 79*(4), 1229–1245.

Lavy, V., Paserman, M., & Schlosser, A. (2012). Inside the black box of ability peer effects: Evidence from variation in the proportion of low achievers in the classroom. *The Economic Journal, 122*(559), 208–237.

Lavy, V., Silva, O., & Weinhardt, F. (2012). The good, the bad, and the average: Evidence on ability peer effects in schools. *Journal of Labor Economics, 30*(2), 367–414.

Lazear, E. P. (2001). Educational production. *The Quarterly Journal of Economics, 116*(3), 777–803.

Murphy, R., & Weinhardt, F. (2020). Top of the class: The importance of ordinal rank. *Review of Economic Studies, 87*, 2777–2826.

Pagani, L., Comi, S., & Origo, F. (2021). The effect of school rank on personality traits. *Journal of Human Resources, 56*(4), 1187–1225.

Poldin, O., Valeeva, D., & Yudkevich, M. (2016). Which peers matter: How social TIes affect peer-group effects. *Research in Higher Education, 57*, 448–468.

Rogers, T., & Feller, A. (2016). Discouraged by peer excellence: Exposure to exemplary peer performance causes quitting. *Psychological Science, 27*(3), 365–374.

Sacerdote, B. (2001). Peer effects with random assignment: Results for Dartmouth roommates. *The Quarterly Journal of Economics, 116*(2), 681–704.

Semenova, V., & Chernozhukov, V. (2021). Debiased machine learning of conditional average treatment effects and other causal functions. *The Econometrics Journal, 24*(2), 264–289.

Stinebrickner, R., & Stinebrickner, T. (2006). What can be learned about peer effects using college roommates? Evidence from new survey data and students from disadvantaged backgrounds. *Journal of Public Economics, 90*(8), 1435–1454.
Thiemann, P. (2022). The persistent effects of short-term peer groups on performance: Evidence from a natural experiment in higher education. *Management Science, 68*(2), 1131–1148.
Vardardottir, A. (2015). The impact of classroom peers in a streaming system. *Economics of Education Review, 49*, 110–128.
Xu, D., Zhang, Q., & Zhou, X. (2022). The impact of low-ability peers on cognitive and noncognitive outcomes: Random assignment evidence on the effects and operating channels. *Journal of Human Resources, 57*(2), 555–596.