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

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IAAE 2025 - Torino

June 26, 2025

Objectives

- Evaluate heterogeneous treatment effects of Swiss Active Labor Market Programs and provide program recommendations using causal machine learning
- **Contributions**:
  - Recent data: Extended evaluation period
  - Advanced methods:
    - Uncover effect heterogeneity
    - Policy recommendations

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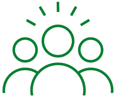

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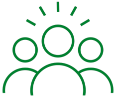

Get assigned to active labor market policy

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

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Optimal Policy	Assignments maximizing expected outcomes

Identification

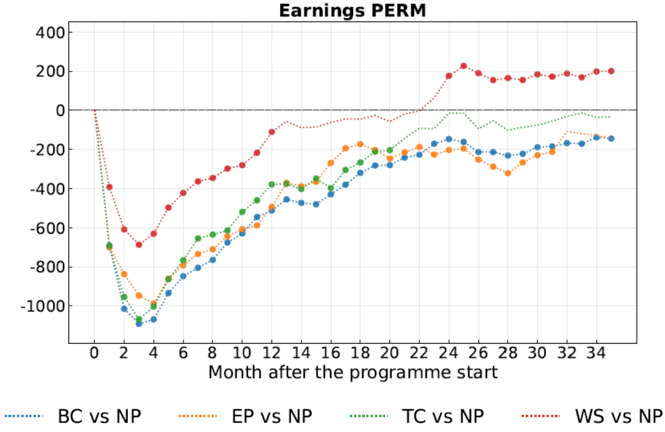
- **Conditional independence assumption**:
  - Control for most of the information caseworkers observe at the point of the assignment
  - Condition on key confounders identified in the literature
  - Placebo analysis: no evidence for violations
- **Common support assumption**: exclude observations outside 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)

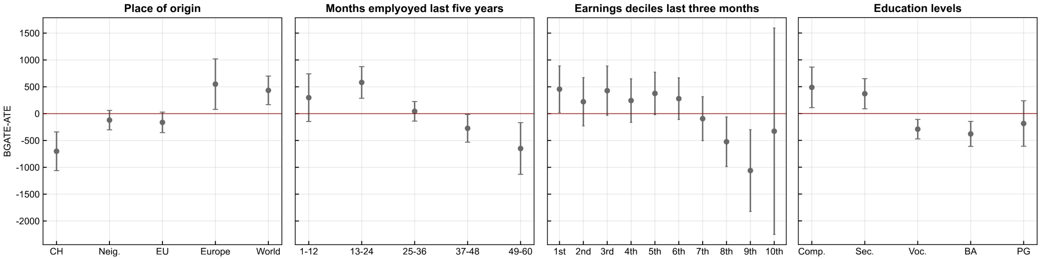
- Non-parametric estimator
- Extension of CF (Wager and Athey, 2018) using a splitting rule accounting for heterogeneity and selection
- Harmonized weighted estimation and inference procedure

Average Treatment Effects



BGATE

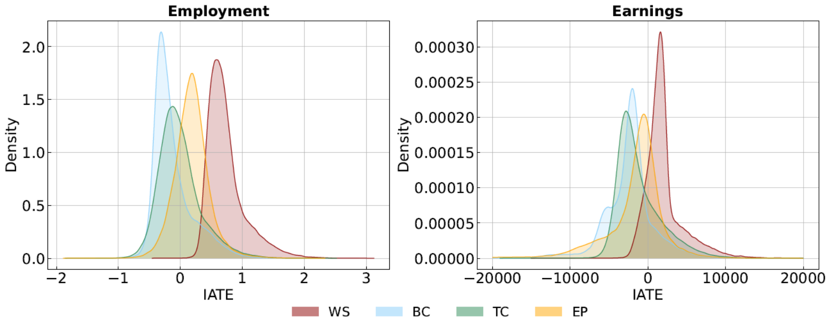
Difference BGATE - ATE (Wage Subsidy, PERM sample)



Group Heterogeneity Insights

- Main drivers: education, place of origin, labor history
- **Basic Course**: Stronger for earnings deciles
- **Training Course**: No significant heterogeneity
- **Employment Program**: Less harmful for women

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)

Table: IATEs with respect to non-participation and descriptive statistics for groups that benefit the least and most from each programme

Programme	**WS**	**BC**	**TC**	**EP**
	Permanent Residents			
Mean IATE of least and most benefiting groups	-3,252 – 9,685	-9,930 – -255	-5,047 – 5,881	-17,360 – 368
Selected covariates	Values for the last and most benefiting groups by programme			
	Least – Most	Least – Most	Least – Most	Least – Most
Age	37 – 47	51 – 38	49 – 38	50 – 36
Female	0.22 – 0.47	0.22 – 0.55	0.30 – 0.36	0.13 – 0.64
Education (1: compulsory – 5: post-grad.)	3.36 – 4.31	3.34 – 1.99	2.22 – 4.19	3.85 – 2.23
Local language knowledge (1: basic – 7: mother tongue)	6.64 – 5.87	6.60 – 5.34	5.90 – 6.07	6.57 – 5.43
Citizenship Swiss	0.83 – 0.51	0.90 – 0.48	0.70 – 0.54	0.80 – 0.47
Months in employment 10 years before	105 – 104	113 – 78	109 – 96	113 – 80
Cumulative earnings 10 years before	690,963 – 1,631,465	1,304,895 – 290,765	813,079 – 1,084,605	1,821,614 – 279,768
% of obs. in cluster	2 – 2	2 – 16	6 – 2	1 – 18

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

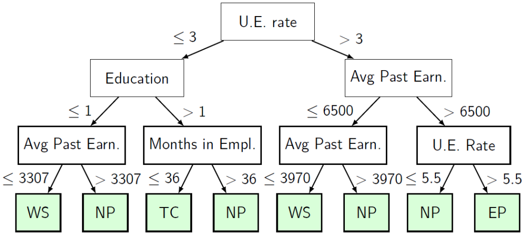


Figure: Depth-3 Policy Tree

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

THE QR CODE GENERATOR

References I

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- 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.