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(In)Efficiency of Matching - the Case of a Post-transition Economy

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Abstract

This paper approaches the question of efficiency in job placement using regional data for Polish regions (policy-relevant NUTS 4 level) over the time span of 2000-2008. Using a unique data set we estimate the matching function using stochastic frontier as well as difference-in-difference estimators. We have also combined this unique data set with another unique source of data on the ALMPs coverage, unemployment structure across time and regions as well as the individual capacity of local labour offices. We use these data to explain the exceptional variation in estimated efficiency scores.

Our findings suggest that matching abilities are highly driven by demand fluctuations, while unemployment structure, ALMPs and individual labour office capacities have little explanatory power. Although without individual data it is fairly impossible to provide a reliable counterfactual, we raise some arguments to support the claim of job placement inefficiency by public employment services in Poland.

Keywords:
matching function, stochastic frontier, Poland

JEL:
P3, J64, J69, C33

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1 Introduction

When evaluating the effectiveness of differentiated active labour market policies (ALMPs), one typically resorts to two approaches. The first, basing on individual data, should allow to estimate the treatment effect of differentiated instruments, taking into account the developments in a control group (*i.e.* average treatment effect on the treated). However, this approach requires not only relatively detailed micro-level data, but also observing individuals after the completion of activisation programmes. Therefore, the policy relevant conclusions can only be drawn some years after policy implementation.

The alternative approach focuses on regional data instead. The obvious shortcoming of this strand of analyses is that either quite strong assumptions need to be made concerning the distribution of the unemployed among regions (essentially imposing homogeneity during the estimation procedures), or one is left with much weaker underpinnings for policy implications of the findings. Furthermore, regional data rarely allow to measure the scale of some negative indirect effects like displacement, substitution or redistribution effects.

Among the strategies within the second approach the most frequent in the literature are the matching functions. An extensive theoretical framework for the effects of ALMPs on employment has been developed by Calmfors (1993)[1], while the empirical applications were extensively evaluated by Petrongolo and Pissarides (2001). As stated by Hagen (2003), raising the efficiency of matching process is usually regarded as the main aim of ALMPs, and can be reached by adjusting the human capital of job seekers to the requirements of the labour market (especially important in transition countries with large structural disparities) and by increasing the search intensity (as well as search capacity) of (former) participants.

In this paper we attempt to evaluate the changes in the matching efficiencies using local (NUTS 4 level) data for Polish regions. We resort to NUTS 4 regions for two main reasons. First of all, this is a policy-relevant level, as all instruments are designed and implemented by local labour offices, subject to the financing algorithm which gives a premium to regions with relatively higher unemployment rate, relatively higher number of unemployed and relatively higher job market turnover rates. Secondly, higher level of data aggregation is statistically meaningless in as far as properties of unemployment dynamics are concerned, Tyrowicz and Wójcik (2009).

In order to approach the matching efficiency two main techniques are usually employed in the empirical literature: stochastic frontier estimation and panel data regressions. They approach this problem basing on somewhat different theoretical premises, thus performing both techniques may permit a comprehensive testing of the theories of the matching efficiency. We use administrative registry and ALMPs data, as well as a unique survey about the quality of matching procedures and IT tools applied in respective local labour offices. This allows to enrich the standard policy effectiveness analysis by enabling the analysis of "production" conditions (individual capacity of the local labour offices).

The paper is organised as follows. The next section focuses on the brief description of the institutional environment of Polish labour market in order to justify the use of multiple empirical strategies. These are outlaid in section 3, while results for respective analyses are presented in section 4. Conclusions focus on policy implications, as well as some directions for future research.

2 Institutional context

For the two decades after the transition, Poland has belonged to a group of countries with by far highest and most persistent unemployment in the EU. Financing of active labour market policies has been intensified

[1] See also: Calmfors and Skedinger (1995) and Calmfors, Forslund and Hemström (2002)

gradually as of 2004, reaching slightly more than 0.2% of GDP in 2006 and 0.33% in 2008. Although it is still less than in any of EU25 Member States, these policies covered 20% of the unemployed, which is considerable if one takes into account that the pool of unemployed amounted at the time to approximately 1 500 000 people.

Some qualitative research suggest anecdotic evidence in support of purposeful "creaming" by public employment services (PES), (Tyrowicz 2006). Incidental surveys among PES employees demonstrate that the odds for success individually perceived by the job counselors constitute the main criterion during the ALMPs recruitment process, *cfr.* ML&SA (2004). Consequently, despite general decrease in national unemployment rate over the second half of 2006 and throughout 2007, some regions still struggle with 35-40% unemployment rate thresholds.

2.1 Structural traits of unemployment

Some research suggest that approximately 80% of unemployment can be characterised as structural, (Sztanderska and Socha 2001). However, these findings comprise both frictional and *stricte* structural unemployment, while geographical and targeted group issues are not explored, partly for the lack of adequate data. Currently, more than 85% of unemployed are no longer entitled to the unemployment benefit, thus suggesting that most of the unemployed are either long-term unemployed or have a long record of unstable employment[2].

According to registry data, almost 70% of Polish unemployed have primary or vocational education only, frequently in outdated professions or with no longer applicable skills. Moreover, half of them expresses little or no willingness to upgrade their qualifications, *cfr.* ML&SA (2006). Professional and geographic mobility is very low, while transitory migration of almost 1 million Poles to Ireland, Sweden, Norway, Germany, UK and other EU countries concerns predominantly those aged under 30 years old[3]. Long term unemployment rate is the highest in EU (currently app. 9%, EU average falls short of 4%). Employment in agriculture still exceeds 17%, which is extremely high by European standards, while half of the registered unemployed live in the rural areas. In addition, forecasts concerning the agricultural sector at large suggest that due to the increasing productivity, hidden over-employment in this sector will soon transform to *de facto* unemployment[4]. Thus, low skills, low mobility and excessive employment in the agriculture are the main structural traits of the labour market problems in Poland.

At the same time, as noted by Munich, Svejnar and Terrel (1998), Poland had one of the lowest among the CEECs outflow rates. Vacancies ratios are dramatically low throughout the whole transition period, with averages around a thousand job-seekers per one offer[5]. Finally, this is not high unemployment that creates the main labour market challenge, but low activity and employment rates (currently employment rate at 52%, the lowest in EU25). Not only does this phenomenon hinder the development process, but also social security imbalances are reinforced. Currently average exit age falls short of 58 years (with legal ages of 60 for women and 65 for men), while employment rate for 55+ age group amounts to only 28% (55 till *de iure* retirement).

2.2 ALMPs and their financing

Public Employment Services (PES) are the main actor in ALMPs. They are subordinated to the public administration (separately at regional and local level), thus being only marginally responsive to central policies.

[2]Under Polish legislation, unemployment benefit is only awarded for the first 12 months after registration, subsequently individuals may be entitled to social assistance - which, unlike unemployment benefit, is means-tested.

[3] Kaczmarczyk and Tyrowicz (2008) report the share of people under 30 years in the so-called "new" wave of migration to approximately 80%.

[4]The NUTS 2 level region of lowest agricultural productivity and lowest GDP *per capita* in EU25 is located in Poland, with 36% of active working age population employed in the agricultural sector.

[5]The principal studies in this area are carefully surveyed in Münich, Svejnar and Terrell (1997).

They struggle with underinvestment both in terms of IT and in terms of HR (employment officers and managers constitute only 29% of the PES employees). On average, in 2007 there were 1600 unemployed per one job broker and over 4600 per one job counselor.

ALMPs are financed from the Employment Fund (and so are passive labour market policies), which originates solely from employers contributions, currently at 0.22% of GDP[6]. As of 2004 ESF funds are used for employment policy as well, including the high risk groups as specified in Human Resources Development Sectoral Operational Programme 2004-2006 (HRD SOP) and subsequently Human Capital Operational Programme 2007-2013 (HC OP). This allows to increase PES spending by 30% annually, but only part of this additional funding will contribute directly to ALMPs.

ALMPs instruments are highly regulated. They comprise subsidised employment (public work schemes - despite their low efficiency, strongly preferred by local authorities - and public service employment), scholarships for youth, on-the-job training as well as specific and general training (including the ability to navigate on the labour market). Finally, there are also instruments supporting self-employment (micro-enterprise development) and a subsidies for creating a new position. In addition, there are some specific incentives for fostering employment among handicapped, among whom only 12% remain active on the labour market.

Financing of these policies is decided *ex ante* on an annual basis along the regulations allowing to treat this process as a form of a natural experiment. Namely, Ministry of Finance in January each year divides the Employment Fund financing among NUTS2 level representatives of the public employment services along an algorithm that provides a premium to regions with higher than average unemployment and higher than average number of unemployed. Interestingly, the unemployment rate differentials are relatively small on NUTS2 level in Poland (approximately 1:1.5). Afterwards, at NUTS2 level allocations to NUTS4 level are determined up front for the whole year, while different NUTS2 level authorities apply different mechanisms in an uncoordinated manner. NUTS4 level regional differentials amount to as much as 1:26, *cfr.* Tyrowicz and Wójcik (2009). Finally, since these funds are treated as budgetary funds, whenever there seems to be a surplus at the end of the year, each NUTS2 level authority encourages NUTS4 labour offices to spend the reminder by the end of December.

For the ALMPs financing based on European Social Fund, for the programming period 2004-2006 all financing was allocated through competitions for all NUTS4 labour offices within a particular NUTS2 region. They were closed competitions (only PES could have applied), while in case of excessive or insufficient funding the financing agreements were annexed either extending the coverage of the programme or postponing the implementation to the next budgetary year, respectively. These funds need to be pre-financed by Polish government, which essentially meant that first government financing to ALMPs (*i.e.* Employment Fund) needed to be spent. Throughout 2005 and 2006 annual ALMPs within the HRD SOP exceeded annual Employment Fund allocation by approximately 20% (*cfr.* quarterly reports on ESF implementation by Ministry of Regional Development). Regardless of the financing source, it can cover only instruments specified above.

Consequently, the mechanism of ALMPs financing virtually excludes any possibility of endogeneity due to simultaneity suggested in the literature (*cfr.* Dmitrijeva and Hazans (2007)). Conversely, this financing suggests a natural experiment to which NUTS4 local labour markets were subjected in terms of ALMPs financing availability.

2.3 Regional differentiation

The component of natural experiment is especially interesting in the context of the regional determinants of unemployment in Poland. Basing on the findings of **?** and **?** one can state that for the majority of NUTS2

[6]Topping the benefits makes it 0.8% of GDP). Poland is the only country in EU with no budgetary contribution to ALMPs.

regions no general σ convergence can be traced, instead convergence of clubs finds support in data for some regions. These results suggests that the NUTS4 regions follow different patterns of evolution despite belonging to the same NUTS2 region, while some clubs exist. The method of kernel density estimates does not allow to incorporate the spatial dimension and verify if the clubs are clustered in space and whether these clusters are confined by regional borders.

Consequently, one could ask if over the past seven years of locally conducted labour market policies, the algorithm discriminating among the NUTS2 levels on the basis of measured unemployment provides a mechanisms and incentives sufficient to to alleviate the consequences asymmetric responses to external shocks on the local level. There is no data in support of the claim that offices who succeed in combating unemployment do so due to higher availability of ALMPs financing. On the contrary, apparent divergence of unemployment rates exhibiting in growing relative rates in high unemployment regions exists independently if the financing availability in general. In this paper we intend to inquire exactly the impact of the ALMPs on the matching efficiency.

3 Empirical strategies

In order to evaluate the effects of ALMPs on the matching efficiency, one typically resorts to the matching function, which explains the number of inflows to regular employment by the number of vacancies available and job seekers. This approach may be augmented to distinguish between the stocks and the flows (of both vacancies and unemployed), as advocated by Coles and Smith (1998), Greg and Petrongolo (2005) as well as Coles and Petrongolo (2002). Namely, newly arriving unemployed may match better the needs of employers (flow of job-seekers and stock of vacancies) or, alternatively, newly advertised job opportunities may fit better the competencies of existing unemployed (stock of unemployed and flow of vacancies). Using a neutral Cobb-Douglas matching function specification, this would imply:

$$\begin{aligned} M_{i,t} &= m(U_{i,t-1}, V_{i,t-1})e_{i,t} \\ &= E_{i,t} \cdot (U_{i,t-1}^{stock})^{\alpha_{us}} \cdot (U_{i,t-1}^{flow})^{\alpha_{uf}} \cdot (V_{i,t-1}^{stock})^{\alpha_{vs}} \cdot (V_{i,t-1}^{flow})^{\alpha_{vf}}, \end{aligned} \tag{1}$$

with M denoting successful matches, and U and V corresponding to unemployed and vacancies, respectively. Establishing a log-linear version applicable in empirical studies with shorthand notation $x = lnX$, one obtains:

$$m_{i,t} = \alpha_{us} u_{i,t-1}^{stock} + \alpha_{uf} u_{i,t-1}^{flow} + \alpha_{vs} v_{i,t-1}^{stock} + \alpha_{vf} v_{i,t-1}^{flow} + log\epsilon_{i,t}, \tag{2}$$

where $log\epsilon_{i,t}$ can be assumed to comprise α_0 (time and entity indifferent random component), γ_i (identity characteristics) and δ_t (time trend), while constant returns to scale require $\alpha_{us} + \alpha_{uf} + \alpha_{vs} + \alpha_{vf} = 1$.

This baseline model specification is neutral in terms of empirical strategy - any econometric technique validated by the data properties is suitable for estimation. However, this model does not allow to account for any effects of labour market policies - neither those addressing the flow dynamics, nor those enhancing the skills of the workers.

3.1 Incorporating the effects of ALMPs

Following Lehmann (1995), Dmitrijeva and Hazans (2007) suggest that policy relevant variables (*e.g.* ALMPs) can be introduced to this model if the assumption about the homogeneity of unemployed is relaxed by varying the individual search intensities. In this approach, unemployed that have completed an activisation programme are assumed to have higher search intensities (and, thus, effectiveness) than their non-trained peers, *ceteris*

paribus. Although this implies neglecting the lock-in effects (demonstrated by individual-level studies to last approximately 3 to 4 months), this statement has also far more reaching consequences in terms of designing the empirical strategy. These are:

- Adverse selection problem. Unemployed are allocated to activisation programmes basing on some explicit (like in the case of Germany after the Hartz Reform) or implicit criteria. Consequently, their ability to find employment is already partly incorporated in the allocation decision. Case workers may either facilitate the chances of "better" job seekers or ameliorate the difficulties of "worse" ones. In either case, individual search effectiveness varied already before the intervention, while basing on the fact that someone participated in the project, researchers can actually only reason about the actual motivation of the job seekers *ex ante* and thus not about the programme influence *ex post*. Econometrically, this leads to the sample selection bias (participants of activisation programmes are non-randomly drawn from the unemployed pool), which invalidates eventual findings. This problem can only be solved using individual data and the adequate matching of the participants with non-participants prior to policy effects evaluation.

- Reverse causality problem. Basing on the above statement, it is obvious that participants are bound to have systematically different chances on the labour market as the non-participants (higher or lower - depending on whether case workers apply positive or negative selection criteria). Consequently, the eventual differences in the matching performance for participants and non-participants are not necessarily an effect of ALMPs, but essentially a measure of the statistical consistency of applying the screening criteria.

Because of these obstacles, differentiated estimating strategies have been employed so far. Fahr and Sunde (2002) estimate for Germany separately elasticities and stochastic production functions technical efficiency coefficients by occupation and by region and furthermore try to explain the differentiation in the efficiencies by the properties of respective labour markets (*e.g.* size, turnover, properties of the neighbourehooding regions). Vassiliev, Ferro Luzzi, Fluckiger and Ramirez (2006) apply Data Envelopment Analysis to Swiss data instead of the stochastic production frontier, but the approach is virtually the same.

Some innovation has been introduced by Ibourk, Maillard, Perelman and Sneessens (2001) on French data, who developed a model allowing to disentangle matching efficiency by taking the unemployment structure and other characteristics of the labour markets as determinants of efficiency estimates and not matching directly. Building on this approach, Fahr and Sunde (2005) reiterate their research on German labour market, enriching it also by the spatial approach with the use of spatial weights. Most recently Destefanis and Fonseca (2007) apply the frontier estimation to the case of Italy to see if the so called Treu Act contributed to the higher matching efficiency. Interestingly, since for Italy no official vacancies data exist, they construct a measure basing on indicators taking into account effective job creation. This paper finds a sort of a ladder effect, namely that due to the policy change efficiency was improved for all but low skilled job seekers, which is exactly the opposite of the policy makers motivation.

3.2 Levels *versus* difference-in-difference estimations

At the same time, another strand of literature focused on Beverige curve rather than the matching function. Most recently, Dmitrijeva and Hazans (2007) analyse the Latvian data differentiating between stocks and flows of job seekers and vacancies. They find that dynamics between stocks of unemployed and flows of vacancies fit best the nature of the matching process. They also incorporate indicators of ALMPs in the matching functions,

namely they include the share of job seekers subjected to training programmes and find statistically significant but less than proportional impact. Unfortunately, Dmitrijeva and Hazans (2007) take the share of trained directly in the stochastic frontier estimation instead of the two stage approach, thus risking the endogeneity consequences.

For a larger selection of the transition economies this was done by Munich and Svejnar (2006) and Munich and Svejnar (2007). They demonstrate that inflow rates were rising gradually in the western part of Germany as well as in the Czech Republic, Hungary, Poland, and Slovakia. Their analysis suggests that the extent to which the these transition economies undertook reforms and had some private enterprise activities before the transition appears to have influenced these countries' subsequent restructuring and growth paths, limiting the spread of the restructuring-lead unemployment. Munich and Svejnar (2007) find that West German part of Germany is an economy with slow trends of rising unemployment and inflow, declining vacancies and relatively efficient matching (thus: high returns to scale). Czech Republic appears to be in a similar situation enjoying - despite transitory decreases in outflow rates - high returns to matching. Conversely, Slovak economy displays high unemployment and inflows, low vacancies, outflows and increasing returns to scale as well as a positive trend in efficiency. Finally, for Poland high unemployment persists in the presence of low vacancies and outflows with constant returns to matching.

Munich and Svejnar (2007) argue that in order to obtain consistent estimates of the latter one needs to apply difference-in-difference approach. Namely, they argue that, since any local labour market mean is computed from all local labour market observations over time, these means contain all values of the error terms, which creates correlation between transformed explanatory variables and transformed error terms and hence leads to biased estimates. On the other hand, the first difference transformation contaminates the transformed variables only with recent error terms, thus enabling the use of Δu_{t-1} as instruments and making the error terms no longer contemporaneously correlated with the predicting variables.

3.3 Final specifications for estimation

Matching efficiency for Poland has been analysed by Puhani (1999) with main findings suggesting that public training programmes can indeed be used to reduce unemployment. However, in the way Puhani (1999) uses the augmented matching function, endogeneity accusation cannot be dismissed[7]. Using regional administrative data prior to 1999 administrative reform (49 *voivodship* units at approximately current NUTS3 level) he puts ALMPs expenses directly in the matching function. This yields directly interpretable coefficients (*e.g.* average cost to reduce unemployment by one person in Poland through training programmes was estimated to amount between 200 and 500 euro). However, the time period covered in this study comprised mainly unemployment reductions, while ALMPs at the time were not implemented at a level at which their effects have been measured. Therefore, the positive outcome may actually be a spurious result.

In this paper we cover the period covering both the increases and decreases in the unemployment rate. There have been also considerable changes in the reported vacancies (beyond seasonal variation), Figure 1. Consequently, it seems that flows may actually play an important role in observed changes in matching efficiency.

[7]Prior to 1999 ALMPs financing was allocated to *voivodship* level directly by the Ministry of Finance based on an algorithm, which gave preference to regions with relatively more severe labour market outlooks and the needs expressed by the local labour offices at the end of each prior fiscal year. Thus, one could claim that Puhani (1999) results suffer from endogeneity. Due to the change of ALMPs financing regime as of 1999, as suggested earlier, activisation expenses is no longer endogenous by construction. Since allocations - highly differentiated across time and regions - provide conditions similar natural experiment, one could attempt including financing directly in the stochastic frontier estimation. On the other hand, however, it may effectively prove endogenous, since local budgets are frequently based on some implicit "roll-over" rules and individual bargaining power of local labour office heads. Therefore, we will resort to a two-stage approach.

Therefore, following Greg and Petrongolo (2005) and Dmitrijeva and Hazans (2007) empirical specification allows to include separately stocks and flows in both vacancies and job seekers. Thus the first empirical specification is altered to:

$$m_{i,t} = \alpha_{us} u_{i,t-1}^{stock} + \alpha_{uf} u_{i,t-1}^{flow} + \alpha_{vs} v_{i,t-1}^{stock} + \alpha_{vf} v_{i,t-1}^{flow} + \epsilon_{i,t}. \tag{3}$$

Vacancies (as well as vacancy ratios) demonstrate high volatility over time, since labour market outlooks have changed significantly over the analysed period. Average vacancy ratios (number of offers per one job seeker) have ranged between 0.001 and 0.059, with the mean value of 0.01 offer per one job seeker. Naturally, this property of the data may lead to many estimation problems. Among others, it seems that time trend needs to be controlled for in a non-linear way, taking into account up and down swings in the labour market outlooks. Secondly, large part of observed heterogeneity will be an interaction of time and unit characteristics. Since one should expect that units "react" differently to country-wide shocks, the response in the labour market may owe a lot to the local response to shock apart from efficiency of a local labour office. Finally, larger labour markets are characterised by larger flows, including outflows to employment *without* any support from the public employment services. Figure (1) demonstrates the (average) anti-cyclicality of vacancies over time vis-a-vis the pro-cyclicality dynamics of flows to employment in relation to a number of job offers at the disposal of labour offices.

Actually, the relatively high values observed at the left scale imply that indeed public employment services dispose of only a fraction of unsubsidised vacancies available in the economy. In the periods of high labour demand (both cyclical and seasonal), considerably more unemployed find jobs than are at the disposal of local labour offices. In fact, as seen from the outflows to non-seasonal employment, not all of these transitions are of strictly temporary character, while strong short and medium term cyclicality remains.

In as far as the effects of ALMPs are concerned, although by construction ALMPs and other variables should not be simultaneously correlated, endogeneity might occur in the form of the statistical phenomenon. Therefore, building on the contributions briefed above, we follow the approach commenced by Ibourk et al. (2001), incorporating the ALMPs effects to determine the technical efficiency scores, but not the matching process itself. Namely, we consider the model in which one could demonstrate that different groups of job seekers may exhibit different search intensities, either due to the individual characteristics (*e.g.* gender, age, education) or because of ALMPs (to be specific, the likelihood of having been subjected to ALMPs). The Cobb-Douglas matching function can be written as:

$$\begin{aligned} M_{i,t} &= E_{i,t} \cdot (V_{i,t-1}^{stock})^{\alpha_{vs}} \cdot (V_{i,t-1}^{flow})^{\alpha_{vf}} \\ &\left[\sum_j (1+c_j)^{\frac{\alpha_{us}}{\alpha_{us}+\alpha_{uf}}} (U_{j,i,t-1}^{stock})^{\frac{\alpha_{us}}{\alpha_{us}+\alpha_{uf}}} \cdot \sum_j (1+c_j)^{\frac{\alpha_{uf}}{\alpha_{us}+\alpha_{uf}}} (U_{j,i,t-1}^{flow})^{\frac{\alpha_{uf}}{\alpha_{us}+\alpha_{uf}}} \cdot \right]^{\alpha_{us}+\alpha_{uf}}. \end{aligned} \tag{4}$$

In this setting, c_j coefficients correspond to the actual group-wise search intensities, so that negative values of c_j are characteristic for less than average search effort. Rearranging, one obtains:

$$\begin{aligned} M_{i,t} &= E_{i,t} \cdot (V_{i,t-1}^{stock})^{\alpha_{vs}} \cdot (V_{i,t-1}^{flow})^{\alpha_{vf}} \cdot (U_{i,t-1}^{stock})^{\alpha_{us}} \cdot (U_{i,t-1}^{flow})^{\alpha_{uf}} \cdot \\ &\left[1 + \sum_j c_j \frac{U_{j,i,t-1}^{stock}}{U_{i,t-1}^{stock}} \right]^{\alpha_{us}} \cdot \left[1 + \sum_j c_j \frac{U_{j,i,t-1}^{flow}}{U_{i,t-1}^{flow}} \right]^{\alpha_{uf}}. \end{aligned} \tag{5}$$

When equation (5) is subjected to logarithmisation, it yields:

$$\begin{aligned} m_{i,t} &\approx \alpha_0 + \alpha_{us} u_{i,t-1}^{stock} + \alpha_{uf} u_{i,t-1}^{flow} + \alpha_{vs} v_{i,t-1}^{stock} + \alpha_{vf} v_{i,t-1}^{flow} + \\ &+ \sum_j \rho_j \gamma_i \frac{u_{j,i,t-1}^{flow}}{u_{i,t-1}^{flow}} + \sum_j \varrho_j \frac{u_{j,i,t-1}^{stock}}{u_{i,t-1}^{stock}} + \gamma_i + \delta_t + log\epsilon_{i,t-1}, \end{aligned} \tag{6}$$

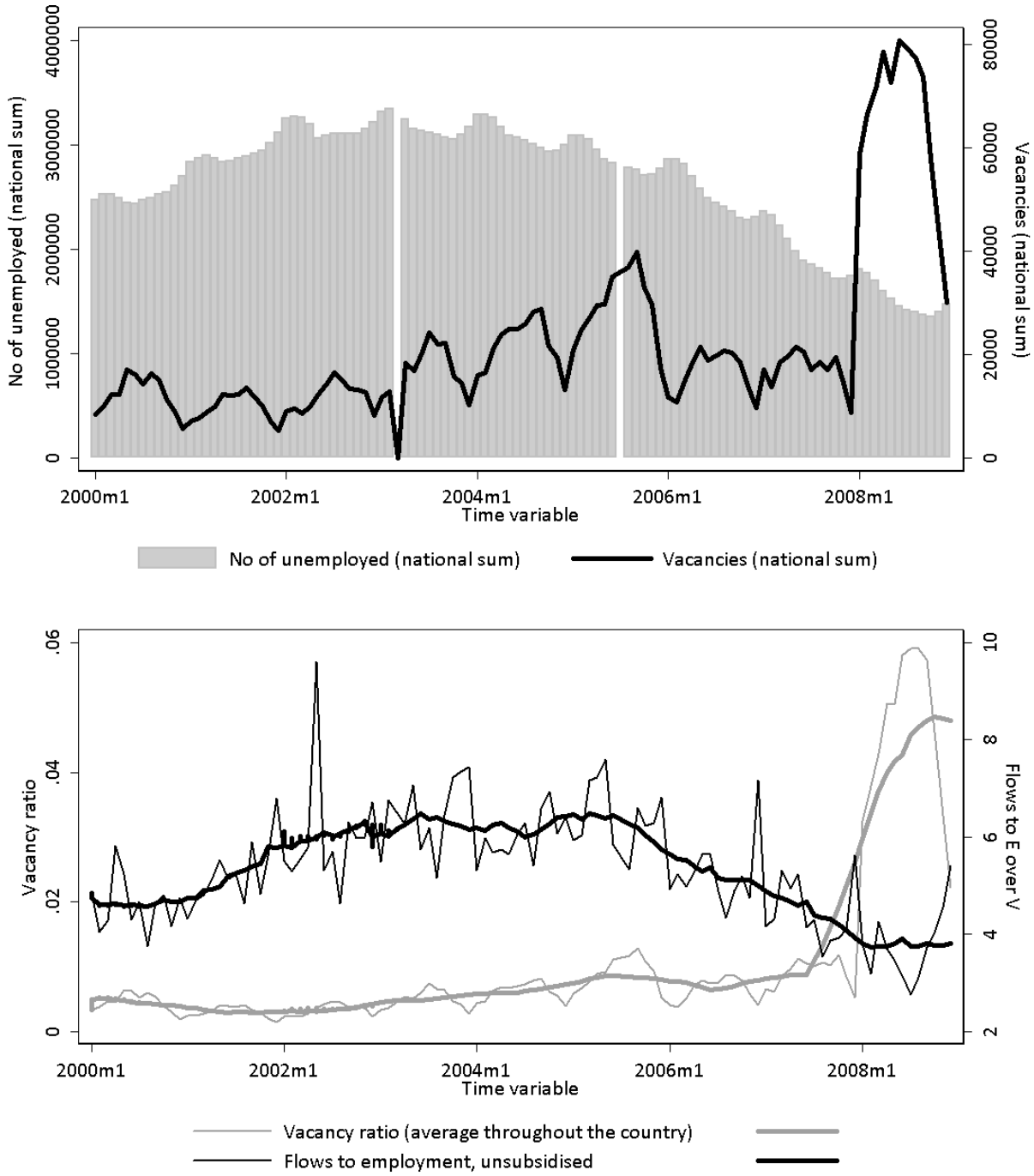

Figure 1: Unemployed, vacancies, vacancy ratio and unsubsidised flows from unemployment to employment. *Source:* own computations based on ML&SA, 2000-2008.

where $\rho_j \equiv c_j \alpha_{uf}$ and $\varrho_j \equiv c_j \alpha_{us}$. Similar transformation could be made for the vacancies. In other words, as suggested by Ibourk et al. (2001), the total number of matches is the function of vacancies, job seekers plus a set of variables representing the share of each group j in the total unemployment. Efficiency can indeed be seen as the product of two factors, one measuring the rate at which job seekers and employers meet and the other measuring the probability that a contact leads to a successful match.

$$e_{i,t} = \exp^{\max_i\{\hat{\gamma_i}+t\hat{\delta}\}-\{\hat{\gamma_i}+\delta_t\}}. \tag{7}$$

To account for the ALMPs effects one can transform equation (5) to include either a group of job seekers who were subjected to activisation programmes (as in the case of Dmitrijeva and Hazans (2007)) or finance allocated to ALMPs in a particular labour office (as in the case of Puhani (1999)). Ibourk et al. (2001) argue that if $M_{i,t}$ does not include the number of job seekers de-listed from unemployment registers due to activisation (*e.g.* inflows into training programmes), one can formulate a model in which these workers have below average search intensities, *i.e.* an increase in the size of special training programmes mechanically increases the average observed matching efficiency.

Unfortunately, throughout the 2000-2008 period, for which detailed regional data is available, there have been continuous changes of the reporting standards with job seekers in activisation programmes and programmes themselves were defined differently across years. While the construction of the data set makes it impossible to unequivocally separate some categories of job seekers in treatment, we were able to obtain the reliable sums of people covered by programmes in each local labour office at each point in time. Therefore, in this paper we have decided to consider ALMPs coverage. The starting point for this approach is to assume:

$$e_{i,t} = E_{i,t}Z_{i,t}^{\theta} = E_{i,t} \cdot C_{i,t}^{\theta_F} \cdot T_i^{\theta_T} \cdot S_i^{\theta_S}, \tag{8}$$

where $C_{i,t}$ corresponds to the coverage in a a particular labour office i in time t, while T_i refer to the technology facilities available in a particular office. Similarly, S try to control for the skills available in a respective offices, namely for example the number of job brokers per number of job seekers. Taking logarithm of (8) and plugging it to equation (5) one can see that the technical efficiency score obtained through the stochastic frontier estimation can be in the second stage tested to depend on ALMPs, labour market structure and capacity in each labour office.

If we additionally specify that efficiency of a labour office might depend on internal resources at disposal, equation (8) yields the standard technical efficiency (7) to change for

$$e_{i,t} = \exp^{\max_i\{\hat{\gamma_i}+\Theta_F+\Theta_T+\Theta_S+t\hat{\delta}\}-\{\hat{\gamma_i}+\hat{\Theta_F}+\hat{\Theta_T}+\hat{\Theta_S}+\delta_t\}}. \tag{9}$$

After obtaining the results of equation (9) *via* the estimation of (5) as a stochastic frontier, estimated values of equation (9) will yield left-hand side variables for equation (8). This last equation can be estimated as a regular panel regression, correcting for eventual heteroscedasticity.

The second approach taken in this paper is to estimate the Beveridge curves. Unlike Dmitrijeva and Hazans (2007) we chose to follow Munich and Svejnar (2007) by using the difference-in-difference estimators. Namely, for m denoting matches,

$$\Delta m_{i,t} = m_{i,t} - m_{i,t-1} = \beta(u_{i,t-1} - u_{i,t-2}) + \gamma(v_{i,t-1} - v_{i,t-2}) + \epsilon_t - \epsilon_{t-1} \tag{10}$$

$$\Delta m_{i,t} = \beta\Delta u_{i,t-1} + \gamma\Delta v_{i,t-1} + \Delta\epsilon_{i,t}, \tag{11}$$

where $u_{i,t-1}$ represents the log of job seekers and $v_{i,t-1}$ corresponds to vacancies. In addition, Munich and Svejnar (2007) suggest that further lags of $\Delta u_{i,t}$ will be uncorrelated with $\epsilon_{i,t}$ and $\epsilon_{i,t-1}$, which they use as an argument in favour of the instrumental variables as a method of estimation.

Throughout the study numbers of job seekers/vacancies are used (in logs). However, Munich et al. (1998) suggest that prior to estimation data should be scaled by the size of labour force, to avoid "spurious scale effects". However, the size of labour force is highly variable in Poland - across the seven years in the sample the turnover in the national activity rate exceeds 3 000 000 people, which is a striking number when compared

to approximately 14 500 000 people in the labour force[8]. Therefore, we avoid scaling by the labour force size, as it would introduce additional variation negatively affecting statistical properties of the model. However, model is estimated on a subsample without large cities.

Finally, since these are relatively high frequency data, controlling for seasonal variation seems particularly important. Therefore, estimations include monthly dummies to control for differentiated vacancies and job seekers arrival rates throughout each year. In addition, linear and quadratic trends are included to control for country wide labour market fluctuations.

4 Data and results

Data set covers the period of January 2000 till December 2008 of monthly data for eventually 380 local labour offices at policy relevant NUTS4 level. It includes registry information about the number of job seekers, reported vacancies, basic structural characteristics of the local labour markets (*i.e.* share of female, inexperienced, youth, restructuring and inhabitants of the rural areas among the unemployed). In addition, for each local labour office monthly budgetary data as well as annual human capital endowment data is available. Finally, in 2006 a survey about the use of IT tools in brokering was conducted, providing additional data.

Since these are registry data, they suffer from many well-known shortcomings. First of all, vacancies are systematically underreported and therefore cannot serve for more than a proxy of the employers needs, cfr. Meyer and Sullivan (2003). Unlike in the Czech Republic, in Poland the obligation to declare vacancies is not effectively enforced. Therefore, local labour offices posses information about the vacancies more or less voluntarily submitted by the employers. This problem is severe, because the extent of underreporting may differ from region to region. Namely, in more dynamic labour markets (for example in the big agglomerations) smaller share of employers resorts to use the assistance of labour offices in staffing. Thus, outflow to employment may represent to a lesser extent the effectiveness of matching.

The main interest of this paper lies in the matching efficiency. At the same time, without individual level data it is virtually impossible to evaluate the efficiency of subsidised employment schemes. Therefore, throughout the paper we only analyse unsubsidised (open market) matches, computed as a difference between total matches and subsidised flows into employment[9]. Summary statistics for the data are presented in Table (1).

As discussed earlier, vacancies (as well as vacancy ratios) demonstrate variability across time, but also the variance across local labour markets is very large. Vacancy ratio (number of offers per one job seeker) has ranged between 0 and 0.89 in 2008 and between 0 and 0.11 in 2001. Since in respective years severity of this problem was of different magnitudes, one should expect varying output *levels* - but not necessarily the *relative performance* - for labour offices in respective years. Consequently, the ranking of labour offices based on time-specific technical efficiency estimators may be unaffected by the general changes in the labour market outlooks while difference-in-difference estimators may demonstrate variability in the coefficients.

[8]This is due to the fact that unemployed frequently deactivate temporarily - one falls out of the labour force if the registration in the local labour office is not confirmed, while the incentives for confirmation partially disappear 12 months after the incidence of unemployment. Each registered unemployed receives health insurance covered by Employment Fund. Once the title to the unemployment benefit expires, this is the only incentive to register, since social assistance benefits are operated by social assistance administration, organisationally and financially independent of PES and means-tested. In some instances, social assistance case workers require registration with the labour office, but this is subject to internal local regulations. In case of households, it is sufficient for one family member to be registered, to assure family coverage.

[9]Nonetheless, for the purpose of comparison, we also report subsidised employment summary statistics.

Table 1: Summary statistics

Variable	Whole sample		Without cities	
	Mean	Standard deviation	Mean	Standard deviation
No of unemployed, eom	6969.449	5348.735	6126.451	2946.669
- women, eom	3755.331	2777.538	3320.1	1593.179
- who got employed, tm	269.9385	212.2181	241.5626	136.8289
- who got into unsubsidised employment, tm	231.294	191.3631	205.0533	118.6461
- with benefit, eom	1131.606	1004.941	996.0444	656.0441
- without experience, eom	1643.636	1137.356	1479.113	791.6034
- due to restructuring, eom	397.5729	634.392	320.4045	308.5412
- living in the rural areas, eom	2957.358	2427.115	2930.844	2132.929
- first time registered, tm	151.9213	179.8534	128.9772	91.4853
- previously registered, tm	418.8874	295.6705	378.9129	211.533
- delisted, tm	193.529	181.4074	170.546	117.9093
- graduates, eom	670.1103	918.6154	586.5711	507.4942
- youth, eom	1785.384	1147.971	1629.493	841.3273
- long-term, eom	3752.195	3075.152	3357.739	1898.423
No of job offers, tm	185.1997	228.128	165.7901	163.8259
No of job offers, tm, subsidised	73.739	82.9689	68.9568	73.5387
Layoffs, public sector, no of people	6.4239	45.6036	4.6172	30.8325
Layoffs, private sector, no of people	14.7009	82.616	9.7182	45.3107
Coverage of ALMPs	0.0178	0.0178	0.0182	0.0181
Vacancy ratio	0.0103	0.0307	0.0104	0.0313
Flows from U to E over V	2.2503	2.547	2.2246	2.3828
No. of observations	40 417		38 096	

Source: Ministry of Labour and Social Affairs monthly reports from local labour offices (MPiPS-01 and MPiPS-02). EOM stands for the end-of-month figures, TM stands for this-month figures. Coverage of ALMPs denotes the share of unemployed in ANY treatment (training, public or intervention, etc.).

4.1 Results of difference-in-difference estimations

Following Munich and Svejnar (2006) and Munich and Svejnar (2007) we adopted a standard procedure. All variables were taken in logs and subsequently first differences (when relevant, lagged). Naturally, this procedure leads to narrowing the sample (one observation for each local labour market is lost due to differentiating and yet one for lagging). We analyse both unsubsidised and subsidised employment. The results are reported in Table (2).

Table 2: Estimates using difference-in-difference estimators

	Unsubsidised employment		Total employment	
Variables	All unemployed	Only newly registered	All unemployed	Only newly registered
Offers	0.0835***	0.0839***	0.166***	0.169***
	(0.00195)	(0.00197)	(0.00307)	(0.00312)
Job seekers	-1.328***	0.0265***	-1.919***	0.0120
	(0.0501)	(0.00684)	(0.0636)	(0.00883)
Time trend	-0.140***	-0.122***	-0.175***	-0.151***
	(0.00653)	(0.00656)	(0.00839)	(0.00844)
Square of time trend	0.000130***	0.000114***	0.000164***	0.000141***
	(6.12e-06)	(6.14e-06)	(7.85e-06)	(7.91e-06)
Constant	37.33***	32.61***	46.72***	40.02***
	(1.731)	(1.737)	(2.221)	(2.236)
Monthly dummies	Yes	Yes	Yes	Yes
Annual dummies	Yes	Yes	Yes	Yes
Returns to scale	Decreasing	Decreasing	Decreasing	Decreasing
R^2	0.380	0.369	0.298	0.282
F statistic	1 079.86***	1 063.59***	743.44***	685.88***
No. of observations	38 567	38 567	38 880	38 880

Notes: Dependent variable: monthly changes in logs of the flows to employment out of unemployment (unemployed de-registered due to commencing employment). Unit-specific IV fixed effects regression. Lagged unemployment used as instrument. Monthly and annual dummies included, but not reported (all highly statistically significant results available upon request). Standard errors reported in parentheses. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.

The results seem to suggest that the availability of unemployed affects the matching in a negative ways, while the positive effects of access to vacancies is surprisingly small. One might expect that this effect is a spurious scale effect, but such presumption finds no confirmation in data[10]. Indeed, the estimator for vacancies is surprisingly small, especially if one considers how low its values with respect to the number of unemployed and employed are (see: Figure 1).

On the other hand, it seems that the availability of the newly registering job seekers affects positively the matching, which is consistent with the hypothesis, that the newcomers may fit better the needs of the employers. However, we are reluctant in interpreting these high values as evidence that newly unemployed match better with vacancies than the existing unemployed. In fact, 87% of unemployment inflows in Poland comprise formerly unemployed, which is confirmed in Munich and Svejnar (2007) (they find the difference in estimators for newly coming unemployed and those already in the registers insignificant for Poland). Moreover, according to the self-reported modes of operations, Piotrowski (2005), newcomers are more likely to receive treatment and job brokering than the individuals with longer unemployment tenure.

Furthermore, the values of estimators seem to suggest in almost each case decreasing returns to scale. All the estimations tend to support the hypothesis of generally decreasing efficiency (negative coefficients with the time trend, and very low but positive of the squared term). The magnitudes of the vacancies estimators are fairly consistent with Munich and Svejnar (2007). However, the changing of the sign between all unemployed and newly registered unemployed seems puzzling. More specifically, one should expect lower inflows when labour market prospects are better, which implies that our results may be just spurious. To verify this hypothesis we have additionally performed rolling window estimates (with one month step size and 30-month size of the window). These original input variables have been averaged for all units (non-weighted average) to perform the estimation on national aggregates, while the results are depicted on the Figure (3). Visibly, the evolution in across 2002-2003 was very different than in the other periods, while this period coincides with large increase in the unemployment rate and contraction in labour demand.

Our findings differ significantly from the ones presented by Munich and Svejnar (2007). Namely, we use policy relevant data - information about unemployed, vacancies and flows to employment is collected directly from the respective labour offices (districts). Secondly, we present the estimation for unsubsidised employment, which constitutes our preferred specification, columns (1) and (2). As suggested by Figure 1, outflows to employment are considerably bigger over the whole time period than actual matching by the labour offices. Therefore, matching does not correspond to directly to the activities of labour offices but the shallowness of a local labour market[12]. Finally, these estimates have demonstrated that despite inclusion of monthly and annual dummies, one can demonstrate negative trend, which was not analysed by Munich and Svejnar (2007), while there is little stability of the matching processes (large responsiveness to the changing labour market outlooks). This is confirmed despite sizeable improvement as of 2005.

Although these findings provide some useful insights, they do not allow to capture the relation between local conditions and the matching performance. This is enabled if one takes stochastic frontier approach, which is pursued in the next section.

[10] In fact, this finding holds even if one considers regions with below average pool of unemployed. Detailed results available upon request.

[12] If one compares the districts with highest ratios of outflows to number of vacancies to the population of districts in general, they are comparable in as far as number of unemployed is concerned, but the general population records considerably higher number of vacancies. Detailed results available upon request.

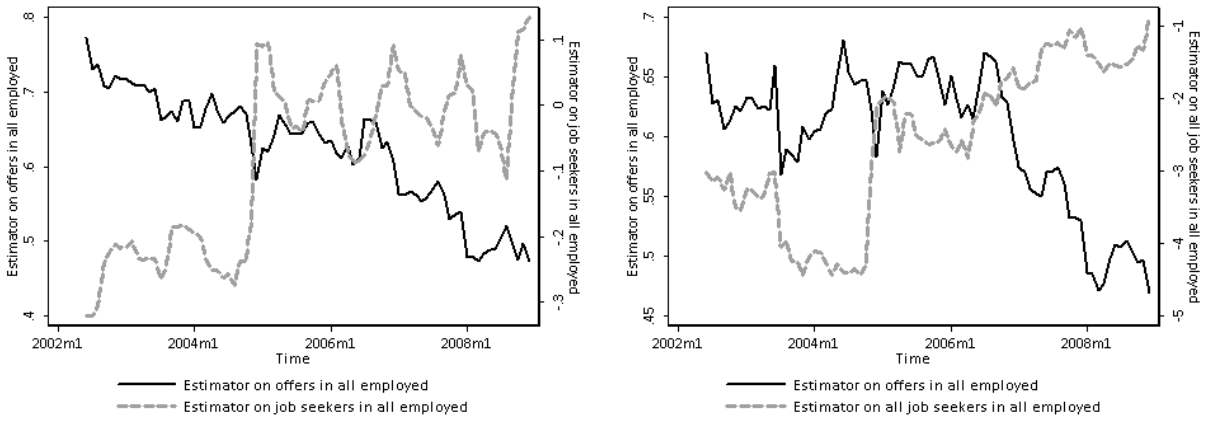

Figure 2: Upper left and right: all employed are the predicted variable

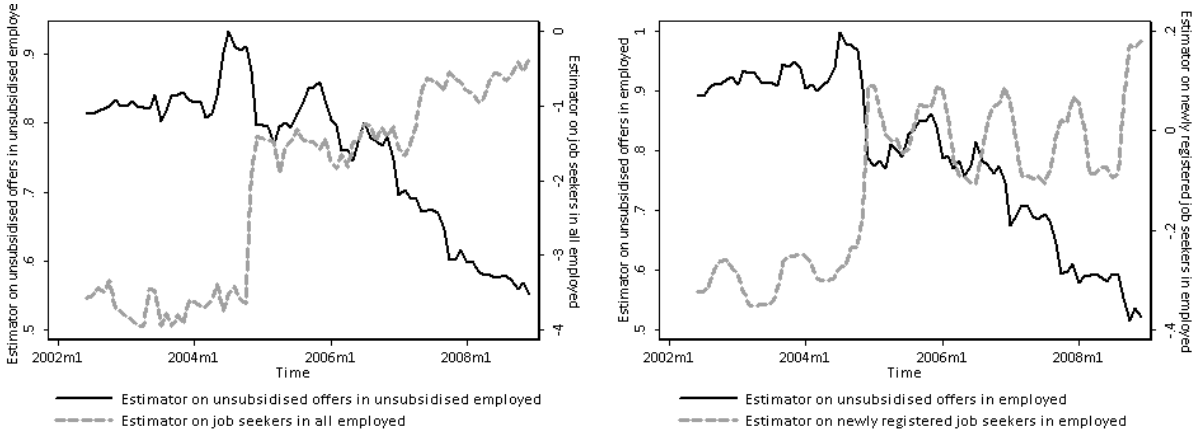

Figure 3: Unsubsidised employment is the predicted variable[11].

4.2 Stochastic frontier estimations

For the estimation of stochastic frontier we have used a time-varying decay model, *i.e.* Battese-Coelli parameterisation of time effects. Consequently, the inefficiency term is modeled as a truncated-normal random variable multiplied by a specific function of time. In both models, the idiosyncratic error term is assumed to have a normal distribution, while the random inefficiency term constitutes the only panel-specific effect. Results are reported in Table (3).

These results are somewhat more intuitive than difference-in-difference estimators. Firstly, all specifications consistently confirm decreasing returns to scale. Secondly, estimates are fairly stable across specifications. Thirdly, estimators by the pool of unemployed are considerable, while the ones by vacancies tend to be minuscule[13]. Intuitively, "newly coming" unemployed diminish the matching capacity (negative and significant coefficient), while arriving job offers increase it. While the latter is consistent with Dmitrijeva and Hazans (2007), the former is supported by the self-reported usus of operation by labour offices, Piotrowski (2005), as discussed earlier.

Unlike in the case of Estonia, as discussed by Dmitrijeva and Hazans (2007), inclusion of flows does not lead to lowering the significance of stocks. Nonetheless, the elasticity with respect to the unemployed seems to

[13]Please, note that since all variables were taken in logarithms, these estimators denote effectively elasticities, which implies they can be compared directly.

Table 3: Stochastic frontier estimations

	Subsidised and unsubsidised jobs				Only unsubsidised jobs			
	Total sample			No large cities	Total sample			No large cities
Variables	Stocks	Flows	Both	Both	Stocks	Flows	Both	Both
Unemployed (stock)	0.660***		0.523***	0.509***	0.645***		0.653***	0..642***
	(0.00869)		(0.00785)	(0.00901)	(0.00989)		(0.0108)	(0.00902)
Unemployed (flow)		-0.0752***	-0.0534***	-0.0557***		-0.0569***	-0.0642***	-0.0643***
		(0.00580)	(0.00544)	(0.00568)		(0.00652)	(0.00643)	(0.00624)
Vacancies (stock)	0.198***		0.0861***	0.0868***	n.a.	n.a.	n.a.	n.a.
	(0.00260)		(0.00261)	(0.00270)				
Vacancies (flow)		0.296***	0.242***	0.246***	0.153***	0.153***	0.152***	0.153***
		(0.00237)	(0.00261)	(0.00268)	(0.00201)	(0.00208)	(0.00203)	(0.0020)
Annual dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Monthly dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Returns to scale	DRS	DRS	DRS	DRS	DRS	DRS	DRS	DRS
Constant	-1.047***	6.115***	-0.0155	0.1117	1.716***	36.24***	-0.174	-0.238***
	(0.0747)	(0.193)	(0.0744)	(0.0839)	(0.0858)	(3.732)	(0.160)	(0.1055)
χ^2	***	***	***	***	***	***	***	***
No of observations	37 753	40 026	37 746	35 927	38 708	39 837	38 708	36 837
No of units	381	381	381	358	381	381	381	358

Notes: Dependent variable: log of monthly flows to employment out of unemployment (unemployed de-registered due to commencing employment). Monthly and annual dummies statically significant, detailed results available upon request. "Flows" of variables are original data (reported by labour offices as "this month" registrations and "this month" vacancies). "Stocks" of unemployment are originally reported (as "end of month"), however stock of vacancies was computed as a sum of this month vacancies and the lagged "end of month" status (the number of unfilled vacancies reported on the last day of the previous month). Variables taken in logarithms, lagged when necessary. Standard errors reported in parentheses. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively

be the largest, with one 1% more people in the stock of unemployed resulting in 0.6-0.7% persons employed. However, if one accounts for the dynamic effects, *increase* by 1% of the inflows leads effectively lowers the employment by slightly more than a half of a percentage point. Having established the production function as specified in Table 3 one may obtain a variety of technical efficiency estimates. Indeed, they differ across specifications. Figure 4 depicts evolutions across time (averaged over units).

Clearly, all these estimates are fairly stable across time, with a maximum of two-three percentage points of changes. The average across specifications ranges between 0.57 (unsubsidised jobs, total sample) and 0.68 (all jobs, without large cities), standard deviation ranges from 0.12 to 0.13. Based on schemes in Figure 4 one can say that average efficiency of matching lowers with the growth of vacancies (upper left and upper right schemes). The clear downward trend in the upper left panel may signify either of the two effects: either the best districts (usually large cities) move the frontier outwards consistently, which leaves everybody else lagging behind or efficiency for leaders decreases slower than for everybody else. The scheme in the upper right corner seems to lend support to the former hypothesis, since without large cities the trend is downward sloping as well.

At the same time, lower left and right schemes reveal an interesting pattern. Namely, for unsubsidised job offers - our preferred specification - there seems to be a clear growing trend for the total sample, which changes to a u-shaped one if large districts are excluded. This u-shaped pattern is a reverse of the general labour market outlooks, but demonstrates no correspondence either across units or across time to the ratio of unsubsidised over subsidised offers (correlation of 0.038 within and 0.071 between).

Large variability of estimated technical efficiency scores across units guarantees sufficient variation to perform the second step analyses. Although we do not determine unequivocally the direction of causality, we attempt to analyse which characteristics correlate well with technical efficiency estimators obtained in the optimisation procedure. These are analysed in subsequent section.

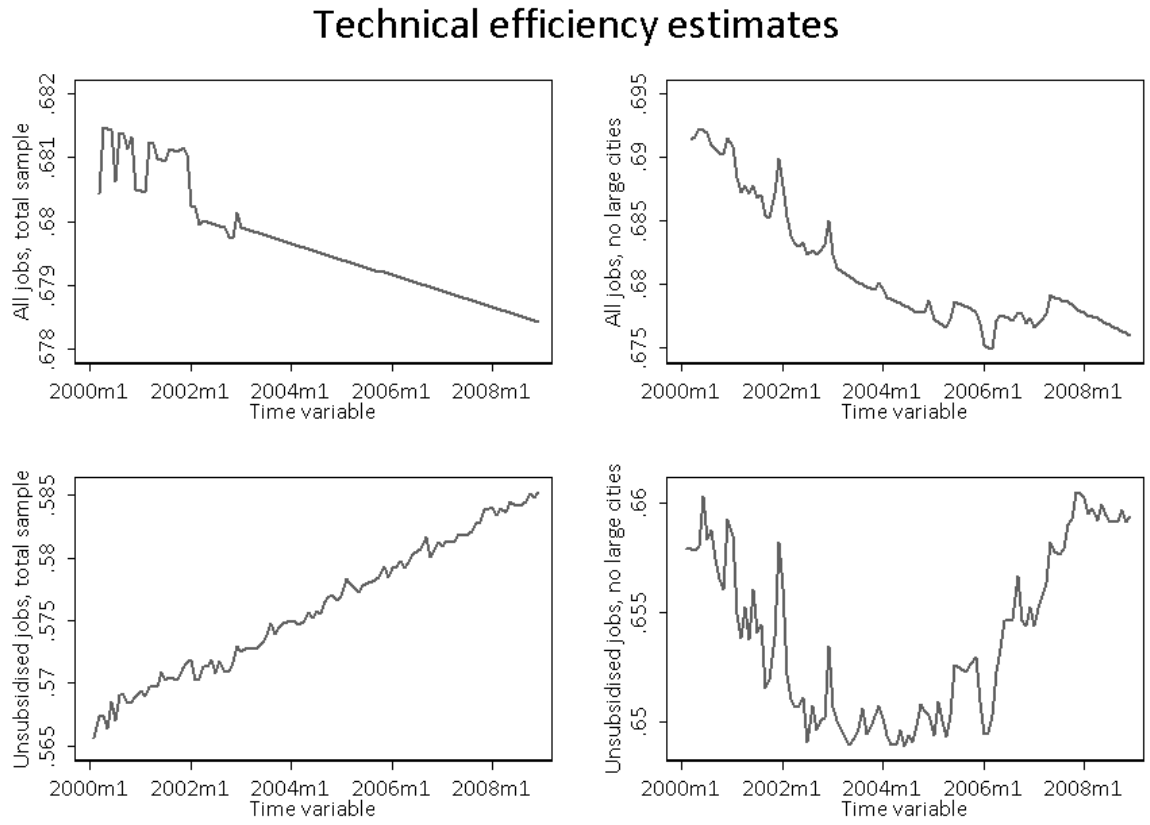

Figure 4: Distributions across specifications, time and unit dimensions

4.3 Covariates of technical efficiency

Following Ibourk et al. (2001) we analyse the covariates of technical efficiency scores. Naturally, the best approach would have been to adopt difference-in-difference, but the actual scores of efficiency at each point in time are estimated in a relative way. Therefore, the change in the score from time t to time $t+1$ does not necessarily give any information as to the actual performance of a particular labour market. Therefore, we estimate the regression in levels. Although, the regression construct specifies causality direction from the RHS variables to the LHS one - we are only trying to establish if there is a link between some control factors and the individual efficiency scores[14]

The characteristics of a local labour market are approached by the means of proxies. Namely, some local markets may be more dynamic than others, while some may be populated by more "difficult" unemployed than others. To account for this differentiation we have used the following measures:

- Labour market structure
  - Share of females in total unemployment (mean 0.544, min 0.39 max 0.79) and in total flows to employment (mean 0.464, min 0.026, max 0.981). In general this corresponds to the diversity of job

[14]While theoretical foundations discussed earlier suggest that endogeneity should no longer be a problem if a two stage approach is adopted, where first step "blind estimates" efficiency scores - it may emerge as a statistical phenomenon. We lack data enabling the determination of causal relationship *via* reliable instrumental variables. Resorting to GMM and using lags or first differences as instruments is deceiving, because some of the covariates are actually pretty stable across time, characteristic for particular units.

creation and destruction in particular labour markets.

  - Share of rural unemployed in total unemployment (mean 0.483, min 0, max 1). In general rural labour markets are less dynamic. Therefore we expect this variable to account for relative labour market hardship.
  - Share of youth (mean 0.265, min 0.047, max 0.527) in the pool of unemployed. Youth demonstrate usually higher adaptability.
  - Share of no or low skilled unemployed among jobless (mean 0.244, min 0.052, max 0.544). These workers represent typically lower value to the employers, which may constitute an obstacle in smooth unemployment-to-employment transitions.
  - Share of first-time registrants in inflows (mean 0.022, min 0.002, max 0.155). This measure captures the availability of "new" job seekers that may foster the quality of the matching process.
  - Share of delisted in the total unemployment (mean 0.030, min 0.009, max 0.226). This measure captures the so-called "discouraged" job seekers.
  - Ratio of first time to returning registrants (mean 0.404, min 0.032, max 11.08)
  - Ratio of employed to delisted (mean 1.897, min 0.170, max 222.049) and unsubsidised employed to delisted (mean 1.584, min 0.135, max 192.665).
  - No of job brokers per one unemployed (mean 0.00002, min 0.000004, max 0.00083).

- Coverage of ALMPs (mean 0.017, min 0.005, max 0.277). As discussed earlier, this measure is constructed as a number of individuals in ANY treatment (trainings, intervention employment, public works) over the pool of unemployed in a respective district at each point in time[15].

- Size of the labour market (no. of unemployed, inflows and offers).

Results of these estimations are reported in Table (4).

The capacity in the public employment services to match employers needs with the job seekers may be negatively affected by some structural characteristics, but is supposed to be positively affected by policy variables, e.g. number of job brokers (per no of unemployed) or ALMPs coverage. However, the verification of these hypotheses is largely discouraging. Namely, despite statistical significance, most of the obtained estimators are extremely low. Consequently, it seems that all of these covariates have little power to explain the differentiation of technical efficiency scores. This contention is confirmed by R^2 - between values are mostly negligible, while within values are driven by regularities in trends. Although signs are consistent across samples and specification, they are also intuitive and mostly confirm common sense relations.

As to the structural variables larger percentage of females in the pool of unemployed signifies less diversified labour markets, which correlates well with lower capacity for matching. At the same time, higher share of female outflows signifies exactly the opposite, which is consistent with a positive and significant estimator. Counter intuitively, rural areas seem to be characterized by higher matching efficiency, but - as we already argued - the between variance is poorly addressed by our model. Consequently, the significance of the estimator refers to the changes in the shares of rural unemployed, which tend to grow with labour market improvements (people in small and mid-sized towns outflow to employment) and decrease in the downturns on the labour market (see Figure 6).

[15]Despite numerous efforts by non-governmental organisations, public employment services still hold virtually a monopoly over activisation instruments, since providing such services is subject to licensing while public financing is essentially unavailable to non-public providers.

Table 4: Determinants of technical efficiency

	All jobs		Unsubsidised jobs		All jobs		Unsubsidised jobs		Unsubsidised jobs	
Variables	Total sample	No large cities	Total sample	No large cities	Total sample	No large cities	Total sample	No large cities	Total sample	No large cities
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Share of females	-0.00622***	-0.0511***	-0.0495***	-0.00175***	-0.00866***	-0.000487***	-0.00160***	-0.0143***	-0.0142***	-0.000775***
in unemployment	(0.000187)	(0.00152)	(0.00143)	(0.0000)	(0.000648)	(0.0000)	(0.000128)	(0.00110)	(0.000643)	(0.0000)
Share of females	0.000743**	0.00713***	0.00680***	0.000120	0.0114***	0.000693***	0.00209***	0.0190***	0.0162***	0.000824***
in employment	(0.000296)	(0.00238)	(0.00230)	(0.0000)	(0.00118)	(0.0000)	(0.000236)	(0.00196)	(0.00100)	(0.0000)
Share of people	-0.00643***	-0.0507***	-0.0492***	-0.00163***	-0.00745***	-0.000444***	-0.00201***	-0.0166***	-0.00739***	0.000436***
with low or no skills	(0.000148)	(0.00119)	(0.00117)	(0.0000)	(0.000482)	(0.0000)	(7.93e-05)	(0.000650)	(0.000509)	(0.0000)
Share of laid off	0.00298***	0.0234***	0.0281***	0.000738***	0.00284***	-0.000132***	0.000384***	-0.00286***	0.00385***	0.000189***
(due to restructuring)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.000367)	(0.0000)	(7.28e-05)	(0.000598)	(0.000369)	(0.0000)
Share of people	0.00321***	0.0258***	0.0288***	0.00103***	0.00471***	0.000314***	0.000259**	0.00464***	0.00698***	0.000369***
living in the rural areas	(0.0000)	(0.00151)	(0.00142)	(0.0000)	(0.000554)	(0.0000)	(0.000113)	(0.000931)	(0.000576)	(0.0000288)
Share of first-time	-0.00559***	-0.0452***	0.0452***	0.00138***	-0.00504***	-0.000259***	0.00132***	0.0107***	-0.00134	0.00000655
registrants	(0.000508)	(0.00413)	(0.00372)	(0.0000)	(0.00144)	(0.0000)	(0.000289)	(0.00251)	(0.00147)	(0.0000)
Share of people delisted	-0.00166***	-0.0128***	-0.0151***	-0.000425***	-0.00129**	-0.000782***	-0.000447***	-0.00384***	-0.000893	-0.00000346
from the registries	(0.000186)	(0.00150)	(0.00143)	(0.0000)	(0.000537)	(0.0000)	(0.000110)	(0.000923)	(0.000620)	(0.0000)
Share of youth	0.00948***	0.0741***	0.0866***	0.00249***	0.00147***	0.0523***	0.000117	0.00139**	0.00332***	0.000124***
(under 25/27 years)	(0.0000)	(0.00075)	(0.0000)	(0.0000)	(0.0000)	(0.00052)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Ratio of first-time to	0.000254***	0.00202***	0.00199***	0.00005***	0.00010*	0.00005*	0.00011	0.00095	0.000136	0.000279
returning registrants	(0.0000)	(0.000212)	(0.000189)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Ratio of employed to	0.00000649	0.00000550*	0.00000280	0.00000123*	0.00000780	0.00000510*	0.00000302	0.0000277*	0.000683	0.000453*
delisted	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Ratio of employed to	0.0000116**	0.0000782**	0.000131***	0.000295**	0.0000215*	0.0000125**	0.0000504**	0.0000450**	0.0000240*	0.0000162**
delisted in the rural areas	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Ratio of unsubsidised	-0.0000720	-0.0000621	0.0000228	-0.0000112	0.0000705	0.0000505	0.0000443*	0.0000390**	0.0000280	-0.00000339
employed to delisted	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
No of job brokers	0.00812***	0.0275	0.00554***	0.000007	0.00788***	0.000005	0.00820***	0.000008	0.0045***	0.000006
per one unemployed	(0.000183)	(0.0014)	(0.0014)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.00086)	(0.0000)	(0.0000)
ALMPs coverage	-0.00346***	-0.0275***	-0.0254***	-0.000807***	-0.00380***	-0.000150***	-0.000820***	-0.00587***	-0.00245***	-0.000106***
	(0.000183)	(0.00147)	(0.00144)	(0.0000481)	(0.000509)	(0.0000251)	(0.000104)	(0.000862)	(0.0000)	(0.0000)
Fixed effects	Unit	Unit	Unit	Unit	Unit	Unit	Unit	Unit	Year, month and unit	
No of registered					Negative***	Negative***	Negative***	Positive***		
No of unemployed					Negative***	Negative***	Negative***	Negative***		
No of vacancies					Negative***	Negative***	Negative***	Negative***		
Time trend					Negative***	Negative***	Negative***	Negative***		
Squared time trend					Negative***	Negative***	Negative***	Positive***		
Constant	0.672***	0.610***	0.646***	0.648***	0.568***	0.647***	0.668***	0.554***	0.568***	0.650***
R^2 between	0.083	0.073	0.054	0.077	0.000999	0.000770	0.0141	0.000609	n.a.	n.a.
R^2 within	0.791	0.788	0.832	0.790	0.977	0.937	0.930	0.925	n.a.	n.a.
No of units	379	314	380	315	378	315	378	314	360	314
No of observations	31 189	30 638	31 962	31 396	31 962	31 396	31 189	30 638	31 962	31 396

Note: Dependent variables: estimates of the technical efficiency from the stochastic frontier as reported in Table 3. Monthly and annual dummies statically significant, detailed results available upon request. Heckman test confirms the use of fixed effects. Robust standard errors in parentheses. ***, ** and * denote significance at 1%, 5% and 10% respectively.

Similarly, although the statistical significance is very high, the relationship between restructuring and matching efficiency is clearly spurious - it changes signs across specifications, while clearly the effects of restructuring decreased in time, which correlates positively with downward sloping estimations of technical efficiency and negatively with upward sloping ones (please, recall Figure 4). Indeed, graphical inspection reveals higher variation in this variable in earlier years (see Figure 7). Youth, on the other hand, is steadily positively related to efficiency, which is consistent with the creaming hypothesis, as suggested by Tyrowicz (2006).

The interesting findings concern the proxy for job brokering capacity - namely the number of job brokers over the number of unemployed. Naturally, the estimators are positive, but they loose significance if large cities are excluded from the sample. This may be a consequence of the fact that predominantly the labour offices in the large cities have larger numbers of job brokers (mean for total sample is around 5.7, mean for large cities is around 22.6). Because these are larger labour markets, also the potential for obtaining vacancies is larger, which means that job brokers may actually be more productive.

Finally, the ratios of the nature of inflows and the reasons for outflows have the intuitive signs, but their significance is not too high. Also, the sizes of the estimators are extremely low. Again, as revealed by graphical inspection - most of the "explanatory" power is driven by the year effects, Figures 8 - 10.

As to the active labour market policies, the results suggest consistently negative and significant estimators, which would suggest either a very high lock-in effect or essentially ineffectiveness of ALMPs. Either way, these findings are rather counterintuitive and striking. However, it seems that the significance is largely driven by some spurious effects. Namely, graphical inspection fails to provide any convincing evidence supporting the negative slope in the relationship - other than higher dispersion of ALMPs coverage in mid-ranges of technical efficiencies, Figure 5. Such "coincidence" is natural if one recognises that the mid-range is also usually mostly diversified in terms of all underlying structural characteristics.

Summarising, there seem to be little systematic covariates of the technical efficiency estimates - be it policy variables of structural characteristics of the local labour markets. The fit of the model is satisfactory only in the within context - the between variance has remained unaddressed despite inclusion of a wide variety of measures. The conclusions suggest however, that the efficiency of matching has not been affected by the increase of the ALMPs coverage that has occurred over this period. Consequently, although failure to reject the null hypothesis of no relationship between these two variables is not a strong finding - it points to the lack of efficiency fostering mechanism in the algorithms of ALMPs financing.

5 Conclusions

The "black box" of Petrongolo and Pissarides (2001) is somewhat more comprehensible when differentiated estimation techniques are applied, but remains fairly "black" in the case of Poland. In this paper we have used a unique data set and estimated the matching function at a policy relevant level of local labour markets. We sought to link the matching efficiency with the ALMPs and this link has proven to be nonexistent.

This paper approaches the question of efficiency in job placement using regional data for Polish regions (policy relevant NUTS 4 level) over the time span of 2000-2008. Using a unique data set we estimate the matching function using stochastic frontier as well as difference-in-difference estimators. The former provides an estimate of the matching efficiency changes observed in both time and regional dimensions. The latter provided point estimates, but employing rolling window estimation on averaged data revealed high time variation of the parameters.

We use also managed to combine this unique data set with another unique source of data on the ALMPs coverage, unemployment structure across time and regions as well as the individual capacity of local labour

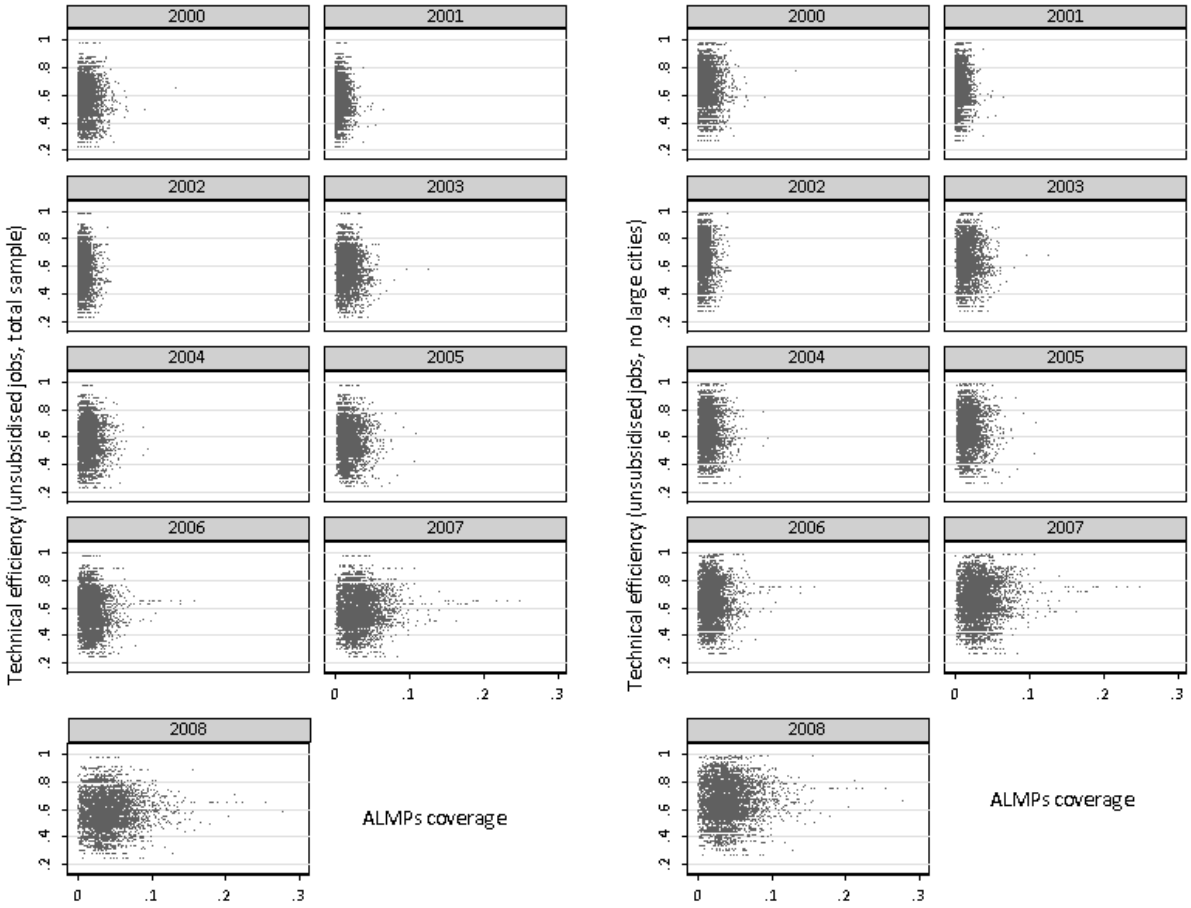

Figure 5: Scatterplots for coverage and estimated technical efficiency scores for unsubsidised employment.

offices. We use these data to explain the exceptional variation in estimated efficiency scores. Our findings suggest that matching abilities are highly driven by demand fluctuations, while unemployment structure, ALMPs and individual labour office capacities have little explanatory power.

Analysing the data for Polish regions over 2000-2008 is barely an analysis of a transition country. Despite extremely high values of unemployment rates throughout this period, transition has commenced in 1989, while the period of 1999-2002 is believed to convey the so-called "second" wave of unemployment. Regional differentiation of labour market conditions - exceptionally large in the region, Tyrowicz and Wójcik (2010) - is not only persistent, but also cannot be explained by the structural factors. As this research demonstrates, currently ALMPs and in principle the capacity of local labour offices do not translate to higher matching efficiency. This may be explained by two competing hypotheses. In the first, the dynamics of this relationship may require some thresholds, which has not yet been attained. However, the values of ALMPs coverage have increased considerably, while no clear pattern of relation may be said to emerge. The other hypothesis involves the incentives associated with the algorithm allocating funds for ALMPs. If availability of funds is not related to the effectiveness, increasing the financing (and thus the coverage) does not have to lead to better matching efficiency.

Consequently, our findings seem to have policy implications. First, the elasticity with respect to offers is much lower than the one with respect to job seekers, while difference-in-difference estimators of the latter are actually negative. These two findings combined suggest that neither the potential of vacancies nor that of job

seekers are exploited. Secondly, the fact that none of the analytical techniques was able to link reliably changes in technical efficiency to active labour market policies, while the individual capacity of labour offices was only relevant as a filter between large cities (with large labour markets) and the majority of the districts. Thus, it seems that if availability of finance was more directly related to results, funds allocated to ALMPs and labour offices could yield better, more tangible results.

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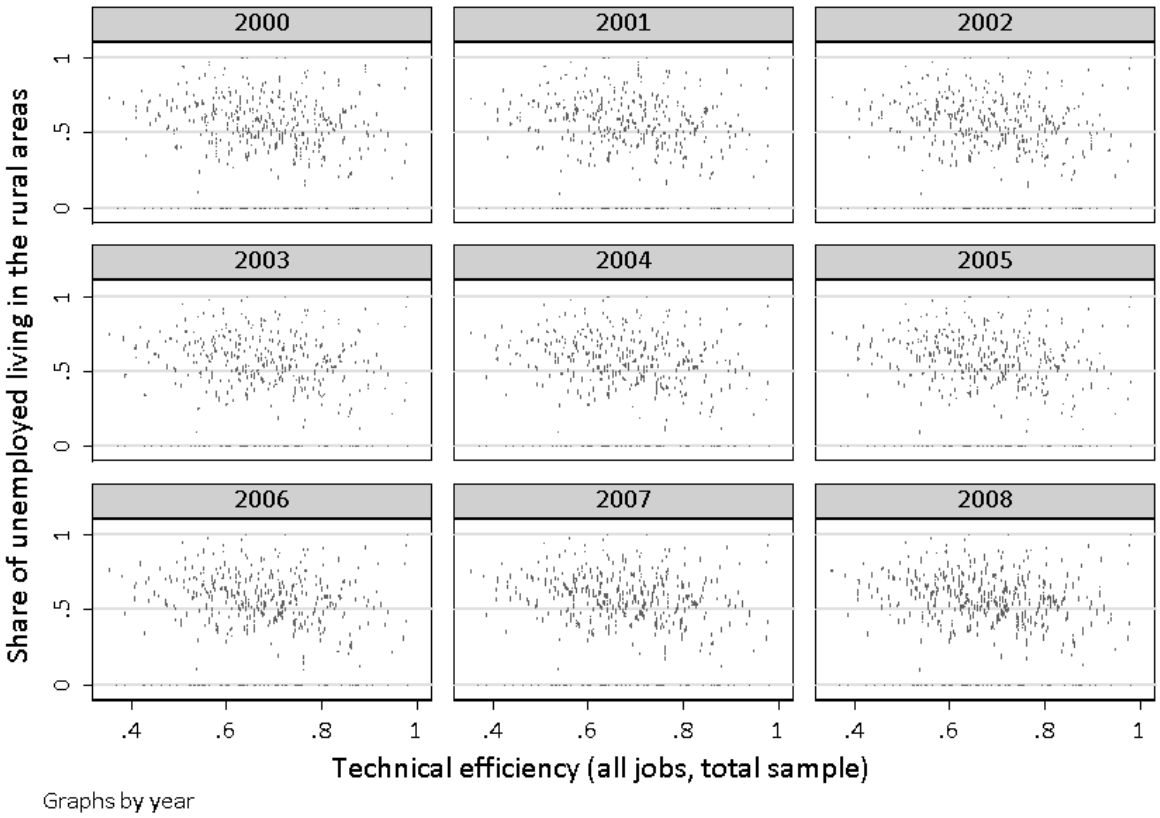

Figure 6: Scatterplot, share of rural inhabitants in the pool of unemployed *versus* estimated efficiency

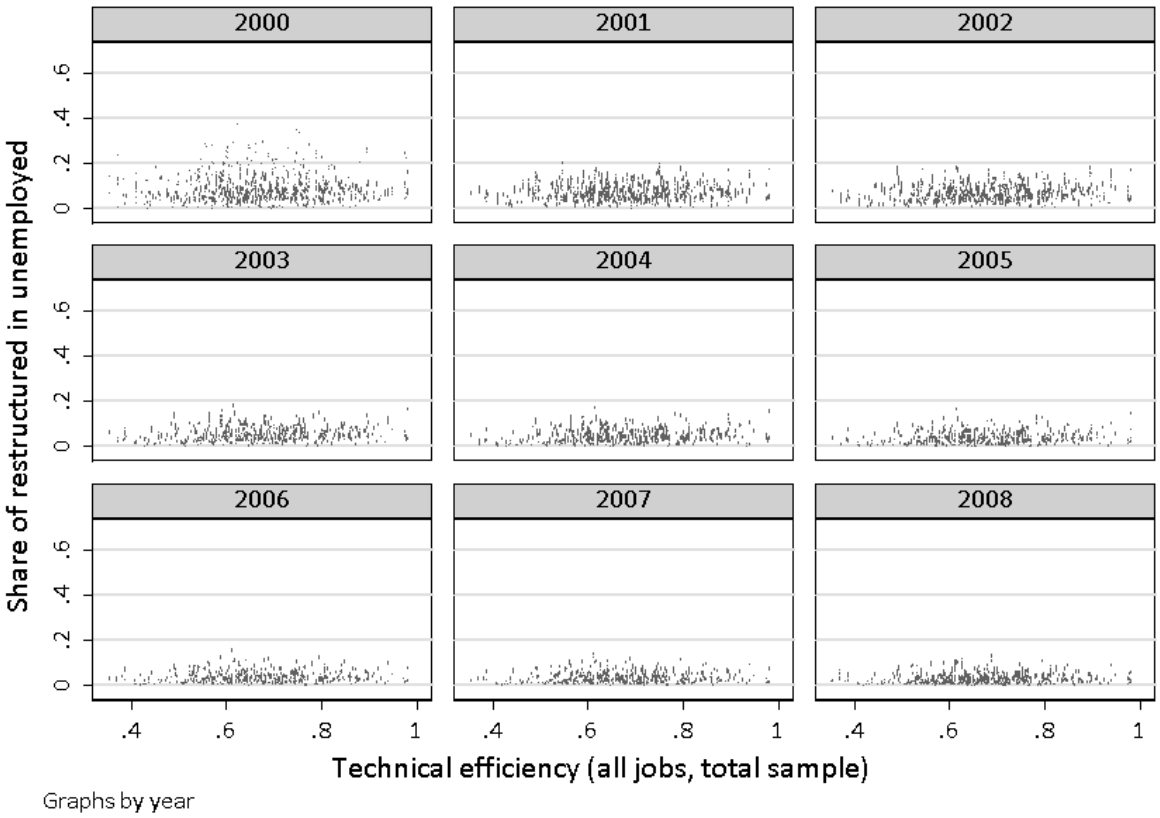

Figure 7: Scatterplot, share of unemployed due to restructuring in the pool of unemployed *versus* estimated efficiency

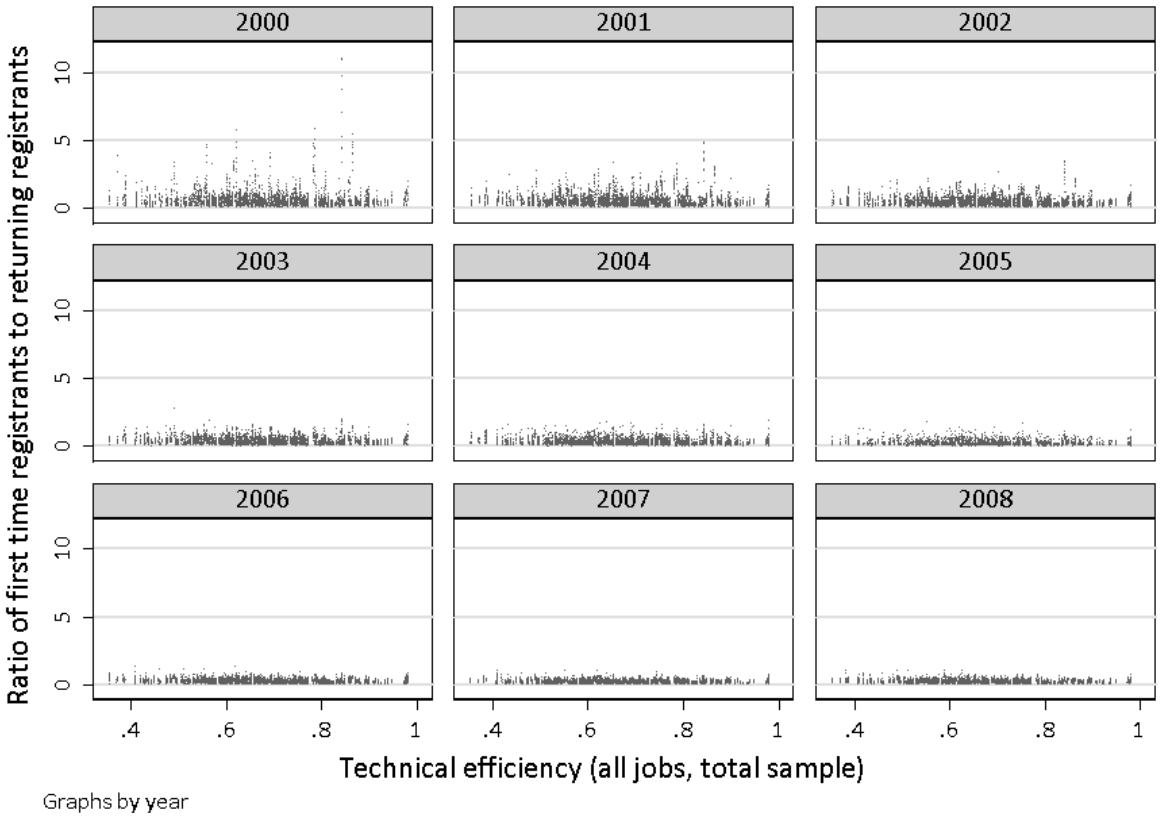

Figure 8: Scatterplot, share of first time registrants *versus* estimated efficiency

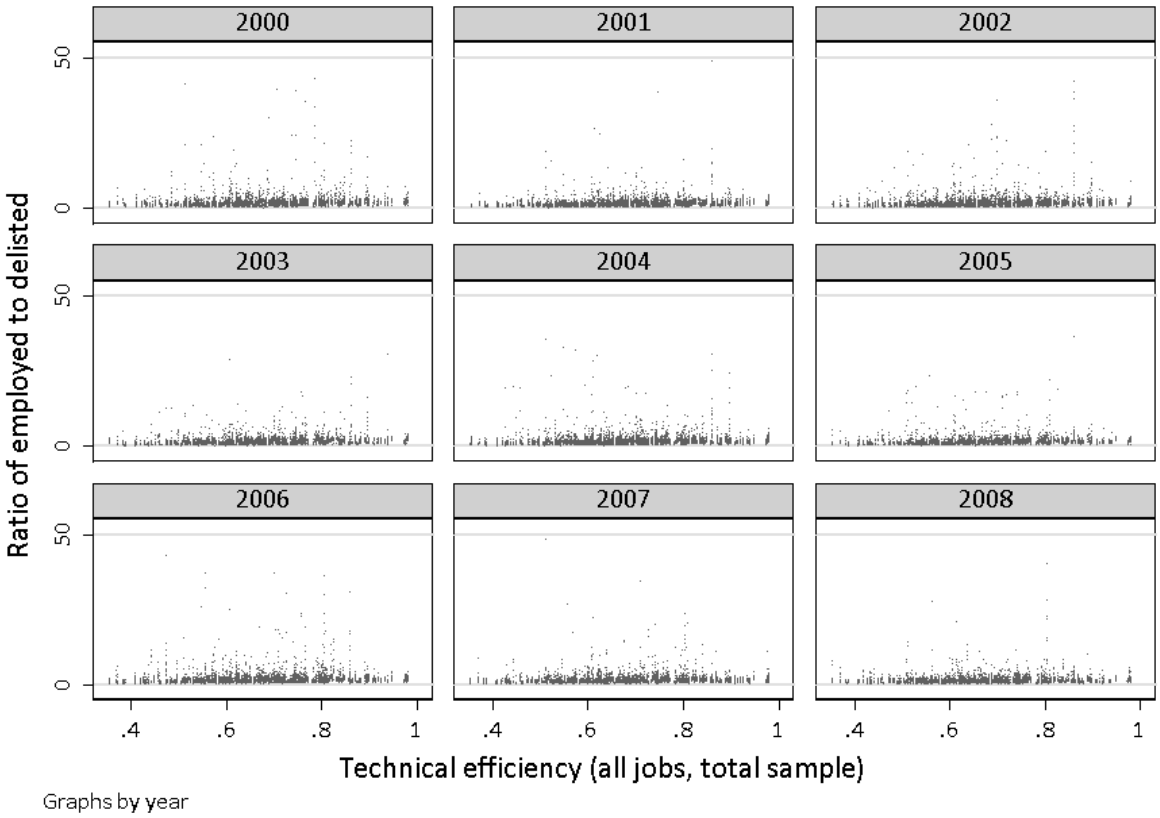

Figure 9: Scatterplot, share of delisted *versus* estimated efficiency

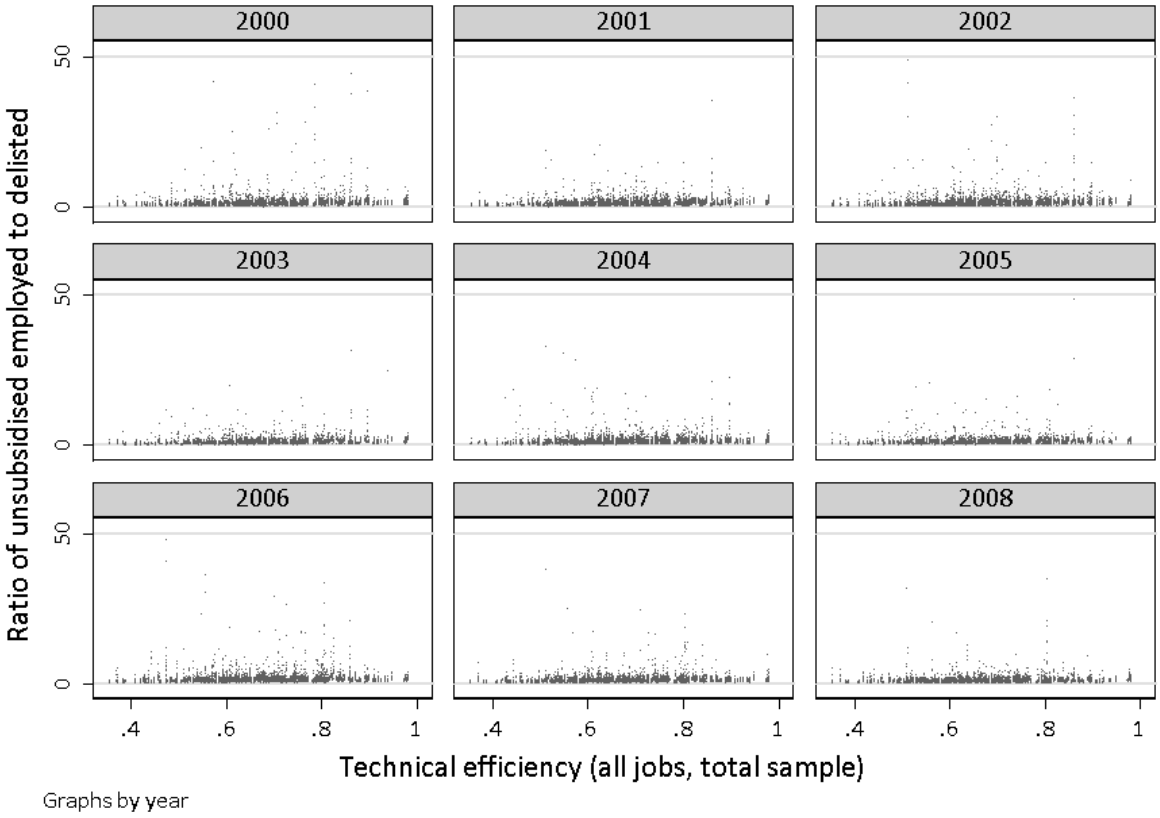

Figure 10: Scatterplot, share of unsubsidised job offers in all job offers *versus* estimated efficiency

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