Swiss Leading House VPET-ECON

A Research Center on the Economics of Education, Firm Behavior and Training Policies

University of Zurich[UZH] — **Co-Director**
Prof. Dr. Dr. h.c. Uschi Backes-Gellner

UNIVERSITÄT BERN — **Co-Director**
Prof. Dr. Stefan C. Wolter

Fall Term 2026

Leading House Ph.D. Course
Causal Machine Learning for Education Economists
– Preliminary Syllabus –

Lecturer:	Prof. Dr. Martin Huber; University of Fribourg
Workshop dates:	November 2 – 6, 2026
Location:	University of Zurich (tba)
Preliminary Schedule:	The lectures take place in the form of an intensive 5-day course.
	Monday, Nov 2, 2026: 14:00-17:30 Tuesday, Nov 3, 2026: 09:00-17:30 Wednesday, Nov 4, 2026: 09:00-17:30 Thursday, Nov 5, 2026: 09:00-17:30 Friday, Nov 6, 2026: 09:00-12:30
Module Number; ECTS:	(tba); 3 ECTS
Course webpage:	http://www.business.uzh.ch/de/professorships/emap/teaching.html

Course overview

This course provides an introduction to causal machine learning with applications in the statistical software R and its interface RStudio.

The primary focus is on assessing the causal effects of policies, interventions, or treatments - such as offering an educational intervention like a training program - on outcomes like employment or income, in the presence of high-dimensional data. Credible causal analysis requires careful consideration of identifying assumptions and appropriate statistical methods to ensure comparability between treated and non-treated units.

Machine learning methods can be integrated into causal analysis to construct such comparable groups in a flexible, data-driven way. They allow researchers to estimate treatment effects under high-dimensional settings with many possible control variables, assess effect heterogeneity, and determine which subgroups benefit most from an intervention. These tools further enable optimal policy learning, i.e. assigning treatments to subgroups in a way that maximizes overall effectiveness. Finally, the course introduces reinforcement learning, where repeated treatment assignment over time allows learning about the most effective intervention strategy.

Because causal machine learning methods rely on algorithms for prediction and forecasting as building blocks, the course also includes an introduction to predictive machine learning. All methods are illustrated using real-world data in R.

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www.economics-of-education.ch
Leading House VPET-ECON
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Objectives

- Understand the foundations of causal inference and identification assumptions.
- Distinguish between predictive and causal machine learning.
- Understand strengths and limitations of major causal machine learning methods.
- Understand the intuition of predictive machine learning as building block for causal machine learning.
- Understand and distinguish various causal machine learning algorithms for controlling high-dimensional covariates when assessing treatment effects.
- Understand and distinguish causal machine learning methods for analyzing treatment effect heterogeneity and for designing optimal treatment policies.
- Implement causal machine learning methods in R using real data.

Course Structure (Thematic Blocks)

1. Introduction to Causal Inference

- Purpose and goals of causal analysis
- Potential outcome framework
- Identifying assumptions (e.g. selection-on-observables, instruments, parallel trends, regression discontinuities)

2. Foundations of Predictive Machine Learning

- Basic concepts including performance measurement, bias–variance tradeoff, sample-splitting/cross-validation for model tuning
- Penalized regression algorithms (lasso, ridge, elastic net)
- Tree-based methods (trees, bagging, random forests)
- Further algorithms: overview of boosting, SVMs, neural networks, ensemble methods

3. Causal Machine Learning Based on Lasso Regression

- Double selection and partialling-out procedures for linear models
- Properties of treatment effect estimators with and without sample splitting/cross-fitting

4. Causal Machine Learning Based on Tree Methods

- Causal trees and causal forests for nonparametric (flexible) models
- Average treatment effect estimation
- Effect heterogeneity analysis: estimating conditional average treatment effects within subgroups defined in terms of observed covariates

5. Double Machine Learning

- Doubly robust estimation combined with machine learning
- Average treatment effect estimation based on doubly robust functions
- Effect heterogeneity analysis based on doubly robust functions
- Optimal policy learning: learning optimal treatment assignment rules from data

7. Reinforcement Learning

- Repeated treatment assignment over time
- Learning optimal intervention strategies
- Exploration vs. exploitation tradeoff

Methodology

The course combines conceptual lectures, discussion of statistical properties, and hands-on empirical sessions using real-world data in R and RStudio.

Prerequisites

Introductory statistics (probability theory, conditional expectations, linear regression).
Basic knowledge of R.

Participants who are not yet familiar with R should prepare before the course. The video *RStudio for the Total Beginner* provides a concise introduction and covers the basic software skills required for the course. Participants who would like a more comprehensive introduction may additionally consult the online course *An Introduction to R*.

Course Material
Lecture slides, R code, and data files will be provided.

Textbooks
- For predictive machine learning: G. James, D. Witten, T. Hastie, and R. Tibshirani (2021): An Introduction to Statistical Learning with Applications in R, Springer, New York. Freely available at: https://www.statlearning.com/
- For causal machine learning: M. Huber (2023): Causal analysis - Impact evaluation and causal machine learning with applications in R, MIT Press, Cambridge. Free online version available at: https://mitpress.ublish.com/ebook/causal-analysis-impact-evaluation-and-causal-machine-learning-with-applications-in-r-preview/12759/162

Target audience and preconditions for participation

The course is particularly designed for doctoral students in economics of education. Doctoral students in economics or business economics with a strong interest in econometric analyses in economics of education are welcome as well.

Credit requirements and grading

1. Full course attendance is required to receive ECTS-Points. Students are expected to come prepared to the course. It will facilitate discussions and improve overall learning. Course materials will be sent to participants ahead of time.
2. Individual take-home exam

Application

The number of participants is limited. Course registration until **September 14, 2026**, is mandatory. Please send your application (including a one-page CV) to Chiara Zisler (chiara.zisler@business.uzh.ch).

WWF Statutory Course Policies

According to WWF study regulations, all exam dates are final as published in the VVZ and syllabus. This means that the final exam date is not negotiable. It will not be possible to take any exams on different dates.
Academic dishonesty in any form will not be tolerated. Anyone caught cheating or engaging in unethical behavior will be reported to the Dean's office according to the guidelines on academic dishonesty set forth by the University of Zurich.
The information in this syllabus supports the official information in the electronic university registration tool (VVZ – Vorlesungsverzeichnis). In cases of doubt, the official information at the VVZ is decisive.
For UZH students: Don't forget to officially register using the registration tool of the University of Zurich.

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