Sitting Next to a Dropout: Academic Success of Students with More Educated Peers

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Introduction (1/3)

Note. - left scale: university and UAS students; right scale: university dropouts at UAS

- Increasing numbers of university (darkgreen) and University of Applied Sciences (UAS; mint) students in Switzerland
- 24% university BA students do not graduate from university within 8 years
- 8% university BA students instead graduate from an UAS (or other college)

Introduction (2/3)

- An increasing number of university dropouts choose to re-start studies at UAS
- Share of university dropouts at UAS increased from 2009 to 2018 ($6 -> 7$ %)
- Those university dropouts...
  - have more and higher quality compulsory education ▸ more
  - already took part in (potentially difficult or ”technical”) lectures
- ... have a ”head start” compared to their fellows.

$\rightarrow$ Whats the impact of university dropouts on UAS students?

- Classmates could benefit if knowledge/experience is shared (peer effects)
- Classmates could suffer if university dropouts raise the benchmark, i.e., grading on the curve or the lecturer speeds up in lecture (benchmark effects)

Introduction (3/3)

Research Question

What's the influence of university dropouts in the UAS on regular (first-enrolled) UAS students' study success?

Findings:

- No effect of university dropouts on first-time students on average

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- Higher share of "same-field" university dropouts in UAS classes lead to crowding out of regular starters
- Higher share of "different-field" university dropouts in UAS classes lead to lower dropout and higher completion rates for "regular" UAS students

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- Higher share of "same-field" university dropouts in UAS classes lead to crowding out of regular starters
- Higher share of "different-field" university dropouts in UAS classes lead to lower dropout and higher completion rates for "regular" UAS students
- **Effects are non-linear**
- **Effects differ by treatment dose and treatment level**

We are in-between two strands of literature

Repeaters

- e.g., Lavy, Paserman, & Schlosser (2012); Gottfried (2013); Hill (2014); Bietenbeck (2020); Xu et al. (2022)
- Negative effects of Repeaters on peers, but...
- $\rightarrow$ Repeaters are usually low-ability

High-ability peers

- e.g., Sacerdote (2001); Carrell, Fullerton, & West (2009); Feld, & Zolitz (2017); Berthelon et al. (2019); Humlum & Thorsager (2021)
- Positive effects of high-ability students on peers
- Effect turns negative once difference in ability becomes large
- $\rightarrow$ High-ability students have spent the same amount of time as their peers in the education system

Setup - Data

- Administrative data on all students entering the UAS from 2009 to 2018 $\rightarrow$ > 100000 observations
- Outcomes: Dropout/exmatriculation at the UAS in 1 (2) year(s); Completion of studies in (4) 5 years.
- Treatment: Share of University dropouts in UAS class, separated into two different treatment variables.
  1. enrolled (without graduation) in university (before entering UAS) and UAS in the same field *(SF)*
  2. enrolled in university and UAS in different field *(DF)*
- Classes are defined as the group enrolled in the same year, institute (and location), full-vs-part-time, and detailed field of study.

Setup - Empirics

- Quasi-random variation in the share of university dropouts in UAS cohorts
- Controlling for
  - (Characteristics of) field of study
  - Institute (details)
  - Class characteristics
  - (Personal characteristics)

$\rightarrow$ Three estimation methods.

1.) Linear regression (fixed effects regression),

2.) (Doubly robust) Nonparametric Kernel regression (Kennedy, Ma, McHugh and Small, 2017).

3.) Best linear prediction method (Semenova and Chernozhukov, 2021)

▸ Methods: Why CML ▸ Methods (2+3): Details

Results (1/4) - ATE: dropout from UAS within 1 year (first-time UAS students)

	(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					
Share univ.	-0.033	0.001	-0.003	0.021	-0.059
dropouts in class	(0.024)	(0.028)	(0.030)	(0.046)	(0.054)
Panel B: univ. dropouts enrolled in the same field (SF) at college					
Share SF univ.	0.082**	0.086***	0.085**	0.093*	0.119***
dropouts in class	(0.032)	(0.033)	(0.035)	(0.056)	(0.035)
Panel C: univ. dropouts enrolled in a different field (DF) at college					
Share DF univ.	-0.168***	-0.163***	-0.164***	-0.132***	-0.166***
dropouts in class	(0.035)	(0.040)	(0.036)	(0.040)	(0.028)
Base covariates	X	X	X	X	X
All covariates		X	X	X	
Institute-by-Year FE			X		
Institute-by-Field FE				X	

Results (2/4) - ATE: other outcomes

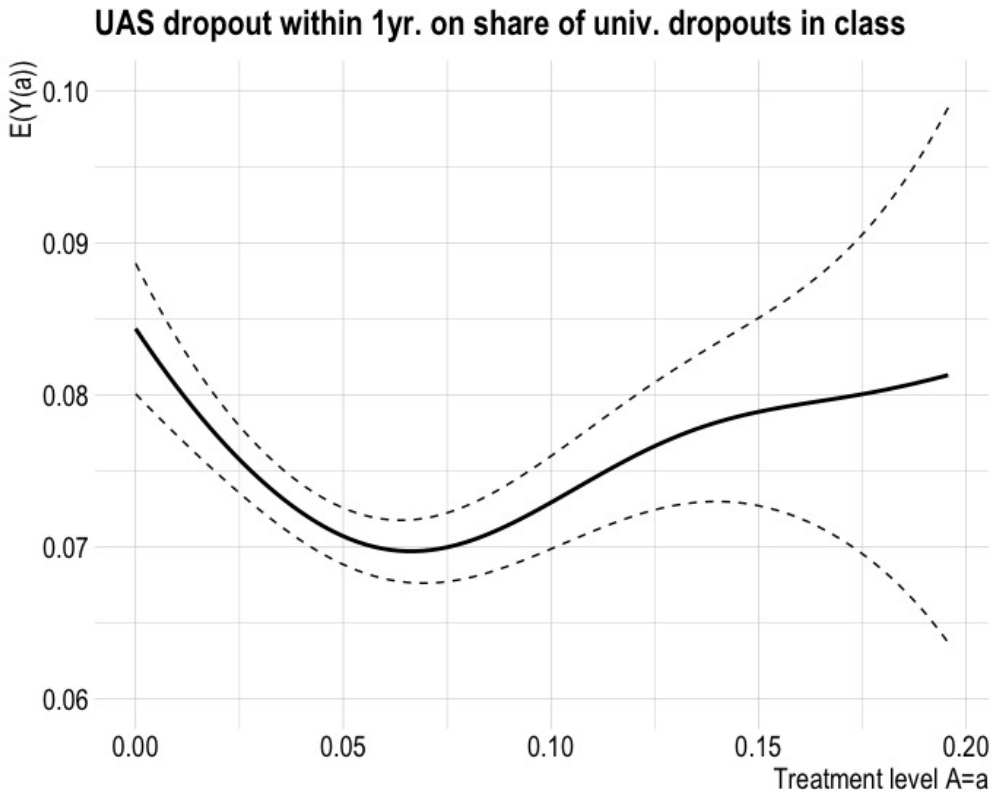
*Panel B: Dropout from UAS within **2 years***			
Share UH	-0.038		
dropouts in class	(0.033)		
Share UH SF		0.157***	
dropouts in class		(0.046)	
Share UH DF			-0.266***
dropouts in class			(0.047)
*Panel C: UAS graduation within **4 years***			
Share UH	-0.077		
dropouts in class	(0.074)		
Share UH SF		-0.378***	
dropouts in class		(0.092)	
Share UH DF			0.296**
dropouts in class			(0.118)
*Panel D: UAS graduation within **5 years***			
Share UH	-0.006		
dropouts in class	(0.068)		
Share UH SF		-0.323***	
dropouts in class		(0.094)	
Share UH DF			0.363***
dropouts in class			(0.099)

Interpretation

Interpretation of those coefficients is...

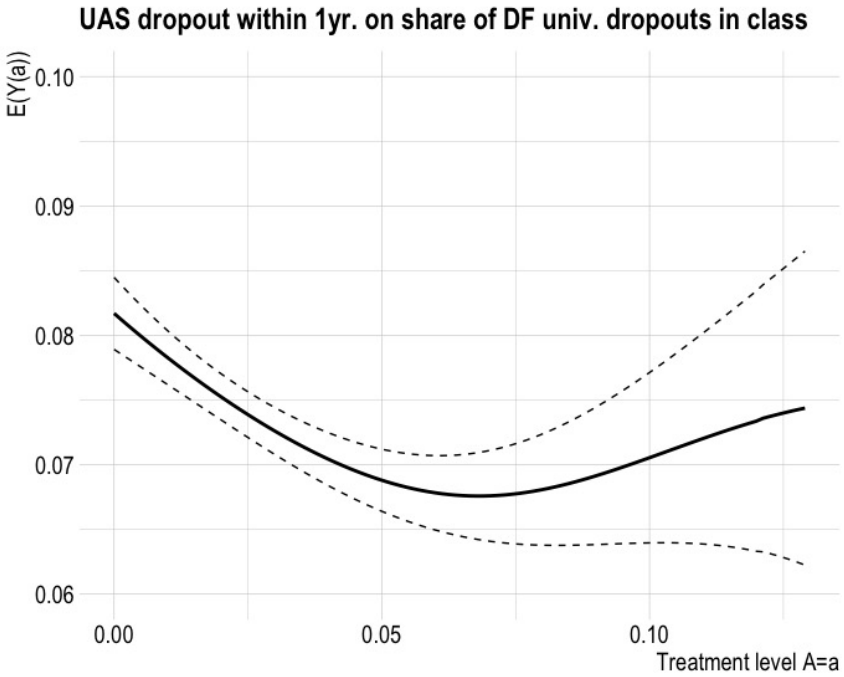
- ... not straight forward
  - Coefficients are usually interpreted for a change in the treatment variable from 0 to 1 $\rightarrow$ impossible in our case
  - a realistic increase is 1 additional university dropout in a class of 50, i.e., 0.02
  - Interpretation: 16 additional dropouts within 1 year from UAS for 10000 first-time UAS students
- ... potentially misleading
  - is this true for every treatment dose ...
  - ... and at every treatment level?
  - Are the estimates precise enough or is it extrapolation?

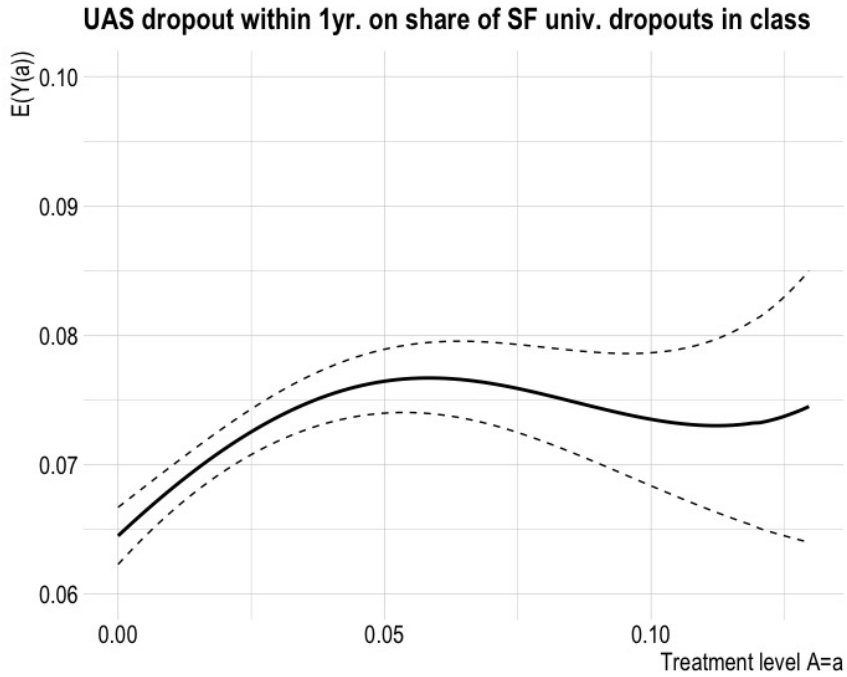
Results (3/4) - Nonparametric estimates



- Effect in fact non-linear
- Dropout probability decreases until share of about 7% university dropouts in class is reached
- For classes with higher shares dropout probability *rather* increases...

Results (4/4)





→ Same minimum for the different field university dropouts (left)

→ Minimum for the same field university dropouts is for a share of zero in class. (right)

▸ Effects by Fields ▸ Effect on university dropouts ▸ Placebo Treatment Test

Summary

- Same field dropouts are negative for first-enrolled UAS students
- Different field dropouts are positive for first-enrolled UAS students
- 'Optimum': 7% university dropouts in UAS classes, consisting of different field university dropouts and no SF university dropouts
- Effects mainly driven by full time students & large classes

$\rightarrow$ might be optimal to suggest a policy that does not allow to study the same field at UAS if already studied this at university, but:

- SF university dropouts themselves are less likely to drop out and more likely to graduate from their UAS studies compared to the first-enrolled UAS students and different field university dropouts!

Questions?

Remarks?

Suggestions?

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Appendix

Standardized PISA test scores - grade 9

Students who later dropped out of a university and subsequently entered a UAS had $\frac{1}{2}$ sd higher competencies than the first-time UAS students.

	Reading		Math	
	(1)	(2)	(3)	(4)
University dropout	0.535***	0.500***	0.502***	0.465***
	(0.091)	(0.096)	(0.091)	(0.094)
Field Fixed Effects	X		X	
Institution Fixed Effects	X		X	
Field by Institution FE		X		X
N	2272	2272	2272	2272

Notes: Data source: SEATS data. Outcome variables (test scores) are standardized.

$\rightarrow$ The differences correspond to about $\frac{3}{4}$ years of formal education and is thus economically relevant.

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Methodology (1/2)

Why causal machine learning?

- Linear additivity of controls
  - to be free from functional form dependence

$\rightarrow$ Need a flexible way to account for confounding influences

- Constant treatment effect
  - Speciality: continuous treatment
  - Potentially different effect for different 'doses'
  - Potentially different effect for different treatment level

$\rightarrow$ Need a flexible way to estimate the effect(s)

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Methodology (2/2)

Both approaches build on the same first step, i.e., constructing the pseudo-outcome:

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

For which $\mu(x,A)$ and $\pi(A|x)$ are estimated using a Random Forest.

$\rightarrow$ The pseudo-outcome is free from confounding influences.
$\rightarrow$ The pseudo-outcome is doubly robust, i.e., only one of the nuisance functions need to be consistent, not both.

In the second step $\xi(\pi,\mu)$ is estimated on the treatment variable in two different ways

- ... in a linear regression (Semenova and Chernozhukov, 2021)
- ... in a (non-parametric) kernel regression (Kennedy et al., 2017)

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Results (5/4) - Results by fields of study

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

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Results (6/4) - Results for the university dropouts

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

$\rightarrow$ Effects are similar to those of first-enrolled UAS students, especially for different field dropouts.

$\rightarrow$ Same field university dropouts are more successful compared to different field dropouts.

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Results (7/4) - Placebo Treatment Test

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

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