Essays in Empirical Economics using Microeconometric and Causal Machine Learning Methods

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The «What if …?» questions

- What if this guy did something else?

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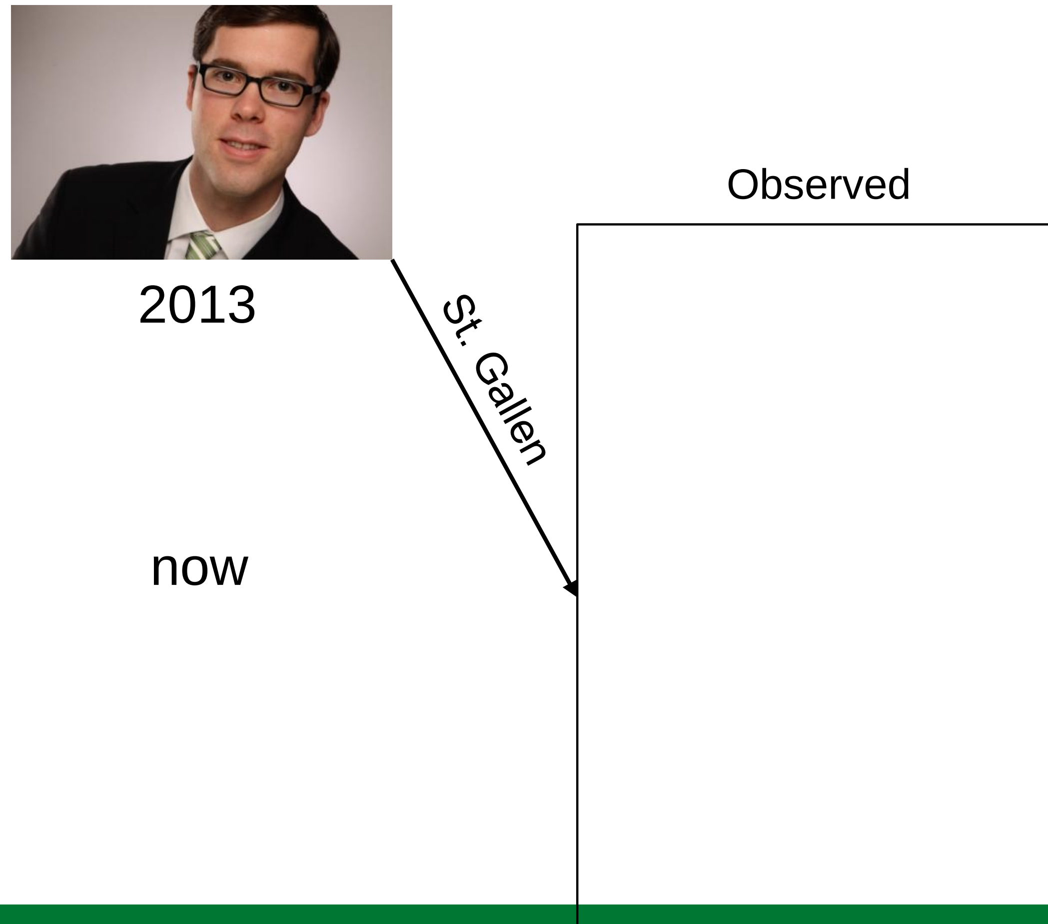

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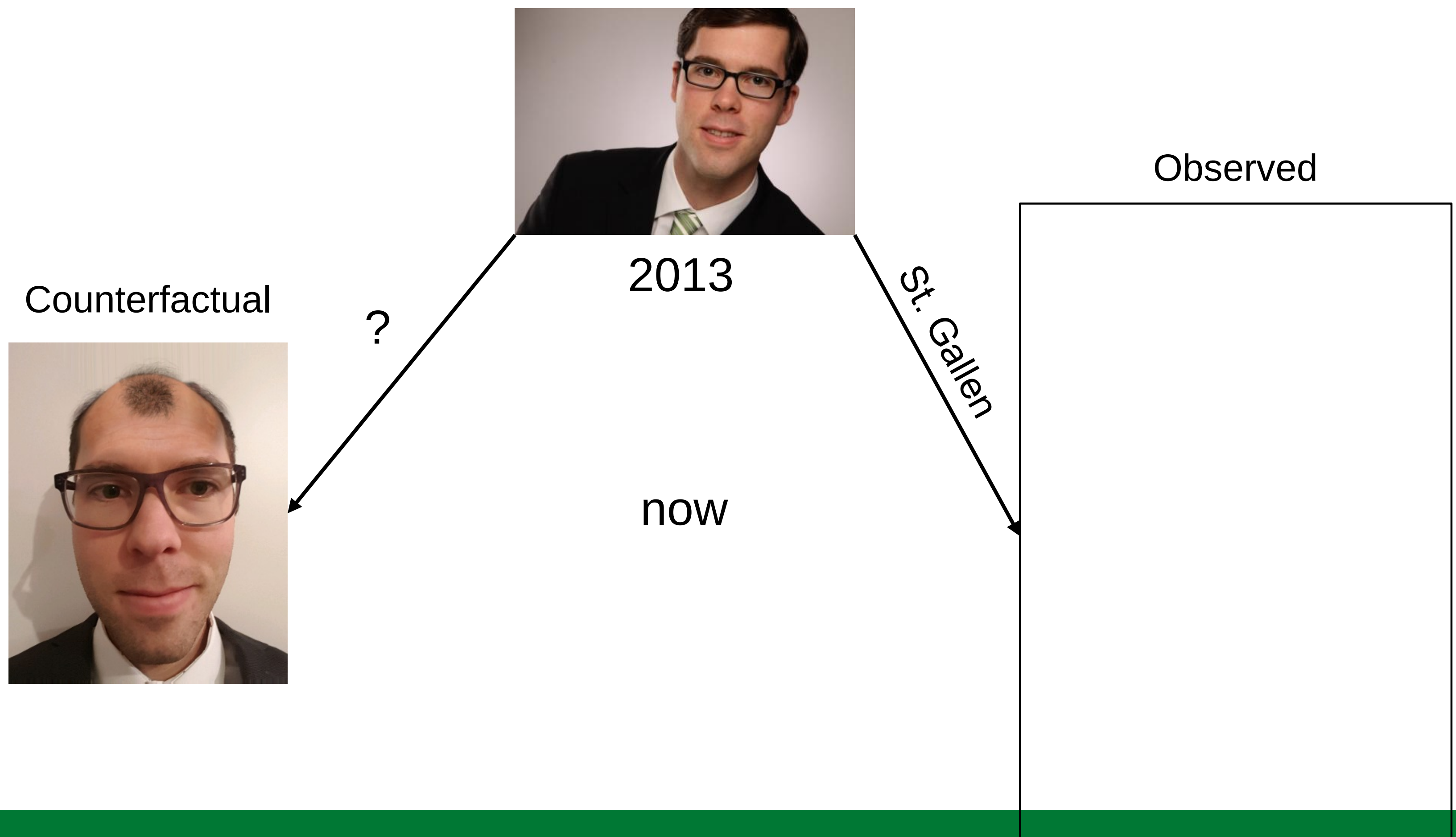

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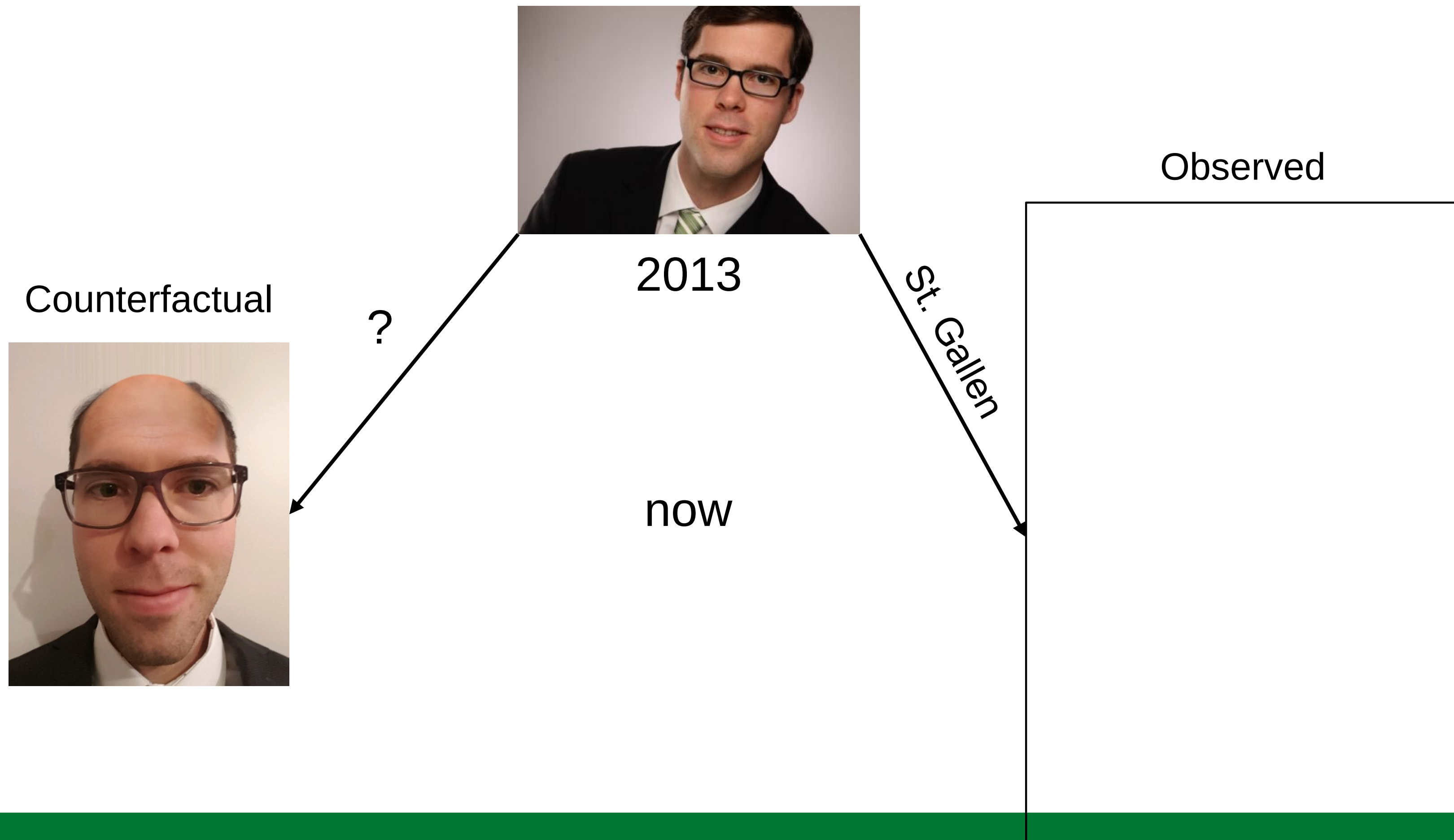


The «What if …?» questions

- It is impossible to observe the counterfactual on the individual level

$\Rightarrow$ The *causal* effect of different choices is not observed

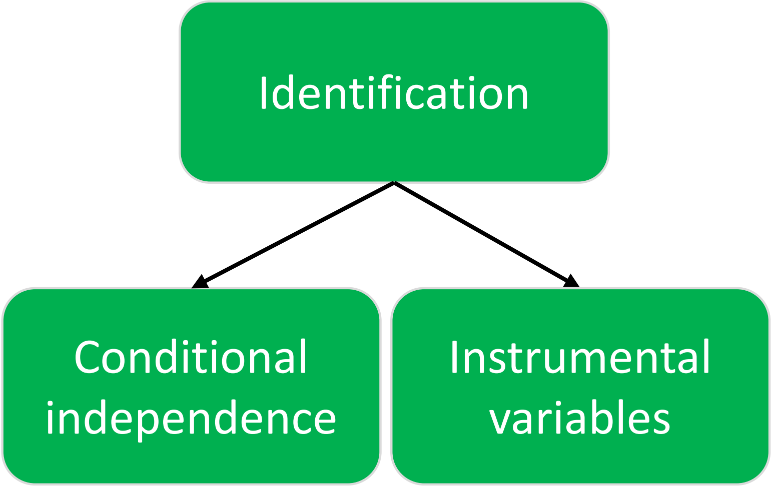
- *Goal* of the analyses in this *dissertation* is to estimate at least *average causal effects* of
  - Playing music (Ch. 1)
  - Physical education (Ch. 2)
  - Active labor market policy (Ch. 3)
  - Job changes (Ch. 4)

Ingredients of causal analyses

- Identification: Arguments that the *research design* allows to identify the *causal* effect of interest
  - Requires institutional and contextual knowledge of the problem
  - Involves untestable assumptions

- Estimation: *Statistical techniques* to estimate the causal effect of interest
  - Large and steadily increasing toolbox of methods
  - Might require additional assumptions

Ingredients of the analyses in the thesis



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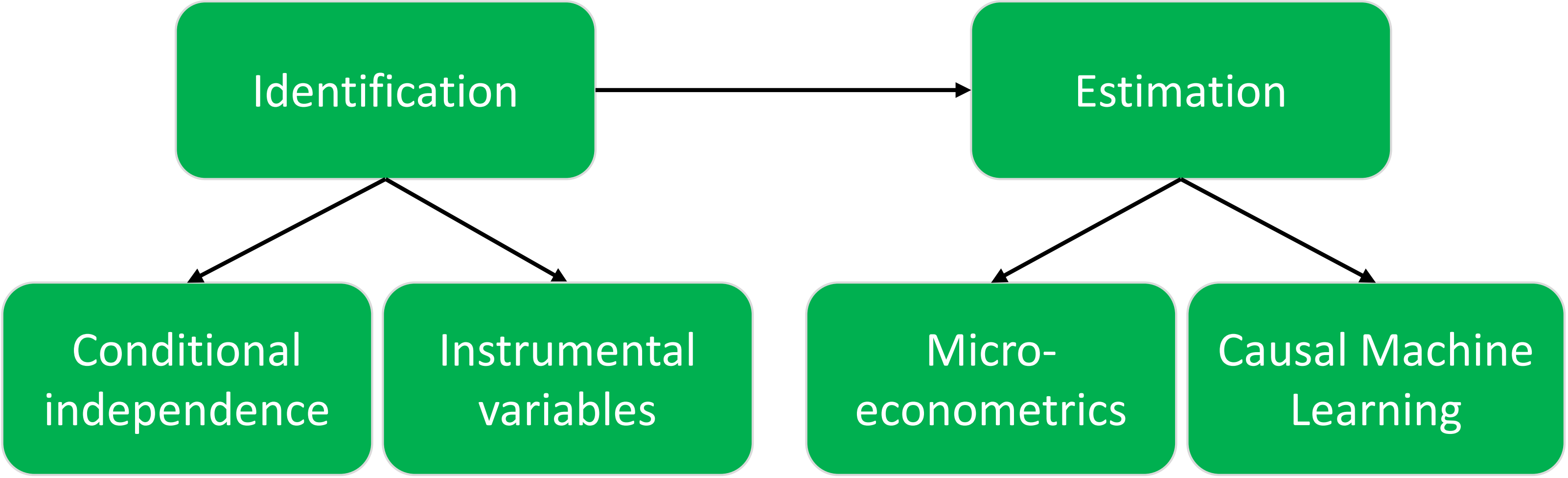
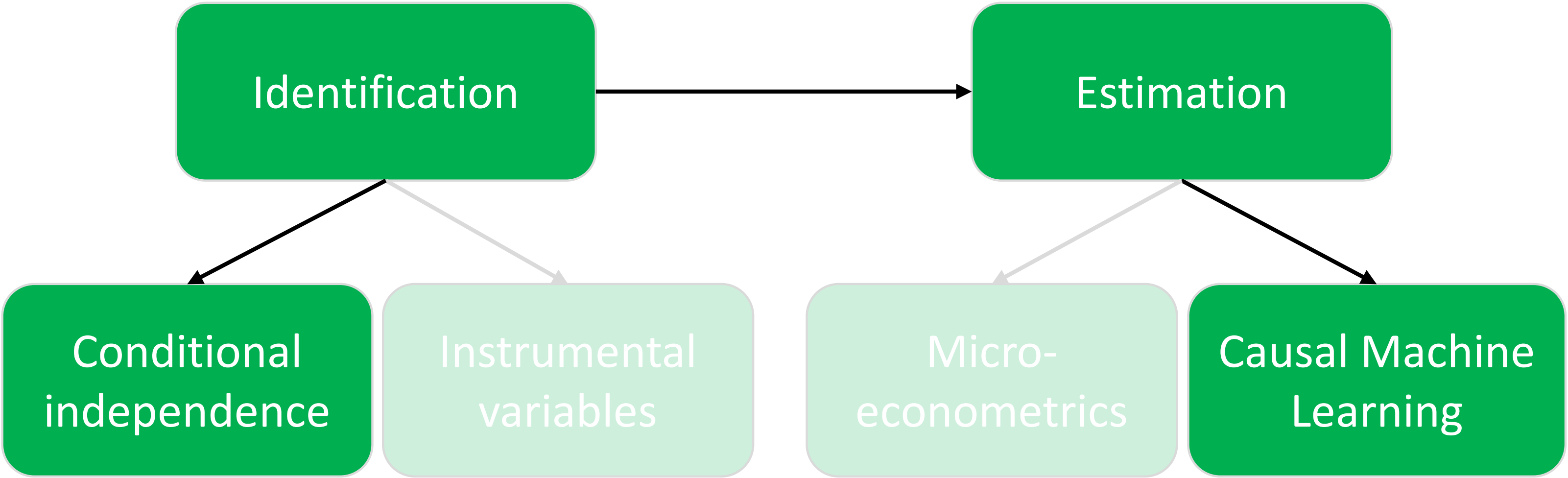


Microeconometrics vs. Causal Machine Learning

	Microeconometrics	Causal Machine Learning
Identification	Same	
Model selection	Manual (at least to some degree)	Data-driven
Statistical inference	God gave us the final model	Accounts for the model selection step

- Causal machine learning *splits* the *estimation* of causal effects into several *prediction problems*
- The predictions problems are then solved by standard or adapted machine learning tools

Chapter 1: Intensity of Musical Practice and Youth Development



Chapter 1: Intensity of Musical Practice and Youth Development

- Motivation: Understand the impact of *extracurricular activities* on cognitive and non-cognitive *skills*

- Contribution:
  - *Dose-response* relation between musical practice and skill development
  - Observed parental tastes increase *credibility* of *identification*

- Data: *German National Educational Panel Study* with ~7,000 9th graders

Chapter 1: Intensity of Musical Practice and Youth Development

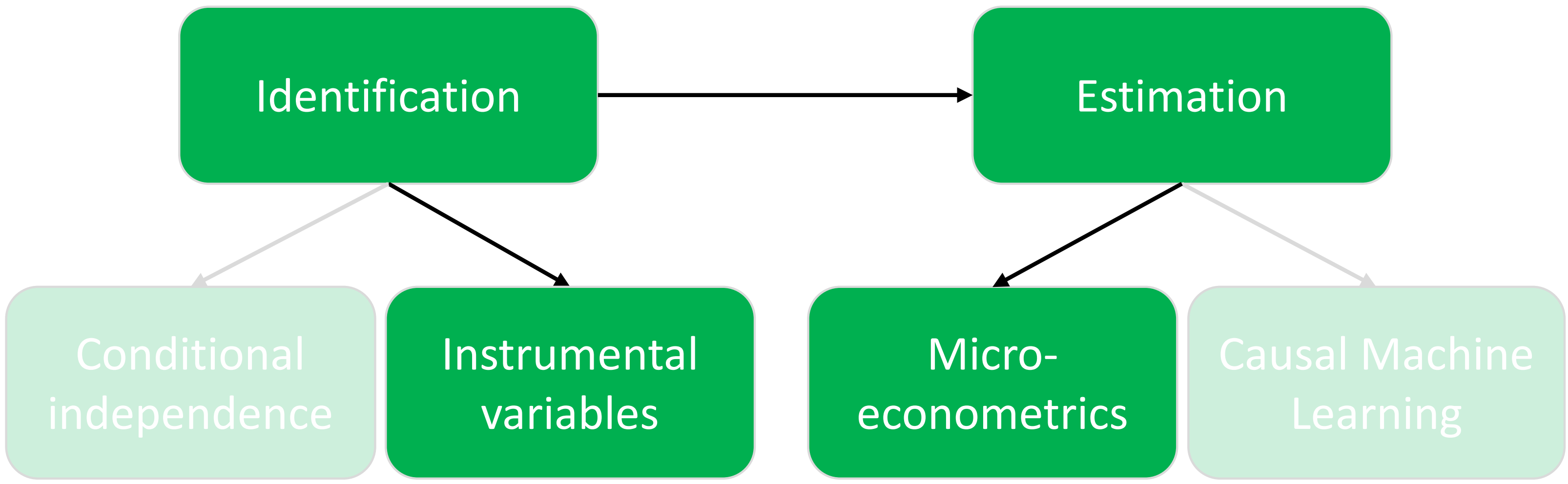
- Identification: *Conditional independence assumption*
  - Detailed parental background
  - Individual characteristics

- Estimation: *Double Machine Learning* (Farrell, 2015)

- Results:
  - *Improved cognitive skills* for medium and high intensity
  - *Improved grades* already for low intensity, mainly for German
  - Agreeableness and openness in *Big Five signficantly improved*

Chapter 2: For better or worse? - The Effects of Physical Education on Child Development

with Michael Lechner and Anne Reimers



Chapter 2: For better or worse? - The Effects of Physical Education on Child Development

- Motivation:
  - *Discussions* about *increasing physical education* (PE)
  - *Scarce evidence* regarding effect of *regular PE* on child development

- Contribution:
  - Comprehensive analysis of *all five domains* of intended PE effects:
    - Cognitive / non-cognitive / motor skills
    - Extracurricular physical activity
    - Health and fitness

- Data: *German Motorik-Modul* with ~5,500 observations

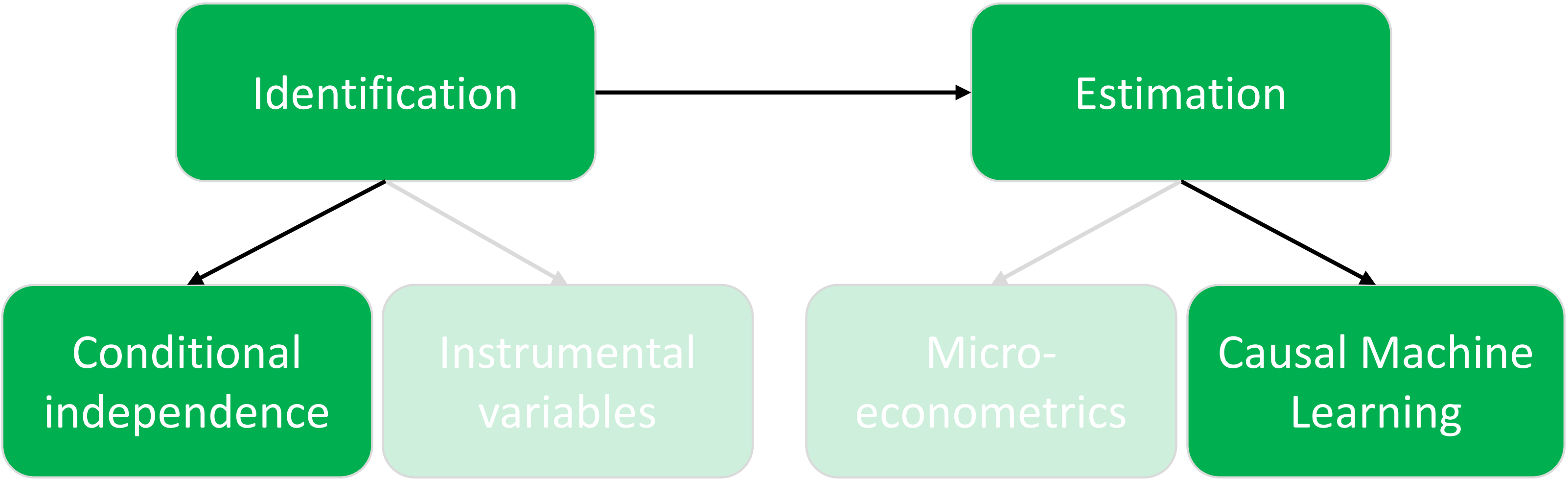
Chapter 2: For better or worse? - The Effects of Physical Education on Child Development

- Identification: *Instrumental variable*
  - Exploit variation in PE requirements across federal states
- Estimation: Semi-parametric IV using Inverse Probability Tilting
- Results:

Outcome group	**All**	**Boys**	**Girls**
Cognitive skills	+	+	+
Non-cognitive skills	-	-	+
Motor skills	+	∘	+
Physical activity	∘	∘	+
Health	∘	∘	∘

Chapter 3: Heterogeneous Employment Effects of Job Search Programmes: A Machine Learning Approach

with Michael Lechner and Tony Strittmatter



Chapter 3: Heterogeneous Employment Effects of Job Search Programmes: A Machine Learning Approach

- Motivation: Estimate *conditional average treatment effects* (CATEs) of job search programmes

- Research questions:
  - Do "*causal machine learning*" methods provide *useful* tools to uncover *heterogeneous causal effects* in policy evaluations?
  - Did *Swiss* job search programmes have *differential effects* for different groups of unemployed?

- Data: Administrative data of Swiss unemployed and caseworkers

Chapter 3: Heterogeneous Employment Effects of Job Search Programmes: A Machine Learning Approach

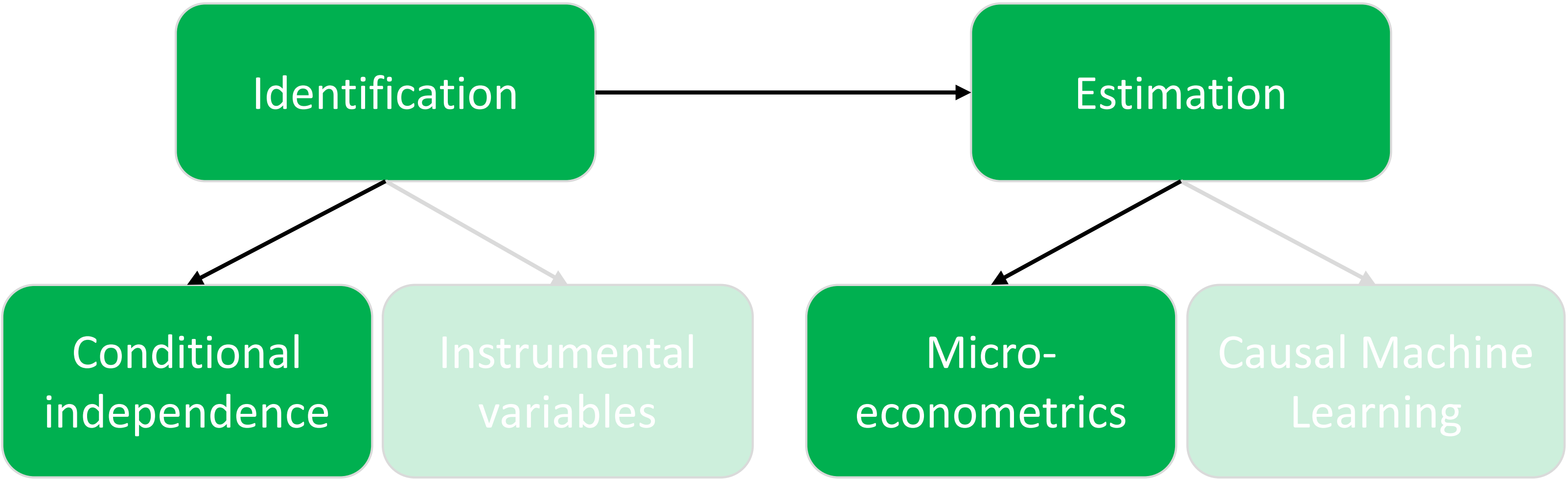
- Identification: *Conditional independence assumption*
    - Detailed unemployed and caseworker characteristics

- Estimation: *Modified Covariate Method* (Tian et al., 2014) and several alternatives

- Results:
    - On average *substantial lock-in effects* of the programme
    - Substantial *heterogeneity detected* behind standard average effects
    - *Assignment mechanisms fail* to identify individuals with *gains*

Chapter 4: Work Hour Mismatch and Job Mobility: Adjustment Channels and Resolution Rates

with Steffen Otterbach



Chapter 4: Work Hour Mismatch and Job Mobility: Adjustment Channels and Resolution Rates

- Motivation:
  - Existing literature interprets *increased work hour flexibility* of *job movers* as *evidence* for *free hour choice* across jobs
  - Suggests that job movers can resolve work hour mismatches

- Contribution:
  - Comprehensive analysis including actual resolution of work hour mismatch in the analysis

- Data: *German Socio-Economic Panel* providing rare measure of desired work hours in numbers

Chapter 4: Work Hour Mismatch and Job Mobility: Adjustment Channels and Resolution Rates

- Identification: *Conditional independence assumption*
  - Detailed socio-demographic, job-related, and regional information

- Estimation: *Propensity score matching* with bias adjustment

- Results:
  - *Confirm previous finding* of larger adjustments in actual work hours
  - Job mobility *only moderately increases* the probability to *resolve* work hour *mismatches*

Concluding remarks

- *Machine learning* adds *new interesting options* to the causal analysis toolbox
- However, it does *not solve* the fundamental *identification* problem that counterfactuals are unobserved
- Still, ML can be used to create hypothetical counterfactuals

Concluding remarks

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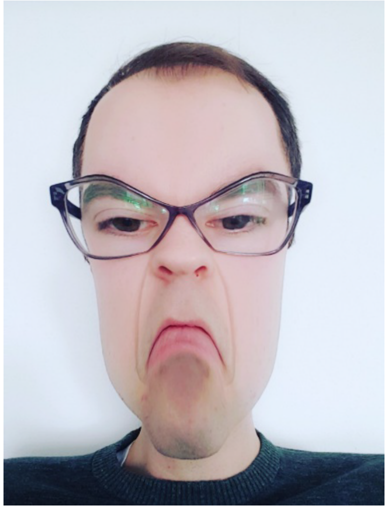

Thank you for your attention!