Locking in or Pushing out: The Caseworker Dilemma

Lukáš Laffërs*, Miroslav Štefánik**

*Matej Bel University
**Slovak Academy of Sciences

(supported by VEGA 1/0398/23 and APVV-21-0360)

June 21, 2023

In a nutshell

- Active Labor Market Programs (ALMP) for young people in Slovakia
- sequences of treatments
- lots of information $\rightarrow$ Double-machine-learning (DML) framework
- less employable client vs more employable client

Motivation

- young unemployment - significant issue with far-reaching implications
- ALMPs potentially important tools to tackle this problem
- more resources allocated to ALMPs recently
- expensive - how much do they work
- we have a lot of information about job-seekers. How can we use it?

Contribution

- we document the impact of ALMPs in Central and Eastern Europe (CEE), which is underexplored
- while using a wealth of information thanks to DML estimator
- we consider different comparison scenarios for the caseworkers
- we confirm many of the different findings related to ALMPs from previous literature

Literature

- Early career unemployment appears to have a scarring effect (De Fraja et al., 2021, Schmillen and Umkehrer, 2017)
- European Union (EU)- wide Youth Guarantee (YG) initiative (Escudero and Lopez, 2017).
- Evidence ambiguous (Caliendo and Schmidl (2016); Eichhorst and Rinne (2018); Kluve et al. (2019)).

Programs (ALMPs)

Delivered through 46 PES offices.

Employment incentives - 75% of labour costs for up to 12 months, followed by up to 6 months of mandatory employment, dominantly in the private sector.

Graduate practice - less expensive ALMP programme, paying pocket money (subsistence minimum) for 20 hours weekly spend at the workplace, dominantly in clerical jobs in the public sector. ”cream-skimming”

Training - a wide supply of short-term trainings (covered 100% percent). Vocational training is merged with soft-skills training. Comparing internationally, less used in Slovakia.

Public works - Covering direct-job creation in the public sector either through the community services organised by the municipalities or comparable programmes. ”last-resort programme”

Programs

- Role of caseworker is crucial for selection/veto the ALMP
- Selection also driven by budget/availability/regional characteristics

Setup

Y - employment status after 3 years (absence in Public Employment Services register)

D_1 - treatment in the first period

D_2 - treatment in the second period

X_0 - set of covariates measure before period 1

X_1 - set of covariates measure before period 2

$Y(d_1, d_2)$ - potential outcome for a sequence of treatments

$E[Y(d_1, d_2)] - E[Y(d_1^*, d_2^*)]$ - ATE

$E[Y(d_1, d_2)|S = 1] - E[Y(d_1^*, d_2^*)|S = 1]$ - ATE for $S = 1$

e.g. $S = I\{D \in \{d_1, d_1^*\}\}$

Treatments

(0) Not participating in any program
(1) Employed or exited the register for another reason
(2) Employment incentives
(3) Graduate practice
(4) Training
(5) Public works

$Y(d_1, d_2)$

$Y(4, 2)$ - counterfactual employment for a person who went through training followed by employment incentives programme

Identification - based on Bodory et al. (2022)

Assumption A1

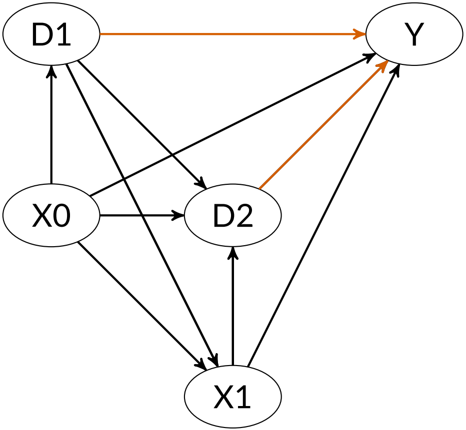
$$Y(d_1, d_2) \perp\!\!\!\perp D_1 | X_0$$

Assumption A2

$$Y(d_1, d_2) \perp\!\!\!\perp D_2 | D_1, X_0, X_1 .$$

Assumption A3

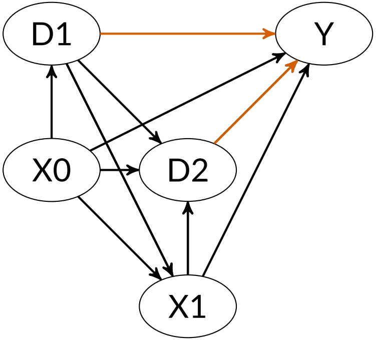
$$P(D_1 = d_1 | X_0) > 0,$$
$$P(D_2 = d_2 | D_1, X_0, X_1) > 0$$



DML and dynamic ATE - Bodory et al. (2022)

Moment function:

$$\begin{aligned}
\psi(W;\theta_0,\eta) &= \frac{I\{D_1=d_1\}\cdot I\{D_2=d_2\}\cdot[Y-\mu^Y(d_1,d_2,X_0,X_1)]}{p^{d_1}(X_0)\cdot p^{d_2}(d_1,X_0,X_1)} \\
&+ \frac{I\{D_1=d_1\}\cdot[\mu^Y(d_1,d_2,X_0,X_1)-\nu^Y(d_1,d_2,X_0)]}{p^{d_1}(X_0)} \\
&+ \nu^Y(d_1,d_2,X_0)-\theta_0. \\
E\Big[\psi(W;\theta_0,\eta)\Big] &= E\Big[Y(d_1,d_2)\Big]-\theta_0=0
\end{aligned}$$



Data: $W=(Y,D_1,D_2,X_0,X_1)$

Nuisance functions: $\eta=(p^{d_1},p^{d_2},\mu^Y,\nu^Y)$

- $p^{d_1}(X_0)\equiv \Pr(D_1=d_1|X_0)$
- $p^{d_2}(D_1,X_0,X_1)\equiv \Pr(D_2=d_2|D_1,X_0,X_1)$
- $\mu^Y(D_1,D_2,X_0,X_1)\equiv E[Y|D_1,D_2,X_0,X_1]$
- $\nu^Y(D_1,D_2,X_0)\equiv E_{X_1}[E[Y|D_1,D_2,X_0,X_1]|D_1,X_0]$.

DML (Chernozhukov et al. 2018) allows to make use of the rich set of information we have.

It can automatically select among many covariates and avoid both regularization bias (via Neyman-orthogonal score) and overfitting bias (via cross-fitting) and provide root-n consistent and asymptotically normal estimator.

We used random-forest based estimators for nuisance functions.

Data

- admin. data provided by the Slovak PES - Central Office for Labour Social Affairs and Family of the Slovak Republic
- unemployed JSs during 2016,
- 15 – 29 years old
- unemployed > 3months, < 3years
- late participation clients (> 12months) and those with multiple unempl. spells dropped
- 57,716 PES clients of which 49,854 (86%) no program
- 36 combinations of sequences - for 18 of which had enough data

Variables X_0 (239vars)

- **employment history**, info on previous jobs (NACE2/ISCO2, commute, part-time, self-reported working experience, previous income, employability (by caseworker)
- **socio-economic vars**: age, gender, marital status, kids, nationality, education
- **competences**: foreign languages, driving license, computer skills,
- **preferences**: willingness to relocate, move abroad, start a business
- **regional vars**: region, distance to PES office/region capital/capital city, local unempl rate, share of minorities, share of segregated groups, average wage in the region
- **health**: disability, self-accessed health

Variables X_1 (10vars)

- participation in consulting programmes
- social assistance benefit application
- registered employment 4,5,6 months after registration into the database of unemployment

6 monts
6 months
2 years
Registration into the database of unemployment
0
Unemployed - NO ALMP
1
Employed or exited register for another reason
2
Employment incentives
3
Graduate practice
4
Training
5
Public works
Another programmes
1
Employed or exited register for another reason
0
Unemployed - NO ALMP
3
Graduate practice
4
Training
2
Employment incentives
5
Public works
Another programmes
1
Employed
0
Unemployed

Caseworker dilemma

Caseworker may **lock-in** an easily employable client into a too intensive or lengthy ALMP program or **push him/her out** of the register.

Caseworker may choose different counterfactual scenarios. Who should we compare the job-seeker to??

Less employable client
12 months of unemployment

$$Y(0,0)$$

More employable client
6 months of unemployment,
followed by an exit in months 7-12

$$Y(0,1)$$

Results: Less employable client

Treatment sequences		Results					Observations	
Treated	Control	y0	Effect	SE	p-value	sig.	N	Trimmed
0-1	0-0	0.84	**0.06**	0.01	0.00	***	27,320	87
0-2	0-0	0.83	**0.03**	0.01	0.00	***	27,320	4,155
0-3	0-0	0.84	0.02	0.02	0.35		27,320	20,151
0-4	0-0	0.83	**0.04**	0.02	0.06	.	27,320	10,976
0-5	0-0	0.79	-0.05	0.06	0.40		27,320	25,208
1-1	0-0	0.84	**0.07**	0.01	0.00	***	51,863	21,223
2-0	0-0	0.84	**0.12**	0.03	0.00	***	28,501	21,971
2-1	0-0	0.84	**0.13**	0.01	0.00	***	28,501	13,200
3-0	0-0	0.86	**0.08**	0.01	0.00	***	33,025	20,011
3-1	0-0	0.86	**0.10**	0.01	0.00	***	33,025	15,582
3-2	0-0	0.86	**0.06**	0.01	0.00	***	33,025	22,989
4-0	0-0	0.84	**0.06**	0.02	0.00	***	29,607	17,899
4-1	0-0	0.85	**0.11**	0.01	0.00	***	29,607	7,239
4-2	0-0	0.83	**0.13**	0.02	0.00	***	29,607	24,782
4-4	0-0	0.84	**0.14**	0.01	0.00	***	29,607	28,124
5-0	0-0	0.80	0.06	0.05	0.21		28,165	22,889
5-1	0-0	0.82	**0.08**	0.01	0.00	***	28,165	15,725
5-2	0-0	0.80	**0.07**	0.02	0.00	***	28,165	26,794

Results: Less employable client

Treatment sequences		Results					Observations	
Treated	Control	y0	Effect	SE	p-value	sig.	N	Trimmed
0-1	0-0	0.84	**0.06**	0.01	[illegible]	[illegible]	[illegible]	87
0-2	0-0	0.83	**0.03**	0.01	[illegible]	[illegible]	[illegible]	4,155
0-3	0-0	0.84	0.02	0.02	[illegible]	[illegible]	[illegible]	20,151
0-4	0-0	0.83	**0.04**	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
0-5	0-0	0.79	-0.05	[illegible]	[illegible]	[illegible]	[illegible]	25,208
1-1	0-0	0.84	**0.07**	0	[illegible]	[illegible]	[illegible]	21,223
2-0	0-0	0.84	**0.12**	[illegible]	[illegible]	[illegible]	[illegible]	21,971
2-1	0-0	0.84	**0.13**	0.01	[illegible]	[illegible]	[illegible]	13,200
3-0	0-0	0.86	**0.08**	0.01	0.00	***	33,025	20,011
3-1	0-0	0.86	**0.10**	0.01	0.00	***	33,025	15,582
3-2	0-0	0.86	**0.06**	0.01	0.00	***	33,025	22,989
4-0	0-0	0.84	**0.06**	0.02	0.00	***	29,607	17,899
4-1	0-0	0.85	**0.11**	0.01	0.00	***	29,607	7,239
4-2	0-0	0.83	**0.13**	0.02	0.00	***	29,607	24,782
4-4	0-0	0.84	**0.14**	0.01	0.00	***	29,607	28,124
5-0	0-0	0.80	0.06	0.05	0.21		28,165	22,889
5-1	0-0	0.82	**0.08**	0.01	0.00	***	28,165	15,725
5-2	0-0	0.80	**0.07**	0.02	0.00	***	28,165	26,794

earlier is better

Results: Less employable client

Treatment sequences		Results					Observations	
Treated	Control	y0	Effect	SE	p-value	sig.	N	Trimmed
0-1	0-0	0.84	**0.06**	0.01	0.00	***	27,320	87
0-2	0-0	0.83	**0.03**	0.01	0.00	***	27,320	4,155
0-3	0-0	0.84	0.02	0.02	0.35		27,320	20,151
0-4	0-0	0.83	**0.04**	0.02	[illegible]	.	27,320	10,976
0-5	0-0	0.79	-0.05	0.06	[illegible]	[illegible]	[illegible]	[illegible]
1-1	0-0	0.84	**0.07**	0.01	[illegible]	[illegible]	[illegible]	[illegible]
2-0	0-0	0.84	**0.12**	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
2-1	0-0	0.84	**0.13**	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
3-0	0-0	0.86	**0.08**	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
3-1	0-0	0.86	**0.10**	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
3-2	0-0	0.86	**0.06**	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
4-0	0-0	0.84	**0.06**	0.02	[illegible]	[illegible]	[illegible]	17,899
4-1	0-0	0.85	**0.11**	0.01	0.00	***	29,607	7,239
4-2	0-0	0.83	**0.13**	0.02	0.00	***	29,607	24,782
4-4	0-0	0.84	**0.14**	0.01	0.00	***	29,607	28,124
5-0	0-0	0.80	0.06	0.05	0.21		28,165	22,889
5-1	0-0	0.82	**0.08**	0.01	0.00	***	28,165	15,725
5-2	0-0	0.80	**0.07**	0.02	0.00	***	28,165	26,794

Public works worse than other treatments

Results: Less employable client

Treatment sequences		Results					Observations	
Treated	Control	y0	Effect	SE	p-value	sig.	N	Trimmed
0-1	0-0	0.84	**0.06**	0.01	0.00	***	27,320	87
0-2	0-0	0.83	**0.03**	0.01	0.00	***	27,320	4,155
0-3	0-0	0.84	0.02	0.02	0.35		27,320	20,151
0-4	0-0	0.83	**0.04**	0.02	0.06	.	27,320	10,976
0-5	0-0	0.79	-0.05	0.06	0.40		27,320	25,208
1-1	0-0	0.84	**0.07**	0.01	0.00	***	51,863	21,223
2-0	0-0	0.84	**0.12**	0.03	0.00	***	28,501	21,971
2-1	0-0	0.84	**0.13**	0.01	0.00	***	28,501	13,200
3-0	0-0	0.86	**0.08**	0.01	0.00	***	33,025	20,011
3-1	0-0	0.86	**0.10**	0.01	0.00	***	33,025	15,582
3-2	0-0	0.86	**0.06**	0.01	[illegible]	[illegible]	[illegible]	[illegible]
4-0	0-0	0.84	**0.06**	0.02	[illegible]	[illegible]	[illegible]	[illegible]
4-1	0-0	0.85	**0.11**	0.01	[illegible]	[illegible]	[illegible]	[illegible]
4-2	0-0	0.83	**0.13**	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
4-4	0-0	0.84	**0.14**	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
5-0	0-0	0.80	0.06	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
5-1	0-0	0.82	**0.08**	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
5-2	0-0	0.80	**0.07**	0.02	[illegible]	[illegible]	[illegible]	26,794

Combinations of treatments are better

Results: Less employable client

Treatment sequences		Results					Observations	
Treated	Control	y0	Effect	SE	p-value	sig.	N	Trimmed
0-1	0-0	0.84	**0.06**	0.01	0.00	***	27,320	87
0-2	0-0	0.83	**0.03**	0.01	0.00	***	27,320	4,155
0-3	0-0	0.84	0.02	0.02	0.35		27,320	20,151
0-4	0-0	0.83	**0.04**	0.02	[illegible]	[illegible]	[illegible]	10,976
0-5	0-0	0.79	-0.05	0.06	[illegible]	[illegible]	[illegible]	[illegible]
1-1	0-0	0.84	**0.07**	0.01	[illegible]	[illegible]	[illegible]	[illegible]
2-0	0-0	0.84	**0.12**	0.03	[illegible]	[illegible]	[illegible]	[illegible]
2-1	0-0	0.84	**0.13**	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
3-0	0-0	0.86	**0.08**	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
3-1	0-0	0.86	**0.10**	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
3-2	0-0	0.86	**0.06**	0.01	[illegible]	[illegible]	[illegible]	[illegible]
4-0	0-0	0.84	**0.06**	0.02	[illegible]	[illegible]	[illegible]	[illegible]
4-1	0-0	0.85	**0.11**	0.01	0.00	***	29,607	7,239
4-2	0-0	0.83	**0.13**	0.02	0.00	***	29,607	24,782
4-4	0-0	0.84	**0.14**	0.01	0.00	***	29,607	28,124
5-0	0-0	0.80	0.06	0.05	0.21		28,165	22,889
5-1	0-0	0.82	**0.08**	0.01	0.00	***	28,165	15,725
5-2	0-0	0.80	**0.07**	0.02	0.00	***	28,165	26,794

Shortening unemployment works

Results: Less employable client

Treatment sequences		Results					Observations	
Treated	Control	y0	Effect	SE	p-value	sig.	N	Trimmed
0-1	0-0	0.84	0.06	0.01	0.00	***	27,320	87
0-2	0-0	0.83	0.03	0.01	0.00	***	27,320	4,155
0-3	0-0	0.84	0.02	0.02	0.35		27,320	20,151
0-4	0-0	0.83	0.04	0.02	0.06	.	27,320	10,976
0-5	0-0	0.79	-0.05	0.06	0.40		27,320	25,208
1-1	0-0	0.84	**0.07**	0.01	0.00	***	[illegible]	21,223
2-0	0-0	0.84	**0.12**	0.03	[illegible]	[illegible]	[illegible]	[illegible]
2-1	0-0	0.84	**0.13**	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
3-0	0-0	0.86	**0.08**	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
3-1	0-0	0.86	**0.10**	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
3-2	0-0	0.86	**0.06**	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
4-0	0-0	0.84	**0.06**	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
4-1	0-0	0.85	**0.11**	0.01	[illegible]	[illegible]	[illegible]	[illegible]
4-2	0-0	0.83	**0.13**	0.02	0.00	***	29,607	24,782
4-4	0-0	0.84	**0.14**	0.01	0.00	***	29,607	28,124
5-0	0-0	0.80	0.06	0.05	0.21		28,165	22,889
5-1	0-0	0.82	**0.08**	0.01	0.00	***	28,165	15,725
5-2	0-0	0.80	**0.07**	0.02	0.00	***	28,165	26,794

Shortening alone better than other treatments.

Results: Less employable client

Treatment sequences		Results					Observations	
Treated	Control	y0	Effect	SE	p-value	sig.	N	Trimmed
0-1	0-0	0.84	**0.06**	0.01	0.00	***	27,320	87
0-2	0-0	0.83	**0.03**	0.01	0.00	***	27,320	4,155
0-3	0-0	0.84	0.02	0.02	0.35		27,320	20,151
0-4	0-0	0.83	**0.04**	0.02	0.06	.	27,320	10,976
0-5	0-0	0.79	-0.05	0.06	0.40		27,320	25,208
1-1	0-0	0.84	**0.07**	0.01	0.00	***	51,863	21,223
2-0	0-0	0.84	**0.12**	0.03	0.00	***	28,501	21,971
2-1	0-0	0.84	**0.13**	0.01	0.00	***	28,501	13,200
3-0	0-0	0.86	**0.08**	0.01	0.00	***	33,025	20,011
3-1	0-0	0.86	**0.10**	0.01	0.00	***	33,025	15,582
3-2	0-0	0.86	**0.06**	0.01	[illegible]	[illegible]	[illegible]	[illegible]
4-0	0-0	0.84	**0.06**	0.02	[illegible]	[illegible]	[illegible]	[illegible]
4-1	0-0	0.85	**0.11**	0.01	[illegible]	[illegible]	[illegible]	[illegible]
4-2	0-0	0.83	**0.13**	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
4-4	0-0	0.84	**0.14**	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
5-0	0-0	0.80	0.06	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
5-1	0-0	0.82	**0.08**	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
5-2	0-0	0.80	**0.07**	0.02	[illegible]	**	[illegible]	26,794

Combinations of treatments are better than shortening

Results: More employable client

Treatment sequences		Results					Observations	
Treated	Control	y0	Effect	SE	p	sig.	N	Trimmed
0-0	0-1	0.90	**-0.06**	0.01	0.00	***	27,320	87
0-2	0-1	0.90	**-0.03**	0.01	0.00	***	27,320	4,096
0-3	0-1	0.92	**-0.05**	0.02	0.00	***	27,320	20,136
0-4	0-1	0.90	**-0.03**	0.02	0.10	.	27,320	10,944
0-5	0-1	0.87	**-0.13**	0.05	0.02	*	27,320	25,208
1-1	0-1	0.91	**0.01**	0.00	0.00	***	51,863	538
2-0	0-1	0.90	**0.07**	0.03	0.02	*	28,501	22,040
2-1	0-1	0.91	**0.06**	0.00	0.00	***	28,501	13,260
3-0	0-1	0.92	**0.02**	0.01	0.00	***	33,025	20,173
3-1	0-1	0.93	**0.04**	0.00	0.00	***	33,025	15,736
3-2	0-1	0.93	0.00	0.01	0.90		33,025	23,149
4-0	0-1	0.90	0.00	0.02	0.86		29,607	18,056
4-1	0-1	0.92	**0.04**	0.01	0.00	***	29,607	7,362
4-2	0-1	0.92	**0.04**	0.01	0.00	***	29,607	24,841
4-4	0-1	0.92	**0.06**	0.01	0.00	***	29,607	28,229
5-0	0-1	0.85	0.00	0.05	0.95		28,165	23,004
5-1	0-1	0.89	0.01	0.01	0.23		28,165	15,834
5-2	0-1	0.89	-0.02	0.02	0.30		28,165	26,895

Results: More employable client

Treatment sequences		Results					Observations	
Treated	Control	y0	Effect	SE	p	sig.	N	Trimmed
0-0	0-1	0.90	-0.06	0.01	0.00	***	27,320	87
0-2	0-1	0.90	-0.03	0.01	0.00	***	27,320	4,096
0-3	0-1	0.92	-0.05	0.02	0.00	***	27,320	20,136
0-4	0-1	0.90	-0.03	0.02	0.10	.	27,320	10,944
0-5	0-1	0.87	-0.13	0.05	0.02	*	[illegible]	25,208
1-1	0-1	0.91	**0.01**	0.00	0.00	[illegible]	[illegible]	538
2-0	0-1	0.90	**0.07**	0.03	0.02	[illegible]	[illegible]	22,040
2-1	0-1	0.91	**0.06**	0.00	[illegible]	[illegible]	[illegible]	[illegible]
3-0	0-1	0.92	**0.02**	0.01	[illegible]	[illegible]	[illegible]	[illegible]
3-1	0-1	0.93	**0.04**	0.00	[illegible]	[illegible]	[illegible]	[illegible]
3-2	0-1	0.93	0.00	0.01	[illegible]	[illegible]	[illegible]	[illegible]
4-0	0-1	0.90	0.00	0.02	[illegible]	[illegible]	[illegible]	[illegible]
4-1	0-1	0.92	**0.04**	0.01	[illegible]	[illegible]	[illegible]	[illegible]
4-2	0-1	0.92	**0.04**	0.01	[illegible]	[illegible]	[illegible]	[illegible]
4-4	0-1	0.92	**0.06**	0.01	[illegible]	[illegible]	[illegible]	[illegible]
5-0	0-1	0.85	0.00	0.05	0.95		[illegible]	[illegible]
5-1	0-1	0.89	0.01	0.01	0.23		28,165	15,834
5-2	0-1	0.89	-0.02	0.02	0.30		28,165	26,895

treat early

or don't

Findings (1)

- The impact of ALMPs is **higher** if the intervention takes place earlier in the unemployment period (Martin and Grubb, 2005)
- Workplace experience collected under Public-works types of programs has a **smaller** impact than does that collected in the private sector or regular employment (Caliendo and Schmidl, 2016)
- Combinations of interventions appear to **increase** the impact of some program types (Kluve et al., 2019)

Findings (2)

- The shortening of the unemployment period is associated with a **positive impact** on the long-term probability of employment.
- The shortening of the unemployment period, by itself, without any ALMP participation, **outperforms** ALMP support provided later in the unemployment period.
- Sequences of at least two short-term TRs **outperform** the shortening of the unemployment period in terms of impact on the long-term employment.

Heterogeneity analysis

- gender
- educational level
- share of Roma population
- size of settlement

- main conclusions hold
- sequences of trainings have **greatest impact** on less educated and on residents in municipalities with high share of Roma population

Conclusions

Double machine learning appears to be attractive approach for ALMP evaluation.

Slovak data confirms what has been known in the literature.

We suggest different comparison units for the caseworkers.

Thank you for your attention.

www.lukaslaffers.com

Literature

- Chernozhukov, Victor, Denis Chetverikov, Mert Demirer, Esther Duflo, Christian Hansen, Whitney Newey, and James Robins. "Double/debiased machine learning for treatment and structural parameters." (2018): C1-C68.
- Knaus, M. C. (2022). Double machine learning-based programme evaluation under unconfoundedness. The Econometrics Journal, 25(3), 602-627.
- Bodory, Hugo, Martin Huber, and Lukáš Lafférs. "Evaluating (weighted) dynamic treatment effects by double machine learning." The Econometrics Journal 25.3 (2022): 628-648.
- Martin, J.P., Grubb, D., 2005. What Works and for Whom: A Review of OECD Countries' Experiences with Active Labour Market Policies. SSRN Electronic Journal URL: https://papers.ssrn.com/abstract=348621, doi:10.2139/SSRN.348621.
- Knaus, M.C., Lechner, M., Strittmatter, A., 2022. Heterogeneous employ- ment effects of job search programs. Journal of Human Resources 57, 597–636.
- Caliendo, M., Schmidl, R., 2016. Youth unemployment and active labor market policies in europe. IZA Journal of Labor Policy 5, 1.
- De Fraja, G., Lemos, S., Rockey, J., 2021. The wounds that do not heal: The lifetime scar of youth unemployment. Economica 88, 896–941.
- Schmillen, A., Umkehrer, M., 2017. The scars of youth: Effects of early- career unemployment on future unemployment experience. International Labour Review 156, 465–494.
- Escudero, V., Lopez, M., 2017. The european youth guarantee a systematic review of its implementation across countries. ILO Working Papers 21.
- Eichhorst, W., Rinne, U., 2018. Promoting youth employment in europe: Evidence-based policy lessons, in: European Youth Labour Markets. Springer, pp. 189–204.
- Kluve, J., Puerto, S., Robalino, D., Romero, J.M., Rother, F., Stoterau, J., Weidenkaff, F., Witte, M., 2019. Do youth employment programs improve labor market outcomes? A quantitative review. World Development 114, 237–253.