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Efficiency in Spatially Disaggregated Labour Market Matching[*]

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Abstract

We analyse the efficiency in a labour market matching process. We understand efficiency as a share of the mean number of matches (conditional on given covariates) in the number of matches that would occur if search and matching was optimal, bearing in mind that, contrary to the production function, being unemployed or vacant is not freely chosen or changed. We apply a stochastic matching frontier for random, job queuing and stock-flow models. We use data for Poland, a country with a highly regionally diversified unemployment rate. We contribute to the literature by comparing different spatial aggregation levels – NUTS-1 to NUTS-4 in monthly and annual perspectives. We analyse whether and how the efficiency changes over time. We find spatial and temporal heterogeneity in the labour market. Thus, various policy measures should be designed to improve labour market matching efficiency at certain regional levels.

Keywords: matching function, matching efficiency, spatial aggregation, stochastic frontier
JEL codes: C23, J64

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1. Introduction

We analyse the efficiency in a labour market matching process from a spatial perspective in Poland. By efficiency we mean a share of the mean number of matches (conditional on given covariates) in the number of matches that would occur if search and matching was optimal (a distance to frontier efficiency), bearing in mind that, contrary to the production function, being unemployed or vacant is not freely chosen or changed. We argue that this efficiency differs at certain levels of data spatial aggregation, and different factors affect it. Thus, various policy measures should be designed to improve the labour market matching process. We aim at identifying the determinants of the efficiency of the matching process, so that we are able to formulate policy recommendations. We apply a stochastic matching frontier method to the matching function models at NUTS-1 to NUTS-4 units. Due to data availability we refer to the period: 2000(3)-2014, and we conduct the analysis from monthly and annual[1] perspectives.

Augmented matching function (see e.g. Puhani 1999) and stochastic frontier analysis (see e.g. Ilmakunnas and Pesola 2003) are the two most common methods used to identify determinants in a labour market matching process. The augmented matching function explicitly verifies how certain factors affect the matching efficiency. Technically, this function assumes full efficiency of matching at a certain level of data aggregation, as it constitutes an upper boundary to the possible number of matches at a given number of inputs. The stochastic frontier analysis focuses on determinants of the inefficiency. At the country level we assume full efficiency of matching, but at a lower level of data aggregation we model changes in the efficiency loss separately from the matching function. Both methods indicate factors that affect the matching process efficiency, but the stochastic frontier analysis is a more general approach.

[1] We indirectly refer to the bias resulting from temporal aggregation in the data. Such bias arises when continuous economic processes are described using discrete data (Coles and Smith 1998). Burdett et al. (1994) indicate that the lower frequency of the data the more severe the bias.

The literature review on the matching process efficiency indicates some common findings. The efficiency improves with the level of economic development (Münich et al. 1999), population density (Coles and Smith 1996) and during the business cycle (Anderson and Burgess 2000, Fahr and Sunde 2001). The efficiency deteriorates with unemployment duration (Burgess 1993, Lehmann 1995) and with spatial autocorrelation; it is also worse between travel-to-work areas than within them (Burda and Profit 1996, Fahr and Sunde 2005, Coles and Smith 1996). Other factors that affect the efficiency of matching are: demographic characteristics, occupation and education (Ibourk et al. 2004, Fahr and Sunde 2001, Abid and Drine 2011) or regional and sectoral specificity (Altavilla and Caroleo 2013, Broersma and van Ours 1999, Fahr and Sunde 2005, Robson 2006).

Previous analyses of the matching process efficiency on the Polish labour market were primarily conducted at the NUTS-2 level using the augmented matching function concept[2]. Jeruzalski and Tyrowicz (2009) and Tyrowicz (2011) applied the stochastic frontier analysis at the NUTS-4 level, although the second study was focused on the hysteresis effect at the local level. Jeruzalski and Tyrowicz (2009) found that matching abilities depended on demand fluctuations, while the impact of unemployment structure, active labour market policies (ALMPs) and individual labour office capacities was less significant.

We contribute to the literature in two manners. We ask the questions: Does the job matching process vary at different levels of regional aggregation? Does it vary from different time perspectives? Are different labour market policies needed to improve the process efficiency? We address these questions by providing the results at different levels of data spatial aggregation: from NUTS-1 to NUTS-4 and using two temporal perspectives (monthly and annual data). The spatial disaggregation shows how the efficiency of matching differs in certain spatial units and what the potential determinants of this (in)efficiency in the labour market

[2] Gałecka (2008) presents the literature review.

matching are at all aggregation levels. Temporal aggregation matters as the search and matching process is time-consuming and it differs in various time frames: monthly and annual. The results can be used to design tailor-made policy instruments at different aggregation levels to improve the functioning of the labour market. We test different matching mechanisms and stochastic frontier characteristics. We have not encountered such a broad approach in the literature.

We find heterogeneity in the labour market across all analysed dimensions and a few significant determinants of the matching efficiency. These determinants are: the business cycle phase (NUTS-1), vocational schools and technical university graduates (NUTS-2), migrations and ALMP (NUTS-3 and NUTS-4). It thus appears that different measures of economic policy should be applied to improve the efficiency of the labour market matching at certain levels of spatial aggregation and in different time horizons.

2. Stochastic Frontier Matching Function

Random (stock-based or job queuing) and non-random (stock-flow) are two main technologies that describe the labour market matching mechanism. Random trade can be expressed by a stock-stock (stock-based) model or a job queuing model. In the first one the unemployment stock trades with the vacancy stock. In the job queuing model matching takes place between the unemployment stock and the vacancy inflow. Here, we assume large discrepancies between unemployment and vacancies. The demand side always clears, while the unemployed individuals wait for new job opportunities. In a stock-flow model heterogeneous agents have perfect information about the market and in the equilibrium the stock trades with the inflow: the unemployment stock trades with the vacancy inflow and the vacancy stock trades with the unemployment inflow.

Particular models can be formalised in a matching function, usually of the Cobb-Douglas form. The stock-based model is $m = m(U, V)$, the job queuing model is $m = m(U, v)$, and the stock-flow model is $m = m(U, V, u, v)$ (Blanchard and Diamond 1994, Coles and

Smith 1998, Gregg and Petrongolo 2005); where U is the unemployment stock, V is the vacancy stock, u is the unemployment inflow, and v is the vacancy inflow. We apply a stochastic frontier model to each of the frameworks[3]. Thus, the random (stock-based) model is:

$$m_{i,t} = \alpha_0 + \alpha_1 V_{i,t} + \alpha_2 U_{i,t} + \left(\varepsilon_{i,t} - \vartheta_{i,t}\right) \tag{1}$$

the job queuing model is:

$$m_{i,t} = \alpha_0 + \alpha_2 U_{i,t} + \alpha_3 v_{i,t} + \left(\varepsilon_{i,t} - \vartheta_{i,t}\right) \tag{2}$$

and the stock-flow model is:

$$m_{i,t} = \alpha_0 + \alpha_1 V_{i,t} + \alpha_2 U_{i,t} + \alpha_3 v_{i,t} + \alpha_4 u_{i,t} + \left(\varepsilon_{i,t} - \vartheta_{i,t}\right) \tag{3}$$

where $m_{i,t}$ is the outflow from unemployment to employment, $V_{i,t}$ and $U_{i,t}$ are, respectively, vacancy and unemployment stocks at the beginning of a period, $v_{i,t}$ and $u_{i,t}$ are, respectively, vacancy and unemployment inflows during a period. α's are parameters of the matching function. i denotes a region and, t denotes time. The variables are expressed in natural logarithms. $\varepsilon_{i,t} \sim NID(0, \sigma_\varepsilon^2)$ and $\vartheta_{i,t}$ are independently distributed non-negative random variables, obtained by truncation at zero of the normal distribution.

We have three cases of the inefficiency, when we impose certain restrictions on the $\vartheta_{i,t}$. Each option can be applied to each labour market matching mechanism. The most restricted model assumes time-invariant efficiencies (Battese et al. 1989):

$$\vartheta_{i,t} = \vartheta_i \tag{4}$$

where $\vartheta_i \sim N(\mu, \sigma^2)$ is truncated at zero. Technical efficiency of matching is computed as $TEM_i = \exp(-\vartheta_i)$.

The second model assumes time-variant efficiencies (Battese and Coelli 1992). In this case ϑ_i varies in time according to the following process:

[3] From an econometric point of view models (1) and (2) are nested in (3). Thus, we use the likelihood ratio (LR) test to choose between the models. However, economically there are different theories behind all three models, thus we avoid calling them "nested".

$$\vartheta_{i,t} = \eta_{i,t}\vartheta_i = \vartheta_i\{\exp[-\eta(t-T)]\} \qquad (5)$$

where $\vartheta_{i,t} \sim N(\mu, \sigma^2)$ is truncated at zero, η is a parameter that represents a change in the efficiency. In this model, the change in the efficiency of matching is deterministic and computed as $TEM_{i,t} = \exp(-\vartheta_{i,t})$, where T is the length of the time series. When we impose restriction 4 or 5 we obtain an error components' frontier model.

In the third option we model the efficiency effects. It allows for a stochastic change in the efficiency of matching and the analysis of its determinants (Battese and Coelli 1995):

$$\vartheta_{i,t} = z_{i,t}\beta + \xi_{i,t} \qquad (6)$$

where $\vartheta_{i,t} \sim N(z_{i,t}\beta, \sigma^2)$ is truncated at zero and shows the technical inefficiency of matching. $z_{i,t}$ is a vector of the variables that affect the technical efficiency of matching in the following way $TEM_{i,t} = \exp\left(-\vartheta_{i,t}\right) = \exp(-z_{i,t}\beta - \xi_{i,t})$. β's are parameters of the efficiency of matching. $\xi_{i,t}$ is a random variable and results from truncation of the normal distribution at $z_{i,t}\beta$.

Variance parameter $\gamma = \sigma^2/\sigma_S^2$, where $\sigma_S^2 = \sigma_\varepsilon^2 + \sigma^2$ allows us to test the significance of the estimated efficiency. For comparison purposes one can also calculate 'mean efficiency' as an average over i and t.

3. The dataset

We based the research on registered individual unemployment data, which have certain characteristics. A person can register as an unemployed individual or as a job seeker. She fills out the registration form specifying certain characteristics including occupation, expected wage, professional experience, etc. A person has to confirm periodically her readiness and eagerness to work. She is supposed to accept the proposed job offer or socially useful work. Otherwise, she has to present a valid explanation of the refusal or she is removed from the registry.

Registration in a public employment office is a necessary condition for free health insurance for non-employed workers. Registration is also required in certain social welfare programmes. Thus, there may be a fraction of the unemployment pool who actually do not seek employment actively. There might also be workers who work in the shadow economy, even though they are registered job seekers (due to other incentives) or even work abroad (keeping in mind that they have to come back periodically).

Job seekers and companies use various search and recruitment methods. Enterprises are supposed to publish every job vacancy in a public employment office, but this regulation is virtually not obeyed[4]. Public employment offices do not possess every job offer available on the market. There might be overrepresentation of the jobs a company has the incentive to announce in a public employment office, i.e. refunded trainings, publicly sustained workplaces for the disabled. The unemployed may also search for a job on their own. Thus, the number of available job offers is underestimated and the outflow from unemployment to employment often exceeds the number of available job offers. We cannot equate the unemployment-to-employment flow with public employment intermediation. Nevertheless, the registration data have some valuable properties. They provide consecutive time series of the necessary stocks and flows of unemployment and vacancies. The job offers are directed to the registered unemployed individuals and in the analysis we refer to public employment intermediation only.

We used registered unemployment data (from Public Employment Services, PSZ) for Poland for the period 2000-2014. The monthly data were collected at NUTS-4 level and then aggregated to other spatial units. Thus, we had the following data: at NUTS-0: 1 cross-section, 180 periods; at NUTS-1: 6 cross-sections, 180 periods; at NUTS-2: 16 cross-sections, 180 periods; at NUTS-3: 66 cross-sections, 145 periods and at NUTS-4: 379 cross-sections, 145

[4] Act on promotion of employment and labour market institutions of 2004, art. 36, p. 5 (Dz. U. 2004, no. 99, 1001 with later amendments). In 2012 approximately only 16.5% of companies announced job offers at public employment offices (NBP 2012).

periods. The data included the unemployment stock, unemployment inflow, vacancy stock, vacancy inflow and outflow from unemployment to employment.

We used other variables to account for changes in the efficiency of the labour market matching process. These variables included: active labour market policy, characteristics of the unemployed individuals and specific aspects of regional economies. Certain variables were available in monthly, quarterly or yearly perspectives. We aggregated the annual ALMP data, originally available at NUTS-4 level, up to NUTS-0. We used the Denton-Cholette (Dagum and Cholette 2006) method[5] to temporally disaggregate quarterly GDP to monthly values. Table A2 (in the Appendix) lists all covariates of the matching efficiency we examined.

Table 1 Summary statistics of the main variables at NUTS-1 to NUTS-4 units, monthly data

	NUTS-1					NUTS-2				
	u	U	v	V	m	u	U	v	V	m
Mean	36867	395204	12012	6178	16657	13825	148201	4504	2317	6247
Median	37214	383415	11829	5643	16612	13168	137692	4035	1628	5987
Min	16829	133382	1806	516	5997	3655	31127	357	33	1142
Max	58995	625159	26279	26411	34556	35191	381454	17787	19523	17430
Range	42166	491777	24473	25895	28559	31536	350327	17430	19490	16288
Standard deviation	8256	117883	4570	4177	4455	5807	68924	2529	2287	2753
Coefficient of variation	22%	30%	38%	68%	27%	42%	47%	56%	99%	44%
Skewness	-0.005	-0.038	0.374	1.274	0.318	0.708	0.876	1.195	2.287	0.603
Kurtosis	-0.425	-0.900	-0.317	2.591	0.115	0.149	0.674	1.973	8.053	0.017
	NUTS-3					NUTS-4				
	u	U	v	V	m	u	U	v	V	m
Mean	3400	34054	1194	659	1550	592	5930	208	115	270
Median	3176	31485	1076	502	1430	486	4868	149	51	221
Min	993	5167	110	0	347	60	268	0	0	13
Max	10508	99918	5826	6601	5037	6584	67647	5500	6601	3325
Range	9515	94751	5716	6601	4690	6524	67379	5500	6601	3312
Standard deviation	1276	15251	620	608	653	443	4778	239	252	205
Coefficient of variation	38%	45%	52%	92%	42%	75%	81%	115%	220%	76%
Skewness	0.893	1.028	1.294	2.990	1.077	4.210	4.970	5.738	9.622	4.134
Kurtosis	0.854	1.094	2.719	15.140	1.542	30.326	42.922	57.434	146.753	31.775

Notes: u – unemployment inflow, U – unemployment stock, v – vacancy inflow, V – vacancy stock, m – unemployment-employment flow.

Table 1 compiles summary statistics of the main variables. The mean exit rate (m_t/U_{t-1}) was the higher the more disaggregated regions we looked at. Labour market tightness indices (V_t/U_t and v_t/U_t) were also higher at more disaggregated units. The stock of vacancies had the largest relative variation. Distribution of most of the variables was right-

[5] We applied an R package 'tempdisagg' provided by Sax and Steiner (2013).

skewed, especially at lower NUTS aggregation levels. Values visibly focused around mean (leptokurticity) at NUTS-4 level.

4. Stochastic frontier analysis of the matching function

We estimated each matching function model – random, job queuing and stock-flow at NUTS-0 to NUTS-4 levels of data spatial aggregation. Mean efficiency was higher for random and job queuing matching than for the stock-flow model at less disaggregated levels (NUTS-1 and NUTS-2), but lower at more disaggregated levels (NUTS-3 and NUTS-4). However, the LR test results indicated that the stock-flow matching best described labour market matching (table A1 in the appendix). The random matching was rejected in each case. The job queuing model was accepted at NUTS-3 level only. It means that both stocks and flows of vacancies and the unemployed engage in labour market matching.

In table 2, we compile the estimates of the stock-flow error components' frontier models. The results were obtained for certain levels of data spatial aggregation and two levels of data temporal aggregation. Unemployment stock and vacancy stock affected the matching process less at lower levels of data spatial aggregation. It means that flows are more important the more disaggregated units we look at. However, the vacancy inflow had higher elasticity at higher levels of data spatial aggregation. Newly unemployed (unemployment inflow) caused congestion in the trade process, and the elasticity was negative at NUTS-1 to NUTS-3 units. Once we moved from more to less aggregated data (from NUTS-1 to NUTS-3) this negative effect diminished or became statistically insignificant. At NUTS-4 level, the unemployment inflow positively affected the matching process. This suggests, that employers wait for new workers to form a match. If newly unemployed fit better than the stock, the unemployment stock may experience mismatch with vacancies. Monthly data yielded generally lower parameter estimates of the vacancy stock, vacancy inflow and unemployment stock than the annual ones. This may reflect the fact that from an annual perspective there is more time to find a matching partner, thus the inputs affect the matching more than from a monthly perspective.

We did not reject constant returns to scale hypothesis at higher levels of spatial aggregation, especially at the country level (NUTS-0). The decreasing returns to scale prevailed especially at lower levels of data spatial aggregation. They occurred at NUTS-3 and NUTS-4 units for annual data and for NUTS-1 to NUTS-4 for monthly data. This means that when we increase the number of agents[6], congestion hinders proportional increase in the outflow from unemployment to employment.

At the national level the results produced no inefficiency in matching. The stochastic frontier model yielded better results than the OLS equivalent, i.e. the one that assumed fully efficient matching. The inefficiency was significant at all regional levels (compare estimates of the variance parameter γ in table 2).

We found time-varying (increasing) efficiency of the matching process. The annual data produced lower efficiency of the matching process at lower levels of data aggregation. The monthly analysis indicated that the efficiency was the highest at NUTS-3 and NUTS-4 levels. Moreover, the annual data yielded higher efficiency compared to monthly results (compare 'mean efficiency' in table 2). These results suggest that in a shorter time horizon smaller markets are more efficient. However, over a longer perspective (e.g. annual data) larger markets produce more matches. It comes from the fact that we assume homogeneity in a market of a given size, so in larger markets agents can seek among more potential matching partners and once they have more time, they produce more matches.

[6] We neglect spatial interactions, but when the number of agents increases they may seek work in the adjacent areas as well.

Table 2 **Comparison of stock-flow matching error components' frontier models estimates at different level of spatial and temporal aggregation**

	NUTS-0	NUTS-1	NUTS-2	NUTS-3	NUTS-4
ANNUAL DATA					
$const$	1.752	1.087	0.712	2.090**	1.228***
	(1.000)	(1.012)	(0.571)	(0.326)	(0.102)
$V_{i,t}$	0.142	0.091**	0.054**	0.004	0.003
	(0.998)	(0.018)	(0.010)	(0.006)	(0.002)
$U_{i,t}$	0.691	0.608***	0.562***	0.504***	0.384***
	(0.994)	(0.035)	(0.025)	(0.016)	(0.008)
$v_{i,t}$	0.333	0.352***	0.385***	0.299***	0.187***
	(0.995)	(0.039)	(0.026)	(0.016)	(0.007)
$u_{i,t}$	-0.258	-0.114	-0.050	-0.018	0.260***
	(0.994)	(0.077)	(0.055)	(0.034)	(0.016)
time				0.015**	
				(0.005)	
mean efficiency	0.995	0.901	0.901	0.824	0.781
σ^2	0.001	0.017*	0.020**	0.056**	0.106***
	(0.192)	(0.009)	(0.007)	(0.011)	(0.009)
γ	0.050	0.847***	0.782***	0.884***	0.877***
	(1.000)	(0.089)	(0.085)	(0.025)	(0.011)
returns to scale	constant	constant	constant	decreasing	decreasing
log-likelihood	32.6	121.9	270.8	684.9	2191.0
model type	TI	TI	TI	TV	TI
sample	2000-2014	2000-2013	2000-2013	2003-2013	2003-2013
MONTHLY DATA					
$const$	-0.937	0.515	0.985**	0.614**	0.130**
	(0.998)	(0.452)	(0.245)	(0.104)	(0.040)
$V_{i,t-1}$	0.138**	0.009	-0.015*	0.004	-0.004**
	(0.030)	(0.015)	(0.008)	(0.003)	(0.001)
$U_{i,t-1}$	0.630***	0.585***	0.545***	0.518***	0.480***
	(0.043)	(0.017)	(0.013)	(0.007)	(0.004)
$v_{i,t}$	0.221**	0.343***	0.341***	0.195***	0.143***
	(0.052)	(0.022)	(0.011)	(0.005)	(0.002)
$u_{i,t}$	-0.059	-0.090**	-0.088**	0.015	0.128***
	(0.065)	(0.028)	(0.018)	(0.010)	(0.005)
time		$1.24\cdot10^{-3}$**	$1.49\cdot10^{-3}$**	$2.78\cdot10^{-3}$**	$2.11\cdot10^{-3}$***
		($4.40\cdot10^{-4}$)	($2.45\cdot10^{-4}$)	($1.78\cdot10^{-4}$)	($7.36\cdot10^{-5}$)
mean efficiency	1.000	0.485	0.490	0.765	0.687
σ^2	0.006**	0.432	0.417*	0.080**	0.189***
	(0.001)	(0.374)	(0.210)	(0.014)	(0.013)
γ	$2.92\cdot10^{-5}$***	0.981***	0.972***	0.798***	0.776***
	($6.47\cdot10^{-3}$)	(0.017)	(0.014)	(0.035)	(0.015)
returns to scale	constant	decreasing	decreasing	decreasing	decreasing
seasonal dummies	yes	yes	yes	yes	yes
log-likelihood	198.1	1026.2	2268.8	5952.6	7269.4
model type	TI	TV	TV	TV	TV
sample	2000-2014	2000-2014	2000-2014	2003-2014	2003-2014

Standard errors reported in parentheses. TI – time-invariant, TV – time-variant, chosen on the basis of LR test.
*** means significant at p=0.01, ** means significant at p=0.05 and * means significant at p=0.1.

5. Determinants of the matching efficiency

We present detailed results for the stock-flow model only, as it seems to most properly describe the labour market matching process in Poland at different regional levels. The results of the previous section show that matching inefficiency exists at every regional aggregation level (descriptive statistics are presented in table A3 in the Appendix). Now we aim at identifying determinants of trade process efficiency. We tested various factors behind matching inefficiency, including regional specificity, unemployment structure and ALMPs (table A2 in the Appendix). We used annual data, since only such information was available for most of the efficiency covariates. The data on ALMP are available from 2009, thus we estimated its effect separately, not to shorten the sample of the 'basic model'. Nevertheless, the models at NUTS-1 and NUTS-2 levels produced insignificant results, thus we present the impact of ALMP at NUTS-3 and NUTS-4 levels only.

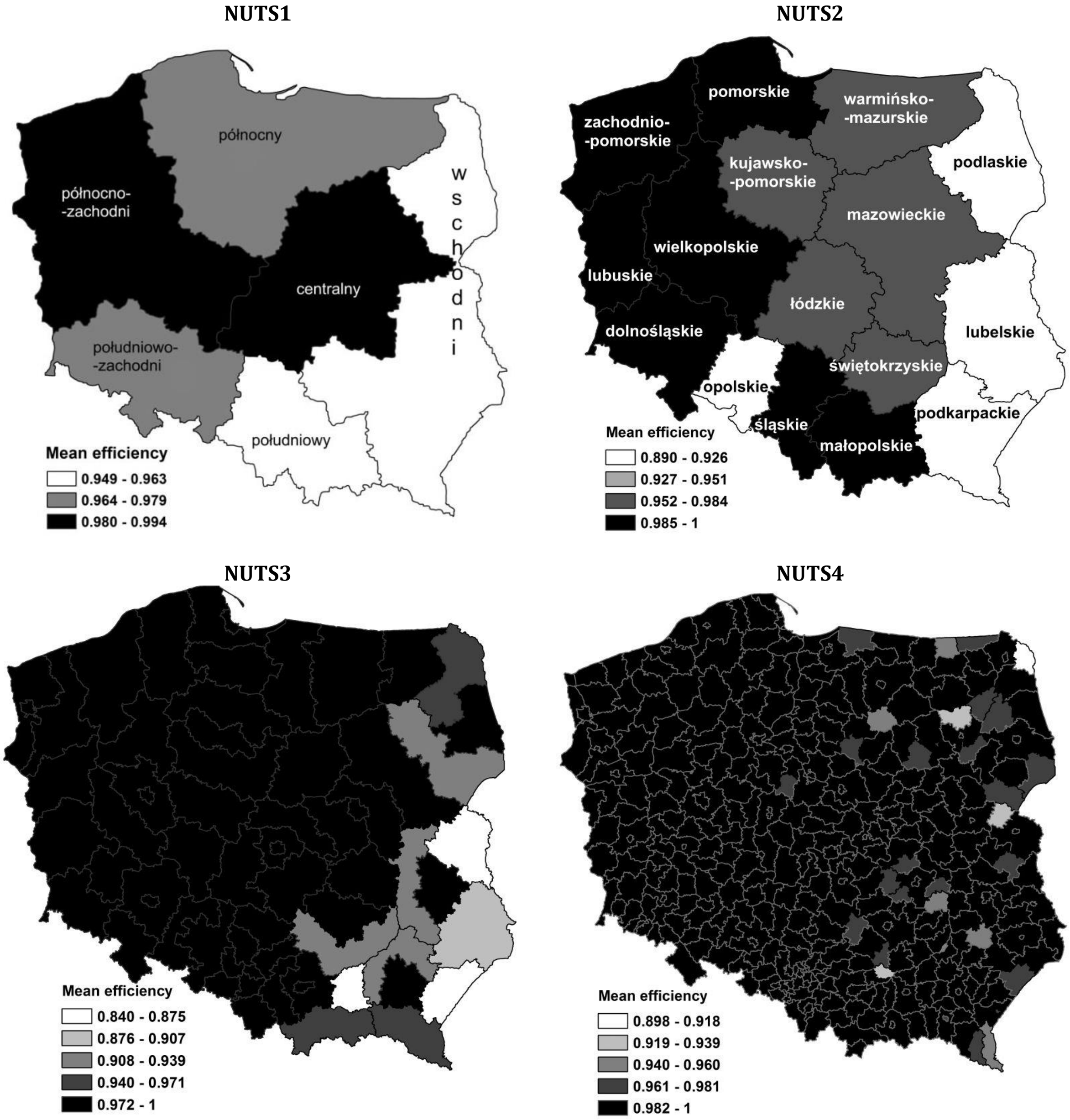
Table 3 Determinants of inefficiency of matching at different levels of spatial aggregation, annual data

	NUTS-1	NUTS-2	NUTS-3	NUTS-4
$const$	2.450**	4.266**	1.797**	1.638**
	(0.673)	(0.875)	(0.308)	(0.741)
$GDP\_growth_{i,t}$	-0.020**	-0.032**	-0.013**	
	(0.006)	(0.007)	(0.003)	
$new\_entities_{i,t}$	$-3.39\cdot10^{-3}$**	$-2.17\cdot10^{-3}$**	$-5.56\cdot10^{-3}$**	
	$(6.15\cdot10^{-4})$	$(7.91\cdot10^{-4})$	$(8.10\cdot10^{-4})$	
$enrol\_vocat_{i,t}$		$-7.30\cdot10^{-3}$**		
		$(3.99\cdot10^{-4})$		
$tech\_grads_{i,t}$		$-2.77\cdot10^{-2}$**		
		$(6.47\cdot10^{-3})$		
$net\_temp\_migr_{i,t}$				$-5.30\cdot10^{-3}$**
				$(2.48\cdot10^{-3})$
$in\_perm\_migr_{i,t}$				$-1.20\cdot10^{-2}$**
				$(5.33\cdot10^{-3})$
$const$			0.181**	-0.014
			(0.027)	(0.155)
$almp\_all_{i,t}$			$-8.90\cdot10^{-5}$**	$-1.75\cdot10^{-4}$**
			$(1.52\cdot10^{-5})$	$(9.42\cdot10^{-5})$

Job queuing model for NUTS3 level, stock-flow model for all other levels. Negative values desirable since they mean 'negative determinant of inefficiency'. Standard errors reported in (). For models with GDP, the sample ends with 2012 due to availability of regional accounts. *** means significant at p=0.01, ** means significant at p=0.05 and * means significant at p=0.1.

The annual growth of real GDP and newly registered economic entities were the only factors that affected the efficiency of matching at NUTS-1 level (table 3). Both of them increased the efficiency. The efficiency of matching depended on a business cycle. It increased during economic expansions, up to almost 100% (figure A1 in the Appendix). During the economic downturns in 2005, 2009 and 2012 the efficiency of matching decreased. These periods were characterised by low GDP growth and slow new economic entities creation. The efficiency of matching was highest in central and north-western regions, lowest in eastern and southern regions (map 1).

Map 1 Mean efficiency in Polish regions



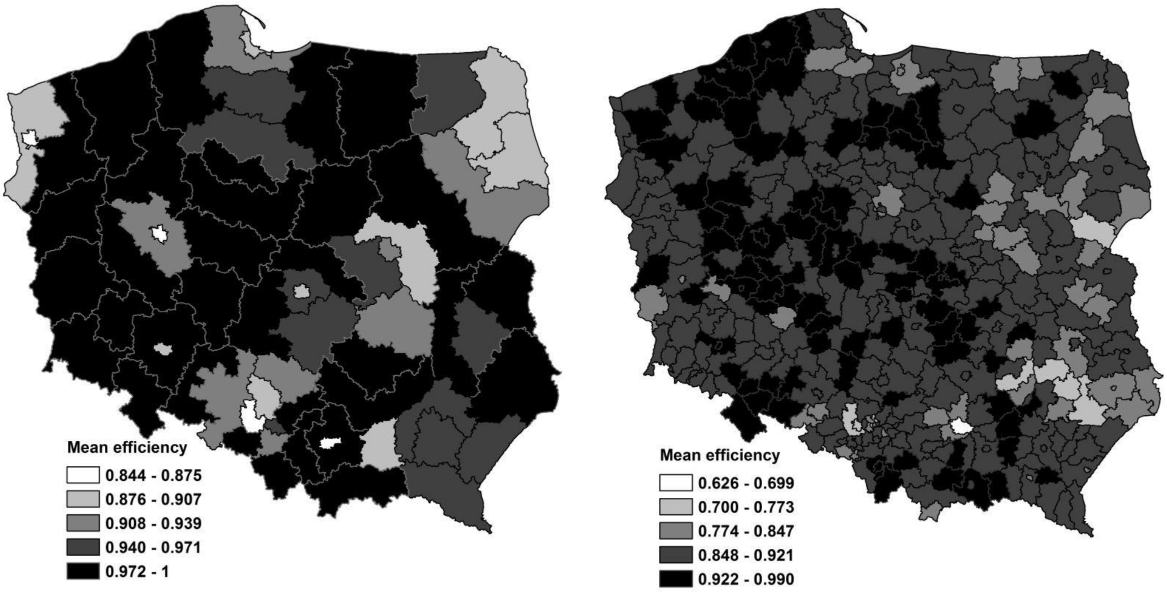
Spatial disaggregation of the data from NUTS-1 to NUTS-2 regions (voivodeships) resulted in slightly different estimates. At NUTS-2 level the GDP growth rate influenced the matching efficiency to a larger extent than at NUTS-1 level while the new entities formation rate had less impact. Additionally, the gross enrolment ratio for vocational school students and the percentage of technical studies graduates positively affected the efficiency of matching (figure A2 in the Appendix). This suggests that particular attention of NUTS-2 region policy-makers should be paid to shaping the educational policy, directing it to the cooperation of universities and businesses as well as regional needs. So far this policy was to a high degree centralised. Similarly to NUTS-1 level, the efficiency of matching in NUTS-2 regions also benefited from increased economic activity and decreased during contractions. Economic activity and vocational education positively affected the efficiency of matching during most of the period since 2007, except 2011 when their influence was negative. Mean efficiency during 2007-2012 was the highest in southern and western regions, and the lowest in the eastern region. The highest discrepancy was observed in the south-western region. ALMP estimates, although generally insignificant, produced lower efficiency in the capital cities of certain voivodeships (NUTS-2 regions). These were the voivodeships with the highest economic development and cities with the lowest rate of unemployment. Full efficiency of matching most often occurred in eastern and north-western regions.

The job queuing model yielded better results than the stock-flow one at the NUTS-3 level. Here, the annual growth rate of GDP[7] and the flow of economic entities had a statistically significant impact on the matching efficiency. The influence of these variables decreased during 2003-2010 and increased afterwards (figure A3 in the Appendix). Most of the regions with lower efficiency of matching were in the eastern region with the exception of the southern region. It resulted from low GDP, low entrepreneurship and a slow pace of new industry creation. ALMP positively affected the efficiency of matching during 2009-2012, and negatively in 2013. The variation of efficiency between regions was relatively high (map 2). The lowest efficiency was present in southern and north-eastern Poland.

Map 2 Mean efficiency in Polish regions in models with ALMP instruments

NUTS3 **NUTS4**

[7] In opposition to the higher levels of spatial aggregation, at NUTS-3 level nominal GDP growth was included. The Central Statistical Office in Poland does not compute real GDP at this level of aggregation nor does it publish price indices.



At NUTS-4 level the results indicate that migrations were the main factors behind labour market matching efficiency. The efficiency was positively influenced by net temporary migrations and inflow of intraregional permanent migrants. Thus, policy should be designed to increase labour supply. Additionally, human capital affects unemployment flows, which in turn matter at disaggregated regional units. During 2010-2013 the efficiency of matching did not change significantly. Until 2012 the influence of migrations increased, while in the following year it decreased (figure A4 in the Appendix). Most of the NUTS-4 regions with lowest efficiency were located in eastern Poland. In the rest of the country, there was no visible spatial pattern in the efficiency of matching. The ALMP improved the matching efficiency, but only in general. No particular ALMP instrument had any significant meaning. The least efficient regions were located in the eastern part of the country, while those with the highest efficiency were in north-western and central Poland.

6. Discussion

Estimates based on annual data indicated a decrease in the matching efficiency once we moved from less to more disaggregated data, i.e. from NUTS-1 to NUTS-4. The monthly data analysis produced higher efficiency at NUTS-3 and NUTS-4 units than in more aggregated ones (besides the national level, in which the efficiency is full). These differences may result from search and matching frictions. We neglect spatial interactions and assume homogenous markets of a given size. Thus, from a monthly perspective, the search process enjoys the spatial proximity of firms and workers in local labour markets. Annual data show that in larger markets, e.g. at a country level, agents create more matches once they have time to search. These results also indicate that from an annual perspective mismatch matters more as it takes more time to form a match. From a monthly perspective, in local markets, search frictions affect the matching process more. Additionally, if temporal aggregation matters, the annual data should produce more biased estimates (Burdett et al. 1994). We do not expect this bias to change the direction of the efficiency changes from less to more disaggregated data, but it may affect the relative importance of stock and inflow variables in the matching process.

We found that different factors affect the efficiency of matching at certain levels of data spatial aggregation. The growth of real GDP, the number of newly registered economic entities, the gross enrolment ratio in vocational school students, the percentage of technical studies graduates, participation in active labour market programs (overall), net temporary migrations and inflow of intraregional permanent migrants positively and statistically significantly affected the efficiency of the matching process. Thus different policies may be implemented to improve the matching process. Moreover, these policies may be shaped by different authorities and various regional levels.

The labour market matching efficiency increased during 2000-2013 and it was changing during the business cycle. The expansion phase improved the efficiency, while contractions decreased it. This finding is in line with those for other countries (Fahr and Sunde 2001, Anderson and Burgess 2000). This may suggest that firms are more willing to accept a low-skilled unemployed individual during expansion rather than offer a vacancy during recession. Our finding of increasing efficiency of matching in a post-transition economy confirms what Tomić (2014) found for another such economy – Croatia. It shows positive long-run structural change occurring in these markets. We found heterogeneity from a regional perspective. Generally, the local labour markets located in the western part of the country experienced higher efficiency than those from the eastern part of the country (with some exceptions). Such a differentiation is common, for instance Altavilla and Caroleo (2013) found different matching efficiency in northern and southern Italy. These results prove segmentation of the regional labour markets, which at least partially originates from historic conditions (Ministry of Regional Development 2013).

The ALMP improved matching efficiency, but some interesting results emerged. The effects were significant only at NUTS-3 and NUTS-4. This finding is in line with previous results. Góra et al. (1996) and Puhani and Steiner (1996, 1997) did not find any significant effects of ALMP expenditures in Poland at NUTS-2 level during the early 1990s. The estimates indicated lower efficiency in the capital cities of certain voivodeships (with the highest economic development and the cities with the lowest rate of unemployment). Comparable results were found by Kano and Ohta (2005) for Japan. They proved that more urbanized areas exhibited poorer matching efficiency. Kano and Ohta (2005) interpreted this finding as an argument for their hypothesis that the efficiency of matching is negatively correlated with the degree of conflicts among firms' hiring standards and workers' skill levels. Our findings may suggest that tight labour markets face some barriers and certain ALMPs are insufficient to decrease the mismatch. In such labour markets high heterogeneity of labour demand lowers the applicability of ALMPs, as it demands perfectly tuned programmes. It might be easier to organise certain programmes, e.g. trainings in markets with few enterprises, wherein specialised labour supply skills are needed.

Some of the results indicated that various subsamples of the main dataset may significantly alter the estimation results. Therefore, to check the robustness of the results, we verified how the estimates would differ if we used various subsamples of the dataset, e.g.

without cities with district rights, without sub-region cities or only with the short-term unemployment stock. Table A4 (in the Appendix) provides summary statistics for these subsamples. Spatial units without cities with district rights had lower unemployment, a number of vacancies and outflow from unemployment to employment. Exclusion of the biggest cities in Poland, i.e. subregion-cities, increased unemployment and decreased the number of vacancies, but the number of matches slightly increased. Additionally, we found that the contraction phase of the business cycle worsened the situation in the regional labour markets, but only marginally. Once we split the country into the western and eastern parts, we found that more vacancies and more matches took place in western labour markets. In western Poland the unemployment inflow was higher, but the stock lower. The short-term unemployed (registered as unemployed for at most 12 months in the last two years) constituted, on average, slightly more than a half of all unemployed individuals.

Table 4 contains the comparison of models for different subsamples with the general model. Most of the differences in efficiency were negligible, with the exception of the short- and long-term unemployed division. Inclusion of the short-term unemployed generally increased the matching efficiency. However, these unemployed individuals matched more often than other unemployed at more aggregated levels only. Exclusion of the biggest Polish cities, i.e. subregion-cities and cities with district rights, did not change the matching efficiency considerably. The western regions proved to be more efficient. The business cycle produced a contrary finding. The matching process proved to be more efficient in the contraction phase. In the presence of a lower number of vacancies and a similar number of unemployed, a similar number of matches occurred. We think that this may result from long lags of unemployment in the business cycle, which distorts the relation between labour market and GDP[8].

[8] We consider here periods during which annual real GDP growth increases (expansion) and decreases (contraction). We do not analyse the periods of prolonged "good" and "bad" times as in Taulbut and Robinson (2015), who also take into account also structural changes.

Table 4 Comparison of models for subsamples with the general model

	$const$	$V_{i,t}$	$U_{i,t}$	$v_{i,t}$	$u_{i,t}$	mean efficiency
		NUTS1				
Short-term unemployed	3.172	0.027	0.683	0.400	-1.245	-0.003
		NUTS2				
Short-term unemployed	0.874	0.064	0.060	0.136	-0.272	0.084
Western regions	-0.666	0.011	0.026	-0.020	0.042	0.025
Contraction phase	-0.480	0.001	0.054	0.029	-0.043	0.024
		NUTS3				
Short-term unemployed	0.101	0.007	-0.140	0.058	0.088	0.020
Without subregion-cities	0.141	0.002	0.000	0.016	-0.028	0.005
		NUTS4				
Short-term unemployed	-0.515	0.005	-0.433	-0.052	0.515	0.049
Without cities with district rights	0.194	-0.001	-0.001	0.002	-0.021	-0.009

Numbers are differences in estimates between parameters of the restricted model and the model for the whole sample.

7. Conclusion

Our article contributes to the literature on the efficiency of labour market matching from a regional perspective. We based the research on the data from public employment offices in Poland and analysed the efficiency of the matching process from NUTS-1 to NUTS-4 levels using annual and monthly data. We found the time- and regionally-varying labour market matching process and its efficiency. The stochastic frontier analysis produced statistically significant inefficiency at all regional levels. In the long-run this inefficiency was gradually decreasing, while in the short-run it was correlated to the business cycle. Thus, we found positive structural changes but in the short-run economic activity affected the matching process in the labour market. The efficiency was higher with an annual analysis than with a monthly one. From a monthly perspective search frictions had larger meaning, while from an annual perspective the mismatch affected the efficiency of matching more.

The matching process is complex and time-consuming. We found the stock-flow model best explains it in the Polish labour market. But, in some cases, the job queuing model also had some explanatory power. At more disaggregated levels the impact of certain stock and flow variables decreased (apart from the unemployment inflow, which became more positive) and returns to scale decreased (from constant to decreasing). Decreasing returns to scale may suggest that local labour markets treated separately are not efficient enough and that spatial interactions should be taken into consideration (compare Antczak et al. 2016).

We found that different factors affect the efficiency of matching at different levels of spatial aggregation: GDP growth and new economic entities creation at NUTS-1 level; the same factors plus vocational and technical education at NUTS-2 level; GDP and new economic entities at NUTS-3 level (in some models migrations were significant); migrations at NUTS-4 level. ALMP variables produced mixed results. ALMP did not affect the efficiency of matching significantly at NUTS-1 and NUTS-2 levels. At NUTS-3 and NUTS-4 levels ALMP improved the efficiency of the matching process, but results were diversified between large cities and other regions.

Our results do not provide narrowly oriented policy recommendations. We found time- and regionally varying efficiency of the matching process. Different factors affect it at NUTS-1 to NUTS-4 levels. It thus appears that different measures of economic policy should be applied to improve the efficiency of the labour market matching at certain levels of spatial aggregation and in different time horizons.

Our findings have some limitations that may affect the qualitative inference. Due to data limitations we used the public employment offices data only. These data reflect only a portion of total job creation and some other factors with different strength may affect the job creation process which takes place on the labour market without public intermediation. Some of the results indicate that local labour markets should not be treated separately. Thus, the analysis that incorporates spatial interactions should contribute to the robustness of the results. We plan to refer to these issues in future research.

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Appendix

Table A1 Comparison of three types of matching error components' frontier models, monthly data

	stock-flow matching	random matching	job queuing	stock-flow matching	random matching	job queuing
		NUTS-1			NUTS-2	
$const$	0.515	-1.136**	-0.254	0.985**	0.120	0.117
	(0.452)	(0.465)	(0.306)	(0.245)	(0.297)	(0.168)
$V_{i,t}$	0.009	0.283***		-0.015*	0.227***	
	(0.015)	(0.011)		(0.008)	(0.006)	
$U_{i,t}$	0.585***	0.668***	0.570***	0.545***	0.596***	0.544***
	(0.017)	(0.032)	(0.016)	(0.013)	(0.023)	(0.011)
$v_{i,t}$	0.343***		0.347***	0.341***		0.317***
	(0.022)		(0.011)	(0.011)		(0.007)
$u_{i,t}$	-0.090**			-0.088**		
	(0.028)			(0.018)		
mean efficiency	0.485	0.859	0.510	0.490	0.846	0.551
σ^2	0.432	0.075**	0.369	0.417	0.082**	0.287*
	(0.374)	(0.029)	(0.347)	(0.210)	(0.017)	(0.151)
γ	0.981***	0.588**	0.977***	0.972***	0.513**	0.959***
	(0.017)	(0.160)	(0.022)	(0.014)	(0.102)	(0.022)
LR test	50.26***	1390.6***	11.63***	2457.30***	3504.00***	22.44***
	[<0.01]	[<0.01]	[<0.01]	[<0.01]	[<0.01]	[<0.01]
log-likelihood	1026.2	330.9	1020.4	2268.8	516.8	2257.6
sample	2000-2014	2000-2014	2000-2014	2000-2014	2000-2014	2000-2014
		NUTS-3			NUTS-4	
$const$	0.614**	1.597***	0.744***	0.130**	1.905***	1.535***
	(0.104)	(0.080)	(0.066)	(0.040)	(0.043)	(0.041)
$V_{i,t}$	0.004	0.065***		-0.004**	0.045***	
	(0.003)	(0.003)		(0.001)	(0.001)	
$U_{i,t}$	0.518***	0.530***	0.518***	0.480***	0.473***	0.436***
	(0.007)	(0.007)	(0.006)	(0.004)	(0.004)	(0.003)
$v_{i,t}$	0.195***		0.199***	0.143***		0.151***
	(0.005)		(0.004)	(0.002)		(0.002)
$u_{i,t}$	0.015			0.128***		
	(0.010)			(0.005)		
mean efficiency	0.765	0.718	0.755	0.687	0.452	0.522
σ^2	0.080**	0.137**	0.085***	0.189***	0.828***	0.578***
	(0.014)	(0.021)	(0.015)	(0.013)	(0.063)	(0.045)
γ	0.798***	0.865***	0.811***	0.776***	0.943***	0.922***
	(0.035)	(0.021)	(0.034)	(0.015)	(0.004)	(0.006)
LR test	498.08***	1380.10***	4.20	18215.00***	5167.40***	1341.70***
	[<0.01]	[<0.01]	[0.12]	[<0.01]	[<0.01]	[<0.01]
log-likelihood	5952.6	5262.5	5950.5	7269.4	4075.8	5988.6
sample	2003-2014	2003-2014	2003-2014	2003-2014	2003-2014	2003-2014

Standard errors reported in parentheses, p-values reported in square brackets. LR tests restricted model vs. stock-flow matching equivalent, and stock-flow vs. time invariant equivalent (always better than OLS). *** means significant at p=0.01, ** means significant at p=0.05 and * means significant at p=0.1.

Table A2 Covariates of technical efficiency of matching considered

No.	Variable	Short name	Original frequency	Annual / Monthly	NUTS	Period since
1	Unemployed with benefit rights (at the end of the month)	$unemp\_benef$	Monthly	+ / +	0-2	2001
2	Unemployed in the age 18-24 (at the end of the month)	$unemp\_1824$	Monthly	+ / +	0-2	2001
3	Unemployed in the age 55-59 (at the end of the month)	$unemp\_5559$	Monthly	+ / +	0-2	2001
4	Unemployed under active labour market policy instrument (at the end of the month)	$unemp\_almp$	Monthly	+ / +	0-2	2011
5	Long-term unemployed (at the end of the month)	$unemp\_long$	Monthly	+ / +	0-2	2001
6	Unemployed terminated for company reasons (at the end of the month)	$unemp\_comp$	Monthly	+ / +	0	2000
7	Unemployment benefits (sum, in PLN)	$benefits$	Monthly	+ / +	0	2000
8	Average monthly gross wages and salaries in enterprise sector (in PLN)	$wages\_enter$	Monthly	+ / +	0-2	2010
9	Average monthly gross wages and salaries in national economy (in PLN)	$wages\_econ$	Annual	+ / +	0-4	2002
10	Permanent internal migrations – net	net_perm_migr	Quarterly	+ / +	0-4	2010
11	Permanent internal migrations – inflow	in_perm_migr	Quarterly	+ / +	0-4	2010
12	Temporary migrations – net	net_temp_migr	Annual	+ / -	0-4	2000
13	Temporary migrations – inflow	in_temp_migr	Annual	+ / -	0-4	2000
14	Temporary migrations – outflow	out_temp_migr	Annual	+ / -	0-2	2000
15	GDP per capita (current prices, in PLN)	gdp_pc	Annual	+ / -	0-3	2000
16	GDP growth rate (previous year = 100, volumes, in %)	gdp_growth	Annual	+ / -	0-3	2001
17	Registered economic entities per 10,000 inhabitants	$entities$	Annual	+ / -	0-4	2002
18	Newly registered economic entities per 10,000 inhabitants	$new\_entities$	Annual	+ / -	0-4	2003
20	Gross enrolment ratio – general secondary school	$enrol\_gen$	Annual	+ / -	0-3	2006
21	Gross enrolment ratio – vocational secondary school	$enrol\_vocat$	Annual	+ / -	0-3	2002
22	Students per 10,000 inhabitants	$students$	Annual	+ / -	0-2	2002
23	Share of technical university graduates (in %)	$tech\_grads$	Annual	+ / -	0-3	2005
24	Expressways and highways per 100 km^2	$highways$	Annual	+ / -	0-2	2005
25	Hardened surface roads per 100 km^2	$rods$	Annual	+ / -	0-4	2005
26	Number of inhabitants	$inhab$	Annual	+ / -	0-4	2000
27	Surface in km^2	$surface$	Annual	+ / -	0-4	2000
28	Population density (in km^2)	$pop\_density$	Annual	+ / -	0-4	2000
29	Value of signed contracts for funding from the EU (in PLN)	eu_signed	Annual	+ / -	0-4	2011
30	Value of completed projects finances by the EU (in PLN)	$eu\_financed$	Annual	+ / -	0-4	2011
31	Unemployed who started intervention work	$almp\_b\_interv$	Annual	+ / -	0-4	2009
32	Unemployed who started socially useful work	$almp\_b\_social$	Annual	+ / -	0-4	2009
33	Unemployed who started vocational training for adults	$almp\_b\_adults$	Annual	+ / -	0-4	2009
34	Unemployed who started public work	$almp\_b\_public$	Annual	+ / -	0-4	2009
35	Unemployed who started internship	$almp\_b\_intern$	Annual	+ / -	0-4	2009
36	Unemployed who started training in active job search methods	$almp\_b\_search$	Annual	+ / -	0-4	2009
37	Unemployed who started training	$almp\_b\_training$	Annual	+ / -	0-4	2009
38	Unemployed who started ALMP treatment	$almp\_b\_all$	Annual	+ / -	0-4	2009
39	Unemployed who finished intervention work	$almp\_interv$	Annual	+ / -	0-4	2009
40	Unemployed who finished socially useful work	$almp\_social$	Annual	+ / -	0-4	2009
41	Unemployed who finished vocational training for adults	$almp\_adults$	Annual	+ / -	0-4	2009
42	Unemployed who finished public work	$almp\_public$	Annual	+ / -	0-4	2009
43	Unemployed who finished internship	$almp\_intern$	Annual	+ / -	0-4	2009
44	Unemployed who finished training in active job search methods	$almp\_search$	Annual	+ / -	0-4	2009
45	Unemployed who finished training	$almp\_training$	Annual	+ / -	0-4	2009
46	Unemployed who finished ALMP treatment	$almp\_all$	Annual	+ / -	0-4	2009

Monthly data available to December 2014, annual data available to 2013; regional accounts data available to 2012.

Source: Public Employment Services and Central Statistical Office of Poland (GUS).

Table A3 Descriptive statistics of mean efficiencies across regions at different regional levels

	NUTS-1	NUTS-2	NUTS-3 a	NUTS-3 b	NUTS-4 a	NUTS-4 b
Mean	0,97506	0,96454	0,98429	0,95493	0,99103	0,88566
Median	0,97636	0,97127	1	0,97045	0,99396	0,89168
Min	0,94937	0,8896	0,83998	0,84379	0,89826	0,62618
Max	0,99366	1	1	1	0,99991	0,96688
Standard deviation	0,017528	0,03758	0,036518	0,045697	0,010599	0,046147
Coefficient of variation	0,017977	0,038962	0,037101	0,047853	0,010695	0,052105
Skewness	-0,28652	-0,74475	-2,617	-0,82312	-4,228	-1,3399
Kurtosis	-1,2241	-0,75239	6,059	-0,60343	25,177	3,2399
Percentile 5%			0,87726	0,86872	0,97545	0,80127
Percentile 95%			1	1	0,9988	0,94288
Range Q3-Q1	0,034909	0,065267	0,00671	0,079466	0,007724	0,057403

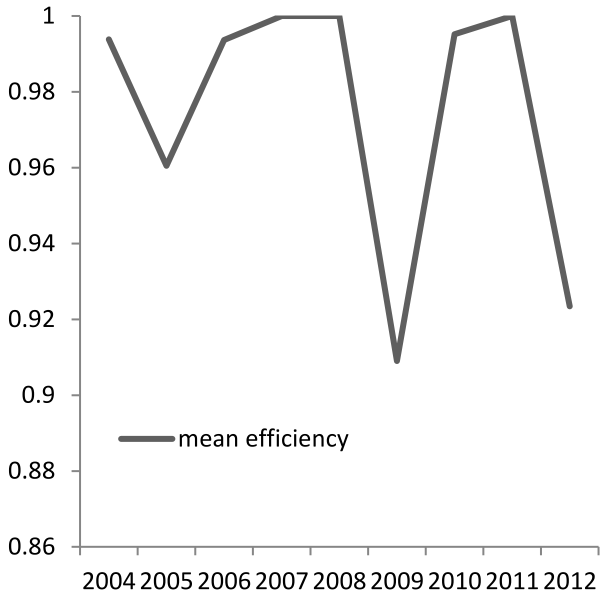
a means general model, b means the model with ALMP.

Table A4 Summary statistics for the general sample and chosen subsamples, annual data

	u	U	v	V	m
			NUTS-4		
Whole sample	7163 (5066)	5901 (4648)	2458 (2528)	64 (182)	3225 (2281)
Without cities with district rights	6286 (3004)	5325 (2922)	1974 (1327)	35 (60)	2906 (1484)
Short-term unemployed	-	3265 (2624)	-	-	-
			NUTS-3		
Whole sample	41131 (13757)	33888 (15103)	14116 (6128)	368 (429)	18519 (6889)
Without subregion-cities	41882 (13609)	34562 (14928)	13992 (5893)	310 (308)	18901 (6818)
Short-term unemployed	-	18749 (7138)	-	-	-
			NUTS-2		
Whole sample	166802 (64436)	150167 (69265)	53025 (26803)	1278 (1436)	74573 (29319)
Contraction phase of the business cycle	166829 (64745)	150401 (68492)	50461 (24880)	1147 (1187)	72084 (28676)
Western regions	176635 (68199)	147024 (69969)	58627 (28751)	1632 (1748)	79083 (30510)
Short-term unemployed	-	77338 (30805)	-	-	-
			NUTS-1		
Whole sample	444502 (70411)	387950 (119735)	142888 (44285)	206236 (47081)	197495 (37330)
Short-term unemployed	-	206236 (47081)	-	-	-

Results are shown as: mean (standard deviation).

Figure A1 Mean efficiencies (left chart) and mean marginal effects of efficiency covariates (right chart) across time, NUTS-1 level



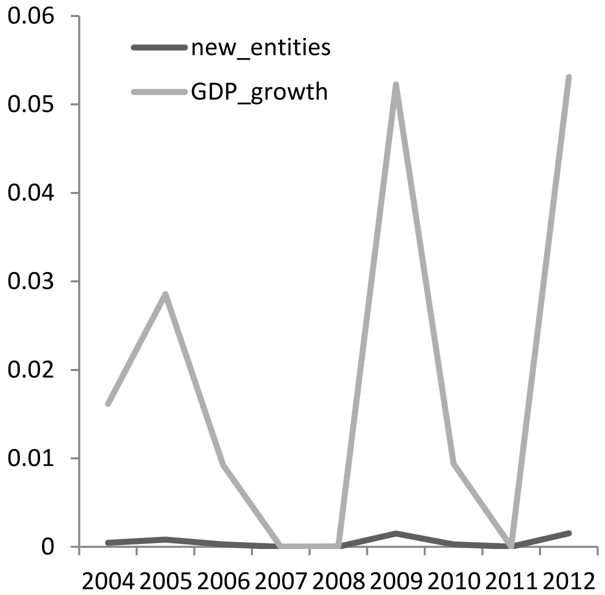
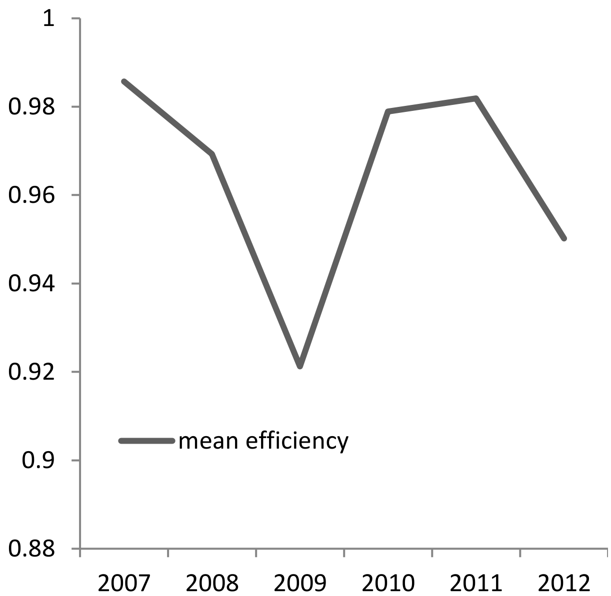


Figure A2 Mean efficiencies (left chart) and mean marginal effects of efficiency covariates (right chart) across time, NUTS-2 level



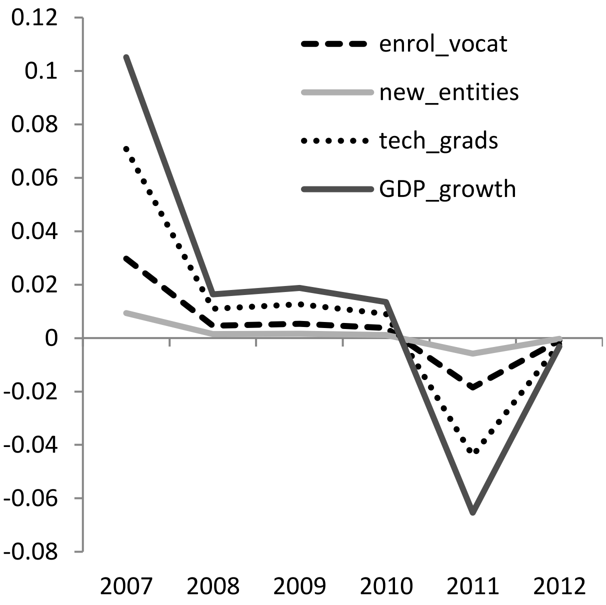
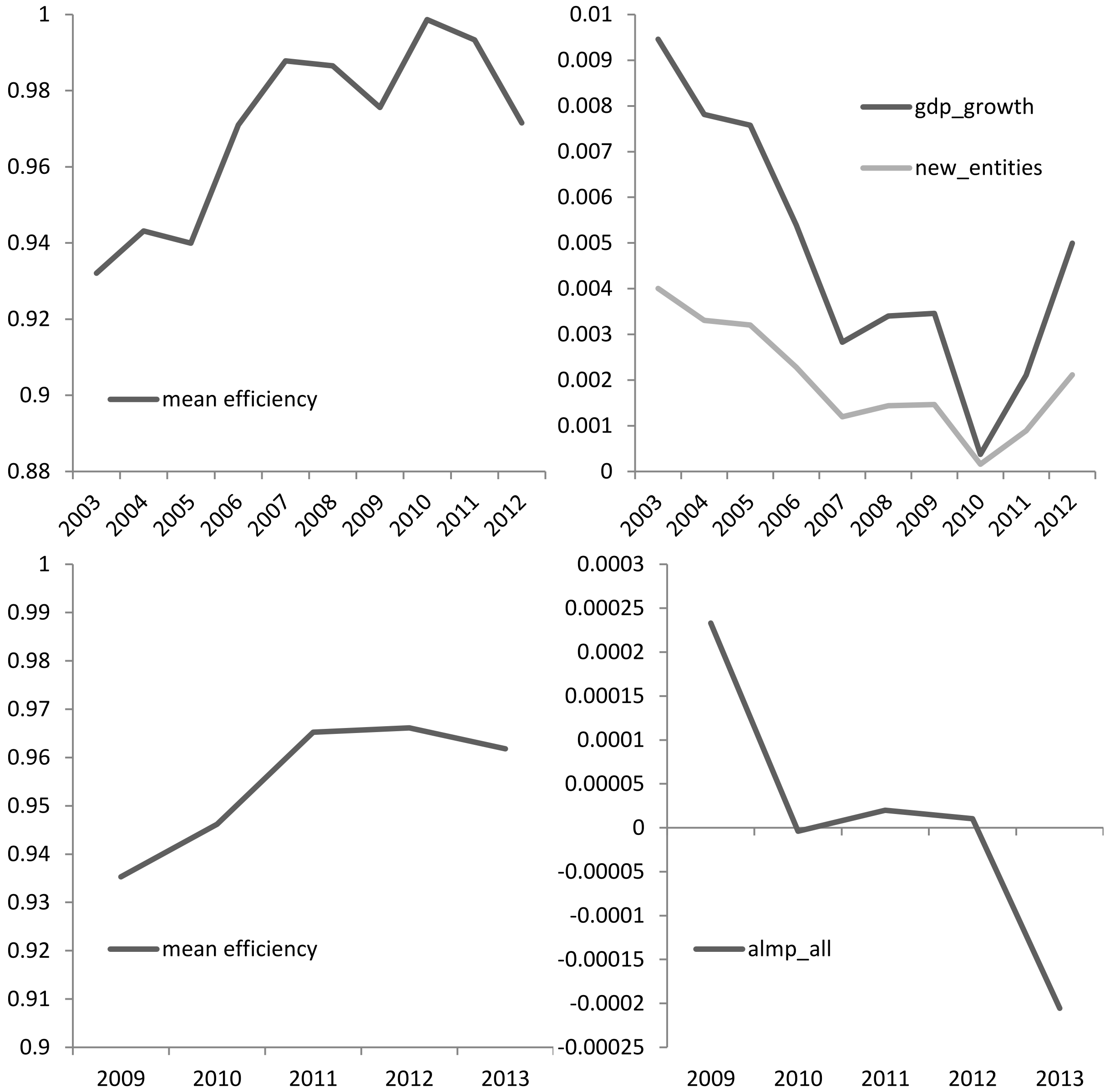
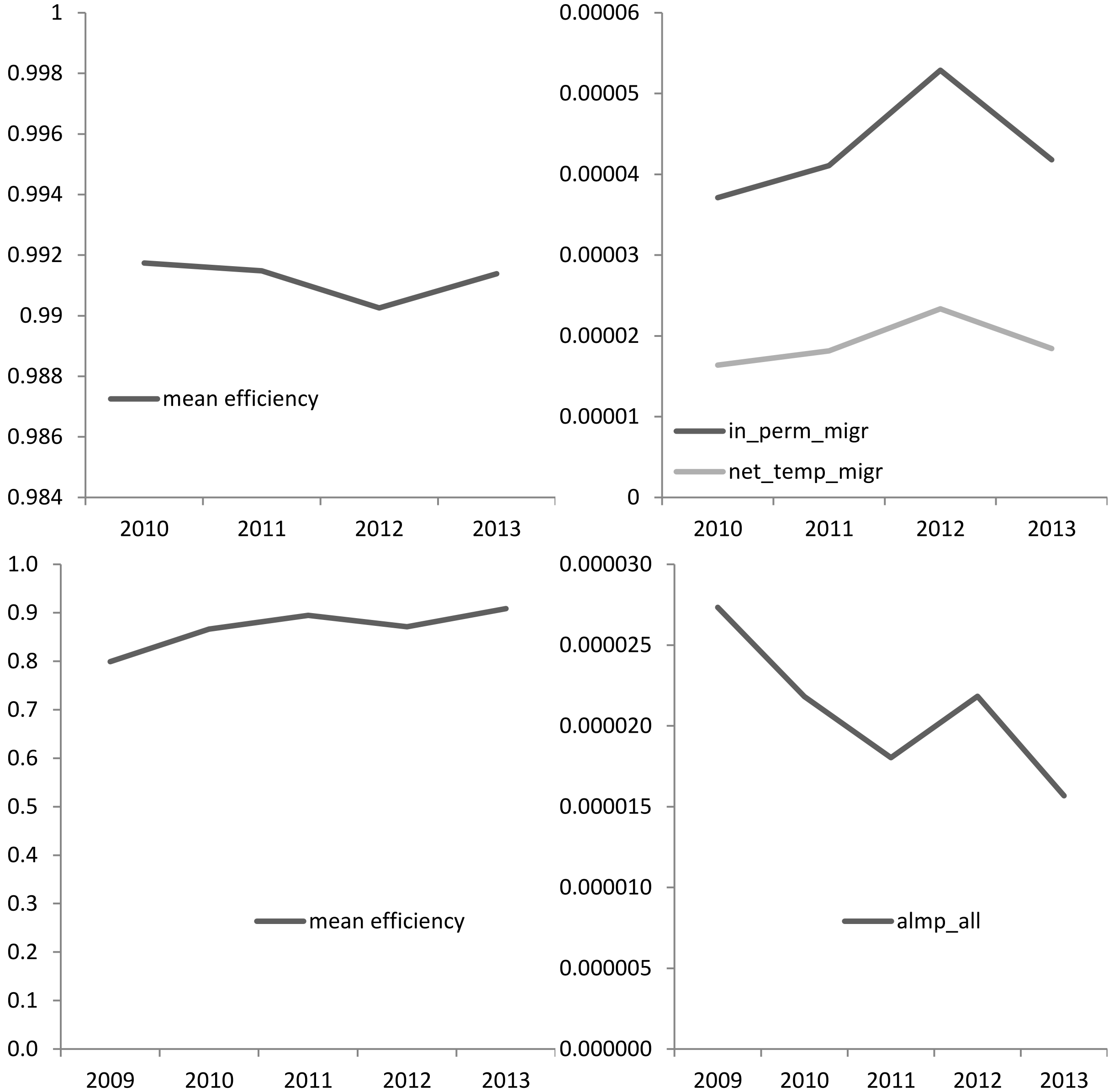


Figure A3 Mean efficiencies (left chart) and mean marginal effects of efficiency covariates (right chart) across time, NUTS-3 level



The upper charts refer to 'basic' models, shown in the upper portion of table 4. The lower charts refer to models with ALMP (estimated separately because of the short sample) and refer to the results shown in the lower portion of table 3.

Figure A4 Mean efficiencies (left chart) and mean marginal effects of efficiency covariates (right chart) across time, NUTS-4 level



The upper charts refer to 'basic' models, shown in the upper portion of table 4. The lower charts refer to models with ALMP (estimated separately because of the short sample) and refer to the results shown in the lower portion of table 3.

Abstrakt

Ve své práci analyzujeme efektivitu párování nabídky a poptávky na trhu práce. Efektivitu chápeme jako poměr průměrného počtu párů, jenž je podmíněný i jinými proměnnými, k počtu párů, které by byly vytvořeny v případě, že párování by bylo optimální. Zvolený koncept efektivity zohledňuje fakt, že zaměstnanecký vztah nelze měnit bez omezení. Aplikujeme stochastickou hranici párových možností pro tři různé modely tvorby párů na trhu práce. Používáme data pro Polsko, což je země, jejíž jednotlivé kraje mají značně odlišnou míru nezaměstnanosti. K dosavadnímu výzkumu přispíváme tím, že porovnáváme měsíční a roční data pro různé úrovně územní agregace a to od úrovně NUTS-1 až po úroveň NUTS-4. Zkoumáme, zda a jak se efektivita párování nabídky a poptávky mění v čase. Naše výsledky poukazují na prostorovou a časovou různorodost na trhu práce, z tohoto důvodu by se měla hospodářská politika zaměřit na zlepšení efektivity párování poptávky a nabídky na konkrétních regionálních úrovních.

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