Bureaucrats' Beliefs and Disparities in Service Provision

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Disparities in Bureaucratic Service Provision

- What is the source of service disparities?
  - Differences in eligibility or discrimination?
- What is the source of discrimination?
  - Preferences ("tastes", Becker 1957) or beliefs about uncertain eligibility?

Inaccurate/Biased Beliefs

- Identification problem (Manski 2004; Bohren et al. 2023)
- Policy problem

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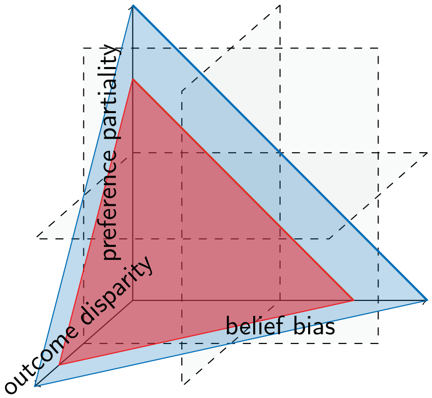
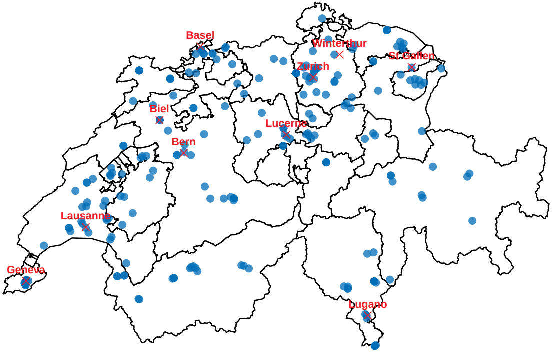


UI Provision in Switzerland



Registration ⟶ First Meeting ⟶ Consultation

Assessment of Employability ⟶ *Decision(s)*

- **Employability**
  (legal directive)
  - "probability of finding a new job in case of job loss"
  - "ensure that claimants with the same prerequisites are treated equally"
  - "ensure the efficient allocation of resources"

  (performance metric, 90%)
  - days on benefits (50%)
  - long-term unempl. (20%)
  - expiry of benefits (20%)

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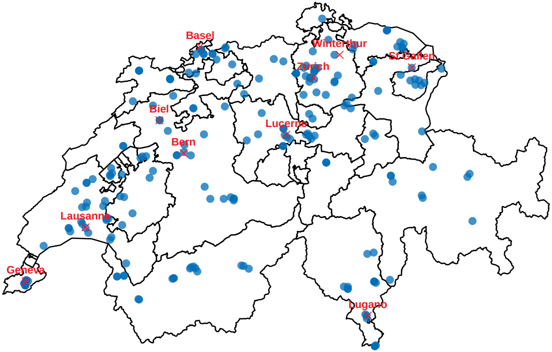

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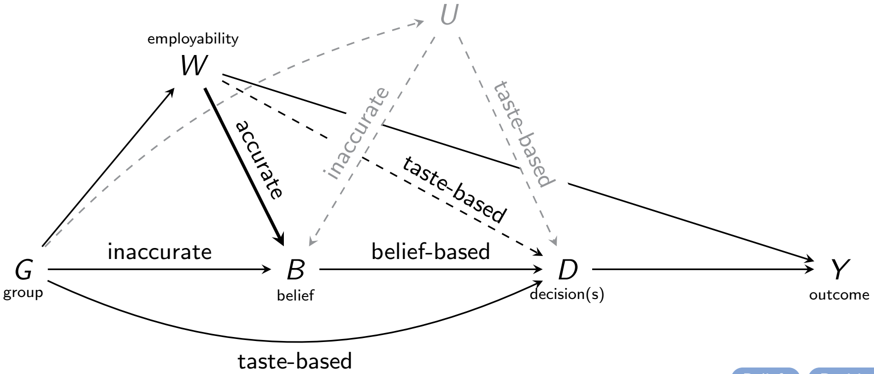
Data

	CH	WE	EE	MENA	SSA
Employability Beliefs	2.069	2.049	2.216	2.285	2.244
Age	34.695	35.679	33.775	33.116	33.859
Female	0.506	0.401	0.442	0.326	0.369
Married	0.583	0.437	0.196	0.224	0.260
Primary Education	0.107	0.370	0.530	0.523	0.508
Secondary Education	0.673	0.435	0.346	0.300	0.296
Tertiary Education	0.173	0.121	0.045	0.054	0.092
Manager	0.049	0.039	0.010	0.016	0.006
Professional	0.271	0.175	0.066	0.070	0.082
Worker	0.500	0.471	0.412	0.382	0.348
Laborer	0.129	0.296	0.498	0.510	0.536
Primary Sector	0.004	0.013	0.006	0.002	0.005
Secondary Sector	0.186	0.236	0.296	0.201	0.151
Tertiary Sector	0.804	0.743	0.693	0.793	0.840
Mobility	2.132	2.134	2.026	2.025	2.049
Insured Income	4432.536	4533.945	3749.069	3442.667	3050.758
Allowance	389.089	400.167	384.439	370.010	352.821
Replacement Rate	76.368	76.752	78.324	78.428	79.042
Program Participation	0.27	0.28	0.38	0.43	0.45
UE Duration	315.362	314.377	406.912	470.029	499.606
Caseworker	2970	2965	2944	2736	2173
N	471086	165441	89593	32447	13324

Identification



Beliefs Decisions

Unwarranted/Unjustified Belief Disparity:

e.g. Arnold et al. 2022

$$\Delta_B = E[B|G=1, W=w] - E[B|G=0, W=w]$$

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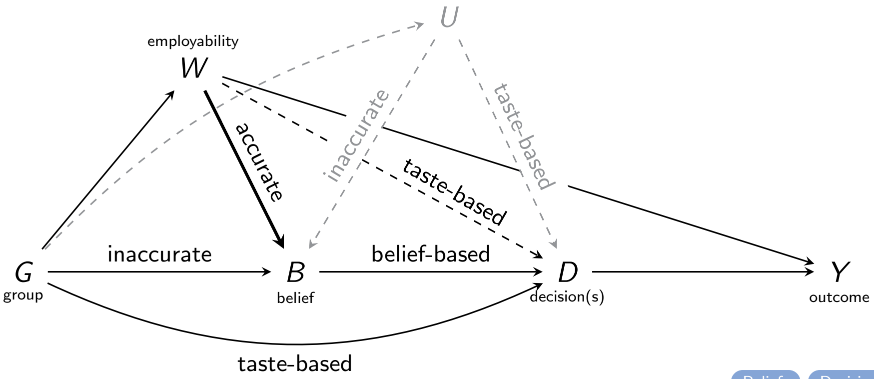

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Estimating W

1. **Proxy-based:** $W \approx X^{Researcher}$ ("all else equal")
2. **Outcome-based:**
   1. $W = Y$: sharp-null for $D \rightarrow Y$ holds
   2. $Pr(D = d|X)$
      a) Quasi-Experimental Variation in D (e.g. Arnold et al. 2018; 2022)
      b) Debiased Machine Learning (Chernozhukov et al. 2018 for (C)ATE; used e.g. in Knaus 2022; Knaus et al. 2021; 2022; Mascolo et al. 2024)

$$\hat{w}(x) = \hat{y}_{d=0}(x) = E\left[\underbrace{\hat{y}(d=0,x) + \frac{D_j(d=0)(Y_j - \hat{y}(d=0,x))}{\hat{e}_{d=0}(x)}}_{AIPW} \,\middle|\, X_j = x\right]$$

- Unconfoundedness, Weak Overlap ($\hat{e}_{d=0}$), Consistency, SUTVA
- How to estimate $\hat{e}_{d=0}(x)$ to account for preferences?
  - Categorical boosting (Dorogush et al. 2018) CatBoost

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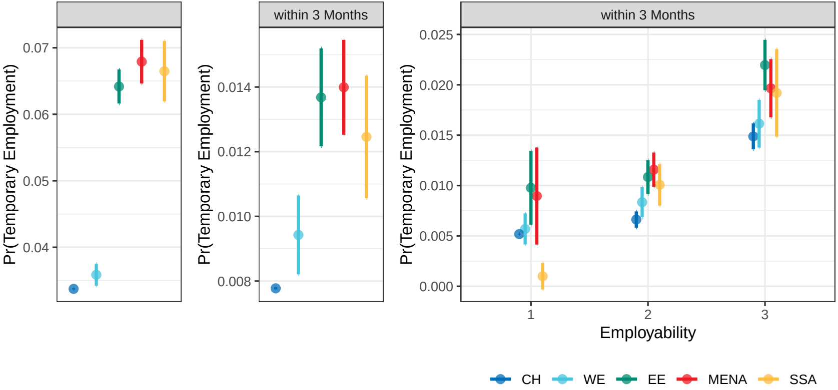
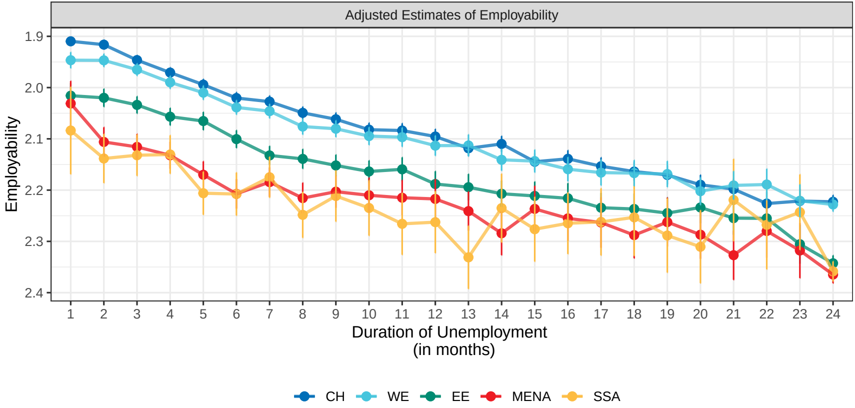
Relevance: Workfare



Adjusted estimates with caseworker, month, and year fixed effects.

Biased Beliefs



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Biased Beliefs

	Employability: Pr(Low)			
Switzerland (CH)	0.161***			
	(0.0006)			
Western Europe (WE)	-0.014***	0.012***	0.009***	-0.028***
	(0.001)	(0.001)	(0.001)	(0.004)
Eastern Europe (EE)	0.107***	0.103***	0.073***	0.017***
	(0.001)	(0.003)	(0.002)	(0.004)
Middle East and North Africa (MENA)	0.161***	0.158***	0.116***	0.054***
	(0.002)	(0.004)	(0.003)	(0.004)
Sub-Saharan Africa (SSA)	0.130***	0.151***	0.109***	0.040***
	(0.003)	(0.005)	(0.005)	(0.006)
UE Duration			✓	
Controls				✓
Caseworker ID		✓	✓	✓
Month / Year		✓	✓	✓
R^2	0.01628	0.20602	0.24685	0.26298
Within R^2		0.01688	0.00904	0.00238
N	771,891	771,891	771,891	766,812

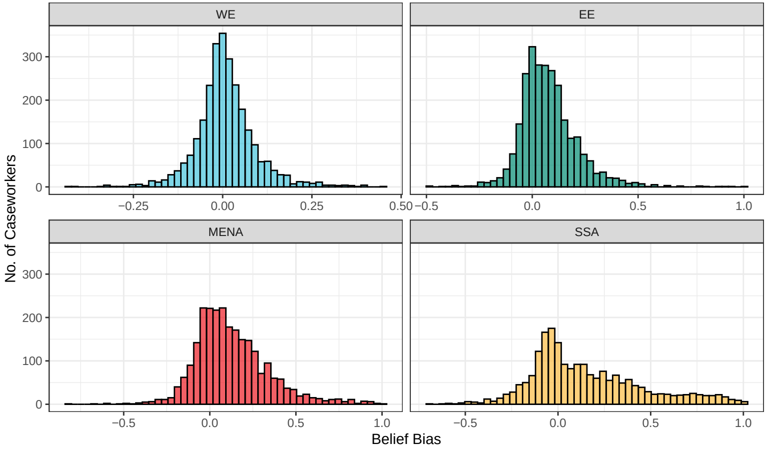
Controls: Age (in 10 years), allowance, civil status, gender, education (SECO code), insured income (in 1000 CHF), language skills (English, French, German, Italian), mobility, occupation (ISCO-3), replacement rate, residence permit, sector (NOGA-2).

Biased Beliefs

	Employability: Pr(Low)			
Western Europe (WE)	0.009***	0.009***	0.006***	0.008***
	(0.001)	(0.001)	(0.001)	(0.001)
Eastern Europe (EE)	0.059***	0.061***	0.043***	0.052***
	(0.003)	(0.002)	(0.002)	(0.002)
Middle East and North Africa (MENA)	0.111***	0.114***	0.091***	0.103***
	(0.004)	(0.002)	(0.002)	(0.002)
Sub-Saharan Africa (SSA)	0.111***	0.114***	0.087***	0.101***
	(0.006)	(0.004)	(0.004)	(0.004)
log(UE Duration)		0.055***		
		(0.003)		
log(UE Duration), debiased				0.120***
				(0.010)
UE Duration	✓			
UE Duration, debiased			✓	
Caseworker ID	✓	✓	✓	✓
Month / Year	✓	✓	✓	✓
R^2	0.23899	0.23636	0.23343	0.23004
Within R^2	0.00754	0.03248	0.00423	0.02447
N	570,946	570,946	570,946	570,946

Debiased ML

Outlook: Caseworker-Specific Belief Bias



Thank You

Categorical Boosting

- How to estimate $\hat{y}(d=0,x)$, $\hat{e}_{d=0}(x)$, and $\hat{w}(x)$?
  - One-hot encoding
  - Target encoding
  - Ordered target encoding

$$c^*_{\sigma_p} = \frac{\sum_{i=1}^{p-1}[c_{\sigma_i} = c_{\sigma_p}]\mathrm{Y}_{\sigma_i} + \alpha \cdot \mathrm{P}}{\sum_{i=1}^{p-1}[c_{\sigma_i} = c_{\sigma_p}] + \alpha}$$

c: categorical feature (and interaction)

Y: target (either unemployment duration or the propensity score)

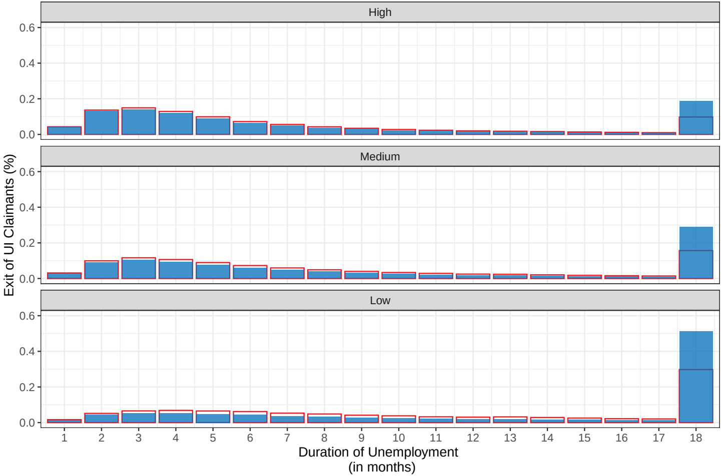
P: prior for the target (the global mean of the target)

α: regularization parameter

σ: random permutation of the dataset

Go back

Employability Beliefs



Go back

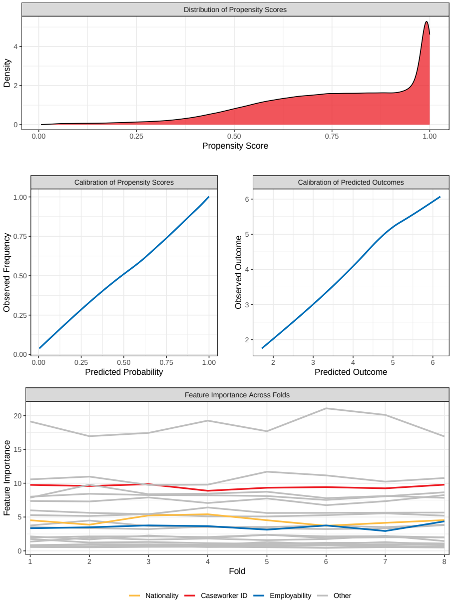
Contamination

	CH	WE	EE	MENA	SSA
No Program	343845 (73%)	119523 (72%)	55673 (62%)	18546 (57%)	7271 (55%)
Job Search Assist.	59334 (13%)	18615 (11%)	15889 (18%)	5448 (17%)	1811 (14%)
Temp. Employment	15464 (3%)	6377 (4%)	5771 (6%)	2172 (7%)	885 (7%)
Training	19280 (4%)	5580 (3%)	2861 (3%)	1376 (4%)	830 (6%)
Language Course	10456 (2%)	7973 (5%)	6014 (7%)	3386 (10%)	1549 (12%)
Personality Course	16360 (3%)	5748 (3%)	2892 (3%)	1319 (4%)	850 (6%)
Subsidy	2778 (1%)	915 (1%)	253 (0%)	92 (0%)	39 (0%)
Internship	3569 (1%)	710 (0%)	240 (0%)	108 (0%)	89 (1%)
N	471086	165441	89593	32447	13324

Program Participation

Go back

Debiased Machine Learning: Results



- Outcome
  - censored
  - log-transformed
- Hyperparameters
  - 8-fold cross-fitting
  - 4 random permutations
  - tree depth: 7
  - learning rate: 0.1
  - 1000 iterations

  - trade-off between granularity of categorical variables and influence of the target mean

Go back