From Average Effects to Targeted Assignment: A Causal Machine Learning Analysis of Swiss Active Labor Market Policies

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Objectives

- Evaluate heterogeneous treatment effects of Swiss Active Labor Market Programs and provide program recommendations
- **Contributions**:
  - Recent data: Extended evaluation period
  - Advanced methods:
    - Uncover effect heterogeneity (Causal Machine Learning)
    - Policy recommendations (Policy Learning)

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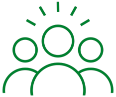

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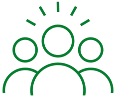

Get assigned to active labor market policy

If insufficient search efforts: get sanctioned

Active Labor Market Policies (ALMPs)

- **Basic course (BC)**: Orientation and job search skills
- **Training course (TC)**: Language, IT, or vocational training
- **Employment Program (EP)**: Unpaid work in non-regular jobs
- **Temporary Wage Subsidy (WS)**: Incentives for low-wage employment

- **No Program (NP)**

Data

- Administrative records (2004 - 2018)
- Individuals unemployed between 01/2014 and 06/2015
    - Unemployment rate in CH: 4.8%
- **Samples**:
    - **PERM**: Swiss and long-term migrants (113,329)
    - **TEMP**: Recent migrants (34,229)

Data

Outcomes:

- Employment status, earnings over 36 months (monthly and several aggregates)

Covariates:

- Employment and earnings history over 10 years,
- Socio-demographic characteristics,
- Job/unemployment data,
- Regional labor market characteristics

Parameters of Interest

ATE Population-level average treatment effect

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BGATE	Group-level average treatment effect, balanced on observed characteristics

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IATE	Individual-level average treatment effect
Policy	Assignments maximizing expected outcomes

Identification

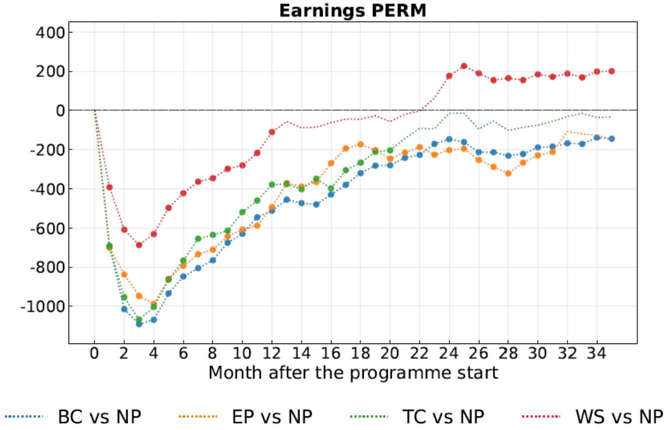
- **Conditional independence assumption**:
  - Control for most of the information caseworkers observe at the point of the assignment
  - Condition on key confounders identified in the literature
  - Placebo analysis: no evidence for violations
- **Common support assumption**: exclude observations outside support
- **Stable unit treatment value assumption**: no-spillover effects
- **Exogeneity of covariates**: only pre-treatment covariates

Estimation - Effects

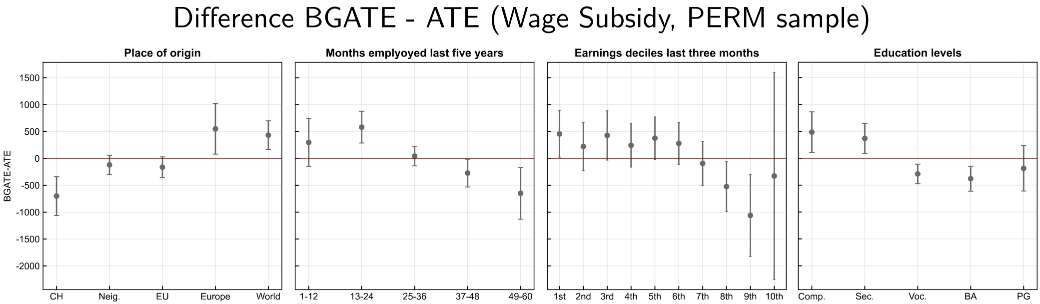
Modified Causal Forest (MCF) (Lechner, 2018; Lechner and Mareckova, 2022)

- Non-parametric estimator
- Extension of CF (Wager and Athey, 2018) using a splitting rule accounting for heterogeneity and selection
- Harmonized weighted estimation and inference procedure

Average Treatment Effects



BGATE

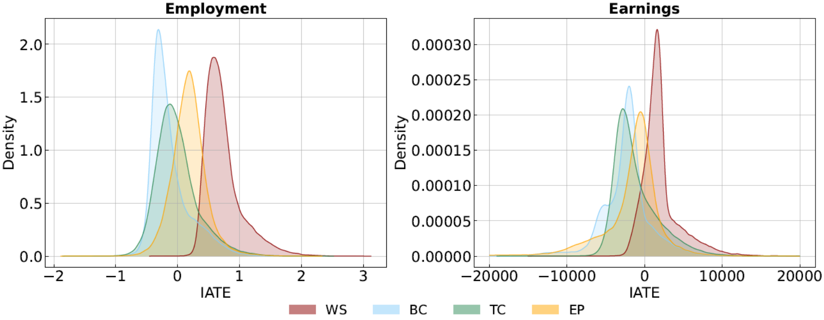

Difference BGATE - ATE (Wage Subsidy, PERM sample)
Place of origin
Months emplyoyed last five years
Earnings deciles last three months
Education levels
BGATE-ATE
1500
1000
500
0
-500
-1000
-1500
-2000
CH
Neig.
EU
Europe
World
1-12
13-24
25-36
37-48
49-60
1st
2nd
3rd
4th
5th
6th
7th
8th
9th
10th
Comp.
Sec.
Voc.
BA
PG

Group Heterogeneity Insights

- BGATE - ATE

Program	**Gender**	**Education**	**Empl.**	**Earnings**	**Nationality**
Wage Subsidy		Low (+)	Short (+)	Low (+)	CH (–), non-EU (+)
Basic Course		Low (+)	Short (+)	Low (+)	CH (–), non-EU (+)
Employment Program	F (+)			Low (+)	CH (–), non-EU (+)
Training Course					CH (–), non-EU (+)

Individualized Average Treatment Effects



PERM sample. Average standard error of IATES for the first (second) plot is 0.15 (1,523) for WS, 0.19 (1,701) for BC, 0.27 (2,281) for TC and 0.28 (2,565) for EP.

- Input for: Policy Trees or Clustering

Cluster Analysis

Unsupervised machine learning method that partitions data into distinct clusters (Arthur and Vassilvitskii, 2007)

Clusters with high IATEs (by program):

Program	Age	Gender	Education	Earnings	Nationality
Wage Subsidy	Older			Higher	Non-Swiss
Basic Course	Young	Female	Low	Lower	Non-Swiss
Employment Program	Young	Female	Low	Lower	Non-Swiss
Training Course	Young		High		Non-Swiss

Estimation - Optimal Policy

Policy Trees (Bodory, Mascolo and Lechner, 2024)

- Decision tree (based on Zhou, Athey and Wager (2023))
- Exhaustive search
- Optimal tree of a given depth maximizing average welfare by assigning all observations in one final leaf to one specific treatment

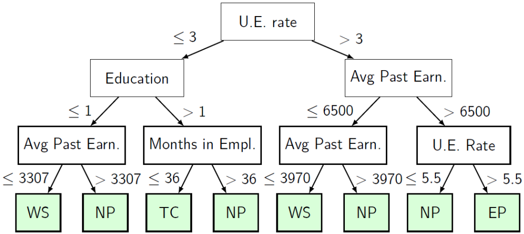


Figure: Depth-3 Policy Tree

Policy Tree Simulations

ALMP Allocation by Scenario (Employment Months)

Policy	Months	NP	WS	BC	TC	EP
Observed	9.04	43%	26%	19%	7%	5%
Depth-3	9.07	67%	23%	0%	5%	5%
Depth-4	9.06	65%	22%	2%	7%	4%
Depth-4+3	9.09	64%	21%	2%	8%	5%
2x WS	9.24	49%	51%	0%	0%	0%
3x WS	9.39	23%	75%	0%	0%	2%

Conclusions

- **Findings**:
  - Swiss and long-term migrants: Mixed results, Wage Subsidy effective
  - Recent migrants: Positive across all programs
- **Heterogeneity**:
  - Non-EU individuals gain more
  - Driven by background and job history
- **Policy**:
  - Expand Wage Subsidy
  - Use trees to optimize across all programs

Paper - QR Code

References I

- Arthur, D., & Vassilvitskii, S. (2006). **k-means++: The advantages of careful seeding**. Stanford.
- Bodory, H., Mascolo, F., & Lechner, M. (2024). **Enabling Decision Making with the Modified Causal Forest: Policy Trees for Treatment Assignment**. Algorithms, 17(7), 318.
- Lechner, M. (2018). **Modified causal forests for estimating heterogeneous causal effects.** arXiv preprint arXiv:1812.09487.
- Lechner, M., & Mareckova, J. (2022). **Modified causal forest**. arXiv preprint arXiv:2209.03744.

References II

- Wager, S., & Athey, S. (2018). **Estimation and inference of heterogeneous treatment effects using random forests**. Journal of the American Statistical Association, 113(523), 1228-1242.
- Zhou, Z., Athey, S., & Wager, S. (2023). **Offline multi-action policy learning: Generalization and optimization**. Operations Research, 71(1), 148-183.