Ho do Routine Tasks and Offshorability Influence Unemployment Duration and Subsequent Job Quality

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Motivation

- Increasing public concern about job instability, especially among those with 'ordinary' skills.
- Workers in middle-skill occupations are hardest hit during economic downturns (Jaimovich and Siu, 2014).
- Loss of routine jobs has been documented for numerous countries (e.g. Acemoglu and Autor, 2011; Dustmann et al., 2009; Goos et al., 2009).
- Task requirements in previous employment might affect job search.
- Active labor market policy can be used to ameliorate problems of routine workers.

This Research

- Investigates the effect of previous job content on the individual transition rates from unemployment to employment.
- Studies, if previous task inputs have an effect on future match quality of unemployed workers.
- Takes explicitly labor market policies and unobserved heterogeneity into account.
- Assesses if unemployment training can mitigate the effect of a changing working environment.

Findings

- Routine job content reduces the transition rate into employment.
- Routine job content reduces significantly the probability of being employed in better or equal paying jobs.
- Routine job content is positively related with receiving unemployment training.
- Training has positive effect on hazard into jobs and can also ameliorate some of the disadvantages

Data - Unemployment Sample

- (ASSD data): Administrative data from Social Security and Employment Office, covering the universe of Austrian workers and containing daily labor market status.
- Unemployment duration observed up to 2 years and information about training measures.
- All unemployment entries during 2000-2004 from male and female workers between 20 and 60 years:
  - Excluding spells from tourism, construction and public services.
  - Excluding individuals with highly irregular U-E patterns (no. of unemployment spells $\geq$ 15).
- Random draw of 70,000 individuals from this pool.

Data - Job Content

- We calculate routine task index following Autor and Dorn (2013)
- Offshorability according to Blinder and Krueger (2013)
- Can be linked via ISCO code to Austrian unemployment sample.

Routine-Index

- Define three task groups:

  routine cognitive/manual, non-routine manual, abstract.

- Definition of groups follows closely Spitz-Oener (2006).

- Calculate the index for occupation *o* as:

$$RTI_o = ln\left(\frac{TI^{Routine}}{TI^{Abstract} + TI^{NR\ Manual}}\right)$$

- Index is increasing in the relative importance of routine tasks.

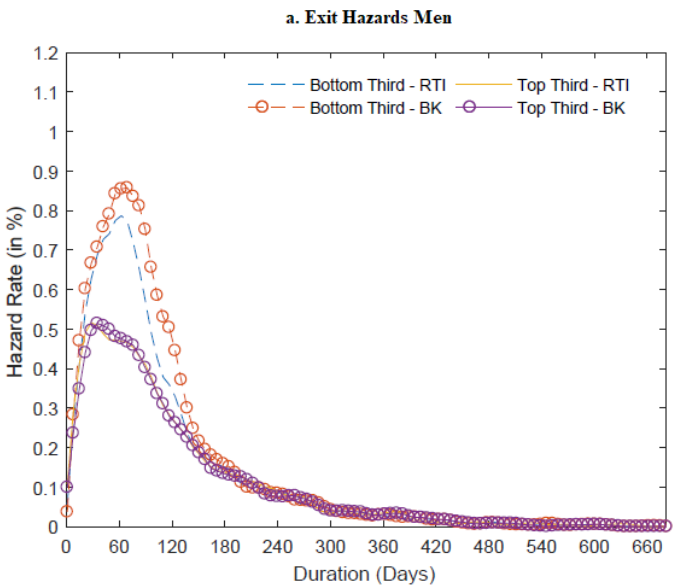
- Analysis is based on 240 occupations (ISCO-88, 4-digit level) and index is based on 25 tasks.

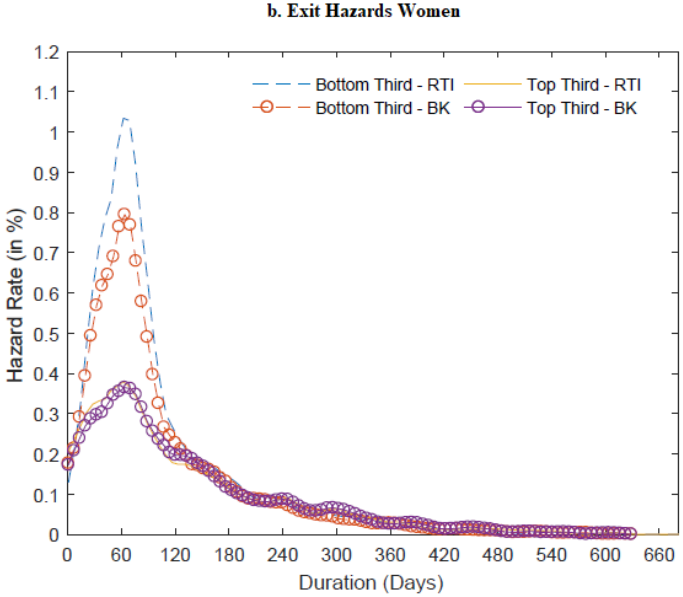
Routine-Index: Tasks

Tasks
Non-Routine Cognitive & Interactive Analyzing, Planning, Programming , Buying, Advertising, Teaching, Using and Interpreting Law/ Prescriptions, Instructing & Supervising, Care-Taking, Entertaining, Organizing
Non-Routine Manual Gardening& Breeding, Repairing, Building & Installing, Restoring, Driving, Guarding, Cleaning & Disposing, Accommodating
Routine Cognitive Paper Work, Calculating, Book Keeping
Routine Manual Equipping Machines, Handling Machines, Producing

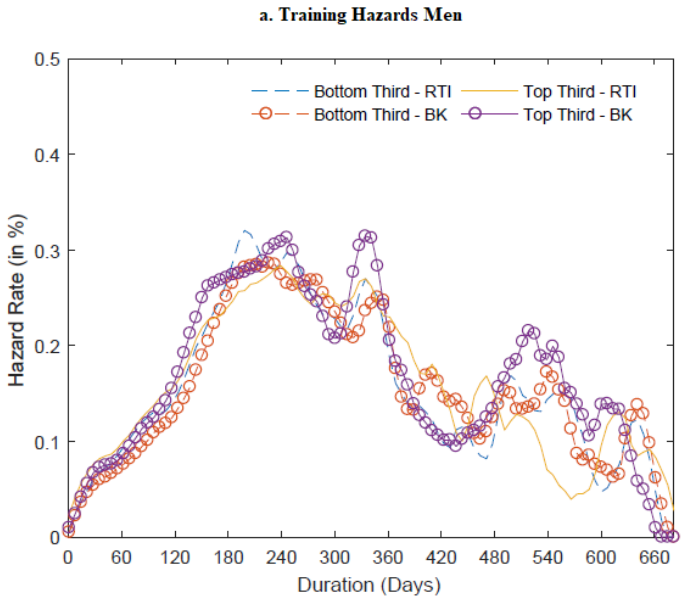
	Men	Women
Individuals & Spells		
Individuals	35,000	35,000
No. of Spells	1.95	2.08
Outflow & Training		
Outflow	86.80%	85.71%
to New Job	61.37%	53.82%
to Out of Labor Force	27.27%	33.57%
Training Received	14.83%	20.22%
Pers. Characteristics		
Age	43.18	42.83
Non-Austrian	18.37%	17.04%
at most Com. Schooling	17.74%	29.41%
Apprenticeship/ High-School	62.77%	51.84%
Matura/ University	19.49%	18.75%
Children	44.85%	63.34%
Married	40.79%	45.26%
Divorce	10.97%	15.76%
Others	48.24%	38.98%
Last Employment		
Tenure in Last Job (Days)	375.64	394.11
Daily Wage in Last Job (Euros)	76.74	49.83
Access to Extended Benefits	50.40%	41.79%
Inflow Year		
Year 2012	55.79	52.03
Year 2013	44.21	47.97

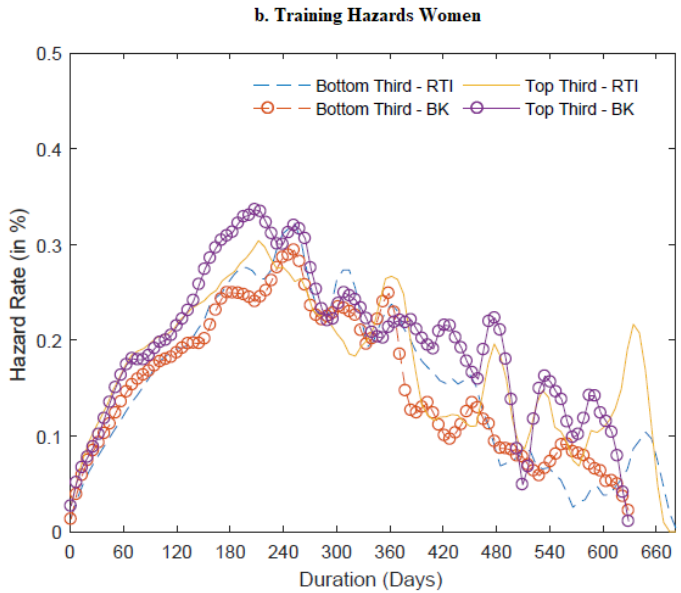
Empirical Transition Rates– Exit





Empirical Transition Rates– Training





Econometric Method

- Training may compensate for problems of routine workers, but is not strictly exogenous.
- We jointly model selection into training and unemployment duration using the 'Timing-of-Events' Approach (Abbring and van den Berg, 2003)
- Identification: no-anticipation condition
  - Exact beginning of training cannot be anticipated by job-searchers
- Approach is popular in the policy evaluation literature (van den Berg et al, 2004; Abbring et al., 2005; Richardson and van den Berg, 2013).

Econometric Method

- We assume that the exit and treatment transition rates have a multivariate-proportional hazard form.
- The exit rates are modeled as

$$\theta_{E_s}(T|x, \nu_{E_s}, D) = \lambda_{E_s}(T)exp(x'\beta_{E_s} + \gamma_{E_s}RTI + \delta_s(x)\mathbb{1}(T > D) + \nu_{E_s})$$

- The transition into training is modeled as

$$\theta_P(D|x, \nu_P) = \lambda_P(D)exp(x'\beta_P + \gamma_P RTI + \nu_P)$$

- We allow $\delta_s(x)$ to depend on covariates (Richardson and van den Berg, 2013): heterogeneity in training effect.
- We assume distribution of $\{\nu_{E_s}, \nu_P\}$ to be unknown and approximate it by means of a discrete distribution.

Likelihood Function

- We imposes that an individual has the same heterogeneity term across unemployment spells.
- The likelihood function is defined as

$$L = \sum_{i=1}^{N} \log \left\{ \sum_{m=1}^{M} p_m \prod_{j=1}^{J_i} \prod_{s=1}^{S} \theta_{E_s}(T_{ij}|x_{ij}, \nu_{E_s}^m, D_{ij})^{\Delta_{ij,E_s}} exp\left(- \int_0^{T_{ij}} \theta_{E_s}(T_{ij}|x_i, \nu_E^{m_s}, D_{ij}) \right) \right.$$
$$\left. \theta_P(D_{ij}|x_{ij}, \nu_P^m)^{\Delta_{ij,P}} exp\left(- \int_0^{D_{ij}} \theta_P(D_{ij}|x_{ij}, \nu_P^m) \right) \right\}$$

- Maximization procedure follows suggestions of Gaure et al. (2007).
- Model with the lowest Akaike-Information Criterion is chosen.

Model (I) Results for Homogeneous Treatment Effects

	Male			Female		
	Treatment hazard θ_{Training}	Employment hazard $\theta_{\text{Employment}}$	Out-of-Labor Force hazard $\theta_{\text{Out-of-Labor Force}}$	Treatment hazard θ_{Training}	Employment hazard $\theta_{\text{Employment}}$	Out-of-Labor Force hazard $\theta_{\text{Out-of-Labor Force}}$
Panel A: Occ. Requirements						
γ^{RTI}	0.041	−0.067	−0.017	0.191	−0.362	0.00
	(0.017,)	(0.009,)	(0.012,)	(0.017,)	(0.014,)	(0.012,)
γ^{OFF}	0.101	−0.245	0.039	0.084	−0.265	0.047
	(0.019,)	(0.012,)	(0.014,)	(0.017,)	(0.015,)	(0.012,)
$\gamma^{RTIxOFF}$	−0.065	0.133	−0.020	−0.088	0.223	−0.018
	(0.014,)	(0.008,)	(0.009,)	(0.011,)	(0.010,)	(0.008,)
Panel B: Training						
δ		0.415	0.321		0.888	0.281
		(0.038,)	(0.040,)		(0.040,)	(0.034,)
Unobs. Heterogeneity	Yes			Yes		
Control Variables	Yes			Yes		
Log-Likelihood	-35,386.29			-44,080.61		

Standard errors are reported in parentheses. Model contains control variables and unobserved heterogeneity with seven mass points. In total, 98 parameters were estimated

Can ALMP Reduce Disadvantage of Routine and Offshoring Workers?

- Estimated treatment effect not necessarily homogeneous.
- Employment officer may take previous job content into account when assigning training.
- Gains from training might be related to previous job content.
- We model the training effect as

  $\delta(x) = \delta + \psi_\delta RTI + \rho_\delta OFF$.

Model (II) Results for Heterogeneous Treatment Effects

	Male			Female		
	Treatment hazard θ_{Training}	Employment hazard $\theta_{\text{Employment}}$	Out-of-Labor Force hazard $\theta_{\text{Out-of-Labor Force}}$	Treatment hazard θ_{Training}	Employment hazard $\theta_{\text{Employment}}$	Out-of-Labor Force hazard $\theta_{\text{Out-of-Labor Force}}$
Paenl A: Occ. Requirements						
γ^{RTI}	0.045	−0.066	−0.017	0.192	−0.375	0.000
	(0.017,)	(0.009,)	(0.012,)	(0.018,)	(0.015,)	(0.012,9)
γ^{OFF}	0.100	−0.251	0.041	0.083	−0.273	0.043
	(0.019,)	(0.012,)	(0.014,)	(0.017,)	(0.015,)	(0.013,)
$\gamma^{RTIxOFF}$	−0.065	0.135	−0.021	−0.089	0.219	−0.0162
	(0.014,)	(0.008,)	(0.009,)	(0.012,)	(0.001,)	(0.008,)
Panel B: Training						
δ		0.425	0.312		0.871	0.282
		(0.038,)	(0.040,)		(0.040,)	(0.034,)
β_{δ}^{RTI}		−0.025	0.024		0.138	−0.018
		(0.028,)	(0.029,)		(0.027,)	(0.024,)
β_{δ}^{BK}		0.072	−0.028		0.078	0.023
		(0.029,)	(0.029,)		(0.027,4)	(0.023,)
Unobs. Heterogeneity	Yes			Yes		
Control Variables	Yes			Yes		
Log-Likelihood	-35,355.59			-43,986.88		

Standard errors are reported in parentheses. Model contains control variables and unobserved heterogeneity with a total of seven mass points. In total, 102 parameters were estimated.

Quality of the new job

- So far we have not taken re-employment quality into account.
- High-Routine worker who find a new job might be employed in worse matches than before.
- We calculate two variations
  - Duration of the new match after unempmloyment; simple addition to the hazard rate model
  - Wage of the new job (model of Donald et al. (2000): cumulative distribution function of wages can be modeled as a duration hazard

Model (III) Results including Post-Unemployment Job Duration

	Male				Female			
	Treatment hazard θ_{Training}	Employment hazard $\theta_{\text{Employment}}$	Out-of-Labor Force hazard $\theta_{\text{Out-of-Labor Force}}$	Duration New Job hazard $\theta_{\text{New Job}}$	Treatment hazard θ_{Training}	Employment hazard $\theta_{\text{Employment}}$	Out-of-Labor Force hazard $\theta_{\text{Out-of-Labor Force}}$	Duration New Job hazard $\theta_{\text{New Job}}$
Panel A: Occ. Requirements								
γ^{RTI}	0.043	−0.068	−0.016	0.032	0.167	−0.312	−0.013	−0.125
	(0.016,)	(0.009,)	(0.011,)	(0.011,)	(0.017,)	(0.014,)	(0.012,)	(0.014,)
γ^{OFF}	0.096	−0.252	0.040	−0.080	0.073	−0.224	0.035	−0.187
	(0.019,)	(0.012,)	(0.013,)	(0.014,)	(0.016,)	(0.014,)	(0.011,)	(0.015,)
$\gamma^{RTIxOFF}$	−0.061	0.135	−0.018	−0.004	−0.077	0.194	−0.009	0.098
	(0.013,)	(0.008,)	(0.009,)	(0.010,)	(0.011,)	(0.009,)	(0.008,)	(0.010,)
Panel B: Training								
δ		0.393	0.338	0.237		0.810	0.238	−0.065
		(0.037,)	(0.039,)	(0.047,)		(0.037,)	(0.033,)	(0.049,)
Unobs. Heterogeneity	Yes				Yes			
Control Variables	Yes				Yes			
Log-Likelihood	-49,302.96				-54,122.42			

Standard errors are reported in parentheses. Model contains control variables and unobserved heterogeneity with seven mass points. In total, 129 parameters were estimated.

Model (IV) Results including Post-Unemployment Wage

	Male				Female			
	Treatment hazard θ_{Training}	Employment hazard $\theta_{\text{Employment}}$	Out-of-Labor Force hazard $\theta_{\text{Out-of-Labor Force}}$	Wage θ_{ω}	Treatment hazard θ_{Training}	Employment hazard $\theta_{\text{Employment}}$	Out-of-Labor Force hazard $\theta_{\text{Out-of-Labor Force}}$	Wage θ_{ω}
Panel A: Occ. Requirements								
γ^{RTI}	0.043	−0.067	−0.015	0.040	0.175	−0.306	−0.014	0.024
	(0.016,)	(0.009,)	(0.011,)	(0.008,)	(0.017,)	(0.013,)	(0.012,)	(0.011,)
γ^{OFF}	0.098	−0.238	0.038	−0.095	0.071	−0.233	0.041	−0.098
	(0.019,)	(0.012,)	(0.013,)	(0.011,)	(0.016,)	(0.013,)	(0.012,)	(0.012,)
$\gamma^{RTIxOFF}$	−0.062	0.127	−0.019	0.093	−0.077	0.190	−0.011	0.034
	(0.013,)	(0.008,)	(0.009,)	(0.007,)	(0.011,)	(0.009,)	(0.008,)	(0.008,)
Panel B: Training								
δ		0.398	0.343	0.329		0.815	0.281	0.152
		(0.036,)	(0.040,)	(0.033,)		(0.037,)	(0.033,)	(0.036,)
Unobs. Heterogeneity	Yes				Yes			
Control Variables	Yes				Yes			
Log-Likelihood	-41,002.15				-57,053.38			

Standard errors are reported in parentheses. Model contains control variables and unobserved heterogeneity with seven mass points. In total, 129 parameters were estimated.

Conclusion

- High-Routine job content and risk of offshorability increase unemployment duration.
- ALMP in general is increasing the hazard out of unemployment and – in three of four cases – it can also reduce unemployment duration more for workers with routinisation or offshorability handicaps.
- Results on new job stability and wages a bit mixed.