

How much to offer?

Offered income and OJA attractiveness.

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OJA data processed

- Database of OJAs from a dominant OJA provider in Slovakia
 - 77% of the online job searches based on Google Trends
 - second most popular OJA provider (13%)
 - third most popular OJA provider is the public employment service (6,6%), based on Google trends
- The provider is general, not focusing on any segment of the labour market
- One-provider data comparable to OJA aggregators

Aggregated OJA data

- Aggregated (quarterly) number of newly published OJAs.
- A potential predictor of the main statistical labour market indicators:
 - the number of vacancies, employed and unemployed persons.
- Predictions of all observed periods (one to four quarters ahead) are significantly improved if OJA data are used in the autoregression equations
 - prediction error improvement is more observable in the later periods.

Štefánik, M., Lyócsa, Š., & Bilka, M. (2022). Using online job postings to predict key labour market indicators. *Social Science Computer Review*, 41(5), 1630-1649. <https://doi.org/10.1177/08944393221085705>

Individual OJA data

- Data include complete information published in 355 k OJAs (after cleaning) between March 2022 and March 2023
 - Coded and semi-coded:
 - Economic sector, region, occupation, skills, and additional information ...
 - Offered salary and non-financial benefits
 - Text information:
 - Job title, job description, job requirements, ...
- Measures of OJA attractiveness
 - Number of OJA views (during the first week)
 - Number of reactions to the OJA
 - *The reaction rate* =
$$\frac{\text{Number of reactions to the OJA}}{\text{Number of OJA views}}$$

Predicting OJA attractiveness – modelling strategy

Table 3. Forecasting errors: Predicting OJV attractiveness.

	Views	Reactions	Conversions
<i>Panel A: Mean square error</i>			
<i>Benchmarks</i>			
Unconditional historical mean	370.388	499.769	0.214
Business sector-specific mean	371.311	501.511	0.214
Job classification	318.946	457.153	0.184
<i>Competing models</i>			
OLS	285.097	433.753	0.174
LASSO	284.323	432.711	0.174
Ridge	284.550	433.363	0.174
Elastic net	284.217	432.769	0.174
Random forest	187.868 †	323.338 †	0.139 †

Predicting OJA attractiveness – predictor importance

- Occupation is the strongest predictor
 - Sensitive to the level of aggregation/clustering
- Text morphology (title length, length of job description, ...)
- Job-related benefits

- Occupation-specific predictors (esp. skills)
- Offered wage is important only in the case of some occupations

Offered wage and OJA attractiveness – Work in progress!

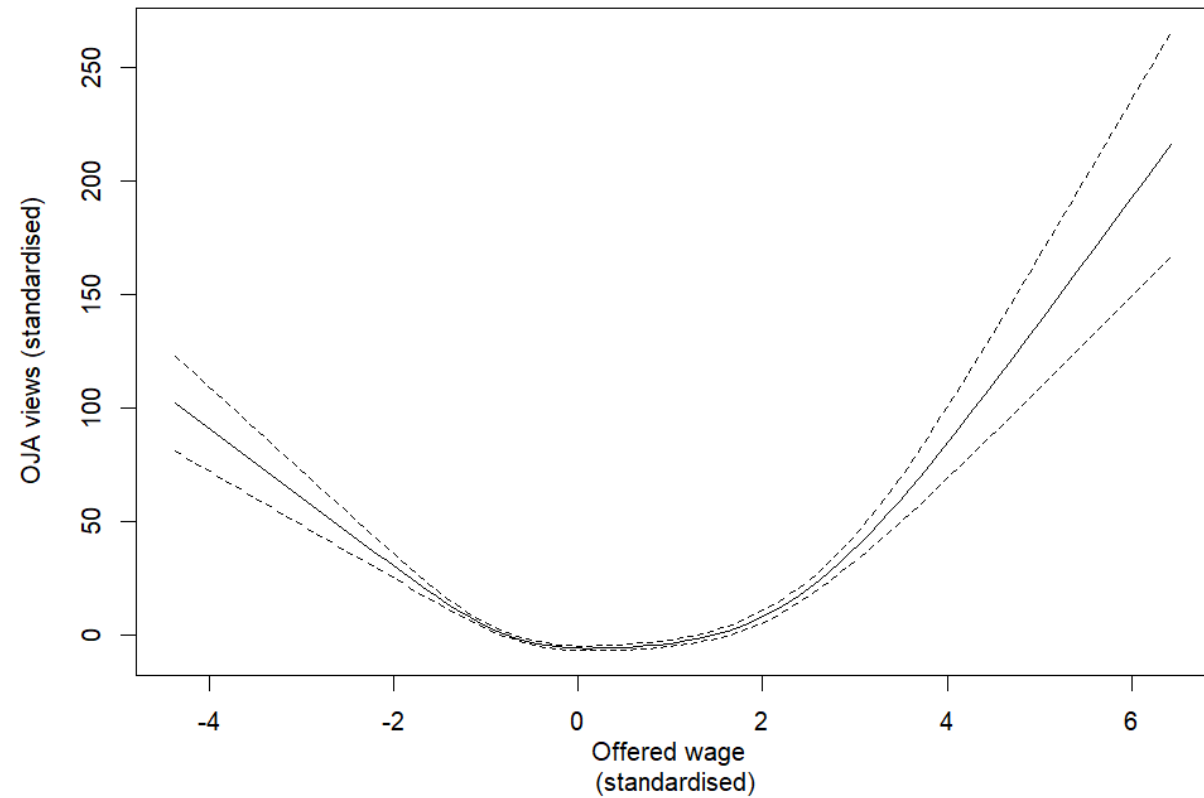
- **Classical search and matching model (Mortensen-Pissarides)** struggles to explain shorter vacancy duration in offers with higher wage (Mueller et al. 2023).
- **Theory of directed search:** higher wage attracts more applications (Moen, 1997).
- **Theories of random search:** higher rate results into a higher acceptance probability (Burdett and Mortensen, 1998).
- Our data allow us to add evidence to this discussion, by estimating the function of offered wage/OJA attractiveness:
 - the number of views during the first week
 - the reaction rate

Estimation strategy

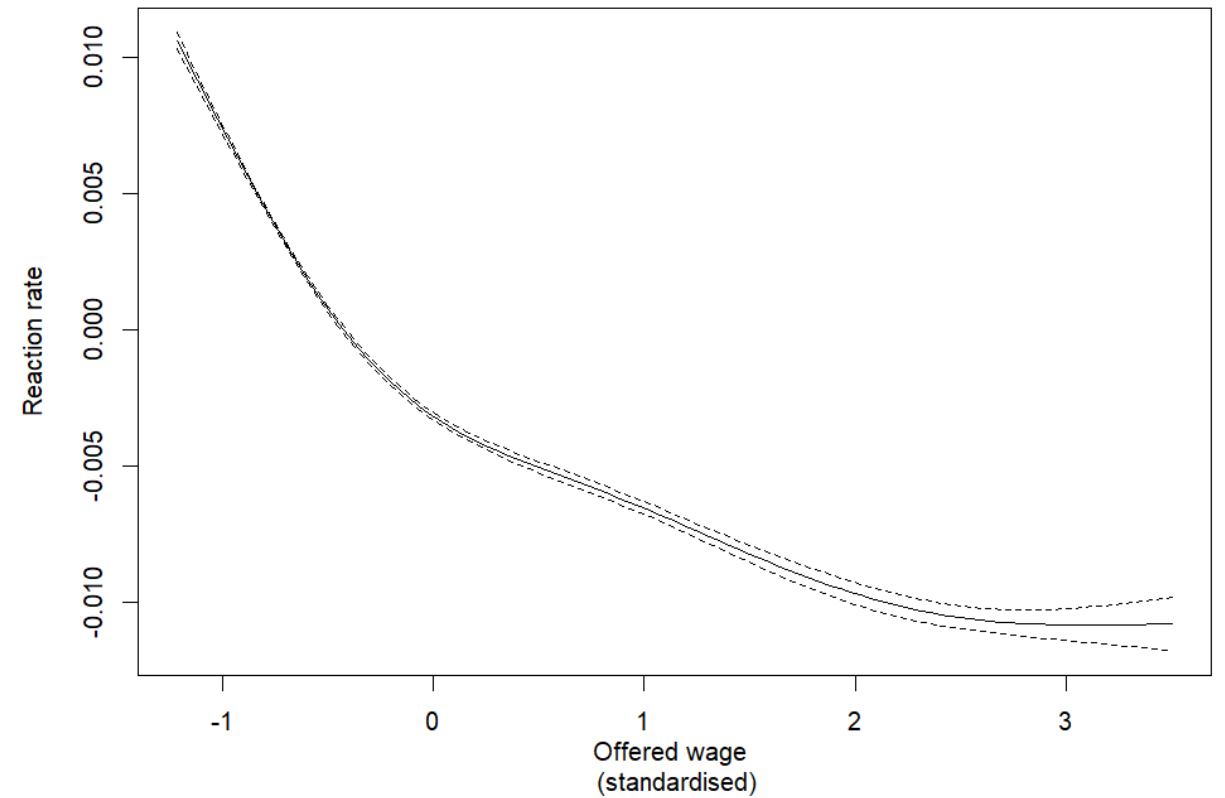
- Aggregation to ISCO 4-digit (occupations with over 750 OJAs)
- Controlling for an occupation-specific list of predictors
- Generalized Additive Models

Offered wage and OJA attractiveness - model with no covariates

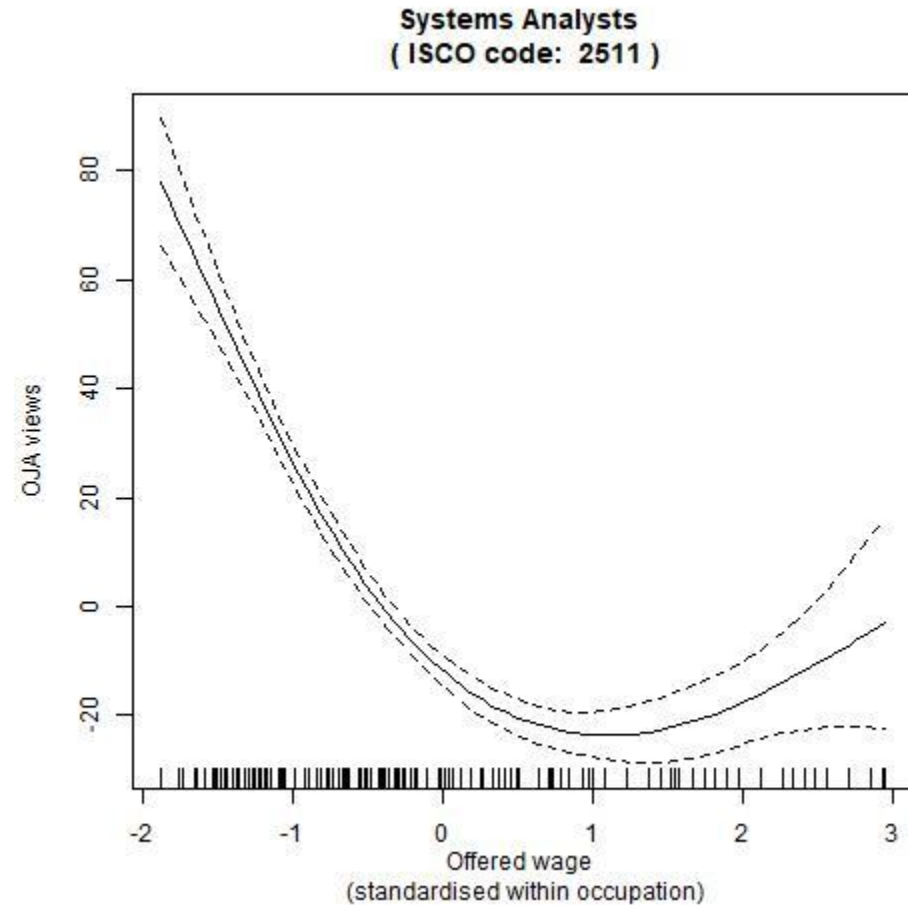
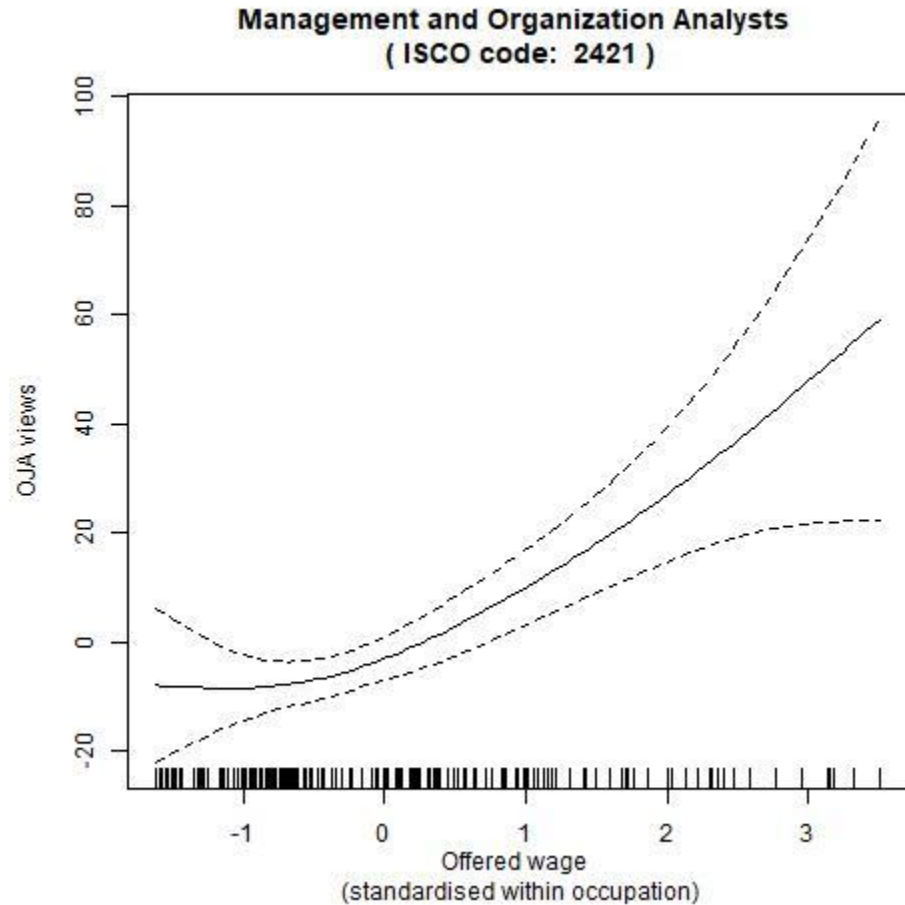
OJA views



Reaction rate



Offered wage and OJA views (Occupation-specific estimations)



Next steps

- Refine the estimation technique
- Try to explain the differences in the occupation-specific patterns of the offered wage/OJA attractiveness function through:
 - Supply-side factors
 - Demand-side factors (hiring strategies)
 - Adding contextual predictors (through geo/time information)

Thank you/Ďakujem

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Predictive potential of aggregated OJA data (on job vacancy statistics)

	$h = 1$			$h = 2$			$h = 3$			$h = 4$		
	M1	M2	M3	M1	M2	M3	M1	M2	M3	M1	M2	M3
Intercept	2107*	3139†	4355*	3660*	5194‡	3561*	7143†	5150*	4420*	13451‡	9477*	9499*
Trend	-32	-81	-91	-34	-107	-91	34	-255	-247	211	-188	-188
JVSt-1	0.92†	0.50*	0.49*	0.84†	0.22	0.23	0.57	0.03	0.03	0.01	-0.41	-0.41
JVSt-1 × Q1,t+h	0.05†	0.09‡	0.08†	0.01	0.06†	0.07†	-0.01	0.11†	0.11†	-0.02	0.13*	0.13*
OJvt		0.15†	0.15†		0.23‡	0.23‡		0.36†	0.36†		0.40†	0.40†
Ult			-0.03			0.04			0.02			0.00
R2	76.2%	83.8%	84.0%	61.7%	75.6%	79.7%	41.0%	75.6%	75.7%	41.0%	71.0%	71.0%
adj. R2	74.3%	82.0%	81.8%	58.6%	72.8%	76.8%	35.9%	72.8%	72.1%	35.9%	67.5%	66.6%

Notes. Values in the table correspond to regression coefficients. $h = 1, 2, 3, 4$ corresponds to prediction horizons; for example, $h = 4$ means that the regression models predict the JVS value realized in 4 quarters' time. *, †, and ‡ denote statistically significant coefficients at the 0.10, 0.05 and 0.01 levels. M1, M2, and M3 correspond to models as defined in the Methodology section.