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Efficiency in spatially disaggregated labour market matching[♠]

Introduction

In this study we analyse the efficiency of a labour market matching process in spatially disaggregated markets in Poland. We argue that this efficiency differs at certain levels of data spatial aggregation and that different factors affect the trade between demand and supply of labour. 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. We include two temporal aggregation levels – annual and monthly. We test different matching types and stochastic frontier characteristics. Due to data availability we refer to the period: 2000(3)-2014.

The analysis of the efficiency in a labour market matching process most often focuses on identifying factors, other than the number of agents, that affect the trade process. Augmented matching function (Puhani 1999) and stochastic frontier analysis (Ilmakunnas and Pesola 2003) are the two most common methods. Most of the previous analyses concerning the Polish labour market were conducted on NUTS2 level. They were primarily focused on determining particular variables impact on the process efficiency and applied the augmented matching

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function concept[1]. Jeruzalski and Tyrowicz (2009) and Tyrowicz (2011) applied the stochastic frontier analysis at the NUTS4 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, ALMPs and individual labour office capacities was less significant.

Our contribution to the literature is twofold. We provide the results at different levels of data spatial aggregation: from NUTS-1 to NUTS-4 and two levels of temporal aggregation that we have not encountered in the literature. We check how the efficiency of matching changes in different spatial units and we seek for potential determinants of this (in)efficiency in labour market matching. We find heterogeneity in the labour market across all analysed dimensions and a few significant determinants of the matching inefficiency.

Stochastic Frontier Matching Function

There are two main technological processes that describe labour market matching: random and non-random. In random matching the trade occurs randomly between demand and supply. This framework is formalised in a stock-based or in a job-queuing model. In the stock-based model the unemployment stock trades with the 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. As a result, the demand side always clears, while the unemployed individuals wait for new job opportunities. The stock-flow model presents non-random matching. 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 $m = m(U, v)$,

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

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 stochastic frontier model to each of the frameworks. Thus, the random (stock-based) model is:

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

the stock-flow model is:

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

and the job queuing model is:

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

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 $TEM_{i,t} = \exp\left(-\vartheta_{i,t}\right) = \exp(-z_{i,t}\beta - \xi_{i,t})$. 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 $z_{i,t}\beta$. 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 unemployment data. Individual administrative data 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). External economic migrations are likely to happen due to a few reasons. High exchange rate of British pound and euro is a considerable incentive. Polish housing market is underdeveloped and it discourages undertaking an internal migration.

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[2]. Public employment offices do not possess every job offer present on the market. There might be an overrepresentation of the jobs a company has incentive to show 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. 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.

[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). In 2012 approximately only 16.5% of companies announced job offers at public employment offices (NBP 2012).

We also used other variables to account for changes in the efficiency of the labour market matching process. These variables were referred to as: active labour market policy (ALMP), 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 active labour market policy (ALMP) data, originally available at NUTS-4 level, up to NUTS-0. We used Denton-Cholette (Dagum and Cholette 2006) method[3] 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
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. It equalled 0.045 for NUTS-1 and 0.049 for NUTS-4 regions. 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

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

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.

Spatial and temporal aggregation

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 tests 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 flow 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, and its 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 equivalent, and matching inefficiency exists at every spatial aggregation level (table A2 in the Appendix). We aim at identifying determinants of the trade process efficiency. First we present the analysis for NUTS-1 and NUTS-2 levels. The computations for NUTS-3 and NUTS-4 levels are extended by the analysis of the active labour market policy (ALMP) measures impact on the efficiency of matching. Due to data availability we estimated separate models where we accounted for ALMP only[4].

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 and at that time equalled almost 100% (figure A1 in the Appendix). During economic downturns in 2005, 2009 and 2012 it 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)	
$new\_entities_{i,t}$	$-3.39\cdot10^{-3}$	$-2.17\cdot10^{-3}$	$-5.56\cdot10^{-3}$	
	$(6.15\cdot10^{-4})$	$(7.91\cdot10^{-4})$	$(8.10\cdot10^{-4})$	
$enrol\_vocat_{i,t}$		$-7.30\cdot10^{-3}$		
		$(3.99\cdot10^{-4})$		
$tech\_grads_{i,t}$		$-2.77\cdot10^{-2}$		
		$(6.47\cdot10^{-3})$		
$net\_temp\_migr_{i,t}$				$-5.30\cdot10^{-3}$
				$(2.48\cdot10^{-3})$
$in\_perm\_migr_{i,t}$				$-1.20\cdot10^{-2}$

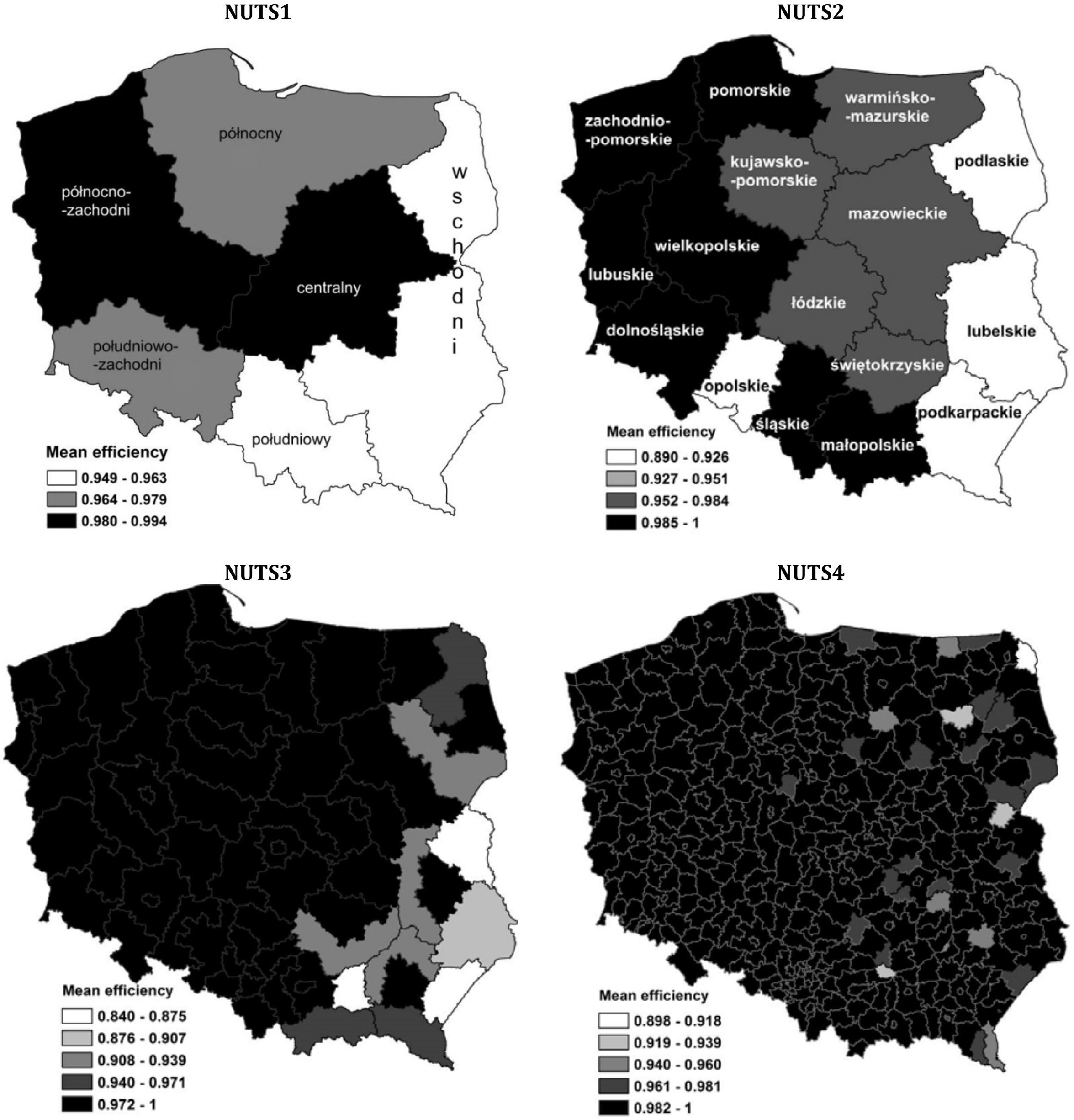
[4] Data on ALMP instruments were available since 2009. At NUTS1 and NUTS2 levels these instruments proved to be insignificant as determinants of matching process.

		($5.33\cdot10^{-3}$)
$const$	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 with the exception of Opolskie, and it was the lowest in eastern region with the exception of Swietokrzyskie. The highest discrepancy was observed in south-western region with high efficiency in Dolnoslaskie and low in Opolskie.

Map 1 Mean efficiency in Polish regions



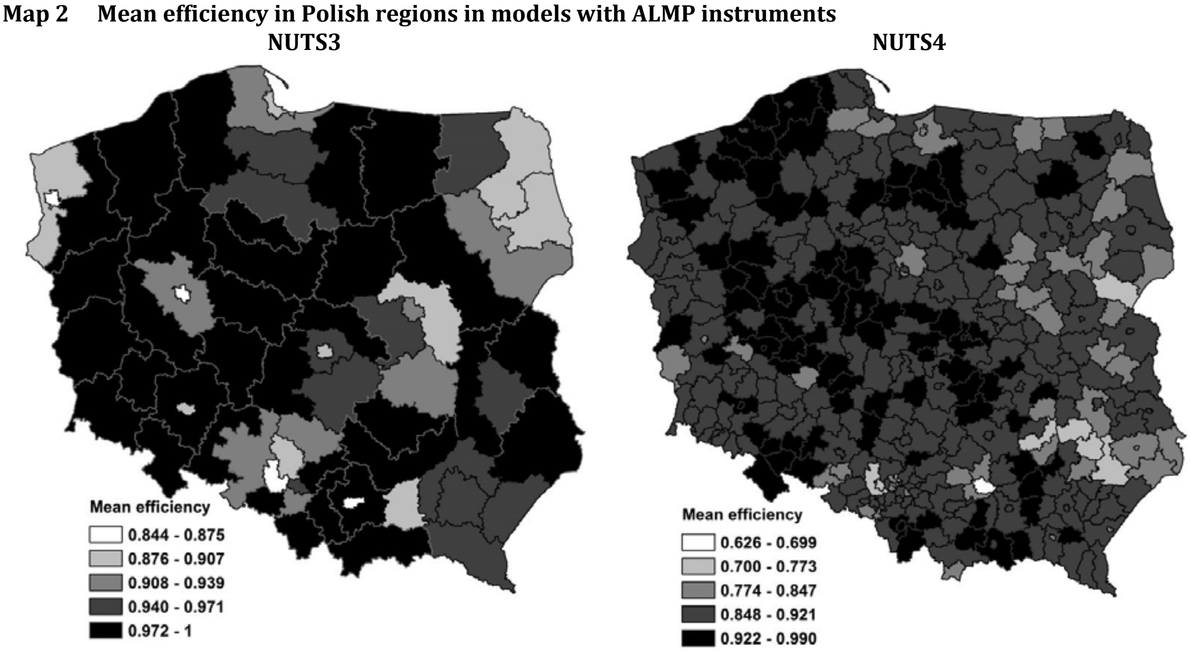
The NUTS-3 regions level was the only one at which the job queuing model yielded better results than the stock-flow framework. At this level again yearly growth rate of GDP[5] and the flow of economic entities had a statistically significant impact on the matching efficiency. The influence of these variables decreased during 2003-2010 and increased afterwards (figure A3 in the Appendix). Most of the regions with lower efficiency of matching

[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.

were in eastern region with one exception in southern region. It resulted from low GDP, low entrepreneurship and slow pace of new industries creation.

Data for ALMP instruments were available since 2009. Not to shorten the sample for the general model, we modelled their effects in a separate one. ALMP measures (overall) 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 Opolskie and Slaskie (southern Poland), and Podlaskie (north-eastern Poland). ALMP estimates 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 2 Mean efficiency in Polish regions in models with ALMP instruments



An analysis at NUTS-4 level indicated 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 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 yearly perspective, agents have time to match and it might be easier to do at a country level. The annual data yielded higher efficiency of matching than the monthly ones. This may indicate that a mismatch is a more significant problem than search frictions.

Different factors affected the efficiency of matching at certain levels of data spatial aggregation. We found the impact of 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 to be statistically significant. These variables positively influenced the efficiency of the matching process. Generally, the efficiency increased during 2000-2013 and was changing over the business cycle. The expansion phase improved the efficiency, while contractions decreased it. We also 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).

The ALMP improved the matching efficiency, but some interesting results emerged. The estimates indicated lower efficiency in the capital cities of certain voivodeships (with highest economic development and the cities with lowest rate of unemployment, NUTS-2 regions). This 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. They are easier to effectively apply 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 improve the results robustness, we checked 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 part, we found that more vacancies and more matches occurred 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. A finding to the contrary was made with respect to the business cycle impact. 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.

Conclusions

The stochastic frontier analysis proved statistically significant inefficiency in the matching process at all regional levels. In the long-run this inefficiency has been gradually decreasing, while in the short-run it was correlated to the business cycle. The stock-flow model explained the matching process in the Polish labour market. In some cases, at spatially disaggregated levels, the job queuing model proved to be a more adequate specification. When we moved to more disaggregated markets the impact of vacancy and unemployment stocks declined, the vacancy inflow became unimportant, while the impact of unemployment inflow became more positive and returns to scale decreased (from constant to decreasing).

Temporal aggregation revealed some differences in the results. The annual data produced decreasing returns to scale at levels NUTS-3 and NUTS-4. The yearly estimates indicated that the lower the level of spatial aggregation the lower the efficiency of matching. The monthly analysis showed that the efficiency is highest at NUTS-3 and NUTS-4 levels and much lower at larger spatial aggregation units (NUTS-1 and NUTS-2). The inefficiency of matching was generally constant over time in the yearly analysis, but it increased in the monthly estimates. The efficiency was higher in the yearly analysis than in the monthly one.

We found different factors to affect the efficiency of matching at different levels of spatial aggregation. At NUTS-1 level the business cycle phase was the most important determinant. At NUTS-2 level also the vocational and technical education supported the efficiency. The graduates of these types of schools or universities matched more efficiently than other graduates. At NUTS-3 level the estimates proved the importance of GDP and new economic entities. At NUTS-4 level migrations became the driving force behind the changes in the matching process efficiency. ALMP policy measures did not affect the efficiency of matching in a significant way at NUTS-1 and NUTS-2 levels. At NUTS-3 and NUTS-4 levels application of overall ALMP measures improved it.

References

1. Act on promotion of employment and labour market institutions of 2004, art. 36, p. 5 (Dz. U. 2004, no. 99, 1001 with later amendments).
2. 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.
3. 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.
4. 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.
5. Blanchard O., Diamond P., 1994, Ranking, Unemployment Duration, and Wages, Review of Economic Studies 61, pp. 417 – 434.

6. Coles M. G., Smith E., 1998, Marketplace and Matching, International Economic Review, vol. 39 nr 1, pp. 239 – 254.
7. Dagum E.B., Cholette P.A., 2006, Benchmarking, Temporal Distribution, and Reconciliation Methods for Time Series. Lecture Notes in Statistics, Springer-Verlag New York.
8. 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.
9. Gregg P., Petrongolo B., 2005, Stock – flow matching and the performance of the labor market, European Economic Review nr 49, pp. 1987 – 2011.
10. Ilmakunnas P., Pesola H., 2003, Regional Labour Market Matching Functions and Efficiency Analysis, Labour, 17(3), 413-437.
11. Jeruzalski T., Tyrowicz J., 2009, (In) Efficiency of Matching - The Case of A Post-Transition Economy, MPRA Paper No. 16598.
12. NBP, 2012, Badanie Ankietowe Rynku Pracy. Raport 2012. Instytut Ekonomiczny National Bank of Poland, http://www.nbp.pl, (accessed 01.03.2013).
13. 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.
14. 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.
15. 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 adults	$almp\_adults$	Annual	+ / -	0-4	2009
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

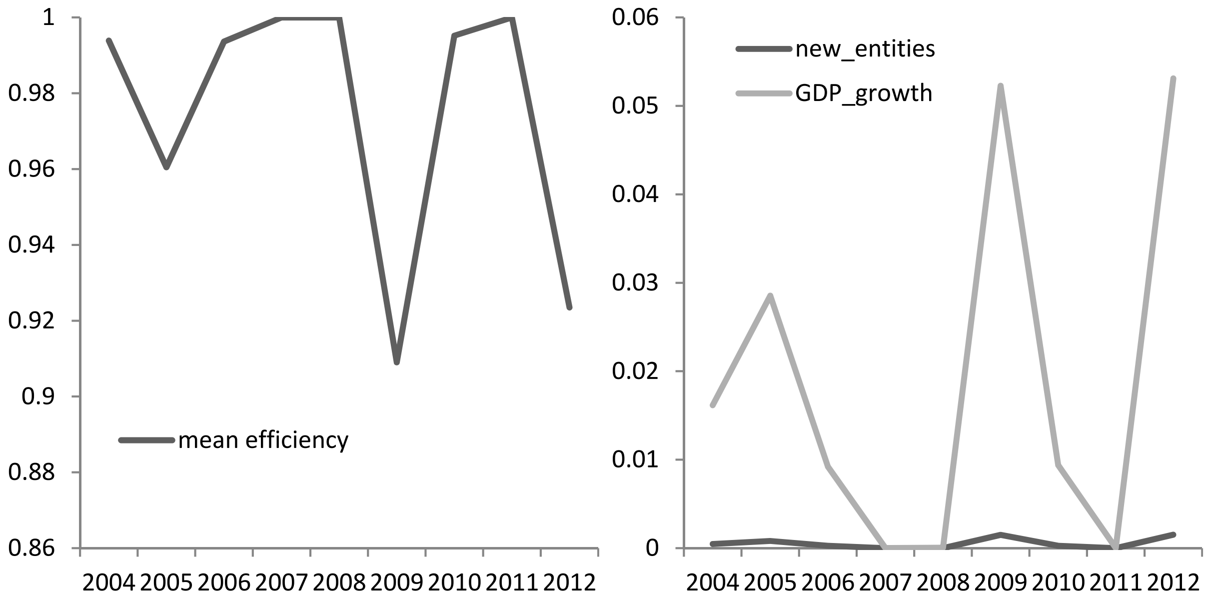


Figure A2 Mean efficiencies and marginal effects across time, NUTS-2 level

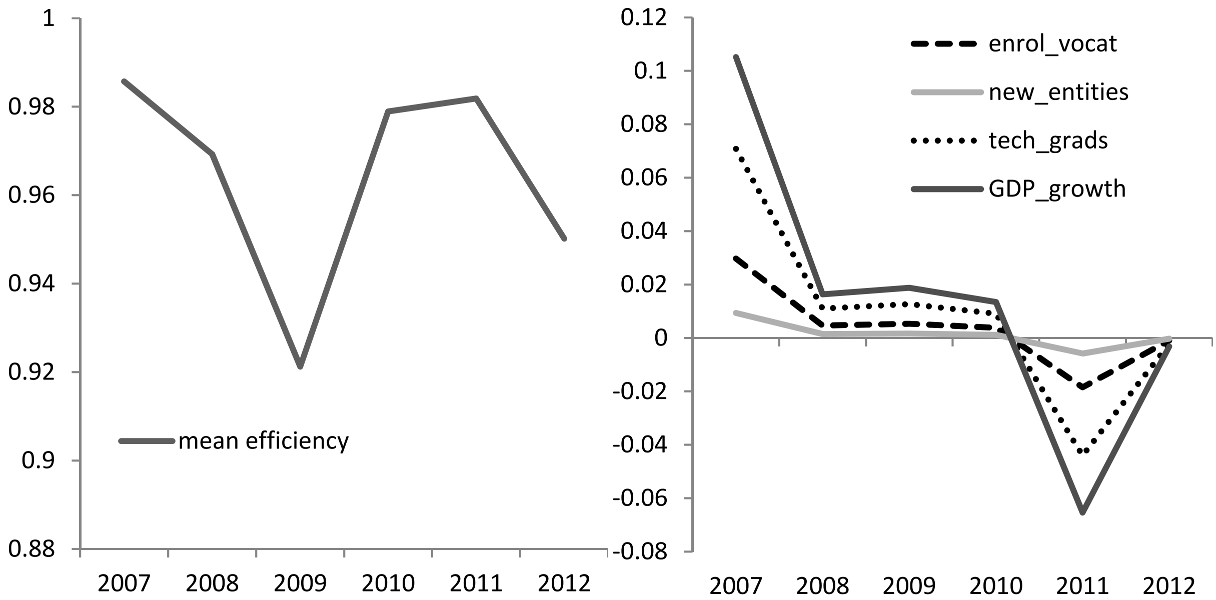


Figure A3 Mean efficiencies and marginal effects across time, NUTS-3 level

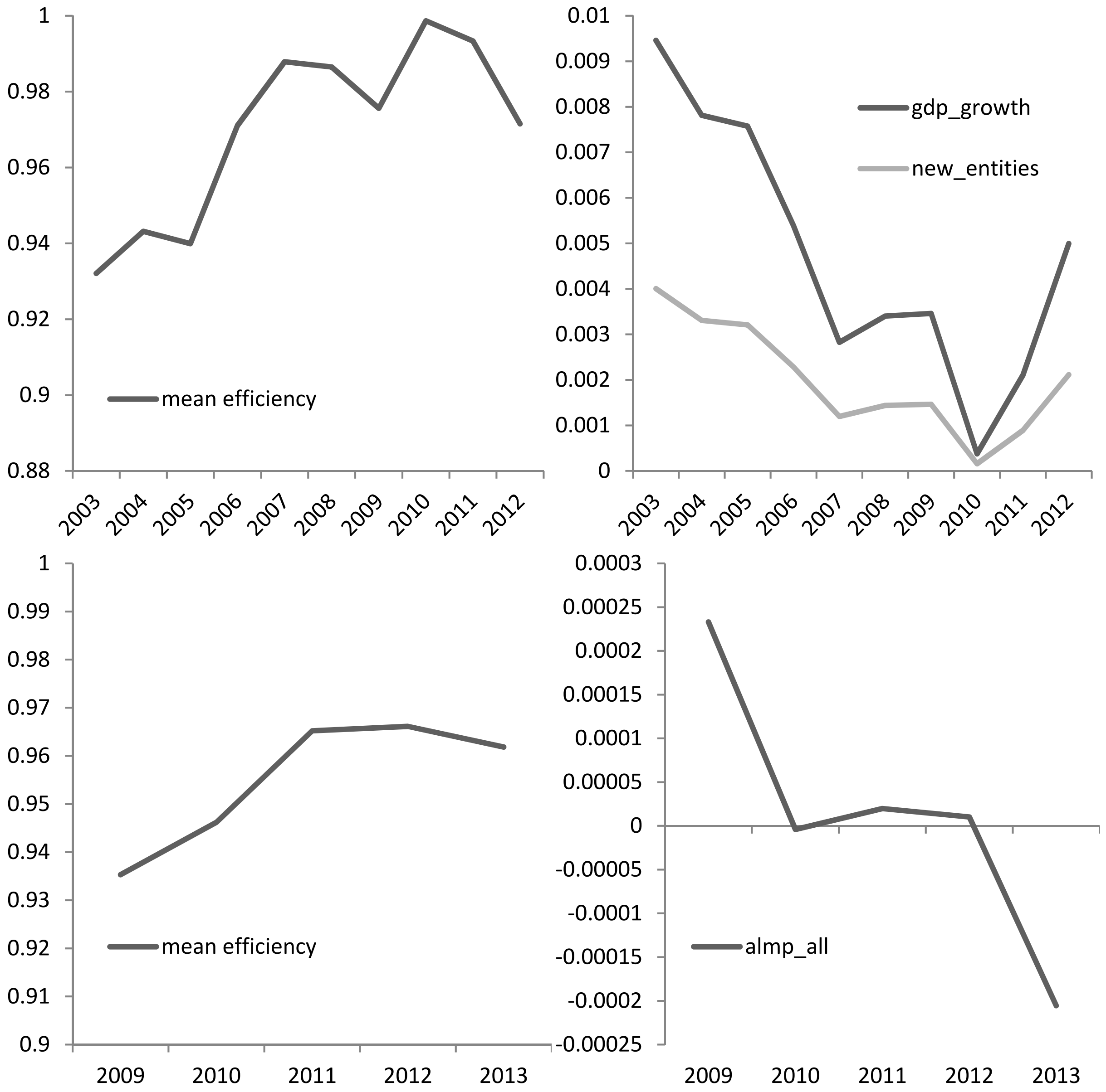


Figure A4 Mean efficiencies and marginal effects across time, NUTS-4 level

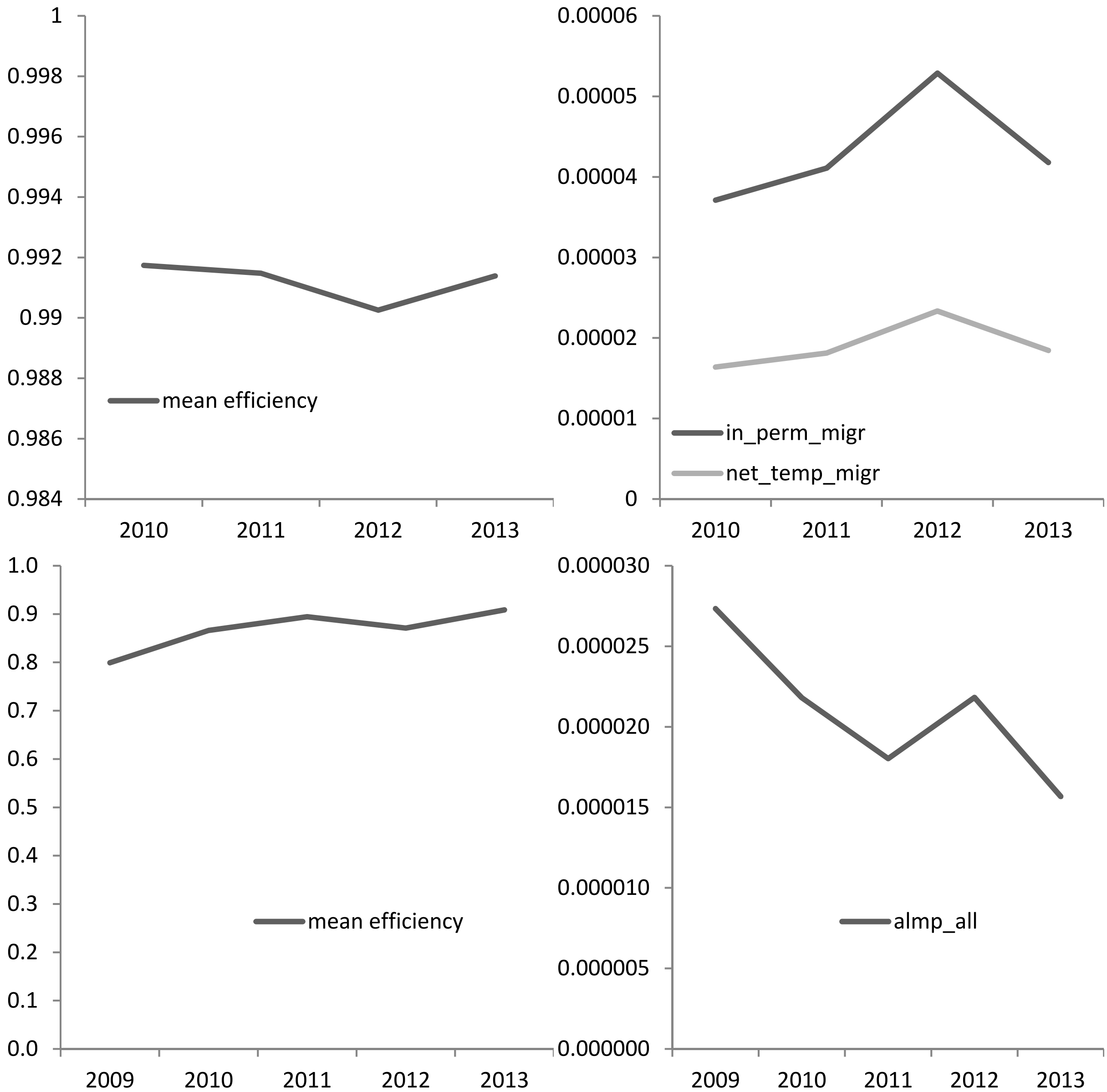


Table A3 Summary statistics for the general sample and chosen subsamples, annual data

	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).