# A stock-flow matching approach to evaluation of public training program in a high unemployment environment*

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**Abstract**

Monthly panel (1998-2003) data from regional labor offices in Latvia are used to analyze the matching process in a high unemployment – low labor demand environment and to evaluate the impact of active labor market policy programs on outflows from unemployment.

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

We find positive and significant effect of training programs on outflows from unemployment to employment, thus providing strong evidence against recent cuts in training expenditures.

**Keywords:** stock-flow matching, augmented matching function, labor market policy, training, transition countries.
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# 1 Introduction

Transition from centrally planned to market economy has confronted all Central and Eastern European and Baltic countries with a number of new challenges. Among them is the problem of dealing with high and persistent unemployment. In line with OECD suggestions and European experience a great importance has been given to active policies, i.e. employment stimulating programs that usually include direct job creation, job subsidies, self-employment promotion, as well as labor training and re-qualification schemes. Implementation strategies have differed across countries: while in the Czech Republic, Hungary, Bulgaria, Poland and Slovenia subsidized employment and direct job creation have been promoted, in Latvia, Estonia and Lithuania more than a half of active labor market policy budget has been devoted to labor training and re-qualification. The dominant role of training programs in the Baltic countries can be justified by the unemployment patterns of in this region - a strong mismatch between the *old* skills of the labor force and the *new* requirements of employers. Nevertheless in Latvia, one of the transition economies which have recently joint the European Union, the priorities of policymakers have recently changed and the funds allocated to active labor market policy have been reduced. These budget cuts have mostly attained training and re-qualification programs: the weight of these programs in total active policy expenditure has dropped from about 60 percents 1996-2001 to 34 percents in 2003[1]. In order to justify these changes it has been argued that training programs were not efficient, while any serious study, bringing the proofs for such statements has not ever been developed in Latvia.

This paper aims to fill this gap and to test the validity of the training inefficiency argument. We will evaluate the effects of training programs on outflows from unemployment by estimating the augmented matching function on monthly cross section data from Latvian regions. This approach seems to be most relevant for our study since the matching function, giving the number of new hires conditional on the number of available unemployed and vacancies, presumes the presence of search frictions in the labor market[2]. Indeed, in transition economies, such as Latvia, frictions are considerable. Therefore the matching function approach is frequently used for labor market analysis and policy evaluation in Central and Eastern European countries[3].

[1]See Figures 1 and 2.

[2]These frictions may originate from information imperfections, underdevelopment of insurance markets, low labor mobility, high individual heterogeneity, high qualification mismatch and other similar factors.

[3]See for example Burda (1993), Boeri and Burda (1996), Profit (1997), Burda and Profit (1996), Minich et al. (1999).

The existing empirical literature, however, seldom goes beyond the basic matching function specification, despite the fact that the expanding literature has recently proposed a number of extensions, allowing for a large variety of externalities, market imperfections and particular forms of matching process[4]. A likely reason why these wealth of theoretical tools have been under-utilized in transition context is that data of relevant quality have not been available to scholars.

Thus, the simple matching function, traditionally used for studies on transition economies, assumes the random matching between the stocks of unemployed and vacant jobs. Meanwhile this standard matching function may be misspecified: some recent developments by Coles and Smith (1998), Gregg and Petrongolo (2002) and Coles and Petrongolo (2003) reveal the importance of flow variables (inflows of new unemployed and jobs) in determining outflows from unemployment. They show on U.K. data that the matching is realized between stocks and flows, due to the existence of non-random patterns in the matching process.

Latvian data feature very high vacancy turnover rates and significant correlations between matches and new vacancies, hence giving rise to the question on the true nature of Latvian matching process. Can it be described by the standard stock-stock matching function (used in the previous studies on transitional labor markets), or a more detailed specification should be called for? To answer this question and to avoid the misspecification we will employ both stock-stock and stock-flow specifications of the matching function for active labor market policy evaluation.

The rest of the paper is organized as follows. Section 2 develops the concept of an augmented matching function and gives more intuition on different types of matching. Section 3 describes data and variables used in the analysis. Section 4 discusses the estimation procedure and results. Section 5 concludes and provides policy suggestions.

# 2 The matching function

## 2.1 Standard matching function

In a labor market with search frictions, both unemployed and firms are involved in a costly and time consuming process of searching and finding the appropriate match. This complex process can be summarized by a well-behaved *matching function*, which acts like a production function for new hires and relates the outflows from unemployment to employment (matches)

[4] See Petrongolo and Pissarides (2001) for a detailed survey.

$M_{i,t}$ in region $i$ at period $t$ to the numbers of unemployed job seekers $U_{i,t}$ and available job vacancies $V_{i,t}$ in the same region[5].

When employing the simplest version of the matching function one treats the pool of unemployed as homogenous, assumes that the beginning of the month *stocks* of unemployed and vacancies determine the outflows to employment and supposes that firms and unemployed meet at random. Denoting $A_{i,t}$ a scale parameter, that captures different mismatch possibilities, the simple matching function can be formalized as follows:

$$M_{i,t} = A_{i,t} m(U_{i,t}, V_{i,t}), \quad \text{where } m_U > 0, m_V > 0 \tag{1}$$

We specify the matching function by a Cobb-Douglas form:

$$M_{i,t} = A_{i,t} \left(U_{i,t}\right)^{\alpha_U} \left(V_{i,t}\right)^{\alpha_V}$$

After a logarithmic transformation of both sides, one obtains the following regression equation:

$$\ln M_{i,t} = \alpha_0 + \alpha_U \ln U_{i,t} + \alpha_V \ln V_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \tag{2}$$

The mismatch parameter is transformed in order to capture the efficiency of matching over time, across regions and to allow for random variations in hiring ($\ln A_{i,t} = \alpha_0 + \mu_i + \lambda_t + \varepsilon_{i,t}$).

The parameters $\alpha_U$ and $\alpha_V$ can be interpreted as elasticities with respect to the size of the unemployment and vacancy pools. The empirical analysis of the matching function is quite similar to the one of the production function and thus, wherever $(\alpha_U + \alpha_V)$ exceeds, is less than, or equals unity implies respectively increasing, decreasing or constant returns to scale. The empirically estimated matching functions often display constant or slightly decreasing returns to scale in developed countries, while the results are more diverse for the transition countries[6].

### 2.2 Augmented matching function: the role of the policy

The matching function, reflecting the efficiency of the labor market, can be used as a simple and efficient tool for policy evaluation. The approach consists in testing for a positive relationship between the policy variables (expenditure, participation) and the number of matches. The underlying idea

[5] We do not consider the presence of spatial effects in this article.

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

is that active labor market programs (ALMPs) can speed up the matching process by helping to adjust the skills of unemployed to the structure of labor demand. It can also make the search of program participants more efficient and thus allow them to find jobs more rapidly. This will result in an increased number of new hires - more matches would be produced at the labor market during a reference period.

A model including policy variables among the possible determinants of job matches is referred to as "*augmented matching function*". The key reference for this approach is Lehmann (1995). Relaxing the assumption of homogeneous unemployment pool, one assumes that unemployed can have varying search efficiencies. The aggregate matching function can then be written as:

$$M_{i,t} = A_{i,t} m(\psi U_{i,t}, V_{i,t}) \tag{3}$$

where $\psi U_{i,t}$ is the search effective stock of unemployed. The average search efficiency of the unemployed $\psi$ is assumed to be positively affected by ALMPs.

In order to integrate the participation in training programs in the analysis we suppose that the unemployed pool is composed by a fraction $\gamma$ of trained individuals and a fraction $(1-\gamma)$ of untrained. Assuming that trained individuals have the search effectiveness $\psi_T$ and non-trained $\psi_{NT}$ , we can represent the search-effective stock of unemployed as follows:

$$\psi U_{i,t} = \gamma_{i,t} \psi_T U_{i,t} + (1-\gamma_{i,t})\, \psi_{NT} U_{i,t} \tag{4}$$

Denoting $\psi_T/\psi_{NT} = k$ the coefficient giving the relationship between two search effectiveness ($k > 1$as it is reasonable to assume that trained individuals are more efficient in their search), it follows that:

$$\psi U_{i,t} = [1 + \gamma_{i,t}(k-1)]\, \psi_{NT} U_{i,t} \tag{5}$$

Approximating the matching function as previously by a Cobb-Douglas form, taking logarithms of both sides and decomposing the mismatch parameter as previously ($\ln A_{i,t} = \alpha_0 + \mu_i + \lambda_t + \varepsilon_{i,t}$) leads to the following regression equation:

$$\begin{aligned} \ln M_{i,t} = \alpha_0 + \alpha_U \ln \psi_{NT} + \alpha_U \ln U_{i,t} + \alpha_V \ln V_{i,t} \\ + \alpha_U \ln \left(1 + \gamma_{i,t}(k-1)\right) + \mu_i + \lambda_t + \varepsilon_{i,t} \end{aligned} \tag{6}$$

The non-linear term in Equation (6) can be linearized by applying the second order Taylor's approximation, so

$$\ln \left(1 + \gamma_{i,t}(k-1)\right) \approx \gamma_{i,t}(k-1) - \frac{1}{2}(k-1)^2 \gamma_{i,t}^2$$

The equation (6) can then be rewritten as the following regression equation:

$$\ln M_{i,t} = \beta_0 + \beta_U \ln U_{i,t} + \beta_V \ln V_{i,t} + \beta_{TR}(\gamma_{i,t}) + \beta_{TR2}(\gamma_{i,t}^2) + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (7)$$

where $\beta_0 = \alpha_0 + \alpha_U \ln \psi_{NT}$, $\beta_U = \alpha_U$, $\beta_V = \alpha_V$, $\beta_{TR} = \alpha_U(k-1)$ and $\beta_{TR2} = -\frac{1}{2}\alpha_U(k-1)^2$.

Equation (7), representing the augmented matching function, will be estimated on Latvian data. Like before, $\beta_U$ and $\beta_V$ are elasticities of number of matches with respect to the size of the unemployment pool and available jobs. The impact of policy can be evaluated by the use of the semi-elasticity of outflows with respect to share of trained unemployed. This semi-elasticity is measured by:

$$\partial \ln M / \partial \gamma = \beta_{TR} + 2\beta_{TR2}(\gamma_{i,t}) \quad (8)$$

Positive and statistically significant RHS of (8) would suggest that training facilitates the matching process and increases outflows from unemployment, thus providing the arguments in favor of training and re-qualification programs.

### 2.3 Particular forms of matching process: Stock-Flow matching

The traditional version of the matching function, described above, assumes that outflows to employment are driven by the matching between the beginning of period *stocks* of unemployed and vacancies. Coles and Smith (1998), followed by Gregg and Petrongolo (2002) and Coles and Petrongolo (2003) discuss the appropriateness of this assumption and claim that the hiring process is not well captured by a simple "stock-stock" matching function. They show that flows (inflows of new vacancies and unemployed during the reference period) can play even a more significant role than stocks in determining the outflows to employment. These studies show on U.K. data that matching is realized between *stocks* and *flows*, rather then between *stocks* and *stocks* as predicted by a simple version of the matching function. Coles and Smith (1998), when estimating a log-linear matching function, find that only the *inflow of new vacancies*, but not the *stock of vacancies*, increases the job-finding rates for long-term unemployed. Gregg and Petrongolo (2002) by estimating quasi-structural outflow equations for unemployed and vacancies and allowing for higher exit rates of flows also provide an empirical support to stock-flow matching.

Along with empirical evidence Coles and Smith (1998) also develop a theoretical model which explains why trade at the labor market may result in matching between stocks and flows. We briefly provide here the basic intuition underlying this theoretical model, while a more detailed exposition can be found in the original article by Coles and Smith (1998) and in a matching function survey by Petrongolo and Pissarides (2001).

The key idea behind stock-flow matching relies on non-random patterns in unemployed search. To understand why such patterns in search behavior will result in stock-flow matching one should consider the unemployed who enters the unemployment pool. It is assumed that upon his arrival at the marketplace the job seeker does not contact employers at random (in contrast with traditional setting), but scans the bulk of advertisements (journals, newspapers, TV, employment agencies and ect.) before deciding where to apply. There are no frictions due to information imperfections, so unemployed can locate at no cost all appropriate jobs and apply to them. Moreover, Coles and Smith (1998) make a clear distinction between contact and stages in the hiring process. They assume that the heterogeneity between jobs and unemployed implies a positive probability that unemployed will not fit the requests of the employer. Thus there are two possible outcomes for the unemployed that has contacted several employers: (a) he may match with one of them or (b) he may remain unmatched. Let us consider the implications of these outcomes:

**(a)** if the job seeker have been accepted by the employer, he will be hired and thus outflow to employment. At the aggregate level, this job seeker is accounted in unemployed *flow* (as we have assumed that he has just entered the unemployment pool), while the job he has obtained has been accounted in *vacancy stocks* (as he has consulted only available job proposals, i.e. already existing at the market, at the moment of his arrival). Thus if the match is realized, it is a match between the *vacancy in stock* and the *job seeker in flow.*

**(b)** if the unemployed remains unmatched it means that his match (the job he will fit and that would suit him) does not exist on the market (recall that if job seeker has not been matched this is because he did not fit to *any* of selected employers, while applications have been sent to *all* jobs that have been considered as appropriate). Thus it is reasonable to suppose that the job seeker will wait for the inflow of new job proposals and try to locate his "match" among them, ignoring the old vacancies. In this case when the new vacancies will appear on the market, at the beginning of the next period, the unemployed will be accounted in *stocks* of unemployed and if he would find the appropriate job during this period, the match will be realized between *unemployed in stock* and *vacancy in flow.*

Thus, when old vacancies would match with new unemployed or new vacancies would match with old unemployed, at the aggregate level, we will observe stock-flow rather then stock-stock matching.

With regard to the estimation of stock-flow version of the matching function, it is suitable to retain the most basic specification originally proposed by Coles and Smith (1998). We using, as previously, a Cobb-Douglas form:

$$M_{i,t} = A_{i,t}\left(U_{i,t}^{S}\right)^{\alpha_{SU}}\left(U_{i,t}^{F}\right)^{\alpha_{FU}}(V_{i,t}^{S})^{\alpha_{SV}}(V_{i,t}^{F})^{\alpha_{FV}}$$

Technically, we simply augment the traditional specification with variables describing inflows of new unemployed and new opened job vacancies and estimate the following log-linear relationship:

$$\ln M_{i,t} = \alpha_0 + \alpha_{SU}\ln U_{i,t}^{S} + \alpha_{SV}\ln V_{i,t}^{S} + \alpha_{FU}\ln U_{i,t}^{F} + \alpha_{FV}\ln V_{i,t}^{F} + \mu_i + \lambda_t + \varepsilon_{i,t} \tag{9}$$

where $\alpha_{SU}$ and $\alpha_{SV}$ are elasticities with respect to the size of the stocks $U^S$ and $V^S$, while $\alpha_{FU}$ and $\alpha_{FV}$ measure the elasticities of outflows with respect to flow variables $U^F$ and $V^F$. The function exposes constant returns to scale if $(\alpha_{SU} + \alpha_{SV} + \alpha_{FU} + \alpha_{FV})$ equals unity.

Concerning the augmented matching function the same strategy can be employed. We assume a Cobb-Douglas matching function with separate elasticities of stocks and flows and normalize the search efficiency of new unemployed (flows) to unity:

$$M_{i,t} = A_{i,t}\left(\psi U_{i,t}^{S}\right)^{\alpha_{SU}}\left(U_{i,t}^{F}\right)^{\alpha_{FU}}(V_{i,t}^{S})^{\alpha_{SV}}(V_{i,t}^{F})^{\alpha_{FV}}$$

When decomposing the search efficiency of unemployed in stock as previously ($\psi = [1 + \gamma_{i,t}(k-1)]\,\psi_{NT}$) it simply turns to augment the equation (7) by flow variables. We will thus estimate the following regression equation:

$$\begin{aligned}\ln M_{i,t} = {} & \beta_0 + \beta_{SU}\ln U_{i,t}^{S} + \beta_{SV}\ln V_{i,t}^{S} + \beta_{FU}\ln U_{i,t}^{F} + \beta_{FV}\ln V_{i,t}^{F} \\ & + \beta_{TR}(\gamma_{i,t}) + \beta_{TR2}(\gamma_{i,t}^{2}) + \mu_i + \lambda_t + \varepsilon_{i,t}\end{aligned} \tag{10}$$

where $\beta_0 = \alpha_0 + \alpha_{SU}\ln\psi_{NT}$, $\beta_{SU} = \alpha_{SU}$, $\beta_{SV} = \alpha_{SV}$,$\beta_{FU} = \alpha_{FU}$, $\beta_{FV} = \alpha_{FV}$, $\beta_{TR} = \alpha_{SU}(k-1)$ and $\beta_{TR2} = -\frac{1}{2}\alpha_{SU}(k-1)^2$.

# 3 Data and Variables

Data used in this analysis originates from the regional data base of Latvian State Employment Agency[7], covers 33 Latvian administrative regions for a period from January 1998 to October 2003 on monthly basis. We use the following variables in our analysis:
*(i)* the **stock of unemployed** $U^S$ which is given as the number of unemployed at the beginning of the month; *(ii)* the **flow of unemployed** $U^F$

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

which refers to the number of individuals entering the unemployment pool during the current month (new unemployed); *(iii)* $V^S$ the **vacancy stocks** at the beginning of the month; *(iv)* the **vacancy flows** $V^F$ given as the number of new job offers that have been places through State Employment Agency during the month; *(v)* **outflows** $M$ measured by the number of registered unemployed exiting to employment during a month; *(vi)* a **policy variable** $PTU$ which corresponds to the share of trained unemployed in the pool.

The descriptive statistics being summarized in Table 1, let us clarify some points concerning definitions and patterns of certain variables as well as relations between them, revealed by our data.

### 3.1 Main components of the matching function: unemployed, vacancies and matches

Unemployment data covers only registered jobseekers (there is no information on non-registered jobseekers available on monthly basis). This may be thought as a serious limitation of our analysis since empirical evidence from transition economies[8] reports high level of job-to-job transitions and points out that employment pool in such countries is in large part sourced by the flows of non-registered job-seekers and those out-of labor force. This limitation, however, is unlikely to bias our results for several 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 thus in the first place available to registered unemployed. Third, in order to participate in any of employment promoting programs, one should be registered at the State Employment Agency.

Another issue on adequacy between unemployed and vacancy data concerns the qualification structure of the matching pools. In Latvia, the share of registered unemployed with manual occupation is above 80 percents (Table 3). On the other hand, vacancies posted through State Employment Agency usually refer to low-qualification jobs: 83 percent of reported vacancies concern manual jobs in Latvia. From this perspective, the matching function estimated in this study refers to a segment of labor market which to large extent excludes professional jobs.

In what concerns the outflows from unemployment, data reveal that on average about 3 percent of unemployed find jobs during a month. An outflow rate below 1 percent has been observed just once (Tukums district, March 1999), while the highest rates exceed 10 percent (Limbazi, December 1999; Saldus,

[8] Boeri (2001), Boeri and Terell (2002).

August 2000; Kuldiga, September 2002). Figure 3 reports mean transition rate for each of the 33 regions; Riga (the capital city of Latvia) and Saldus district top the list with about 5 percent of registered unemployed finding job every month. Figures 4 and 5 show the aggregate dynamics of matches, unemployed and vacancy stocks and flows. Outflows from unemployment seem to be quite sensible to the movements in vacancy inflows. More intuition on the role of flow variables can be derived from Table 4, which shows the turnover rates and correlations between different variables.

The observed unemployed turnover rate (ratio of the inflow to the stock) is 0.09, which is about eight times lower than reported for developed countries (for Great Britain see Gregg and Petrongolo (2002)). The inflows into unemployment in Latvia are actually important, but loose their significance when are compared to extremely high stock of unemployed (in some regions unemployment rate is above 20%). In contrast, the vacancy turnover rate is about 1.5, which is comparable to the rate reported for Great Britain (2.59 from Gregg and Petrongolo (2002)), and is 17 times higher than the unemployed turnover rate. This suggests that vacancies are filled very rapidly in Latvia. Moreover the correlation between matches and vacancy inflows is two times higher that the one with vacancy stocks. The above confirms the importance of the inflow of new vacancies in the process of job matching, approving it's relevance for our analysis.

### 3.2 Policy variable

To conclude the description of data and variables, let us have a closer look at the training policy variable used in the analysis. In order to evaluate the effects of training programs, the matching function has to be augmented with the share of trained unemployed. We construct a proxy for this share using two data sets: for month $t$ and region $i$, $CT_{i,t}$ is the number of persons completing training and re-qualification programs, while $TE_{i,t}$ is the number of trained individuals that have outflowed to jobs[9] during $t$. If the number of trained unemployed at the beginning of our sample period $TU_{i,0}$ would be known, we would simply add to this number $CT_{i,t}$ and subtract $TE_{i,t}$ every month, in order to obtain the number of persons, who have been trained, but are still unemployed at time $t$.

Since $TU_{i,0}$ was not available, we have used the difference between the number of persons completing training programs and the number of trained

[9]Available data from this set 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.

unemployed who have outflowed to employment over a long enough period (a year) as a proxy for the number of trained unemployed.

Let $CCT_{i,t}$ be a cumulated (over all past periods) sum of unemployed who have completed a training program in the region $i$, and let $CTE_{i,t}$ be the cumulated sum of trained individuals that have outflowed to jobs in the same region. Hence $TU_{i,t} = CCT_{i,t} - CTE_{i,t}$ is a proxy for the number of trained persons who, at the beginning of given month, are still unemployed. In our estimations we use $PTU_{i,t} = TU_{i,t}/U_{i,t}$ which is the proxy for the share of trained individuals in the unemployment pool. We construct this policy variable starting from 1:1998, but perform estimations on the period starting from 1:1999, to have a reasonable proxy for initial share of trained unemployed[10].

In general the majority of studies that perform policy evaluations use as policy variables expenditure on ALMPs or number of current participants in ALMPs. These studies are often concerned by the problem of endogeneity[11]. The ALMPs is likely to be an endogenous variable since local labor market offices may raise their expenditures on these programs if labor market situation becomes worse (Hagen (2003)). However this serious problem does not seem to concern our study as in the $PTU$ variable we account for unemployed that have completed training. Training programs last about 3-4 months. Thus if authorities react to worsening in current labor market situation and increase expenditures on ALMPs (and number of participants) at period $t$, these new participants will only appear in our variable $PTU_{i,t+4}$ (i.e. in 4 months). Thus there is no link between current decrease of matches and increase in our policy variable.

Figure 6 suggests a positive relationship between regional outflow-to-job rates and the share of trained unemployed in the pool (variables are averaged over time). The best performance in terms of training efficiency is observed in Saldus, Limbazi, and Valmiera districts and in the capital city Riga. In these areas the share of trained unemployed lies between 12 and 18 percent, and monthly outflow-to-job rate is around 5 percent. By contrast the districts located in the depressed eastern part of Latvia (Daugavpils, Rezeknes, Ludzas, Preilu, Balvu, Kraslavas) and the port city of Liepaja are

[10]It is quite likely that at the end of estimation period, we over-evaluate the policy variable, by accounting in $TU_{i,t}$ for the trained unemployed who have transited to other labor market states (non-activity, participation in other programs). To control for this issue we have run the estimations on a shorter period (1:1999 - 1:2002), and find our conclusions unchanged.

[11]As Heckman et al.(1999) remark, the problems faced by evaluation studies are numerous. The one that could be thought to lie in the field of our concerns is for example the selection bias. In our study data limitations do not allow to address the selection issue, but it is unlikely that this compromise our results: most of training is either state language, or computer literacy, or accounting courses and it is unlikely that without these skills the same persons would be equally able to find jobs.

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. Districts of Ogre and Gulbene substantially promote training programs, but the impact does not seem to be sufficient. These conclusions are of course preliminary - a more rigorous analysis is performed in the next section.

# 4 Estimation procedure and results

## 4.1 Estimated models

Let us first recall the relationships that we estimate in our study. In order to evaluate the impact of training and re-qualification programs on outflows from unemployment we estimate the augmented matching function given by equation (7).

$$\ln M_{i,t} = \beta_0 + \beta_U \ln U_{i,t} + \beta_V \ln V_{i,t} + \beta_{TR}(\gamma_{i,t}) + \beta_{TR2}(\gamma_{i,t}^2) + \mu_i + \lambda_t + \varepsilon_{i,t}$$

Estimated model 1: Stock-Stock matching

$PTU_{i,t}$ stands for the share of trained unemployed (denoted $\gamma$ previously) while $PTUSQ_{i,t}$ is squared (denoted $\gamma^2$).

On the other hand, the exposition on stock-flow matching and the evidence supplied by descriptive statistics raise the question of the relevance of the standard matching function in Latvian case. We address this issue by allowing for stock-flow matching in our analysis. We thus also estimate the following equation which represents the stock-flow augmented matching function (corresponds to the equation (10) in previous section):

$$\begin{aligned}\ln M_{i,t} = \beta_0 &+ \beta_{SU} \ln U_{i,t}^S + \beta_{SV} \ln V_{i,t}^S + \beta_{FU} \ln U_{i,t}^F + \beta_{FV} \ln V_{i,t}^F \\ &+ \beta_{TR}(\gamma_{i,t}) + \beta_{TR2}(\gamma_{i,t}^2) + \mu_i + \lambda_t + \varepsilon_{i,t}\end{aligned}$$

Estimated model 2: Stock-Flow matching

## 4.2 Estimation procedure

We use cross sectional time series (CSTS), which allows exploiting both regional and time dimensions of our data. Since CSTS data typically exhibit group-wise heteroscedastic, contemporaneously and serially correlated residuals, we must take into account the existence of a non-spherical error structure.

We first run the fixed effect regression by Ordinary Least Squares (OLS), but taking into account that error structure does not conform to OLS assumptions, we use further special procedures to bring necessary corrections. In this order we use two methods: Parks-Kmenta method and Beck-Katz PCSE method.

Parks-Kmenta method performs the estimation by Generalised Least Squares (GLS) and consists in applying two sequential transformations on the estimated model. The first transformation removes the serial correlation, while second corrects simultaneously for contemporaneous correlation and heteroscedasticity[12]. Parks-Kmenta method has been revised by Beck and Katz (1995), (1996). They confirm that GLS have optimal properties for CSTS data, but remark that GLS can only be used when the variance-covariance matrix of errors is known. Otherwise it should be estimated from the sample implying the use of Feasible Generalised Least squares (FGLS) instead of GLS. Beck and Katz (1995), (1996) claim that although FGLS uses the estimate of the error process (thus giving consistent and efficient coefficient estimates), the FGLS formula for standard errors assumes variance-covariance matrix of the errors to be known (and not estimated). As a result the application of FGLS leads to downwards biased standard errors.

Beck and Katz (1995),(1996) propose a less complex method, retaining OLS parameter estimates (consistent but inefficient) and replace OLS standard errors by panel-corrected standard errors (PCSE). We present the estimations based on both Parks-Kmenta[13] and Beck -Katz methods. We also include regional and time fixed effects in our estimated models: Region fixed effects capture unobserved region-specific factors, remove average region effect and focus the model on within region variation over time. Time fixed effects capture developments over time that is common to all regions. Combining both time and region specific effects give the model with pure effects of explanatory variables, as all unobserved effects (region and time) are removed.

### 4.3 Estimation results

We can now turn to the discussion of estimation results. As previously discussed we estimate the augmented matching function in two specifications representing stock-stock and stock-flow matching functions (Table 5).

[12]See Beck and Katz (1995)

[13]GLS estimates account for the presence of heterocsedastic panels, while PCSE results give standard errors corrected for both heteroscedasticity and contemporaneous correlation across panels. The presence of panel specific $AR1$ process is accounted for in both GLS and PCSE procedures.

Generally, constant returns to scale can not be rejected in most specifications, while the absence of region and time specific effects is always rejected. All reported tests indicate the presence of serial correlation, groupwise heteroscedasticity and panel-level correlation in disturbances, both in traditional stock-stock and stock-flow matching functions.

Considering the main components of the matching function, the estimation results show that the outflows from unemployment are driven in Latvia by matches between the stock of unemployed and the inflow of new vacancies. These variables have positive and statistically significant impact on the number of matches, while the estimated effect of the flow of unemployed and vacancy stock is low, wrongly signed and statistically insignificant in most specifications.

The elasticity of outflows with respect to unemployed pool is slightly above one in the most robust specifications (GLS), while the elasticity with respect to vacancy inflow is around 0.13. Table 2 gives the descriptive statistics on data aggregated over all regions (time averaged values for whole Latvia) and allows establishing a more clear idea on the scale of the effects. One percent increase in unemployed stock, or 980 extra persons, would raise outflows by 1.09 percent, or 35 extra matches. On the other hand, a one percent increase in the inflow of new vacancies (which corresponds to 41 new vacancies) results in 4 more matches per month. Thus, one out of 28 extra unemployed will find a job, and one out of ten additional new vacancies will be filled within a following month[14].

Turning to the policy evaluation issues, our results display positive and statistically significant impact of the share of trained unemployed on outflows to employment. Moreover these results are robust with respect to the chosen specification and do not differ significantly whatever traditional or stock-flow form of the matching function is employed.

The semi-elasticity of outflows with respect to the share of trained unemployed varies[15] between 1.05 and 0.27 with the mean value of 0.60. One percentage point increase in the share of unemployed would increase matches by 0.6 percents[16]. Making use again of aggregated Latvian data from Table 2,

[14]It might be thought that the results contrast the statistics on very high vacancy turnover rates in Latvia. Some precisions should be brought in this respect: our results only refer to the matches between new vacancies and registered unemployed, while total vacancy outflows (appearing in turnover data) are likely to be sourced by the matches with employed, unregistered job seekers or with those from out-of-labor force.

[15]The semi-elasticity can be calculated from estimated coefficients. We use the estimates given by GLS procedure for stock-flow model employing the equation (8): $\partial \ln M/\partial\gamma = 1.16 + 2 * (-1.88)\gamma$ . We can now calculate the semi-elasticity taking into account that the share of trained unemployed varied in Latvia around 0.15 with the minimum 0.03 and maximum 0.237 (Table 2).

[16]Formally the semi-elasticity of $Y$ with respect to $X$ gives the increase (in %) in variable

we can derive the following conclusions: in the share of trained unemployed would increase from 0.15 (mean value for Latvia) to 0.16, which represents about 980 more trained unemployed, this will result in 19 more matches in the following month. Thus on average about 50 persons more should be trained in order to generate one more additional match monthly. This number may however be higher in the periods when the share of trained unemployed is low, since the elasticity of outflows with respect to the policy variable is negatively related to the latter. To address the question on how beneficial is the promotion of the training programs at the aggregate level; we have performed a cost-benefit analysis (Appendix 6.2). We find that, when the share of trained unemployed is already high (above 20 percent), increasing this share by one percentage point (about 900 unemployed more to train) would create about 140 additional transitions to employment in the following year. The training costs could be covered if the additionally matched workers would keep the jobs for at least 6 months.

Our results support a substantial role of training programs in fighting unemployment while the available macroeconomic studies on other transition economies do not seem to have reached the consensus on this issue[17]. Positive effects of different (including non-training) ALMPs programs are found by Burda and Lubyova (1995), Svejnar, Terrell and Munich (1995), Boeri and Burda (1996), while a positive impact of training is only pointed out in Eastern Germany by Steiner and al. (1998). On the contrary, these programs do not seem to have any significant impact on re-employment in Poland and Bulgaria (Lehmann (1995), Gora and al. (1996), Lenkova (1997)). It should be noted, however, that all above listed studies operate with the traditional matching function and most of them choose the active policy expenditures as explanatory variable for the evaluation of policy efficiency. These methodological differences can be responsible for conflicting findings. Another reason can be cross-country differences in composition of the pool of unemployed and the structure of labor demand.

Concerning regional patterns of matching and efficiency of training, Table 6 presents three best and three worst regions in terms of matching efficiency, both with and without controlling for training. Daugavpils, Ludzas and Rezeknes districts, according to specifications without training, have the lowest matching efficiency among all regions and perform significantly worse

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$Y$ against the 1 unit increase in variable $X$. In our case this latter is the share of trained unemployed. Therefore one unit increase corresponds in our case to 1 percentage point increase of this share.

[17]See Puhani (1999) for a more detailed survey on the results of policy evaluations in transition CEE countries on macroeconomic level. Regarding the microeconomic studies, the positive role of training is reported systematically for the OECD and transition countries (see Fay(1996) for OECD countries, Betcherman, Olivas, Dar (2004) for OECD, transition and development countries, Leetmaa, Vork (2003) for Estonia, Kluve, Schmidt, Lehmann (1999) for Poland).

than the capital city Riga. When training is accounted for in the model, Daugavpils and Rezeknes districts are still the worst performers, while the performance in Ludzas district is not significantly different from the one in Riga city. This suggests that lack of training is at least in part responsible for the poor performance in Ludzas district.

The highest, among all regions, matching efficiency is displayed by Limbazu, Saldus and Valkas districts, along with the capital city of Riga (which we use as reference). The results confirm that, while generally the performance in these regions is not significantly different from the one in the capital city, the efficiency gap (in favor of three regions) seems to increase when training is included among the regressors.

## 5 Conclusions and discussion

We estimated an augmented matching function using 1998-2003 monthly data from 33 Latvian municipalities. Our estimations allow to learn about the process of matching between workers and firms in Latvia and to conclude on the role of active labor market policy on the matching process.

Recent developments in related literature by Coles and Smith (1998), Gregg and Petrongolo (2002) and Coles and Petrongolo (2003) suggest that traditionally estimated matching functions, which determine the outflows from unemployment by beginning of period stocks of unemployed and vacancies, may be misspecified. They show that not only stocks but also flows of unemployed and vacancies intensively participate in the matching process. Following this intuition, which is enforced by the descriptive statistics on our data, we estimate both stock-stock and stock-flow matching functions.

When estimating the matching function in it's traditional stock-stock setting, we find that the stock of vacancies has no 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 countries (see Munich et al.(1999)). The estimation including both stocks and flows as explanatory variables confirms our intuition for the presence of stock-flow patterns in Latvian matching process: the key determinants of outflows to employment are the stock of unemployed and the inflow of new vacancies.

The theory underlying the stock-flow matching, derived from Coles and Smith (1998), suggests that such patterns result from the non-random nature of the matching process. One of the main assumptions concerns the presence of systematic elements in the behavior of unemployed: they only consider new job proposals (ignoring the old) when searching for jobs. Although our estimations confirm that matching in Latvia is realized between the stocks of unemployed and the flows of new vacancies, it is difficult to derive the straightforward conclusion on the non-randomness of matching process. Another look on vacancy data highlights that in Latvia the majority of vacancies are new vacancies. Most of these are filled rapidly (within one month) and the remaining stock is therefore insignificant, which implies a high vacancy turnover rate. We believe, therefore, that stock-flow patterns in matching in Latvian labor market do not result from differentiation between old versus new vacancies by the unemployed, but from dominant role of labor demand.

Generally speaking the above findings suggest a stock-flow setting to be the only relevant for describing a marching process in a high unemployment -low labor demand environment, which characterizes the majority of transition economies.

Recent cuts in active labor market policy expenditures have substantially affected public training programs in Latvia. Our results conflict with the policymaker's arguments based on supposed inefficiency of the programs: in fact we find positive and statistically significant effects of training on outflows from unemployment.

Moreover cross-region comparisons reveal that regions in Latvia are homogenous neither in terms of matching efficiency nor in terms of efficiency of training programs. Regions which 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 depressed eastern part of Latvia, namely in Daugavpils and Rezeknes districts.

Several conclusions with regard to active labor market policy programs can be derived by policymakers from this paper. The patterns in the matching process point out the extremely important role played by the new job vacancies in the outflows from unemployment. This suggests intensive use of programs susceptible to promote the creation of new jobs (subsidized jobs, credits to self-employed etc.). On the other hand, despite the driving role of labor demand, training has still an important effect on unemployment reduction. Moreover, according to the cost benefit analysis, program costs can be easily covered. Thus programs are relatively beneficial at the aggregate level. Therefore the further promotion of training programs is strongly suggested.

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# 6 Appendixes

## 6.1 Tables

Table 1: **Descriptive statistics on panel data (regions)**

| Variable | Mean | Variation | S.d. | Min | Max | Obs | |
|---|---|---|---|---|---|---|---|
| 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 |
| Inflow 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 |
| PTU (training) | 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 |

Notes: Between variation is constructed by calculating the means over time for every region ($\overline{x_i}$) ;within variation represents the deviation of individual observations from region's average ($x_{it} - \overline{x_i} + \overline{\overline{x}}$) and can naturally be negative.

Table 2: **Descriptive statistics on data aggregated for whole Latvia**

| Variable | Mean | S.d. | Min | Max | Obs. | |
|---|---|---|---|---|---|---|
| Outflows from unemployment to employment | 3194 | 570 | 2297 | 4832 | $N_t$ | 70 |
| Unemployed stock | 98032 | 10152 | 85096 | 121760 | $N_t$ | 71 |
| Inflow of new unemployed | 9084 | 1424 | 6307 | 15334 | $N_t$ | 70 |
| Stock of vacant jobs | 3006 | 688 | 1721 | 4520 | $N_t$ | 71 |
| Inflows of new vacancies | 4111 | 732 | 2539 | 5764 | $N_t$ | 70 |
| PTU (training) | 0.150 | 0.072 | 0.003 | 0.237 | $N_t$ | 71 |

Notes: All variables represent the aggregated for whole Latvia (over all regions)sample period (1:1998-6:2003) time averages.

Table 3: **Composition of vacant jobs and unemployed by occupation**

| | **Vacancies (flow)** | | **Unemployed (stock)** | |
|---|---|---|---|---|
| Year | Non-manual | Manual | Non-manual | Manual |
| 2000 | 21.5 | 78.5 | 20.1 | 79.9 |
| 2001 | 15.2 | 84.8 | 19.1 | 80.9 |
| 2002 | 15.6 | 84.4 | 18.8 | 81.2 |
| 2003 | 16.4 | 83.6 | 18.0 | 82.0 |

Notes: (a) *"Manual"* for vacancies includes military professions; (b) *"Manual"* for unemployed includes military professions and those without any profession; (c) For year 2003 data covers only the first 6 months.

Source: State Employment Agency of Latvia

Table 4: **Aggregate correlations and other statistics**

| Correlations of number of matches ($M$) with: | |
|---|---|
| Inflow of unemployed $U^F$ | $-0.17$ |
| Stock of unemployed $U^S$ | 0.23 |
| Inflow of vacancies $V^F$ | 0.45 |
| Stock of vacancies $V^s$ | 0.22 |
| **Mean values:** | |
| Vacancy monthly turnover rate $\left(V^F/V^S\right)$ | 1.51 |
| Unemployed monthly turnover rate $\left(U^F/U^S\right)$ | 0.09 |
| Monthly hiring rate $\left(M/U^S\right)$ | 0.03 |

Source: Calculations based on Latvian State Employment Agency data

Note: Constructed on monthly data, 1999-2003.

Table 5: **Estimation results: The augmented matching function**

| | Stock-stock matching function | | | | Stock-flow matching function | | | |
|---|---|---|---|---|---|---|---|---|
| Dep.var: | FE | FE | GLS | PCSE | FE | FE | GLS | PCSE |
| ln outflows | I | I-a | II | III | I | I-a | II | III |
| ln unemployed (stock) | 0.87 *** (0.097) | 0.91 *** (0.099) | 1.02 *** (0.091) | 1.04 *** (0.121) | 0.91 *** (0.096) | 0.94 *** (0.098) | 1.09 *** (0.087) | 1.09 *** (0.113) |
| ln unemployed (flow) | – | – | – | – | −0.11*** (0.040) | −0.10*** (0.040) | −0.04 (0.032) | −0.06* (0.039) |
| ln vacancies (stock) | −0.01 (0.011) | −0.01 (0.011) | 0.01 (0.008) | 0.00 (0.009) | −0.03** (0.011) | −0.02** (0.011) | −0.01 (0.008) | −0.00 (0.009) |
| ln vacancies (flow) | – | – | – | – | 0.13 *** (0.020) | 0.13 *** (0.020) | 0.15 *** (0.012) | 0.14 *** (0.014) |
| PTU (share trained unem.) | 1.04 *** (0.429) | 0.97 *** (0.432) | 1.12 *** (0.461) | 1.00 * (0.599) | 1.07 *** (0.408) | 1.01 *** (0.411) | 1.16 *** (0.433) | 1.07 ** (0.539) |
| PTUSQ (PTU squared) | −2.34*** (0.765) | −2.20*** (0.768) | −1.97*** (0.854) | −1.68 (1.041) | −2.25*** (0.738) | −2.12*** (0.741) | −1.88** (0.813) | −1.73* (0.964) |
| constant | −1.70* (0.999) | −2.92*** (0.913) | −3.43*** (0.947) | −3.53*** (1.249) | −2.14** (1.061) | −3.14*** (0.955) | −4.92*** (0.941) | −4.52*** (1.209) |
| Number of observations | 1777 | 1719 | 1777 | 1777 | 1776 | 1718 | 1776 | 1776 |
| $V(U_i)$ | 0.52 | 0.44 | | | 0.49 | 0.45 | | |
| $R^2$ | 0.70 (0.31/0.81) | 0.56 (0.32/0.76) | | 0.94 | 0.73 (0.35/0.84) | 0.56 (0.36/0.78) | | 0.93 |
| Returns to scale | 0.86 | 0.90 | 1.03 | 1.04 | 0.90 | 0.95 | 1.21 | 1.17 |
| CRS (F-test) | 2.17 | 1.13 | 0.12 | 0.12 | 0.76 | 0.30 | 5.03** | 1.76 |
| Region effects | 52.41*** | 27.77*** | 974.11*** | 1423.90*** | 30.75*** | 21.55*** | 771.42*** | 959.19*** |
| Time effects | 58.13*** | 57.48*** | 712.96*** | 397.36*** | 48.23*** | 47.72*** | 616.78*** | 393.77*** |
| $GR.HET$ | 564.27*** | 558.76*** | 695.49*** | – | 690.17*** | 661.77*** | 903.31*** | – |
| $BP\ LM$ | 743.60*** | 663.83*** | 761.60*** | – | 693.06*** | 624.95*** | 721.51*** | – |
| LM5 (AR1 FE) | 13.11*** | 12.63*** | 13.73*** | | 12.76*** | 12.35*** | 14.13*** | |
| $PHO(AR1)$ | | | 0.27 | 0.27 | | | 0.25 | 0.25 |

Notes:
I - Fixed effects with region and time (monthly dummies)specific effects.
I-a - Fixed effects with region and time (monthly dummies)specific effects; the capital city (Riga) excluded from the sample.
II - FGLS model with region and time fixed effects, allowing for groupwise heteroscedasticity and panel specific error autocorrelation (AR1).
III - PCSE : Prais -Winsten regression with panel corrected standard errors (corrected for heteroscedasticity and contemporaneous correlation between panels and panel specific(AR1)), with region and time specific effects.

- Omitted region: in the model I-a Riga district, in the rest Riga city
- Standard errors in parentheses: for FE models (I,I-a) robust standard errors are reported. For PCSE models (III) standard errors corrected for heteroscedasticity, cross sectional correlation and panel specific AR1 are reported.
- ***, **, * - estimates significantly different from zero at 1,5, 10 percent level respectively.
- $V(U_i)$ fraction of variance due to region specific effects.
- $R^2$: R Squared (Overall); Within/Between reported in parentheses for models I et I-a)
- CRS: F-test for constant returns to scale (the sum of first 2 coefficients=1 for stock- stock model; the sum of first 4 coefficients=1 for stock-flow model)
- Region effects: test for inclusion of region specific dummy variables
- Time effects: test for inclusion of month dummies
- GR HET: modified Wald test for group wise heteroscedasticity (Greene 2000, 598)
- BP LM: Breuch –Pagan LM test for contemporaneous correlation in residuals of fixed effect or GLS model (Greene 2000, 601)
- LM5(AR1 FE): Baltagi test for autocorrelation in fixed effect model.
- PHO (AR1): Averaged autocorrelation coefficient.

Table 6: **Estimation results: Regional performance**

| | FE | | FE | | GLS | | PCSE | |
|---|---|---|---|---|---|---|---|---|
| | I | | I-a | | II | | III | |
| Dep.var: ln outflows | With training | Without training | With training | Without training | With training | Without training | With training | Without training |
| ln unemployed (stock) | 0.91 *** (0.096) | 0.83 *** (0.069) | 0.94 *** (0.098) | 0.86 *** (0.072) | 1.09 *** (0.087) | 0.95 *** (0.059) | 1.09 *** (0.113) | 0.95 *** (0.083) |
| ln unemployed (flow) | −0.11*** (0.040) | −0.11*** (0.039) | −0.10*** (0.040) | −0.10*** (0.040) | −0.04 (0.032) | −0.04 (0.032) | −0.06* (0.039) | −0.07* (0.039) |
| ln vacancies (stock) | −0.03** (0.011) | −0.03*** (0.011) | −0.02** (0.011) | −0.03*** (0.011) | 0.01 (0.008) | 0.00 (0.008) | 0.00 (0.009) | 0.00 (0.009) |
| ln vacancies (flow) | 0.13 *** (0.020) | 0.13 *** (0.020) | 0.13 *** (0.020) | 0.13 *** (0.020) | 0.15 *** (0.012) | 0.15 *** (0.012) | 0.14 *** (0.014) | 0.14 *** (0.014) |
| PTU (share trained unem.) | 1.07 *** (0.408) | – | 1.01 ** (0.411) | – | 1.16 *** (0.433) | – | 1.07 *** (0.539) | – |
| PTUSQ (PTU squared) | −2.25*** (0.738) | – | −2.12*** (0.741) | – | −1.88** (0.813) | – | −1.73** (0.964) | – |
| constant | −2.14* (1.061) | −1.22 (0.778) | −3.14*** (0.955) | −2.37*** (0.701) | −4.92*** (0.941) | −3.31*** (0.629) | −4.52*** (1.209) | −3.31*** (0.878) |
| | Three regions with the highest matching efficiency | | | | | | | |
| Limbazhu district | −0.30 (0.326) | −0.53** (0.259) | 0.47 ** (0.200) | 0.34 ** (0.157) | 0.65 ** (0.273) | 0.22 (0.200) | 0.46 (0.343) | 0.07 (0.261) |
| Saldus district | −0.36 (0.336) | −0.61** (0.260) | 0.42 ** (0.211) | 0.28 ** (0.159) | 0.67 ** (0.295) | 0.20 (0.213) | 0.48 (0.373) | 0.07 (0.285) |
| Valkas district | −0.31 (0.322) | −0.53** (0.257) | 0.47 ** (0.194) | 0.35 ** (0.153) | 0.71 ** (0.276) | 0.28 (0.206) | 0.52 (0.350) | 0.14 (0.274) |
| | Three regions with the lowest matching efficiency | | | | | | | |
| Daugavpils district | −1.19*** (0.263) | −1.40*** (0.204) | −0.44*** (0.134) | −0.54*** (0.098) | −0.38* (0.226) | −0.75*** (0.163) | −0.55* (0.283) | −0.89*** (0.211) |
| Ludzas district | −1.07*** (0.257) | −1.26*** (0.208) | −0.33** (0.129) | −0.41*** (0.103) | −0.23 (0.219) | −0.57*** (0.166) | −0.42 (0.268) | −0.72*** (0.208) |
| Rezeknes district | −1.09*** (0.211) | −1.25*** (0.166) | −0.35*** (0.085) | −0.41*** (0.064) | −0.37** (0.184) | −0.67*** (0.137) | −0.53** (0.227) | −0.79*** (0.172) |

Notes:
I - Fixed effects with region and time (monthly dummies) specific effects.
I-a Fixed effects with region and time (monthly dummies) specific effects; the capital city (Riga) excluded from the sample.
II - FGLS model with region and time fixed effects, allowing for groupwise heteroscedasticity and panel specific error autocorrelation (AR1).
III - PCSE : Prais -Winsten regression with panel corrected standard errors (corrected for heteroscedasticity and contemporaneous correlation between panels and panel specific (AR1)),with region and time specific effects.

- 1776 observations
- standard errors in parentheses : for FE models (I, I-a) robust standard errors are reported; for PCSE models (III) the errors corrected for heteroscedasticity, cross sectional correlation and panel specific AR1 are reported.
- ∗∗∗, ∗∗, ∗ - estimates significantly different from zero at 1,5,10 percent level respectively.

## 6.2 A simple example of training costs and benefits

In order to obtain a more exact idea on the costs and benefits of training program promotion, we propose an applied example. According to our estimation results, the semi-elasticity of outflows with respect to the share of trained unemployed is a decreasing function of this share. It is therefore interesting to consider in our example the "worst scenario", when the share of trained individuals in unemployed pool is high and thus outflows are the most inelastic. In the beginning of 2002 the share of trained unemployed have reached 0.213. Taking into account that the maximum value reached by this variable during the period 1998-2003 was 0.237, the year 2002 seems to fit perfectly our requirements. We thus consider the application for the year 2002. We use yearly data rather than monthly in order to obtain a clearer picture. Table 7 displays some elements of Latvian statistics and some derived numbers, which will be useful for further considerations.

Table 7: **Some statistics elements**

| | Low elasticity 2002 | Higher elasticity 2001 |
|---|---|---|
| Number of unemployed / year beginning | 91642 | 93283 |
| Share of trained unemployed / year beginning ($\gamma$) | 0.213 | 0.174 |
| Number of unemployed corresponding to increase | (0.213 to 0.223) | (0.174 to 0.184) |
| of 1 percentage point in $\gamma$ | 916 | 933 |
| Average expenditure per participant in training program in Ls./ previous year | 434 | 478 |
| Semi-elasticity of outflows with respect | for $\gamma$=0.213 | for $\gamma$=0.174 |
| to share of trained unemployed ($\eta$) | 0.36 | 0.51 |
| Outflows from unemployment/ during current year | 38997 | 39462 |
| Number of unemployed corresponding to increase of $\eta$ percents in outflows | 140 | 201 |
| Average GDP at current prices in mln. Ls / current year | 5689.4 | 5168.3 |
| Number of employed / current year | 989000 | 96000 |

Source: Central Statistical Bureau of Latvia and authors' calculations.

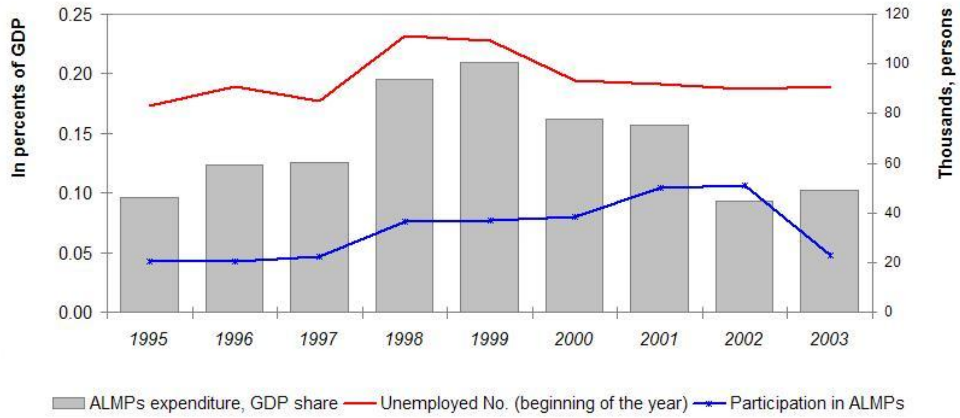
The number of trained unemployed in the beginning of year 2002 was 19520 and corresponded to 21.3 percents of unemployed. In order to increase this share by one percentage points (from 21.3 to 22.3) the state employment agencies should have trained 916 more unemployed, which would cost in 2001 (when training would have taken place) 397544 Ls [18]. The estimated semi-elasticity implies that one percentage point increase in share of trained individuals would increase outflows by 0.36 percents: the outflows would increase by 140 during 2002. According to Latvian Statistics, in 2002 each employed have generated monthly 479 Ls in terms of GDP. Consequently,

[18] 1 Latvian Lat (Ls) makes approximately 1.49 Euros (EUR).

each of additionally trained unemployed should work at least 6 months for the training costs to be covered. Obviously, some of shifted unemployed would get longer work contacts, creating positive surplus in the economy. Thus, even in the "worst scenario" case promoting training seems to be beneficial at the aggregate level. We have also run the same kind of analysis for the "better case": for lower values of policy variable and thus higher elasticity of outflows. We took as example the year 2001, when the share of trained unemployed has only been 0. 174. In this case we find that the employment period required to break-even the training costs would drop below 5 months.

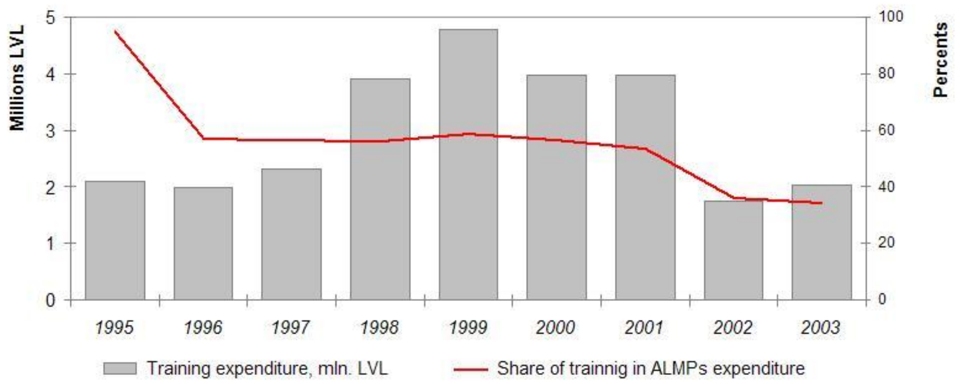
### 6.3 Figures

Figure 1: Unemployment, ALMPs expenditure and participation



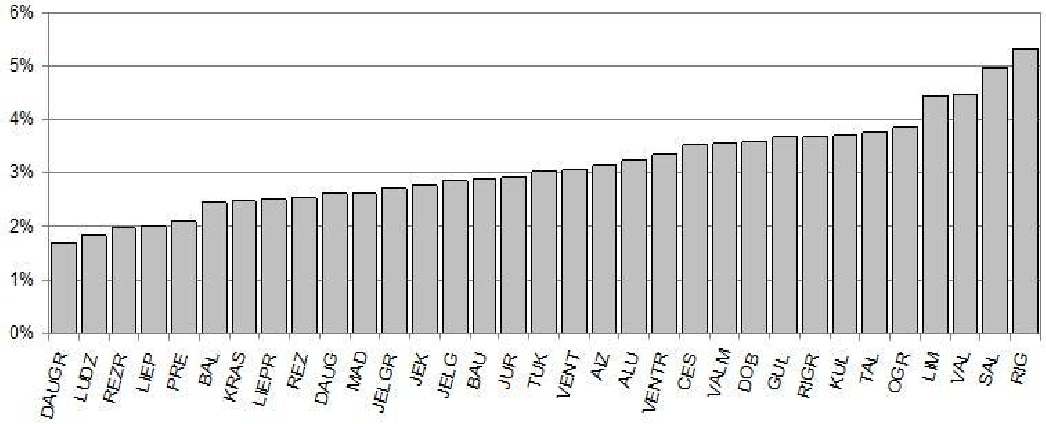

Source: State Employment Agency of Latvia

Figure 2: Training expenditure



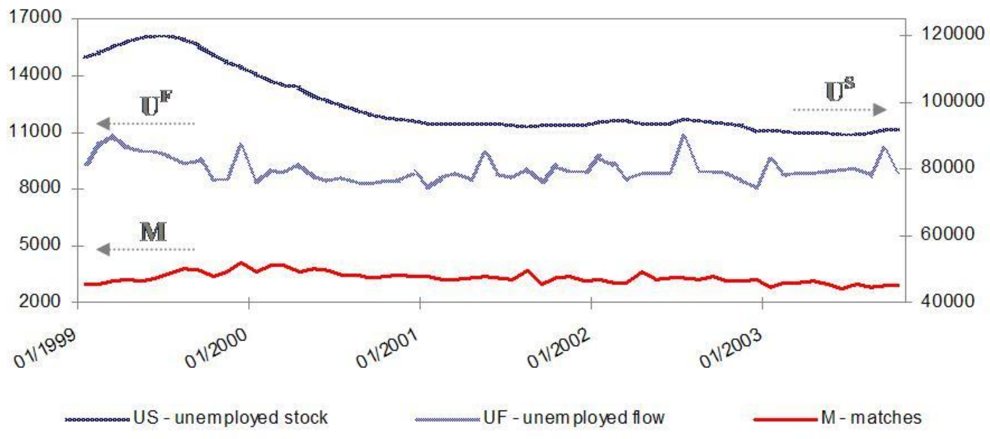

Source: State Employment Agency of Latvia

Figure 3: Mean outflow rate by region



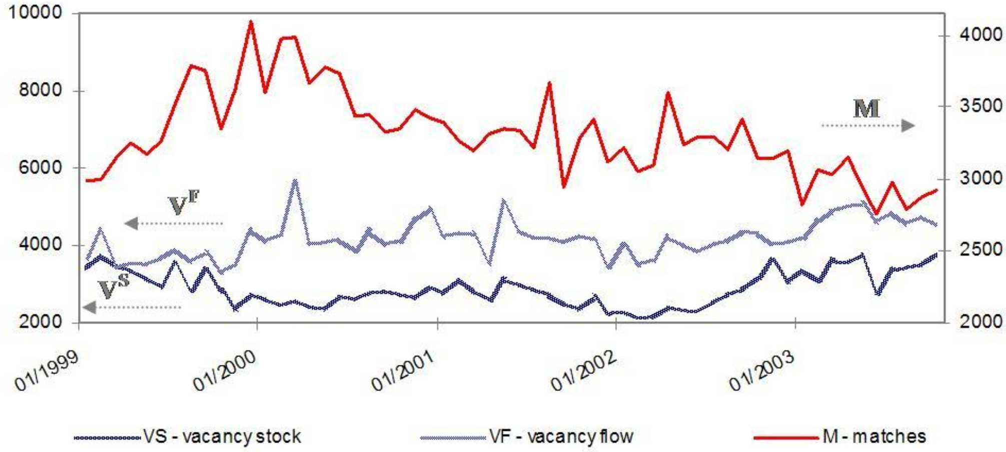

Source: State Employment Agency of Latvia
Note: Period (01:1998 - 10:2003)

Figure 4: Unemployment (stock and flows), outflows to employment



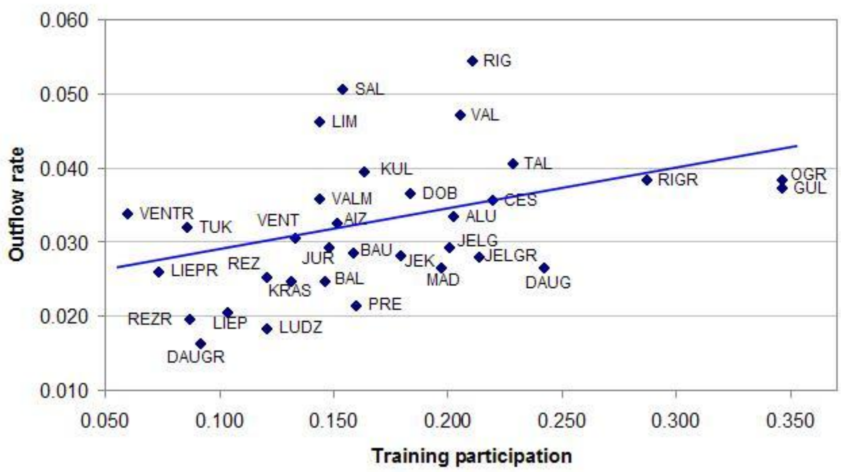

Source: State Employment Agency of Latvia data series
Note: Data seasonally adjusted (X11)

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




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

Figure 6: Outflow rate and participation in training by region




Source: State Employment Agency of Latvia data series
Note: mean values for the period (01:1999-10:2003)

Figure 7: Latvian districts by unemployment rate on April1, 2002


Source: State Employment Agency of Latvia