COLLEGIUM OF ECONOMIC ANALYSIS
WORKING PAPER SERIES

Efficiency in spatially disaggregated labour market matching

Elżbieta Antczak
Ewa Gałecka-Burdziak
and Robert Pater

SGH KAE Working Papers Series Number: 2016/010 May 2016

Elżbieta Antczak[♣]

Ewa Gałecka-Burdziak[♦]

Robert Pater[♥]

Efficiency in spatially disaggregated labour market matching[♠]

Abstract

We analyse the efficiency in a labour market matching process. We contribute to the literature by comparing different spatial aggregation levels – NUTS-1 to NUTS-4 and analysing monthly and annual perspectives. We use data for Poland, a country with highly regionally diversified unemployment rate. We apply a stochastic matching frontier model for random, job queuing and stock-flow frameworks and test properties of the efficiency. Heterogeneity in the labour market in spatial and temporal perspectives and determinants of the matching inefficiency imply that different measures of economic policy should be applied to improve the efficiency of the labour market matching process.

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

[♣] Department of Spatial Econometrics, University of Łódź.
[♦] Department of Economics I, Warsaw School of Economics.
[♥] Department of Macroeconomics, University of Information Technology and Management in Rzeszow.
[♠] The article was prepared within a project financed by the CERGE-EI in the 15th Global Development Network Regional Research Competition (RRC-15).
We wish to thank the Ministry of Labour and Social Policy in Poland for sharing their database.

Introduction

In this study we analyse the efficiency in a labour market matching process in spatial perspective in Poland. We argue that this efficiency differs at certain levels of data spatial aggregation and that various factors affect labour market matching. We aim at identifying these factors. 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 in 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 two most common methods applied 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 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.

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

[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 is.

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 in 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.

Our contribution to the literature is twofold. We ask the questions: Does the job matching process differ at different levels of regional aggregation? Does it differ in 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). We test different matching mechanisms and stochastic frontier characteristics. We have not encountered such broad approach in the literature. We check how the efficiency of matching differs in certain spatial units and seek for potential determinants of this (in)efficiency in the labour market matching. 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 universities graduates (NUTS-2), migrations and ALMP (NUTS-3 and NUTS-

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

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.

Stochastic Frontier Matching Function

Random (stock-based or job queuing) and non-random (stock-flow) are two main technologies that describe labour market matching mechanism. In a stock-based model unemployment stock trades with vacancy stock. In the job queuing model matching takes place between unemployment stock and vacancy inflow. Here we assume large discrepancies between unemployment and vacancies. Demand side always clears, while the unemployed individuals wait for new job opportunities. In a stock-flow model heterogonous 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. Thus, the random (stock-based) model is:

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

the stock-flow model is:

$$m_{i,t} = \alpha_0 + \alpha_1 V_{i,t} + \alpha_2 U_{i,t} + \alpha_3 v_{i,t} + \alpha_4 u_{i,t} + (\varepsilon_{i,t} - \vartheta_{i,t}) \tag{2}$$

and the job queuing model is:

$$m_{i,t} = \alpha_0 + \alpha_2 U_{i,t} + \alpha_3 v_{i,t} + (\varepsilon_{i,t} - \vartheta_{i,t}) \tag{3}$$

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. 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.

When we impose certain restrictions on the $\vartheta_{i,t}$ we have three distinguishable cases of the models (1-3). 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:

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

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 time series.

Imposing restriction 4 or 5 gives 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):

$$\vartheta_{i,t} = z_{i,t}\beta + \xi_{i,t} \tag{6}$$

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 $TEM_{i,t} = \exp(-\vartheta_{i,t}) = \exp(-z_{i,t}\beta - \xi_{i,t})$. 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 $z_{i,t}\beta$. When we impose certain restrictions, we test between different types of matching and inefficiency effects across time and regions.

The dataset

We based the research on the 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 crossed out from the registry.

Registration in a public employment office is a necessary condition for the free health insurance for the 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 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 not virtually obeyed[3]. Public employment offices do not possess every job offer available in the market. There might be an overrepresentation of the jobs a company has incentive to announce in a public employment office, i.e. refunded trainings, publicly supplemented workplaces for the disabled. The unemployed may also search for a job on their own. Thus,

[3] 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).

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 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 Denton-Cholette (Dagum and Cholette 2006) method[4] to temporally disaggregate quarterly GDP to monthly values. Table A1 (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

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

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

Stochastic frontier analysis of the matching function

We estimated each matching function model – random, stock-flow and job queuing 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 prevailed (table 2). The random matching was rejected in each case. The job queuing model was accepted at NUTS-3 level only.

Table 2 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, stock-flow vs. time invariant equivalent (always better than OLS).

In table 3, we compiled 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. Vacancy inflow experienced higher elasticity at higher levels of data spatial aggregation. Unemployment inflow negatively affected the trade process at NUTS-1 to NUTS-3 units. When we moved to less aggregated data this negative effect diminished or became statistically insignificant. The unemployment inflow positively affected the matching process at NUTS-4 level. Parameter estimates of the vacancy stock, vacancy inflow and unemployment stock were generally lower in the monthly results than in the annual ones.

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.

Table 3 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		$1.24 \cdot 10^{-3}$	$1.49 \cdot 10^{-3}$	$2.78 \cdot 10^{-3}$	$2.11 \cdot 10^{-3}$
		$(4.40 \cdot 10^{-4})$	$(2.45 \cdot 10^{-4})$	$(1.78 \cdot 10^{-4})$	$(7.36 \cdot 10^{-5})$
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	$2.92 \cdot 10^{-5}$	0.981	0.972	0.798	0.776
	$(6.47 \cdot 10^{-3})$	(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.

At the national level the results produced no inefficiency in matching. The inefficiency was significant at all regional levels. The stochastic frontier model yielded more efficient results than the OLS equivalent i.e. the one that assumed fully efficient matching.

Annual data analysis proved that the process efficiency was constant over time (the only exception was at NUTS-3 level, where the inefficiency of matching decreased over time, so the efficiency increased). The annual data produced lower efficiency of the matching process at lower levels of data aggregation, although the efficiency was higher compared to the monthly results. The monthly data produced time-varying (increasing) efficiency of the matching process. The monthly analysis indicated that the efficiency was the highest at NUTS-3 and NUTS-4 levels.

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 LR test indicates that efficiency effects model is more appropriate than its OLS counterpart, and matching inefficiency exists at every spatial aggregation level (table A2 in the Appendix). We aim at identifying determinants of the trade process efficiency. We conducted the analysis at NUTS-1 to NUTS-4 levels. The data on ALMP are available since 2009, thus we estimated their effect separately. 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.

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 4). Both of them increased the efficiency. The efficiency of matching depended on a business cycle. It increased during economic expansions, when it equalled almost 100% (figure A1 in the Appendix). During 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).

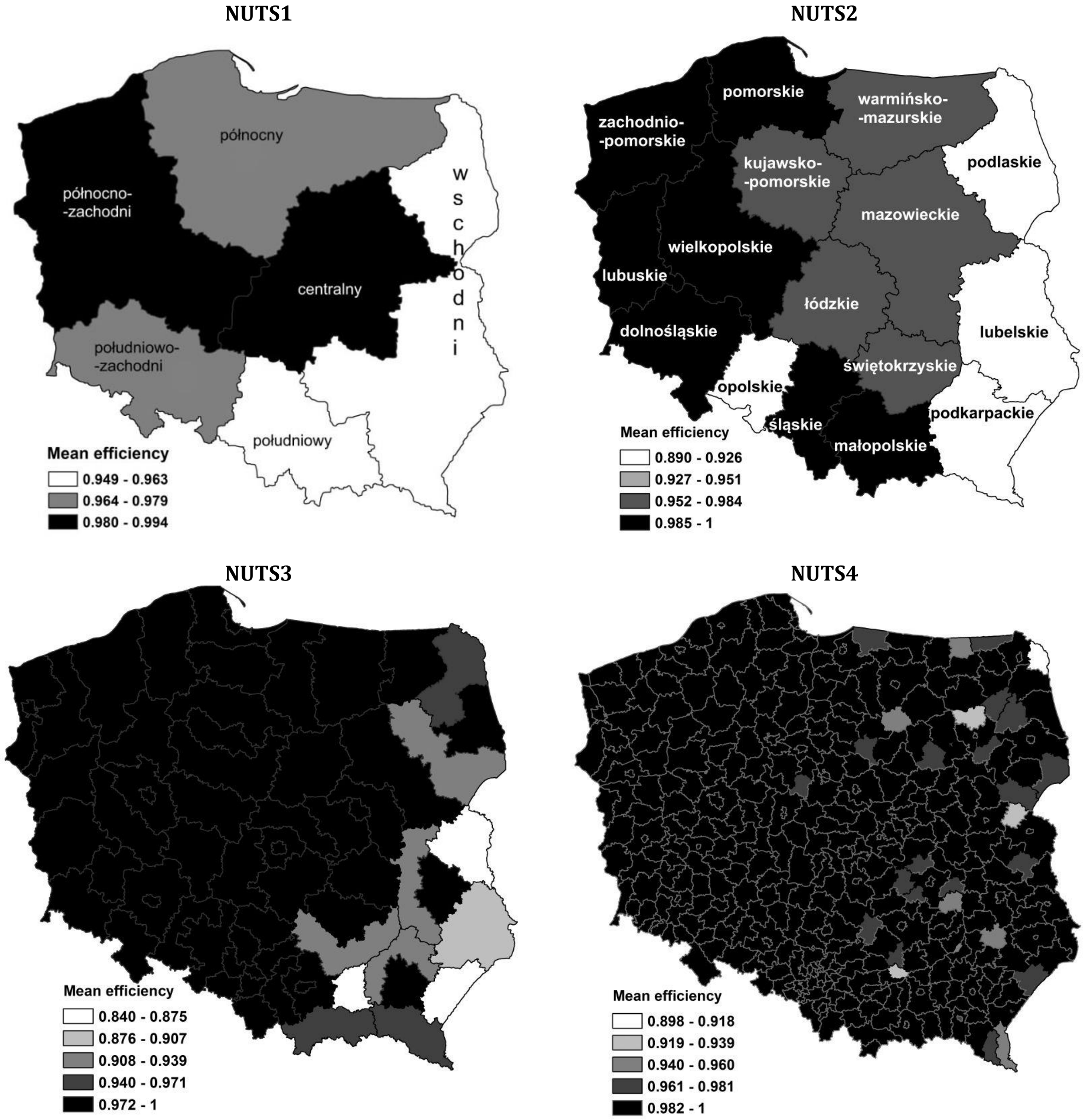
Table 4 Determinants of efficiency of matching at different levels of spatial aggregation, annual data

	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)
$almp\_all_{i,t}$			-8.90·10-5	-1.75·10-4
			(1.52·10-5)	(9.42·10-5)

Job queuing model for NUTS3 level, stock-flow model for all other levels. Standard errors reported in (). For models with GDP, the sample ends with 2012 due to availability of regional accounts.

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). 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 eastern region. The highest discrepancy was observed in 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 highest economic development and cities with lowest rate of unemployment. Full efficiency of matching most often occurred in eastern and north-western regions.

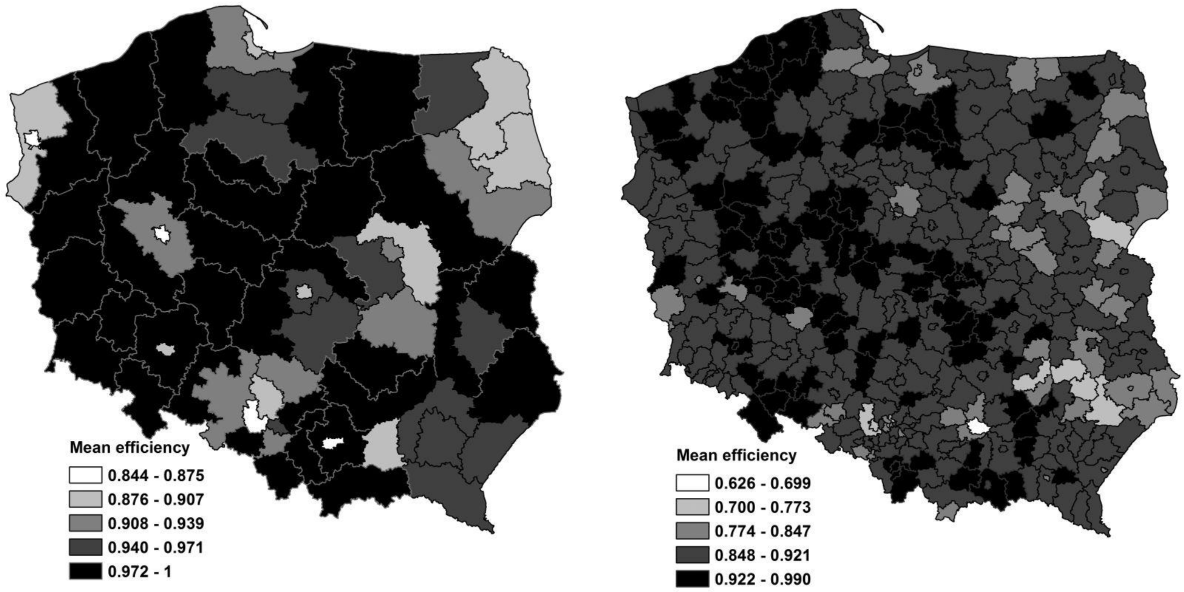
Map 1 Mean efficiency in Polish regions



The job queuing model yielded better results than the stock-flow one at the NUTS-3 level. Here, the yearly growth rate of GDP[5] 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 eastern region with an exception in southern region. It resulted from low GDP, low entrepreneurship and slow pace of new industries 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**



At NUTS-4 level 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. 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

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

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. The least effective regions were located in the eastern part of the country, while those with highest efficiency were in north-western and central Poland.

Discussion

Estimates based on annual data indicated decrease in the matching efficiency once we move from less to more disaggregated data. The monthly data analysis produced the highest efficiency at NUTS-3 and NUTS-4 units. These differences may result from the search and matching frictions. In the monthly perspective the search process is improved due to spatial proximity of firms and workers. In the annual perspective, agents have time to search and it might be easier to match at a country level due to increased variety of firms and job seekers.

The annual data yielded higher efficiency of matching than the monthly ones. Thus, it might be the case that in the annual perspective mismatch matters more, while in the monthly perspective 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 for 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 influenced the efficiency of the matching process.

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 line with those for other countries (Fahr and Sunde 2001, Anderson and Burgess 2000, while Tomić (2014) found increasing efficiency of matching for other post-transition economy – Croatia). We found the heterogeneity in the 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, i.e. Altavilla and Caroleo (2013) found different matching efficiency in northern and southern Italy.

The ALMP improved the matching efficiency, but some interesting results emerged. The effects were significant only at NUTS-3 and NUTS-4. This finding is 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 highest economic development and the cities with 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 organize certain programmes, e.g. trainings in markets with few enterprises, wherein specialized 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 A3 (in the Appendix) provides summary statistics for these subsamples. Spatial units without cities with district rights had lower unemployment, number of vacancies and outflow from unemployment to employment. Exclusion of the biggest cities in Poland, i.e. subregion-cities increased unemployment and decreased number of vacancies, but the number of matches slightly increased. Additionally, we found that 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 the western labour markets. In western Poland 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 7 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.

Table 7 contains comparison of models for different subsamples with general model. 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. Business cycle produced contrary finding. The matching process proved to be more efficient in the contraction phase. In the presence of lower number of vacancies and similar number of unemployed, similar number of matches occurred. We think that this may result from long lags of unemployment in the business cycle, which distort the relation between labour market and GDP[6].

Conclusions

Our article contributes to the literature on the efficiency of labour market matching from regional perspective. We based the research on the data from public employment offices in Poland and analysed the efficiency of the matching process at NUTS-1 to NUTS-4 levels using annual and monthly data. We found 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 the economic activity affected the matching process in the labour market. The efficiency was higher in the annual analysis than in the monthly one. In the monthly perspective search frictions had larger meaning, while in the annual perspective the mismatch affected more for efficiency of matching.

[6] 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 take into account also structural changes.

The matching process is complex and time-consuming. We found the stock-flow model to best explain 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 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, however, 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 in 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 the future research.

References

1. Abid A. B., Drine I., 2011, Efficiency frontier and matching process on the labour market: Evidence from Tunisia, Economic Modelling, 28, 1131-9.
2. Act on promotion of employment and labour market institutions of 2004, art. 36, p. 5 (Dz. U. 2004, no. 99, 1001 with later amendments).
3. Altavilla C., Caroleo F.E., 2013, Asymmetric Effects of National-based Active Labour Market Policies. Regional Studies 47, 1482–506, http://dx.doi.org/10.1080/00343404.2011.635139.
4. Anderson P. M., Burgess S. M., 2000, Empirical Matching Functions: Estimation and Interpretation Using State-Level Data, The Review of Economics and Statistics, 82(1), pp. 93-102.
5. Antczak E., Gałecka-Burdziak E., Pater R., 2016, Spatial labour market matching, unpublished manuscript.
6. Battese G.E., Coelli T., 1992, Frontier production functions, technical efficiency and panel data: with application to paddy farmers in India. Journal of Productivity Analysis 3, 153-169.
7. Battese G.E., Coelli T., 1995, A model for technical inefficiency effects in a stochastic frontier production function for panel data. Empirical Economics 20, 325-332.
8. Battese G.E., Coelli T., Cloby T.C., 1989, Estimation of Frontier Production Functions and the Efficiencies of Indian Farms Using Panel Data from ICRISAT' Village Level Studies, Journal of Quantitative Economics 5, 327-48.
9. Blanchard O., Diamond P., 1994, Ranking, Unemployment Duration, and Wages, Review of Economic Studies 61, pp. 417-34.
10. Broersma L., van Ours J., 1999, Job Searchers, Job Matching and the Elasticity of Matching. Labour Economics, 6(1), pp. 77-93.
11. Burda M. C., Profit S., 1996, Matching across Space: Evidence on Mobility in the Czech Republic, Labour Economics 3(3), 255-78.
12. Burdett K, Coles M, van Ours J, 1994, Temporal Aggregation Bias in Stock-Flow Models. Centre for Economic Policy Research Discussion Paper no. 967, May.
13. Burgess S. M., 1993, A Model of Competition between Unemployed and Employed Job Searchers: An Application to the Unemployment Outflow Rate in Britain, The Economic Journal, 103(420), pp. 1190-204.
14. Coles M. G., Smith E., 1996, Cross-section estimation of the matching function: Evidence from England and Wales, Economica, 63, 589-98.

15. Coles M. G., Smith E., 1998, Marketplace and Matching, International Economic Review, 39(1), pp. 239-254.
16. Dagum E.B., Cholette P.A., 2006, Benchmarking, Temporal Distribution, and Reconciliation Methods for Time Series. Lecture Notes in Statistics, Springer-Verlag New York.
17. Fahr R., Sunde U., 2001, Disaggregate Matching Functions. IZA Discussion Paper No. 335.
18. Fahr R., Sunde U., 2005, Regional Dependencies in Job Creation: An Efficiency Analysis for Western Germany, IZA Discussion Paper No. 1660, July.
19. Gałecka E., 2008, Dopasowania podażowej i popytowej strony rynku pracy. Analiza na przykładzie Polski w latach 1998 – 2007, Dissertation, unpublished manuscript, Department of Macroeconomics, University of Łódź.
20. Gregg P., Petrongolo B., 2005, Stock – flow matching and the performance of the labor market, European Economic Review, 49, pp. 1987-2011.
21. Ilmakunnas P., Pesola H., 2003, Regional Labour Market Matching Functions and Efficiency Analysis, Labour, 17(3), 413-37.
22. Jeruzalski T., Tyrowicz J., 2009, (In) Efficiency of Matching – The Case of A Post-Transition Economy, MPRA Paper No. 16598.
23. Kano S., Ohta M., 2005, Estimating a matching function and regional matching efficiencies: Japanese panel data for 1973–1999, Japan and the World Economy, 17, 25-41.
24. Lehmann H., 1995, Active Labour Market Policies in the OECD and in Selected Transition Economies, Working paper No. 539-96, World Bank Policy Research.
25. Münich D., Svejnar J., Terrel K., 1999, Worker-firm Matching and Unemployment in Transition to a Market Economy: (Why) where the Czechs More Sucessful than Others? Working Paper 107. Davidson Institute, U. Michigan Business School.
26. NBP, 2012, Badanie Ankietowe Rynku Pracy. Raport 2012. Instytut Ekonomiczny National Bank of Poland, http://www.nbp.pl, (accessed 01.03.2013).
27. Puhani P., 1999, Estimating the effects of public training on Polish unemployment by way of the augmented matching function approach, ZEW Discussion Papers, no. 99-38, http://hdl.handle.net/10419/24320.
28. Robson M., 2006, Sectoral Shifts, Employment Specialization and the Efficiency of Matching: An Analysis Using UK Regional Data, Regional Studies, 40, 743–54.
29. Sax C., Steiner P., 2013, Temporal Disaggregation of Time Series, The R Journal, 5(2), pp. 80-88; http://journal.r-project.org/archive/2013-2/sax-steiner.pdf.
30. Taulbut M., Robinson M., 2015, The Chance to Work in Britain: Matching Unemployed People to Vacancies in Good Times and Bad, Regional Studies, 49, 2070-86, DOI: 10.1080/00343404.2014.893058.
31. Tomić I., 2014, Regional matching (in)efficiency on the Croatian labour market, Acta Oeconomica, 64, 287-312.

32. Tyrowicz J., 2011, Histereza bezrobocia w Polsce, Warszawa: Wydawnictwo Uniwersytetu Warszawskiego.

Appendix

Table A1 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 a month)	$unemp\_benef$	Monthly	+ / +	0-2	2001
2	Unemployed in the age 18-24 (at the end of a month)	$unemp\_1824$	Monthly	+ / +	0-2	2001
3	Unemployed in the age 55-59 (at the end of a month)	$unemp\_5559$	Monthly	+ / +	0-2	2001
4	Unemployed under active labour market policy instrument (at the end of a month)	$unemp\_almp$	Monthly	+ / +	0-2	2011
5	Long-term unemployed (at the end of a month)	$unemp\_long$	Monthly	+ / +	0-2	2001
6	Unemployed terminated for company reasons (at the end of a 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 works	$almp\_b\_interv$	Annual	+ / -	0-4	2009
32	Unemployed who started socially useful works	$almp\_b\_social$	Annual	+ / -	0-4	2009
33	Unemployed who started vocational training for adults	$almp\_b\_adults$	Annual	+ / -	0-4	2009
34	Unemployed who started public works	$almp\_b\_public$	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 works	$almp\_interv$	Annual	+ / -	0-4	2009
40	Unemployed who finished socially useful works	$almp\_social$	Annual	+ / -	0-4	2009
41	Unemployed who finished vocational training for	$almp\_adults$	Annual	+ / -	0-4	2009

	adults					
42	Unemployed who finished public works	$almp\_public$	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 A2 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

Figure A1 Mean efficiencies and marginal effects across time, NUTS-1 level

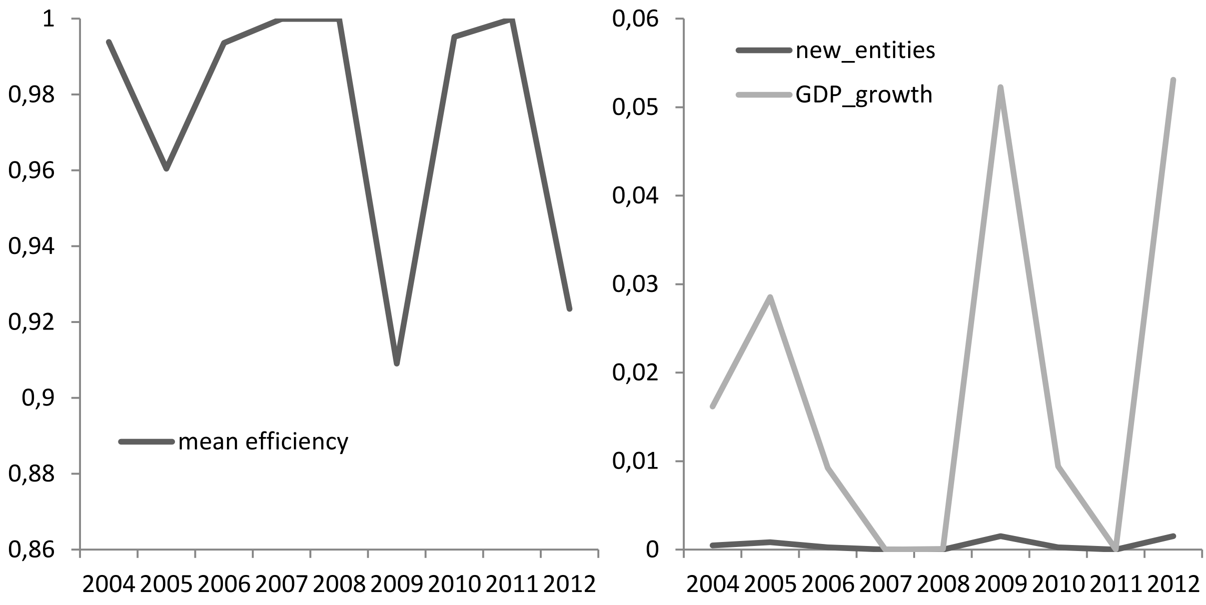


Figure A2 Mean efficiencies and marginal effects across time, NUTS-2 level

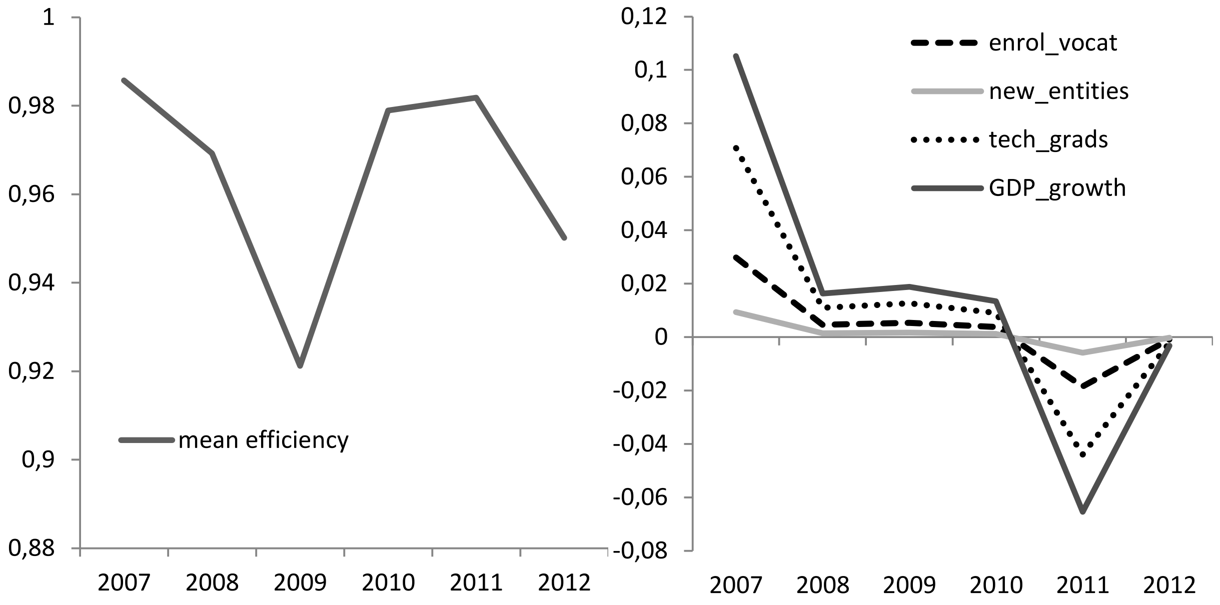
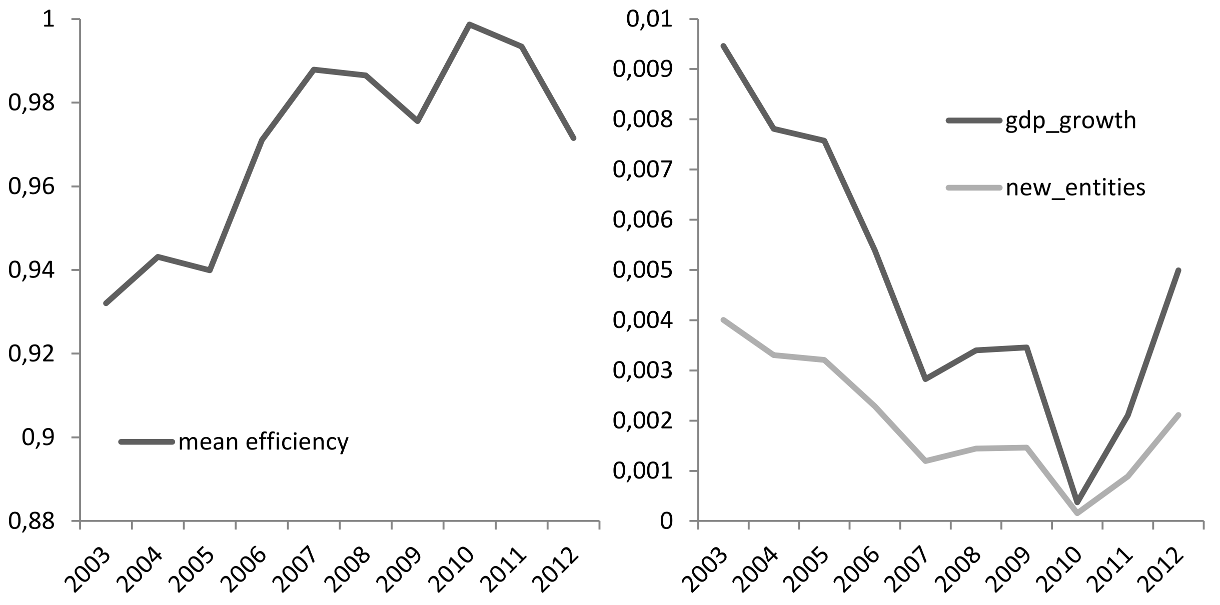


Figure A3 Mean efficiencies and marginal effects across time, NUTS-3 level



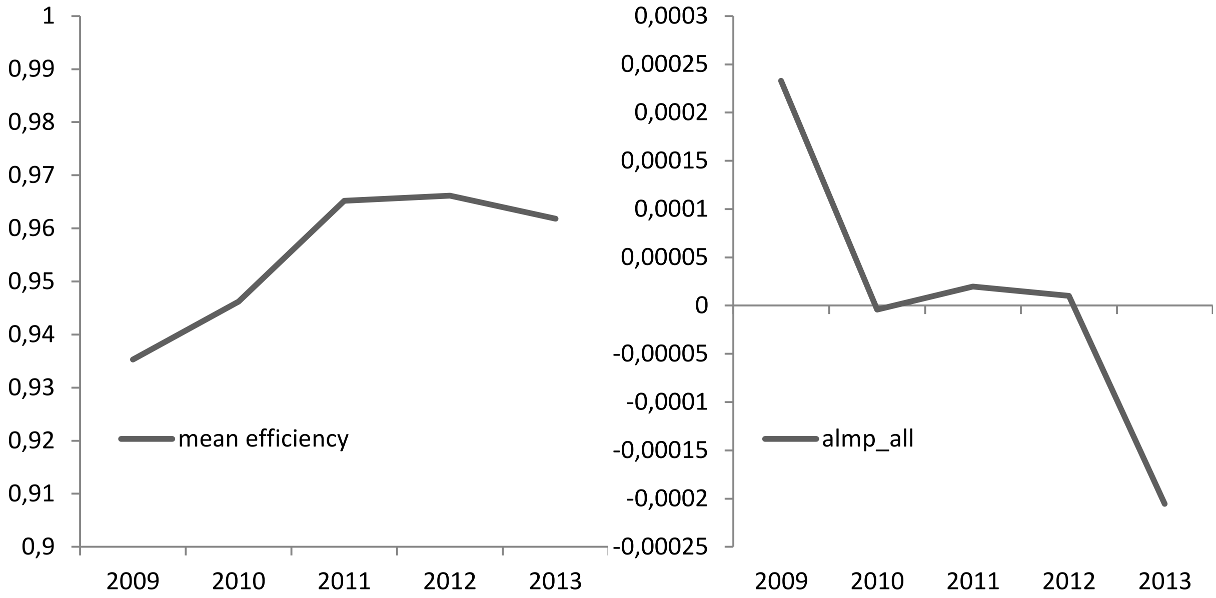
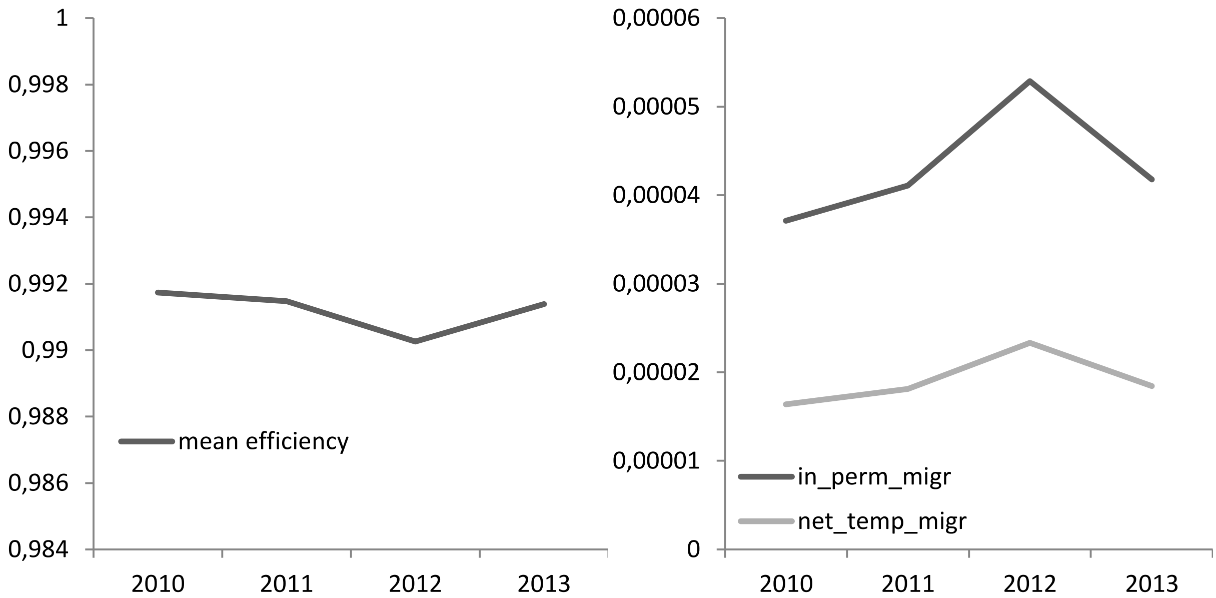
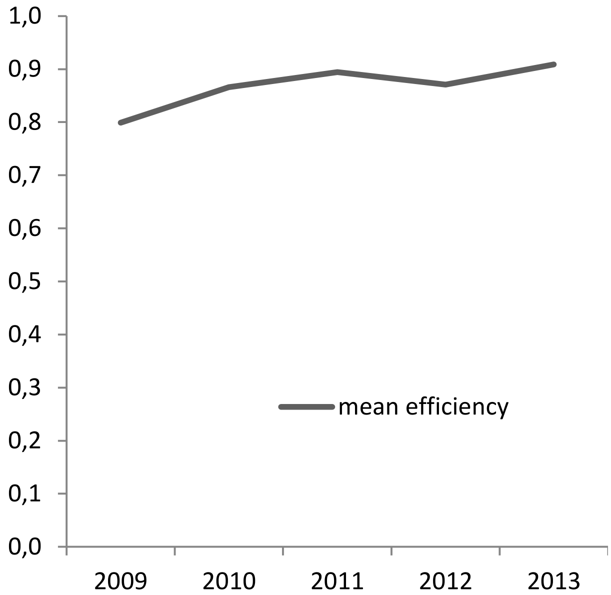


Figure A4 Mean efficiencies and marginal effects across time, NUTS-4 level





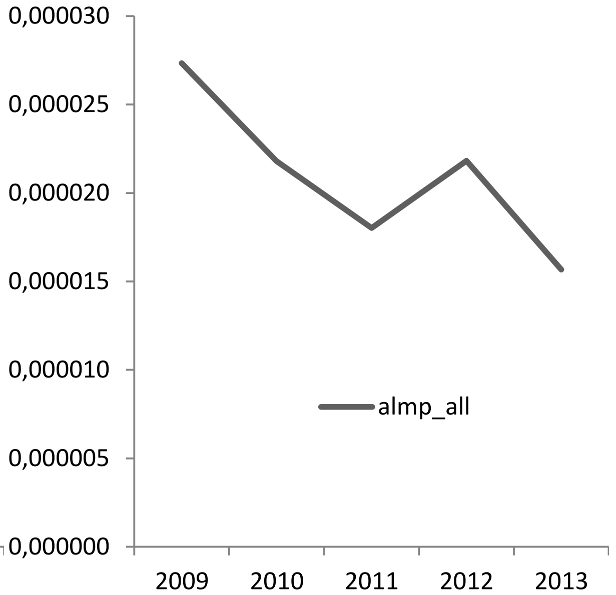


Table A3 Summary statistics for the general sample and chosen subsamples, annual data

	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)	-	-	-

Mean (standard deviation).