Dmitrijeva, Jekaterina; Hazans, Mihails

Conference Paper

Does training increase outflows from unemployment: evidence from Latvian regions

44th Congress of the European Regional Science Association: "Regions and Fiscal Federalism", 25th - 29th August 2004, Porto, Portugal

Provided in Cooperation with:
European Regional Science Association (ERSA)

DOES TRAINING INCREASE OUTFLOWS FROM UNEMPLOYMENT: EVIDENCE FROM LATVIAN REGIONS

JEKATERINA DMITRIJEVA*

MIHAILS HAZANS♦

AUGUST 2004

Abstract:

Monthly panel (1998-2003) data from regional labor offices in Latvia are used to conclude on the specificity of matching process in this transition economy and to evaluate the impact of active labor market policy programs on outflows from unemployment.

Results confirm that the hiring process is driven by stock-flow matching rather than by traditional matching function: stock of unemployed at the beginning of the month and vacancies arriving during the month are the key determinants of outflow from unemployment to employment, while stock of vacancies and inflow of unemployed are not significant.

In the context of such "correct" specification of the matching process, the policy evaluation is performed. We find positive and very significant effect of training on outflows from unemployment to employment, thus providing some evidence against cuts in training expenditures. Fixed effects estimates allow discriminating between regions in terms of matching efficiency.

JEL: J41, J64, J68
Keywords: stock-flow matching, augmented matching function, labour market policy, training

* EPEE (centre d'Etudes des Politiques Economiques de l'université d'Evry), Department of Economics, Université d'Evry- Val d'Essonne, 4 Bd. François Mitterrand, 91025 Evry cedex, France.
E-mail: Jekaterina.Dmitrijeva@eco.univ-evry.fr
I would like to thank Thierry Laurent, Frank Malherbet and Ferhat Mihoubi for very useful comments. All remaining errors are our own.
♦ University of Latvia and BICEPS (Baltic International Centre for Economic Policy Studies), Riga, Latvia

1. Introduction

Transition from centrally planned to market economy has confronted all CEE[1] countries with a number of new challenges. Among them - dealing with the problem of high and persistent unemployment, that has been aggravated by large regional disparities.

In line with OECD suggestions and occidental experience a great importance has been given to active resolution, i.e. employment stimulating policies that usually include direct job creation, job subsidies, self employment promotion, as well as labour training and re-qualification programs.

The Baltic States can be distinguished from other transition economies by a prioritized attitude towards this latter type of programs: more then a half of active labour market policy budget has been devoted here to labour training and re-qualification.

The dominant role of training is determined by the nature of unemployment in this region – a strongly accented mismatch between skills of "old" labour and the requirements of "new" employers (see e. g. OECD, 2003).

However, in Latvia recently policy accents had been changed and the overall expenditure on active labour market policy has been cut. Such action has affected in a most significant way the programs promoting qualifications and skills of unemployed: their weight in total active policy expenditure has dropped from 57-60% in 1996-2001 to 34 percents in 2003[2].

In order to justify such attitude the arguments on low efficiency of such programs are often provided, while any serious study, brining the proofs for such statements has not ever been developed.

This paper aims to test the validity of the "training inefficiency" arguments. To achieve this goal, effects of training programs on outflows from unemployment will be evaluated using augmented matching function approach. Regional disparities in unemployment patterns will be accounted for when deriving the conclusions.

Keeping in mind that the results of such evaluation depend strongly on methodological approach to the analysis, we, prior to policy efficiency test, perform specification search to derive the most appropriate tools.

As the context of transition economy imposes to account for existence of considerable frictions at the labour market[3], matching function approach seems to be the most suitable for our study. Moreover, a

[1] Central and Eastern European
[2] See Figures 1 and 2 (Annex 2)
[3] Originating from information imperfections, underdevelopment of insurance markets, low labour mobility, high individual heterogeneity, high qualification mismatch and other similar factors.

significant number of studies[4] exploiting matching function for the analysis of labour market issues in CEE countries give one more argument in favour of such approach.

Existing empirical literature, however, seldom goes beyond the traditional matching function context, despite the fact that expanding related literature has proposed during the last decades a great number of extensions, allowing for a large variety of externalities, market imperfections and particular forms of matching process[5]. A likely reason why these wealth of theoretical tools have been under-utilised in the transition context is that data of relevant quality have not been available to scholars.

This paper follows recent developments by Gregg and Petrongolo [2002], Coles and Petrongolo [2003]. We test the existence of non-random patterns in matching process and find that stock-flow specification suits better the process of worker-job matching in Latvia than the traditional stock-stock model. We further use this "correct" specification of matching function to evaluate the effects of active labour market policies.

The rest of the paper is organized as follows. Section 2 gives more intuition on different types on matching and specifies our main estimated relationships. Section 3 describes data and variables used in the analysis. Section 4 describes the estimation results. Section 5 concludes, provides policy suggestions and discusses directions of future work.

2. The matching function

2. 1. Theoretical and empirical considerations

Although during last decades the matching function has become a standard tool for labour economists, let us recall briefly it's basic features[6].

The key idea refers to the existence of a well-behaved function, summarizing the trading technology between unemployed job-seekers and the firms, searching to fill vacant jobs. Giving a number of productive worker-job pairs (matches) conditional on these two inputs, matching function acts like a production function for new hires and can be formalised as follows:

$$M = m(U, V) \tag{1}$$

where M denotes a number of matches (number of unemployed shifted to employment, number of filled job vacancies) formed in the economy during the elementary time period (in a discrete time setting). U and V stand, respectively, for the beginning of period stocks of unemployed and vacant

[4] See for example Burda [1993], Boeri and Burda [1996], Profit [1997], Burda and Profit [1997], Munich, Svejnar and Terrel [1999] and others.
[5] See Petrongolo and Pissarides [2001] for a detailed survey on extensions and developments applied to matching approach.

jobs.

Logically, the larger is the pool of unemployed workers and the greater is the number of available jobs, more productive job-workers pairs would be formed in the economy ($\partial M / \partial U > 0, \partial M / \partial V > 0$). Moreover, no matches will occur at the market if at least one of the inputs is absent ($m(0,V) = m(U,0) = 0$).

Nevertheless, matching is not instantaneous and both types of participants (unemployed and the firms) are involved in a costly and time consuming process of searching and finding the appropriate match.

At this stage, existing market and information imperfections, coordination failures, agent heterogeneities and other similar factors tend to lower the efficiency of market in terms of matching, increasing the gap between the numbers of available unemployed and jobs and the number of matches, formed in the economy.

Such ability to model, without any loss of simplicity, markets with frictions explains the attractiveness of matching function approach for labour economists and its intensive use in theoretical and empirical research.

As to the practical use of matching function, the approximation for matching process most frequently used in the empirical and often also in the theoretical literature is the Cobb-Douglas one[7]: $\left[M = AU^{\alpha}V^{\beta}\right]$ where α and β are elasticises with respect to the size of unemployment pool and available jobs, and A stands for a scale parameter capturing matching efficiency, as well as various mismatch possibilities. The efficiency of matching is affected by institutional framework and efficiency of public programs aiming to increase the number of matches and stimulate job creation. Mismatch problems arise from inconsistencies between existing jobseekers and vacancies in terms of occupations, skills or location (spatial mismatch).

The Cobb-Douglas specification implies increasing, decreasing or constant returns to scale if $(\alpha + \beta >, <, or = 1)$ respectively. The empirically estimated matching function often display constant

---

[6] We refer the reader one again to Pissarides and Petongolo [2001] for a very detailed survey of different types of matching.

[7] It should however be stressed that there is gap between the functional forms originally derived by probability theorists and suitable for micro-foundered explanation of existence and properties of the matching function and the one practically used in the literature. This latter corresponds to Cobb-Douglas or less often Translog or CES specification, while the former one can be derived as following: suppose that at the beginning of the period there are U unemployed and V vacant jobs at the market. If all vacancies have the same probability to be contacted, each of them received an application from a particular job-seeker with the probability $1/V$. Thus $(1-1/V)$ is the probability that the vacancy is not contacted by this unemployed, and $(1-1/V)^U$ stands for the probability that none of job-seekers has contacted the vacant job. Hence the probability that at least one unemployed contacts the vacancy is $[1-(1-1/V)^U]$. We assume that matching takes place as soon as firm and unemployed meet, so the number of matches formed in the economy during a considered time period is $M=V[1-(1-1/V)^U]$ The above function can be approximated by $M=V(1-e^{-U/V})$.

or slightly decreasing returns to scale in developed countries, while the results are more diverse for the countries in transition[8].

Stock-Flow matching (SFM)

Although a simple "random stock-to-stock matching" is assumed to nicely fit the reality of the matching process, some authors, originally Coles and Smith [1998] followed by Gregg and Pertongolo [2002], Coles and Petrongolo [2003], claim that the process is more complicated then that – they argue that unemployed, being perfectly informed about all existing vacant jobs[9], display a systematic element in the search and matching process can no longer be considered as random. In their 1998 paper "Marketplaces and matching" Coles and Smith, decompose the matching process in "contact" and "suit" stages and make the following assumptions in this framework:

(i) Upon the arrival at the "marketplace" the unemployed scan all appropriate jobs and applies to all of them (in contrast with traditional assumption, where time consuming nature of such scanning implies that applications are randomly distributed across vacancies).

(ii) If the firm has been contacted is does not mean that the match was created (due to heterogeneity among jobs and unemployed). Such consideration is not common for simple versions of traditional matching function, but is however integrated in the analysis in stochastic matching models. This point is therefore not distinctive of stock-flow matching approach.

(iii) If none of these vacancies suits such unemployed, he will wait for the inflow of new proposals and try to locate his "match" among them, not considering the old vacancies anymore. This last assumption on unemployed differentiation between old and new vacancies is the fundamental for stock-flow approach. .

A symmetric reasoning can be derived for vacancies, thus matching will only be realized between stocks of unemployed or vacancies and the inflows of new trading partners (vacancies or unemployed respectively)[10] .

Formally the above can be represented in the following way: let U^S, V^S denote the stocks and U^F, V^F the inflows of unemployed and vacancies and consider the worker entering the

[8] Burda and Wyplosz [1994] report decreasing returns to scale for France, Germany, Spain and U.K., Pissarides [1986], and Layard et al. [1991] constant returns for U.K., Burda [1993] finds decreasing returns to scale in Czech Republic and Slovakia, while Munich et al [1999] shows that returns to scale in this region are rather increasing.

[9] Although such assumption of full sampling is a simplifying one, this modelling captures a realistic feature of search markets, that a job seeker scans the bulk of advertisements before deciding where to apply and once an advertisement has been scanned and rejected, return is less likely than application to a new one (Gregg and Petrongolo [2002], p.3)

[10] If we consider a period of infinitesimal length we rule out the probability of matching between the inflows

unemployment pool. Let $a \in [0,1]$ denote the probability that the match is unacceptable for job-worker pair: in this case the inflowing worker has the probability α^{V^S} to match with none of existing vacancies. Thus $(1-\alpha^{V^S})$ will denote the probability that there exist at least one vacancy suitable for this worker -probability that he will be matched on the entry. The number of matches between new unemployed and vacancies in stock is then given by $U^F(1-\alpha^{V^S})$. The same reasoning can be applied to inflowing vacancies and the number of matches between new vacancies and stock of unemployed is given by $V^F(1-\alpha^{U^S})$. Thus the aggregate matching function can be written as

$$M = U^F(1-\alpha^{V^S}) + V^F(1-\alpha^{U^S}) \tag{2}$$

It should be noted that the stock- flow matching function fits the regular assumptions: increasing in all it's arguments and there are no matches if the respective stock or inflow is null.

The first empirical support for stock flow matching has also been presented by Coles and Smith [1998]. They estimate a log-linear matching function and find that only inflow of new vacancies increases significantly the job-finding rates for long-term unemployed. Similar result on the significant role of inflow variables have been proposed by Gregg and Petrongolo [2002] when estimated quasi-structural outflow equations for unemployed and vacancies.

2.2. Estimated relationships

The above intuition, gives rise to the question of the true nature of Latvian matching process: can it be described by the standard stock-to-stock function (utilised in the previous studies on transitional labour markets), or a more detailed specification should be called for. To answer this question we in what follows estimate both traditional and the stock-flow matching functions and find a strong support in favour of non-random matching across Latvian regions. Keeping in mind that one of the aims of this study is to evaluate the impact of labour market policy in the context of Latvian regions, we augment this correct specification with the proportion of participants of training programs among the stock of unemployed.

We thus estimate three basic relations:

1. Matching function including only stocks of unemployed workers and job vacancies as explanatory variables, with the standard Cobb-Douglas specification of the matching:

$$\ln(M_{it}) = \alpha_0 + \alpha_1 \ln U_{it}^S + \alpha_2 \ln V_{it}^S + \varepsilon_{it} \tag{3}$$

2. Function allowing for non-random matching: we aim to verify if the match results from stock-stock or stock-flow variables. For results to be comparable with other studies, we retain the most basic specification originally proposed by Stock and Coles [1998] and estimate the following log-linear relationship:

$$\ln(M_{it}) = \alpha_0 + \alpha_1 \ln U_{it}^S + \alpha_2 \ln V_{it}^S + \alpha_3 \ln U_{it}^F + \alpha_4 \ln V_{it}^F + \varepsilon_{it} \qquad (4)$$

Technically we simply augment the traditional with the Cobb-Douglas specification with variables describing inflows of new unemployed and new opened job vacancies.

3. After finding the best specification for the matching function, the augmented matching function approach is used to evaluate the possible effect of active labour market policy by estimating the following model:

$$\ln(M_{it}) = \alpha_0 + \alpha_1 \ln U_{it}^S + \alpha_2 \ln V_{it}^S + \alpha_3 \ln U_{it}^F + \alpha_4 \ln V_{it}^F + \alpha_5 \ln PTU_{it} + \varepsilon_{it} \qquad (5)$$

where *PTU(i,t)* stands for the policy variable. We will discuss the construction of policy variable in what follows, but generally it can be interpreted as the component of scale parameter related to training programs. Higher values of *PTU* are expected to increase the number of transitions to employment for a given number of unemployed and vacant jobs.

3. Data and Variables

Data used in this analysis originates from the regional data base of Latvian State Employment Agency[11], covers 33 Latvian municipalities and a period from January 1998 to October 2003.

Unemployment data covers only registered jobseekers (there is no information on non-registered jobseekers available on monthly basis). This is a serious limitation of our analysis as several studies on transition economies[12] point out that the employment in such countries is in large part sourced by flows from the pool of non-registered job-seekers, those out-of labour force, and high level of job-to - job transitions is reported.

This limitation, however, is unlikely to bias the results for the following reasons: first, our dependent variable (outflows to employment) only concerns outflows from the pool of registered unemployed; second, vacancy data cover job announcements placed through State Employment Agency and are thus in the first place available to registered unemployed; and third, in order to participate in any employment promoting program, one should be registered at state employment office.

[11]The authors would like to thank Ilze Berzina from the Latvian State Employment Agency for cooperation in provision of necessary data.

[12] Boeri [2001], Boeri and Terell [2001]

Another issue on adequacy between unemployed and vacancy data concerns the qualification structure of the matching pools. As displayed by Table 1, the proportion of unemployed with manual occupation in the total pool varied around 75 percents in the last four years. On the other hand,, there is a common comment concerning vacancy data originating from state employment services - these are in majority the low-qualification jobs that are posted through such agencies. This fits very well with the Latvian reality: only about 17 percents of open jobs can be characterised as non-manual. From this perspective, the matching function analysed in this study refers to a segment of relatively low qualification unemployed and jobs.

Table 1: Composition of vacant jobs and unemployed by occupation

Year	Non-manual		Manual	
	VAC[13]	UNEM[14]	VAC	UNEM
2000	21.5	20.1	78.4	74.6
2001	15.2	19.1	84.7	75.3
2002	15.6	18.8	84.4	75.5
2003[15]	16.4	18.0	83.6	75.6

Source : State Employment Agency of Latvia.

Data being monthly spaced, the stock of unemployed is the number of unemployed at the beginning of the month, and the flow of unemployed – the number of individuals entering the unemployment during the current month (new unemployed). Outflows are given by the number of persons who exited to employment during a month period.

The outflows, being an important component of our analysis, deserve a closer look.

On average in Latvia, about 3.3% of all individuals, unemployed in the beginning of the month find jobs during a reference period (one month). This figure varies strongly across regions: from 0.7% in Tukums region (15 outflows from 2012 unemployed in March 1999) to 10-13% in Kuldiga (September 2002), Limbazi (December 1999) or Saldus (August 2000). When averaging across time, the highest mean transition rates have been observed in Riga (the capital city of Latvia) and Saldus: here about 5% of unemployed on average find job every month. Figure 3 reports mean transition rates across regions.

As to the other composites of matching function, the aggregate dynamics of number of matches as well as stocks and flows of unemployed and vacant jobs are displayed in Figures 4 and 5. Descriptive statistics elements, summed up by the Table 2, give the information on turnover rates. We

[13] Vacant jobs (flow).
[14] Stock of unemployed

observe that the ratio between the stocks of unemployed and the inflows only makes 0.09, that is about eight times lower that in Great Britan (Gregg and Petrongolo [2002] report 0.7 for the period 1967-1996): the reason lies in a very large unemployment pool observed in Latvia (in some regions unemployment rate is above 20%). Thus even if the inflows in unemployment are quite considerable, they loose their significance when comparing to stock of unemployed.

On the contrary, the turnover of vacancies can be comparable to the one reported for Britain (2.59 reported by Gregg and Petrongolo [2002]), and is about 17 times higher that the one of the unemployed, discussed above. We can thus conclude that the vacancies are in general filled very rapidly and the inflows of new job proposals represent a very significant variable in the process of job matching. Another proof for such suggestion is brought by the look on the correlation of aggregate totals in the Latvian matching function: the correlation between matches and vacancy inflows is two times higher that the one with vacancy stocks. Negative correlation between unemployed inflows and matches could be explained by the worsening of market situation, when the shrinking companies are not ready to re-employ at once.

Table2: Aggregate correlations and others statistics constructed on monthly data, 1999-2003

Correlations of number of matches with:	
Inflow of unemployed	CORR (M, UF)= -0.17
Stock of unemployed	CORR (M,US) = 0.23
Inflow of vacancies	CORR (M,VF) = 0.45
Stock of vacancies	CORR (M,VS) = 0.22
Mean values	
Vacancy turnover rate (VF/VS)	1.51
Unemployed turnover rate (UF/US)	0.09
Hiring rate (M/US)	0.03

Source: Calculations based on Latvian State Employment Agency data

Moving to panel structure of the data, the descriptive statistics in Table 3 (Annex 1) show that all data series display much more important between-group variability (reflecting inter-regional differences) than the within group one (reflecting changes over time). This observation has direct application to the methodology of our analysis. First, patterns seem to differ significantly across regions, and considerable attention should be paid to this fact. Second, random effects panel estimator seems to be more appropriate than the fixed effects one.

To conclude the description the data and variables, let us have a closer look at the policy variable used

[15] For year 2003 data covers only the first 6 months.

in the analysis. We use two data sets : one gives the number of persons completing training and re-qualification programs every month (by region), while another set gives the information on those that find job after being treated by such program. However none of these data can be directly introduced in the analysis. The reasons are the following :

- Those completing training programs have little chance to transit to employment within the current month, thus monthly outflows from training will not give enough information when explaining monthly outflows from unemployment. Cumulated sum of outflows from training during last several months is used instead;

- On the other hand, cumulating could also give incorrect information: we would account for the persons that have maybe already transited to other labour market states (employment, out of labour force, participation in other programs) and thus should not be considered when explaining shifts from unemployment to employment;

- As stated earlier we have data on those who have found jobs after training, but we can not use it directly.: available data informs (on monthly basis) how much of the persons that have shifted into employment during the current month, have ever participated in training or re-qualification programs. But we can not distinguish when exactly respective individuals have been trained - this month or two years ago. If they have completed training more then a year ago we should conclude that the program has not been efficient enough – even after training unemployment spell is more then 12 months.

Taking into account the above discussion and in order to have the most reliable link between outflows to employment and participation in active labour market policy program, we construct the following proxy:

(i) $CT(i, t)$ is a cumulated over the past 12 months sum of number of unemployed who have completed one of the training programs in the region i;

(ii) $TE(i, t)$ is a total sum of trained individuals that have outflowed to jobs during the past 12 months;

(iii) $TU(i,t) = CT(i, t) - TE(i, t)$ is a proxy for the number of trained persons that, at the beginning of given month, still remain unemployed.

Those who have been trained more than a year ago are not included: we assume that during a year they find a job, or get discouraged and leave labour market, or get re-trained and so appear in our accounts.

(iv) $PTU(i,t) = TU(i,t)/U(i,t)$ is a proxy for the fraction of the pool of unemployed composed by trained individuals.

We examine how this fraction affects the number of matches formed in the economy during a month.

The preliminary intuition can be derived from Figure 6, where regional outflow-to-job rates are plotted against this training participation proxy (time average for each region). The relationship is positive.

The best performers in terms of training efficiency seem to be Saldus, Limbazi, and Valmiera regions, as well as the capital city, Riga, all having average proportion of the (currently) unemployed who have completed training programs in the past between 12 and 18 percents, and monthly outflow-to-job rate between 4.5 and 5.5 percent. Districts of Ogre and Gulbene substantially promote training programs, but the impact does not seem to be sufficient. Six districts located in the depressed eastern part of Latvia (Daugavpils, Rezeknes, Ludzas, Preilu, Balvu, Kraslavas) and the port city of Liepaja are likely to be the worst performers: rates of exit to employment there are too low even when considered against quite low participation in re-qualification and skills-upgrading programs. These conclusions are of course preliminary; a more rigorous analysis is performed in the next section.

4. Econometric issues and estimation results

Prior to the discussion of the results it is useful to consider in more details the data structure. Using cross sectional time series (CSTS) data allows enlarging the range of possible analysis tools and allows fully exploiting both regional and time dimensions of our data, but induces some serious issues in the treatment procedure. Since CSTS data typically exhibit groupwise heteroscedastic, contemporaneously correlated and often serially correlated residuals, we should account for the existence of non-spherical error structure, carefully interpret the results and find the way to obtain the most robust estimates.

We start with an OLS estimate, but taking into account that error structure does not conform to OLS assumptions, use special procedures allowing for necessary corrections. Here two options are possible: Parks-Kmenta method performs the estimation by GLS[16], correcting first for serial correlation in the residuals, and further for contemporaneous correlation (and simultaneously for heteroscedasticity as Beck and Katz [1995, 637] remark). Applying FGLS transformation on the estimated model gives out the results corrected for non-spherical disturbances. Parks-Kmenta method has been revised by Beck and Katz [1995, 1996], who noticed that FGLS procedure assumes variance-covariance matrix of the errors to be known, not estimated. Thus GLS have optimal properties for CSTS data, while FGLS have not. Beck and Katz propose to use a less complex method, retaining OLS parameter estimates

[16] OLS (Ordinary Least Squares), GLS (Generalized Least Squares), FGLS (Feasible Generalized Least squares) .

(consistent but inefficient) and replace OLS standard errors by panel-corrected standard errors (PCSE). While Beck and Katz critics state that Parks –Kmenta method is unusable when time dimension is shorter than the cross-sectional one, and this is not the case with our data, we however present the estimates by both Parks-Kmenta[17] and Beck and Katz methods.

In order to exploit regional differences in matching processes, we also consider in our study fixed and random effects specifications.

Region fixed effects capture unobserved region-specific factors, removes average region effect and focuses the model on within region variation over time. Thus the coefficient represents cross-region average of the longitudal effect.

In contrast, time fixed effects capture developments over time that is common to all regions. The coefficients display average cross-sectional effect and takes into account shifts over time in the position of the regions relative to each other. Small variance of coefficient estimates implies high degree of persistence of such relative position.

Combining both time and region specific effects give the model with a "pure" effect as all unobserved effects (region and time specific) are removed.

Random effects model, which we apply only with regard to regional dimension, assumes unit specific effects to be random.

Latvian matching function

We can now turn to the discussion of our estimation results. Following the logics developed in the rest of this paper, we first tend to validate the assumption of stock-flow matching on Latvian data and aim further to evaluate the effects of active labour market policy.

As previously discussed we estimate in different specifications both traditional and stock-flow matching functions, starting by OLS estimation. Although error structure does not conform to OLS assumptions, it is still worth to look at these results (Table 4).

It is important to note that even OLS results for the traditional matching function display the fact that unemployed stock has a very significant role in determining the outflows to employment, while the coefficient of the stock of the vacancies is very low (although significant in some specifications). This result remains true when applying the corrections for error structure or extracting pure effect by including region and time specific effects in the regressions.

[17] In the current version of the paper GLS estimates only account for the presence of heterocsedastic panels, while PCSE results give standart errors corrected for both heteroscedasticity and contemporaneous correlation

While constant returns to scale are always formally rejected at all significance levels, the sum of estimated coefficients is inferior to unity (varies from 0.77 to 0.92) in all specifications. The absence of region and time specific effects is always rejected as well. All reported tests indicate the presence of serial correlation, groupwise heteroscedasticity and panel-level correlation in disturbances, both in traditional stock-to stock (Table 4) and stock-flow (Table 5) matching functions. Hausman's test for random effects indicates that such specification is appropriate for traditional matching function, but not for the stock-flow one: here the correlation between the regressors and region specific variables suggests the use of the fixed effects model.

Estimated non-random matching function is presented in Table 5. In this case the stock of unemployed is always significant, while the magnitude of the effect varies depending on specification and performed corrections. It should be noted that estimated effect of the stock of unemployed on number of hirings is higher when region fixed effects are accounted for, suggesting that measured efficiency of hiring varies across regions (most likely due to heterogeneity in number of unobserved vacancies per one unemployed; this hypothesis is supported by models, not shown here, where region fixed effects are replaced with employment growth).

The inflows into unemployment have weaker impact: the coefficient varies across specifications and in some cases is insignificant or wrongly signed.

As to the vacancy stocks, as predicted by stock-flow matching theory, this variable does not play any important role in the matching process: coefficient is close to zero and highly insignificant in all specifications.

By contrast, inflow of new vacant jobs is always highly significant (disregarding the estimation method and whether the corrections for non-spherical disturbances are applied or not), and coefficients vary around 0.2.

Constant returns to scale are not rejected in GLS and PCSE models where region and time specific effects are included.

Estimated models support the conclusion that the outflows into employment are driven in Latvia by the matches between the stocks of unemployed and the inflows of vacancies.

Fixed effects models provide also valuable information about efficiency of matching in different regions. These results are discussed in the following subsection.

---

across panels. The presence of panem specific AR1 process is accounted for in both GLS and PCSE precedures.

The effects of training

Table 6 presents estimated correct specification of the matching function, i.e. the stock-flow one, augmented with a proxy for the proportion of participants of training and re-qualification programs among unemployed (see section 3 for the construction of the proxy).

As far as OLS results are concerned, controlling for participation in training increases the effect of the stock of unemployed. This is an expected result, since newly inflowed unemployed do not participate in such programs that usually last 3 to 4 months.

In general, the properties of stock-flow matching, discussed earlier, remain true: the stock of unemployed and inflows of vacancies are the driving forces for the outflows from the unemployment, while inflows of unemployed and stock of vacancies are insignificant.

As to the training effects, our preliminary intuition is confirmed by positive and significant impact of this policy variable. Estimated coefficient of the proportion of trained unemployed varies around 0.1 and is highly significant in most specifications.

In order to complete the discussion on the effects of training and to follow the logics of this paper, we compare the above results to the ones that we would obtain when using the traditional setting instead of "correct" stock-flow matching function for policy evaluation. The estimations [18] show that in the specifications where regional and time fixed effects are accounted for, the results would not differ significantly. But in the rest of the specifications – the coefficients of the policy variable double when using traditional matching function instead of the stock-flow one.

Thus, when using the correct specification for the matching function we protect ourselves from the overestimation of the policy impact, but even in this setting we still opt for the positive impact of training on outflows to employment.

While our results support a significant role of training programs in fighting against unemployment, earlier studies for other transition economies gave came to the opposite conclusion[19]. With regard to active policies in general, positive effects are found by Burda and Lubyova [1995], Svejnar, Terrell and Munich [1995], Boeri and Burda [1996], while training is confirmed to be efficient only by Steiner et al [1998] in Eastern Germany, in West Germany (R. Hujer at all [2002]) and seems not to have any significant role in Poland and Bulgaria (Lehmann [1995], Gora et al [1996], Lenkva [1997]). It should be noted, however, that all these studies operate with the traditional matching function and

[18] Estimated relation is equetion (5) excluding flow variables : $\ln(M_{it}) = \alpha_0 + \alpha_1 \ln U_{it}^S + \alpha_2 \ln V_{it}^S + \alpha_3 \ln PTU_{it}$
Results are not displayed here but are available on request.

[19] See Puhani [1999] for a more detailed survey on the results of policy evaluations in transition CEE countries.

choose the active policy expenditures as explanatory variable for the evaluation of policy efficiency[20]. These methodological differences can well be responsible for conflicting findings. Another reason can be cross-country differences in composition of the pool of unemployed and structure of labour demand.

Concerning regional patterns of matching and efficiency of training, Table 7 presents three best and four worst regions in terms of matching efficiency, both with and without controlling for training. We discuss here robust estimates given by GLS and PSCE procedures.

All specifications (with and without training) point out to Limbazu and Saldus and Valkas districts as by far best performers. When training is accounted for (and also in GLS models without training), matching efficiency in these districts is significantly better than in the capital city, Riga. Four other districts (Cesu, Dobels, gulbenes, Talsu, not shown in Table 7) are behind the best performers but, when training is controlled, are also significantly ahead of Riga. Liepaja city, Daugavpils , Ludzas and Rezeknes districts , according to all specifications have the lowest matching efficiency among all regions. However, when training is accounted for, these three regions are not significantly different from Riga city, suggesting that lack of training is at least in part responsible for the poor performance.

[20] In general the majority of studies that perform policy evaluations use as policy variables rather expenditure on ALMPs or number of participants in ALMPs. These studies are often concerned by the problem of endogeneity : *"The fundamental evaluation problem in macroeconometric evaluation studies is that ALMP is likely to be an endogenous variable. Local labour market offices may raise their expenditures on ALMP if the labour market situation becomes worse." (Hagen [2003]).* However this serious problem does not seem to concern our study. To find the arguments for such statement, let's return to the description of the proxy, that we use as a policy variable. We study how the fraction of trained individuals (in the total unemployment pool) at the beginning of the month influences the outflows from unemployment during the month. It should also be noted that in our proxy we account for people that have completed training during the last 12 months, and that training programs last about 3-4 months. Thus if authorities react to worsening current labor market situation and increase expenditures on ALMPs (and number of participants) today, these new participants will only appear in our proxy in 4 months. Thus there is no link between current decrease of matches and increase in our policy variable.

5. Conclusions and proposals for further work

Aiming to develop the appropriate framework for active labour market policy evaluation in Latvia, we estimate matching function for this country and use for this purpose monthly data from 33 Latvian municipalities for the time period 1998-2003. Preliminary analysis of unemployed and vacancy data reveals high vacancy turnover rate and very low mobility of unemployed across labour market states.

Such considerations suggest that traditional stock-to-stock matching functions may be misspecified.

Following this intuition we estimate several specifications of stock-flow matching function, but to accommodate comparability with earlier studies for other transition countries, provide also results in traditional stock-to-stock setting. When estimating a traditional matching function, we find that stock of vacancies has a very week explanatory power; the elasticity of outflows from unemployment with respect to the number of vacant jobs in stock is low, in contrast with the results for many West European countries, but similarly to transition country studies (see e.g. Munich et al (1999)). Further estimation when including both stocks and flows as explanatory variables confirms our intuition for the presence of non-random patterns in Latvian matching process: the key determinants of outflows to employment are stock of unemployed and the inflows of new vacancies.

Recent cuts in expenditures on active labour market policy, which have significantly affected public training programs in Latvia, have been another motivation for this paper. We have found that arguments for cuts based on supposed "low efficiency of programs" are not consistent with the reality.

We have also made some exercises of cross-region comparison and conclude that those are not homogenous neither in terms of matching efficiency nor in terms of efficiency of training programs. Some of the regions (Saldus and, Limbazi districts in the first place) are the most efficient in terms of matching and this pattern is even reinforced when the role of training in outflows to employment is accounted for. Matching is least efficient in Daigavpils district and Liepaja city, and this, at least in part, is due to the lack of training.

The following policy suggestions can be derived from this paper:

First, new job vacancies being one of main driving elements of outflows from unemployment, hence job creation could have a very important role in the reduction of unemployment.

Second, training programs should not be devalorised as they have a significant positive effect, on the rate of outflows from unemployment to employment.

Third, the study of the determinants of the efficiency of training programs should be performed in order to improve their outcomes in the bad performing regions, using the experience of those where

the programs are more efficient.

This preliminary version of the paper displays the main issues and results of our analysis although work is in progress on the following issues:

- We also plan to include in our policy analysis the information on programs other than training. For example, we are currently working on the effects of public temporary jobs and preliminary results suggest negative, although rarely significant impact. The possible interpretations refer to search behaviour of unemployed and suggest that participation in such programs decreases job search efforts. These are findings in favour of the "locking in" effects of such programs.
- Work is also currently performed on some econometric issues, including serial correlation of orders higher than one.
- Finally, we are going to incorporate regional data on labour demand in the analysis in order to improve the models without fixed effects.

References

Baltagi B.H. [1995], *"Econometric Analysis of panel data"*, Jonn Willey & Sons, England

Beck N. and Katz J.N. [1995], *" What to do (and not to do) with time series cross-sectionsl data"*, American Political Journal Review 89 (1995), 634-647

Beck N. and Katz J.N. [1996], *"Nuisance vs. Substance: Specifying and estimating Times Series Cross Section Models"*, Political Analysis 6 (1996), 1-36

Blanchard O. and Diamond P. [1989], "*The Beveridge curve"*, Brooking Papers on Economic Activity, 1 (1989), 1-60

Blanchard O. and Diamond P. [1994], *Shifts in the beveridge curve, Job matching and Labor market dynamics"*, New England Economic Review 0/9 (1994), 3-19

Boeri T. and Burda M.C. [1996] , "*Active labour market policies, job matching and the Czech miracle* ", European Economic Review 40(1996), 805-817

Boeri [2001], *"Transition with labour supply"*, IZA Discussion Papers No. 257.

Boeri T. and Terrell K. [2002] , "*Institutional Determinants of Labor Reallocation in transition* ", Journal of Economic Perspectives, volume 16, number 1, p.51-76

Burda M. [1993], *"Unemployment, labor markets and structural change in eastern Europe"*, Economic Policy 16, 102-137

Burda M. and Lubyova M. [1995], *"The impact of active labour market policies: a closer look at the Czech and Slovak Republics"*, in Newberry D. (ed) "tax and benefit reform in Central and Eastern Europe", 173-205, London

Burda M.C. and Profit S. [1996] , "*Matching across space:Evidence on mobility in Czech Republic* ", Labour Economics 3(1996), 255-278

Burda M. and Wyplosz C. [1994], *"Gross Worker and Job flows in Europe"*, European Economic Review 38 (1994), 1287-1315

Coles M., and Smith J., [1998], *" Marketplaces and Matching",*International Economic Review 39/1 (1998), 239-54

Coles M. and Petrongolo B. [2003], *"A test between unemployment theories using matching data"*, IZA Discussion Papers No. 723

Butters G. [1977], *" Equilibrium Distributions of sales and advertising prices"*, Review of Economic studies 44/3 (1977), 465-491

Gora M., Lehmann H., Socha M. and Sztanderska U. [1996], *„Labour market policies in polan*", in OECD (ed) "Lessons from labour market policies in transition countries", 151-176, Paris.

Gregg P. and Pertongolo B. [2002], *"Sock-flow matching and the performance of the labour market"*, CEPR Discussion Paper No. 3241, 2002

Greene W.H., *"Econometric analysis "* , 4th edition (2000) and 5th edition (2003) , Pearson Education, New Jersey.

Hagen T., [2003]*"Three approaches to the evaluation of active labour market policy in East Germany using regional data",* ZEW Discussion paper No. 03-27

Hall R., [1979], *"A theory of the natural unemployment rate and Duration of employment"*, Journal of Monetary Economics (/2 (1979), 153-69

Hujer R., Blien U., Caliendo M., Zeiss C., [2002], *"Macroeconomic evaluation of active labour market policies in Germany: A dynamic panel approach usig regional data",* IZA Discussion paper No. 616

Hujer R., Zeiss C., [2003], *"Macroeconomic impacts of ALMPs on the matching process in West Germany",* IZA Discussion paper No. 915

Layard R., Nickell S., Jackman R., [1991], "*Unemployment: Macroeconomic Performance and the Labour Market*", Oxford: Alden Press.

Lehmann H. [1995], " *Active Labor Market Policies in the OECD and in Selected Transition Economies*, World Bank Policy Research Working Paper No.1502, Washington D.C.

Lenkva C. [1997], "*Persistently High Unemployment throughout the Transition –What is the Reason? (The Bulgarian Case)*", CERGE and IHS, Prague and Vienna, mimeo.

Munich D., Svejnar J. And Terrell K. [1999], "*Worker-Firm matching and unemployment in transition to a market economy: (Why) were the Czech more successful than others?" ,* William Davidson Institute Working Paper no.107

Petrongolo B. and Pissarides C.A. [2001] , "*Looking Into the Black Box: A survey of the Matching Function* ", Journal of Economic Literature, 2001, Vol. 39 No.2

Pissarides C. [1979], *"Job matching with state employment agencies and random search"*, Economic Journal 89/356 (1979), 818-833

Pissarides C. [1986], *"Unemployment and vacancies in Britain"*, Economic Policy 3 ,676-690

Pissarides C. A. [2000] , "*Equilibrium unemployment theory, second edition* ",The MIT Press, Cambridge, Massachusetts, London, England

Podesta F. [2002], *"Recent developments in Quantitative Comparative Methodology : the case of pooled time series cross section analysis"*, DSS papers SOC No. 3-02

Profit S. [1997], *"Twin Peaks in Regional Unemployment and Returns to Scale in Job-Matching in the Czech Republic"* Discussion paper No. 63, Humboldt University, Berlin.

Puhani P. [1999], *"Estimating the effects of public training on polich unemployment by way of the augmented matching function approach",* CEPR discussion Papers No. 2244

Steiner, V. *et al.* [1998], „*Strukturanalyse der Arbeitsmarktentwicklung in den neuen Bundesländern, Endbericht für das Bundesministerium für Wirtschaft*", Zentrum für Europäische Wirtschaftsforschung and Rheinisch-Westfälisches, Institut für Wirtschaftsforschung, Mannheim and Essen.

Terrell K. and Sorm V. [1999], "*Labor Market Policies and Unemployment in the Czech Republic*", Journal of Comparative Economics, Vol. 27, no. 1, March 1999, 33-60.

ANNEXE 1 : TABLES

Table 3: Descriptive statistics on panel data

Variable	Mean	*Variation*	*S.d*	*Min*	*Max*	Observations	
Outflows from unemployment to employment	101	*overall*	170	5	1478	N_{it}	1914
		between	168	20	1019	N_i	33
		within	39	-194	559	N_t	58
Unemployed stock	3022	*overall*	3230	510	26369	N_{it}	1914
		between	3209	578	19156	N_i	33
		within	662	-714	10235	N_t	58
Inflows of new unemployed	274	*overall*	419	30	3567	N_{it}	1914
		between	418	55	2522	N_i	33
		within	76	-374	1323	N_t	58
Stock of vacant jobs	88	*overall*	351	0	3416	N_{it}	1914
		between	344	1	1993	N_i	33
		within	92	-748	1511	N_t	58
Inflows of new vacancies	128	*overall*	375	0	3326	N_{it}	1914
		between	370	12	2175	N_i	33
		within	88	-656	1279	N_t	58
Training and re-qualification	0.169	*overall*	0.086	0.013	0.506	N_{it}	1914
		between	0.068	0.058	0.342	N_i	33
		within	0.054	-0.098	0.334	N_t	58

Note: *Between* variation refers to the means over time for every region ($\overline{x}_i$); *within* variation represents the deviations of individual observations from region's average ($x_{it} - \overline{x}_i + \overline{\overline{x}}$).

Table 4: Estimation results: The Traditional Matching Function

	OLS	FE	RE	GLS		PCSE	
Dep.var : ***ln* outflows**	I	II	III	IV	V	VI	VII
***ln* unemployed (stock)**	**0.78***** *(0.018)*	**0.81***** *(0.069)*	**0.84***** *(0.046)*	**0.73***** *(0.023)*	**0.90***** *(0.061)*	**0.73***** *(0.022)*	**0.92***** *(0.090)*
***ln* vacancies (stock)**	**0.09***** *(0.008)*	**-0.02** *(0.011)*	**-0.01** *(0.009)*	**0.04***** *(0.008)*	**0.00** *(0.008)*	**0.04***** *(0.009)*	**0.00** *(0.009)*
constant	**-2.04***** *(0.139)*	**-1.01** *(0.681)*	**-2.33***** *(0.356)*	**-1.56***** *(0.173)*	**-2.09***** *(0.609)*	**-1.53***** *(0.169)*	**-2.26***** *(0.890)*
V(Ui)		0.54	0.51				
R2	0.67	0.31 / 0.80 / 0.69	0.31 / 0.80 / 0.69			0.91	0.94
Returns to scale	0.86	0.79	0.83	0.77	0.91	0.77	0.92
CRS (F-test)	56.85***	8.73***	13.90***	115.05***	2.19	138.30***	0.70
Region effects		67.95 ***			1110.29***		1622.1***
Time effects		59.54 ***	601.07***		748.71***		402.57***
HAUS TEST			10.38				
GR. HET	427.18***	564.51***			681.25***		
BP LM		743.80***		1323.98***	759.21***		
DW FE		1.28***	1.27***				
LM (AR1)	647.39 ***			710.21***			
LM5 (AR1 FE)		13.16***	13.31***		13.68***		
PHO (AR1)				0.516	0.277	0.523	0.282

Notes:
Onservations: 1777
I - Pooled OLS regression
II - Fixed effects with region and time (monthly dummies) specific effects
III - Random effects GLS regression with region random effects and time fixed effects (monthly dummies)
IV - FGLS model with groupwise heteroscedastic residuals and panel specific AR1.
V - FGLS model with groupwise heteroscedastic residuals and panel specific AR1 (see IV) and fixed effects (region, time).
VI - PCSE : Prais -Winsten regression with panel corrected standard errors (corrected for heteroscedasticity and contemporaneous correlation between panels and panel specific AR1)
VII – PCSE : Prais –Winsten regression (see VI) with region and time specific effects

---

- standard errors in parentheses (robust for OLS and FE models, corrected for heteroscedasticity, cross sectional correlation and panel specific AR1 for PCSE models (VI,VII))
- ***, **, * - estimates significantly different from zero at 1%, 5%, 10% level respectively
- V(Ui) – fraction of variance due to region specific effects
- R2: Adjusted for OLS (I), Within/Between/Overall for fixed and random effect models (II, III)
- CRS : F-test for constant returns to scale (the sum of first 2 coefficients=1)
- Region effects : test for inclusion of region specific dummy variables
- Time effects : test for inclusion of month dummies
- HAUS TEST: Hausman's specification test for the random effects model (Greene 2000, 576)
- GR HET : test for groupwise heteroscedasticity in residuals, LR test for OLS, modified Wald test for group wise heteroscedasticity for the rest (Greene 2000, 598)
- BP-LM: Breuch –Pagan LM test for contemporaneous correlation in residuals of fixed effect or GLS model (Greene 2000, 601)
- LM(AR1) : Lagrange-multiplier test for first order residual serial corr. in panel data (Baltagi 1995, 95)
- LM5(AR1 FE) : Baltagi test for autocorrelation in fixed effect model.
- PHO (AR1) : Averaged autocorrelation coefficient

Table 5: Estimation results: Stock –Flow Matching

	OLS	FE	RE	GLS		PCSE	
Dep.var : ***ln* outflows**	I	II	III	IV	V	VI	VII
***ln* unemployed (stock)**	**0.42*****	**0.83*****	**0.81*****	**0.51*****	**0.95*****	**0.56*****	**0.96*****
	(0.025)	*(0.069)*	*(0.043)*	*(0.030)*	*(0.059)*	*(0.041)*	*(0.083)*
***ln* unemployed (flow)**	**0.27*****	**-0.11*****	**-0.05**	**0.11*****	**-0.04**	**0.05**	**-0.07***
	(0.028)	*(0.039)*	*(0.034)*	*(0.027)*	*(0.032)*	*(0.045)*	*(0.039)*
***ln* vacancies (stock)**	**0.00**	**-0.03*****	**-0.02****	**0.01***	**0.00**	**0.02***	**0.00**
	(0.009)	*(0.011)*	*(0.009)*	*(0.008)*	*(0.008)*	*(0.008)*	*(0.009)*
***ln* vacancies (flow)**	**0.22*****	**0.13*****	**0.15*****	**0.20*****	**0.15*****	**0.18*****	**0.14*****
	(0.016)	*(0.020)*	*(0.013)*	*(0.012)*	*(0.012)*	*(0.017)*	*(0.014)*
constant	**-1.31*****	**-1.22**	**-2.33*****	**-1.16*****	**-3.31*****	**-1.18*****	**-3.06*****
	(0.118)	*(0.778)*	*(0.295)*	*(0.164)*	*(0.629)*	*(0.176)*	*(0.878)*
V(Ui)		0.51	0.32				
R2	0.75	0.35 / 0.83 / 0.72	0.35 / 0.85 / 0.74			0.90	0.94
Returns to scale	0.90	0.82	0.88	0.83	1.06	0.81	1.02
CRS (F-test)	45.47 ***	4.43 **	8.60***	69.02***	0.81	76.16***	0.07
Region effects		36.13 ***			848.32***		1220.93***
Time effects		49.42 ***	508.74***		647.22***		386.31***
HAUS TEST			46.41***				
GR HET	365.35***	681.84***			876.84***		
BP LM		691.01***		1127.71***	715.65***		
DW FE		1.29***	1.28***				
LM (AR1)	483.73***			552.28***			
LM5 (AR1 FE)		12.76***	13.12***		14.01***		
PHO (AR1)				0.472	0.258	0.483	0.265

Notes:
Observations : 1776
I - Pooled OLS regression
II - Fixed effects with region and time (monthly dummies) specific effects
III - Random effects GLS regression with region random effects and time fixed effects (monthly dummies)
IV - FGLS model with groupwise heteroscedastic residuals and panel specific AR1.
V - FGLS model with groupwise heteroscedastic residuals and panel specific AR1 (see IV) and fixed effects (region, time).
VI - PCSE : Prais -Winsten regression with panel corrected standard errors (corrected for heteroscedasticity and contemporaneous correlation between panels and panel specific AR1)
VII – PCSE : Prais –Winsten regression (see VI) with region and time specific effects

---

- standard errors in parentheses (robust for OLS and FE models, corrected for heteroscedasticity, cross sectional correlation and panel specific AR1 for PCSE models (VI,VII))
- ***, **, * - estimates significantly different from zero at 1%, 5%, 10% level respectively
- V(Ui) – fraction of variance due to region specific effects
- R2: Adjusted for OLS (I), Within/Between/Overall for fixed and random effect models (II, III)
- CRS : F-test for constant returns to scale (the sum of first 2 coefficients=1)
- Region effects : test for inclusion of region specific dummy variables
- Time effects : test for inclusion of month dummies
- HAUS TEST: Hausman's specification test for the random effects model (Greene 2000, 576)
- GR HET : test for groupwise heteroscedasticity in residuals, LR test for OLS, modified Wald test for group wise heteroscedasticity for the rest (Greene 2000, 598)
- BP-LM: Breuch –Pagan LM test for contemporaneous correlation in residuals of fixed effect or GLS model (Greene 2000, 601)
- LM(AR1) : Lagrange-multiplier test for first order residual serial corr. in panel data (Baltagi 1995, 95)
- LM5(AR1 FE) : Baltagi's test for autocorrelation in fixed effect model.
- PHO (AR1) : Averaged autocorrelation coefficient

Table 6: Estimation results:
Stock -Flow Matching Function Augmented with Participation in Training

	OLS			GLS		PCSE	
Dep.var : ***ln* outflows**	**I**	**II**	**III**	**IV**	**V**	**VI**	**VII**
***ln* unemployed (stock)**	**0.50*****	**0.91*****	**0.94*****	**0.53*****	**1.09*****	**0.58*****	**1.10*****
	(0.028)	*(0.093)*	*(0.095)*	*(0.033)*	*(0.085)*	*(0.041)*	*(0.111)*
***ln* unemployed (flow)**	**0.23*****	**-0.11*****	**-0.11*****	**0.11*****	**-0.04**	**0.05**	**-0.07***
	(0.028)	*(0.039)*	*(0.040)*	*(0.028)*	*(0.032)*	*(0.045)*	*(0.039)*
***ln* vacancies (stock)**	**-0.01**	**-0.03*****	**-0.03*****	**0.01**	**0.01**	**0.01**	**0.00**
	(0.009)	*(0.009)*	*(0.011)*	*(0.008)*	*(0.008)*	*(0.009)*	*(0.009)*
***ln* vacancies (flow)**	**0.20*****	**0.13*****	**0.13*****	**0.19*****	**0.15*****	**0.18*****	**0.14*****
	(0.016)	*(0.014)*	*(0.020)*	*(0.013)*	*(0.012)*	*(0.018)*	*(0.014)*
***ln* proportion of unemployed with completed training (proxy)**	**0.12*****	**0.04**	**0.04**	**0.08*****	**0.07*****	**0.09****	**0.07****
	(0.019)	*(0.026)*	*(0.027)*	*(0.023)*	*(0.027)*	*(0.043)*	*(0.034)*
constant	**-1.36*****	**-2.62****	**-2.85*****	**-1.06*****	**-4.67*****	**-1.06*****	**-4.32*****
	(0.120)	*(0.586)*	*(0.588)*	*(0.174)*	*(0.844)*	*(0.190)*	*(1.110)*
Observations	1776	1776	1718	1776	1776	1776	1776
V (Ui)		0.49	0.44				
ADJ-R2	0.75	0.35 / 0.84 / 0.73	0.36 / 0.78 / 0.59			0.88	0.94
Returns to scale	0.91	0.90	0.94	0.83	1.21	0.81	1.16
CRS (F-test)	35.20***	0.90	0.34	57.03***	5.40**	66.55***	1.88
Region effects		33.27 ***	22.84***		801.88***		1123.85***
Time effects		48.52 ***	47.99 ***		626.96***		396.58***
GR HET	301.88 ***	697.17***	675.68***		904.26***		
BP- LM (cont. corr)		692.48***	624.16***	1050.02***	723.61***		
LM (AR1)	469.20***	164.32***	153.93***	526.61***	200.06***		
LM5 (AR1 FE)	21.66***	12.82***	12.41***	22.95***	14.14***		
PHO (AR1)				0.473	0.259	0.483	0.266

Notes:
I - Pooled OLS regression
II - OLS LSDV regression with region (region dummies) and time (monthly dummies) specific effects
III - OLS LSDV regression (see II) excluding RIGA – capital
IV - Feasible generalized least squares model with groupwise heteroscedastic, residuals and panel specific AR1.
V - FGLS model (IV) with region and time specific effects
VI - PCSE : Prais -Winsten regression with panel corrected standard errors
(corrected for heteroscedasticity and contemporaneous correlation between panels and panel specific AR1)
VII – PCSE : Prais –Winsten regression with panel corrected standard errors (VI) with region and time specific effects
---
- standart errors in paranthness (robust for OLS and LSDV (I-III), corrected for heteroscedasticity, cross sectional correlation and panel specific AR1 in PCSE models (VI, VII))
- ***, **, * - estimates significantly different from zero at 1%, 5%, 10% level respectively.
- CRS (F-test): F-test for constant returns to scale (the sum of first 4 coefficients=1)
- Region effects : test for inclusion of region specific dummy variables
- Time effects : test for inclusion of month dummies
- GR HET: modified Wald test for groupwise heteroscedasticity (Greene 2000, 598)
- BP-LM: Breuch –Pagan LM test for contemporaneous correlation in residuals of fixed effect or GLS model (Greene 2000, 601)
- LM(AR1) : Lagrange-multiplier test for first order residual serial correlation in panel data (Baltagi 1995, 95)
- LM5(AR1 FE) : Baltagi test for autocorrelation in fixed effect model.
- PHO (AR1) : Averaged autocorrelation coefficient

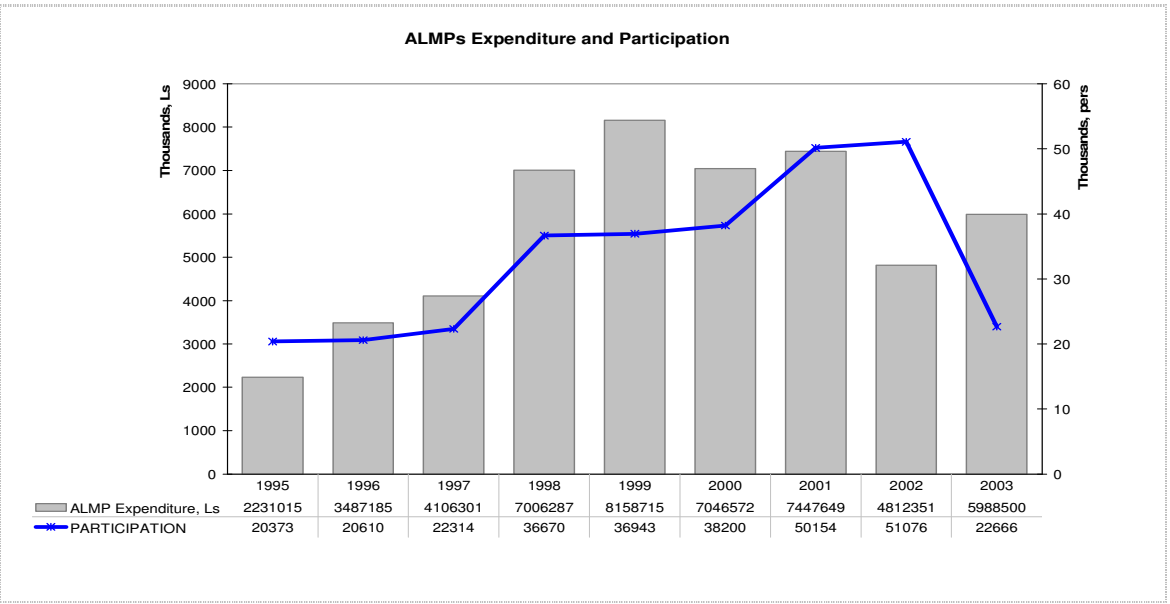
Table 7*:* Estimation results : Regional performance

	LSDV		GLS		PCSE	
Dep.var : *ln* outflows	Without Training	With Training	Without Training	With Training	Without Training	With Training
ln unemployed stock	**0.74*** ** *(0.062)*	**0.96*** ** *(0.086)*	**0.82*** ** *(0.068)*	**1.19*** ** *(0.098)*	**0.87*** ** *(0.108)*	**1.20*** ** *(0.132)*
ln unemployed flow	**-0.14*** ** *(0.040)*	**-0.14*** ** *(0.040)*	**-0.01** *(0.034)*	**0.00** *(0.034)*	**-0.07** *(0.047)*	**-0.05** *(0.045)*
ln vacancies stock	**-0.03*** ** *(0.010)*	**-0.02** ** *(0.010)*	**0.01** *(0.009)*	**0.01** *(0.009)*	**0.00** *(0.011)*	**0.00** *(0.011)*
ln vacancies flow	**0.18*** ** *(0.015)*	**0.18*** ** *(0.014)*	**0.21*** ** *(0.013)*	**0.20*** ** *(0.013)*	**0.18*** ** *(0.017)*	**0.18*** ** *(0.018)*
ln training (tr. pop %)	---	**0.10*** ** *(0.028)*	---	**0.17*** ** *(0.032)*	---	**0.15*** ** *(0.037)*
constant	**-0.43** *(0.656)*	**-2.50*** ** *(0.856)*	**-2.68*** ** *(0.720)*	**-6.15*** ** *(0.981)*	**-2.61** ** *(1.170)*	**-5.62*** ** *(1.375)*
Three regions with the highest matching efficiency						
Limbazu district	**-0.63*** ** *(0.205)*	**-0.01** *(0.265)*	**0.21** *(0.228)*	**1.25*** ** *(0.304)*	**0.08** *(0.355)*	**0.99** ** *(0.420)*
Saldus district	**-0.78*** ** *(0.219)*	**-0.09** *(0.285)*	**0.11** *(0.243)*	**1.26*** ** *(0.327)*	**0.02** *(0.382)*	**1.01** ** *(0.454)*
Valkas district	**-0.65*** ** *(0.216)*	**-0.03** *(0.271)*	**0.26** *(0.233)*	**1.30*** ** *(0.307)*	**0.15** *(0.369)*	**1.05** ** *(0.428)*
Four regions with the lowest matching efficiency						
Liepaja city	**-1.12*** ** *(0.121)*	**-0.78*** ** *(0.150)*	**-0.59*** ** *(0.125)*	**-0.04** *(0.164)*	**-0.70*** ** *(0.184)*	**-0.22** *(0.220)*
Daugavpils district	**-1.44*** ** *(0.171)*	**-0.91*** ** *(0.222)*	**-0.70*** ** *(0.185)*	**0.18** *(0.251)*	**-0.83*** ** *(0.280)*	**-0.06** *(0.339)*
Ludzas district	**-1.28*** ** *(0.175)*	**-0.80*** ** *(0.217)*	**-0.49*** ** *(0.186)*	**0.31** *(0.241)*	**-0.64** * *(0.284)*	**0.04** *(0.328)*
Rezeknes district	**-1.28*** ** *(0.148)*	**-0.87*** ** *(0.184)*	**-0.61*** ** *(0.153)*	**0.08** *(0.203)*	**-0.74*** ** *(0.227)*	**-0.14** *(0.274)*

Notes:
-1776 observations
- LSDV: Least squares dummy variable model (regional effects)
- GLS: error structure *between*: heteroskedastic ; error structure *within:* and panel-specific AR(1)
- PCSE: Prais-Winsten regression, errors corrected for heteroscedasticity, cross-sectional correlation and panel specific AR(1)
- ***, **, * - estimates significantly different from zero at 1%, 5%, 10% level respectively.
- omitted region: Riga city

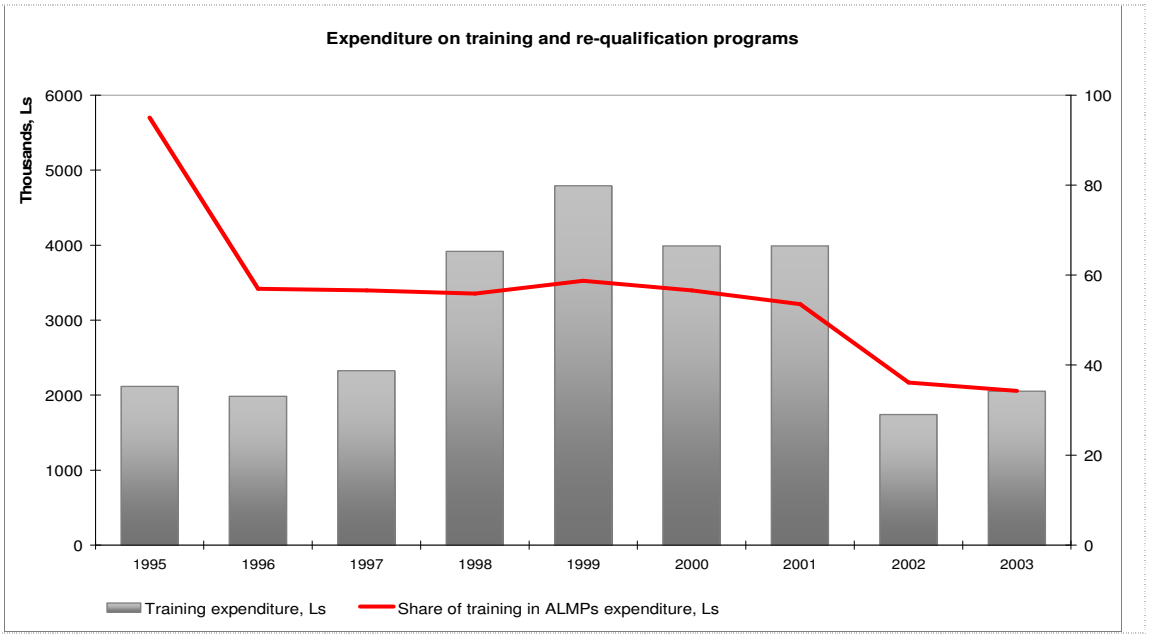
ANNEXE 2 : FIGURES

Figure1: ALMP Expenditure and participation



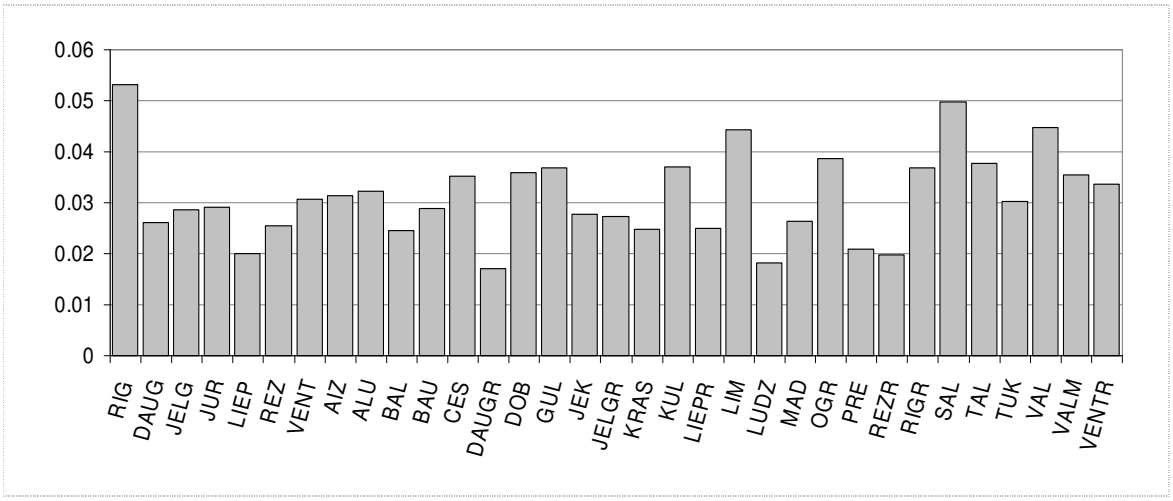
Source: State Employment Agency of Latvia

Figure2: TRAING Expenditure



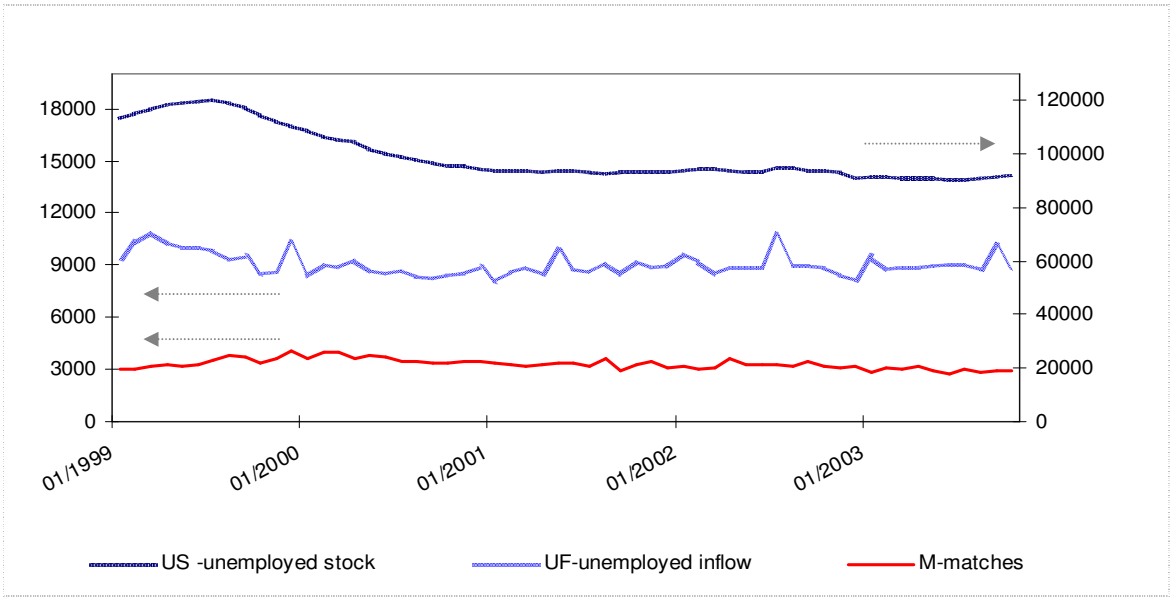
Source: State Employment Agency of Latvia

Figure3: Mean outflow rates by region



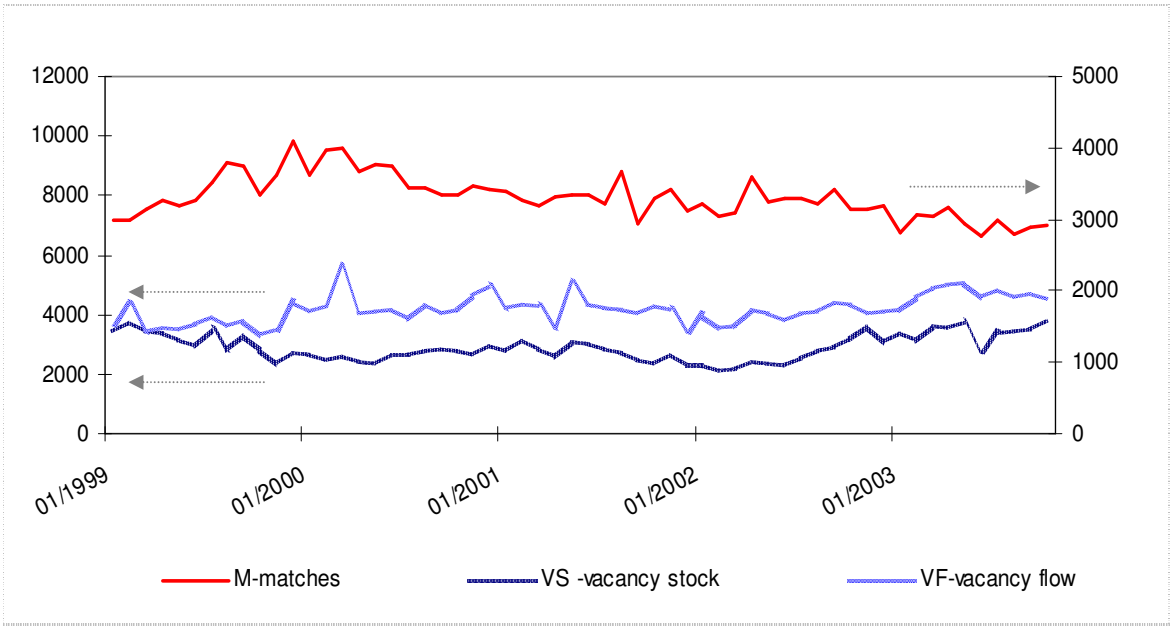
Source: State Employment Agency of Latvia data series

Figure4 : Unemployment (stock and flows), outflows to employment



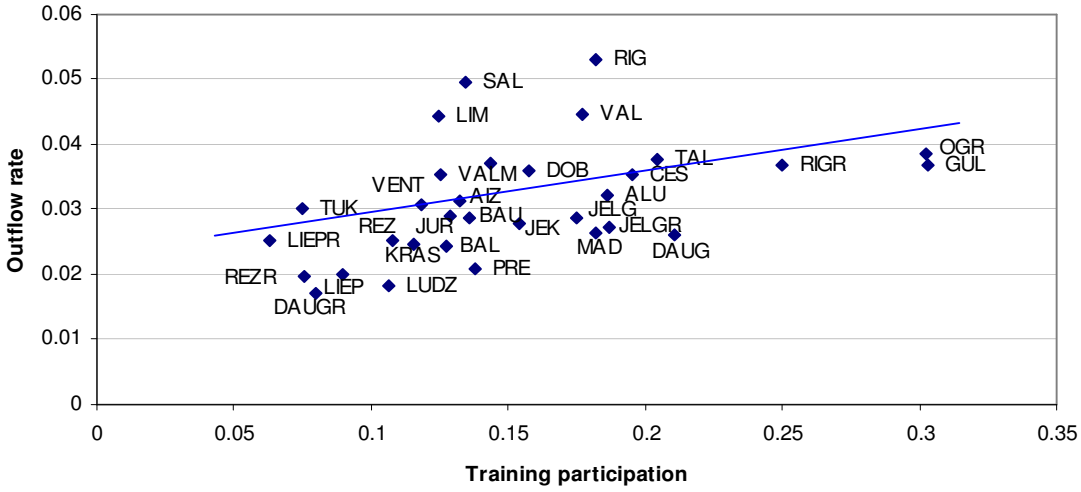
Source: State Employment Agency of Latvia data series
* Data seasonally adjusted (X11)

Figure 5 : Vacant jobs (stock and flows), outflows to employment



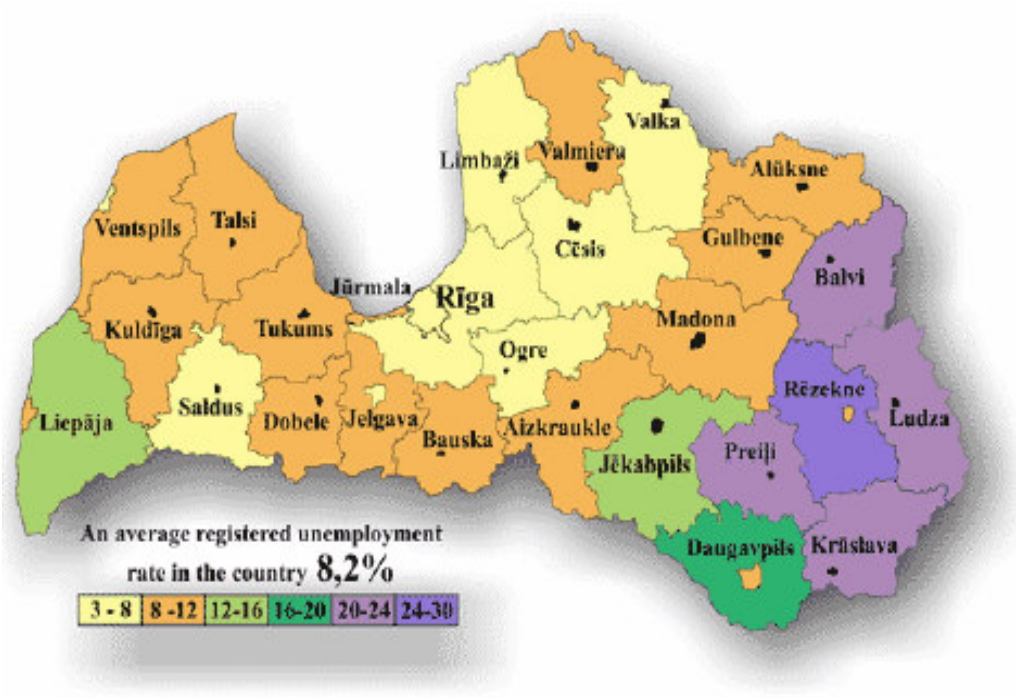
Source: State Employment Agency of Latvia data series
* Data seasonally adjusted (X11)

Figure6 : Outflow rate and participation in training by region



Source: State Employment Agency of Latvia data series

Figure 7: Latvian districts by unemployment rate on April 1, 2002



Source: State Employment Agency of Latvia